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Essays on the Economics of Forced Displacement and Conflict

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Abstract

In Chapter 1, we analyze the determinants of the internal mobility of refugees in Turkey. We track down this mobility relying on geolocalized mobile phone calls data and bring these measures to a micro-founded gravity model in order to estimate the main drivers of refugee mobility across 26 regions in 2017. Our results show that the movements of refugees are sensitive to income differentials and contribute therefore to a more efficient allocation of labor across space. Comparing these findings with those of individuals with a non-refugee status, we find that refugees are more sensitive to variations of income at origin and to distance, while less responsive to changes in income at destination. These findings are robust to the way mobility is inferred from phone data and to the choice of the geographical unit of investigation. Further, we provide evidence against some alternative explanations of mobility such as the propensity to leave refugee camps, transit through Turkey, social magnet effects and sensitivity to agricultural business cycles.

In Chapter 2, we exploit annual variations in the presence of refugees to approximate the resulting changes in diversity in the refugee-hosting areas across 23 countries in sub-Saharan Africa. We then assess the relationship between the refugee-corrected diversity indices and the likelihood of conflict between 2005 and 2016. In line with our theoretical framework, the refugee-corrected polarization exacerbates the risk of conflict. A one standard deviation increase in the polarization index raises the incidence of violent conflict by 5 percentage points. Such an effect corresponds to a 10 percent increase, at the mean. The opposite effect is found for the fractionalization index. Our results should not be interpreted as evidence that refugees *per se* impact the likelihood of violence. Indeed, we do not find any significant correlation between the number of refugees and the occurrence of conflict. Instead, our results point to the risk of conflict when refugees exacerbate ethnic polarization in the hosting communities. On the contrary, a situation where refugee flows raises the level of ethnic fractionalization is likely to see an attenuated risk of violence. This certainly calls for specific interventions in refugee-hosting and polarized communities. We also conduct additional analysis based on individual data and recent COVID-related protests. Results tend to support aggregate results. Refugee-corrected polarization raises the likelihood of experiencing physical assault and interpersonal crime by 2.7 resp. 4.2 percentage points, while no effect can be found for ethnic attachment and trust. Finally, the relevance of our results in the context of the COVID-19 pandemic is explored.

In Chapter 3, we study the impact of independent media networks on political accountability during the Arab Spring across the Middle East and North Africa region. The study focuses on two major media networks in the Arab world: Al Jazeera and Al Arabiya. Political accountability is proxied using principally a measure of protests. Data on both political accountability measures and the media networks derive from the Arab Barometer surveys. The regional-level analysis is based on Jordan, Lebanon and Palestine due to data availability. The study uses regional ruggedness as an instrumental variable for the non-random use of independent media among individuals. Results are estimated using a Two-Stage least Squares (2SLS)

regression analysis and indicate a positive and significant impact of independent media on political accountability. Several extensions are performed. First, the analysis is replicated for the impact of state media networks and results suggest a significant negative impact on participation to protests. Second, the impact of using independent media for public sector workers' participation to protests is compared with non-public workers. While a significant positive impact of using independent media is found among non-public workers, independent media among public workers seem not to affect their participation to protests. Some channels are tested using additional outcomes such as governmental trust, political alignment, signing petitions and general trust as proxies for political accountability.

Chapter 1

A Gravity Analysis of Refugee Mobility Using Mobile Phone Data

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1.1 Introduction

Over the last decade there has been a surge in the number of international refugees in search for a better living outside their country of birth. The civil conflicts in Syria and in other countries have created an almost unprecedented humanitarian crisis leading to about 26 millions refugees at the end of the year 2019 (United Nations High Commissioner for Refugees, 2020). The magnitude of these developments has created a need to better understand the dynamics behind the movements of these individuals in search of durable solutions. On the academic side, economists and other social scientists have started studying key questions related to refugees. As reviewed by Becker and Ferrara (2019) and Maystadt et al. (2019), several papers have addressed a set of important economic questions such as the economic and political consequences of refugees in receiving countries. However, the question of the mobility of these refugees subsequent to their initial settlement has received much less attention form scholars. To the best of our knowledge, both the characterization of the extent to which refugees move after their initial arrival and the understanding of the patterns of this mobility have not really been addressed in the existing economic literature.

The questions regarding the determinants of the mobility of refugees subsequent to their early settlement remain nevertheless of primary importance. Such understanding may be first important for relief operations to better target those in need of assistance. Researchers investigating the consequences of forced displacement in hosting areas have either assumed that forcibly displaced people choose their location in a quasi-random way (Godøy, 2017; Grönqvist et al., 2012) or have overlooked the dynamic nature of such location decision. Anecdotal evidence suggests nevertheless that a significant share of refugees may move multiple times within their country of asylum (Bose, 2013, 2014), suggesting that they follow some systematic patterns. If one aims to uncover these patterns, knowing whether refugees tend to be stuck in their initial place of settlement or, on the contrary, show a high propensity to move to other locations is important for authorities in order to supply the right level of public assistance to these individuals. If refugees do not move, public infrastructures at entry points are likely to be quickly subject to congestion and need to be expanded. On the contrary, if they tend to be mobile, it is important to know where these refugees tend to relocate, which in turn raises the question of the specific determinants of their mobility. To address these questions, one can fortunately rely on a large literature which has looked at the identification of the main determinants of the internal and international movements of economic migrants, especially using gravity models (Beine et al., 2016). Two broad types of factors emerge from this literature, namely factors shaping the level of attractiveness of the potential locations and factors generating frictions to the mobility of individuals between these various potential locations.

The first factor, which is not specific to refugees, is income or wage differentials. The existence of differences in the level of expected income is obviously the main robust determinant of movements of economic migrants, both internationally and internally. It is also a predictor of the selectivity of these migrants, for instance in terms of skills (Grogger & Hanson, 2011). In that respect, the sensitivity of the movements of refugees to income differentials is an important element of knowledge. If refugees are allowed to move and work, and respond significantly to income differentials, their mobility process constitutes a factor of efficiency of the allocation of labor across space since they tend to move from low to high productivity locations. Equally important is the comparison of this sensitivity with other types of workers such as legal economic immigrants.[1] The sensitivity to the second factor, namely migration costs such as distance, is worth being analyzed. The existence of migration costs has been shown to be of primary importance in the literature dealing with economic migration. Accounting for migration costs is key for predicting migration flows as well as the type of migrants settling in each location (Chiquiar & Hanson, 2005). This question is also highly relevant for determining the optimal allocation process of refugees. If refugees are highly sensitive to migration costs, they might be unable to take advantage of attractive locations and could be highly dependent on welfare benefits given by local authorities. This has in turn considerable consequences for public finance. Descriptive evidence provided by the World Bank (2018) tends to show that refugees are likely to move over shorter distances, suggesting a higher sensitivity to migration costs. Sound econometric investigation is nevertheless desirable to confirm this initial piece of evidence.

A primary reason for the absence of existing studies about the determinants of the mobility of refugees lies in the difficulty of relying on the traditional measures of mobility used in the migration literature. Studies usually rely on administrative data to track movements of individuals across and within countries. Data from censuses or population registers are often the main source to identify movements of natives and migrants across locations. Some alternative measures, based for instance on fiscal reports or health data, have also been used to measure movements of households across regions at higher time frequencies (see for instance Hatton and Trani (2005) on British data or Beine and Coulombe (2018) on Canadian data). Due to the elusive status and the unstable situation characterizing refugees, these sources cannot unfortunately be used for tracking consistently their displacement, which calls for alternative creative solutions of data collection. In this paper, we propose to implement such a solution by tracking movements of refugees through the use of cell phone data in Turkey.[2] We exploit geolocalized call detail records provided by Salah et al. (2018) within the Data for Refugees Turkey (D4R) challenge. More specifically, we look at the location of 100,000 randomly selected mobile transactions (involving 50,000 refugees and 50,000 non-refugees) recorded by cell towers to define likely decisions to move across 26 regions in Turkey. This allows us not only to compute bilateral migration flows at a quarterly frequency and at the provincial level for refugees but also to compare our findings with those obtained on a sample of non-refugees (natives and legal immigrants). While the use of phone data to track individuals is not new

[1] A second factor of attractiveness, more specific to refugees, involves the level of local aid these individuals can receive. Aid provided upon arrival is a crucial element to overcome the distress the refugees often face when escaping urgent and dangerous contexts. Nevertheless, if refugees tend to be attracted by more generous locations, the provision of aid might undermine the efficiency of the process of labor reallocation across space. This question connects with the literature on the social magnet effect that has looked to what extent migrants develop opportunistic location strategies with respect to the level of public transfers (Razin & Wahba, 2015). In the last part of the paper, we investigate this issue and look at whether refugees tend to be attracted by the level of aid provided by local authorities.

[2] Furthermore, even when administrative data are available, the mobility patterns identified through the use of mobile phone data are found to contrast with the refugee presence revealed by such data. Such a discrepancy should warn researchers about some of the pitfalls in using a one-shot distribution of refugees within a country. Indeed, the movement of refugees has often been used as a natural experiment to assess the impact of migration (Tumen, 2015). Most of these studies have considered the potential threat of native displacement but the threat of refugee displacement in the country of asylum has rarely been discussed. The nature of the resulting bias will depend on the composition of such re-displaced refugees. The risk has been mostly overlooked since extant studies on the impact of refugees on hosting economies, including in Turkey, mostly rely on registration or administrative data. Such data would not be able to capture such internal patterns of displacement. For Turkey, exceptions are Altindag et al. (2020) and Tumen (2019) who are able to exploit time variation in the concentration of refugees in Turkey. The issue is acknowledged in Akgunduz et al. (2018) but the proposed use of a distance-based IV approach constitutes only a partial solution since it will capture the LATE effect of the initial population shock. The issue is particularly relevant in Turkey since refugees have spread to the rest of Turkey from the second half of 2014 onward (Ceritoglu et al., 2017; Tumen, 2016).

(see among others Blumenstock et al. (2016), Wesolowski et al. (2012) and Deville et al. (2014)), we are, to the best of our knowledge, the first ones to use this approach to measure mobility in order to characterize the determinants of internal mobility of refugees.[3]

Based on the mobility measures inferred from phone data, we estimate the determinants of refugee movements across 26 Turkish regions in 2017. Turkey is an interesting case to study the mobility of forcibly displaced people within a country of asylum. The movement of Syrian refugees in Turkey started in 2011 as a result of the Syrian Civil War. Currently the official statistics report approximately 6.6 million refugees (United Nations High Commissioner for Refugees, 2020). The ongoing conflict induced many refugees to remain in Turkey while others moved to farther European countries. Furthermore, due to a bilateral agreement reached in 2015, borders between the EU and Turkey have been closed to refugees, which lowers significantly their movements for the purpose of transiting to European countries. According to official figures, in 2015, the population of Syrian refugees was approximately 2.8 million, in 2016 about 3.1 million while in 2017 approximately 3.8 million (United Nations High Commissioner for Refugees, 2017a). The number of refugees living in camps was approximately 250,000 in 2017, i. e., less than 7% (United Nations High Commissioner for Refugees, 2017b) compared to approximately 260,000 in 2016, i. e., less than 8.5% (United Nations High Commissioner for Refugees, 2016) and 270,000 in 2015 (Bahçekapili & Çetin, 2015), approximately 9.6%. Overall, the number of the Syrian population in camps decreases over time, despite the actual increase in the number of refugees, thus suggesting an increasing mobility over time and highlighting the need to further uncover its determinants.

While the Turkish law does not grant relocation rights but only temporary protection status, yet this temporary status is accompanied with the right to apply for a work permit in certain areas and certain professions. As such, internal mobility within the borders of Turkey is rather free for Syrian refugees. In some cases, relocation has even been encouraged in an attempt to close down and relieve some camps (United Nations High Commissioner for Refugees, 2019). The freedom to move, combined with the right to work, are important elements for the purpose of eliciting the determinants of the mobility of refugees and to compare their pattern with the one of the non-refugee population. There is an emerging literature assessing the impact of refugees on the hosting economies in Turkey[4] but, in line with the general literature on refugees, little attention has been paid to the determinants of the mobility of refugees in this country.

In order to estimate the sensitivities of movements of refugees to income and distance, we bring our measures of mobility based on cell phone data to a standard gravity equation. The gravity model is itself derived from a Random Utility Model applied to refugees (and non-refugees) in which factors of attractiveness and friction enter in the deterministic component of utility associated to each location. In the benchmark estimations, the model is estimated on data defined at the NUTS–2 level involving 26 Regions.

Our main results can be summarized as follows. First, we find that refugees react to income differentials. Refugees tend to leave relatively poor locations and are attracted by wealthier ones. Second, their sensitivity to income differs in two ways from the one of non-refugees. On the one hand, refugees react less to income levels at destination than non-refugees. One

[3] Beine et al. (2019) characterize internal mobility as a measure of integration of refugees in Turkey and focus on the response to news about protests and demonstrations. In contrast to this paper, they do not rely on micro-foundations to derive the gravity equation. There exist major differences on the methodological side: no fixed effects in the specification, regional income proxied by nightlight data from satellites, analysis only at the NUTS 3 geographical level to list the main ones. While they find that refugees are sensitive to distance, they do not find that they move in response to income differentials, a result that contrasts with the findings of this paper.

[4] The related literature has analyzed the impact of refugees on the labor markets (Ceritoglu et al., 2017; Del Carpio & Wagner, 2015; Tumen, 2016), firm entry and performance (Akgunduz et al., 2018; Altindag et al., 2020), consumer prices (Balkan & Tumen, 2016), and high-school enrollment (Tumen, 2019).

possible explanation might be the lack of information available to refugees. On the other hand, non-refugees do not show any propensity to leave relatively poor areas, which might be due to a higher degree of attachment to their current location. In that sense, allowing refugees to move or incentivizing refugees with reliable information may contribute to a more efficient allocation of the labor force across space. Third, refugees are indeed more sensitive to distance than other individuals, even though the discrepancy is not as high as one could expect (their estimated elasticity is about 35% higher compared to non-refugees). Finally, refugees appear to be sensitive to humanitarian aid and asylum grants. Nevertheless, while we find that humanitarian aid and asylum grants discourage refugees from migrating, we do not find any evidence of a social magnet effect, i. e. a systematic attraction by more generous locations. Our results resist a set of robustness checks. They are robust to alternative procedures through which we map phone calls to mobility measures. The results are broadly similar when we change the geographical definition of our unit of analysis (using larger and smaller regions than in the benchmark analysis). We also provide evidence that the economic motivation of movements that we document for refugees is not confounded by alternative explanations of mobility such as the propensity to leave refugee camps, motivations of transit in Turkey or seasonal moves driven by agricultural business cycles.

The remainder of our paper is structured as follows. Section 1.2 derives our gravity equation from a Random Utility Model (Section 1.2.1) that we develop to characterize location choices of refugees and non-refugees (Section 1.2.2). Section 1.3 presents the data (Section 1.3.1) and some descriptive statistics to help understand better the sample of our study (Section 1.3.2). Section 1.4 provides the empirical results for our main research question (Section 1.4.1) and shows that our findings survive various robustness tests (Section 1.4.2). Section 1.5 provides some implications for policy and concludes.

1.2 A RUM model for refugees

The economic literature has for long widely relied on the gravity model to understand migration decisions (Ravenstein, 1985, 1989). Despite its simplicity, the gravity model has shown impressive predictive power, making it an essential tool for forecasting mobility between and within countries (Beine et al., 2016; Crozet, 2004; Garcia et al., 2015; Mayda, 2010). As the main determinants of migration, the gravity model has identified differentials in employment opportunities and income per capita between the areas of origin and destination, together with the geographical and cultural distance, as proxies for migration costs. In this paper, we build on the large literature on the gravity model and apply it to the mobility of refugees across Turkish regions. In that respect we follow two recent strands of that literature.

First, while the applicability of the gravity model to forcibly displaced people is limited to international movements of asylum-seekers to OECD countries (Hatton, 2009, 2016, 2017), it seems that the same set of factors explains the movements of economic migrants and refugees across countries, albeit with different intensities. In particular, geographical and political factors have stronger weight for refugees or asylum-seekers compared to economic ones. Such conclusion is confirmed in the cross-sectional analysis of the gravity model proposed by the World Bank (2018). The applicability of the gravity model to forced displacement shows that the forced nature of population movement should not hide the potential agency played by forcibly displaced people in their migration decision (Ibánez, 2014; Maystadt et al., 2019). However, the cross-country nature of this literature is limited in shedding light on the determinants of mobility in complex emergencies. To the best of our knowledge, we are the first ones to apply the gravity model to the mobility of forcibly displaced populations within a recipient country in conjunction with highly disaggregated phone data that allows to track people in a consistent way.

Second, the recent literature has emphasized the need for using sound micro-foundations to derive gravity equations applied to migration. Anderson (2011) derives a gravity equation in a full equilibrium framework, emphasizing the importance of the concept of multilateral resistance. Grogger and Hanson (2011) and Beine et al. (2011) derive gravity equations from a Random Utility Model (RUM). The use of a RUM model allows to uncover explicitly the various underlying assumptions on which the gravity equation relies. We follow this route and to that aim develop a RUM model from which we derive our gravity equation.

1.2.1 A RUM Model of location decision

Let us consider the location choice for an individual of type $l = \{R, NR\}$ who has to decide where to locate among K ($k = \{1, ..., K\}$) potential locations over the next period of time t ($t = 1, ..., T$). We denote location i as his current location. For refugees ($l = R$), this location can be seen as the first location in which he has settled when arriving in Turkey from his country of origin. For non-refugees ($l = NR$), location i is the most recent residing place. Suppose that individuals work in their living place (no commuting) and that every individual is allowed to work and to locate freely among all the K potential locations.

The level of utility of a type-l individual associated to staying in his initial location i is given by the following equation:

$$U^l_{ii,t} = ln(w_{i,t}) + A_{i,t} + \epsilon^l_{ii,t} \tag{1.1}$$

where $w_{i,t}$ denotes the level of wage prevailing in location i in period t.[5] $A_{i,t}$ captures other factors shaping the attractiveness of area i, including humanitarian aid and asylum grants. It also includes the occurrence of particular events such as outbreaks of violence that could affect their perception of the level of attractiveness of the location. $\epsilon_{ii,t}$ is an error term capturing the stochastic part of the alternative-specific utility and following an iid extreme value distribution of type 1.

If individual l chooses to move from the current location i to another location j, the level of utility associated to this choice is given by:

$$U^l_{ij,t} = ln(w_{j,t}) + A_{j,t} - C_{ij} + \epsilon^l_{ij,t} \tag{1.2}$$

where C_{ij} denotes the level of the (time-invariant) migration costs between areas i and j that individual has to incur if he chooses to move in that corridor. Given that we consider only locations within Turkey and given that all individuals are allowed to move freely (no visa costs), we capture variation in C_{ij} through the geodesic distance between these locations.

Let N^l_{it} denote the size of population of type l residing in location i at time t. Assuming that $\epsilon^l_{ii,t}$ and $\epsilon^l_{ij,t}$ follow an iid extreme value distribution of type 1 allows us to apply the results of McFadden (1984) and to derive the share of individuals from location i choosing to locate in j at time t. This share is given by solving the following maximization problem :

$$Prob[U^l_{ij,t} = Max_k(U^l_{ik,t})] = \frac{N^l_{ijt}}{N^l_{it}} = \frac{exp[ln(w_{j,t}) + A_{j,t} - C_{ij}]}{\sum_{k=1}^{K} exp[ln(w_{k,t}) + A_{k,t} - C_{ik}]} \tag{1.3}$$

A similar expression can be derived for the share of stayers in the population ($\frac{N^l_{iit}}{N^l_{it}}$), assuming that $C_{ii} = 0$. Combining these expressions, we can obtain the ratio of the number of movers

[5] See Anderson (2011) about a discussion on the type of utility function to include in the RUM. In particular, our utility function implies a degree of risk aversion equal to 1 and implies that only relative incomes between locations matter rather than absolute differences.

from i to j at time t over the number of stayers in location i as :

$$\frac{[N^l_{ijt}/N^l_{it}]}{[N^l_{iit}/N^l_{it}]} = \frac{N^l_{ijt}}{N^l_{iit}} = \frac{exp[ln(w_{j,t}) + A_{j,t} - C_{ij}]}{exp[ln(w_{i,t}) + A_{i,t}]} \tag{1.4}$$

Taking logs of expression (1.4), we get an equilibrium expression of the odd ratio between movers and stayers :

$$ln(\frac{N^l_{ijt}}{N^l_{iit}}) = ln(w_{j,t}) - ln(w_{i,t}) + A_{j,t} - A_{i,t} - C_{ij} \tag{1.5}$$

1.2.2 RUM-based gravity equation

We can build on the equilibrium condition (1.5) to derive a gravity equation that we bring to the data to characterize mobility patterns of both types l. Adding an error term to allow for random variation in observed migration flows N^l_{ijt}, we estimate the following specification for the gravity equation:

$$ln(\frac{N^l_{ijt}}{N^l_{iit}}) = \alpha^l_i + \alpha^l_j + \alpha^l_t + \beta^l_1 ln(w_{j,t}) + \beta^l_2 ln(w_{i,t}) + \beta^l_3 C_{ij} + u^l_{ijt} \tag{1.6}$$

This equation is estimated on two different samples spanning refugees ($l = R$) and non-refugees ($l = NR$), which in turn allows to compare the β^l coefficients between the two populations. The non-refugees include natives and former legal immigrants. Several remarks need nevertheless to be formulated in order to clarify a set of assumptions and limitations that arise when moving from the theoretical condition of equation (1.5) to the estimable equation (1.6).

First, in contrast with most studies using micro-founded gravity equations, our dependent variable in equation (1.6) is fully consistent with the equilibrium condition (1.5) but implies that we compute N^l_{iit}.[6] N^l_{iit} is computed from $N^l_{it} - \sum_{k=1}^{K \ni i} N^l_{ijt}$. As an alternative to the inclusion of N^l_{iit}, other studies include origin-time fixed effects (α^l_{it} using the current notations) which would further prevent the inclusion of income at origin.[7]

Second, equation (1.6) includes separate coefficients between origins and destinations in the levels of wages and other factors of attractiveness, while the equilibrium condition of the RUM model implies similar coefficients ($\beta^l_1 = \beta^l_2$). One reason for this is the discrepancy in the access to information between the current and the potential external locations. The standard RUM model assumes that individuals have similar access to information regarding the key factors across different locations. In reality, individuals have much less and more noisy information on external locations compared to their current one. This is especially true for refugees that discover a country new to them. It implies that the role of conditions at origin and destination can be different, calling for different regression coefficients in equation (1.6).

Third, our RUM model and our gravity equation both ignore some network effect, i. e. the attraction effect exerted by individuals from their community in other locations. Once again, due to their low variation over time, network effects at the aggregate level are difficult to introduce within a short period of time. Nevertheless, to the extent that networks do not grow much over the period, they could be reasonably well accounted for by the destination fixed effects α_j in equation (1.6). In general, the location fixed effects α_i and α_j partially capture the role of $A_{j,t}$ and $A_{i,t}$ terms in equation (1.5).

Finally, since equation (1.6) relies on a double-log functional form, there are two types of

[6] This is made possible because we have an exhaustive choice set for refugees.

[7] In a robustness check, we do that and show that we obtain similar results for β^l_1 and β^l_5.

issues that arise in the estimation in the presence of a significant share of zeros values for N^l_{ijt}. The first issue is the usual selection problem $\grave{a}$ la Heckmann since observations for which $N^l_{ijt} = 0$ would be dropped from the sample in an OLS estimation of equation (1.6). This would lead to an obvious bias in the estimated coefficients since this regression would drop corridors that are found to be rather unattractive for individuals. The second issue is more subtle and has been identified by Santos Silva and Tenreyro (2006). In the presence of a significant share of zeros, equation (1.6) is likely to be subject to an heteroscedastic error term, which in turn creates a dependence between higher moments of this term and the key covariates, generating another type of bias in the estimated coefficients. To solve both issues, Santos Silva and Tenreyro (2006) propose to use the Poisson Pseudo-Maximum Likelihood (PPML) estimator.[8] We follow this recommendation and use the PPML estimator for the estimation of equation (1.6). We also cluster all standard errors at the origin and destination levels.

1.3 Data and Descriptive Statistics

We first describe our data in Section 1.3.1. Second, we provide some descriptive statistics that will help visualize and therefore better explore our sample in Section 1.3.2 .

1.3.1 Data

The D4R Challenge and Constraints. The source of our data is the D4R, a non-profit challenge with the aim of improving the living conditions of Syrian refugees currently residing in Turkey. Türk Telekom (TT)[9], in collaboration with the Scientific and Technological Research Council of Turkey and Boğaziçi University, along with other academic and non–governmental organizations, organized an anonymized dataset of mobile call detail records (CDRs) of phone-calls and SMS messages of TT customers. The data collected and provided by the company cover the time period between 1 January 2017 to 31 December 2017.

The D4R dataset is collected from a sample of 992,457 TT customers. 184,949 are identified as refugees and 807,508 as Turkish citizens. While not much is revealed concerning the individual characteristics of the customers, we know that approximately 25% of the refugee customers are identified as "female" and the remaining 75%, as "male". Overall it provides three distinct datasets.[10] We employ Dataset 3 (Coarse Grained Mobility) in our analysis in order to construct the refugee mobility measures aggregated at the regional level. Dataset 3 is a randomly selected dataset of 50.000 refugees and 50.000 non-refugees that is being followed throughout the whole year. To ensure privacy the data is provided with reduced spatial resolution, i. e. at the district (rather than the antenna which was the case in the other datasets) level. Each individual is associated with an ID number. The ID of the traced individual starts with a number: 1 if the individual is a refugee, 2 if the individual is not a refugee and 3 if this information is unknown. We thus have detailed information on whether the call belongs to a particular person, being a refugee or not, as well as the day and time of

[8] Regarding the first issue, PPML estimator involves an exponential model, which automatically includes the zero values in N^l_{ijt}.

[9] Formerly state-owned, TT is the first integrated telecommunications operator in Turkey. Vodafone and Turkcell are the two other operators in Turkey. As of the fourth quarter of 2016, TT, Turkcell and Vodafone have respectively a subscriber market share of 30%, 45% and 25% (Türk Telekom, 2019).

[10] Dataset 1 (Antenna Traffic) includes one year site-to-site traffic on an hourly basis and it provides information about the traffic between each site for a year period. Dataset 2 (Fine Grained Mobility) randomly chooses a group of active users (who make calls and send SMS) every two-week period and reports cell tower identifiers. Datasets 1 and 2 are described in more detail in the appendix.

the call.[11]

The D4R challenge is a unique initiative that allows to study various aspects associated with refugee mobility. However, addressing such a sensitive issue is a major challenge and maximum protection of personal data is a prerequisite. To this end the data comes with several restrictions and shortcomings. The main restriction is associated with the fact that the refugee ID is not entirely clear. Analytically, the data provider highlights that the term "refugee" is entailing to asylum seekers, migrants, and any individual that may have a "temporarily protected foreign individual" ID number in Turkey. To give the refugee status to a number, three conditions should be satisfied: i) the customers in the database have ID numbers that are given to foreigners and refugees in Turkey; ii) the customer should be registered with Syrian passports; and iii) use special tariffs reserved for refugees (Salah et al., 2018). Moreover, on 3 September 2020, Turkey's Directorate General of Migration Management (2020) state that Turkey hosts 3,612,694 Syrian refugees with temporary protected status plus 93,299 Syrians with legal residency permit and 110,000 with granted citizenship. Consequently, it is highly unlikely that we capture patterns of mobility that are not associated with other groups than Syrian refugees.[12]

Another constraint is that we cannot be entirely sure if the actual caller is indeed a refugee or a non-refugee. While individuals register with their refugee cards in order to connect, there is no guarantee on who is eventually using the phone. It is however more likely that refugees may use non-refugee phones rather than vice versa (refugee contracts have more limitations with respect to the number of calls they can do). Last, we cannot exclude noise in the exact location of the call. In some cases, the antenna location may not be precise as a line might connect to a different antenna due to the capacity of the network. Last, missing data is another concern as in some cases whole days of data may not be reported in the dataset (Salah et al., 2018).

For all the above reasons and given the scope of our research, we use the Nomenclature of Territorial Units for Statistics (NUTS) by Eurostat. Similar to a large literature in regional studies applied to the EU regions (Combes & Overman, 2003; Crozet, 2004; Fischer & Pfaffermayr, 2018; Hirschle & Kleiner, 2014), we conduct our analysis at the NUTS-2 administrative level, i. e. for 26 regions in Turkey.[13] More recently, Mitze (2019) finds a stronger explanatory power of local labor markets conditions during the global financial crisis at the NUTS-2 level, compared to NUTS-3 level. We also aggregate the data over time, i. e. we construct quarterly measures of mobility from location measures drawn from the phone call data. This approach mitigates most of the above mentioned concerns. First, it allows us to combine information and construct measures from D4R datasets. Second, it summarizes flows to other NUTS regions irrespectively of who is using the phone (it could thus capture movement of the whole family). Also, aggregating mobility at the NUTS-2 level, would nevertheless reveal systematic patterns of refugee mobility even if less than 100% is composed of Syrian refugees. And last, it resolves imprecise location concerns since the data at NUTS–2 level is very accurate. It also mitigates the concern from the absence of reporting data on a daily basis. This level of aggregation is also in line with our research question. Since we want to capture "internal migration" flows, the desirable property of our geographical unit of analysis is that it is not too small, in which

[11] See 1.A.1 for more information on the data provided by the D4R.

[12] An example would be people with Syrian passports falsely claiming the refugee status to benefit from reduced tariffs or Syrians who initially got the refugee status, later they obtained legal residency and retained their past connections. In both cases the analogy would be much less than 200,000 Syrians with legal residency permit or granted citizenship versus more than 3.60 million Syrian refugees. We thus view quite unlikely that these numbers can systematically influence our mobility patterns at any level, especially at the NUTS-2 level.

[13] Information on the NUTS statistical regions of Turkey is provided in Table 1.B.1 and Figure 1.B.1 in the Appendix.

case it could potentially capture commuting flows or regular social exchange patterns. As such we chose NUTS–2 which balances the trade-off between a sufficiently large unit of analysis and a large number of observations. Last, the NUTS–2 level allows us to combine our constructed measure of mobility with high quality administrative data available at quarterly level as well.[14]

A last concern about the D4R data is that while the sample of refugees is representative, it may not be the case for non-refugees who are sampled based on the sample of refugee customers.[15] While it is unclear whether this sampling process generates any systematic bias in the data, we focus our analysis on the refugee population to understand the determinants of their internal migration. While we benchmark the analysis using the sample of non-refugees, we undertake this exercise only for comparison reasons. This is also in line with our research contribution, i. e. the gravity model for the refugee population, since the gravity model for natives has been more analyzed in the relevant literature.

Dependent Variable: Refugee Mobility. Our main variable is the measure of mobility, which we construct using Dataset 3, i. e. the dataset that follows 50,000 refugees and 50,000 non-refugees throughout the whole year. We construct migration rates at the NUTS–2 level and at a quarterly frequency.

The migration rate has the form *Migration Rate_'l'_'i'* where *'l'* refers to the refugee (i. e. *'l'=R*) or non-refugee (i. e. *'l'=NR*) status of the observation, and *'i'* corresponds to the minimum number of calls generated from a given province to characterize the latter as the residence location (i. e. frequency filter of *'i'* calls, in our case, we set *'i'*=10). If there are several calls from different places within a given quarter, we choose the place from which the majority of calls comes from. To increase the likelihood that our measure properly reflects location of residence and not workplace, we restrict our analysis to calls that take place only between 8 pm to 8 am, i. e. hours that are less likely to be working hours, following the usual approach in this literature using phone data (Blumenstock et al., 2016).[16]

To define mobility, we compare the residency (as defined above) between sequential quarters. If residence is the same NUTS–2 area, the caller is a stayer, if not, (s)he is a mover. Subsequently, we compute mobility between quarters based on a migration rate $ln(\frac{N^l_{ijt}}{N^l_{iit}})$ where N^l_{ijt} corresponds to leavers and N^l_{iit} to stayers. As mobility is observed at the quarter frequency, it represents movers between quarters $t-1$ and t. By construction, any explanatory variable in our analysis is therefore measured prior to the mobility at quarter t.

Under Section 1.4.2, we test the robustness of our analysis using a stricter mobility measure, i. e. with a frequency filter of 20 calls, and using a more flexible mobility measure, i. e. with a frequency filter of 5 calls. We undertake another robustness check, i. e., we use a second filter where we impose the supplementary condition that a minimum number of calls (5, 10, 20) has taken place at least during a number of different days (5, 10, 20) during the quarter.

Standard Gravity Model Determinants. We employ two main sets of determinants of mobility. First, we use the standard gravity model controls, i. e. variables that relate to the attractiveness (resp. repulsiveness) of region j (resp. i) for prospective refugees, the so-called pull (resp. push) factors.

At the NUTS–2 level we have systematic regional GDP data available at the quarterly level. We obtain data on regional GDP from the Turkish Statistical Institute (TurkStat, 2020a).

Proximity between pairs of NUTS–2 regions is measured using geodesic distances, i. e. the length of the shortest curve between two points along the surface of a mathematical model of

[14] Our results are robust to defining mobility at NUTS–1 (larger) and NUTS–3 (smaller) regional levels. These results are reported in Section 1.4.2.

[15] As mentioned in Salah et al. (2018), Turkish citizen customers have been mainly sampled "from the cities with registered refugee presence, to simplify comparisons" (p.4).

[16] For the sake of following the terminology of the standard gravity model, we frequently refer to the residence place of the refugee as the origin.

the earth, based on the centroid coordinates.[17] Distance here captures practical difficulties of moving across these regions.

1.3.2 Descriptive Statistics

Our sample is composed of 1,950 bilateral observations for which we have information about all variables in our baseline specification (Table 1.1).[18] According to our mobility measure, bilateral movements of refugees between NUTS–2 regions are limited, and amount to 0.6%, i. e. on average, 6 refugees per thousands moves to another NUTS–2 region from one quarter to another.

Table 1.1: Summary Statistics of the Variables.

	Obs.	Mean	Std. Dev.	Min.	Max.
Dependent Variables					
Mobility of Refugees	1950	0.006	0.022	0	0.333
Mobility of Non-Refugees	1950	0.012	0.054	0	1.375
Explanatory Variables					
Income Per Capita	1950	855.898	276.491	327.743	1734.066
Distance	1950	580.118	314.576	95.520	1398.486
Humanitarian Aid	1950	2.902	4.732	0	30
Asylum Grant	1950	0.529	0.900	0	9
Violent Protest	1950	3.655	13.154	0	68

Figure 1.1 shows the presence of refugees in Turkey in 2017. More precisely, the Directorate General of Migration Management in Turkey provides yearly data on the presence of refugees at the regional level. We divide these figures by the measure of the regional distribution of refugees that we have obtained from our mobile phone data. The map indicates that administrative data overestimate the presence of refugees in Southeast Anatolia – at the Syrian border – and underestimate their presence in the northwestern (Istanbul, East Marmara and West Anatolia), Aegean and Mediterranean regions. Figure 1.2 shows the mobility of refugees in Turkey in 2017 as obtained from the D4R data. The first map corresponds to out-migration of refugees, their origin, while the second map shows in-migration of refugees, their destination. As can be seen from Figure 1.2, refugees tend to leave regions in the eastern part of Turkey for regions in the northwestern, Central Anatolia, Mediterranean and Istanbul.

For the levels of income at origin and destination, we use data on quarterly GDP per capita from TUIK (Turkish Statistical Institute). Numbers are reported in Turkish Lira. As can be seen from Table 1.1, based on our study sample, the lowest income corresponds approximately to 328 TRY and this is the income in *Şanlıurfa* region (in first quarter). The highest income is approximately 1,734 TRY in *İstanbul* region (in third quarter). The mean income is approximately 856 TRY and this is equivalent to the income in *Konya* region.

The shortest distance is approximately 96 kilometers and this is the distance between the *Gaziantep* and *Hatay* regions while the longest distance is approximately 1,400 kilometers, between *Van* and *Tekirdağ* regions. The mean distance is approximately 580 kilometers and this is equivalent to the distance between *İstanbul* and *Samsun* regions.

[17] The centroid coordinates are based on the WGS 1984 datum and we rely on Vincenty (1975) equations to calculate distances.

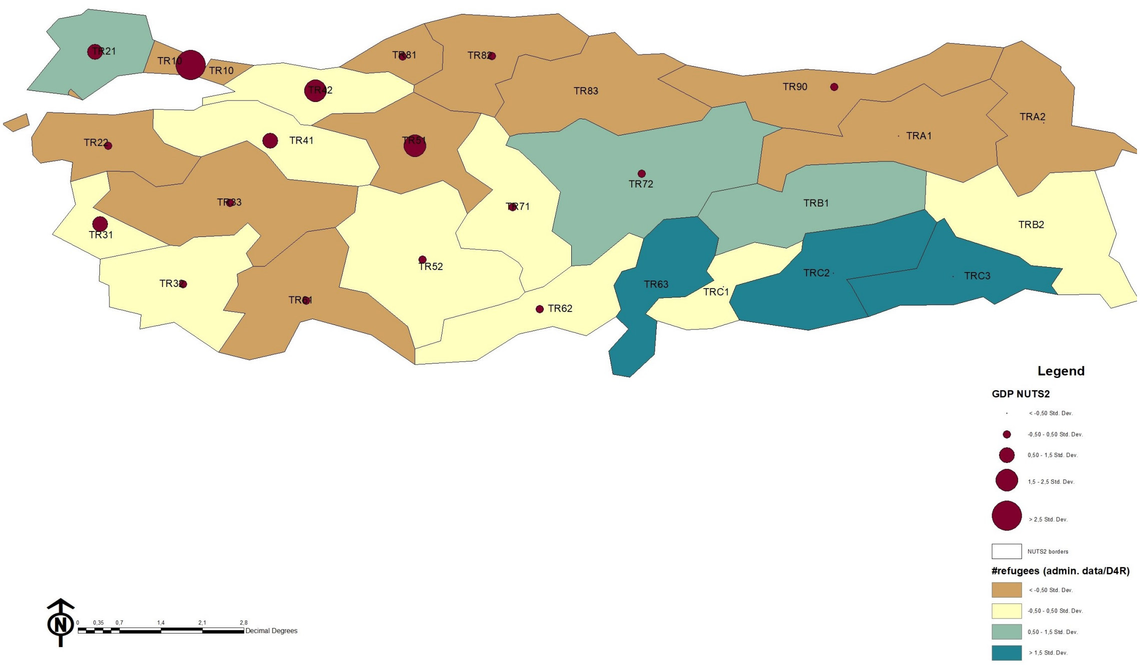
[18] The number of observations results from pairing each NUTS–2 region with another NUTS–2 region, given the bilateral nature of mobility. We do so for every quarter of the year 2017. Mobility is constructed from one quarter to another, resulting in 1,950 bilateral observations ($26 * 25 * 3$). Table 1.B.2 in the Appendix provides a detailed description for all the variables we use in our study.

Table 1.2: Average Traveled Distance and Number of Moves of Refugees and Non-Refugees.

