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**Abstract.** Our research report employs the D4R data and combines it to several other sources to study one of the multiple aspects of integration of refugees, namely the mobility of refugees across provinces in Turkey. In particular, we employ a standard gravity model to empirically estimate a series of determinants of refugee movements. These include the standard determinants such as province characteristics, distances across provinces, levels of income, network effects as well as some refugee-specific determinants such as the presence of refugee camps and the intensity of phone call interaction among refugees. Importantly, we explore the effect of certain categories of news events, notably protests, violence and asylum grants. Considering news as an indicator of policy implemented at the provincial level we gain a better understanding as to how policy can facilitate refugee mobility and thus enhance integration. To benchmark our findings, we estimate the same model for the mobility of individuals with a non-refugee status.

**Keywords:** Social Integration, Refugee Mobility, Gravity Model of Migration, Poisson Pseudo-Maximum Likelihood

**JEL-Classification:** J6, 015

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## 1 Introduction

Predicting human mobility in complex emergencies is essential for both operational and methodological reasons. For the former, understanding how displaced population make their mobility decisions may help relief operations to better target those in need of assistance. For the latter, researchers investigating the consequences of forced displacement on hosting areas have either assumed that forcibly displaced people have little agency, considering their location as quasi-random [Godøy, 2017; Grönqvist et al., 2012] or have overlooked the dynamic nature of such location decision. Anecdotal evidence suggests that for instance, refugees may move multiple times in their country of asylum [Bose, 2013; Bose, 2014].

In our study, we aim at better understanding the mobility of refugees within Turkey, which we consider as being a potential measure of social integration. Under the terms of the 1951 Refugee Convention, refugees are entitled to enjoy the freedom of movement. The determinants of refugee movements however are scarcely studied in the literature so far. To this end, we exploit spatially explicit 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 (50,000 refugees and 50,000 non-refugees) recorded by cell towers to define likely decisions to move between provinces. Reconstructing bilateral migration flows at the monthly and at the province level, we can then apply a gravity model to understand the main determinants of refugee movement across provinces – in contrast to the mobility of non-refugees in Turkey. Our empirical findings suggest that distance, levels of GDP, network effects and policy likely influence refugees' mobility decisions. In particular, we highlight the importance of policy-related events and changes on movements across the country.

To benchmark our results we use the same model to study the mobility of the non-refugee population in our sample of individuals. We find that while the standard gravity model determinants also matter for the non-refugee population mobility, the policy-related determinants have a differential effect in magnitude.

Comparing the two groups of individuals, the data suggests that the non-refugee population moves not only more frequently but also longer distances than the refugee population. In the light of the fact that refugees are mostly free to move within Turkey (in some provinces restrictions may be in place but they are not strictly implemented), we can thus infer that the imperfect integration of refugees in the society (economic, market and/or social integration) is the main reason for reduced mobility. As convergence of the mobility of the two groups is thus a desirable outcome and a good proxy of the level of integration, it is essential to study some of the drivers of refugee mobility in order to be able to develop policies that can further facilitate and encourage it.

Beyond the relevance of our study for relief operations, our contribution is threefold. First, we contribute to an emerging literature exploiting mobile phone data to characterize human mobility in emergency situations. To the best of our knowledge, existent studies have focused on mobility responses to natural disasters (e.g. Blumenstock et al., 2016) and predicting disease propagation (e.g. Wesolowski et al., 2012).[5] Our analysis relates bilateral migration flows among refugees (and non-refugees to benchmark our results) who live in provinces in Turkey to push and pull factors.

Second, the economic literature has a long tradition of exploiting the gravity model to model migration decisions (Ravenstein, 1985, 1989). Despite its simplicity, the gravity model has shown impressive predictive power, making it an essential input for forecasting exercises between and within countries (Crozet, 2004; Mayda, 2010; Garcia et al., 2015; Beine et al., 2016)]. However, to the best of our knowledge, none of these studies have applied the gravity model to refugee migration. Combined with highly disaggregated data, its simplicity and predictive power may make it an interesting tool for emergency operations.

Third, aggregating the individual data at the province level allows us to further enrich the mobile phone data with a number of additional resources. We have two types of additional data. First, we construct a series of socioeconomic characteristics of provinces (notably using satellite data) which we can easily combine with our proxies for integration. Second, we construct a number of indices related to the incidence of news that could directly or indirectly concern the refugee population. In particular we have indices for the following types of news: leadership change, boycotts, violent protests, economic aid, humanitarian aid and asylum grants. We can then use the gravity model to study whether the implementation of some policies or the incidence of events (as captured and disseminated by the news) can affect refugee and non-refugee mobility.

[5] This strand of the literature builds upon advancements over the last two decades on the use of new technologies such as remote sensing, geographical information systems, and global positioning systems to study mobility patterns in non-emergency contexts (Deville et al., 2014).