		Refugees	Non-Refugees
Average Traveled Distance (km/movers)		581,7	733,2
Number of Moves	0	21645	30197
	1	1006	806
	2	225	645
	3	14	51

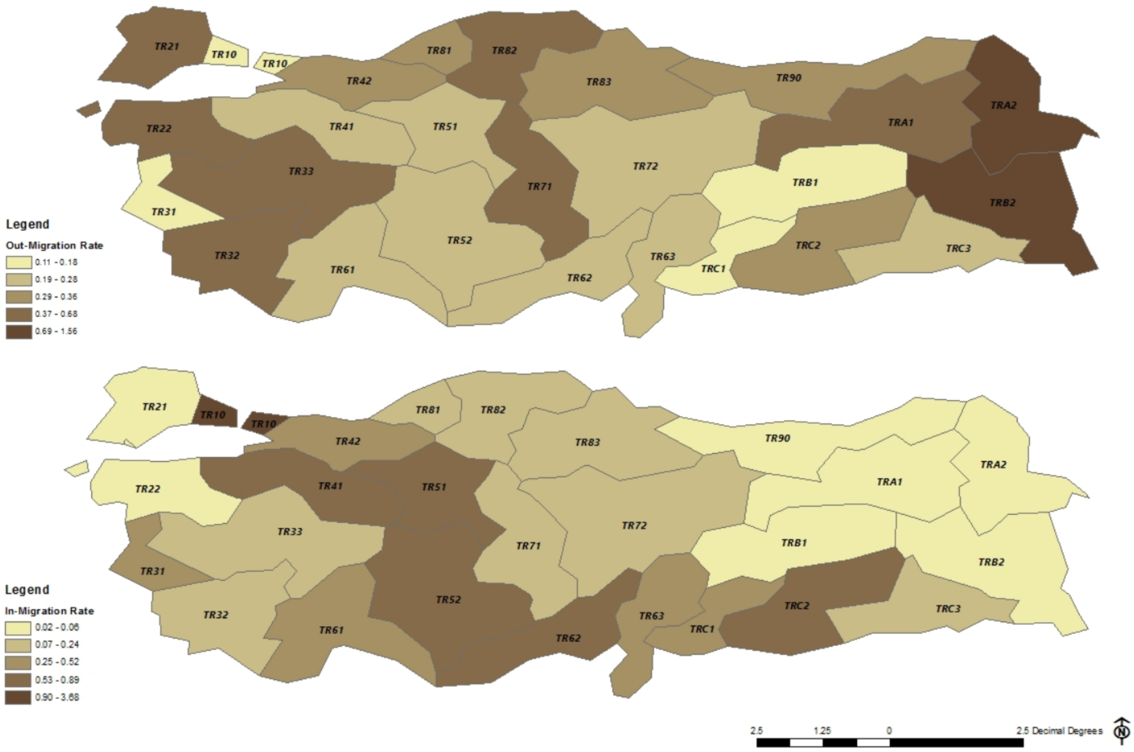
Table 1.2 offers a comparison between the mobility of refugees and non-refugees in our sample based on the frequency of their moves and the distance they travel. Interestingly, according to our mobility measure, non-refugees move more often and further than refugees. On average, refugees travel 582 kilometers while non-refugees travel 733 kilometers. No refugee in our sample covers a cumulated distance larger than 2,500 kilometers while cumulated distance over the total year 2017 exceeds 3,000 kilometers for some non-refugees. However, the distance of refugee and non-refugee mobility is similar for distances between 0-1000 kilometers and non-refugees move more and further for distances exceeding 1,000 kilometers. Overall, this analysis of distance for refugees and non-refugees is in line with some previous evidence (World Bank, 2018).[19]

Figure 1.1: The Presence of Refugees in Turkey in 2017: Administrative Data versus D4R Data.



[19] An histogram of the distance covered by refugees and non-refugees is shown in Figure 1.B.2 in the Appendix.

Figure 1.2: Mobility of Refugees in Turkey in 2017:
Out-Migration versus In-Migration of Refugees.



1.4 Results

We first present our benchmark results for the determinants of mobility for refugees and compare those to the ones for non-refugees (Section 1.4.1). Then we show that our results are robust to the geographical level of analysis and to the filtering procedure of phone data that we adopted to construct our measures of mobility (Section 1.4.2). We then assess whether our estimates reflect a story of mobility of refugees driven by the attractiveness of incomes at origin or destination or by a set of alternative patterns.

1.4.1 Benchmark Results

Our benchmark results are based on the estimation of equation (1.6). In the benchmark results, we measure bilateral movements using a 10-call filtering procedure to capture the respective locations at origin and destination, use calls taking place between 8.00 pm and 8.00 am and define regions based on the NUTS–2 geographical level. Table 1.3 reports these benchmark results. Column (1) provides our benchmark estimation for the refugees, with a focus on income levels at origin and at destination. These results suggest that refugees tend to follow patterns of mobility emphasized in the empirical literature on internal and international migrants. Like other types of migrants, refugees in Turkey tend to leave poorer locations and to be attracted by richer ones. Income differential across regions seems therefore to matter a lot for their location choice. Like in most gravity estimate of mobility, the elasticity of distance is negative and comprised between 0 and -1. A limitation of the estimation in column (1) is that it does not account for origin-time specific shocks beyond income at origin. The same holds for destination-time specific shocks. To overcome this limitation, columns (2) and (3) include estimation results obtained respectively with origin-time and destination-time fixed effects.[20] Results of column (1) are found to be similar with these ones.

An important dimension of the analysis is the comparison of the mobility patterns of refugees with other categories of individuals. To that aim, column (4) provides the estimates based on the same benchmark specification, but for non-refugees. It should be emphasized that non-refugees represent an heterogeneous group of individuals, composed by both natives and traditional immigrants of Turkey. Having said that, settled immigrants are expected to behave closer to natives than refugees. The comparison between columns (1) and (4) shows that in contrast with refugees, non-refugees do not react at variations of income at origin, reflecting possibly a stronger attachment to their current location. They also react slightly more to changes in income at destination, reflecting maybe better information about outside economic opportunities. Estimations show that the elasticity of distance is about one-third higher for refugees than for non-refugees, in line with the evidence provided by the World Bank (2018). Nevertheless, estimates provide evidence that refugees in Turkey respond to economic opportunities in their location choice and are not excessively constrained by factors hampering their mobility.

Table 1.3: Benchmark Analysis: Determinants of Refugee Mobility in Turkey.

Variable	(1)	(2)	(3)	(4)
		Refugees		**Non-Refugees**
Log Income at origin	-0.759***	-	-0.759***	-0.156
	(0.219)		(0.219)	(0.212)
Log Income at destination	1.405***	1.405***	-	2.019***
	(0.196)	(0.196)		(0.167)
Log Distance	-0.595***	-0.595***	-0.595***	-0.436***
	(0.111)	(0.111)	(0.111)	(0.088)
Constant	-5.172**	-10.86***	5.170***	-14.85***
	(2.244)	(1.530)	(1.757)	(1.951)
Origin FE	Yes	No	Yes	Yes
Destination FE	Yes	Yes	No	Yes
Time FE	Yes	No	No	Yes
Origin-time FE	No	Yes	No	No
Destination-time FE	No	No	Yes	No
Regions	26	26	26	26
Observations	1,950	1,950	1,950	1,950
R-squared	0.357	0.445	0.425	0.656

Notes: Estimated Equation: Equation (1.6) using PPML except columns (2) and (3). 10-call filtering procedure used and time window between between 8 pm and 8 am. Level of regional analysis: NUTS–2. Dependent variable is measured by a quarterly migration rate $\frac{N_{ij,t}}{N_{ii,t}}$, where N_{ij} corresponds to migrants in the ij corridor and $N_{ii,t}$ to stayers. Robust standard errors clustered at the origin and destination are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0.01$), ** at the 5 percent level ($p < 0.05$), and * at the 10 percent level ($p < 0.10$), all for two-sided hypothesis tests.

[20] On top of accounting for unobserved time varying shocks, these estimations account for issues of multilateral resistance of migration, respectively at origin and destination. See Anderson (2011) and Bertoli and Fernández-Huertas Moraga (2013) on the issue of multilateral resistance.

1.4.2 Robustness checks to methodological choices

Since our measures of mobility are inferred and not directly observed, it is desirable to conduct several robustness checks to assess the sensitivity of our results to alternative methodological choices. We consider two main choices, i. e. the level of geographic aggregation to define locations and the filtering procedures of phone data to infer location choices and mobility.

Geographical level of aggregation

First, we look at the sensitivity to alternative choices with respect to the geographical level at which data are aggregated. The choice of the NUTS–2 level to define the locations underlying our measures of mobility can be seen as the result of a trade-off between small and large areas. On the one hand, the choice of excessively large areas would conceal important movements of interest within each area. On the other hand, the use of very precise locations can lead to a confounding effect of commuting or simple visits to close locations. The RUM model and the derived gravity equation should describe mobility choices based on differences in economic attractiveness across locations. Therefore, it is desirable to get rid of mobility patterns based on other motivations (such as shopping). While not preventing totally some movements related to commuting, our choice of locations at the NUTS–2 level should mitigate the concerns compared to the choice of NUTS–3 areas.

To assess the robustness of our results to the geographical definition of a location, column (1) of Table 1.4 reproduces the estimation from column (1) of Table 1.3 for the sake of comparison. Columns (2) and (3) show respectively the results from conducting the analysis at regional NUTS–1 and NUTS–3 levels respectively. There are 12 NUTS–1 regions in Turkey while NUTS–3 regions correspond to the 81 Turkish provinces.

As can be seen from Table 1.4, results are in general robust to performing the analysis at different geographic aggregations. We interpret this result as a support for the absence of strong spatial dependence in our estimations.[21] Columns (2) and (3) respectively indicate that a 10% increase in the GDP decreases the likelihood to migrate of refugees by roughly 5% and 6% while at destination a 10% increase in the GDP increases the likelihood to migrate by roughly 11% and 35%. At a NUTS–1 level, a 10% increase in the distance to be covered decreases the migration likelihood by roughly 5%, and 9% at a NUTS–3 level.

Alternative filters of phone calls

Since our location and mobility measures are inferred from phone calls, it is important to assess the robustness of the results to the way these calls are filtered. First, there is a trade-off between taking a too low minimum call threshold to assess location and a too strict minimum level. If a too low minimum threshold is used, this can lead to noisy measures of locations polluted by individuals giving calls from locations they just visit temporarily. On the other hand, if a too high threshold is imposed, this can lead to the dismissal of many valid observations of location since some individuals do not call that much. The minimum 10-call threshold that we use in the benchmark analysis can be seen as a value taking this trade-off into account.

Table 1.5 contains results considering different minimum frequency filters to compute the mobility. Column (1) of Table 1.5 is once again our benchmark. In column (2), refugee mobility is computed such that at least 20 calls in a given NUTS–2 region are used to define the latter as the residency of an individual. In column (3), refugee mobility is computed such that at least 5 calls in a given NUTS–2 region are used to define the latter as the residency of an individual, i. e. any individual characterized by less than 5 calls is dropped from our sample.

[21] Geographers refer to this issue as the Modifiable Areal Unit Problem (MAUP), which results from relying on arbitrarily chosen areas to represent information and results in statistically biased effects.

As can be seen from Table 1.5, results remain robust to having a more flexible approach as under column (3) or a more restrictive approach as under column (2).

A second filter can also be considered to avoid capturing temporary movements of refugees rather than more permanent moves. If one individual gives, say, more than 10 calls from a location but during one single day, this can indicate a temporary move to that location but not a permanent settlement. A second condition regarding the minimum number of days these calls are spread can be imposed to infer the location of individuals. Once again, if this minimum number becomes too high, this can lead to the loss of many valid observations of locations. To assess the sensitivity of our results to this choice, columns (4) to (6) of Table 1.5 report the results based on mobility measures obtained with this double filtering procedure, with the three values of the frequency filter. Results are in line with those reported in columns (1) to (3) based on a single filter.[22]

Table 1.4: Robustness Tests on the Level of Regional Analysis.

	Dep. Var: Mobility of Refugees		
	NUTS–2	NUTS–1	NUTS–3
Variable	(1)	(2)	(3)
Log income at origin	-0.759***	-0.463**	-0.585*
	(0.219)	(0.271)	(0.357)
Log income at destination	1.405***	1.098***	3.515***
	(0.196)	(0.193)	(0.841)
Log Distance	-0.595***	-0.447***	-0.914***
	(0.111)	(0.129)	(0.131)
Constant	-5.172**	-6.135**	-20.11***
	(2.244)	(2.725)	(6.591)
Origin FE	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Regions	26	12	81
Observations	1,950	396	14,085
R-squared	0.357	0.622	0.151

Notes: Estimated Equation: Equation (1.6) using PPML. 10-call filtering procedure used and time window between between 8 pm and 8 am. Dependent variable is measured by a quarterly migration rate $\frac{N_{ij,t}}{N_{ii,t}}$, where N_{ij} corresponds to migrants in the ij corridor and $N_{ii,t}$ to stayers. Robust standard errors clustered at the origin and destination are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0.01$), ** at the 5 percent level ($p < 0.05$), and * at the 10 percent level ($p < 0.10$), all for two-sided hypothesis tests.

[22] To mitigate concerns that some individuals in the raw data are not present throughout the whole period, we did an additional robustness check where we excluded those individuals who did not make at least 10 calls in all four quarters. This yields a "balanced panel" of individuals. Our results, though not reported in the text, remain qualitatively the same despite the large decrease in the number of individuals entering the construction of the mobility measure.

Table 1.5: Robustness checks to alternative filters of phone calls.

	Dep. Var: Mobility of Refugees					
Frequency Filter:	10-calls	20-calls	5-calls	10-calls	20-calls	5-calls
Min. number of calling days:		1		10	20	5
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Log income at origin	-0.759***	-0.873***	-0.668***	-0.832***	-1.060***	-0.856***
	(0.219)	(0.251)	(0.200)	(0.273)	(0.312)	(0.197)
Log income at destination	1.405***	1.063***	1.583***	0.999***	0.890***	1.276***
	(0.196)	(0.222)	(0.168)	(0.210)	(0.226)	(0.221)
Log Distance	-0.595***	-0.561***	-0.532***	-0.628***	-0.732***	-0.590***
	(0.111)	(0.145)	(0.102)	(0.145)	(0.193)	(0.125)
Constant	-5.172**	-2.704	-7.297***	-2.125	0.363	-3.819
	(2.244)	(2.596)	(1.927)	(2.711)	(2.981)	(2.386)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Regions	26	26	26	26	26	26
Observations	1,950	1,950	1,950	1,950	1,950	1,950
R-squared	0.357	0.144	0.529	0.139	0.134	0.282

Notes: Estimated Equation: Equation (1.6) using PPML. 10-call filtering procedure used and time window between between 8 pm and 8 am.Dependent variable is measured by a quarterly migration rate $\frac{N_{ij,t}}{N_{ii,t}}$, where N_{ij} corresponds to migrants in the ij corridor and $N_{ii,t}$ to stayers. Robust standard errors clustered at the origin and destination are reported in parentheses. Cols 1 and 4:10-call filtering procedure. Cols 2 and 5: 20-call filtering procedure. Cols 3 and 6: 5-call filtering procedure. Cols 1-3 : minimum number of days of calls : 1. Cols 4-6 : minimum number of days of calls : 10. *** denotes statistical significance at the 1 percent level ($p < 0.01$), ** at the 5 percent level ($p < 0.05$), and * at the 10 percent level ($p < 0.10$), all for two-sided hypothesis tests.

1.4.3 Alternative explanations to economic attractiveness of locations

Our benchmark results suggest that refugees are likely to respond to the economic attractiveness of locations in their mobility choice. They tend to leave current locations that are less attractive in terms of income and to head to places with higher expected income. While they are more sensitive to factors of friction in their mobility compared to non-refugees, the estimations suggest that this sensitivity does not prevent them to grab attractive economic opportunities. In short, refugees in Turkey behave very much like other categories of workers and their movements from low to high productivity locations can be seen as contributing to a more efficient process of allocation of labor across space. Nevertheless, it is important to check whether alternative mechanisms driving the mobility patterns could be also consistent with our data. In this section we explore various alternative stories.

Westward movements

Since refugees are initially settled in the southeastern part of the country, one may be concerned that the estimated attractive nature of the income per capita at destination is entirely driven by other factors (e. g. proximity to Europe, ...) associated with a Western move by refugees. Such a move would simply capture a positive income gradient along the East-West axis. While this is a legitimate concern, we believe that this threat should not be overstated. First, we cover the year 2017, i. e. after the EU and Turkey decided to close their common border to refugees. Therefore, motivations of movements based on pure transit to Europe are lower than before. Second, Figure 1.2 indicates that beyond the Westwards general pattern, there is more variation than one would expect in terms of in- and out-migration among refugees. For instance, the Southern regions of Adana (TR62), Konya (TR52), and Şanlıurfa (TRC2) feature relatively high in-migration rates. In contrast, other Western regions such as e. g. Tekirdağ (TR21), Balıkesir (TR22), Aydın (TR32), and Manisa (TR33) have high rates of out-migration. Nevertheless, in order to assess the importance of this phenomenon in explaining internal mobility of refugees, we generate a dummy variable indicating whether the move is a westward movement. To do so, we compute the centroid (i. e. longitude and latitude) of every NUTS unit and for every dyad, we then compare longitudes to determine whether it implies a westward movement. Columns (1) and (2) of Table 1.6 show the results of the benchmark specification augmented with an interaction term between income at origin or income at destination and this dummy variable. While these interaction terms turn out to be statistically significant, their magnitude is very low in absolute terms, suggesting that the income elasticities are similar between refugees going westward and those going in other directions.

Dyadic fixed effects and network movements

Another way of investigating the specificity of westward movements is through the inclusion of dyadic fixed effects in equation (1.6). The dyadic fixed effects will indeed capture the specific mobility related to westward movements. Nevertheless, this specification is really demanding given the structure of our data. The identification of income elasticities will rely only on the time variation within a corridor. With 3 observations per dyad, this leads to estimation issues. These issues are reflected by the fact that the Poisson maximum likelihood estimation drops a substantial proportion of observations.[23] Furthermore, a drawback of this specification is that the role of distance is no longer estimated while this is one of the key interests of our analysis. Results of the specification with dyadic fixed effects are reported in column (3) of Table 1.6. The previous results regarding income elasticities are qualitatively similar with this specification. Once again, refugees seem to be attracted by high income regions and tend to leave poorer ones.[24]

A by-product of the inclusion of dyadic effects is that it provides a way to overcome the absence of a network variable in the benchmark specification. Networks at destination could be a confounding factor of income at destination since networks are likely to be located in attractive places. In other terms, it could be that refugees tend to settle in wealthy locations not only because of the expected high income but also because of the presence of a large network in these locations that will help them to settle and integrate. In contrast with Blumenstock et al. (2019) and in absence of information about the dyadic nature of specific calls, our data do not allow us to recover the topology of the network, preventing us to estimate the role of strong ties between individuals (Giulietti et al., 2018). Given the limited representativeness of our data for refugees, it is also difficult to have a good measure of the aggregate network, i. e. to estimate the role of weak ties in the network.[25] Nevertheless, since our investigation period is short (only one year) and that networks of refugees are already substantial at the end of the year 2016, one can expect that networks will not vary too much over time, even in locations receiving net inflows of refugees. If this assumption is correct, the inclusion of dyadic fixed effects can account for the impact of networks. The results show that the high income elasticity that we obtain in the benchmark specification is not driven by the absence of a role

[23] On the issue of dropping some observations, see Correia et al. (2020) for a discussion about the so-called separation problem in Poisson models with a rich set of fixed effects. Another issue is that standard errors are no longer double-clustered at origin and at destination.

[24] The estimation of this specification for non-refugees (not reported here for the sake of brevity) also gives similar results than the benchmark ones. Furthermore, the comparison between refugees and non-refugees gives rise to the same conclusions regarding their relative sensitivity to income at origin and at destination.

[25] In a previous version of this paper, we used the total calls from refugees in a given location. Nevertheless, this measure was very noisy and it is unknown to what extend it correlates with the size of the network at destination.

for network. If any, and with all the reservations regarding the different samples and the non causal interpretation of our estimates, the elasticity of income at destination is found higher in column (3) of Table 1.6 compared to the benchmark specification.

Accounting for contiguity

A limitation of the benchmark specification is that frictions in the mobility patterns are only captured through distance. Refugees have been reported to travel on short distances (World Bank, 2018). A question is whether they move mainly to areas that are very close and to what extend distance plays a significant role. In other words, it could be that the negative elasticity of distance reflects only that refugees move to contiguous provinces to the extend these exhibit higher income. To address this question, we supplement our benchmark specification with a contiguity dummy (taking 1 if the origin and destination share a common border, 0 otherwise). Columns (4) and (5) of Table 1.6 report the results of this extended specification, respectively for refugees and non-refugees. The results confirm that refugees and non-refugees tend to move more to contiguous locations, emphasizing the role of frictions in their mobility. Nevertheless, this specification confirms that refugees are still sensitive to distance and overall more sensitive to distance than non-refugees.

Accounting for agricultural business cycles

The evidence of high in-migration rates in locations such as Adana (TR52) and Şanlıurfa (TRC2) presented in Figure 1.2 raises the attention to the role of demand in agriculture. These regions are indeed known to generate a high demand for seasonal workers in Turkey, including Syrian refugees. The specificity of this labor demand could confound the estimations of the income elasticities at destination to the extend that these regions benefit from an increase in income during the harvesting season.[26] To tackle this issue, we augment our benchmark specification with an interaction term capturing the increase in income during the harvesting period (third quarter of 2017) in an agricultural province. The definition of an agricultural location relies on the share of agriculture in its provincial GDP (TurkStat, 2020b). We use two thresholds: 30% and 50% of agricultural output in the provincial GDP. Based on a threshold of 30%, we obtain 20 agricultural regions. Based on a threshold of 50%, 14 regions out of the 26 regions are classified as agricultural locations. Columns (6) and (7) of Table 1.6 provide the results with each threshold. The results obtained using this extended specification show that our estimated income elasticities are robust to the inclusion of agricultural business cycles generating a specific labor demand for refugees.

Refugee camps

Another version of the West-East different gradient would be that refugees being resettled primarily in refugee camps on the Eastern part of the country would be more or less keen to leave these regions, whether the areas are poor or rich. On the one hand, refugee camps provide some basic infrastructure and host large communities of refugees on which these individuals can rely on. On the other hand, many refugees clearly prefer to live outside these camps as their facilities do not match their expectations. These considerations suggest that refugees living initially in these camps can exhibit different sensitivities to income at origin. Furthermore, refugee camps tend to be mostly located in poor regions although there are a

[26] It could also affect the estimation of the elasticity of income at origin for refugees already settled in these agricultural provinces.

few exceptions.[27] The inclusion of origin fixed effects account for this last aspect. It might nonetheless be desirable to investigate the possible heterogeneity of the income elasticities with respect to the camps.

To that aim, we carry-out regressions getting rid of the phone data generated in the NUTS–3 region containing a camp. This means that we still consider refugees in the NUTS–2 regions hosting a camp but only those living in areas without camps. Column (8) of Table 1.6 reports these estimates. The estimated income and distance elasticities are in line with the benchmark specification. Income elasticities are found to be slightly higher in absolute terms, although the magnitude of the difference is not substantial. The same holds for the sensitivity to distance. All in all, the results point to a modest heterogeneity in the behavior of refugees located in areas with and without camps. Further investigation based on individual data would be welcomed to better understand this heterogeneity.

Social Magnet

Another pattern of mobility is related to the provision of aid given to refugees. The literature on the social magnet effect has investigated to what extent migrants develop opportunistic location strategies with respect to the level of public transfers (Razin & Wahba, 2015). A similar type of motivation could be theoretically expected for refugees regarding their choice of location within the country of settlement. Aid provided upon arrival is a crucial element to overcome the distress refugees often face when escaping urgent and dangerous contexts. Nevertheless, if refugees also tend to be attracted by more generous locations, the provision of aid might undermine the efficiency of the process of labor reallocation across space. It could also be the case that more attractive locations in terms of expected level of wage are also more (or less) generous in the level of transfers provided to refugees. If this is the case, this can affect the quality of estimation for the income elasticities.

To deal with the aspect related to the social magnet channel, we extend the benchmark specification with two types of aid targeted to refugees, both at origin and at destination. Based on the Global Database of Events, Language and Tone (GDELT) dataset, we create variables for news that are relevant to the refugee population. In particular we have chosen the following categories: humanitarian aid and asylum grants. We aggregate these 2 types of events quarterly and at the NUTS–2 level.[28] Events related to humanitarian aid are therefore related to the literature showing that welfare benefits may attract or retain potential migrants (Razin & Wahba, 2015). The news for asylum grants are directly linked with policy considerations that have a direct impact on the decisions of refugees and their ability to integrate and to move freely around the country. Events related to the granting of asylum status can also be directly interpreted as a possible change in expectations (Cortes, 2014) and therefore, local integration at origin or destination. We should acknowledge that the interpretation given to these hypothesized drivers are subject to discussion and that a lack of evidence may also be due to measurement errors. Nonetheless, the extension of the gravity model to political factors allows us to compare our results to a recent and growing literature on international migration.

We look at the effect of humanitarian aid (column (9) of Table 1.6) and the effect of asylum grants (column (10) of Table 1.6). We find that refugees are moderately sensitive to humanitarian aid and asylum grants. An increase of the provision of these services tends to decrease their probability of moving out of their current location. In contrast, we do not find any evidence of a social magnet effect through which refugees would favor locations providing higher levels

[27] In 2017, there are 25 refugee camps in Turkey and these are located in 6 NUTS–2 regions: Adana, Gaziantep, Hatay, Malatya, Mardin and Şanlıurfa. Among them, Adana, Gaziantep and Hatay are among the middle-income regions on Turkey while Malatya, Mardin and Şanlıurfa are poorer regions. See Figure 1.B.1 in the Appendix.

[28] A detailed description of GDELT and the variables construction are provided in the 1.A.2.

of these transfers. These conclusions should nevertheless be drawn with much caution due to the non causal estimation of the effect of such transfers. In particular, the level of transfers at origin and destination could definitely be dependent on the level of (unobserved) attractiveness of these locations in equation (1.6). Further econometric investigation is therefore needed before drawing more clear-cut conclusions about the (internal) social magnet effect of aid to refugees. Nevertheless, the income elasticities at origin and destination when accounting for the aid to refugees are found to be rather similar to those estimated in the benchmark specification.

Table 1.6: Alternative stories of patterns of refugees mobility

	Dependent Variable: Mobility of Refugees (columns (1-4), (6-11)) and Non-Refugees (column (5))										
	Westward movements			Contiguity		Agric. BC		Camps	Soc. Magnet		Protests
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Log income Orig	-0.995***	-1.031***	-0.807***	-0.642***	-0.051	-0.759***	-0.759***	-0.799***	-0.726***	-0.636***	-0.673***
	(0.248)	(0.251)	[0.262]	(0.233)	(0.214)	(0.219)	(0.219)	(0.165)	(0.223)	(0.221)	(0.230)
Log income Dest	1.554***	1.591***	3.530***	1.414***	2.025***	1.424***	1.427***	1.595***	1.375***	1.361***	1.313***
	(0.212)	(0.218)	[0.722]	(0.167)	(0.156)	(0.193)	(0.195)	(0.234)	(0.190)	(0.199)	(0.209)
Log Distance	-0.645***	-0.630***	-	-0.303***	-0.197	-0.595***	-0.595***	-0.712***	-0.589***	-0.586***	-0.599***
	(0.107)	(0.107)		(0.147)	(0.122)	(0.111)	(0.111)	(0.113)	(0.112)	(0.113)	(0.111)
West*Log Inc.Orig	-0.065***	-	-	-	-	-	-	-	-	-	-
	(0.025)										
West*Log Inc.Dest	-	-0.064***	-	-	-	-	-	-	-	-	-
		(0.025)									
Contiguity	-	-	-	0.551***	0.487**	-	-	-	-	-	-
				(0.196)	(0.194)						
Agric. Inc (30% GDP)	-	-	-	-	-	0.011	-	-	-	-	-
						(0.045)					
Agric. Inc (50% GDP)	-	-	-	-	-	-	0.013	-	-	-	-
							(0.061)				
Hum aid. Orig	-	-	-	-	-	-	-	-	-208.3*	-	-
									(0.113.9)		
Hum aid. Dest	-	-	-	-	-	-	-	-	71.75	-	-
									(93.94)		
Asyl. Grants Orig	-	-	-	-	-	-	-	-	-	-1307***	-
										(450)	
Asyl.Grants Dest	-	-	-	-	-	-	-	-	-	280.7	-
										(368.0)	
Violent Protests Orig	-	-	-	-	-	-	-	-	-	-	-118,825
											(118,431)
Violent Protests Dest	-	-	-	-	-	-	-	-	-	-	129,722
											(138,288)
Constant	-4.116*	-4.197*	-24.96***	-7.848***	-17.09***	-5.295**	-5.326**	-5.605**	-5.143**	-5.699**	-5.105**
	(2.275)	(2.276)	[6.004]	(2.494)	(2.057)	(2.204)	(2.175)	(2.224)	(2.219)	(2.254)	(2.312)
Origin FE	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dyadic FE	No	No	Yes	No	No	No	No	No	No	No	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Orig-Dest FE	No	No	Yes	No	No	No	No	No	No	No	No
Regions	26	26	26	26	26	26	26	26	26	26	26
Observations	1,950	1,950	1,032	1,950	1,950	1,950	1,950	1,950	1,950	1,950	1,950
Pseudo R^2	0.363	0.144	0.482	0.366	0.655	0.358	0.358	0.362	0.364	0.366	0.364

Notes: Estimated Equation: Equation (1.6) using PPML except column (3). 10-call filtering procedure used and time window between between 8 pm and 8 am. Dependent variable is measured by a quarterly migration rate $\frac{N_{ij,t}}{N_{ii,t}}$, where N_{ij} corresponds to migrants in the ij corridor and $N_{ii,t}$ to stayers. Migration rate is for refugees except in column (5) which reports results for non-refugees. Robust standard errors clustered at the origin and destination are reported in parentheses. Robust standard errors are reported in brackets (see footnote 25). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Reaction to news about protest

Finally, one could hypothesize that refugees will also move in reaction to specific events such as protests and demonstrations against immigrants. Based on GDELT, we create a variable for news related to violence and protests. In particular, we have chosen the category: violent protests. We aggregate this type of events quarterly and at the NUTS–2 level.

As the occurrence of such events is not randomly distributed across potential locations, this type of events could also confound the estimation of income elasticities. We capture such events at origin and destination and supplement equation (1.6) with these variables. Results (column (11) of Table 1.6) do not support a role of protests and demonstrations in our framework.

Once again, caution is needed about the conclusions to be drawn due to the non-causal nature of these estimates. Income elasticities remain basically unaffected by the inclusion of these variables.

1.5 Policy Implications and Conclusion

In this paper, we look at the determinants of the internal mobility of refugees after their early settlement in Turkey. Turkey is home of more than 3 million refugees that are allowed to move and work freely. It therefore provides an ideal context to address this topic. A good understanding of the patterns of refugees' mobility is key for an optimal provision of aid and support by the hosting authorities. Evaluating to what extent location choices of refugees respond to the factors of economic attractiveness is also important to know whether their movements contribute to an efficient allocation of labor across space.

The existing empirical literature on the mobility of refugees is scarce, especially due to the absence of reliable data that track the movements of this category of immigrants. Due to the elusive status and the unstable situation characterizing refugees, one cannot rely on traditional measures of mobility based on administrative data. This calls for alternative ways of measuring movements of refugees. In this paper, we use a unique dataset of mobile phone data to measure internal movements of refugees across Turkish regions over the year 2017. An additional appealing feature is that we can compute similar measures for non refugees, which allows to make useful comparisons between the two categories.

This big data approach allows us to conduct a traditional gravity approach applied to migration and to identify the main determinants of their movements as well as to compare these to the non refugee population. Although we do not exploit exogenous changes in those determinants, the risk of confounding factors is minimized through the use of a large set of combined fixed effects and the short nature of our period of investigation. We find that refugees are highly sensitive to distance, in line with the literature on economic migration showing that this sensitivity is increasing in the skill level of immigrants. Refugees also tend to move more often, but on shorter distances.

We also find that refugees respond to income differences between regions. They are likely to leave poor areas and are attracted by high-income regions. This contrasts with the patterns of non refugees who do not display any sensitivity to income at origin. Our conclusion regarding the sensitivity to income differential is robust to possible alternative explanations of mobility, including the propensity to cross Turkey from East to West, the propensity to leave refugee camps and the attraction to agricultural areas during the harvest season. Finally, we find that refugees are sensitive to humanitarian aid and asylum grants. An increase in the provision of these services tends to decrease their probability of moving out of their current location. Nevertheless, we do not find any evidence of a social magnet effect through which refugees would favor locations providing higher levels of these services.

Further investigation on the nature of mobility of refugees would be welcome. First, the non-experimental nature of our estimates calls for further studies based on a causal identification strategy to confirm our main conclusions. Second, while Turkey is one of the major location of refugees, similar analyses relying on other sources of data would be welcome to evaluate the degree of external validity of our findings. Finally, the access to individual data on calls allowing to recover the topology of the personal network would be valuable to capture more consistently the role of networks in explaining location choices of refugees.

Appendix

1.A Data

1.A.1 The D4R Challenge-Datasets 1 and 2

Türk Telekom (TT) and the D4R Challenge gave access to three distinct datasets providing different types of information. Two additional datasets (beyond Dataset 3 which is the one we use in our analysis) are the following:

Dataset 1 (Antenna Traffic) includes one year site-to-site traffic on an hourly basis and it provides information about the traffic between each site for a year period. A prerequisite is of course that one of the involved parties is registered with TT and in this case the information is available only for the TT customer. Information such as the total number of calls and total duration of the calls are available only in an aggregate format. This information is available both for voice calls and SMS messages. While no personal characteristics are revealed, there is information on the total number and the total duration of refugee calls and SMS by antennae.

Dataset 2 (Fine Grained Mobility) randomly chooses a group of active users (who make calls and send SMS) every two-week period and reports cell tower identifiers. This random-sampling process is repeated for the whole year period. As in Dataset 1, there is no personal information revealed, beyond the refugee or non-refugee status. The dataset provides information about the base station ID, whether the call or SMS is incoming or outgoing as well as the day and hour.

Crucially, as phone call data contain highly sensitive information, there is no possibility to link the three datasets.

1.A.2 GDELT

The Global Database of Events, Language and Tone (GDELT) dataset is a world-wide news media platform that is available for over 30 years, in over 100 languages and is updated daily to construct a number of indices related to the incidence of news that could directly or indirectly concern the refugee population (GDELT, 2019). The database consists of over a quarter billion geo-referenced event records in over 300 categories. The platform is open for research and analysis. It uses the Conflict And Mediation Event Observations (CAMEO) system where a code corresponds to a type of event and is defined in a three-level taxonomy. Each observation provides information in several layers. For instance, every observation has information about the location, the involved actors, the impact of the event, the type of action, to mention a few of the available categories. Another element available in GDELT that is essential for our analysis is the tone of the news, i. e. whether it has a negative or a positive connotation for the refugee population. Since the same type of news may have a different effect depending on the tone, we also aggregate the news based on the tone.

With respect to location, each observation provides latitude and longitude, thus the data are being reported at a very fine level. Using geographic information system (GIS), we are able to construct our events variables at the NUTS–2 level, in line with our main analysis. Moreover, the news coverage also has time variation at a fine level and we can thus construct the same measures at the quarterly level between January 2017 and December 2017.

Using the EVENT Record Exporter tool[29] provided by GDELT, we first obtain all events that took place in 2017 in Turkey. We then choose the following categories: humanitarian aid, asylum grants and violent protests. Indeed, GDELT provides information about several types of news events, which are given an id *GlobalEventID* and a variable *EventBaseCode*, which shows to which category this particular event belongs to.

Examples of news in our analysis are e. g., delivery of financial aid and other essential items to patients and other injured in the Syrian war, during a visit to several hospitals in the city of Kilis or the Turkish government setting up new refugee health-care centers and employ Syrian medical staff in various Turkish cities. To explore the effect of "social magnet" (Section 1.4.3) at the NUTS–2 region and the quarterly levels, we aggregate the number of news reporting information on "humanitarian aid, mainly in the form of emergency assistance" and on "grant[ing] asylum to persons". For these events, we focus on those with a positive tone to ensure that selected events relate to actual provisions of aid and asylum. To assess the role of violent protests (Section 1.4.3) at the NUTS–2 region and the quarterly levels, we aggregate the number of news reporting information on "protests forcefully, in a potentially destructive manner", For these events, we focus on those with a negative tone to ensure that selected events relate to actual occurrence of violent protests.

The distribution of these events in 2017 across the NUTS-2 regions in Turkey is shown in Table 1.B.3.

[29] The EVENT Record Exporter allows to export small subsets of data from the GDELT Event Database that match the search criteria. By specifying a set of criteria for the event type and actors involved, along with an optional date range, the system will search the entire GDELT Event Database for all matching entries and export matching records as a CSV file (GDELT, 2014).

1.B Supplementary Tables and Figures

Table 1.B.1: NUTS Statistical Regions of Turkey.

NUTS–1 Regions	NUTS–2 Subregions	NUTS–3 Provinces
Istanbul (TR1)	Istanbul (TR10)	Istanbul (TR100)
West Marmara (TR2)	Tekirdağ (TR21)	Tekirdağ (TR211)
		Edirne (TR212)
		Kırklareli (TR213)
	Balıkesir (TR22)	Balıkesir (TR221)
		Çanakkale (TR222)
Aegean (TR3)	Izmir (TR31)	İzmir (TR310)
	Aydın (TR32)	Aydın (TR321)
		Denizli (TR322)
		Muğla (TR323)
	Manisa (TR33)	Manisa (TR331)
		Afyonkarahisar (TR332)
		Kütahya (TR333)
		Uşak (TR334)
East Marmara (TR4)	Bursa (TR41)	Bursa (TR411)
		Eskişehir (TR412)
		Bilecik (TR413)
	Kocaeli (TR42)	Kocaeli (TR421)
		Sakarya (TR422)
		Düzce (TR423)
		Bolu (TR424)
		Yalova (TR425)
West Anatolia (TR5)	Ankara (TR51)	Ankara (TR510)
	Konya (TR52)	Konya (TR521)
		Karaman (TR522)
Mediterranean (TR6)	Antalya (TR61)	Antalya (TR611)
		Isparta (TR612)
		Burdur (TR613)
	Adana (TR62)	Adana (TR621)
		Mersin (TR622)
	Hatay (TR63)	Hatay (TR631)
		Kahramanmaraş (TR632)
		Osmaniye (TR633)

Central Anatolia (TR7)	Kırıkkale (TR71)	Kırıkkale (TR711) Aksaray (TR712) Niğde (TR713) Nevşehir (TR714) Kırşehir (TR715)
	Kayseri (TR72)	Kayseri (TR721) Sivas (TR722) Yozgat (TR723)
West Black Sea (TR8)	Zonguldak (TR81)	Zonguldak (TR811) Karabük (TR812) Bartın (TR813)
	Kastamonu (TR82)	Kastamonu (TR821) Çankırı (TR822) Sinop (TR823)
	Samsun (TR83)	Samsun (TR831) Tokat (TR832) Çorum (TR833) Amasya (TR834)
East Black Sea (TR9)	Trabzon (TR90)	Trabzon (TR901) Ordu (TR902) Giresun (TR903) Rize (TR904) Artvin (TR905) Gümüşhane (TR906)
Northeast Anatolia (TRA)	Erzurum (TRA1)	Erzurum (TRA11) Erzincan (TRA12) Bayburt (TRA13)
	Ağrı (TRA2)	Ağrı (TRA21) Kars (TRA22) Iğdır (TRA23) Ardahan (TRA24)
Central East Anatolia (TRB)	Malatya (TRB1)	Malatya (TRB11) Elazığ (TRB12) Bingöl (TRB13) Tunceli (TRB14)
	Van (TRB2)	Van (TRB21) Muş (TRB22) Bitlis (TRB23) Hakkâri (TRB24)
Southeast Anatolia (TRC)	Gaziantep (TRC1)	Gaziantep (TRC11) Adıyaman (TRC12) Kilis (TRC13)
	Şanlıurfa (TRC2)	Şanlıurfa (TRC21) Diyarbakır (TRC22)
	Mardin (TRC3)	Mardin (TRC31) Batman (TRC32) Şırnak (TRC33) Siirt (TRC34)

Table 1.B.2: Definitions of the Variables.

	Definition
Dependent Variables	
Mobility of Refugees	A quarterly migration rate $\frac{N_{ij}}{N_{ii}}$, where N_{ij} corresponds to leavers and N_{ii} to stayers, which is of the form *migr_rate_'R'_'10'* where *'R'* indicates the refugee status of the observation, and *'10'* corresponds to the frequency filter, e. g. the minimum number of incoming and outgoing calls generated from a given NUTS–2 region between 8 pm and 8 am to characterize the latter as the residence location of an individual. **Source.** Dataset 3 – Coarse Grained Mobility, D4R Challenge
Mobility of Non-Refugees	A quarterly migration rate $\frac{N_{ij}}{N_{ii}}$., where N_{ij} corresponds to leavers and N_{ii} to stayers, which is of the form *migr_rate_'NR'_'10'* where *'NR'* indicates the non-refugee status of the observation and *'10'* corresponds to the frequency filter, e. g. the minimum number of incoming and outgoing calls generated from a given NUTS–2 region between 8 pm and 8 am to characterize the latter as the residence location of an individual. **Source.** Dataset 3 – Coarse Grained Mobility, D4R Challenge.
Explanatory Variables	
Income Per Capita	Quarterly GDP in Turkey, weighted by the share and divided by the population of each NUTS–2 region. **Source.** Turkish Statistical Institute
Distance	Geodesic distances (Vincenty, 1975), i. e. the length of the shortest curve between two points along the surface of a mathematical model of the earth, based on the WGS 1984 datum coordinates of the centroids of each NUTS–2 region. **Source.** Eurostat
Humanitarian Aid	Number of news reporting information defined as "Extend, provide humanitarian aid, mainly in the form of emergency assistance". **Source.** GDELT
Asylum Grants	Number of news reporting information defined as "Provide, grant asylum to persons". **Source.** GDELT
Violent Protests	Number of news reporting information defined as "Protest forcefully, in a potentially destructive manner". **Source.** GDELT

Table 1.B.3: Distribution of Events in 2017 across NUTS–2 regions in Turkey.

NUTS–2 Subregions	Humanitarian Aid	Asylum Grants	Violent Protests
İstanbul (TR10)	87	6	107
Tekirdağ (TR21)	0	1	2
Balıkesir (TR22)	5	1	1
İzmir (TR31)	20	3	7
Aydın (TR32)	2	0	0
Manisa (TR33)	5	0	0
Bursa (TR41)	0	0	1
Kocaeli (TR42)	8	0	0
Ankara (TR51)	81	12	150
Konya (TR52)	3	1	1
Antalya (TR61)	11	0	3
Adana (TR62)	20	3	4
Hatay (TR63)	8	4	0
Kırıkkale (TR71)	0	0	0
Kayseri (TR72)	24	0	6
Zonguldak (TR81)	4	0	0
Kastamonu (TR82)	0	0	0
Samsun (TR83)	2	0	5
Trabzon (TR90)	1	0	0
Erzurum (TRA1)	3	0	11
Ağrı (TRA2)	6	0	0
Malatya (TRB1)	1	5	0
Van (TRB2)	3	0	0
Gaziantep (TRC1)	10	2	5
Şanlıurfa (TRC2)	26	0	6
Mardin (TRC3)	3	0	2

Figure 1.B.1: Turkish Administrative Regions:
Nomenclature des Unités Territoriales Statistiques.

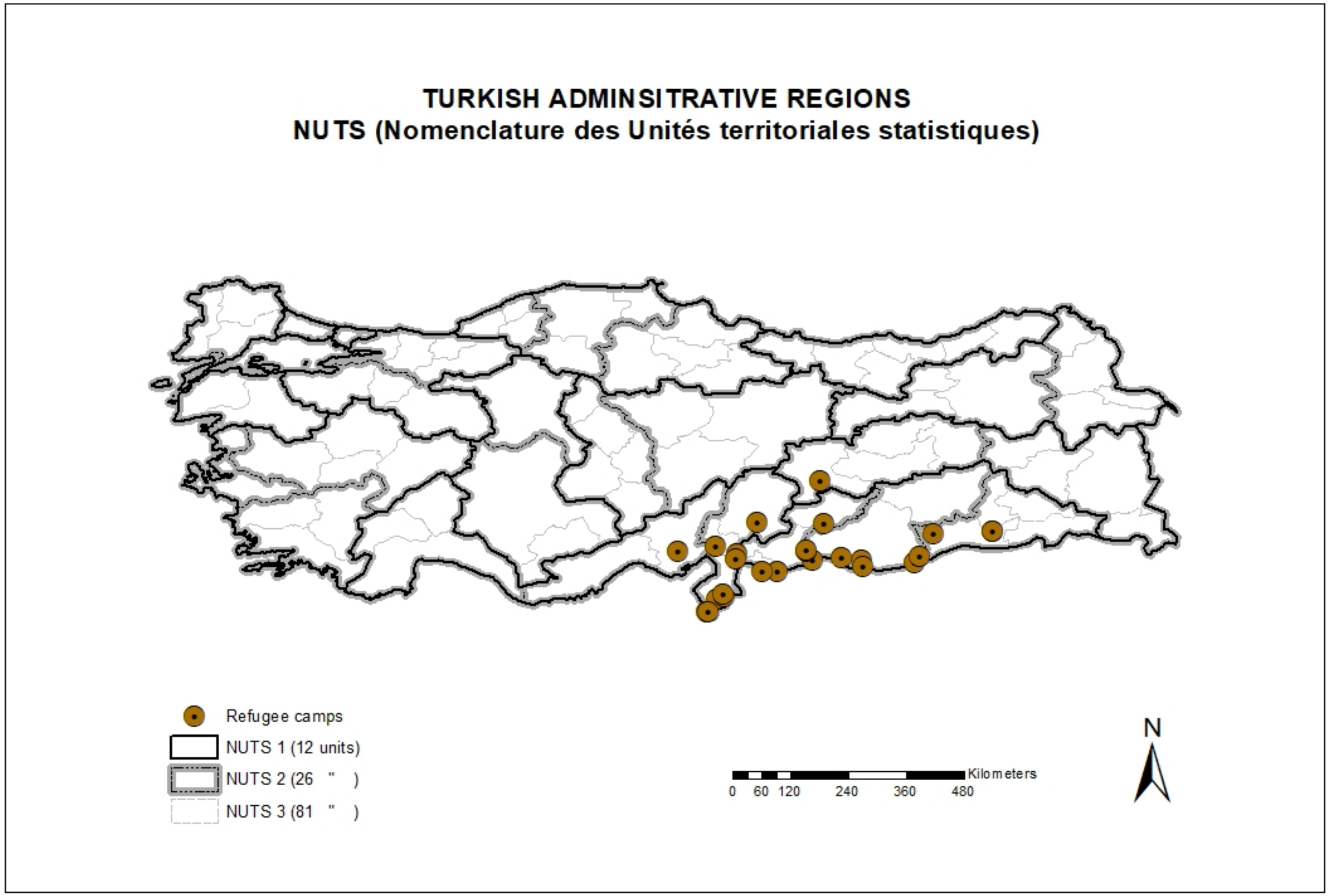
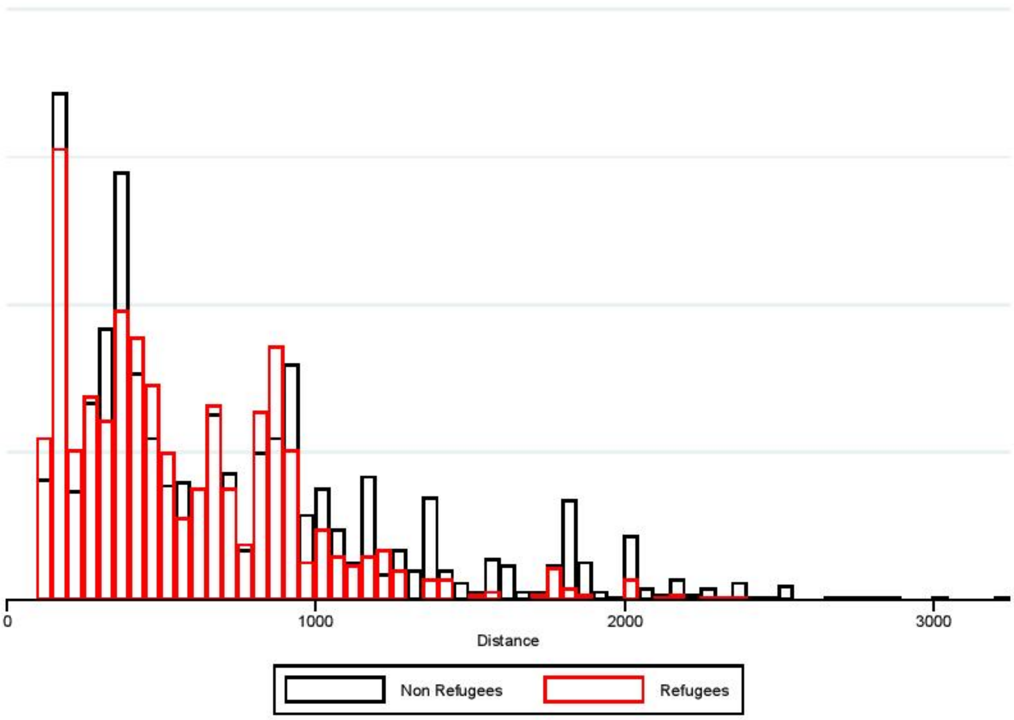


Figure 1.B.2: Histogram of the Distance Covered by Refugees and Non-Refugees.



Chapter 2

Refugee, Diversity and Conflict in Sub-Saharan Africa

2.1 Introduction

Over the last decade, the number of refugees has more than doubled (United Nations High Commissioner for Refugees, 2020) to more than 70 million. Although forced displacement in the Middle East (e. g., from Syria) and Latin America (e. g., from Venezuela) has attracted considerable attention, the African continent continues to host 6.3 million refugees end of 2019, a number that has almost tripled since 2010. Most of them are still accommodated in camps, mainly in neighboring countries and in so-called protracted situations. Over the same period, there has been a boom in the economic literature investigating the impact of refugees on the hosting economies (Maystadt et al., 2019; Ruiz & Vargas-Silva, 2013; Verme & Schuettler, 2021). A relative consensus has emerged where refugees do not necessarily constitute a burden but may induce important distributional changes among the refugee-hosting population. However, the focus on labor markets may not help in fully understanding the structural changes induced by such population flows. For instance, a standard narrative has been that refugees may induce non-cooperative behaviors, and *in fine*, lead to the emergence of conflict between (ethnic) groups (Brzoska & Frohlich, 2016; Burrows & Kinney, 2016; Mach et al., 2020; Mach et al., 2019).

The objective of this study differs from the literature cited above and aims to assess the consequences of forced migration on ethnic diversity and in turn, conflict in sub-Saharan Africa. We combine a unique georeferenced dataset on refugees camps with individual data from the Afrobarometer Surveys across 23 African countries for the period 2005-2016. We construct two standard measures of ethnic diversity, i. e., indices of ethnic fractionalization (EF) and ethnic polarization (EP) at a precise location provided by the Afrobarometer. Although these indices have been widely used, little time variation has often been found, making causal inference a difficult challenge. The innovative part of our analysis is to exploit data on the precise location of refugee camps, their yearly size and more importantly, their annual composition in terms of countries of origin. Combined with the Ethnic Power Relations - Ethnicity of Refugees 2019 dataset, we are able to predict the changes in ethnic diversity induced by refugees inflows. We then assess the relationship between the refugee-corrected diversity indices and the likelihood of conflict. In additional analysis, we also exploit individual data from the Afrobarometer surveys to assess how refugee-induced changes in diversity affect incidences of theft and violence, participation into protest, and perceptions with respect to ethnic attachment, inter-personal and institutional trust.

The present paper complements other papers commissioned by the World Bank. First, a set of papers directly test the links between displacement and social conflict or social cohesion in contexts as diverse as Columbia (Laia Balcells), Greece (Elie Murard), and Germany (Benjamin Elsner). Closer to our context, Alexander Betts and Phuong Pham study the impact on social cohesion in Uganda, Kenya, Ethiopia and the Democratic Republic of Congo. Our paper contributes to that literature by focusing on one particular channel, i. e., the changes in ethnic diversity. In line with the theoretical model offered by Esteban and Ray (2011), we do find a positive effect for the refugee-corrected polarization index on the occurrence of various types of conflict. A one standard deviation increase in the polarization index raises the incidence of violent conflict by 5 percentage points. Such an effect corresponds to a 10 percent increase, at the mean. The opposite effect is found for the fractionalization index. Our results should not be interpreted as evidence that refugees *per se* impact the likelihood of violence. Indeed, we do not find any significant correlation between the number of refugees and the occurrence of conflict. Even in terms of magnitude, the corresponding coefficient is basically null, confirming previous results in the literature (Zhou & Shaver, 2021). Instead, our results point to the risk of conflict when refugees exacerbate ethnic polarization in the hosting communities. On the contrary, a situation where refugee flows raises the level of ethnic fractionalization is likely to see an attenuated risk of violence. Our results are robust to alternative definitions of conflict, constructions of the diversity indices, specifications and samples. Overall, our results call for paying particular attention to the reception of refugees in highly polarized communities. Specific interventions aiming at reducing prejudice and strengthening cooperation between groups need to be promoted. Additional analysis suggests that the unemployed might be particularly sensitive to the effect of changing diversity in refugee-hosting and highly polarized communities.

The remainder of our paper is structured as follows. Section 2.2 provides the context of our study. Section 2.3 introduces our theoretical motivations. Section 2.4 presents our research design. First, we present our identification strategy (Section 2.4.1). Second, we describe our data with some descriptive statistics to help understand better the sample of our study (Section 2.4.2). Finally, we propose an instrumental variable approach (Section 2.4.3). In Section 2.5 we first present our main results (Section 2.5.1), then conduct some robustness tests (Section 2.5.2) and finally we present results from our instrumental variable approach (Section 2.5.3). Section 2.6 concludes with some implications for policy by discussing alternative explanations, heterogeneity and the relevance of our analysis in the context of the COVID-19 pandemic.

2.2 Context

Over the last decade, the number of refugees has increased from about 10 million in 2010 to 20.4 million at the end of 2019 (United Nations High Commissioner for Refugees, 2020).[30] Although refugees have been found to travel longer distances, compared to the 1980s (Devictor et al., 2021), the majority of refugees are still hosted in neighboring countries, which face themselves challenging socio-economic conditions. United Nations High Commissioner for Refugees (2020) estimates that 73 percent of refugees reside in neighboring countries and developing countries are hosting about 85 percent of the world's refugees.

The number of refugees under the United Nations High Commissioner for Refugees (UNHCR) mandate and residing in sub-Saharan Africa also rises from 2.2 to 6.3 million over the same period (United Nations High Commissioner for Refugees, 2020). These numbers magnify when including other people of concern for UNHCR, while the overall trends remain. Other regions have seen two significant changes. The war in Syria translated into a significant increase after 2011 in Europe and the Middle East (aggregated into Asia and Pacific in Figure 2.B.1). A more recent rise in Latin America has been driven by the recent surge in Venezuelan refugees. But these recent events should not hide the fact that Africa has seen a continuous increase of displaced people between 2005 and 2020. These population movements have been largely driven by civil wars and political instability in countries like South Sudan, the Democratic Republic of Congo, the Central African Republic, Somalia, Burundi and Eritrea (Figure 2.B.2). Until 2016, the majority of refugees were hosted in neighboring countries, but we confirm the general trend observed by Devictor et al. (2021) of a lower weight on geographical proximity over time (Figure 2.B.3). Chad, the Democratic Republic of Congo, Ethiopia, Rwanda, South Sudan, Sudan, the United Republic of Tanzania and Uganda are among the Least Developed Countries hosting the largest number of refugees (Figure 2.B.4).

Finally, forced displacement in sub-Saharan Africa is further characterized by the protracted nature of refugee situations (Verwimp & Maystadt, 2015). Figure 2.B.5 shows that the number of protracted refugee situations is not only higher in Africa but has also been increasing sharply

[30] Refugee is defined as "a person who has been forced to flee his or her country because of persecution for reasons of race, religion, nationality, political opinion or membership in a particular social group." (1951 Convention Relating to the Status of Refugees and the 1967 Protocol, Art 1.A.2.) and includes people on refugee-like situations.

over the last decade.[31]

2.3 Theoretical motivation

Ethnic diversity has been argued to be strongly linked to the non-cohesiveness of a society (Alesina et al., 2016; Arbatli et al., 2020), leading for example to its most extreme outcome of organized violence (Amodio & Chiovelli, 2018; Bazzi & Gudgeon, 2021; Collier & Hoeffler, 1998; Esteban et al., 2012b; Esteban & Ray, 1994, 1999; Fearon & Laitin, 2003). Others have investigated intermediary outcomes, as reflected by the prevalence of mistrust (Robinson, 2017), the sub-optimal provision of public goods (Desmet et al., 2020; Habyarimana et al., 2007), the lower quality of institutions (Alesina et al., 1999; Alesina & Zhuravskaya, 2011) or the resulting rise in socio-economic inequalities and associated grievances. In contrast to a long-standing cross-country literature on the role of ethnic diversity (Alesina et al., 2003; Easterly & Levine, 1997; Habyarimana et al., 2007; Miguel & Gugerty, 2005), we follow a more recent approach to investigate similar research questions at the local level (Desmet et al., 2020; Gomes, 2020; Montalvo & Reynal-Querol, 2020). We build our empirical investigation on the theoretical implications of Esteban and Ray (2011)'s game-theoretic model. Esteban and Ray (2011) presents a contest model between different groups. According to the unique Nash equilibrium of the game, conflict is more likely to occur when the population is highly polarized in presence of so-called public payoffs. On the contrary, group fractionalization is expected to matter much less in this case.[32] We argue that the presence of refugees and the public resources that usually accompany such population flows are associated with the risk of conflict over public goods. There is indeed a large literature suggesting that refugees and their hosts are competing over existing resources and services (Maystadt et al., 2019). In this context, we expect ethnic polarization to matter much more for conflict, than ethnic fractionalization. Our empirical analysis also indirectly tests for the assumption of the publicness of conflict payoffs in refugee settings. If all conflict payoffs are private, polarization cannot matter. On the contrary, if all conflict payoffs are public, fractionalization cannot matter. In theory, all the information on preferences and group sizes can be aggregated into just the fractionalization and polarization indices. However, given our identification, we also control for the direct impact of refugees on these preferences and hence, conflict.

Our contribution is twofold. First, identification has been challenging since most of the literature only uses a time-constant measure of diversity (Desmet et al., 2012; Montalvo & Reynal-Querol, 2005). The problem is that ethnic diversity may be correlated with many unobserved characteristics. As far as we know, two other papers have recently exploited time-varying changes in ethnic diversity. First, Bazzi et al. (2019) investigate how changes in inter-group diversity affect national identity, social capital, public goods and ethnic conflict in Indonesia. To that purpose, they exploit a resettlement program in Indonesia. They shed light on the distinction between ethnic fractionalization and polarization. The former is associated with a greater sense of national identity (in contrast to ethnic attachment), the opposite for the later. Polarization is also associated with adverse effects on social capital, as reflected by lower intergroup tolerance and trust, community engagement and preferences for redistribution. Second, Amodio and Chiovelli (2018) exploit the variation in ethnic diversity

[31] Although it recognizes the statistical limits of such a definition, United Nations High Commissioner for Refugees (2020, p. 24) "defines a protracted refugee situation as one in which 25,000 or more refugees from the same nationality have been in exile for at least five consecutive years in a given host country" (excluding Palestine refugees under the United Nations Relief and Works Agency (UNRWA)'s mandate).

[32] Similar to Esteban et al. (2012b), we ignore the role of the Greenberg-Gini index that theoretically vanishes with large population size.

induced by migration flows resulting from the repeal of apartheid segregation laws in South Africa. They show that stronger polarization among the Black population at the district level is associated with a higher number of armed confrontations. Our paper differs since we are investigating changing ethnic diversity induced by international movements of refugees in Africa. By focusing on the changes in diversity induced by non-voting migrants, we abstract from mechanisms that rely on the median voter theorem or the seize of power.[33]

Second, we contribute to another strand of the literature assessing the impact of forced migration on hosting societies (Becker & Ferrara, 2019; Maystadt et al., 2019; Ruiz & Vargas-Silva, 2013; Verme & Schuettler, 2021). More specifically, we investigate the impact of refugees in low-income countries. While the literature has mainly focused on labor and good markets (Maystadt et al., 2019; Verme & Schuettler, 2021), little is known about the long-term effects on the hosting population, including on trust and identity formation. Exceptions are provided by Zhou (2018, 2019). Zhou (2018) uses similar georeferenced data to analyze how the presence of refugees affect the local citizens' opposition to citizenship inclusion in sub-Saharan Africa. Zhou (2019) also shows how the presence of refugees affects national identity formation in Tanzania as a way for local citizens to distance themselves from a new migrant out-group. We differ from these insightful studies since we focus on the way refugees affect those outcomes through a particular channel, i. e., the changes in ethnic diversity. Another difference is that we do not assume refugees to be an homogeneous group by exploiting their likely ethnic attachment. Although different, these studies are important to stress the need to control for the direct effect of the presence of refugees in our research design. Finally, Zhou and Shaver (2021) have revisited a long-standing claim that refugees are fueling conflict across borders (Salehyan, 2006, 2008). We qualify their results by showing that refugees may increase conflicts if their composition exacerbates between-group antagonism in polarized communities.

2.4 Research design

2.4.1 Identification strategy

Our aim is to assess how changes in ethnic diversity affect the incidence and the intensity (i. e. the number) of conflict. Our first empirical exercise consists in regressing conflict on refugee-induced ethnic fractionalization and ethnic polarization in the following way:

$$Conflict_{jt} = \alpha_j + \tau_t + \beta_1 CorrEF_{jt-1} + \beta_2 CorrEP_{jt-1} + \beta_3 Ref_{jt-1} + \beta_4 Q_{jt} + \epsilon_{jt} \tag{2.1}$$

where $Conflict_{jt}$ represents the incidence or the intensity of conflict in location j in year t. We define location using information from the Afrobarometer Enumeration Areas. These correspond to locations classes (administrative regions, e. g., states or provinces, populated places, e. g., cities or villages, structures, e. g., buildings, bridges or roads, and other topographical features, e. g., rivers, mountains or national parks) with exact or approximate geographic information. They are provided with a precision code allowing the user to choose the desired level of geographical unit. We restrict our analysis to observations with a precision code of maximum 2 covering therefore locations that are defined at a finer level than administrative

[33] In relation to Esteban and Ray (2011)'s most recent game-theoretic model, we argue that the presence of refugees and the public resources that usually accompany such population flows are associated with the risk of conflict over public goods. If all conflict payoffs are private, polarization cannot matter. If all conflict payoffs are public, fractionalization cannot matter. That is why, it is so important to also control for the direct effects induced by the presence of refugees.

regions.[34] In the remainder of our paper we refer to the Afrobarometer Enumeration Areas as clusters.

The number of conflict events is transformed into Inverse Hyperbolic Sine to ease interpretation (Bellemare & Wichman, 2020). $CorrEF_{jt-1}$ and $CorrEP_{jt-1}$ respectively refer to *refugee-corrected ethnic fractionalization* and *ethnic polarization*. They capture the change in ethnic diversity induced by the refugee inflows at time $t-1$. We capture the changes in ethnic diversity by correcting standard measures of diversity based on the Afrobarometer with the changes in ethnic diversity induced by the refugee flows within a certain buffer around the cluster j. That is certainly the main difference compared to the existing literature since we correct the standard ethnic diversity indices by the annual variation in refugees' ethnicity.[35] We then construct a measure of proximity between the clusters in the host country and refugees in the surrounding camps by defining a 80-km buffer around each cluster.[36]

To control for the unobserved heterogeneity and changes within a given cluster, we introduce cluster and year fixed effects, α_j and δ_t. To minimize the risk of confounding the refugee-induced changes in diversity with the annual changes in refugees present in the surroundings, we also control for the presence of refugees, based on the same buffer than the one used to construct the refugee-induced change in diversity. More specifically, the variable Ref_{jt-1} counts the number of refugees present in cluster j at year $t-1$ within the pre-defined buffer. The variable is also transformed into Inverse Hyperbolic Sine to ease interpretation.

Finally, Q_{jt} controls for yearly shocks at cluster level such as weather shocks. In particular, we control for rain and temperature anomalies. Standard errors are clustered at the Afrobarometer cluster level.

2.4.2 Data and Descriptive Statistics

Our analysis combines various sources of data: the Afrobarometer, the UNHCR Refugee Camps Data, the Armed Conflict Location and Event Data (ACLED), the Uppsala Conflict Data (UCDP) and the Ethnic Power Relations - Ethnicity of Refugees (EPR-ER) 2019 dataset.

As explained in Section 2.4.1, the geographical unit of our study is provided by the Afrobarometer. The Afrobarometer is a pan-African research institution conducting public attitude surveys on democracy, governance, the economy and society in countries of the African continent repeated on a regular cycle (Afrobarometer, 2020). Using the Afrobarometer geocoded surveys, we focus on clusters as our units of observations.[37] Our sample consists of 7,547 such locations[38] and 76,518 individuals in 23 countries in sub-Saharan Africa.[39] Afrobarometer provides geocoded data for 6 rounds, which correspond to the period 1991-2016 with the in-

[34] We conduct robustness checks with a precision code of maximum 3 (therefore also covering administrative regions) and without imposing any restriction on the geocoded locations (therefore approximate geographic information) (Section 2.5.2)

[35] We explain the construction of theses indices in Section 2.4.2.

[36] We test the robustness of our results with a lower (40-km) and a higher (120-km) radius in Section 2.5.2. The choice of the range of buffer size assures us that between 75 percent and virtually all refugee camps fall within a cluster buffer. Other studies relying on Afrobarometer data construct buffers ranging from 25-km (e.g. Michaelopoulos and Papaioannou (2011) investigating ethnic-specific pre-colonial institutional structures) to 100-km (e.g. McGuirk and Burke (2020b) analyzing the impact of food price shocks on conflicts).

[37] As a reminder, these are populated places, e. g., cities or villages, structures, e. g., buildings, bridges or roads, and other topographical features, e. g., rivers, mountains or national parks (a precision code ≤ 2).

[38] There are 10,449 clusters with a precision code ≤ 3 and 10,851 clusters with no restriction on the precision code.

[39] Countries in our sample are: Benin, Burkina Faso, Burundi, Cameroon, Gabon, Ghana, Guinea, Ivory Coast, Kenya, Liberia, Malawi, Mali, Mozambique, Namibia, Niger, Nigeria, Senegal, Sierra Leone, Tanzania, Togo, Uganda, Zambia and Zimbabwe. See Table 2.B.1 for more information on the full set of countries present in our study.

formation on an individual's ethnicity available from Round 3 (corresponding to 2005-2006). We therefore restrict our analysis to the period 2005-2016.

Below, we describe how these data have been used to define our main variables of interest and present some descriptive statistics in Table 2.B.2.[40]

Conflict. In Equation 2.1, we first relate variations in ethnic diversity with data on conflict from the ACLED (Linke et al., 2010). Two main definitions are used: the *incidence* of conflict and the *intensity* of conflict. *Incidence* is captured by an indicator equal to one if conflict is occurring in a particular year within a pre-defined buffer around the cluster j. *Intensity* is measured by summing the number of conflict events occurring in a particular year within the same buffer area. A conflict event is defined as a single altercation wherein force is used by one or more groups for a political end (Linke et al., 2010). We further classify events into non-exclusive groups, such as violent, non-violent events, violence against civilians and riots. In our main analysis, we focus on violent conflict incidence (Section 2.5.1) and report results with intensity and other outcomes as robustness (Section 2.5.2). In doing so, we follow a recent and large literature that has combined the ACLED dataset with geographically disaggregated data in Africa (Berman & Couttenier, 2015; Berman et al., 2017; Besley & Reynal-Querol, 2014; Eberle et al., 2020; Harari & Ferrara, 2018; McGuirk & Burke, 2020a; Michaelopoulos & Papaioannou, 2016).

As a robustness check, we also use data on conflict incidence and intensity from the UCDP which uses a more conservative definition of conflict. The UCDP dataset is manually curated and compiled with automated computer assistance (Sundberg & Melander, 2013). The UCDP defines an armed conflict event as "an incident where armed force was used by an organized actor against another organized actor, or against civilians, resulting in at least one direct death at a specific location and a specific date" (Pettersson et al., 2020). We extract daily event observations from the UCDP dataset where the location of the actual event is exactly known, the event location is within a radius of less than 25 km around a known point, or at least the administrative district where the event happened is known. As pointed by Eberle et al. (2020), the UCDP events are more likely to capture violence between large-scale and more structured groups.

Table 2.B.2 shows that on average, conflict events seem to occur more in refugee-hosting areas. This is of course not a causal interpretation but a simple correlation. As can be seen from both Panel A and Panel B, non-violent conflicts seem to occur slightly more than violent conflicts. On average, the likelihood of violent conflict stands at about 48% while this figure increases to 52% in refugee-hosting areas. Conflict among more structured and large groups, as captured by the UCDP data, appear to be less frequent.

UNHCR Refugee data. As we exploit the variation in ethnic diversity induced by the annual variation in refugees (and also control for the direct effect of refugees on our outcomes), we exploit data on refugee camps provided by the UNHCR. The dataset contains detailed time-series information on the location and size of 1,453 refugee camps across the world and 821 refugee camps in sub-Saharan Africa covering the years 2000-2016.

To the best of our knowledge, the UNHCR currently provides the most comprehensive information available on refugees at subnational level, which has so far only been used to study the effect of refugees on environmental degradation (Maystadt et al., 2020). More importantly, the composition of the camps had not yet been exploited, which is key for our research question. First, we exploit the country of origin of refugees recorded for each year at the camp level to

[40] Panel A of Table 2.B.2 shows descriptive statistics for our data in refugee-hosting areas whereas Panel B of Table 2.B.2 shows descriptive statistics for our data in all covered areas.

approximate for ethnic composition. Second, we restrict data on refugees to those aged 18 and above to make it comparable to the Afrobarometer-based individual data. Third, we limit the identification of refugees to those hosted within the boundaries of the host country.

Merging data on refugee camps with the Afrobarometer, we end up exploiting information about 172 camps, which are at a distance of 80-km from the 7,547 clusters.[41] Figure 2.4.1 shows the location of these refugee camps and clusters. Clusters are represented in green while clusters in vicinity of the refugee camps are represented in red. Refugee camps are allocated with a red + sign.

There are some important limitations associated with this data. First, the data only provides information on refugees residing in the UNHCR monitored camps. In Figure 2.B.6, we aggregate the UNHCR refugee camp data on the annual number of refugees and the UNHCR official statistics on refugees (including people in refugee-like situations) at the country level.[42] Although overall trends match, our constructed dataset clearly underestimates the true refugee population in Africa. It is not surprising since our camp-specific data does not contain dispersed refugees or refugees out of the camps.

While our data seem to represent quite fairly the number of refugees in camps, there is quite a large heterogeneity across countries. Based on visual inspection from Figure 2.B.7, the quality of the refugee data appears less reliable for the following countries in our sample: Gabon, Mali, Senegal and Togo. We conduct robustness tests excluding these 4 countries from our sample (Section 2.5.2).

Refugee-corrected diversity indices. We first exploit the Afrobarometer data to construct standard indices of diversity, namely the EF and the EP indices. We follow Bazzi et al. (2019) in adopting the seminal indices introduced by Esteban and Ray (1994).

The EF index describes the probability that two randomly selected individuals from a given location belong to two different ethnic groups (Alesina et al., 2003; Alesina et al., 2016; Gomes, 2020). The EF index can be defined as:

$$EF_{jt} = \sum_{e=1}^{N_{jt}} g_{et}(1 - g_{et}) \tag{2.2}$$

where N_j is the number of ethnic groups in the cluster j at time t and g_{et} is the population share of ethnic group e at time t. It can also be expressed as one minus the Herfindahl index (Alesina et al., 2016).

In turn, the EP index gives more weight to intergroup differences at the expense of within group homogeneity. It can be defined as (Esteban & Ray, 1994, 1999; Montalvo & Reynal-Querol, 2005):[43]

$$EP_{jt} = \sum_{e=1}^{N_{rt}} (g_{et}^2)(1 - g_{et}) \tag{2.3}$$

We compute this index for each cluster at the time of each Afrobarometer survey to assess how our refugee-induced changes in diversity differ from standard indices of diversity.

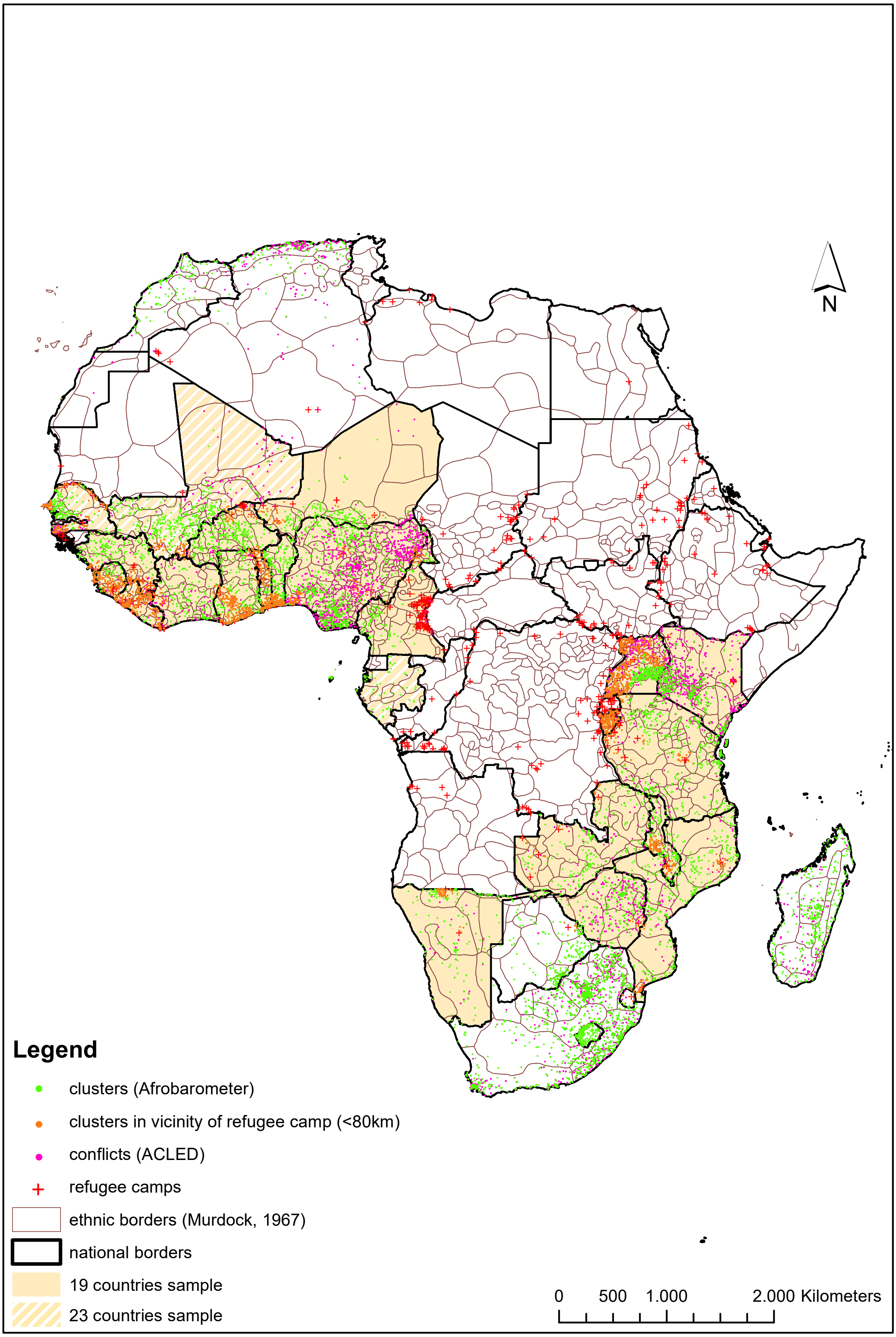
The main data challenge is the construction of the refugee-corrected diversity indices according to ethnicity e. To do so, we first combine information about the country of origin

[41] There are 189 camps at a distance $\leq$ 120-km and 113 camps at a distance $\leq$ 40-km from these clusters.

[42] $https://www.unhcr.org/refugee-statistics/download/?url=R1xq$.

[43] As pointed by Desmet et al. (2020, footnote 13), Esteban and Ray (1994) offers a slightly more general index. That is actually the formulation proposed by Reynal-Querol (2002).

Figure 2.4.1: Clusters, Refugee Camps and Conflicts.



of refugees hosted in refugee camps c in year t with the data from the EPR-ER 2019 dataset. The EPR-ER records the ethnic composition of refugee stocks originating from neighboring countries and countries in proximity to each other (maximal distance between country borders $\leq$ 950 km) with at least 2,000 refugees and provides the ethnic composition of refugees (Vogt et al., 2015).

More specifically, the EPR-ER gives us the share of refugees from ethnic group e moving from country o to country d at year t. The EPR-ER gives us the three main ethnic groups. The number of refugees belonging to camp c at year t is therefore approximated by the following formula :

$$\sum Ref_{cet} = Ref_{ocdt} * Share_{odet} \tag{2.4}$$

Doing so we obtain the number of refugees Ref_{cet} from ethnicity e per camp c at time t. We can then sum the number of refugees by group e at year t for each cluster j within a buffer of e. g., 80-km. We also restrict the count of refugees hosted within the boundaries of the host country. Figure 2.4.2 shows, for each cluster of interest (i. e. $\oplus$) in our data, the refugee camps (i. e. red $+$) within a buffer of 40-km, 80-km and 120-km in the host country.