The policy implications of our research are direct as we can trace mobility reactions to particular policy measures and assign a positive or a negative sign to it. Our research agenda aspires to expand the measures of integration used and further study the reaction of integration measures to policy decisions as well as to the incidence of various events.

The structure of the report is the following. Section 2 describes the empirical strategy used in this report. Under section 3, sub-sections 3.1 and 3.2 respectively present the data used and some descriptive statistics to help understand better the sample of our study. Section 4 provides the empirical results for our main research question. Section 5 conducts some robustness tests on the estimation of mobility determinants from section 4. Section 6 provides the implications of our results for policy and derive some recommendations. Section 7 concludes. The corresponding tables and figures are presented in section 8 at the end of this present report.

## 2 Methodology

Our empirical strategy is based on the utility maximization approach, proposed by Roy (1951), and further extended by Grogger and Hanson (2011) and Beine et al. (2011). The model has been frequently applied to migration (Beine et al., 2016). It is based on agents' decision to migrate in order to maximize their well-being, and leads to the pseudo-gravity framework, which can be readily estimated. The model predicts that migration flows can be expressed as follows:[6]

$$M_{odt} = \frac{e^{ln(y_{dt})+s_{dt}-\phi_{odt}}}{\Sigma_k e^{ln(y_{kt})+s_{kt}-\phi_{okt}}} \tag{1}$$

where $M_{odt}$ is the expected migration flows between location $o$ and location $d$ at time $t$; $\phi_{odt}$ represents the accessibility of location $d$ for potential migrants (i.e. migration costs); $y_{dt}$ represents the attractiveness of location $d$ in terms of utility (e.g. expected wage, ...); $s_{dt}$, the ability of location $o$ to send migrants (e.g. public expenditures, ...); and $k$ stands for all locations, other than $o$, i.e. potential destinations. The parameters of the model can then be estimated after a logarithmic transformation. In our application, we are estimating these parameters over a relatively short time-frame, spanning January to December 2017. We can derive the following specification:

$$ln(M_{odt}) = \beta' ln\frac{y_{dt}}{y_{ot}} + \gamma' s_{dt} - \delta' s_{ot} - \epsilon\phi_{odt} + \varepsilon_{odt}. \tag{2}$$

where $\varepsilon_{odt} = \phi_o + \psi_d + \pi_t + \varepsilon_{odt}$ can measure origin, destination and time fixed effects, and an independent and identically distributed (iid) error term. $M_{odt}$ represents the bilateral mobility flow of refugees between provinces $o$ and $d$ at month $t$. $\phi_(odt)$ will take account of the cost of moving to $d$ for potential candidates to mobility in province $o$. $y_{dt}$ and $y_{ot}$ capture both pull and push factors in provinces $d$ resp. $o$, proxied by province level income. Month fixed effects are introduced to correct for seasonality in migration patterns.

Finally, given the large number of zeros in the bilateral migration flows, relying on standard estimation techniques (e.g. OLS) would likely lead to inconsistent coefficient estimates. As widely adopted in the literature (Beine et al., 2011), we call upon Poisson regression models that relies on pseudo maximum likelihood estimates (Santos Silva and Tenreyro, 2006; Santos Silva and Tenreyro, 2011).

[6] Beine et al. (2016) detailed the derivation of the random utility maximization model of migration providing micro-foundations to the empirical specification of the gravity model.

## 3 Data and descriptive statistics

We first describe our data in sub-section 3.1. Second, we provide some descriptive statistics in sub-section 3.2 that will help visualize and therefore better explore our sample.

### 3.1 The Data

In the above specification, the construction of our dependent variable is of key importance. In order to make the most of the D4R dataset, we aggregate our data at the province level. This allows us not only to use any of the three available datasets at this level, but also to combine it with any other data that can be collected or constructed at the same level. In the current project, we proxy integration with a measure of mobility. This is measured by a migration rate, which is of the form *Migration Rate_'r'_'i'* where *'r'* refers to the refugee (i.e. $R$) or non-refugee (i.e. $NR$) 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 ou case, we set *'i'*=10).[7] It is worthwhile noticing that we have restricted our analysis only to calls occurring during weekends, thereby increasing the likelihood to focus on location of residence rather than workplace.

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 district $d$ (resp. $o$) for prospective refugees, the so-called pull (resp. push) factors.

In the absence of systematic data at the province-monthly income level for Turkish provinces we proxy for the economic attractiveness using night-light density at province and month level. We obtain data on province-level night-lights in Turkey 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. 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., Henderson et al. (2011, 2012)).

Networks at the destination province also play a key role in reducing migration and assimilation costs (Beine et al., 2011). Networks are an essential pull factor as they are likely to provide information or financial support to newcomers [Munshi, 2003; Beaman, 2012]. In the absence of official measures for refugee networks at the province-monthly level, we proxy for such existing networks, using the number of calls from refugees. We construct this variable by using the dataset 1 provided by Salah et al. (2018) where we compute the total number of calls from refugees per province.

Proximity between pairs of provinces is measured using geodesic distances. It captures practical difficulties of moving across provinces. Last, we construct a binary variable indicating the presence or the absence of a refugee camp.

The second set of variables that we construct is aimed to capture policy related issues. Our source dataset is the Global Database of Events, Language and Tone (hereinafter referred as to "GDELT"). GDELT captures world-wide news media over 30 years, in over 100 languages and is updated daily. The provided database consists of over a quarter billion georeferenced event records in over 300 categories. The platform is open for research and analysis. It provides news for a large number of events.

The variables we have relied upon are as follows: rally for leadership change; boycotts; violent protest; economic aid; humanitarian aid and asylum grants. In GDELT, an event is given an id *GlobalEventID* and there exists a variable *EventBaseCode* which shows to which category this

[7] Under section 5, we construct a stricter mobility measure, i.e., we replicate our analysis with a frequency filter of 20 calls.

particular event belonged to. CAMEO (Conflict and Mediation Event Observations) event codes are defined in a three-level taxonomy. This enables us to aggregate events at various resolutions of specificity. In our study we also aggregate the data at the province level that allows us to merge it with the existing dataset.

The aid variables indicate news that either humanitarian and/or economic aid is provided in province $d$ (resp. $o$) at month $m$. Aid is crucial as it eliminates or at least partially alleviates financial concerns. Political factors have also been found to matter in other contexts. Researchers from various disciplines have been interested in measuring the impact of national policies on asylum seekers' health (Steele et al., 2002; Mills, 2012; Ziersch et al., 2017). A study from Greyling (2016) finds that government assistance, culture, economic factors, crime, refugee status, reasons for leaving the home countries, time spent and number of people staying in a house in the host country are all policies that affect asylum seekers in South Africa. We therefore augment the specification with variables capturing political factors such as boycotts, rally for leadership change and protest against the local authorities. Last, 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.

### 3.2 Descriptive Statistics

Our sample is composed of 64,800 bilateral observations for which we have information about all variables in our baseline specification (See Table 1).[8]

According to our mobility measure, bilateral movements of refugees between provinces is limited, and amounts to 0.1%, i.e. on average, one refugee out of 1000 changes province from one month to another.

As we have already mentioned, we use the level of night-light density to infer income in different provinces (see Figure 1 for a Map in August 2017). Based on our study sample, every province in Turkey is shown to have at least one district for which the night-light density is the highest. ($\approx 49.80$). This generally corresponds to the city center of the provincial capital. Almost half of the provinces in Turkey have at least one district with a night-light density level of 0. The mean night-lights density equals $\approx 1.82$, and its distribution is skewed to the right.

The shortest distance corresponds to the distance between the provinces *Gaziantep* and *Kilis* while the longest distance is between *Hakkari* and *Edirne*. The mean distance is $\approx$ 574km and approximately corresponds to the distance between *Mus* and *Yozgat*.

The total number of calls in our sample is almost 10 times higher than the number of refugee calls.[9] *Istanbul* is the province with the largest amount of calls, while *Bayburt* receives the lowest amount of calls.

In October 2017, *Ankara* was the province in which most events related to economic and humanitarian aid took place and also in which most events related to violent protests occurred in May 2017. Events related to asylum grants also concerned mainly *Ankara* during the same month, whereas most events related to rallies for leadership change took place in *Istanbul* in April 2017.

There are 10 provinces in which refugee camps are present. These provinces are *Adana*, *Adiyaman*, *Gaziantep*, *Hatay*, *Kahramanmaras*, *Kilis*, *Malatya*, *Mardin*, *Osmaniye* and *Sanliurfa*.

[8] The number of observations results from pairing each province with another province, given the bilateral nature of mobility. We do so for every month of the year 2017. We miss information on night-light for the month of June.

[9] It is worthwhile keeping in mind that the number of calls is based on the universe of calls from dataset 1 from Salah et al. (2018), whereas our mobility variable is computed using the sample provided from the third dataset.

Finally, tables 2 and 3 offer a comparison between the mobility of refugees and non-refugees in our sample based on the frequency of their moves and the distance they traveled. Interestingly, according to our mobility measure, non-refugees move more often and further than refugees. Approximately 94% of refugees did not move with $\approx$ 4% of them moving once and $\approx$ 2% twice. While also a large amount ($\approx$ 87%) of non-refugees in our sample did not move, the remaining $\approx$ 12% moved at least once. Table 3 shows that while non-refugees traveled $\approx$ 112 km on average, non-refugees only traveled $\approx$ 37 km. Among the sub-sample of non-refugees who moved, $\approx$ 840 km were traveled in comparison with $\approx$ 615 km for refugees. This result implies that while most refugees did not move, those who did, according to our mobility measure, did travel quite a long distance.