In order to obtain a sample-based number of hosts comparable to a population-based number of refugees, we multiply the number of respondents from the Afrobarometer by the ratio $\frac{N}{n}$ where N is the total population of the surveyed country at year t and n is the sample size of the survey collected at year t. Intuitively, we need to make sure that one refugee is comparable to a host in the computation of the corrected diversity indices. Based on the World Development Indicators, the country population aged 18 and above at $t-1$ is considered as equivalent to the most recent official national census used as the sampling frame for the Afrobarometer surveys. As individuals in the Afrobarometer are aged 18 and above, for comparison purposes, we also restrict our analysis to refugees aged 18 and above.[44]

There is one limit to our approximation in Equation 2.4. The ethnic composition of refugees in each year t for a given origin-destination pair of countries obtained from the EPR-ER database is assumed to be equal across camps of the same origin-destination pair of countries for the refugees at year t. This may appear as a strong assumption. However, the risk of mis-allocating refugees is reduced as the annual variation in the EPR-ER is generated by a few dominant groups for a given origin-destination pair. In effect, there are mainly two major ethnic groups.[45]

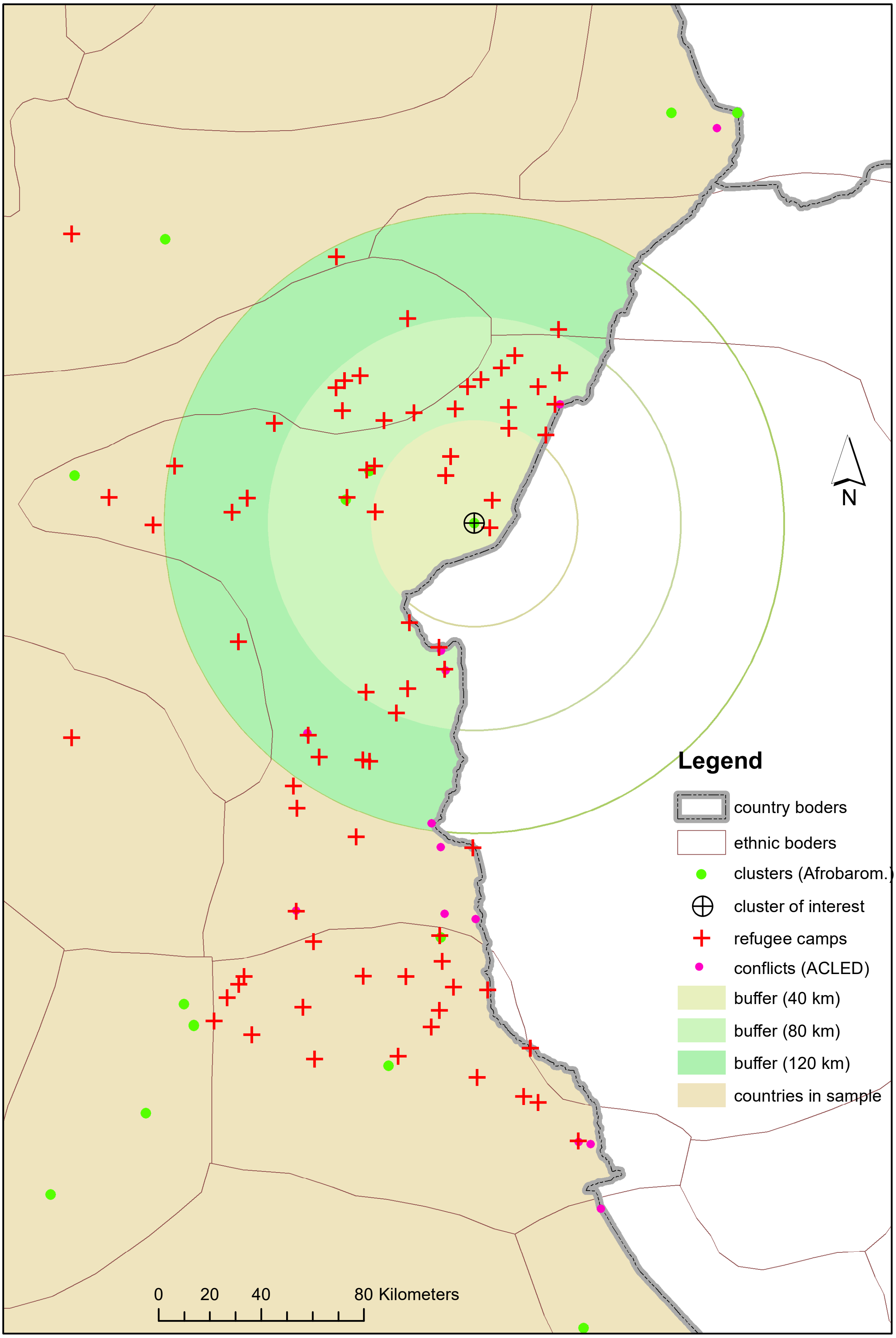
As can be seen from Panel A of Table 2.B.2, in refugee-hosting areas, on average, both the EF and the EP seem to increase quite importantly when they are *corrected* with refugees in a 80-km buffer. The mean value of the standard EF index is 25.58% while the mean value of the refugee-corrected EF index is 37.90%. The mean value of the standard EP index is 10.11% while the mean value of the refugee-corrected EP index is 14.07%.

Ethnicity. Finally, a major task in the above data construction is the ability to combine data on ethnicity across various datasets. Indeed, linking ethnic groups is challenging, in particular in Africa, where ethnic identities are socially constructed and where there are different definitions, categorizations or even conceptual approaches when it comes to identifying ethnicities in various databases or scientific disciplines. This makes the task of treating,

[44] On average, 45% of refugees in the camps are aged 18 and above.

[45] We cannot exclude the fact that our approximation is noisy and could potentially induce non-random measurement errors. In Section 2.4.3 we propose an instrumental variable approach and estimate the $Share_{odet}$ from the EPR-ER using a gravity model. Our findings concerning the number of ethnic groups across time for a given origin-destination pair are in line with the EPR-ER data. It seems that refugees for a given origin-destination pair across time mainly belong to two major ethnic groups.

Figure 2.4.2: Refugee-Corrected Diversity Indices.



combining and analyzing ethnicities extremely daunting as it requires substantial background knowledge of hundreds of ethnicities and mostly manual treatment, which would inevitably lead to inconsistencies, errors of manipulation or subjective choices. Fortunately, we could rely on the LEDA open-source software package, which contains a full pipeline to link ethnic datasets from Africa constructed by Müller-Crepon et al. (2020) in a consistent and replicable way.

In our analysis, we obtain ethnicities of refugees from the EPR-ER while the ethnicity of the individuals in the hosting areas stem from the Afrobarometer. These ethnicities are not systematically reported at the same level with a similar categorization process, instead the information could relate to an individual's linguistic ethnicity, dialect or an ethnic group comprising several languages all together. In our main analysis, we use LEDA's binary linking at the 'dialect' level based on the minimum linguistic distance to link these ethnic groups.[46] As a robustness check (Section 2.5.2), we use an alternative linkage type based on the relations of sets of language nodes associated with two groups. We describe further in Section 2.A.1 the use of the LEDA software package.

2.4.3 An instrumental variable approach

In the previous Section 2.4.1, we acknowledged that non-random measurement errors might be a concern. Another major identification challenge is the risk that our corrected measures of diversity is biased due to the selection of hosting areas by refugees. We should first acknowledge that it is one advantage to use refugees movements as exogeneous variations, since their ability to select their places of residence is much more limited than economic migrants. However, we cannot exclude the possibility that refugees would sort into areas with particular ethnic characteristics.

In order to address this potential endogeneity, we implement an instrumental variable (IV) approach. We are in particular concerned about certain ethnic groups from certain countries of origin to move to specific destination countries with similar ethnic characteristics. Such endogenous selection would be reflected in the EPR-ER data.[47] To deal with the plausibly endogenous nature of the resulting refugee-corrected EF and EP indices, we are implementing a gravity model to predict the number of refugees of a certain ethnic group e moving from country o to d at time t, based on EPR-ER. The predicted (and plausibly exogeneous) number of refugees by ethnic group e is then used to create other (plausibly exogeneous) diversity indices, to be used as instrumental variables. More specifically, we are estimating the following gravity model:

$$REF_{odet} = \alpha_{od} + \gamma_e + \tau_t + \beta_1 Conflict_{ot-1} + \beta_2 Conflict_{et-1} + \beta_3 Distance_{ed} + \epsilon_{odet} \tag{2.5}$$

where REF_{odet} is the stock of refugees of ethnic group e from country o in country d at year t. As we have data on yearly refugee stocks and would like to estimate the changes in these stocks over time using a gravity model, we include dyadic origin-destination fixed effects α_{od} so that identification is based only on changes in stock over time (Zylkin, 2019).[48] We also include time τ_t and ethnic group fixed effects γ_e. Here we obtain data on the ethnicity of refugees from Murdock's Atlas, which provides a map of ethnographic regions for Africa

[46] We also use this method to link data from EPR-ER on ethnicities of refugees with data from Murdock Atlas on their historical homeland (Section 2.4.3).

[47] In turn, we should not be concerned too much about the selective nature of ethnic composition at the camp level since it is dictated by the country of origin of refugees and the ethnic composition given by EPR-ER.

[48] We conduct a robustness on Equation 2.5 replacing the dyadic origin-destination fixed effects by origin and destination fixed effects (Section 2.5.3).

and historical homelands of refugees (Murdock, 1967). Again we use LEDA[49] to link data on ethnicity from Murdock's Atlas with data on ethnicity from the EPR-ER and later on with data on Afrobarometer to construct our diversity indices.

We use the sum of conflict events occurring in the historic homeland of ethnic group e in the previous year $t-1$, denoted $Conflict_{et-1}$ and the mean distance between historic homeland of ethnic group e and the border of country d to predict the number of refugees of certain ethnic group e moving from country o to d at time t, only based on exogeneous push factors.[50]

In order to comply to EPR-ER data construction, we restrict our analysis to all origin-destination country pairs that are at a maximum distance $\leq$ 950 km of each other. Predicted numbers of refugees are then transformed into predicted shares for the three largest groups to follow the logic used by EPR-ER. We then plug these exogenous share in the following way:

$$\sum \widehat{PredictedRef}_{cet} = Ref_{ocdt} * \widehat{Share}_{odet} \tag{2.6}$$

The predicted value of refugees per camp c is then used to compute—as documented above—exogeneous refugee-corrected diversity indices, as instrumental variables. The first-stage equations corresponding to the 2SLS-equivalent of Equation 2.1 can be expressed as:

$$CorrectedEF_{jt} = \alpha_j + \tau_t + \delta_1 PredictedEF_{jt} + \delta_2 PredictedEP_{jt} + \delta_3 Refuges_{jt} + \delta_5 Q_{jt} + \epsilon_{1,jt} \tag{2.7}$$

and

$$CorrectedEP_{jt} = \alpha_j + \tau_t + \delta_1 PredictedEF_{jt} + \delta_2 PredictedEP_{jt} + \delta_3 Refuges_{jt} + \delta_5 Q_{jt} + \epsilon_{2,jt} \tag{2.8}$$

2.5 Results

In this section, we discuss our results from our benchmark analysis (Section 2.5.1), from a number of robustness tests with alternative outcome variables and alternative specifications (Section 2.5.2) and from our IV approach, in which we obtain diversity indices using a gravity model (Section 2.5.3).

2.5.1 Main Results

In Table 2.5.1, we present our results from a linear probability model with the incidence of violent conflicts as the dependent variable. As suggested by the theoretical framework proposed by Esteban and Ray (2011), we introduce both indices, e. g., EF and EP, in the same specification.

Columns (1) and (2) introduce the standard diversity indices while from Column (3), refugee-corrected diversity indices are introduced. In Columns (2), (4) and (6), the presence of refugees within a distance of 80-km is introduced. Indeed, despite the recent literature rejecting the conflictive impact of refugees in their hosting areas (Zhou & Shaver, 2021), the magnitude of our coefficients might be explained by the confounding presence of refugees. Columns (5) and (6) further introduce climatic controls. Column (6) corresponds to Equation 2.1 and refers to our benchmark specification.

Columns (1) and (2) show that not exploiting the flows of refugees as variation in diversity indices, would not allow us to identify a relationship between diversity and violent conflicts.

[49] More information on LEDA in 2.A.1.

[50] The construction of the IV follows a long tradition in using the gravity model to predict bilateral migration flows (Beine et al., 2016; Crozet, 2004; Garcia et al., 2015; Mayda, 2010; Ravenstein, 1985, 1989). In our analysis, a major difference is that we have an additional dimension, which is the ethnic group e.

In Column (3), the refugee-corrected fractionalization index has a negative and significant coefficient while the refugee-corrected polarization index has a positive and significant effect on the incidence of violent conflicts.

In Columns (2), (4) and (6), our coefficients of interest are of the same order of magnitude when the number of refugees is controlled for. Introducing climatic controls in Columns (5) and (6), our results are not altered by augmenting the different specifications with rainfall and temperature anomalies. Estimates become slightly more precise.

According to Column (6), our benchmark specification, a one standard deviation rise in the refugee-corrected fractionalization index decreases the incidence of violence conflict by 5 percentage points. At the mean, it corresponds to a fall of about 10 percent. On the contrary, a similar increase in the refugee-corrected EP index raises the likelihood of violent conflict by 5 percentage points. The magnitude of our results appear to be relatively large. Our results on polarization qualify the seminal findings by Esteban et al. (2012a) and Esteban et al. (2012b). In their cross-country study (Esteban et al., 2012a), they indeed indicate that moving from the 20th percentile of polarization to the 80th percentile increases the likelihood of conflict by 16 percentage points. Performing the same exercise with our geographically disaggregated analysis and time-varying polarization index would increase the risk of conflict by 9 percentage points.[51] Our results are much more in line with Bazzi et al. (2019). Replicating their results for the incidence of conflict, a one standard deviation increase in polarization results in a 4.2 percentage points rise in the likelihood of conflict.[52] Although contrasting with Esteban et al. (2012a) and Esteban et al. (2012b), the negative effect found for the fractionalization index is again consistent with findings by Bazzi et al. (2019). Our decrease by 5 percentage points following a 1 standard deviation change in ethnic fractionalization is close to their corresponding 3.7 percentage points. As pointed by these authors, the negative sign is still consistent with Esteban and Ray (2011) in a situation where conflict materializes around public resources. Esteban et al. (2012a) and Esteban et al. (2012b) indeed interpret the positive coefficient found for fractionalization as evidence that private components, such as the existence of natural resources, matter. In our context, where refugees are likely to be accompanied by contestable public resources, intergroup contact with many small groups (large fractionalization) is likely to reduce the risk of conflict.

Last, the magnitude of our results—i. e.. 5 percentage points change due to a 1 standard deviation change in diversity or a 10 percent change at the mean—can be compared with other major determinants of conflicts in Africa, namely the role of economic shocks (often associated to climatic shocks), natural resources, and price shocks.[53] First, one of the most robust findings is the role of economic shocks in explaining the incidence of conflict in Africa (Blattman & Miguel, 2010). The seminal paper by Miguel et al. (2004) shows that a 1 standard deviation increase in economic growth leads to a change in the likelihood of conflict by more than 16 percentage points.[54] Although the income effect is not the unique interpretation (Mach et al., 2019), economic shocks in Africa have often been associated with climatic shocks (Harari & Ferrara, 2018). In their meta-analysis, Hsiang et al. (2013) indicate that a 1 standard

[51] The magnitude of our polarization effect is not only smaller than the cross-country study by Esteban et al. (2012a) and Esteban et al. (2012b) but also compared to Amodio and Chiovelli (2018), with a reported increase of 30 percentage points following a 1 standard deviation rise in polarization.

[52] We use the replication files provided by Bazzi et al. (2019) to replicate column (4) of their Table 11 and retrieve the corresponding descriptive statistics.

[53] Since Collier and Hoeffler (1998) and Fearon and Laitin (2003), there has been a booming literature in the economics of conflict. We limit our comparison to time-varying factors. It is indeed difficult to compare with long-term (time-constant) determinants of conflict such as ethnic partitioning (Michaelopoulos & Papaioannou, 2016) or historical conflict (Besley & Reynal-Querol, 2014).

[54] We should acknowledge that the validity of these results beyond 1999 has been questioned (Ciccone, 2011; Miguel & Satyanath, 2011).

deviation change in climate towards warmer temperature or more extreme rainfall increases the frequency of conflict by 14 percent at the mean. A second major determinant of violence in Africa has pointed towards the presence of natural resources. For instance, Berman et al. (2017) found that a 1 standard deviation increase in the price of minerals translates into a 5.6 percentage points rise in conflict. Other price shocks matter too. For instance, a 1 standard deviation increase in producer prices reduces the incidence of conflict by 17 percent at the mean (McGuirk & Burke, 2020a). The equivalent change in consumer price exacerbates conflict by 8 percent. According to Berman and Couttenier (2015), a 1 standard deviation increase in world demand for agricultural commodities also increases conflict by 1 to 3 percentage points. Overall, it is certainly not our intention to provide an exhaustive review of the literature but our estimated effect sizes are clearly comparable with the existing studies, placing ethnic diversity *on par* with other major determinants of conflict in Africa.

Table 2.5.1: Benchmark Analysis: Diversity and Violent Conflict, Incidence.

	(1)	(2)	(3)	(4)	(5)	(6)
	Violent Conflict, Incidence					
EF	-0.1090	-0.1096				
	(0.0716)	(0.0718)				
EP	0.2263	0.2278				
	(0.2103)	(0.2108)				
Refugees (80km, IHS)		0.0004		0.0012		0.0008
		(0.0028)		(0.0030)		(0.0030)
Corrected EF (80km, Min. Ling. Dist.)			-0.1593*	-0.1686**	-0.1717**	-0.1780**
			(0.0814)	(0.0856)	(0.0815)	(0.0858)
Corrected EP (80km, Min. Ling. Dist.)			0.4181*	0.4238*	0.4450**	0.4487**
			(0.2180)	(0.2196)	(0.2186)	(0.2202)
Rain anomalies (80km)					-0.0008**	-0.0008**
					(0.0004)	(0.0004)
Temp anomalies (80km)					-0.0834***	-0.0832***
					(0.0230)	(0.0230)
Observations	14,441	14,441	14,441	14,441	14,441	14,441
R-squared	0.661	0.661	0.661	0.662	0.662	0.662
Year FE	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS, presented in Column (6). Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. Refugee camps in a 80-km buffer around each cluster. The 'minimum linguistic distance' function from LEDA* to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

[*] More information on LEDA in 2.A.1.

2.5.2 Robustness

We now examine the sensitivity of these main results to a battery of robustness checks. First, we assess the robustness of our results to the use of alternative outcomes (Table 2.5.2). Second, we conduct robustness tests with some alternative specifications (Table 2.5.3).

Each Line corresponds to the same specification as in the previous Table 2.5.1 with an alternative outcome. Only results for refugee-corrected EF and EP - our variables of interest

- from Column (6) corresponding to Equation 2.1 are presented for sake of space.[55] Line A presents results from our benchmark estimation in Column (6) of Table 2.5.1.

Being transformed into Inversed Hyperbolic Sine, our results can then be interpreted as quasi-elasticities. As can be seen from this Table 2.5.2, the refugee-corrected EP significantly impacts other conflict events with the exception of non-violent conflicts and protests intensity (Lines C and J). Our diversity indices point to a null relationship with the intensity of non-violent events and protests. The magnitude of the coefficient for the intensity of civilian conflicts and violent conflicts are particularly high (Lines B and F). The refugee-corrected EF seems to also have a significant and negative impact on civilian conflict incidence and intensity (Lines E and F). Interestingly, our results are not robust to violence perpetrated by larger-scale and more structured groups and their intensity, as captured by the UCDP data (Lines I and J).

Second, as can be seen from Table 2.5.3, our results do not depend on the choices made in the construction of our main variables of interest. Here, each Line brings a modification to our benchmark specification corresponding to the Equation 2.1 and are conducted in the same way as in Table 2.5.1. Again, only results for refugee-corrected EF and EP - our variables of interest - from last Column (6) are presented for sake of space.[56] Line A presents results from our benchmark estimation in Column (6) of Table 2.5.1.

Using a more restrictive linking, e. g., binary linking based on the relations of sets of language nodes associated with two groups between the ethnic groups from LEDA (Line B), between the ethnic groups from the Afrobarometer and the EPR-ER, also identifies a negative coefficient (significant at 10%) for the refugee-corrected EF and a positive coefficient for EP (significant at 10%).

Another arbitrary choice relates to the size of the buffer used to capture the number of refugees in vicinity of clusters and their contribution to ethnic composition. Using a smaller (40-km) vs. a larger (120-km) buffer, our results also seem to remain robust, albeit less significant and the coefficient for refugee-corrected EF is no more significant with a larger buffer.

As in our benchmark analysis, we have used so far a linear probability model. We also conduct robustness tests implementing a non-linear model with a conditional logit (Line E). Our results remain robust to a non-linear estimation.

Our results are robust to alternative variable construction and specifications, however, rest on strong identifying assumptions. We may be concerned about the existence of confounding trends. We therefore augment our main specification with country-specific time trends (Line F). The magnitude of our coefficients is even slightly higher for refugee-corrected EF and similar for refugee-corrected EP.

As discussed in Section 2.4.2, data on refugee camps for some countries in sub-Saharan Africa seem dubious.[57] These countries are Gabon, Mali, Senegal and Togo. We therefore

[55] Notes below Table 2.5.2 include references for Tables with the full set of specifications corresponding to each Line.

[56] Notes below Table 2.5.3 include references for Tables with the full set of specifications corresponding to each Line.

[57] See Figure 2.B.7.

exclude these 4 countries. Both the magnitude and significance of our results improve using this restricted sample of countries.

We also perform a check relaxing the criteria on the exactness of the geographic information provided by the Afrobarometer by taking a precision code ≤ 3 (Line H) and by completely disregarding it (Line H I). Our results are overall similar to such modifications in the sample.

Table 2.5.2: Summary Table: Alternative Outcomes.

	(1)	(2)
	Corrected EF (80km, Min. Ling. Dist.)	Corrected EP (80km, Min. Ling. Dist.)
A. Benchmark Results (N=14,441)[a]	-0.1780**	0.4487**
	(0.0858)	(0.2202)
B. Violent conflict, Intensity (N=14,441)[b]	-0.3088	0.9170*
	(0.2086)	(0.5183)
C. Non-Violent Conflict, Incidence (N=14,441)[c]	-0.0536	0.3654*
	(0.0797)	(0.2127)
D. Non-Violent Conflict, Intensity (N=14,441)[d]	-0.2402	0.8250
	(0.2092)	(0.5588)
E. Civilian Conflicts, Incidence (N=14,441)[e]	-0.1460*	0.4032*
	(0.0847)	(0.2169)
F. Civilian Conflicts, Intensity (N=14,441)[f]	-0.3762**	1.1916**
	(0.1892)	(0.4660)
G. Protests, Incidence (N=14,441)[g]	-0.0853	0.4754**
	(0.0809)	(0.2160)
H. Protest, Intensity (N=14,441)[h]	-0.1891	0.8323
	(0.2062)	(0.5536)
I. Conflict (UCDP), Incidence (N=14,441)[i]	0.0642	-0.2532*
	(0.0638)	(0.1514)
J. Conflict (UCDP), Intensity (N=14,441)[j]	-0.0143	-0.1200
	(0.1624)	(0.3972)

Notes: Estimated Equation: Equation (2.1) using OLS with alternative dependent variables. Level of analysis, Period, LEDA function: similar to Table 2.5.1. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

See Column (6) for: [a] in Table 2.5.1; [b] in Table 2.B.3; [c] in Table 2.B.4; [d] in Table 2.B.5; [e] in Table 2.B.6; [f] in Table 2.B.7; [g] in Table 2.B.8; [h] in Table 2.B.9; [i] in Table 2.B.10; [j] in Table 2.B.11.

[*] More information on LEDA in 2.A.1.

Table 2.5.3: Summary Table: Alternative Specifications.

	(1)	(2)
	Corrected EF	Corrected EP
A. Benchmark Results (N=14,441)[a]	-0.1780**	0.4487**
	(0.0858)	(0.2202)
B. Alternative Ethnicity Linking (N=14,441)[b]	-0.1597**	0.3202*
	(0.0690)	(0.1939)
C. Buffer at 40km (N=14,441)[c]	-0.1188*	0.3145*
	(0.0711)	(0.1827)
D. Buffer at 120km (N=14,441)[d]	-0.1090	0.3311*
	(0.0755)	(0.1999)
E. Non-Linear Model (N=5,761)[e]	-0.2259**	0.5649**
	(0.1030)	(0.2486)
F. Incl. Country-Time Trends (N=14,441)[f]	-0.1887**	0.4343**
	(0.0855)	(0.2194)
G. Excl. Countries with Bad Camps Data (N=12,397)[g]	-0.2316***	0.6038***
	(0.0891)	(0.2323)
H. Precision Code $\leq$ 3 (N=22,415)[h]	-0.1469**	0.2874*
	(0.0655)	(0.1635)
I. Incl. All Geocoded Locations (N=23,256)[i]	-0.1675***	0.3608**
	(0.0631)	(0.1584)

Notes: Estimated Equation: Equation (2.1) using OLS with alternative specifications. Except for Line E estimated using LOGIT and Line F, which included country-time trends. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests.

See Column (6) for: [a] in Table 2.5.1; [b] in Table 2.B.12; [c] in Table 2.B.13; [d] in Table 2.B.14; [e] in Table 2.B.15; [f] in Table 2.B.16; [g] in Table 2.B.17; [h] in Table 2.B.18; [i] in Table 2.B.19.

2.5.3 Results with Instrumented Diversity Indices

Despite the plausible nature of our identifying assumptions, we cannot exclude the possibility that refugees sort out ethnically. As an additional analysis, we therefore implement the 2SLS approach, using the results of a gravity equation to predict where refugees would go, only based on plausibly exogenous factors. In Table 2.5.4, we first report results from our gravity model. Column (1) of Table 2.5.4 corresponds to the Equation 2.5. Column (2) follows the same specification with the exception that the dyadic origin-destination fixed effects are replaced by origin and destination fixed effects. Conflict at the origin country and distance between the origin and destination countries have an expected negative impact on the predicted number of refugees. Conflicts at ethnic group's historical homeland and their distance to the destination country seem not to have an impact on this prediction.

We report our results in Table 2.5.5.[58] Panel A presents second-stage results while Panel B

[58] Our results using an IV obtained by estimating the Equation 2.5 but replacing the dyadic origin-destination fixed effects by origin and destination fixed effects (Column (2) of Table 2.5.4) are reported in Table 2.B.20.

and Panel C present first-stage results. All Columns include climatic controls. Columns (2) and (4) include the number of refugees within a distance of 80-km from the clusters. Columns (3) and (4) further include country-specific time trends. The 2SLS equivalent of Equation 2.1 and first-stage results from Equation 2.7 and Equation 2.8 are presented in Column (2) of respectively Panels A, B and C.

Our results are confirmed. The first-stage results in Panels B and C indicate that our main variables of interest are almost perfectly correlated with the plausibly exogeneous instrumental variables. Our main variables of interest can be considered as quasi-random.[59]

Table 2.5.4: Instrumental Variable Approach: Gravity Model.

	(1)	(2)
	Stock of Refugees Per Ethnic Group	
Conflict events at origin	0.0008***	0.0008***
	(0.0003)	(0.0003)
Distance, origin-destination	-	-0.0034***
	-	(0.0011)
Conflict events at hist. ethnic homeland	-0.0002	-0.0002
	(0.0002)	(0.0002)
Distance, hist. ethnic homeland-destination	-0.0001	-0.0014**
	(0.0005)	(0.0007)
Destination FE	N	Y
Ethnic Group FE	Y	Y
Origin FE	N	Y
Origin-Destination FE	Y	N
Year FE	Y	Y
Observations	4,068	4,140
Pseudo $\hat{R2}$	0.667	0.607

Notes: Estimated Equation: Equation (2.5) using PPML, presented in Column (1). Equation (2.5) with alternative fixed effects, presented in Column (2). Nb. of countries: 23. Period: 2005-2016. The 'minimum linguistic distance' function from LEDA* to link ethnicities between the Murdock Atlas and the EPR-ER. Robust standard errors clustered at the origin and destination are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.
* More information on LEDA in 2.A.1.

[59] Results remain robust to the use of alternative IVs, however less significant (10%) for the refugee–corrected EP.

Table 2.5.5: Instrumental Variable Approach: Diversity and Violent Conflict, Incidence.

	(1)	(2)	(3)	(4)
	Violent Conflict, Incidence			
Panel A:	**Second-Stage**			
Corrected EF (80km, Min. Ling. Dist.)	-0.1983**	-0.2090**	-0.1968**	-0.2100**
	(0.0888)	(0.0923)	(0.0885)	(0.0920)
Corrected EP (80km, Min. Ling. Dist.)	0.5595**	0.5722**	0.5546**	0.5702**
	(0.2572)	(0.2601)	(0.2563)	(0.2590)
R-squared	0.0018	0.0019	0.0029	0.0030
Kleibergen-Paap rk Wald F	885.8	916.2	888	918.6
Root MSE	0.290	0.290	0.290	0.290
Panel B:	**First-Stage (Corrected EF)**			
Predicted Corrected EF	0.9552***	0.9616***	0.9542***	0.9603***
	(0.0072)	(0.0086)	(0.0072)	(0.0084)
Predicted Corrected EP	0.0400**	0.0330*	0.0367**	0.0304
	(0.0181)	(0.0189)	(0.0183)	(0.0186)
Panel C:	**First-Stage (Corrected EP)**			
Predicted Corrected EF	0.0125***	0.0064**	0.0124***	0.0066**
	(0.0018)	(0.0029)	(0.0018)	(0.0028)
Predicted Corrected EP	0.9663***	0.9731***	0.9661***	0.9720***
	(0.0050)	(0.0061)	(0.0052)	(0.0060)
Observations	14,441	14,441	14,441	14,441
Year FE	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y
Country-Time Trends	N	N	Y	Y
Refugees (80km, IHS)	N	Y	N	Y
Climatic Controls	Y	Y	Y	Y

Notes: Estimated Equation in Panel A: Equation (2.1) using 2SLS. Predicted EF in Panel B: Equation (2.7). Predicted EP in Panel C: Equation (2.8). Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. Refugee camps in a 80-km buffer around each cluster. The 'minimum linguistic distance' function from LEDA* to link ethnicities between the Afrobarometer surveys, the Murdock Atlas and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

* More information on LEDA in 2.A.1.

2.6 Discussion

In this section we provide some implications for policy by discussing some alternative explanations and heterogeneity exploiting individual data from the Afrobarometer. We also discuss the relevance of our study given the current context of the COVID-19 pandemic.

Alternative explanations. The theoretical framework used to guide this analysis is mainly driven by a competition over resources between (ethnic) groups. Social conflict is mainly driven by a combination of inter-group differences and within-group cohesion. Such a theory hypotheses that polarization is more likely to capture intergroup antagonism and competition between a few large groups. In that way, our results indicate that refugees inflows affect group sizes, the diversity indices, incentives to compete over resources and, in turn, conflict. Alternative explanations may question the fixed nature of the groups and the distance between them. For instance, Bazzi (2019) shows that polarization increases ethnic attachment. Others have highlighted the reduction in trust, either inter-personal trust or institutional trust (Alesina and La Ferrara 2002; Beugelsdijk and Klasin 2016).

To assess the importance of alternative explanations, we first replicate our analysis using individual data on violence. In addition to the participation to protests, we follow McGuirk and Burke (2020a) in using the Afrobarometer survey data on interpersonal crime and physical assault. We then assess the same relationship with the refugee-corrected diversity indices, with alternative individual outcomes such as ethnic vs. national identity, generalized trust, trust in neighbors and institutional trust (trust in government). The below mentioned questions from the Afrobarometer are used as a proxy for these outcomes:[60]

1 Attack: Over the past year, how often (if ever) have you or anyone in your family: Been physically attacked?
2 Crime: Over the past year, how often (if ever) have you or anyone in your family: Feared crime in your own home?
3 National Identity: Let us suppose that you had to choose between being a [Ghanaian/Kenyan/etc.] and being a [respondent's identity group]. Which of these two groups do you feel most strongly attached to? Ethnic or national identity
4 Protest: Here is a list of actions that people sometimes take as citizens. For each of these, please tell me whether you, personally, have done any of these things during the past year. If not, would you do this if you had the chance: Attended a demonstration or protest march?
5 Theft: Over the past year, how often (if ever) have you or anyone in your family: Had something stolen from your house?
6 General Trust: Generally speaking, would you say that most people can be trusted or that you must be very careful in dealing with people?
7 Neighborhood Trust: How much do you trust each of the following types of people: Your neighbors?
8 Institutional Trust: How much do you trust each of the following, or haven't you heard enough about them to say: The President/Prime Minister?

To do so, we adopt a similar specification to our benchmark estimation at the individual level:

$$Y_{ijt} = \alpha_j + \tau_t + \gamma_1 CorrEF_{jt-1} + \gamma_2 CorrEP_{jt-1} + \gamma_3 Refuges_{jt-1} + \gamma_4 X_{ijt} + \gamma_5 Q_{jt} + \nu_{ijt} \quad \textbf{(2.9)}$$

[60] These questions are available in all rounds 3-6 of our analysis with the exception of 'General Trust' and 'Neighborhood Trust', which are available in rounds 3 and 5.

where Y_{ijt} represents a number of outcomes such as the likelihood to experience attacks, crimes or theft, to participate to a protest, the ethnic (v.s. national) attachment, inter-personal, neighborhood and institutional trust of individual i, in cluster j surveyed in year t. The other variables are similar to Equation 2.1 with the exception of X_{ijt}. X_{ijt} is a vector of individual control variables such as age, education, gender, marital status, and rural/urban status. To assess the risk of bad controls, we introduce these control variables progressively. Sampling weights are used to render our estimates representative at the country level.[61]

As shown in Table 2.B.22, our results with physical assault and to some extent, interpersonal crime confirm our main results. We find that a one standard deviation increase in refugee-corrected polarization raises the likelihood of experiencing physical assault by 2.1 percentage points. Such a change represents an increase by about 18.2 percent, at the mean. Inversely, a similar change in refugee-corrected fractionalization decreases the risk of physical assault by 1.9 percentage points, i. e., 16.3 percent at the mean (although not precisely estimated). For interpersonal crime, the equivalent change would translate into a fall by 4.2 percentage points, 13 percent at the mean. However, although similar in magnitude, the estimated coefficient for the refugee-corrected polarization is not statistically different from zero. Table 2.B.22 also indicates that none of our coefficients of interest statistically impact the other individual outcomes of ethnic attachment, generalized trust, trust in neighbors and institutional trust.

Heterogeneity. Another way to identify possible entry points for policy interventions is to exploit the heterogeneity provided by the individual data. The conflict literature indeed indicates that the likelihood to participate to violence is negatively correlated with age, being a female, wealth, and employment. The hypothesized mechanism is usually a higher opportunity cost among the old, the female and wealthy segments of the population (Blattman & Miguel, 2010). To shed light on particular vulnerabilities, we assess the effect of the refugee-corrected fractionalization and polarization indices on samples stratified on the basis of these individual characteristics. Our results are presented in Figure 2.B.8. Our analysis certainly lacks power in detecting clear-cut heterogeneous effects. However, it seems that our refugee-corrected polarization and fractionalization indices are stronger in magnitude to explain the likelihood to experience physical assault and theft when the respondent is unemployed. The same is true for the likelihood to participate to a protest. Other heterogeneous effects are much less clear. We remain cautious about the lack of power of this heterogeneous analysis, but the group of unemployed might be a particular target for intervention seeking to reduce prejudice and strengthen cooperation between groups.

Overall, our results question previous results on the impact of refugees on conflict. The relationship largely depends on the way diversity changes as a result. When polarization increases, the risk of conflict exacerbates. For fractionalization, it is the opposite. It is therefore important to consider that risk increases when refugees tend to strengthen polarization between a few large groups. In that case, fostering intergroup interactions will not necessarily reduce

[61] We provide the descriptive statistics of these variables in Table 2.B.21.

inter-group prejudice and strengthen cooperation, like in other contexts (Corno et al., 2018; Finseraas & Kotsadam, 2017). Given the lack of results for alternative outcomes like trust or ethnic attachment, competition between polarized groups is the most likely driver of our results. Identifying specific interventions in refugee-hosting and polarized communities is strongly needed.[62]

Relevance in the context of the COVID-19 pandemic. Our analysis seeks to identify the role of diversity in the occurrence of conflicts in sub-Saharan Africa between 2005 and 2016. While we have shown that ethnically more polarized locations tend to have a higher propensity to conflict, here we assess the relevance of our analysis in the context of the COVID-19 pandemic. During the COVID-19 crises, restrictions imposed on populations are to a large extent of a public good nature (e. g., mask wearing, social distancing etc.). Even though the literature has been supporting the fact that such social norms are more difficult to enforce in ethnically diverse contexts (Alesina & Ferrara, 2000), opposite results have been highlighted more recently in the context of COVID-19 (Egorov et al., 2021).

In the present context, we analyze the link between COVID-19 protests (as collected from ACLED[63]) and ethnic diversity, by assessing the correlation between the predicted likelihood of conflict induced by the refugee-corrected diversity and events of protest with respect to COVID measures. In particular, we correlate the predicted conflicts based on observed polarization and fractionalization indices, averaged over the sample period (multiplied by the estimated coefficients of our benchmark results), with disorder events directly related to the COVID-19 pandemic during the year 2020. These events are provided by ACLED and range from "violence targeting front line health care workers to demonstrations against government lock downs" to "Violent mobs attacking individuals due to fears of their alleged links to the coronavirus (e.g. Muslims in India; foreigners in Africa; etc.)". Figure 2.B.9 highlights the positive correlation between our ability to predict violent conflict within our sample and the occurrence of COVID-19 related violence in 2020.[64] Far from being causal, these cross-sectional correlations offer supportive evidence of the persistence of the diversity effects found in our analysis. Further research is needed to better understand the long-term consequences of changing ethnic diversity.

[62] See Paluck (2012) for a review of possible interventions to reduce prejudice and conflict. For instance, intergroup sports have been shown to help rebuilding intergroup social cohesion among displaced people in Northern Iraq (Moussa, 2020).

[63] ACLED provides data of events directly related to COVID-19, which they refer to as "curated data". Indirect events, such as ceasefires announced in response to COVID-19 are not typically included.

[64] To ease interpretation, we plot the negative value of the linear projection of the refugee-corrected fractionalization index. Figure 2.B.9 also presents the fitted line when COVID-19 events have been partialled out based on country fixed effects. Not imposing such transformation does not change the visual correlations.