## 4 Empirical Findings

This section presents our main empirical results.

Columns (1) to (6) of Table 4 explore the determinants of refugee movements. Each column corresponds to a new specification with the addition of events which respectively relate to rallies for leadership change, boycotts, violent protests, economic aid, humanitarian aid and asylum grants. Each event is considered both at the origin and destination provinces. All columns include a month fixed effect, a dummy variable for the presence of refugee camps at both the origin and destination districts. All these regressions also include level of night-lights at origin and destination, distance, number of calls and number of refugee calls (at origin and destination) as explanatory variables. Following the underlying pseudo-gravity model in a double log form, we use a logarithmic transform of these variables. We report robust standard errors to ensure the accuracy of inference.

As shown from the coefficients of night-lights at origin in columns (1) to (6), (low) income acts as a push factor for refugees in all specifications (even though it is marginally insignificant at standard levels in two cases). This result is quite standard in the migration literature, where people tend to leave low income places, to join higher income destinations.[10] However, in the present case, we are unable to highlight this latter feature, i.e. even though refugees seem to leave above all low income provinces, our results do not systematically indicate that higher income regions are preferred destinations. Put differently, refugees might not be able to reach wealthier regions although they tend to leave poorer ones, which deviates from the standard pull factor story, where higher incomes are usually considered as an important motivation for the choice of destination by migrants.

Proximity between provinces has an expected negative impact on movements and is significant at the 1% confidence level. This is a standard result in the literature on population movement. Also number of calls has an expected positive impact on mobility, which is again significant at the 1% confidence level. However a very interesting result emerges here; the number of refugee calls positively influences mobility with a significance of 5% (even 1% in specification column (2)). This result is in accordance with the literature around migration networks; migrants tend to move to regions where other migrants have already settled.

The second half of the explanatory variables in Table 4 focus on event data, as described in 3.1. As observed from Column (1), refugees tend to leave provinces with an ongoing rally for leadership change. Perhaps this captures political instability and a pre-election rhetoric that might be directed against the presence of refugees. Interestingly though it does not act as a pull factor. Column (2) illustrates that higher incidence of boycotts is associated with lower

[10] it is also reassuring as to the fact that light density is a good proxy for income per capita at the province level.

mobility. Provinces with higher number of boycott-related news could be more active on the political and humanitarian front and this may encourage immigrants to settle. As in Column (1), higher incidence of boycotts at the destination though does not attract immigrants. Violent protest news (Column 3) also do not confer any statistically significant effect on refugee mobility. Column (4) shows that refugees tend to move to provinces with more economic aid and leave as economic aid decreases. Humanitarian aid (Column 5) does not have any effect on the decision to move. Last, Column (6) shows that grants of asylum generate mobility towards these regions and results are significant at the 5% level.

Finally, the presence of a refugee camp in the origin or destination province does not attract or distract refugees from these places.

## 5 Robustness

This section presents results from the robustness tests we have conducted. Table 5 is subdivided in two panels, displaying only the results of our main variables of interest while Table 6 displays the results for all variables of the baseline specification in which dependent variable becomes the mobility of non-refugees.[11]

In Table 5 and under panel 1, we test for the robustness of the frequency filter that has been adopted to include observations in our dependent variable. In particular, we take districts for which at least 20 calls have been reported as opposed to 10 calls in our main specification. Although the significance of our results is overall reduced, interpretations remain qualitatively the same; in particular (i) rallies for leadership change at the origin are no longer significant, however the coefficient becomes significant for rallies at the destination; (ii) results on protest variables are mixed. In this specification they matter when they take place at the destination; (iii) economic aid at origin reduces the number of leavers, whereas it increases the number of new comers at destination; (iv) the same is true for (destination) provinces where more asylum has been granted.

Panel 2 of Table 5 reports results when adding origin and destination fixed effects. This allows us to take account of time invariant determinants specific to departure resp. arrival provinces, such as geographic feature, climatic factors, but also political institutions and demographic factors which can be hypothesized to be stable across our period of observation (i.e. January to December 2017). Results of these regressions do not deviate substantially from previous outcomes, i.e.rallies for leadership and boycotts, economic aid and asylum grants (and the absence thereof) remain important factors for refugees' decision to move and where to go.

In Table 6, we rely on the same specification as in Table 4, but change the sample, from refugees to non-refugees. The purpose of this is to serve as a counter-factual, i.e. do determinants of mobility of refugees differ from the rest of the population? Furthermore, mobility of refugees and the determinants thereof, is part of a component of social integration, and should therefore be compared to the reference group of non-refugees. We find that low income at origin plays a strong repulsive role for non-refugees, which is similar to our results on refugees, but the magnitude is stronger here. As expected, distance is negatively linked to migration. The refugee network (measured as the number of refugee calls) turns out to be insignificant, which is reassuring in terms of relevance of our measures. Also of noteworthinesses is the strong repellent effect that the presence of refugee camp at the province level have on potential non-refugees. Interestingly, the coefficients on event variables provide analogous results compared to Table 4, as to the direction of the coefficients. The same type of policy/events has the same (qualitatively) impact on the decision to move. However what changes is the magnitude of the effect which is systematically

[11] Complete result tables are available from the authors of this report upon request.

higher for non-refugees. This formalizes the summary statistics that indicate that refugee mobility is more constraint compared to non-refugee mobility.