2.7 Conclusion

Refugees have often been blamed for propagating social conflicts in their hosting countries. Previous research has rejected a causal effect of hosting refugees on violence (Zhou & Shaver, 2021). We qualify this previous conclusion by highlighting a particular channel through which refugees may impact violence in their hosting communities, namely the resulting changes in ethnic composition. We indeed exploit annual variations in the presence of refugees to approximate for the resulting changes in diversity in refugee-hosting areas in 23 countries in sub-Saharan Africa between 2005 and 2016. In line with our theoretical framework, our results point to the risk of conflict when refugees exacerbate ethnic polarization in the hosting communities. A one standard deviation increase in the polarization index raises the incidence of violent conflict by 5 percentage points, representing 10 percent, at the mean. On the contrary, a situation where refugee flows raise the level of ethnic fractionalization is likely to see an attenuated risk of violence, with similar order of magnitude. Compared to other determinants of conflicts like economic, price, and climatic shocks, our estimated effect sizes are comparable in magnitude. It is therefore important for policy-makers and practitioners to consider that the risk of violence increases when refugees tend to strengthen polarization between a few large groups. In that case, fostering intergroup interactions will not necessarily reduce inter-group prejudice and strengthen cooperation, like in other contexts (Corno et al., 2018; Finseraas & Kotsadam, 2017). For instance, intergroup sports have been shown to help rebuilding intergroup social cohesion among displaced people in Northern Iraq (Moussa, 2020). Identifying specific interventions in refugee-hosting and polarized communities is strongly needed.

Our results exploiting individual data also highlight the importance of ethnic diversity in refugee-hosting situation. For instance, we find that a one standard deviation increase in refugee-corrected polarization raises the likelihood of experiencing physical assault by 2.1 percentage points. Such a change represents an increase by about 18.2 percent, at the mean. Inversely, a similar change in refugee-corrected fractionalization decreases the risk of physical assault by 1.9 percentage points, i. e., 16.3 percent at the mean. Of particular interest, our refugee-corrected polarization and fractionalization indices are stronger in magnitude to explain the likelihood to experience physical assault when the respondent is unemployed. The group of unemployed might therefore be a particular target for interventions seeking to reduce prejudice and strengthen cooperation between groups. We know for example that cash transfers programs have been particularly effective (compared e.g. to skill training and microfinance) in stimulating employment and social stability in poor and fragile states (Blattman & Ralston, 2015). Increased cooperation between UNHCR and other development and peace-building actors since the Global Compact on Refugees offers a suitable framework for supporting such interventions. Finally, our strong correlation between our ability to predict violent conflict within our sample and the occurrence of COVID-19 related violence in 2020 also suggest that these effects may be persistent over time, pointing to possible structural changes in refugee-hosting communities. More research is certainly needed on the long-term consequences of hosting refugees (Becker & Ferrara, 2019; Maystadt et al., 2019), including through this – so far – unexplored channel of changing ethnic composition.

Appendix

2.A Data

2.A.1 Linking Ethnic Data from Africa (LEDA)

LEDA offers an interface - a language tree - to flexibly link ethnic groups from different databases to each other and calculate linguistic distances between them. LEDA is currently structured around lists of ethnic groups from 12 original datasets, which are the following:

- Afrobarometer Surveys
- All Minorities at Risk (AMAR)
- Census data from IPUMS
- Ethnic Power Relations Dataset (EPR)
- Ethnologue languages
- Political Relevant Ethnic Groups from Posner (2004)
- Ethnic groups in Francois, Trebbi & Rainer (2015)
- Ethnic groups from Fearon (2003)
- GREG Data (based on the Russian Atlas Miradova)
- Demographic and Health Surveys
- Murdock Atlas
- Spatially Interpolated Data on Ethnicity (SIDE)

These lists are structured in LEDA's interface by data source, country, year, or, in the case of survey data, survey rounds. In our analysis we use the Afrobarometer Survey, EPR and Murdock Atlas therefore we can use LEDA functions to link the different ethnic groups to each other.

LEDA consists of three main linkage types: binary linking based on the relations of sets of language nodes associated with two groups; binary linking based on lingustic distances; and a full computation of dyadic linguistic distances.

In our main analysis, we use the second type of linkage: binary linking based on lingustic distances and set the level of linking to 'dialect'. This is done using the "mindistlink" function of LEDA, which computes the minimum linguistic distance between the two ethnic groups and therefore provides the closest linguistic neighbor for each given ethnic group. This function also computes a variable called *distance*, which measures the linguistic distance between two ethnic groups. Mathematically, these distances are calculated as:

$$D_{L_1L_2} = 1 - \left(\frac{2d(\omega(L_{1,\ldots,O}) \cap \omega(L_{2,\ldots,O}))}{d(\omega(L_{1,\ldots,O})) + d(\omega(L_{2,\ldots,O}))} \right)^{\delta} \tag{2.10}$$

where $d(\omega(L_{1,\ldots,O})$ is the length of the path from the first language to the tree's origin and $d(\omega(L_{1,\ldots,O}) \cap \omega(L_{2,\ldots,O})$ is the length of the intersection of the paths from the first and second language to the origin. δ is an exponent to discount distances further away from the root of the tree; it is typically set to .5.

As a robustness, we also use the first type of linkage: binary linking based on the relations of sets of language nodes associated with two groups. This is done using the "setlink" function of LEDA. With this function, the two groups are linked to each other as soon as they share any language node at the level of the language tree specified by link level.

Concretely, we first obtain, from LEDA, linkage tables between the Afrobarometer Survey and the EPR for our main analysis and the Murdock Atlas and the EPR for our IV strategy using the "mindistlink" function. We also obtain the same tables using the "setlink" function for robustness. We choose "dialect" as our link level - node on the language tree - adopting therefore a strict definition of ethnic similarity (vs. difference). We also obtain these tables choosing "language" as our link level - node on the language tree - for robustness. We therefore end up with 4 linkage tables. Note that using the "setlink" function, choosing "dialect" or "language" as our link level provides exactly the same linkage table between the Afrobarometer and the EPR.

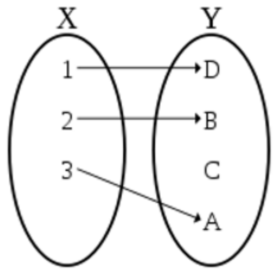
As a reminder, we use the data on ethnicity from the Afrobarometer to obtain the diversity indices in the host country (data on the ethnicity of the surveyed individuals in the host country) while we use the data on ethnicity from the EPR to define the refugee-corrected diversity indices (data on the ethnicity of the refugees in the camps in the host country). Finally we use the data on ethnicity from the Murdock Atlas to obtain the historical homeland of refugees that we use in our IV approach.

These linkage tables between the different databases from LEDA do not provide one-to-one links. Indeed, ethnicities being identified at different levels in these different databases, they may be linked to several others. In other words, we still need to determine an approach in order to end up with a single definition of ethnicity in our analysis. After investigation, we understand that the Afrobarometer and the Murdock Atlas ethnicities are overall defined at a more disaggregated level than the EPR ethnicities. As we can aggregate the disaggregated ethnicities but cannot disaggregate the aggregated ones, where possible, we will rename the Afrobarometer and the Murdock Atlas ethnicities based on the EPR ethnicities.

We merge these tables with the data on ethnicity we have in rounds 3-6 of the Afrobarometer and the UNHCR refugee camps data for the corresponding period, 2005-2016. We drop all pairs of links between the ethnicities when they do not occur in the Afrobarometer and the UNHCR refugee camps data simultaneously. In other words, we only keep the data on the link between the ethnicities that are present in our database.

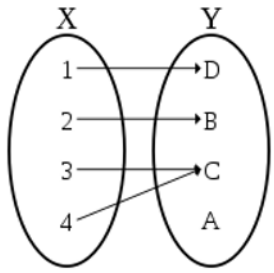
We isolate one-to-one (injective) relations between ethnicities of the Afrobarometer and the UNHCR refugee camps data. These are trivial to handle (See Fig 2.A.1).

Figure 2.A.1: Injective Relations.



We also isolate many-to-one (bijective) relations. In this case, we have to aggregate the Afrobarometer ethnicities with their unique and more aggregated correspondence in the UNHCR refugee camps data (See Figure 2.A.2).

Figure 2.A.2: Bijective Relations.



The remaining correspondences, are either (i) one-to-many (bijective) but opposite to Figure 2.A.2 (i. e., many ethnicities from the UNHCR refugee camps data correspond to one ethnicity from the Afrobarometer), or (ii) many-to-many relations. For both cases, we apply a more pragmatic approach:

a. In both cases, we disregard ethnicities, which do not appear, either on the Afrobarometer or on the UNHCR refugee camps data. This means that for the remaining ethnicity which has no counterpart in either the Afrobarometer or the UNHCR refugee camps data, we simply keep the name of the ethnicity as such, i. e., this information is not dropped.
b. Then, after ignoring ethnicities that have no occurrence in our datasets, we check whether the one-to-many or the many-to-many relation has not boiled down to a one-to-one resp. many-to-one relation again. If so, we can treat them as above.
c. For the remaining one-to-many relations, we keep these ethnicities in the Afrobarometer as such and consider those as a single ethnic group. Some manual treatment can even further improve the correspondence.
d. For the remaining and very few many-to-many relations, we consider the ethnicities on either sides as separate ethnicities. Here also, some further manual treatment can

improve the correspondence.

2.B Supplementary Tables and Figures

Table 2.B.1: Summary Table for Data Availability and Quality for Countries in Sub-Saharan Africa.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Data	**The Afrobarometer**							**UNHCR Refugee Camps**[I]	**EPR-ER**
	Round 1[II]	Round 2[II]	Round 3	Round 4	Round 5	Round 6	Round 7[III]		
Period	1999-2001	2002-2003	2005-2006	2008-2009	2012-2013	2014-2015	2016-2017	2000-2016	1975-2017
Benin			1,198	1,200	1,200	1,200	1,200	Good Quality	Available
Botswana	1,200	1,200	1,200	1,200	1,200	1,200	1,198	Bad Quality	Not Available
Burkina Faso				1,200	1,200	1,200	1,200	Good Quality	Available
Burundi					1,200	1,200	1,200	Good Quality	Available
Cape Verde		1,268	1,256	1,264	1,208	1,200	1,202	Not Available	Not Available
Cameroon					1,200	1,182	1,200	Good Quality	Available
Gabon						1,198	1,200	Bad Quality	Available
Gambia							2,400	Bad Quality	Available
Ghana	2,004	1,200	1,197	1,200	2,400	2,400	1,194	Good Quality	Available
Guinea					1,200	1,200	1,599	Good Quality	Available
Ivory Coast					1,200	1,199	1,200	Good Quality	Available
Kenya		2,398	1,278	1,104	2,399	2,397	1,200	Good Quality	Available
Lesotho	1,177	1,200	1,161	1,200	1,197	1,200	1,200	Not Available	Available
Liberia				1,200	1,199	1,199	1,200	Good Quality	Available
Madagascar			1,350	1,350	1,200	1,200	1,200	Not Available	Not Available
Malawi	1,208	1,200	1,200	1,200	2,407	2,400	1,200	Good Quality	Available
Mali	2,089	1,283	1,244	1,232	1,200	1,200	1,200	Bad Quality	Available
Mauritius					1,200	1,200	1,200	Not Available	Not Available
Mozambique		1,400	1,198	1,200	2,400	2,400	1,200	Good Quality	Available
Namibia	1,183	1,199	1,200	1,200	1,200	1,200	1,200	Good Quality	Available
Niger			2,363		1,199	1,200	1,600	Good Quality	Available
Nigeria	3,603	2,428		2,324	2,400	2,400	1,200	Good Quality	Available
Sao Tome and Principe						1,196	1,200	Not Available	Not Available
Senegal		1,200	1,200	1,200	1,200	1,200	1,200	Bad Quality	Available
Sierra Leone					1,190	1,191	1,840	Good Quality	Available
South Africa	2,200	2,400	2,400	2,400	2,399	2,390	1,200	Not Available	Available
Sudan[IV]					1,199	1,200	2,400	Good Quality	Available
Swaziland					1,200	1,200	1,199	Bad Quality	Not Available
Tanzania	2,198	1,223	1,304	1,208	2,400	2,386	1,200	Good Quality	Available
Togo					1,200	1,200	1,199	Bad Quality	Available
Uganda	2,271	2,400	2,400	2,431	2,400	2,400	1,200	Good Quality	Available
Zambia	1,198	1,198	1,200	1,200	1,200	1,199	1,200	Good Quality	Available
Zimbabwe	1,200	1,104	1,048	1,200	2,400	2,400	1,200	Good Quality	Available

I Quality refers to the exactness of UNHCR refugee camps data for a given country, which is determined by comparison with UNHCR official bilateral data in Figure 2.B.7.
II There is no data on ethnicity in Rounds 1 and 2 of the Afrobarometer
III There is no geocoded data for Round 7 of the Afrobarometer.
IV The question on an individual's ethnicity is not asked in Sudan.

Table 2.B.2: Descriptive Statistics: Cluster Level.

	(1) Obs.	(2) Mean	(3) Std. Dev.	(4) Min.	(5) Max.	(6) Obs.	(7) Mean	(8) Std. Dev.	(9) Min.	(10) Max.
	Panel A: Refugee-Hosting Areas					**Panel B: All Areas**				
Diversity Indices.										
EF	2,327	0.2558	0.2529	0	0.8791	14,441	0.2897	0.2705	0	0.8828
EP	2,327	0.1011	0.0911	0	0.2500	14,441	0.1072	0.0905	0	0.25
Corrected EF (80-km, Min. Ling. Dist.)	2,327	0.3790	0.2446	0	0.8494	14,441	0.2818	0.2637	0	0.8664
Corrected EP (80-km, Min. Ling. Dist.)	2,327	0.1407	0.0782	0	0.2500	14,441	0.1072	0.0911	0	0.25
Refugees (80km, HIS)	2,327	6.9173	4.6184	0	13.7611	14,441	1.1146	3.1471	0	13.7611
Conflict Events.										
Violent Conflict, Incidence	2,327	0.5170	0.4998	0	1	14,441	0.4802	0.4996	0	1
Violent Conflict, Intensity (IHS)	2,327	0.8992	1.0807	0	5.6131	14,441	0.9743	1.2658	0	6.5367
Non-Violent Conflict, Incidence	2,327	0.6162	0.4864	0	1	14,441	0.5728	0.4947	0	1
Non-Violent Conflict, Intensity (IHS)	2,327	1.2188	1.1382	0	4.8521	14,441	1.4067	1.5436	0	5.7808
Civilian Conflict, Incidence	2,327	0.4083	0.4916	0	1	14,441	0.3968	0.4892	0	1
Civilian Conflict, Intensity (IHS)	2,327	0.6370	0.8938	0	4.1591	14,441	0.7444	1.1157	0	6.5309
Protest, Incidence	2,327	0.5548	0.4971	0	1	14,441	0.5363	0.4987	0	1
Protest, Intensity	2,327	1.0622	1.1148	0	4.7708	14,441	1.3011	1.5196	0	5.7746
UCDP Conflicts, Incidence	2,327	0.0812	0.2732	0	1	14,441	0.1322	0.3387	0	1
UCDP Conflicts, Intensity (IHS)	2,327	0.1309	0.5543	0	5.4468	14,441	0.2371	0.7017	0	5.5373
Climate Data.										
Rain anomalies	2,327	1.0191	10.1544	-48.2476	44.6816	14,441	0.2015	10.4917	-57.7804	44.8193
Temperature anomalies	2,327	0.1001	0.2171	-0.5537	1.2996	14,441	0.1138	0.2206	-0.5938	1.2996

Notes: EF, EP: standard diversity indices. Corrected EF (80-km, Min. Ling. Dist.), Corrected EP (80-km, Min. Ling. Dist.): refugee-corrected diversity indices. Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. Refugee camps in a 80-km buffer around each cluster. The 'minimum linguistic distance' function from LEDA* to link ethnicities between the Afrobarometer surveys and the EPR-ER.

* More information on LEDA in 2.A.1.

Table 2.B.3: Diversity and Violent Conflict, Intensity.

	(1)	(2)	(3)	(4)	(5)	(6)[a]
	Violent Conflict (IHS), Intensity					
EF	0.0940	0.1214				
	(0.1954)	(0.1959)				
EP	-0.1074	-0.1827				
	(0.5490)	(0.5502)				
Refugees (80km, IHS)		-0.0179***		-0.0170***		-0.0170***
		(0.0058)		(0.0065)		(0.0065)
Corrected EF (80km, Min. Ling. Dist.)			-0.4386**	-0.3022	-0.4447**	-0.3088
			(0.1980)	(0.2072)	(0.1994)	(0.2086)
Corrected EP (80km, Min. Ling. Dist.)			0.9754*	0.8923*	0.9987*	0.9170*
			(0.5133)	(0.5151)	(0.5168)	(0.5183)
Rain anomalies (80km)					0.0017**	0.0017**
					(0.0008)	(0.0008)
Temp anomalies (80km)					-0.0842*	-0.0891**
					(0.0451)	(0.0450)
Observations	14,441	14,441	14,441	14,441	14,441	14,441
R-squared	0.806	0.807	0.806	0.807	0.807	0.807
Year FE	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS and an alternative dependent variable: violent conflict intensity, presented in Column (6). Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. 80-km buffer around each cluster to *correct* standard ethnic diversity measures with refugees in the camps within this distance. The 'minimum linguistic distance' function from LEDA* used to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0:01$), ** at the 5 percent level ($p < 0:05$), and * at the 10 percent level ($p < 0:10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Line B of Table 2.5.2.

* More information on LEDA in 2.A.1.

Table 2.B.4: Diversity and Non-Violent Conflict, Incidence.

	(1)	(2)	(3)	(4)	(5)	(6)[a]
	Non-Violent Conflict, Incidence					
EF	0.0493	0.0443				
	(0.0672)	(0.0675)				
EP	0.1136	0.1273				
	(0.2040)	(0.2041)				
Refugees (80km, IHS)		0.0033		0.0019		0.0018
		(0.0025)		(0.0027)		(0.0027)
Corrected EF (80km, Min. Ling. Dist.)			-0.0395	-0.0549	-0.0395	-0.0536
			(0.0760)	(0.0802)	(0.0754)	(0.0797)
Corrected EP (80km, Min. Ling. Dist.)			0.3656*	0.3750*	0.3568*	0.3654*
			(0.2114)	(0.2136)	(0.2106)	(0.2127)
Rain anomalies (80km)					-0.0018***	-0.0018***
					(0.0003)	(0.0003)
Temp anomalies (80km)					0.0375*	0.0380*
					(0.0198)	(0.0197)
Observations	14,441	14,441	14,441	14,441	14,441	14,441
R-squared	0.704	0.704	0.704	0.704	0.705	0.705
Year	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS and an alternative dependent variable: non-violent conflict incidence, presented in Column (6). Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. 80-km buffer around each cluster to *correct* standard ethnic diversity measures with refugees in the camps within this distance. The 'minimum linguistic distance' function from LEDA[*] used to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Line C of Table 2.5.2.

[*] More information on LEDA in 2.A.1.

Table 2.B.5: Diversity and Non-Violent Conflict, Intensity.

	(1)	(2)	(3)	(4)	(5)	(6)[a]
	Non-Violent Conflict (IHS), Intensity					
EF	0.2519	0.2758				
	(0.1980)	(0.1966)				
EP	-0.8126	-0.8784				
	(0.5905)	(0.5880)				
Refugees (80km, IHS)		-0.0157***		-0.0154**		-0.0152**
		(0.0056)		(0.0062)		(0.0062)
Corrected EF (80km, Min. Ling. Dist.)			-0.3714*	-0.2478	-0.3619*	-0.2402
			(0.2109)	(0.2101)	(0.2101)	(0.2092)
Corrected EP (80km, Min. Ling. Dist.)			0.9248	0.8494	0.8981	0.8250
			(0.5720)	(0.5607)	(0.5699)	(0.5588)
Rain anomalies (80km)					-0.0006	-0.0007
					(0.0006)	(0.0006)
Temp anomalies (80km)					0.0900**	0.0855*
					(0.0447)	(0.0445)
Observations	14,441	14,441	14,441	14,441	14,441	14,441
R-squared	0.862	0.862	0.862	0.862	0.862	0.862
Year	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS and an alternative dependent variable: non-violent conflict intensity, presented in Column (6). Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. 80-km buffer around each cluster to *correct* standard ethnic diversity measures with refugees in the camps within this distance. The 'minimum linguistic distance' function from LEDA[*] used to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Line D of Table 2.5.2.

[*] More information on LEDA in 2.A.1.

Table 2.B.6: Diversity and Civilian Conflict, Incidence.

	(1)	(2)	(3)	(4)	(5)	(6)^a
	Civilian Conflict, Incidence					
EF	0.0348	0.0422				
	(0.0711)	(0.0715)				
EP	-0.0612	-0.0816				
	(0.2115)	(0.2132)				
Refugees (80km, IHS)		-0.0049*		-0.0043		-0.0048*
		(0.0027)		(0.0029)		(0.0029)
Corrected EF (80km, Min. Ling. Dist.)			-0.1730**	-0.1384	-0.1843**	-0.1460*
			(0.0824)	(0.0845)	(0.0826)	(0.0847)
Corrected EP (80km, Min. Ling. Dist.)			0.4101*	0.3890*	0.4262**	0.4032*
			(0.2163)	(0.2163)	(0.2167)	(0.2169)
Rain anomalies (80km)					-0.0025***	-0.0025***
					(0.0004)	(0.0004)
Temp anomalies (80km)					-0.0404*	-0.0418*
					(0.0217)	(0.0216)
Observations	14,441	14,441	14,441	14,441	14,441	14,441
R-squared	0.674	0.674	0.674	0.674	0.676	0.676
Year	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS and an alternative dependent variable: civilian conflict incidence, presented in Column (6). Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. 80-km buffer around each cluster to *correct* standard ethnic diversity measures with refugees in the camps within this distance. The 'minimum linguistic distance' function from LEDA* used to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Line E of Table 2.5.2.

* More information on LEDA in 2.A.1.

Table 2.B.7: Diversity and Civilian Conflict, Intensity.

	(1)	(2)	(3)	(4)	(5)	(6)[a]
	Civilian Conflict (IHS), Intensity					
EF	0.2347	0.2607				
	(0.1821)	(0.1827)				
EP	-0.4596	-0.5309				
	(0.5107)	(0.5128)				
Refugees (80km, IHS)		-0.0170***		-0.0162***		-0.0163***
		(0.0050)		(0.0056)		(0.0056)
Corrected EF (80km, Min. Ling. Dist.)			-0.5070***	-0.3767**	-0.5061***	-0.3762**
			(0.1843)	(0.1895)	(0.1839)	(0.1892)
Corrected EP (80km, Min. Ling. Dist.)			1.2741***	1.1947**	1.2696***	1.1916**
			(0.4685)	(0.4667)	(0.4677)	(0.4660)
Rain anomalies (80km)					-0.0005	-0.0005
					(0.0007)	(0.0007)
Temp anomalies (80km)					0.0167	0.0119
					(0.0392)	(0.0391)
Observations	14,441	14,441	14,441	14,441	14,441	14,441
R-squared	0.804	0.804	0.804	0.804	0.804	0.804
Year	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS and an alternative dependent variable: civilian conflict intensity, presented in Column (6). Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. 80-km buffer around each cluster to *correct* standard ethnic diversity measures with refugees in the camps within this distance. The 'minimum linguistic distance' function from LEDA* used to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Line F of Table 2.5.2.

* More information on LEDA in 2.A.1.

Table 2.B.8: Diversity and Protests, Incidence.

	(1)	(2)	(3)	(4)	(5)	(6)[a]
			Protests, Incidence			
EF	0.0494	0.0423				
	(0.0706)	(0.0710)				
EP	0.1070	0.1264				
	(0.2108)	(0.2113)				
Refugees (80km, IHS)		0.0046*		0.0033		0.0033
		(0.0025)		(0.0027)		(0.0027)
Corrected EF (80km, Min. Ling. Dist.)			-0.0590	-0.0853	-0.0593	-0.0853
			(0.0763)	(0.0808)	(0.0763)	(0.0809)
Corrected EP (80km, Min. Ling. Dist.)			0.4597**	0.4757**	0.4597**	0.4754**
			(0.2129)	(0.2157)	(0.2133)	(0.2160)
Rain anomalies (80km)					-0.0001	-0.0001
					(0.0004)	(0.0004)
Temp anomalies (80km)					0.0005	0.0015
					(0.0211)	(0.0211)
Observations	14,441	14,441	14,441	14,441	14,441	14,441
R-squared	0.696	0.697	0.697	0.697	0.697	0.697
Year	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS and an alternative dependent variable: protests incidence, presented in Column (6). Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. 80-km buffer around each cluster to *correct* standard ethnic diversity measures with refugees in the camps within this distance. The 'minimum linguistic distance' function from LEDA* used to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Line G of Table 2.5.2.

* More information on LEDA in 2.A.1.

Table 2.B.9: Diversity and Protests, Intensity.

	(1)	(2)	(3)	(4)	(5)	(6)[a]
	Protests (IHS), Intensity					
EF	0.3196*	0.3411*				
	(0.1890)	(0.1875)				
EP	-0.8972	-0.9561*				
	(0.5683)	(0.5658)				
Refugees (80km, IHS)		-0.0140***		-0.0149***		-0.0143***
		(0.0051)		(0.0056)		(0.0055)
Corrected EF (80km, Min. Ling. Dist.)			-0.3195	-0.2002	-0.3036	-0.1891
			(0.2071)	(0.2057)	(0.2076)	(0.2062)
Corrected EP (80km, Min. Ling. Dist.)			0.9316*	0.8588	0.9011	0.8323
			(0.5633)	(0.5524)	(0.5642)	(0.5536)
Rain anomalies (80km)					0.0019***	0.0019***
					(0.0007)	(0.0007)
Temp anomalies (80km)					0.0897**	0.0855*
					(0.0452)	(0.0449)
Observations	14,441	14,441	14,441	14,441	14,441	14,441
R-squared	0.854	0.854	0.854	0.854	0.854	0.854
Year	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS and an alternative dependent variable: protests intensity, presented in Column (6). Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. 80-km buffer around each cluster to *correct* standard ethnic diversity measures with refugees in the camps within this distance. The 'minimum linguistic distance' function from LEDA* used to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Line H of Table 2.5.2.

[*] More information on LEDA in 2.A.1.

Table 2.B.10: Diversity and UCDP Major Conflicts, Incidence.

	(1)	(2)	(3)	(4)	(5)	(6)[a]
	UCDP Major Conflicts, Incidence					
EF	0.1075*	0.1017*				
	(0.0580)	(0.0574)				
EP	-0.2880*	-0.2719*				
	(0.1601)	(0.1587)				
Refugees (80km, IHS)		0.0038***		0.0043***		0.0044***
		(0.0013)		(0.0015)		(0.0015)
Corrected EF (80km, Min. Ling. Dist.)			0.0937	0.0594	0.0993*	0.0642
			(0.0589)	(0.0641)	(0.0587)	(0.0638)
Corrected EP (80km, Min. Ling. Dist.)			-0.2592*	-0.2383	-0.2743*	-0.2532*
			(0.1503)	(0.1524)	(0.1494)	(0.1514)
Rain anomalies (80km)					-0.0002	-0.0002
					(0.0003)	(0.0003)
Temp anomalies (80km)					0.0503***	0.0516***
					(0.0151)	(0.0151)
Observations	14,441	14,441	14,441	14,441	14,441	14,441
R-squared	0.703	0.703	0.703	0.703	0.703	0.703
Year	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS and an alternative dependent variable: UCDP major conflicts incidence, presented in Column (6). Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. 80-km buffer around each cluster to *correct* standard ethnic diversity measures with refugees in the camps within this distance. The 'minimum linguistic distance' function from LEDA* used to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Line I of Table 2.5.2.

* More information on LEDA in 2.A.1.

Table 2.B.11: Diversity and UCDP Major Conflicts, Intensity.

	(1)	(2)	(3)	(4)	(5)	(6)[a]
Dependent variable:	UCDP Major Conflicts (IHS), Intensity					
EF	0.1119	0.0994				
	(0.1808)	(0.1778)				
EP	-0.3252	-0.2908				
	(0.4983)	(0.4908)				
Refugees (80km, IHS)		0.0082**		0.0096**		0.0099**
		(0.0037)		(0.0044)		(0.0044)
Corrected EF (80km, Min. Ling. Dist.)			0.0544	-0.0224	0.0644	-0.0143
			(0.1499)	(0.1630)	(0.1493)	(0.1624)
Corrected EP (80km, Min. Ling. Dist.)			-0.1444	-0.0976	-0.1673	-0.1200
			(0.3930)	(0.3988)	(0.3915)	(0.3972)
Rain anomalies (80km)					0.0004	0.0004
					(0.0005)	(0.0005)
Temp anomalies (80km)					0.0726**	0.0755***
					(0.0282)	(0.0280)
Observations	14,441	14,441	14,441	14,441	14,441	14,441
R-squared	0.728	0.728	0.728	0.728	0.728	0.728
Year	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS and an alternative dependent variable: UCDP major conflicts intensity, presented in Column (6). Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. 80-km buffer around each cluster to *correct* standard ethnic diversity measures with refugees in the camps within this distance. The 'minimum linguistic distance' function from LEDA* used to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Line J of Table 2.5.2.

* More information on LEDA in 2.A.1.

Table 2.B.12: Diversity and Violent Conflict, Incidence.

	(1)	(2)	(3)	(4)	(5)	(6)[a]
	Violent Conflict, Incidence					
EF	-0.1090	-0.1096				
	(0.0716)	(0.0718)				
EP	0.2263	0.2278				
	(0.2103)	(0.2108)				
Refugees (80km, IHS)		0.0004		0.0018		0.0014
		(0.0028)		(0.0029)		(0.0029)
Corrected EF (80km, SetLink)			-0.1404**	-0.1526**	-0.1500**	-0.1597**
			(0.0666)	(0.0689)	(0.0666)	(0.0690)
Corrected EP (80km, SetLink)			0.2949	0.3017	0.3149	0.3202*
			(0.1930)	(0.1933)	(0.1935)	(0.1939)
Rain anomalies (80km)					-0.0008**	-0.0008**
					(0.0004)	(0.0004)
Temp anomalies (80km)					-0.0833***	-0.0829***
					(0.0230)	(0.0230)
Observations	14,441	14,441	14,441	14,441	14,441	14,441
R-squared	0.661	0.661	0.661	0.662	0.662	0.662
Year FE	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS, presented in Column (6). The 'set link' function from LEDA* as an alternative matching to link ethnicities between the Afrobarometer surveys and the EPR-ER. Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. 80-km buffer around each cluster to *correct* standard ethnic diversity measures with refugees in the camps within this distance. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Line B of Table 2.5.3.

* More information on LEDA in 2.A.1.

Table 2.B.13: Diversity and Violent Conflict, Incidence.

	(1)	(2)	(3)	(4)	(5)	(6)[a]
	Violent Conflict, Incidence					
EF	-0.0049	-0.0056				
	(0.0579)	(0.0578)				
EP	0.0437	0.0455				
	(0.1655)	(0.1651)				
Refugees (40km, IHS)		0.0008		0.0015		0.0014
		(0.0034)		(0.0035)		(0.0035)
Corrected EF (40km, Min. Ling. Dist.)			-0.1055	-0.1139	-0.1113	-0.1188*
			(0.0683)	(0.0710)	(0.0684)	(0.0711)
Corrected EP (40km, Min. Ling. Dist.)			0.2929	0.3008*	0.3074*	0.3145*
			(0.1803)	(0.1823)	(0.1806)	(0.1827)
Rain anomalies (40km)					-0.0005	-0.0005
					(0.0003)	(0.0003)
Temp anomalies (40km)					-0.0404**	-0.0402*
					(0.0205)	(0.0205)
Observations	14,441	14,441	14,441	14,441	14,441	14,441
R-squared	0.696	0.696	0.696	0.696	0.696	0.696
Year FE	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS, presented in Column (6). Refugee camps in an alternative 40-km buffer around each cluster. Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. The 'minimum linguistic distance' function from LEDA* used to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Line C of Table 2.5.3.

* More information on LEDA in 2.A.1.

Table 2.B.14: Diversity and Violent Conflict, Incidence.

	(1)	(2)	(3)	(4)	(5)	(6)[a]
	Violent Conflict, Incidence					
EF	-0.0408	-0.0469				
	(0.0652)	(0.0651)				
EP	0.1837	0.1938				
	(0.2025)	(0.2017)				
Refugees (120km, IHS)		0.0040*		0.0040		0.0034
		(0.0023)		(0.0025)		(0.0025)
Corrected EF (120km, Min. Ling. Dist.)			-0.0583	-0.0937	-0.0792	-0.1090
			(0.0725)	(0.0751)	(0.0726)	(0.0755)
Corrected EP (120km, Min. Ling. Dist.)			0.2824	0.2954	0.3205	0.3311*
			(0.1987)	(0.1989)	(0.1996)	(0.1999)
Rain anomalies (120km)					-0.0019***	-0.0019***
					(0.0004)	(0.0004)
Temp anomalies (120km)					-0.1376***	-0.1363***
					(0.0227)	(0.0227)
Observations	14,441	14,441	14,441	14,441	14,441	14,441
R-squared	0.648	0.648	0.648	0.648	0.650	0.650
Year FE	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS, presented in Column (6). Refugee camps in an alternative 120-km buffer around each cluster. Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. The 'minimum linguistic distance' function from LEDA* used to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Line D of Table 2.5.3.

* More information on LEDA in 2.A.1.

Table 2.B.15: Diversity and Violent Conflict, Incidence.

	(1)	(2)	(3)	(4)	(5)	(6)[a]
	Violent Conflict, Incidence					
EF	-0.1305	-0.1343				
	(0.0970)	(0.0960)				
EP	0.2502	0.2583				
	(0.2602)	(0.2570)				
Refugees (80km, IHS)		0.0016		0.0027		0.0024
		(0.0019)		(0.0022)		(0.0024)
Corrected EF (80km, MLD)			-0.1642*	-0.2049**	-0.1912**	-0.2259**
			(0.0872)	(0.0948)	(0.0958)	(0.1030)
Corrected EP (80km, MLD)			0.4744**	0.5148**	0.5315**	0.5649**
			(0.2244)	(0.2278)	(0.2463)	(0.2486)
Rain anomalies (80km)					-0.0008*	-0.0008*
					(0.0004)	(0.0004)
Temp anomalies (80km)					-0.0741**	-0.0718**
					(0.0327)	(0.0325)
Observations	5,761	5,761	5,761	5,761	5,761	5,761
Number of cluster_id	1,835	1,835	1,835	1,835	1,835	1,835
Year FE	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using LOGIT, presented in Column (6). Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. 80-km buffer around each cluster to *correct* standard ethnic diversity measures with refugees in the camps within this distance. The 'minimum linguistic distance' function from LEDA* used to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Line E of Table 2.5.3.

* More information on LEDA in 2.A.1.

Table 2.B.16: Diversity and Violent Conflict, Incidence.

	(1)	(2)	(3)	(4)	(5)	(6)[a]
	Violent Conflict, Incidence					
EF	-0.1473**	-0.1500**				
	(0.0721)	(0.0717)				
EP	0.2882	0.2952				
	(0.2098)	(0.2092)				
Refugees (80km, IHS)		0.0039		0.0050		0.0048
		(0.0030)		(0.0031)		(0.0031)
Corrected EF (80km, Min. Ling. Dist.)			-0.1493*	-0.1842**	-0.1554*	-0.1887**
			(0.0834)	(0.0853)	(0.0833)	(0.0855)
Corrected EP (80km, Min. Ling. Dist.)			0.4071*	0.4231*	0.4192*	0.4343**
			(0.2194)	(0.2190)	(0.2196)	(0.2194)
Rain anomalies (80km)					-0.0008*	-0.0007*
					(0.0004)	(0.0004)
Temp anomalies (80km)					-0.0947***	-0.0940***
					(0.0237)	(0.0236)
Observations	14,441	14,441	14,441	14,441	14,441	14,441
R-squared	0.671	0.671	0.671	0.671	0.672	0.672
Year FE	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y
Country-Time Trends	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS, presented in Column (6). Includes country specific time trends. Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. Refugee camps in a 80-km buffer around each cluster. The 'minimum linguistic distance' function from LEDA* used to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0:01$), ** at the 5 percent level ($p < 0:05$), and * at the 10 percent level ($p < 0:10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Line F of Table 2.5.3.

[*] More information on LEDA in 2.A.1.

Table 2.B.17: Diversity and Violent Conflict, Incidence.

	(1)	(2)	(3)	(4)	(5)	(6)[a]
			Violent Conflict, Incidence			
EF	-0.1746**	-0.1710**				
	(0.0713)	(0.0720)				
EP	0.4468**	0.4328**				
	(0.2173)	(0.2188)				
Refugees (80km, IHS)		-0.0044		-0.0036		-0.0042
		(0.0030)		(0.0033)		(0.0033)
Refugee EF (80km, Min. Ling. Dist.)			-0.2419***	-0.2163**	-0.2613***	-0.2316***
			(0.0857)	(0.0890)	(0.0858)	(0.0891)
Refugee EP (80km, Min. Ling. Dist.)			0.5712**	0.5619**	0.6137***	0.6038***
			(0.2301)	(0.2313)	(0.2311)	(0.2323)
Rain anomalies (80km)					-0.0004	-0.0004
					(0.0004)	(0.0004)
Temp anomalies (80km)					-0.0990***	-0.1014***
					(0.0238)	(0.0239)
Observations	11,909	11,909	11,909	11,909	11,909	11,909
R-squared	0.665	0.666	0.666	0.666	0.666	0.666
Year FE	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS, presented in Column (6). Countries with bad refugee camps data excluded. Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Level of analysis: cluster. Nb. of countries: 19. Period: 2005-2016. Refugee camps in a 80-km buffer around each cluster. The 'minimum linguistic distance' function from LEDA* used to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Line G of Table 2.5.3.

* More information on LEDA in 2.A.1.

Table 2.B.18: Diversity and Violent Conflict, Incidence.

	(1)	(2)	(3)	(4)	(5)	(6)[a]
	Violent Conflict, Incidence					
EF	-0.0794	-0.0826				
	(0.0597)	(0.0597)				
EP	0.2246	0.2330				
	(0.1621)	(0.1622)				
Refugees (80km, IHS)		0.0024		0.0037*		0.0035
		(0.0020)		(0.0022)		(0.0022)
Corrected EF (80km, Min. Ling. Dist.)			-0.1220*	-0.1454**	-0.1248**	-0.1469**
			(0.0629)	(0.0653)	(0.0630)	(0.0655)
Corrected EP (80km, Min. Ling. Dist.)			0.2774*	0.2826*	0.2826*	0.2874*
			(0.1624)	(0.1631)	(0.1628)	(0.1635)
Rain anomalies (80km)					-0.0013***	-0.0013***
					(0.0003)	(0.0003)
Temp anomalies (80km)					-0.0444**	-0.0439**
					(0.0183)	(0.0183)
Observations	22,415	22,415	22,415	22,415	22,415	22,415
R-squared	0.640	0.640	0.640	0.640	0.640	0.640
Year FE	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS, presented in Column (6). Level of precision set to $\leq$ 3 to increase number of geocoded locations. Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. Refugee camps in a 80-km buffer around each cluster. The 'minimum linguistic distance' function from LEDA* used to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Line H of Table 2.5.3.