## 6 Policy Implications and Recommendations

Our report attempts a preliminary exploration of one dimension of integration, namely mobility of refugees within Turkish provinces. Applying standard econometric techniques on novel data compiled from several sources we can summarize our findings, for the sake of policy making, as follows: (i) Non-refugees move further and more frequently compared to refugees. Thus any policy measures should be directed to convergence of refugee and non-refugee movement. (ii) The standard determinants of mobility for immigrants also apply for refugees, i.e., income of the origin/source province, distance between provinces and network effects.

However access to rich provinces is potentially restricted for refugees. However, as a matter of fact, the very presence of refugees can become an engine of growth for the poor provinces. Besides, access to all provinces should be targeted as a policy measure, in order to assure equal mobility opportunities for everyone. (iii) Ensuring political stability in a province is an essential attracting factor for refugee population. (iv) Economic aid also facilitates the mobility of refugees and eliminates some of the mobility constraints. Economic aid can also attract refugees to particular provinces, thus it is an effective means of intervening in refugee mobility. (v) Asylum grants also matter a lot when it comes to mobility.

Last, but not least what our data hints to is that not only the implementation of particular policies affects the mobility of refugee population but also the proper dissemination of news may as well act as an incentive to this direction.

## 7 Concluding Remarks

This report is an attempt to provide an empirical estimation of the determinants of one measure of integration, i.e., for refugee movements in Turkey using phone data. We apply the standard gravity model to a novel dataset on phone calls conducted by refugees and we combine the data to several other datasets at the province level. We find that the standard gravity determinants apply, such as distance, origin and source income as well as networks. Furthermore, policy interventions that are facilitated with political stability, asylum granting and economic aid also matter thus suggesting that there is ample room for policy making.

We benchmark our analysis with a non-refugee sample to illustrate that any policy should be targeted to the convergence between refugee and non-refugee movement (non-refugees move further and more frequently). The same determinants apply in both samples, however the impact of each of these determinants is stronger for non-refugees. Thus any policy should be targeting at mitigating any factor that cause such differences.

## 8 Appendix

The following pages present tables and figures, which we refer to in the main text.

**Table 1:** Definitions and summary statistics of the variables from baseline specification

| | **Definition** | **Obs.** | **Mean** | **Std.** | **Min.** | **Max.** |
|---|---|---|---|---|---|---|
| **Dependent Variable** | | | | | | |
| Mobility of Refugees | This measure has been built by generating an index *migr_rate_'R'_'10'_'WE'_'In'* from dataset 3[a] where *'R'* indicates calls from refugees, *'10'* corresponds to the frequency filter, e.g. the minimum number of calls generated from a given district to characterize the latter as a destination, *'WE'* includes weekend calls and finally, *'In'* stands for ingoing calls. | 64,800 | 0.001 | 0.02 | 0 | 1 |
| **Explanatory Variables** | | | | | | |
| Night-Lights | Monthly cloud free composites (excludes data impacted by stray light, lightning, lunar illumination, and cloud-cover) in geotiff format and collected across the globe at 750-meter resolution. | 64,800 | 1.82 | 4.57 | 0 | 49.80 |
| Distance[b] | This variable measures the geodesic distances, i.e. the length of the shortest curve between two points along the surface of a mathematical model of the earth, based on the coordinates of the centroids of each province. | 64,800 | 574 | 322.62 | 38.71 | 1,559.53 |
| Number of Calls | Constructed with dataset 1[c] where the total number of calls per antennae is obtained. Relying on GIS software, we link these antennae coordinates to turkish provinces. | 64,800 | 416,922.8 | 1,654,334 | 2,585 | 2,13e+07 |
| Number of Refugee Calls | Constructed with dataset 1[d] where the number of refugee calls per antennae is obtained. Coordinates of the districts in which these antennae are obtained using GIS software. These districts are then linked to their respective provinces. | 64,800 | 50,105.81 | 199,618.8 | 0 | 2,653,137 |
| **Events[e]:** | | | | | | |
| Rally for Leadership Change | Dissent collectively, gather, or rally demanding leadership change | 64,800 | 0.02 | 0.39 | 0 | 11 |
| Boycotts | Refuse to work or cooperate until demands for political, social, economic, or other rights are met | 64,800 | 0.16 | 1.03 | 0 | 13 |
| Violent Protests | Protest forcefully, in a potentially destructive manner | 64,800 | 0.28 | 1.86 | 0 | 27 |
| Economic Aid | Extend, provide monetary aid and financial guarantees, grants, gifts and credit | 64,800 | 1.16 | 5.30 | 0 | 60 |
| Humanitarian Aid | Extend, provide humanitarian aid, mainly in the form of emergency assistance | 64,800 | 0.76 | 3.59 | 0 | 42 |
| Asylum Grants | Provide, grant asylum to persons | 64,800 | 0.37 | 1.94 | 0 | 27 |
| Presence of Refugee Camps[f] | Binary variable indicating the presence or the absence of a refugee camp in a province. | 64,800 | 0.12 | 0.33 | 0 | 1 |

[a] See Salah et al. (2018)
[b] The centroid coordinates are based on the WGS 1984 datum and we rely on Vincenty (1975) equations to calculate distances.
[c] See Salah et al. (2018)
[d] See Salah et al. (2018)
[e] See Gerner et al. (2002).
[f] Data retrieved from https://data.humdata.org/dataset/syria-refugee-sites

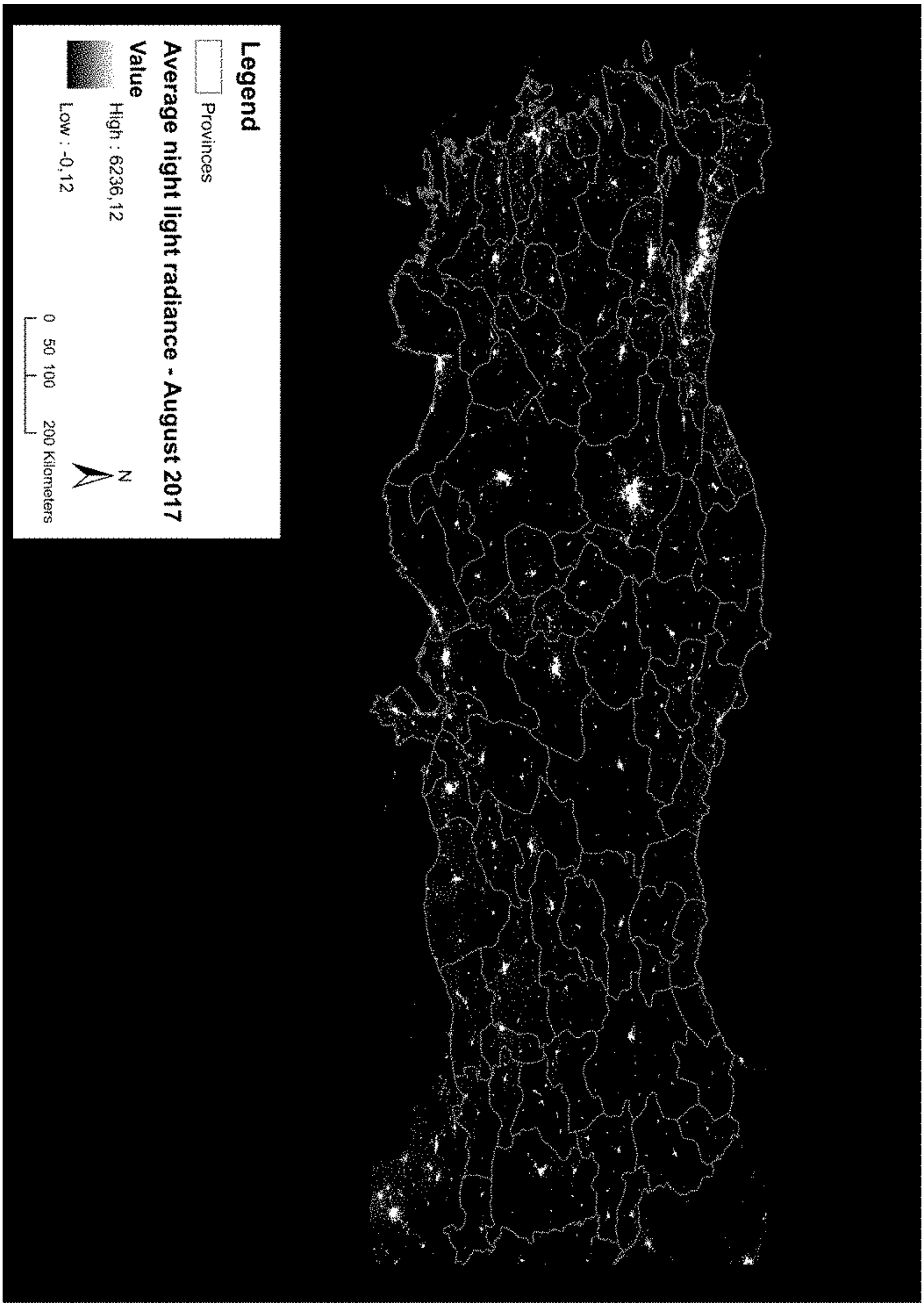


**Fig. 1:** Night-Lights in Turkey (August 2017; province borders)

**Table 2:** Mobility of Refugees and Non-Refugees: Frequency of their moves

| | **Refugee Mobility with a Frequency Filter of 10 calls** | | **Non-Refugee Mobility with a Frequency Filter of 10 calls** | |
|---|---|---|---|---|
| | Number of Refugees | Percent | Number of Non-Refugees | Percent |
| **Moves**: | | | | |
| 0 | 17,797 | 93.93 | 13,766 | 86.65 |
| 1 | 796 | 4.2 | 872 | 5.49 |
| 2 | 294 | 1.55 | 950 | 5.98 |
| 3 | 42 | 0.22 | 176 | 1.11 |
| 4 | 14 | 0.07 | 96 | 0.6 |
| 5 | 4 | 0.02 | 18 | 0.11 |
| 6 | 0 | 0 | 5 | 0.03 |
| 7 | 0 | 0 | 4 | 0.03 |

**Notes**: (i) The variables *Refugee Mobility with a Frequency Filter of 10 calls* and *Non-Refugee Mobility with a Frequency Filter of 10 calls* are of the form *Migration Rate_'r'_'i'* where *'r'* refers to the refugee (i.e. *R*) and non-refugee (i.e. *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 10 calls); (ii) While in our analysis the observations are provided for each pair of districts, here we provide descriptive statistics at the individual level.

**Table 3:** Mobility of Refugees and Non-Refugees: Distance Traveled

| | **Distance Traveled** | |
|---|---|---|
| | Refugees | Non-Refugees |
| Average Distance (km) | 37.3 | 112.1 |
| Average Distance for Movers (km) | 614.9 | 839.7 |

**Table 4:** Determinants of Refugee Movements in Turkey

| | **Dep. Var:** Mobility of Refugees | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Events:** | Rallies for Leadership Change | Boycotts | Violent Protests | Economic Aid | Humanitarian Aid | Asylum Grants |
| Log Night-Lights at Origin | -0.231* | -0.161 | -0.288** | -0.213 | -0.234* | -0.212* |
| | (0.125) | (0.137) | (0.122) | (0.132) | (0.126) | (0.126) |