[*] More information on LEDA in 2.A.1.

Table 2.B.19: Diversity and Violent Conflict, Incidence.

	(1)	(2)	(3)	(4)	(5)	(6)[a]
			Violent Conflict, Incidence			
EF	-0.0668	-0.0694				
	(0.0579)	(0.0580)				
EP	0.2230	0.2301				
	(0.1579)	(0.1580)				
Refugees (80km, IHS)		0.0022		0.0035		0.0033
		(0.0020)		(0.0022)		(0.0022)
Corrected EF (80km, Min. Ling. Dist.)			-0.1435**	-0.1654***	-0.1468**	-0.1675***
			(0.0605)	(0.0629)	(0.0607)	(0.0631)
Corrected EP (80km, Min. Ling. Dist.)			0.3516**	0.3551**	0.3575**	0.3608**
			(0.1573)	(0.1579)	(0.1578)	(0.1584)
Rain anomalies (80km)					-0.0013***	-0.0013***
					(0.0003)	(0.0003)
Temp anomalies (80km)					-0.0502***	-0.0499***
					(0.0175)	(0.0175)
Observations	23,256	23,256	23,256	23,256	23,256	23,256
R-squared	0.642	0.642	0.642	0.642	0.643	0.643
Year FE	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS, presented in Column (6). All geocoded locations are included. Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. Refugee camps in a 80-km buffer around each cluster. The 'minimum linguistic distance' function from LEDA* used to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0:01$), ** at the 5 percent level ($p < 0:05$), and * at the 10 percent level ($p < 0:10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Line I of Table 2.5.3.

[*] More information on LEDA in 2.A.1.

Table 2.B.20: Instrumental Variable Approach: Diversity and Violent Conflict, Incidence.

	(1)	(2)	(3)	(4)
	Violent Conflict, Incidence			
Panel A:	**Second-Stage**			
Corrected EF (80km, Min. Ling. Dist.)	0.9463***	0.9536***	0.9456***	0.9542***
	(0.0086)	(0.0101)	(0.0084)	(0.0094)
Corrected EP (80km, Min. Ling. Dist.)	0.4712*	0.4768*	0.4674*	0.4757*
	(0.2603)	(0.2629)	(0.2593)	(0.2618)
Refugees (80km, IHS)		0.0005		0.0007
		(0.0029)		(0.0029)
Observations	14,441	14,441	14,441	14,441
R-squared	0.0019	0.0019	0.0029	0.0030
Kleibergen-Paap rk Wald F	868.9	890.1	871.2	892.8
Root MSE	0.290	0.290	0.290	0.290
Panel B:	**First-Stage (Corrected EF)**			
Predicted Corrected EF	0.9463***	0.9536***	0.9456***	0.9542***
	(0.0086)	(0.0101)	(0.0084)	(0.0094)
Predicted Corrected EP	0.0501**	0.0426*	0.0447**	0.0367*
	(0.0218)	(0.0227)	(0.0211)	(0.0212)
Panel C:	**First-Stage (Corrected EP)**			
Predicted Corrected EF	0.0095***	0.0054*	0.0091***	0.0056*
	(0.0017)	(0.0029)	(0.0018)	(0.0029)
Predicted Corrected EP	0.9687***	0.9729***	0.9686***	0.9719***
	(0.0052)	(0.0064)	(0.0054)	(0.0064)
Year FE	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y
Country-Time Trends	N	N	Y	Y
Climatic Controls	Y	Y	Y	Y

Notes: Estimated Equation in Panel A: Equation (2.5). Estimated Equation in Panel B: Equation (2.7). Estimated Equation in Panel C: Equation (2.8). Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. Refugee camps in a 80-km buffer around each cluster. The 'minimum linguistic distance' function from LEDA* used to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0:01$), ** at the 5 percent level ($p < 0:05$), and * at the 10 percent level ($p < 0:10$), all for two-sided hypothesis tests. FE: fixed effects.

Corrected EF and Corrected EP predicted using a gravity model presented in Column (2) of Table 2.5.4.

* More information on LEDA in 2.A.1.

Table 2.B.21: Descriptive Statistics: Individual Data

	(1) Obs.	(2) Mean	(3) Std. Dev.	(4) Min.	(5) Max.	(6) Obs.	(7) Mean	(8) Std. Dev.	(9) Min.	(10) Max.
	Panel A: Refugee-Hosting Areas					**Panel B: All Areas**				
Diversity Indices.										
EF	7,893	0.2666	0.2580	0	0.8791	46,528	0.3131	0.2842	0	0.8828
EP	7,893	0.1029	0.0900	0	0.2500	46,528	0.1078	0.0873	0	0.2500
Corrected EF (80-km, Min. Ling. Dist.)	7,893	0.3818	0.2481	0	0.8494	46,528	0.3038	0.2773	0	0.8664
Corrected EP (80-km, Min. Ling. Dist.)	7,893	0.1385	0.0768	0	0.2500	46,528	0.1075	0.0876	0	0.2500
Refugees (80km, IHS)	7,893	6.9647	4.6902	0	13.7611	46,528	1.1815	3.2503	0	13.7611
Socio-Demographic Variables.										
Age	7,893	36.6117	13.9844	18	100	46,528	35.7502	13.8922	18	105
Basic Education	7,893	0.3532	0.4780	0	1	46,528	0.2911	0.4543	0	1
Secondary Education	7,893	0.3248	0.4683	0	1	46,528	0.3664	0.4818	0	1
Tertiary Education	7,893	0.0817	0.2740	0	1	46,528	0.1279	0.3339	0	1
Female	7,893	0.4994	0.5000	0	1	46,528	0.5000	0.5000	0	1
Urban/Rural Status	7,893	0.3739	0.4839	0	1	46,528	0.4235	0.4941	0	1
Employment	7,893	0.4208	0.4937	0	1	46,528	0.3746	0.4840	0	1
Marital Status	7,893	0.0552	0.2285	0	1	46,528	0.0679	0.2516	0	1
Outcome Variables.										
Attacks	7,893	0.0889	0.2847	0	1	46,528	0.1139	0.3177	0	1
Crime	7,893	0.2951	0.4561	0	1	46,528	0.3199	0.4664	0	1
Identity: Ethnicity vs. Nationality	7,893	0.5110	0.4999	0	1	46,528	0.4665	0.4989	0	1
Protest	7,893	0.2272	0.4190	0	1	46,528	0.3206	0.4667	0	1
Theft	7,893	0.3012	0.4588	0	1	46,528	0.3055	0.4606	0	1
Trust: General	4,784	0.2255	0.4180	0	1	22,593	0.1954	0.3965	0	1
Trust: Government	7,893	0.6264	0.4838	0	1	46,528	0.6127	0.4871	0	1
Trust: Neighborhood	4,784	0.6166	0.4863	0	1	22,593	0.5993	0.4901	0	1
Climate Data.										
Rain anomalies	7,893	-0.9722	11.4333	-48.2476	28.5457	46,528	-0.8006	11.0475	-57.7804	41.6399
Temperature anomalies	7,893	0.0575	0.2409	-0.5414	1.2996	46,528	0.0811	0.2561	-0.5938	1.2996

Notes: EF, EP: standard diversity indices. Corrected EF (80-km, Min. Ling. Dist.), Corrected EP (80-km, Min. Ling. Dist.): refugee-corrected diversity indices. Level of analysis: cluster. Nb. of countries: 23. Period: 2005-2016. Refugee camps in a 80-km buffer around each cluster. The 'minimum linguistic distance' function from LEDA* to link ethnicities between the Afrobarometer surveys and the EPR-ER.

* More information on LEDA in 2.A.1.

Table 2.B.22: Discussion: Diversity and Individual Outcomes.

	(1) Attack[a]	(2) Crime[b]	(3) National Id.	(4) Protest	(5) Theft[c]	(6) Gen. Trust	(7) Neigh. Trust	(8) Gov. Trust
Panel A:	**Excl. Countries with Bad Camps Data (19 countries)**							
Corrected EF (80km, Min. Ling. Dist.)	-0.0668	-0.1494*	-0.0280	-0.0544	-0.1193*	-0.0577	-0.2156	0.0166
	(0.0452)	(0.0852)	(0.0984)	(0.0584)	(0.0693)	(0.1515)	(0.1562)	(0.0817)
Corrected EP (80km, Min. Ling. Dist.)	0.2368*	0.2337	-0.0396	0.0191	0.1664	-0.0496	0.1815	0.0896
	(0.1264)	(0.2333)	(0.2730)	(0.1739)	(0.2022)	(0.4397)	(0.5312)	(0.2197)
Observations	46,528	46,528	46,528	46,528	46,528	22,592	22,592	46,528
R-squared	0.161	0.199	0.236	0.496	0.176	0.249	0.276	0.276
Panel B:	**Incl. All Countries (23 countries)**							
Corrected EF (80km, Min. Ling. Dist.)	-0.0559	-0.1142	-0.0511	-0.0480	-0.0837	-0.0553	-0.1834	0.0003
	(0.0414)	(0.0819)	(0.0890)	(0.0532)	(0.0694)	(0.1416)	(0.1455)	(0.0764)
Corrected EP (80km, Min. Ling. Dist.)	0.1954*	0.1603	0.1474	-0.0364	0.1291	0.1891	0.4807	0.1574
	(0.1118)	(0.2179)	(0.2406)	(0.1565)	(0.1957)	(0.4072)	(0.4573)	(0.2042)
Observations	56,706	56,706	56,706	56,706	56,706	27,126	27,126	56,706
R-squared	0.160	0.195	0.225	0.496	0.175	0.229	0.295	0.263
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls: Climate, Ref. (80km, IHS), Ind.	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS. Individual controls: age, squared age, education, gender, marital and rural/urban status. Level of analysis: cluster. Period: 2005-2016. Refugee camps in a 80-km buffer around each cluster. The 'minimum linguistic distance' function from LEDA* to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects. See Column (6) for: [a] in Table 2.B.23; [b] in Table 2.B.24; [c] in Table 2.B.25;
[*] More information on LEDA in 2.A.1.

Table 2.B.23: Individual Outcomes: Diversity and Attacks.

	(1)	(2)	(3)	(4)	(5)	(6)[a]
	Attack					
EF	0.0025	-0.0042				
	(0.0434)	(0.0437)				
EP	0.0259	0.0435				
	(0.1226)	(0.1236)				
Refugees (80km, IHS)		0.0037**		0.0038**		0.0033*
		(0.0018)		(0.0018)		(0.0019)
Corrected EF (80km, Min. Ling. Dist.)			-0.0513	-0.0644	-0.0563	-0.0668
			(0.0451)	(0.0455)	(0.0446)	(0.0452)
Corrected EP (80km, Min. Ling. Dist.)			0.2145*	0.2267*	0.2293*	0.2368*
			(0.1287)	(0.1274)	(0.1274)	(0.1264)
Rain anomalies					0.0002	0.0003
					(0.0006)	(0.0006)
Temp anomalies					-0.0361	-0.0303
					(0.0273)	(0.0280)
Observations	46,528	46,528	46,528	46,528	46,528	46,528
R-squared	0.161	0.161	0.161	0.161	0.161	0.161
Year FE	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y
Individual Controls	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS, presented in Column (6). Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Individual controls: age, squared age, education, gender, marital and rural/urban status. Level of analysis: cluster. Nb. of countries: 20. Period: 2005-2016. Refugee camps in a 80-km buffer around each cluster. The 'minimum linguistic distance' function from LEDA* to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Column (1) of Table 2.B.22.

[*] More information on LEDA in 2.A.1.

Table 2.B.24: Individual Outcomes: Diversity and Crimes.

	(1)	(2)	(3)	(4)	(5)	(6)[a]
	Crime					
EF	-0.0888	-0.0952				
	(0.0750)	(0.0743)				
EP	0.1626	0.1794				
	(0.2179)	(0.2173)				
Refugees (80km, IHS)		0.0035		0.0048		0.0046
		(0.0049)		(0.0050)		(0.0049)
Corrected EF (80km, Min. Ling. Dist.)			-0.1310	-0.1476*	-0.1350	-0.1494*
			(0.0824)	(0.0843)	(0.0835)	(0.0852)
Corrected EP (80km, Min. Ling. Dist.)			0.2108	0.2261	0.2234	0.2337
			(0.2284)	(0.2293)	(0.2331)	(0.2333)
Rain anomalies					-0.0001	-0.0001
					(0.0010)	(0.0010)
Temp anomalies					-0.0221	-0.0142
					(0.0531)	(0.0523)
Observations	46,528	46,528	46,528	46,528	46,528	46,528
R-squared	0.198	0.198	0.198	0.199	0.199	0.199
Year FE	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y
Individual Controls	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS, presented in Column (6). Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Individual controls: age, squared age, education, gender, marital and rural/urban status. Level of analysis: cluster. Nb. of countries: 20. Period: 2005-2016. Refugee camps in a 80-km buffer around each cluster. The 'minimum linguistic distance' function from LEDA* to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Column (2) of Table 2.B.22.

* More information on LEDA in 2.A.1.

Table 2.B.25: Individual Outcomes: Diversity and Theft.

	(1)	(2)	(3)	(4)	(5)	(6)[a]
	Theft					
EF	-0.0518	-0.0592				
	(0.0708)	(0.0702)				
EP	-0.0042	0.0153				
	(0.1908)	(0.1904)				
Refugees (80km, IHS)		0.0041		0.0054		0.0053
		(0.0046)		(0.0047)		(0.0047)
Corrected EF (80km, Min. Ling. Dist.)			-0.1065	-0.1250*	-0.1024	-0.1193*
			(0.0672)	(0.0703)	(0.0663)	(0.0693)
Corrected EP (80km, Min. Ling. Dist.)			0.1709	0.1881	0.1543	0.1664
			(0.1999)	(0.2034)	(0.1994)	(0.2022)
Rain anomalies					0.0013	0.0013
					(0.0008)	(0.0008)
Temp anomalies					-0.0087	0.0005
					(0.0386)	(0.0378)
Observations	46,528	46,528	46,528	46,528	46,528	46,528
R-squared	0.176	0.176	0.176	0.176	0.176	0.176
Year FE	Y	Y	Y	Y	Y	Y
PSU FE	Y	Y	Y	Y	Y	Y
Individual Controls	Y	Y	Y	Y	Y	Y

Notes: Estimated Equation: Equation (2.1) using OLS, presented in Column (6). Columns (1) and (2) introduces standard diversity indices. From Column (3), refugee-corrected diversity indices are introduced. Individual controls: age, squared age, education, gender, marital and rural/urban status. Level of analysis: cluster. Nb. of countries: 20. Period: 2005-2016. Refugee camps in a 80-km buffer around each cluster. The 'minimum linguistic distance' function from LEDA* to link ethnicities between the Afrobarometer surveys and the EPR-ER. Robust standard errors clustered at the cluster level are reported in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

[a] Results for Corrected EF and Corrected EP in Column (6) presented in Column (5) of Table 2.B.22.

* More information on LEDA in 2.A.1.

Figure 2.B.1: UNHCR Aggregated Refugee Data by Region of Asylum.

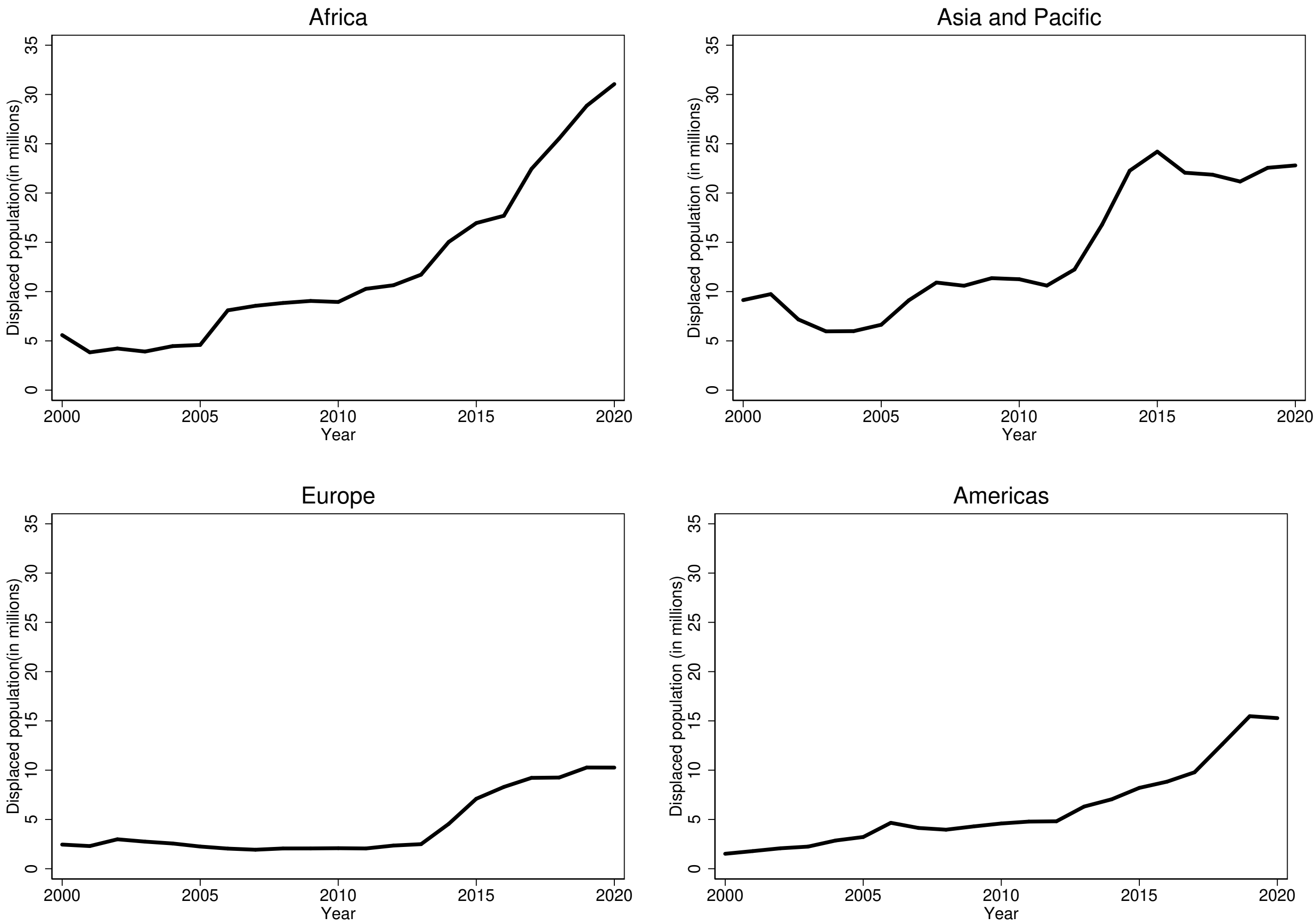
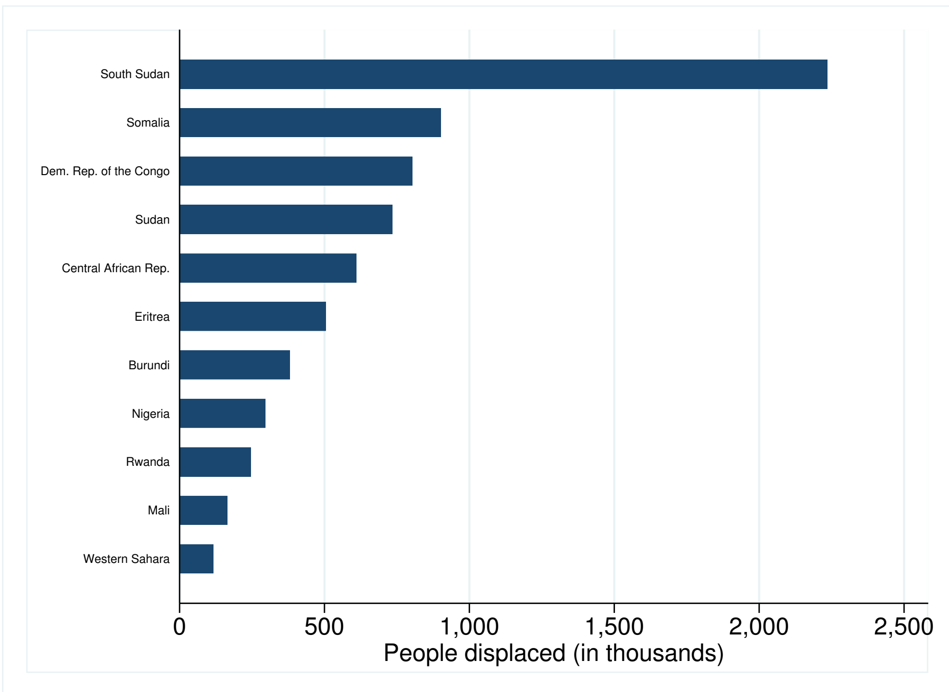


Figure 2.B.2: People Displaced Across Borders by Country of Origin, UNHCR, End-2019.



Note: Countries with more than 100,000 refugees at origin.

Figure 2.B.3: UNHCR Share of Refugees in Neighboring Countries.

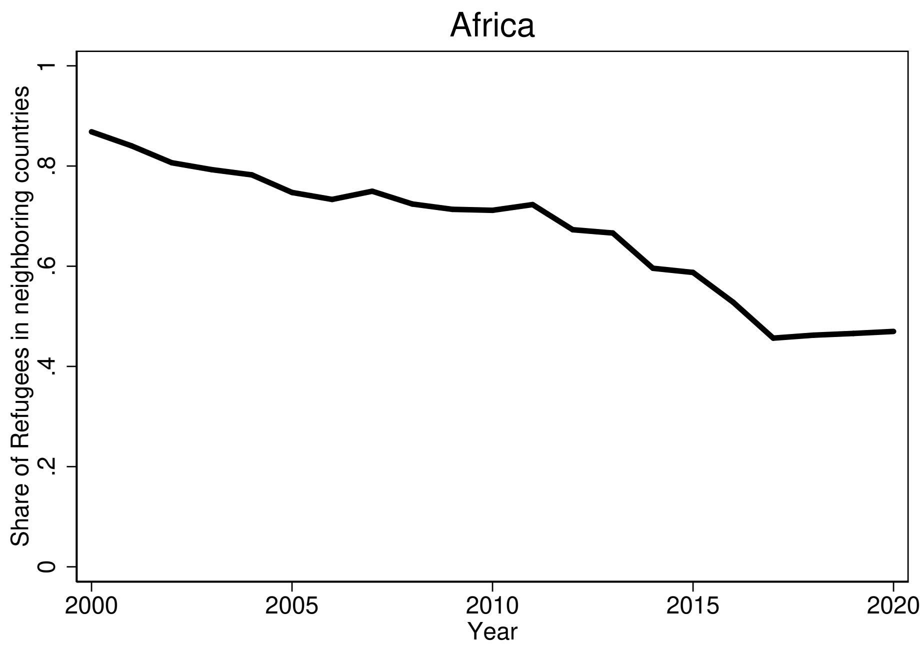
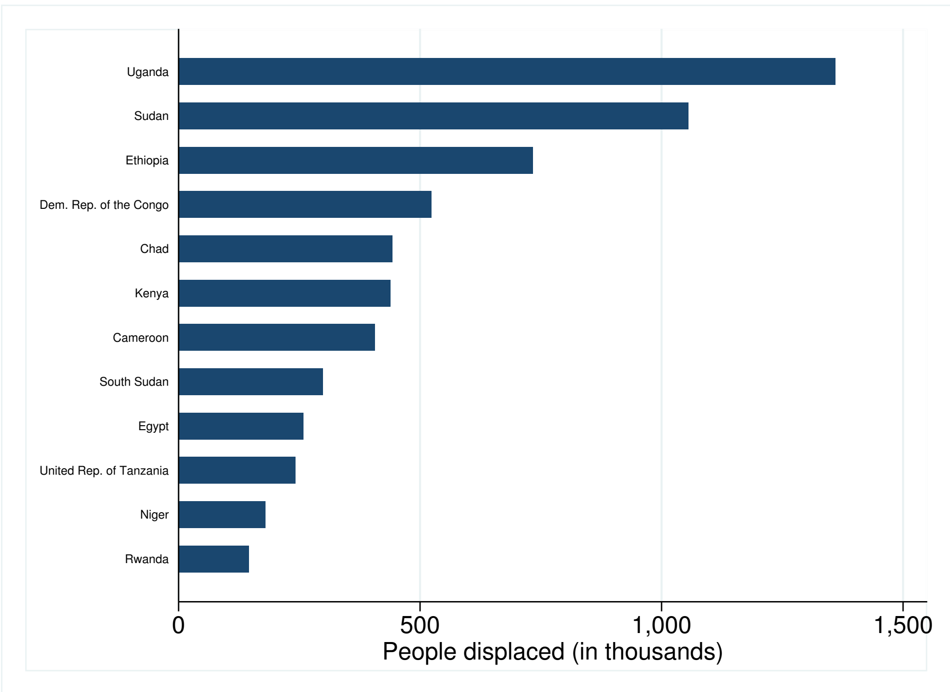


Figure 2.B.4: People Displaced Across Borders by Country of Asylum, UNHCR, End-2019.



Note: Countries hosting more than 100,000 refugees.

Figure 2.B.5: UNHCR Number of Protracted Refugee Situations.

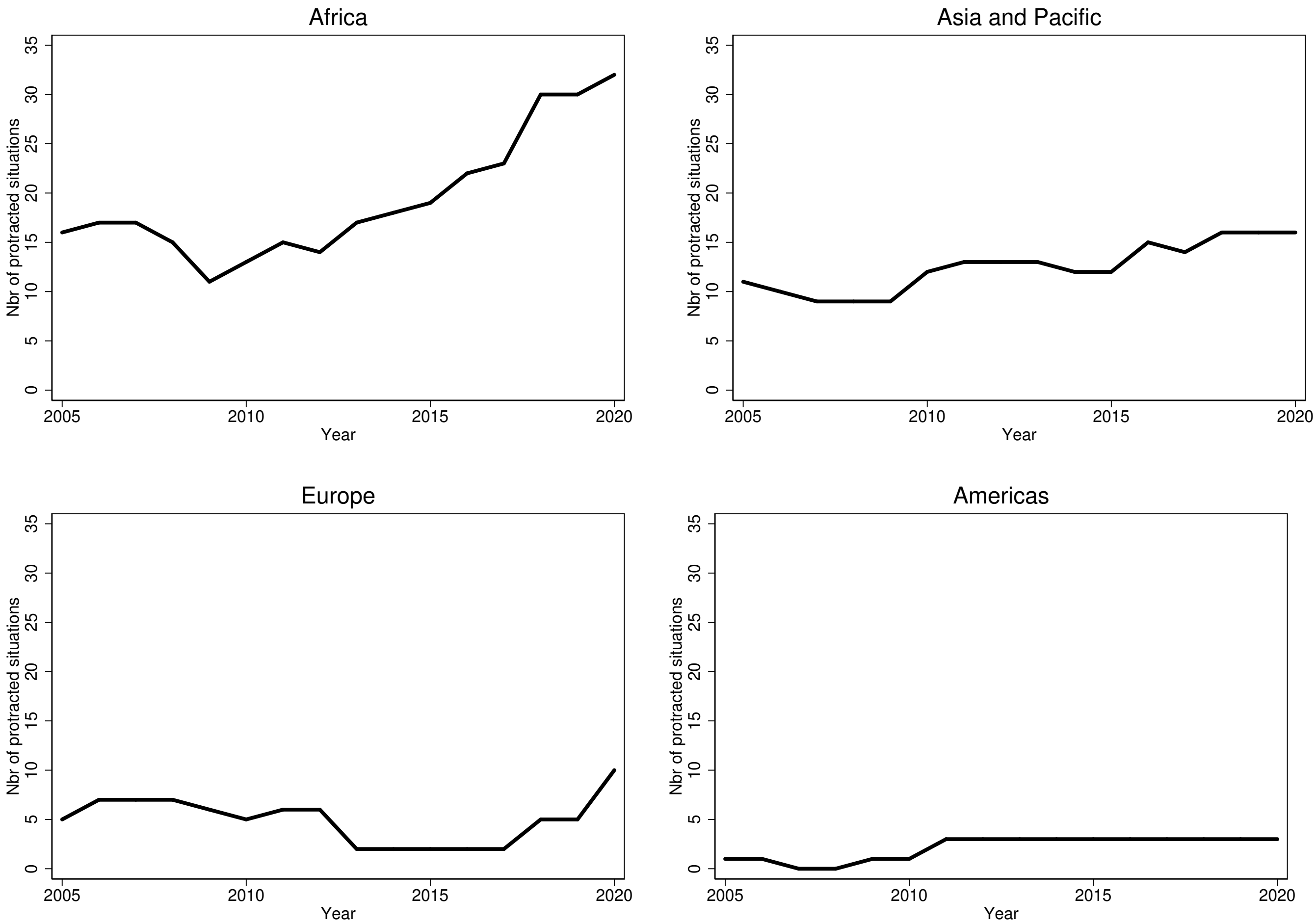


Figure 2.B.6: UNHCR Official Refugee Statistics vs. UNHCR Refugee Camps: Aggregated Data.

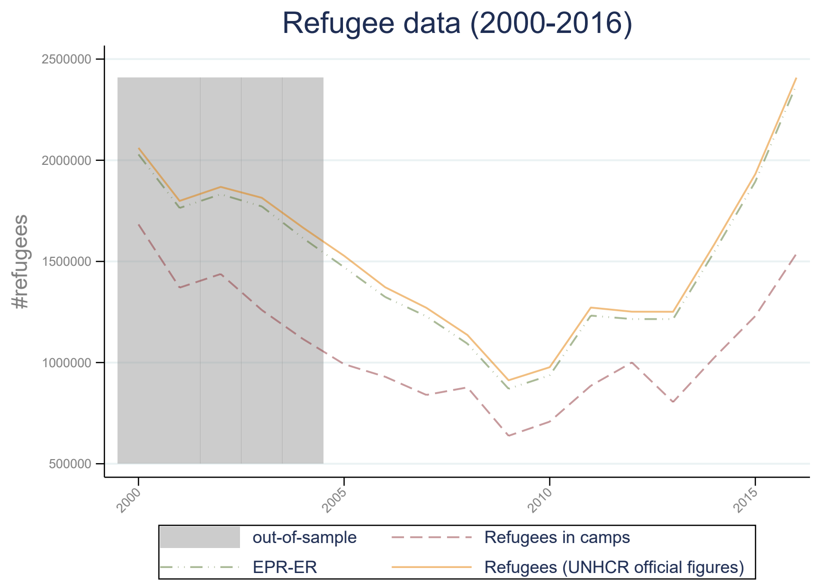


Figure 2.B.7: UNHCR Official Refugee Statistics vs. UNHCR Refugee Camps: Country Level Data.

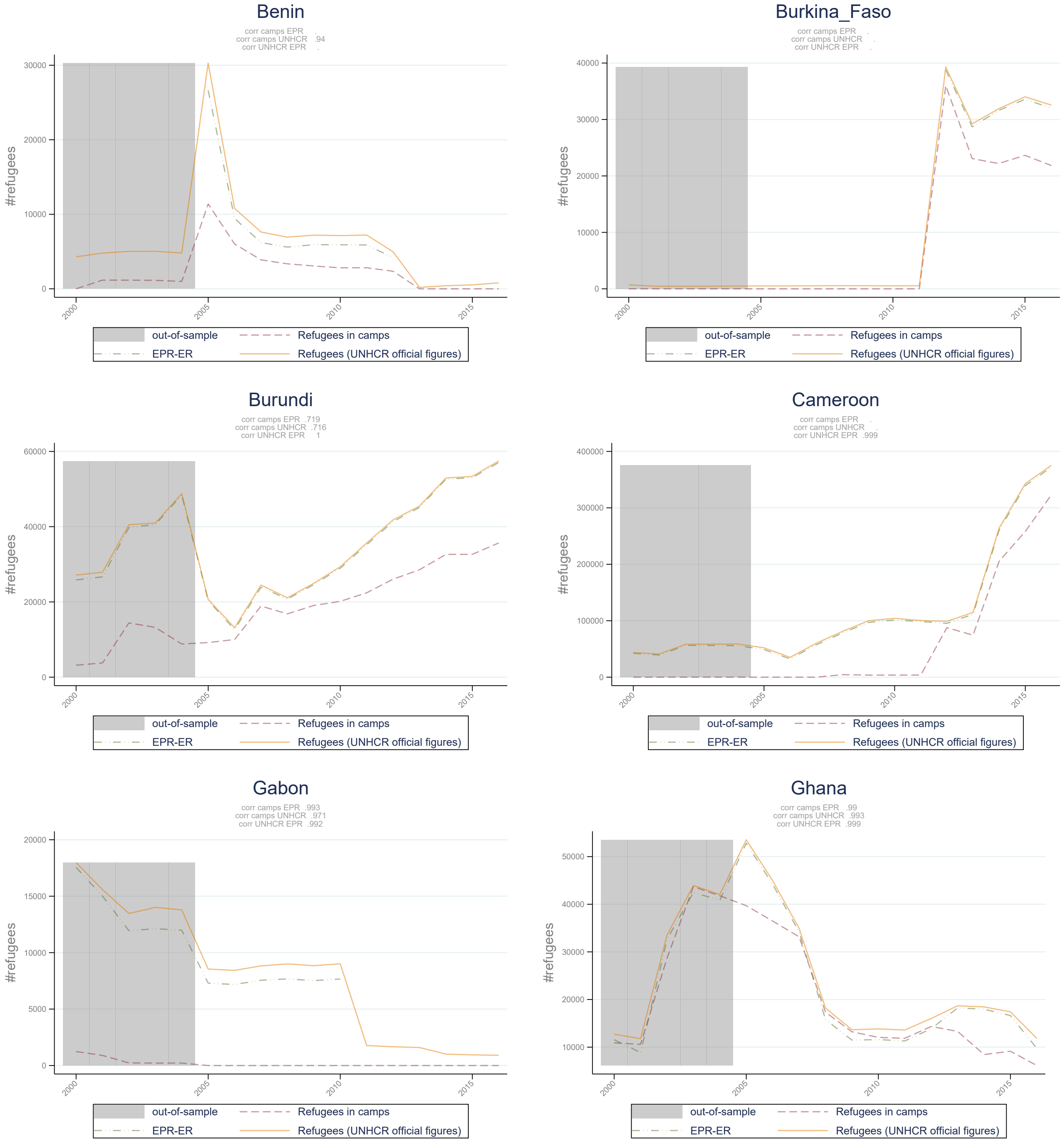


Figure 2.B.7: UNHCR Official Refugee Statistics vs. UNHCR Refugee Camps: Country Level Data.

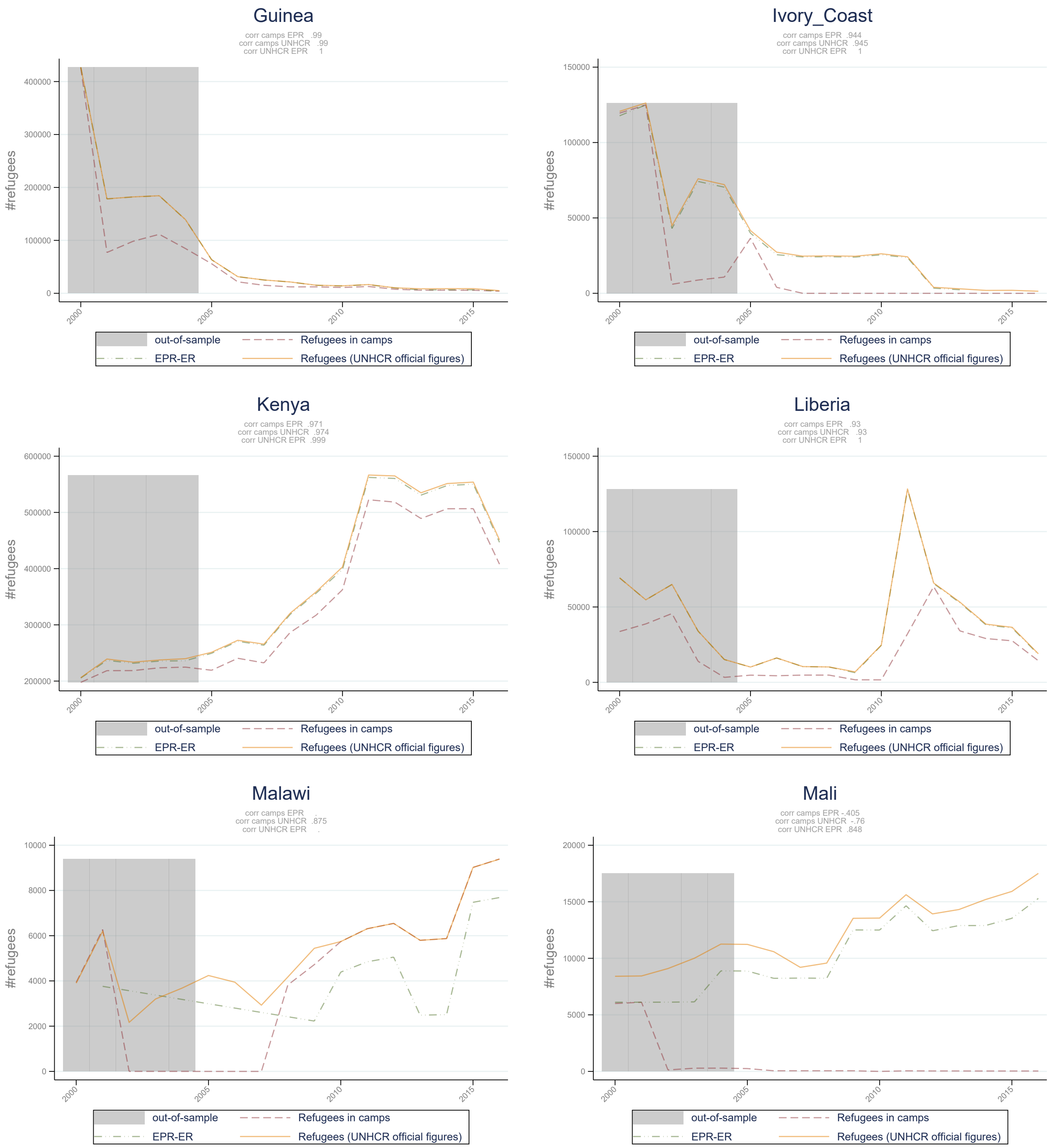


Figure 2.B.7: UNHCR Official Refugee Statistics vs. UNHCR Refugee Camps: Country Level Data.