| Log Night-Lights at Destination | -0.0727 | -0.0822 | -0.0985 | -0.0947 | -0.0843 | -0.0954 |
| | (0.0842) | (0.0868) | (0.0887) | (0.0907) | (0.0870) | (0.0878) |
| Log Distance | -0.950*** | -0.932*** | -0.951*** | -0.943*** | -0.945*** | -0.938*** |
| | (0.112) | (0.114) | (0.113) | (0.114) | (0.113) | (0.113) |
| Log Number of Calls | 0.329** | 0.316** | 0.329** | 0.330** | 0.329** | 0.338** |
| | (0.141) | (0.146) | (0.142) | (0.144) | (0.143) | (0.145) |
| Log Number of Refugee Calls | 0.429*** | 0.356** | 0.419*** | 0.398** | 0.401** | 0.367** |
| | (0.153) | (0.155) | (0.154) | (0.156) | (0.158) | (0.155) |
| Events at Origin | 0.146** | -0.0759*** | -0.0315 | -0.0238*** | -0.0162 | -0.0367** |
| | (0.0710) | (0.0281) | (0.0194) | (0.00744) | (0.0133) | (0.0153) |
| Events at Destination | 0.0570 | -0.0381 | 0.0174 | 0.0169*** | 0.0132 | 0.0347** |
| | (0.0710) | (0.0322) | (0.0185) | (0.00639) | (0.0106) | (0.0146) |
| Refugee Camps at Origin | -0.359 | -0.347 | -0.344 | -0.351 | -0.353 | -0.344 |
| | (0.219) | (0.218) | (0.219) | (0.218) | (0.219) | (0.218) |
| Refugee Camps at Destination | -0.372* | -0.145 | -0.333* | -0.272 | -0.290 | -0.215 |
| | (0.198) | (0.219) | (0.197) | (0.208) | (0.211) | (0.208) |
| Constant | -9.965*** | -9.427*** | -9.845*** | -9.872*** | -9.796*** | -9.610*** |
| | (1.105) | (1.140) | (1.116) | (1.128) | (1.131) | (1.130) |
| Observations | 64,800 | 64,800 | 64,800 | 64,800 | 64,800 | 64,800 |
| R-squared | 0.043 | 0.044 | 0.043 | 0.042 | 0.043 | 0.044 |

**Summary**: This table presents the estimates from our baseline specification (See Section 2) and establishes some determinants of refugee movements within Turkey. Our analysis controls for month fixed effects and includes dummy variables to control for the presence of *refugee camps at the origin* and *refugee camps at destination.* Columns (1) to (6) show the coefficients or our empirical specification 2. Each column corresponds to a new specification with the addition of events which respectively relate to rallies for leadership change, boycotts, violent protests, economic aid, humanitarian aid and asylum grants. Each event is considered both at the origin and destination districts.