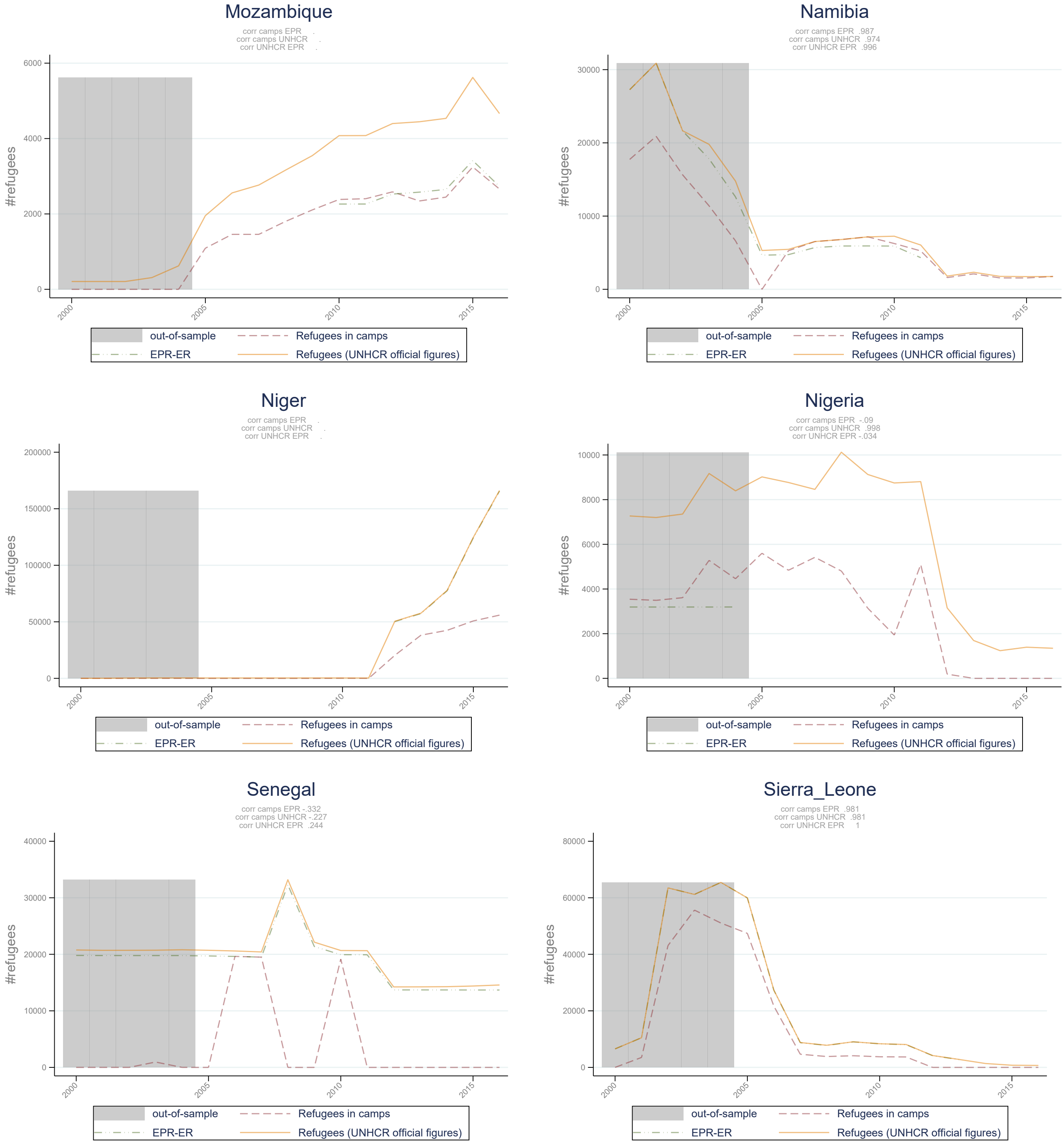


Figure 2.B.7: UNHCR Official Refugee Statistics vs. UNHCR Refugee Camps: Country Level Data.

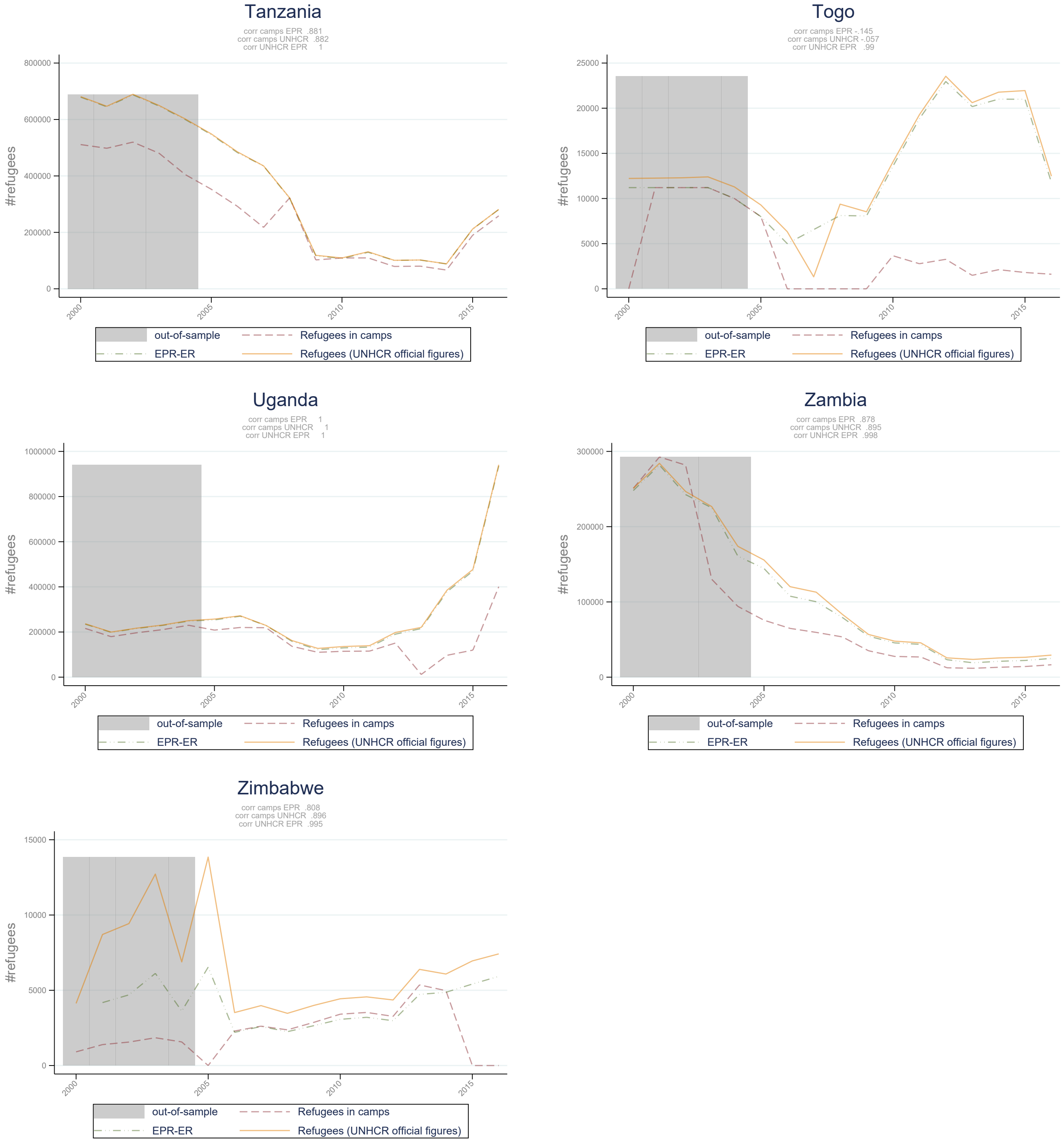


Figure 2.B.8: Heterogeneity Analysis.

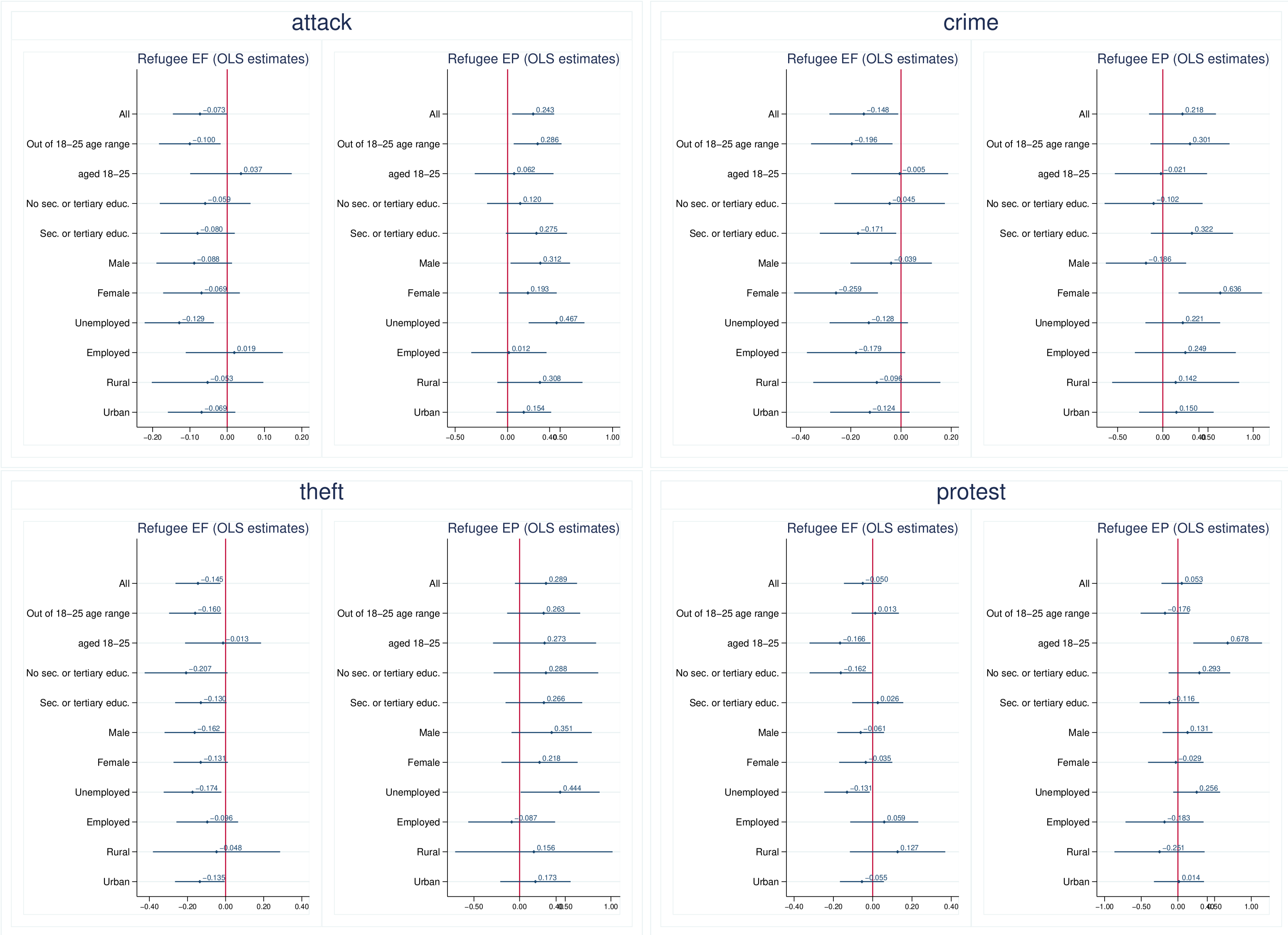


Figure 2.B.9: Relevance with COVID-19 Violence.

Chapter 3

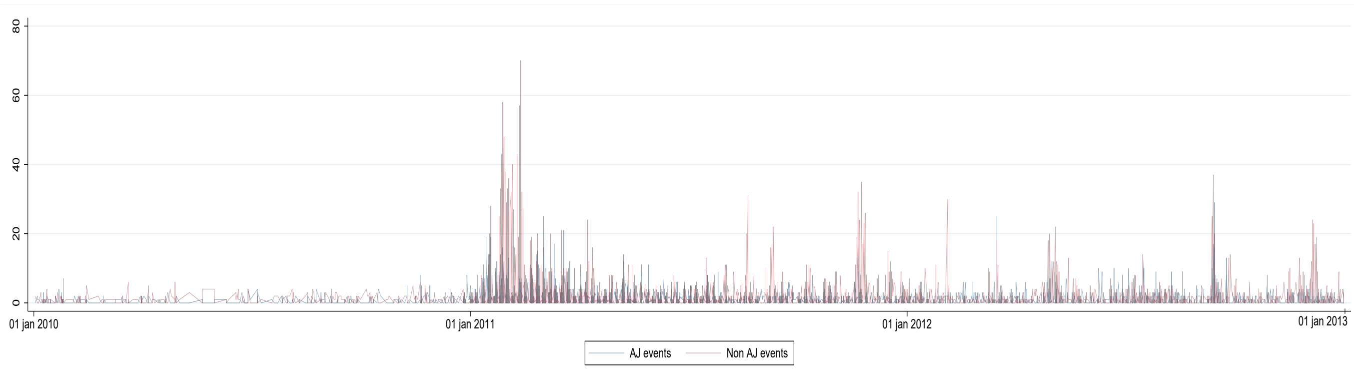
The Impact of Independent Media on Political Accountability during the Arab Spring

3.1 Introduction

In the early 2010s, a number of protests against governments in place flocked across the Arab world, later termed the "Arab Spring", initially sparked by uprisings against corruption in Tunisia in December 2010 (see Figure 3.1.1[65]).The upheaval of the people did not spontaneously happen, but was the result of a long quest for political transparency and accountability, which has been a main subjects of the debate in the Arab World since over a decade (Kazemi & Norton, 2006; Makdisi, 2017; Sakr, 2003).

There is a large literature discussing the causes behind the Arab Spring, reaching from lack of economic opportunities to nepotism and kleptocracy (Campante & Chor, 2012). However, the potential role of media in precipitating and spreading the discontent of the population has been largely ignored. This paper attempts to fill this gap in the literature by quantifying the role of the emergence of independent media networks in the Arab World in explaining Arab Spring protests.

Figure 3.1.1: The Evolution of Protests in the Arab World.



Source:
Arab Barometer surveys for data on media networks.
The Global Database of Events, Language and Tone (GDELT) for data on protests.

Our contribution is twofold.

First, we contribute to the understanding of the political economy of media (see reviews by DellaVigna and Kaplan (2007), DellaVigna and La Ferrara (2015), Durante et al. (2019) and Enikolopov and Petrova (2015)). Among them, it is worth mentioning the seminal paper by DellaVigna and Kaplan (2007), which studies the impact of Fox News on voting behavior in the U.S. and finds that viewing Fox News increased Republican voters suggesting a learning effect and persuasion. In our study, we focus on the emergence of independent media networks in captured environments (Enikolopov & Petrova, 2015). Studies so far focused on the effect of independent TV channels on voting in Russia (Enikolopov et al., 2011), in Italy (Barone et al., 2011) and in East Germany (Kern & Hainmueller, 2009). With the exception of the strategic use of military forces in the Israeli-Palestinian conflict (Durante & Zhuravskaya, 2015), little

[65] AJ events refer to protests in regions, where the share of Al Jazeera media network viewers is greater than its median, while Non AJ events represent protests regions, where this share is below the median.

is known about the impact of media in the Middle East. That is surprising given the recent structural changes in media exposure occurring in that region (Fandy, 2000; Ghareeb, 2000; Khondker, 2011; Wiest & Eltantawy, 2015). In particular, the emergence of independent media with the creation of the Al Jazeera network in 1996 in Qatar and later that of the Al Arabiya network in 2003 in Saudi Arabia were major developments in the Arab world opening up the way for freedom of expression in these regions (Al-Saggaf, 2008; Behravesh, 2014; El-Nawawy & Iskandar, 2002, 2003; Sultan, 2013; Zayani, 2005).[66] To the best of our knowledge, we are the first ones to quantify the role of Al Jazeera and Al Arabiya media networks. Using data from the Arab Barometer surveys, we investigate the effect of these two independent media networks on participation to protests, before and after the Arab Spring, in Middle East and North Africa (MENA) region. In particular, due to data availability, we focus on Jordan, Lebanon and Palestine. We find a significant and positive relationship between independent media usage and participation to protests. In order to address potential endogeneity bias, we further instrument the access to independent media networks with regional ruggedness using Two-Stage Least Squares (2SLS) estimation method. Our results suggest that a 1 % increase in the share of independent media networks users increases the likelihood to participate to protests by roughly 1.6 percentage points (p.p.). We also investigate the role of Al Jazeera and Al Arabiya on protests distinctively. Interestingly, we find that that Al Arabiya had a larger impact in magnitude (roughly 6 p.p.) on protests than Al Jazeera (roughly 2 p.p.) although Al Jazeera emerged earlier than Al Arabiya in the Arab World and occupies the first place as the most frequently used media network.

Second, we contribute to the literature on conflict and mass mobilization. While the economics of conflicts has mainly focused on the role of economic shocks, ethnic diversity, or natural resources (Berman et al., 2017; Blattman & Miguel, 2010), the role of media has been mostly neglected. Beyond the above-mentioned work by Durante and Zhuravskaya (2015), one exception is Yanagizawa-Drott (2014), who studies the impact of radio on violence during the 1994 Rwandan genocide. Our paper differs from Yanagizawa-Drott (2014), which sheds light on the impact of a captured media in promoting violence. In our case, we assess the role of independent media in countries where most media outlets are controlled by the state.[67] According to Besley and Prat (2005), media effect is likely to be salient in this type of environment. A parallel literature sheds light on the determinants of political or social mobilization (Benabou, 2000; Campante & Chor, 2012; Dee, 2004; Putnam, 1995; Sondheimer & Green, 2010). The Arab Spring has been particularly insightful in that respect. These studies discuss the mismatch between large improvements in education and the lack of economic opportunities together with demographic factors (youth), as main drivers of political mobilization (Campante & Chor, 2012, 2014). Our paper does not allow us to investigate fundamentals of economic development such as culture, geography, or institutions. We leave that task e. g. to Chaney

[66] We devote the next section of this paper to some contextual information on the emergence of these two independent media.

[67] Another study mentioned by Enikolopov and Petrova (2015) is Adena et al. (2015) on the role of radio in the 1930s in Germany.

(2012), who highlights the legacy of historical institutional structures in explaining the democratic deficit prevailing in the region prior to the Arab Spring, against alternative explanations based on culture, oil abundance etc. Malik and Awadallah (2013) also highlight economic fragmentation across the region that prevents the private sector to develop and be an actor for change. None of these studies focused on the role of media on conflict. The neglected role of the media in the emergence of the Arab Spring is surprising for two reasons. There is anecdotal evidence (Ghannouchi, 2013; Pew Research Center, 2012), but more importantly independent media has been shown to matter considerably in other contexts (Olken, 2009; Putnam, 2000). Several recent theories have shown that new media can facilitate collective action, by either spreading relevant information or easing coordination (Barbera & Jackson, 2017; Edmond, 2013; Little, 2016). In our research, we analyze the impact of independent media, which refers to the information channel, but provide some additional results by making a distinction between the access to independent media networks through TV (a traditional channel of information) and through internet (both a channel of information and coordination) and their roles on protests. Contrary to the role of social media, coordination here is not about logistical coordination. Coordination may simply be eased when the media better reflects the numbers of participants to protests and hence, increase the returns to political activism and reduce the costs to participate (Barbera & Jackson, 2017; Passarelli & Tabellini, 2017). Our results indicate a lower impact of using independent media through internet on participation to protests (roughly 0.08 p.p.) than through traditional information channels such as TV (roughly 0.5 p.p.).[68]

In our paper, we also conduct some placebo analysis investigating the impact of state media on protests and distinguishing the impact of independent media between public and non-public workers. We do not find any significant impact of state media and independent media for public workers on participation to protests. However, we find a similar effect of independent media for non-public workers on participation to protests. We extend our analysis to additional outcomes such as governmental trust, political alignment, signing petitions and general trust to test some channels behind our results.

The remainder of this paper is structured as follows. Section 3.2 provides the context of the study. Section 3.3 presents our research design, first describing our identification strategy (Section 3.3.1) and second, presenting our data with some descriptive statistics to help understand better the study sample (Section 3.3.2). Section 3.4 first presents our main results (Section 3.4.1). Second, some additional results are provided (Section 3.4.2). Third, results from a series of robustness tests are presented (Section 3.4.3). Section 3.5 offers a discussion around the mechanisms behind our results. Section 3.6 concludes.

[68] A strand of the literature investigates the role of social media on protests (Enikolopov et al., 2020; Fergusson & Molina, 2020; Guriev et al., 2019; Manacorda & Tesei, 2020; Zhuravskaya et al., 2020). These studies make a distinction between the information channel and the collective action channel. The former provides information on the quality of governments and likely plays a strong role in countries where media is largely government-controlled. The latter allows for the exchange of information therefore reduces the costs of coordination and make possible protests.

3.2 The Emergence of Independent Media in the Arab World

The information revolution in the Arab World began with pan-Arab newspapers and continued with satellite networks (Dunn, 2000).[69]

In particular, the creation of Al Jazeera in 1996 was a major development in the Arab world. Al Jazeera is an independent Arabic news channel partly funded by the Qatari government and operated by the media conglomerate Al Jazeera Media Network. It is the first independent news channel in the Arab world dedicated to providing comprehensive news and live debate (Al-Jazeera, 2020). While it has been criticized by the West as giving a voice to Al-Qaida and Talibans and spreading religious extremism, Al Jazeera, under its motto "The opinion ... and the other opinion", has also exposed viewers to opposing views to incumbent leaders (El-Nawawy & Iskandar, 2002, 2003; Zayani, 2005). Arab regimes have indeed often complained about the Al Jazeera network acting as a destabilizing force to their authorities (without criticizing the founder, Qatar). Al Jazeera was even criticized to have facilitated the Arab Spring by providing "the 'gunpowder' needed to fire peoples anger and their desire to join the massive crowds of demonstrators chanting anti-government slogans and demanding regime change." (Sultan, 2013).[70] Several governments, including Egypt and Jordan, stated that Al Jazeera's coverage "threatened the stability of their regimes and exposed them to criticism by their own people." (El-Nawawy & Iskandar, 2003). "Even in Palestine, the Ramallah office of Al Jazeera was closed after Al Jazeera broadcast an unflattering image of chairman Yasser Aaraftat in a promotional trailer for a documentary on the 1975-90 Lebanese Civil war" (El-Nawawy & Iskandar, 2002). Al-Jazeera not only fills a media void but also a political void. In the absence of political will and political pluralism in the Arab world, Al Jazeera serves as a de facto pan-Arab opposition and a forum of resistance (Zayani, 2005).

Other independent media networks emerged in the Arab world following the creation of Al Jazeera. In particular, as a response to Al Jazeera's criticism of the Saudi royal family throughout the 1990s, in 2001, relatives of the Saudi royal family established Al Arabiya in Dubai, the "Saudispeak" of the Arab World (Behravesh, 2014). Al Arabiya is an international news channel based in Riyadh, Saudi Arabia and operated by the media conglomerate Middle East Broadcasting Center epitomizing "Arab modernism" (Allied Media Corp., 2020). Al Arabiya is said to be the second most frequently watched channel after Al Jazeera with its motto 'Know More" (Watkins, 2019). Like Al Jazeera, Al Arabiya aims at providing an objective understanding to citizens of the Arab World, while undoubtedly "keeping with the greater political agenda pursued by the Saudi government in the external and domestic spheres" (Behravesh, 2014). Al Arabiya has also received criticism from authorities of countries in the

[69] Dunn (2000) provide a literature review on the emergence of information revolution in the Middle East.

[70] Such a complain by incumbents was not inconsequential since the closing of Al Jazeera was one of the demand sustaining the trade embargo imposed by Egypt, Saudi Arabia, UAE and Bahrain on Qatar on the 5th of June 2017.

Arab World. On 11 March 2010, Yemeni authorities conducted raids on the offices of Al Jazeera and Al Arabiya and seized their broadcast equipment with the argument that the equipment "should not serve to provoke trouble and amplify events in such a way as to harm public order" (Herd, 2011).

In the rest of our study, we focus our attention on these two influential independent media networks and quantify their impact on political accountability in the Arab World.

3.3 Research Design

In this section, we first present our identification strategy (Section 3.3.1) and second, our data with some descriptive statistics (Section 3.3.2).

3.3.1 Identification strategy

Our aim is to investigate the impact of the use of independent media networks on political accountability. To do so, we first carry out OLS estimations to investigate the link between the use of independent media networks and participation to protests. Second, since our results through OLS estimations are likely confounded with some other factors, we turn to instrumental variable estimation to investigate as to whether there is a causal link between independent media networks and protests.

Our benchmark estimation can be represented as follows:

$$P_{ijct} = Post_t + Region_j + \beta_1(IndepMedia_{jc} * Post_t) + \beta_2 X_{ijct} + \beta_3 Q_{jct} + \epsilon_{ijct} \tag{3.1}$$

where P_{ijt} represents the participation to protest of respondent i, in region j from country c surveyed in year t.[71]

There are two periods in this analysis: before and after the emergence of the Arab Spring, which we set to 17 December 2010, when *"Tunisian vendor Mohammed Bouazizi sets himself on fire to protest the arbitrary seizing of his vegetable stand by police over failure to obtain a permit"* (History.Com, 2020). We include a dummy variable, $Post_t$, which takes the value 0 (vs. 1) before (vs. after) the Arab Spring in our analysis. We also include region fixed effects, $Region_j$.

The main variable of interest, $IndepMedia_{jc} * Post_t$, interacts the regional share of respondents considering independent media networks (Al Jazeera or Al Arabiya) as their most reliable source of information with our dummy variable $Post_t$ if the respondent is interviewed after 17 December 2010.

Following the sampling design from the Arab Barometer, standard errors are clustered at the region-settlement level (Abadie et al., 2017).[72]

[71] In Section 3.5, we discuss some channels behind our results and look at some additional political accountability variables, which we construct in the same way as participation to protests and describe in Section 3.3.2.
[72] Settlement refers to whether the interviewed individual lives in an urban or rural place.

X_{ijct} includes a number of controls at the individual level such as age and its squared term, gender, the level of education, marital status, religion, employment and being a public worker or not. Non-reported results introduced these control variables progressively to avoid the risk of bad controls (Angrist & Pischke, 2009) but for sake of space we only report results with all controls.

Q_{jct} includes a number of controls at the regional level such as shares of internet users, shares of traditional media channels (TV and press) and climatic variables. These variables are average precipitation density, temperature, extreme precipitation and extreme temperature. We also include nightlight density to proxy for regional income.

Endogenous Adoption of Al Jazeera and Al Arabiya Networks. A major challenge is the endogenous nature of the decision of an individual i to view Al-Jazeera and/or Al Arabiya network, which could potentially bias our estimated coefficients in the OLS estimations. There are indeed two likely econometric problems: simultaneity/reverse causality and omitted variable bias. We can safely discard the reverse causality issue as our dependent variable is individual specific while our variable on media networks is regional specific. However, the omitted variable bias is likely to be a more serious issue in our analysis. Indeed, propensity to protest and the use of independent media networks are likely driven by unobservable individual characteristics, which we could summarize in "critical thinking" expression. A critical thinker is more likely to protest and follow independent media. In the present case, individuals, who are interested in hearing a contrasting opinion as opposed to an official - state-controlled- one are more likely to view Al-Jazeera or Al Arabiya media. Given there is no direct mean of measuring the individual propensity of critical thinking, it is an omitted variable in our regression, absorbed by the error term.

A first heuristic approach to address this issue consists in controlling for individual characteristics and examine whether the coefficients remains stable or at least, changes as expected. As explained above, we control for individual and regional characteristics, X_{ijct} and Q_{jct}. A second approach relies on an instrumental variable approach. To do so, we have had recourse to the so-called line-of-sight concept to measure the capacity to access to Al-Jazeera and/or Al Arabiya media networks through satellite.

According to the Arab Media Outlook (2012), satellite has consolidated its position as the dominant TV platform in the Arab world with only a few markets relying on cable TV, such as Bahrain, Kuwait, Lebanon, Qatar and the UAE. But even in these countries, cable TV has been witnessing a declining trend in terms of overall penetration in the early 2010s. In Lebanon, there are two significant television platforms: analogue terrestrial (14% of households) and free satellite (83% of households). More than 90% of Lebanese households have access to satellite television. Similar figures apply to Palestinian territories as well as Jordan.

The line-of-sight is detrimental to capture satellite television. Since satellite TV networks broadcast their programs through signals which are relayed from satellites orbiting around the earth, it results that the least amount of obstructions between an individual's antenna and the satellite, the better reception will be achieved.

Satellite TV transmission is therefore potentially affected by the topography of land (Yu & Qian, 2010). To capture the propensity to properly capture satellite signals, we rely on a measure of ruggedness, which we introduce in our estimation as a potential instrument. Earlier studies have also built on ruggedness measures in different contexts (see e. g. Nunn and Puga (2012) to measure protection from enrollment as slaves, Combes et al. (2010) to estimate employment). Ruggedness is a measure of the topographic relief, and combines altitude and slope. The fact that simple altitude thresholds have not been used permits to avoid excluding lower mountain systems, and overweight areas of relatively high elevation that have little topographic relief (further details are provided in the Section 3.3.2).

In our analysis, we consider ruggedness as a possible instrumental variable. We interact regional ruggedness, which is a time-invariant variable, with our time dummy $Post_t$.

The following equation correspond to the first-stage regressions, in which we predict independent media networks access (Al-Jazeera and Al Arabia) by regional ruggedness:

$$IndepMedia_{jc} * Post_t = Post_t + Region_j + \beta_1(Ruggedness_{jc} * Post_t) + \beta_2 X_{ijct} + \beta_3 Q_{jct} + \epsilon_{jct} \quad (3.2)$$

3.3.2 Data and Descriptive Statistics

This section describes the data used and provides some descriptive statistics in Table 3.3.1.[73]

Media Networks. The main variable of interest in this study is an individual's most reliable source of information and comes from Arab Barometer surveys, which are nonpartisan and reliable public opinion surveys that provide insight into the social, political, and economic attitudes and values of ordinary citizens in the Middle East and North Africa since 2006 (Arab Barometer, 2020). First, individuals are asked the following question:

I *Which of the following sources is most trustworthy with regard to local political news? (One answer only)*

Second, they are asked the following question:

II *Identify the source (One answer only)*
(The name of the television, radio station, the name of the newspaper, magazine, or website)

This second question gives the information on the name of the media that an individual trusts the most and is used as the main explanatory variable on political accountability in our analysis. One challenge is that the information from this question II is only available in wave 2 of the Arab Barometer, which took place in 2010-2011 and therefore the change in political accountability cannot be related to the change in media. However, the triggering factor of the Arab Spring could be exploited. Indeed, on 17 December 2010, a "Tunisian vendor Mohammed

[73] Variables are weighted using Arab Barometer surveys' *weight* variable to produce nationally representative results.

Bouazizi sets himself on fire to protest the arbitrary seizing of his vegetable stand by police over failure to obtain a permit" (History.Com, 2020). In this case, the data on media is used prior to that date. As Arab Barometer surveys consist of cross-sectional surveys, individuals are not followed over time therefore this measure cannot be built at the individual level but is built at the sub-national level (Database of Global Administrative Boundaries GADM 1, e. g. governate in Jordan), at which the data is representative.

The following countries are available since wave 2 of the Arab Barometer: Algeria, Egypt, Iraq, Jordan, Lebanon, Saudi Arabia, Sudan, Tunisia, Palestine and Yemen. Among them, only Jordan, Lebanon and Palestine conducted the survey before that data. Therefore the main analysis is built for these 3 countries and 34 regions.[74] Our sample consists of 7,751 observations, 31,472 individuals and two periods, which respectively correspond to waves 2 and 4 of Arab Barometer Surveys. Waves 2 and 4 respectively refer to the period 2010-2011 and 2016-2017.[75]

Aggregating answers from those who mentioned Al Jazeera or Al Arabiya as being their most reliable source of information, we construct a variable called *Independent Media Networks*, which is the main variable of interest in this paper. This variable measures the regional share of individuals stating independent media (Al Jazeera or Al Arabiya) as being their most trustworthy source of information. Results are reported in Section 3.4.1.[76] Using data from question II, we also construct a measure of state media network[77] and report results as part of a placebo analysis in Section 3.4.3.

Exploiting question I, we build two variables at the regional-level: regional share of individuals using internet as their main source of information and share of those using traditional media such as TV or press as their main source of information. Indeed, there is a large literature investigating the profiles and differences between traditional media users and internet users (Dimmick et al., 2004; Gaskins & Jerit, 2012; Johnson & Kaye, 2004; La Ferle et al., 2000; Yoon & Kim, 2001). We include these variables as part of our regional control variables in our analysis.

As can be seen from Table 3.3.1, on average, regional share of independent media users amount to roughly 4% (4.39%) while that of state media users amount to roughly 6%. As a reminder, the share of independent media networks is simply the sum of the share of Al Jazeera viewers (3.72%) and the share of Al Arabiya viewers (0.67%). Regional share of traditional media users is approximately 33% while share of internet users is roughly 7%.

[74] See Table 3.A.1 for more information on the full set of countries in the sample.

[75] We cannot work with wave 1 of Arab Barometer surveys as there is no data available on an individual's region. We also have to exclude wave 3, which refers to the period 2012-2014 as we need that our outcome variables about political accountability relate to a period after the Arab Spring. However, Arab Barometer surveys interview individuals on whether they participated to protests or attended meetings where they signed petitions during the last three years. Data in wave 3 may therefore relate to a period before the Arab Spring

[76] As a further analysis, we look at impact of 1) Al Jazeera versus Al Arabiya distinctively and 2) independent media through TV versus internet, which we build exploiting data from both questions I and II, on participation to protest in section 3.4.2.

[77] These are media that are under the control of a country's government both financially but also editorially (Webster, 1992).

Figure 3.3.1 shows the distribution of independent - Al Jazeera and Al Arabia - and state media. As can be seen, in Jordan, especially the North with the exception of Jerah region, state media is more prominent. In Amman and Madeba regions, however, independent media usage remains higher than the rest of the country. In Lebanon, except for Beirut where independent media usage is high, state media also seems to be largely used, especially in the Greater South. Finally, in Palestine, independent media seems to be used in more regions than the other two countries but also state media appears to be strongly viewed.

Political Accountability. Our main outcome variable relates to an individual's participation to protests, which we use as a proxy for political accountability in our main analysis. We obtain data from Arab Barometer surveys exploiting the following question:

I Participation to Protests: *Here is a set of activities that citizens usually take part in. During the past three years, did you ...? Participate in a protest, march or sit-in.?*

In Section 3.5, we offer a discussion around some plausible mechanisms behind our results exploiting additional questions from the Arab Barometer surveys, which we use as proxies for political accountability. These additional questions are the following:

II Governmental Trust: *I'm going to name a number of institutions. For each one, please tell me how much trust you have in them. 1. Government (Council of Ministers).*

III Political Alignment: *To what extent do you agree or disagree with the following statement: "Citizens must support the government's decisions even if they disagree with them"?*

IV Signing Petitions: *Here is a set of activities that citizens usually take part in. During the past three years, did you ...? Attend a meeting to discuss a subject or sign a petition.?*

V General Trust: *Generally speaking, do you think most people are trustworthy or not?*

For the 3 countries in our main analysis, data on political accountability is available across multiple years, e. g. waves 3 and 4 of the Arab Barometer.[78]

Table 3.3.1 shows that roughly 15% of individuals in our sample have mentioned that they participated to protests or signed petitions while more than 35% of them trust the government or are *politically aligned*.

Individual Characteristics. In our analysis, we control for the following individual socio-demographic characteristics, which we derive from the Arab Barometer surveys: gender, age and its squared term, education, employment, marital status and religion. In particular, these surveys allow us to identify whether the interviewed individual works for the public sector or not. We use this information and compare the impact of using independent media networks for public versus non-public workers and report our results in Section 3.4.3. Our sample is composed of slightly more women than men. In terms of education, our sample seems to be composed of an equal share of individuals with basic, secondary or tertiary education. Almost half of our sample is composed of employed individuals with around 8% of them working in

[78] More information on the availability of data on political accountability is presented in Table 3.A.1.

public sector. There are more married individuals and around 85% of individuals in our sample report being muslim.

Climate Data. Similar to Manacorda and Tesei (2020), in the absence of systematic data at the regional level for income, we rely on average nightlight density per administrative region. Indeed, the use of satellite data in order to proxy economic activity at fine units for which systematic data are not available, is nowadays a standard practice in economics (see e. g., J. V. Henderson et al. (2012) and V. Henderson et al. (2011)). To do so, we obtain data from National Oceanic and Atmospheric Administration (NOAA)'s National Centers for Environmental Information (NCEI). NOAA provides users with public access to geographical data and information NOAA (2021). We download "Average Visible, Stable Lights, and Cloud Free Coverages" from 2000 to 2013, at yearly intervals. For 12 of the 14 years of data, two satellites provide the data. In these cases, we take the average value of the two. Nightlight data is expressed in light intensity, bounded between 0 and 63: *"The files are cloud-free composites made using all the available archived DMSP-OLS smooth resolution data for calendar years.[. . .] The products are 30 arc second grids."* (NOAA, 2021).

As climatic factors likely impact an individual's likelihood of participating to protests (Klein Teeselink & Melios, 2021; Madestam et al., 2013; Zhang, 2016), we control for regional level precipitation density and temperature, which we also interact with extreme precipitation and temperature to account for non-linear effects in our analysis. We obtain data on climate from Centre for Environmental Data Analysis (CEDA), which runs the UK's national data center for atmospheric and earth observation research, hosting over 18 Petabytes of data (Harris et al., 2020). These data are *"month-by-month variations in climate over the period 1901-2019, provided on high-resolution (0.5x0.5 degree) grids, produced by the Climatic Research Unit at the University of East Anglia and funded by the UK National Centre for Atmospheric Science (NCAS)"* (Harris et al., 2020). In order to merge the monthly-level data on climate with the Arab Barometer surveys, we use the periods of data collection of the latter to construct average monthly cumulative rainfall or average temperature over the last 12 months, 24 months or 36 months. Indeed wave 2 does not contain a variable on dates of interview and this information in waves 3 and 4 is mainly missing. Arab Barometer surveys interview individuals on whether they participated to protests or attended meetings where they signed petitions during the last three years therefore we construct climatic variables by taking the average monthly cumulative rainfall or average temperature over the last 36 months. Precipitation density is then obtained by dividing the average monthly cumulative rainfall by the area. For the other proxies of political accountability, which are governmental trust, political alignment and general trust, we simply take variables over the last 12 months. In order to construct the extreme precipitation and temperature variables, we look at precipitation and temperature anomalies. We then create a dummy variable, which takes the value 11 if the anomalies is above one standard deviation (Pérez-Morga et al., 2013; Sardeshmukh et al., 2011).

As discussed in previous Section 3.3.1, our paper uses regional ruggedness as an instrument to predict our measure of independent media networks. Data for ruggedness comes from the United Nations Environment Programme World Conservation Monitoring Centre (UNEP-WCMC) and *"the mountains dataset shows the location of mountain land estimated from a digital elevation model using criteria based on elevation alone (the upper three classes: $\geq$ 2,500 meters) and at lower elevation, on a combination of elevation, slope and local elevation range" (Harris et al., 2021).*[79] To obtain ruggedness for each administrative region, we calculated the percentage of total area in each region, which is covered by mountains.

[79] Ranges are given by:

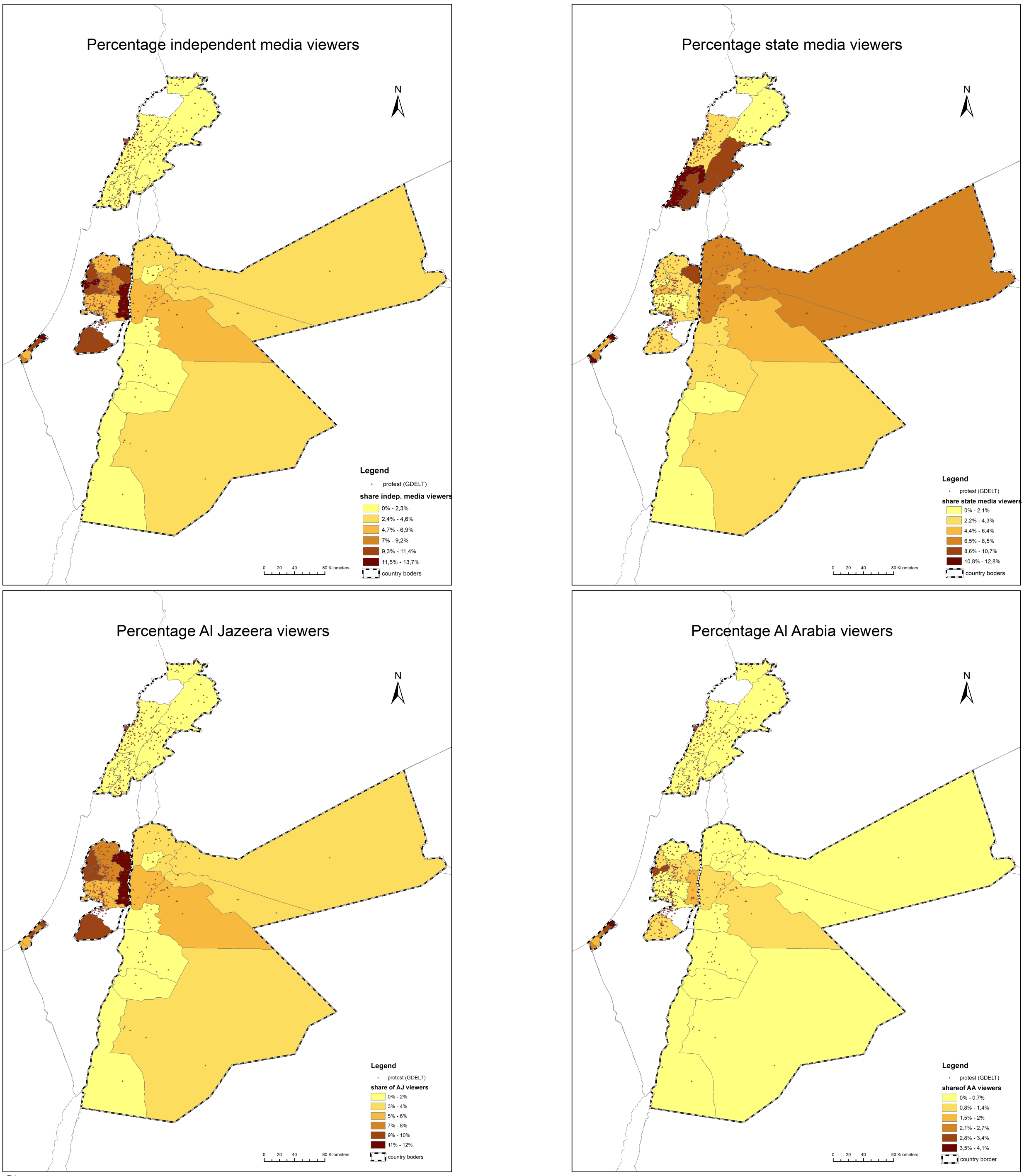
1. Elevation $\geq$ 4500 meters
2. Elevation $<$ 4500 & elevation $\geq$ 3500
3. Elevation $<$ 3500 & elevation $\geq$ 2500
4. Elevation $<$ 2500 & elevation $\geq$ 1500 & slope $>$ 2 degree
5. Elevation $<$ 1500 & elevation $\geq$ 1000 & slope $\geq$ 5 degree OR elevation $<$ 1500 & elevation $\geq$ 1000 & local (7 km radius) elevation range $>$ 300 meters
6. Elevation $<$ 1000 & elevation $\geq$ 300 & local (7 km radius) elevation range $>$ 300 meters
7. Inner isolated areas ($\leq$ 25 sq.km in size) that do not meet criteria but surrounded with mountains.

Table 3.3.1: Descriptive Statistics.

	(1) Mean	(2) Std. Dev.	(3) Min.	(4) Max.
			N=7,751	
Data on Media Networks.				
Independent Media Networks	0.0439	0.0385	0.0010	0.1374
Al Jazeera Media Network	0.0372	0.0316	0.0010	0.1033
Al Arabiya Media Network	0.0067	0.0089	0	0.0406
State Media Network	0.0597	0.0283	0.0017	0.1282
Internet Users	0.0667	0.0704	0	0.2836
Traditional media (TV and Press) Users	0.3308	0.3191	0	1.0719
Data on Political Accountability.				
Participation to Protests	0.1611	0.3677	0	1
Governmental Trust	0.3659	0.4817	0	1
Political Alignment	0.3760	0.4844	0	1
Signing Petitions	0.1556	0.3625	0	1
General Trust	0.1808	0.3848	0	1
Data on Individual Characteristics.				
Age	38.7018	14.1261	18	93
Gender: Female	0.5223	0.4995	0	1
Education: Basic	0.3496	0.4769	0	1
Education: Secondary	0.3089	0.4621	0	1
Education: Tertiary	0.2938	0.4555	0	1
Employment: Employed	0.4716	0.4992	0	1
Employment Sector: Public	0.0791	0.2699	0	1
Marital Status: Married	0.6837	0.4651	0	1
Religion: Islam	0.8414	0.3653	0	1
Religion: Christianity	0.1441	0.3512	0	1
Data on Climatic Variables.				
Nightlight Density	26.6330	13.3118	3.8796	63
Ruggedness	0.4705	0.3619	0	1
Log Precipitation Density	5.8074	1.8598	0.6156	10.2286
Log Temperature	2.8010	0.2189	2.3949	3.1091
Extreme Precipitation	0.5241	0.4995	0	1
Extreme Temperature	0.3043	0.4602	0	1

Notes: Variables are weighted using Arab Barometer surveys' *weight* variable to produce nationally representative results. Data on media networks in shares. Independent Media Networks: Sum of Al Jazeera and Al Arabiya networks. Nb. of countries: 3 (Jordan, Lebanon, Palestine). Nb. of regions: 34.

Figure 3.3.1: Protests and Regional Use of Media Networks in Jordan, Lebanon and Palestine.



Source:
Arab Barometer surveys for data on media networks.
The Global Database of Events, Language and Tone (GDELT) for data on protests.

3.4 Results

This section presents results from our analysis. First, our benchmark results are presented in Section 3.4.1. Second, we propose some additional results under Section 3.4.2. Finally, results from some robustness tests are included in Section 3.4.3.

3.4.1 Main Results

In Table 3.4.1, we first provide some linear probability model results using OLS to show any existing correlation between the share of independent media users and participation to protests. All columns in our analysis include time and region fixed effects.[80]

In Column (1), we include controls on all individual characteristics in addition to investigating the impact of independent media networks on participation to protests. From Column (2) onward, we include climatic variables, which are precipitation density, extreme precipitation, temperature and extreme temperature. In Column (3), we include share of internet and traditional (TV and press) users. Finally, in Column (4), we add nightlight density as a proxy for regional-level income. This last column correspond to our benchmark specification represented by Equation 3.1.

As can be seen from Table 3.4.1, the share of independent media networks users seems to be positively and significantly correlated with participation to protests. Being a female and having tertiary education also seem to be positively and significantly correlated with participation to protests. Regional nightlight density and temperature has a slightly positive correlation while the share of internet users, a negative one on participation to protests.

As described in Section 3.3.1, there is likely an omitted variable bias when investigating the impact of independent media networks on political accountability that is related to an individual's *ability to be critical about the information they receive and their likely willingness to use medias other than state media, such as independent medias*. In order to correct for this endogeneity, we predict the share of independent media users using an exogenous variable - regional ruggedness - and look at the impact of predicted independent media networks on political accountability.

Panel A of Table 3.4.2 reports our previous results with OLS for comparison reasons. In Panel B, we present our second-stage results, e. g. the impact of predicated share of independent media users on participation to protests using 2SLS. Finally Panel C includes first-stage results, e. .g. impact of regional ruggedness of independent media networks. As can be seen from Column (4) of Panel B, which corresponds to Equation 3.1, a 1% increase in the share of independent media increases the likelihood to participate to protests by roughly 1.6 percentage points (p.p). Expectedly, regional ruggedness has a significant and negative impact on the use of independent media networks.

[80] As a reminder, there are 34 regions in our analysis and 2 time periods - before and after the first protests in Tunisia on 17 December 2010. These two periods correspond to waves 2 and 4 of the Arab Barometer surveys.

Table 3.4.1: Main Analysis: Independent Media and Participation to Protests, OLS.

	(1)	(2)	(3)	(4)
	Participation to Protests			
Independent Media Networks	1.1300***	0.8012*	1.0033*	0.8405*
	(0.4259)	(0.4684)	(0.5248)	(0.4421)
Gender: Female	0.0628***	0.0624***	0.0622***	0.0625***
	(0.0142)	(0.0138)	(0.0138)	(0.0140)
Age	0.0029*	0.0027*	0.0028*	0.0028*
	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Age Sq.	-0.0000**	-0.0000**	-0.0000**	-0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Education: Basic	0.0114	0.0082	0.0079	0.0070
	(0.0183)	(0.0185)	(0.0187)	(0.0185)
Education: Secondary	0.0269	0.0232	0.0230	0.0218
	(0.0176)	(0.0177)	(0.0179)	(0.0174)
Education: Tertiary	0.0655***	0.0595***	0.0589***	0.0578***
	(0.0164)	(0.0161)	(0.0161)	(0.0158)
Religion: Islam	0.0258	0.0251	0.0277	0.0276
	(0.0497)	(0.0517)	(0.0511)	(0.0512)
Religion: Christianity	0.0331	0.0329	0.0378	0.0367
	(0.0282)	(0.0306)	(0.0302)	(0.0286)
Marital Status: Married	-0.0103	-0.0100	-0.0097	-0.0089
	(0.0111)	(0.0111)	(0.0110)	(0.0110)
Employment Status: Employed	0.0190	0.0191	0.0193	0.0196
	(0.0129)	(0.0126)	(0.0126)	(0.0126)
Employment Sector: Public	0.0245	0.0260	0.0272	0.0261
	(0.0231)	(0.0227)	(0.0229)	(0.0228)
Share of Internet Users			-0.9755*	-0.9719**
			(0.5455)	(0.4836)
Share of Traditional Media Users			0.2219	0.2146
			(0.1965)	(0.1769)
Nightlight Density				0.0157*
				(0.0087)
Precipitation Density		0.1752	0.1208	0.0343
		(0.2044)	(0.1460)	(0.1294)
Extreme Precipitation		-0.0139	-0.0066	0.0242
		(0.1150)	(0.0954)	(0.0841)
Temperature		0.8402	1.1134	1.5652**
		(0.5910)	(0.7861)	(0.7781)
Extreme Temperature		0.2398	0.0819	-0.9961
		(1.9413)	(2.1527)	(2.1375)
Pre. Density#Pre. Anomalies		0.0058	0.0065	0.0072
		(0.0144)	(0.0149)	(0.0120)
Tmp.#Tmp. Anomalies		-0.1657	-0.1651	0.1234
		(0.5673)	(0.5946)	(0.5878)
Observations	7,751	7,751	7,751	7,751
R-squared	0.1357	0.1403	0.1415	0.1425
Time and Region FE	Y	Y	Y	Y

Notes: Estimated Equation: Equation (3.1) using OLS, presented in Column (5). Independent Media Networks: Sum of Al Jazeera and Al Arabiya networks (%). Level of analysis: individual. Nb. of countries: 3. Nb. of regions: 34. Robust standard errors clustered at the region-settlement level in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

Table 3.4.2: Main Analysis: Independent Media and Participation to Protests, IV Approach.

	(1)	(2)	(3)	(4)
	Participation to Protests			
Panel A:	**Ordinary Least Squares (OLS)**			
Independent Media Networks	1.1300***	0.8012*	1.0033*	0.8405*
	(0.4259)	(0.4684)	(0.5248)	(0.4421)
R-squared	0.1357	0.1403	0.1415	0.1425
Panel B:	**Second-Stage: Two-Stage Least Squares (2SLS)**			
Independent Media Networks	0.8514	0.7527	2.2372**	1.6117**
	(0.8110)	(0.9822)	(0.8959)	(0.7183)
Kleibergen-Paap rk Wald F	19.41	39.50	56.64	63.27
Root MSE	0.330	0.329	0.329	0.328
R-squared	0.1355	0.1403	0.1403	0.1421
Panel C:	**First-Stage: Predicted Independent Media Networks**			
Regional Ruggedness	-0.0556***	-0.0514***	-0.0638***	-0.0669***
	(0.0126)	(0.0082)	(0.0085)	(0.0084)
R-squared	0.8007	0.9377	0.9420	0.9425
Observations	7,751	7,751	7,751	7,751
Time and Region FE	Y	Y	Y	Y
Individual Controls	Y	Y	Y	Y
Regional Controls	N	Y	Y	Y

Notes: Estimated Equation: Equation (3.1) using OLS in Panel A and 2SLS in Panel B. Estimated Equation: Equation (3.2) using Ruggedness as an IV. Independent Media Networks: Sum of Al Jazeera and Al Arabiya networks (%). Individual Controls: age, gender, education, religion, marital status, employment. Regional Controls: share of internet and traditional (TV and press) users, nightlight density, (extreme) precipitation and temperature. Level of analysis: individual. Nb. of countries: 3. Nb. of regions: 34. Robust standard errors clustered at the region-settlement level in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0:01$), ** at the 5 percent level ($p < 0:05$), and * at the 10 percent level ($p < 0:10$), all for two-sided hypothesis tests. FE: fixed effects.

3.4.2 Additional Results

Al Jazeera vs. Al Arabiya Networks. In this section, we look at the role Al Jazeera and Al Arabiya networks likely played on the participation to protests distinctively. Indeed, there are a number of studies offering a comparative analysis between these two leading Arab news websites[81] when it comes to their news coverage on conflict situations in the Arab World such as war, terrorism, socio-economic crisis etc. (Fahmy & Emad, 2011; Kharbach, 2020; Zeng & Tahat, 2012).

As can be seen from Panel A of Table 3.4.3[82], Al Jazeera network does not seem to correlate much to participation to protests while Al Arabiya seem to have a significant and robust

[81] Al Jazeera and Al Arabiya are first and second most visited news websites (Arab Media Outlook, 2012).
[82] Table 3.4.3 is constructed in the same way as Table 3.4.2.

correlation. Columns (4) and (8) of Panel B, corresponding to our Equation 3.1, however, show a positive and significant impact on participation to protests with Al Arabiya having a more significant effect, which is also higher in magnitude. A 1 % increase in the share of Al Jazeera users likely increase participation to protests by roughly 2 p.p. while a 1 % increase in the share of Al Arabiya users increases the likelihood of protests by almost 6 p.p. Although Al Jazeera is the first channel in the Arab World to offer a critical journalism and therefore much of the existing studies look at the impact of independent media in the Arab World focus on Al Jazeera network (El Oifi, 2019; Seib, 2011; Seib, 2005; Zayani, 2005), it seems, from our results, that Al Arabiya did play a role in participation to protests.

Panel C shows the estimates from predicting independent media usage using regional ruggedness. Results show that ruggedness has, in magnitude, a stronger negative impact on accessing Al Jazeera than Al Arabiya.

Independent Media Networks through TV vs. Internet. We now investigate whether there are differences among the individuals who use independent media networks through traditional channels, such as the TV, and those who access them through internet. A number of studies looked at the impact that social media, as opposed to traditional media, has played on the participation to protests (Enikolopov et al., 2020; Fergusson & Molina, 2020; Guriev et al., 2019; Manacorda & Tesei, 2020; Zhuravskaya et al., 2020). These studies distinguish the channel of information from the channel of collective action. In our paper, we cannot analyze the impact that social media has played on Arab Spring protests as such data is not available in Arab Barometer surveys. However, individuals in these surveys provide data on their most reliable channel of information, in addition to their source of information. We therefore propose to look at the usage of independent media through two main information channels: TV and internet. While TV is likely to capture an information channel, internet may, in addition to providing information, help connect masses and coordinate protests.

Our results are reported in Table 3.4.4.[83] Both our OLS estimates ifn Panel A and 2SLS estimates in Panel B show that the effect of using independent media through TV is much higher in magnitude than through internet. As can be seen from Columns (4) and (8) of Panel B, a 1 % increase in the use of independent media through TV increases the likelihood to take part in protests by 0.5 p.p. while for a 1 % increase in the use of independent media for those accessing them through internet increases the likelihood to take part in protests by 0.08 p.p..

Panel C further indicates that ruggedness has a greater impact of decreasing the access of independent media through internet than through TV as individuals in distant areas, where ruggedness is higher, may still have access to TV through cable while less access to internet through satellite.

[83] Table 3.4.4 is constructed in the same way as Table 3.4.2.

Table 3.4.3: Additional Results: Al Jazeera vs. Al Arabiya Media Network and Participation to Protests.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AL JAZEERA				**AL ARABIYA**			
	Participation to Protests							
Panel A:	**Ordinary Least Squares (OLS)**							
Independent Media Networks	1.1653**	0.8112	0.9384	0.7595	7.1006***	4.0720***	6.5390***	5.8036***
	(0.4990)	(0.5965)	(0.6374)	(0.5349)	(1.6068)	(1.4731)	(1.9800)	(1.7137)
R-squared	0.1348	0.1401	0.1412	0.1423	0.1382	0.1407	0.1426	0.1434
Panel B:	**Second-Stage: Two-Stage Least Squares (2SLS)**							
Independent Media Networks	1.0971	1.1051	3.0572**	2.1980**	3.8017	2.3606	7.3587**	6.0420**
	(1.0855)	(1.4475)	(1.2312)	(1.0025)	(3.1702)	(3.0754)	(3.7023)	(2.6306)
Kleibergen-Paap rk Wald F	15.20	24.33	44.22	50	25.77	70.52	50.58	46.64
Root MSE	0.330	0.329	0.329	0.329	0.329	0.329	0.328	0.328
R-squared	0.1348	0.1401	0.1388	0.1412	0.1370	0.1405	0.1425	0.1434
Panel C:	**First-Stage: Predicted Al Jazeera vs. Al Arabiya Media Networks**							
Regional Ruggedness	-0.0431***	-0.0350***	-0.0467***	-0.0490***	-0.0124***	-0.0164***	-0.0171***	-0.0178***
	(0.0111)	(0.0071)	(0.0070)	(0.0069)	(0.0025)	(0.0020)	(0.0024)	(0.0026)
R-squared	0.7943	0.9341	0.9385	0.9389	0.7632	0.9171	0.9235	0.9243
Observations	7,751	7,751	7,751	7,751	7,751	7,751	7,751	7,751
Time and Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Individual Controls	Y	Y	Y	Y	Y	Y	Y	Y
Regional Controls	N	Y	Y	Y	N	Y	Y	Y

Notes: Estimated Equation: Equation (3.1) using OLS in Panel A and 2SLS in Panel B. Estimated Equation: Equation (3.2) using Ruggedness as an IV. Independent Media Networks: Sum of Al Jazeera and Al Arabiya networks (%). Individual Controls: age, gender, education, religion, marital status, employment. Regional Controls: share of internet and traditional (TV and press) users, nightlight density, (extreme) precipitation and temperature. Level of analysis: individual. Nb. of countries: 3. Nb. of regions: 34. Robust standard errors clustered at the region-settlement level in parentheses. *** denotes statistical significance at the 1 percent level (p < 0:01), ** at the 5 percent level (p < 0:05), and * at the 10 percent level (p < 0:10), all for two-sided hypothesis tests. FE: fixed effects.

Table 3.4.4: Additional Results: Independent Media Networks through TV vs. Internet and Participation to Protests.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	TV				**INTERNET**			
	Participation to Protests							
Panel A:	**Ordinary Least Squares (OLS)**							
Independent Media Networks	0.2905**	0.4189**	0.4404***	0.3630**	0.0505***	0.0543**	0.0701**	0.0632**
	(0.1262)	(0.1588)	(0.1503)	(0.1419)	(0.0168)	(0.0241)	(0.0280)	(0.0264)
R-squared	0.1353	0.1413	0.1423	0.1430	0.1365	0.1423	0.1431	0.1439
Panel B:	**Second-Stage: Two-Stage Least Squares (2SLS)**							
Independent Media Networks	0.2410	0.3861	0.7020**	0.5499**	0.0511	0.0924	0.0781*	0.0788**
	(0.2409)	(0.4810)	(0.2941)	(0.2458)	(0.0514)	(0.0840)	(0.0490)	(0.0363)
Kleibergen-Paap rk Wald F	15.96	9.316	44.19	38.02	8.129	4.795	29.95	33.60
Root MSE	0.330	0.329	0.329	0.328	0.331	0.330	0.329	0.329
R-squared	0.1352	0.1413	0.1418	0.1427	0.1365	0.1417	0.1427	0.1439
Panel C:	**First-Stage: Predicted Independent Media Networks through TV vs. Internet.**							
Regional Ruggedness	-0.1964***	-0.1003***	-0.2033***	-0.1960***	-0.8827***	-0.5458**	-1.3069***	-1.3596***
	(0.0492)	(0.0329)	(0.0306)	(0.0318)	(0.3096)	(0.2493)	(0.2388)	(0.2345)
R-squared	0.8146	0.9400	0.9592	0.9594	0.7583	0.9138	0.9535	0.9538
Observations	7,751	7,751	7,751	7,691	7,691	7,691	7,691	7,691
Time and Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Individual Controls	Y	Y	Y	Y	Y	Y	Y	Y
Regional Controls	N	Y	Y	Y	N	Y	Y	Y

Notes: Estimated Equation: Equation (3.1) using OLS in Panel A and 2SLS in Panel B. Estimated Equation: Equation (3.2) using Ruggedness as an IV. Independent Media Networks: Sum of Al Jazeera and Al Arabiya networks (%). Individual Controls: age, gender, education, religion, marital status, employment. Regional Controls: share of internet and traditional (TV and press) users, nightlight density, (extreme) precipitation and temperature. Level of analysis: individual. Nb. of countries: 3. Nb. of regions: 34. Robust standard errors clustered at the region-settlement level in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

3.4.3 Robustness

In this section, we perform two robustness checks to investigate whether our results hold under some placebo analysis. First, we present our results looking at the role of the state. Second, we distinguish individuals working for the public sector from those who are working in non-public sectors.

State Media Network. So far, we have investigated the impact of independent media networks - Al Jazeera and Al Arabiya - on participation to protests and found a positive and significant of the former on the latter. As a placebo analysis, we are now looking at whether state media has an impact on protests.

Our results are reported in Table 3.4.5.[84] Panel A suggests a negative and significant correlation between state media and protests. Further investigation instrumenting state media by regional ruggedness show, however, that there is no causal link between state media networks and participation to protests (Panel B). These results are not surprising and are in line with numerous studies discussing the silent role that state media, both public and private, has played during the Arab Spring manifestations (Charrad & Reith, 2019; Duffy, 2014; Howard & Hussain, 2011; Ufuophu-Biri & Ojoboh, 2017).

In line with the discussion on ruggedness as an instrumental variable in our analysis under Section 3.3.1, ruggedness does not predict the access to state media (Panel C). Indeed, such media, as opposed to Al Jazeera or Al Arabiya, are usually available via cables therefore ruggedness may not impact the availability of state media.

Public vs. Non-Public Workers. We then look at public workers' protests behavior. In effect, workers in public sector may be reluctant to engage in political demonstrations for fear of losing their civil servant positions (Kerkvliet, 2011) or they may be less likely to take part in protests as they tend to perceive more benefits (better wages, improvement in their working conditions etc.) than their counterparts in non-public sectors and therefore are generally more satisfied with the incumbent government (Assaad & Krafft, 2013; Chan et al., 2014; El-Mallakh et al., 2018).

As can be seen from Table 3.4.6[85], independent media networks seem to have an insignificant impact on participation to protests for public workers. However, the positive and significant impact of independent media usage on protests remain robust for workers in non-public sectors.

[84] Table 3.4.5 is constructed in the same way as Table 3.4.2.
[85] Table 3.4.6 is constructed in the same way as Table 3.4.2.

Table 3.4.5: Robustness: State Media and Participation to Protests, Placebo Analysis.

	(1)	(2)	(3)	(4)
	Participation to Protests			
Panel A:	**Ordinary Least Squares (OLS)**			
State Media Network	-1.1252	-1.4761**	-1.4546**	-1.1644**
	(0.7856)	(0.6520)	(0.6483)	(0.5838)
R-squared	0.1342	0.1421	0.1427	0.1430
Panel B:	**Second-Stage: Two-Stage Least Squares (2SLS)**			
State Media Network	8.0422	2.2991	-16.0628	9.0082
	(15.3567)	(4.4124)	(28.5721)	(12.6313)
Kleibergen-Paap rk Wald F	0.317	1.620	0.271	0.680
Root MSE	0.351	0.331	0.364	0.342
R-squared	0.0195	0.1266	-0.0531	0.0682
Panel C:	**First-Stage: Predicted State Media Network**			
Regional Ruggedness	-0.0059	-0.0168	0.0089	-0.0120
	(0.0105)	(0.0132)	(0.0171)	(0.0145)
R-squared	0.8691	0.8975	0.9121	0.9312
Observations	7,751	7,751	7,751	7,751
Time and Region FE	Y	Y	Y	Y
Individual Controls	Y	Y	Y	Y
Regional Controls	N	Y	Y	Y

Notes: Estimated Equation: Equation (3.1) using OLS in Panel A and 2SLS in Panel B. Estimated Equation: Equation (3.2) using Ruggedness as an IV. State Media: All State-Controlled Media Network. Individual Controls: age, gender, education, religion, marital status, employment. Regional Controls: share of internet and traditional (TV and press) users, nightlight density, (extreme) precipitation and temperature. Level of analysis: individual. Nb. of countries: 3. Nb. of regions: 34. Robust standard errors clustered at the region-settlement level in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0{:}01$), ** at the 5 percent level ($p < 0{:}05$), and * at the 10 percent level ($p < 0{:}10$), all for two-sided hypothesis tests. FE: fixed effects.

Table 3.4.6: Robustness: Independent Media for Public vs. Non-Public Workers and Participation to Protests, Placebo Analysis.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PUBLIC WORKERS				**NON-PUBLIC WORKERS**			
	Participation to Protests							
Panel A:	**Ordinary Least Squares (OLS)**							
Independent Media Networks	0.9122	0.4304	-0.0576	-0.1048	1.1130***	0.8225*	1.1138**	0.9299**
	(1.1303)	(1.3691)	(1.4544)	(1.4431)	(0.4177)	(0.4745)	(0.5257)	(0.4308)
R-squared	0.3309	0.3387	0.3415	0.3419	0.1188	0.1230	0.1249	0.1261
Panel B:	**Second-Stage: Two-Stage Least Squares (2SLS)**							
Independent Media Networks	0.7467	1.6184	0.0555	-0.3737	0.7714	0.5535	2.4198***	1.7454**
	(1.7787)	(2.0819)	(2.0975)	(2.1341)	(0.7645)	(1.0309)	(0.9140)	(0.7435)
Kleibergen-Paap rk Wald F	27	30.38	38.20	51.61	18.42	40.97	57.19	62.18
Root MSE	0.336	0.335	0.334	0.334	0.327	0.326	0.326	0.326
R-squared	0.3309	0.3376	0.3415	0.3419	0.1185	0.1229	0.1236	0.1256
Panel C:	**First-Stage: Predicted Independent Media Networks for Public vs. Non-Public Workers**							
Regional Ruggedness	-0.0564***	-0.0550***	-0.0658***	-0.0702***	-0.0554***	-0.0515***	-0.0636***	-0.0666***
	(0.0109)	(0.0100)	(0.0106)	(0.0098)	(0.0129)	(0.0080)	(0.0084)	(0.0084)
R-squared	0.8536	0.9392	0.9415	0.9426	0.7965	0.9395	0.9438	0.9443
Observations	613	613	613	613	7,138	7,138	7,138	7,138
Time and Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Individual Controls	Y	Y	Y	Y	Y	Y	Y	Y
Regional Controls	N	Y	Y	Y	N	Y	Y	Y

Notes: Estimated Equation: Equation (3.1) using OLS in Panel A and 2SLS in Panel B. Estimated Equation: Equation (3.2) using Ruggedness as an IV. Independent Media Networks: Sum of Al Jazeera and Al Arabiya networks (%). Individual Controls: age, gender, education, religion, marital status, employment. Regional Controls: share of internet and traditional (TV and press) users, nightlight density, (extreme) precipitation and temperature. Level of analysis: individual. Nb. of countries: 3. Nb. of regions: 34. Robust standard errors clustered at the region-settlement level in parentheses. *** denotes statistical significance at the 1 percent level (p < 0:01), ** at the 5 percent level (p < 0:05), and * at the 10 percent level (p < 0:10), all for two-sided hypothesis tests. FE: fixed effects.

3.5 Discussion

In this section, we test some possible mechanisms behind our results.

Channels. Several theories argue that social media platforms increase the probability of political protests by facilitating collective action (Barbera & Jackson, 2017; Edmond, 2013; Enikolopov et al., 2020; Little, 2016; Manacorda & Tesei, 2020). On the one hand, they increase the spread of information that motivates protesters to take action, while on the other they facilitate coordination between them. In our study, we propose to look at a number of channels to test these mechanisms. We report our results in Table 3.5.1. Column (1) corresponds to our benchmark estimation in Column (5) of Tables 3.4.1 and 3.4.2. Columns (2) to (5) also correspond to our benchmark estimation where outcome variables respectively refer to governmental trust, political alignment, signing petitions and general trust.

The first mechanism relates to the provision of information and the increase in political accountability. Similar to Guriev et al. (2019), we investigate the effect of independent media networks on governmental trust as a proxy for governmental approval. As can be seen from Column (2) of Table 3.5.1, such a mechanism is rejected in our analysis. We find no significant effect of independent media networks on governmental trust.

A second mechanism relates to the ability of independent media to change the viewers' preferences through persuasion (DellaVigna & Gentzkow, 2009). We look at this effect exploiting the question on political alignment as a proxy for persuasion. Results from Column (3) in Panel A of Table 3.5.1 show a negative and significant impact of independent media on alignment suggesting that this could be a plausible channel. However, results in Panel B seem not to be robust to our instrumental variable approach presented in Panel B.

Finally, another channel is the possibility that independent media simply displaces other forms of engagement, including non violent ones. We investigate this mechanism using questions on signing petitions and general trust. As can be seen from Columns (4) and (5) of Table 3.5.1, such mechanisms seem to be rejected in our analysis, with the exception of a slightly positive impact of independent media on petitions using a 2SLS approach presented in Panel B.

Table 3.5.1: Discussion: Independent Media and Political Accountability, Channels.

	(1)	(2)	(3)	(4)	(5)
	Participation to Protests	Governmental Trust	Political Alignment	Signing Petitions	General Trust
Panel A:	**Ordinary Least Squares (OLS)**				
Independent Media Networks	0.8405*	0.7909	-1.6119**	0.5404	-0.0971
	(0.4421)	(0.6622)	(0.8042)	(0.4385)	(0.4105)
R-squared	0.1425	0.2250	0.1477	0.0957	0.0324
Panel B:	**Second-Stage: Two-Stage Least Squares (2SLS)**				
Independent Media Networks	1.6117**	-1.0509	-1.7005	1.8022**	0.2729
	(0.7183)	(1.4836)	(1.7300)	(0.7715)	(0.8466)
Kleibergen-Paap rk Wald F	63.27	63.27	63.27	63.27	63.27
Root MSE	0.328	0.427	0.452	0.335	0.378
R-squared	0.1421	0.2236	0.1477	0.0944	0.0323
Observations	7,751	7,751	7,751	7,751	7,751
Time and Region FE	Y	Y	Y	Y	Y
Individual Controls	Y	Y	Y	Y	Y
Regional Controls	N	Y	Y	Y	Y

Notes: Estimated Equation: Equation (3.1) using OLS in Panel A and 2SLS in Panel B. Independent Media Networks: Sum of Al Jazeera and Al Arabiya networks (%). Individual Controls: age, gender, education, religion, marital status, employment. Regional Controls: share of internet and traditional (TV and press) media users, nightlight density, (extreme) precipitation and temperature. Level of analysis: individual. Nb. of countries: 3. Nb. of regions: 34. Robust standard errors clustered at the region-settlement level in parentheses. *** denotes statistical significance at the 1 percent level ($p < 0:01$), ** at the 5 percent level ($p < 0:05$), and * at the 10 percent level ($p < 0:10$), all for two-sided hypothesis tests. FE: fixed effects.

3.6 Conclusion

In this paper, we look at the impact of independent media networks on individual participation to protests in the Arab World. Until late 90s, media in the Arab World was predominately state-controlled with little room for opponent views towards the incumbent governments. The emergence of first Al Jazeera in Qatar, leading independent media in the the Arab World, and later Al Arabiya in Saudi Arabia, second leading independent media, have shaped the environment of information in the region giving a voice to citizens displaying dissatisfaction towards their governments' political conduct. This constitutes a relevant context for our study.

With the Arab Spring uprisings, that started at the end of 2010, individual dissatisfactions were made public in many countries in the Arab World and while a large number of studies have so far focused on their reasons, the role of media has largely been overlooked. Especially, the existing literature looked at the potential influence that independent media such as Al Jazeera but also Al Arabiya had on shaping the views of citizens in this region. However, the impact of these media in the context of Arab Spring protests remain largely anecdotal. In our research, we seek to contribute to this gap in the literature by quantifying the impact that these two leading independent media networks - Al Jazeera and Al Arabiya - had on protests during the Arab Spring.

We use Arab Barometer surveys to obtain data on individual use of media, build a measure for independent media networks with Al Jazeera and Al Arabiya and we estimate the impact of their use on participation to protests. A challenge we are facing is that the decision of an individual to use independent media networks may be endogenous due to an unobservable individual characteristics, "critical thinking". To overcome this potential omitted variable bias, we use an instrumental variable approach and measure the capacity to access to Al-Jazeera and/or Al Arabiya media networks through satellite. Satellite TV transmission being potentially affected by the topography of land, we use ruggedness as a potential instrument. Our results indicate a positive and significant impact of independent media networks on participation to protests. We also find that 1) Al Arabiya in the context of our study has a higher impact on protests than Al Jazeera and 2) independent media networks through TV has a stronger impact on protests. We do not find any effect of state media or independent media use among public workers on protests.

A challenge in our study, related to the data from Arab Barometer surveys, is that our main explanatory variable on independent media is not available across time and that there is lack of consistent data for a number of countries. Other sources of data allowing to measure independent media use over time and for more countries would be welcome to evaluate the external validity of our results.

Appendix

3.A Supplementary Tables and Figures

Table 3.A.1: Summary Table for Data Availability on Media Networks and Political Accountability for Countries in MENA Region.

	(1)	(2)	(3)	(4)
Data		**The Arab Barometer**[I]		**Comments**
Period	Wave 2[II] 2010 – 2011	Wave 3 2012 – 2014	Wave 4 2016 – 2017	
Algeria	15 Apr – 11 May 2011	13 Mar – 6 Apr 2013	3 May – 16 May 2016	Data on media network available in wave 2 after 17 December 2010. Data on political accountability available in waves 2 – 4.
Egypt	16 Jun – 30 Jun 2011	31 Mar – 7 Apr 2013	15 Apr – 23 Apr 2016	Data on media network available in wave 2 after 17 December 2010. Data on protest and petition available in waves 3 – 4. Data on political alignment and institutional trust available in waves 2 – 4.
Iraq	20 Feb – 12 Mar 2011	6 Jun – 29 Jun 2013	–	Data on media network available in wave 2 after 17 December 2010. Data on political accountability available in waves 2 – 3.
Jordan	10 Dec – 16 Dec 2010	27 Dec 2012 – 6 Jan 2013	9 Mar – 16 Mar 2016	Data on media network available in wave 2 before 17 December 2010. Data on political accountability available in waves 2 – 4.
Lebanon[III]	24 Nov – 6 Dec 2010 9 Apr – 24 Apr 2011	3 Jul – 26 Jul 2013	20 Jul – 16 Aug 2016	Data on media network available in wave 2 before 17 December 2010. Data on political accountability available in waves 2 – 4.
Saudi Arabia[IV]	5 Jan – 6 Feb 2011 26 Mar to 9 Apr 2011	–	–	Data on media network available in wave 2 after 17 December 2010. Data on political accountability only available in wave 2.
Palestine	2 Dec – 5 Dec 2010	20 Dec – 29 Dec 2012	18 Feb – 27 Feb 2016	Data on media network available in wave 2 before 17 December 2010. Data on political accountability available in waves 2 – 4.
Sudan[V]	12 Dec – 30 Dec 2010 24 Mar – 23 Apr 2011	29 Apr – 29 May 2013 Round 5 (2012 – 2013)	– –	Data on media network available in wave 2 around 17 December 2010. Data on political accountability available in waves 2 – 3.
Tunisia	30 Sep – 11 Oct 2011	3 Feb – 25 Feb 2013	13 Feb – 3 Mar 2016	Data on media network available in wave 2 after 17 December 2010. Data on protest and petition available in waves 3 – 4. Data on political alignment and institutional trust available in waves 2 – 4.
Yemen	5 Jan – 6 Feb 2011 26 Mar – 9 Apr 2011	2 Nov – 4 Dec 2013	–	Data on media network available in wave 2 after 17 December 2010. Data on political accountability available in waves 2 – 3.

I Wave 1 of the Arab Barometer is excluded because there is no data on survey respondents' region.
II Only countries with data on survey respondents' most reliable media network are reported. This information is available in wave 2 of the Arab Barometer.
III Data from supplementary interviews in 2011 (wave 2) excluded as after 17 December 2010.
IV Saudi Arabia is excluded from the study as no data is available after wave 2 of the Arab Barometer.
V As data on survey respondents' most reliable media network is available slightly before and slightly after 17 December 2010, this country is included as a robustness check to the main analysis. Data from supplementary interviews in 2011 (wave 2) excluded as after 17 December 2010. Data on Political Accountability completed with data from round 5 of the Afrobarometer, which corresponds to 2012–2013. Data from rounds 6 and 7 of the Afro Barometer only give a subset of the initial regions and therefore are not used.

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