**Notes**: (i) Our dependent variable is measured by a migration rate, which is of the form *Migration Rate*_'*r*'_'*i*' where '*r*' refers to the refugee (resp. non-refugee) 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 10 calls); (ii) Robust standard errors are reported in parentheses; (iii) *** 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.

**Table 5:** Results from Robustness Tests for the Mobility of Refugees

| | **Dep. Var:** Mobility of Refugees | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Events:** | Rallies for Leadership Change | Boycotts | Violent Protests | Economic Aid | Humanitarian Aid | Asylum Grants |
| Panel 1 | **Mobility of Refugees with a frequency filter of 20 calls** | | | | | |
| Events at Origin | 0.0650 | -0.0647 | -0.0150 | -0.0223** | -0.0281 | -0.0151 |
| | (0.0687) | (0.0466) | (0.0301) | (0.0104) | (0.0188) | (0.0196) |
| Events at Destination | 0.186** | 0.0350 | 0.0696*** | 0.0161* | 0.0143 | 0.0330* |
| | (0.0745) | (0.0293) | (0.0207) | (0.00898) | (0.0133) | (0.0198) |
| Observations | 64,800 | 64,800 | 64,800 | 64,800 | 64,800 | 64,800 |
| R-squared | 0.030 | 0.029 | 0.036 | 0.029 | 0.032 | 0.030 |
| Panel 2 | **Mobility of Refugees with fixed effects** | | | | | |
| Events at Origin | 0.148** | -0.0878** | -0.0131 | -0.0540*** | -0.00698 | -0.0377 |
| | (0.0672) | (0.0417) | (0.0260) | (0.0173) | (0.0174) | (0.0329) |
| Events at Destination | 0.0342 | -0.158** | -0.0247 | 0.0119 | 0.00840 | 0.0429** |
| | (0.0508) | (0.0641) | (0.0265) | (0.0135) | (0.0186) | (0.0195) |
| Observations | 52,510 | 52,510 | 52,510 | 52,510 | 52,510 | 52,510 |
| R-squared | 0.086 | 0.087 | 0.083 | 0.084 | 0.087 | 0.087 |

**Summary**: This table displays results of a number of robustness tests. Under panel 1, the mobility of refugees is measured by a frequency filter of 20 calls instead of 10. Panel 2 corresponds to the case in which fixed effects are introduced in our gravity model equation 2.

**Notes**: (i) Our dependent variables are measured by a migration rate, which is of the form *Migration Rate_'r'_'i'* where *'r'* refers to the refugee (i.e. $R$) status of the observation; (ii) Robust standard errors are reported in parentheses; (iii) *** 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.

**Table 6:** Results from Robustness Tests for the Mobility of Non-Refugees

| | **Dep. Var:** Mobility of Non-Refugees | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Events:** | Rallies for Leadership Change | Boycotts | Violent Protests | Economic Aid | Humanitarian Aid | Asylum Grants |
| Log Night-Lights at Origin | -0.500*** | -0.419*** | -0.629*** | -0.471*** | -0.461*** | -0.465*** |
| | (0.133) | (0.145) | (0.125) | (0.145) | (0.138) | (0.140) |
| Log Night-Lights at Destination | 0.0453 | 0.0538 | 0.0788 | 0.0475 | 0.0516 | 0.0351 |
| | (0.0527) | (0.0531) | (0.0544) | (0.0534) | (0.0526) | (0.0533) |
| Log Distance | -0.754*** | -0.746*** | -0.767*** | -0.753*** | -0.754*** | -0.747*** |
| | (0.0822) | (0.0813) | (0.0825) | (0.0820) | (0.0812) | (0.0819) |
| Log Number of Calls | 0.910*** | 0.906*** | 0.901*** | 0.907*** | 0.898*** | 0.930*** |
| | (0.106) | (0.106) | (0.105) | (0.106) | (0.105) | (0.107) |
| Log Number of Refugee Calls | 0.0288 | 0.0302 | 0.0586 | 0.0446 | 0.0621 | 0.000289 |
| | (0.114) | (0.115) | (0.112) | (0.113) | (0.111) | (0.113) |
| Events at Origin | 0.364*** | -0.0823** | 0.00942 | -0.0301*** | -0.0114 | -0.0326 |
| | (0.0724) | (0.0334) | (0.0183) | (0.00863) | (0.0114) | (0.0227) |
| Events at Destination | -0.0548* | -0.00713 | 0.0144 | 0.00430 | 0.00427 | 0.0225** |
| | (0.0309) | (0.0270) | (0.0131) | (0.00453) | (0.00661) | (0.0100) |
| Refugee Camps at Origin | -0.114 | -0.123 | -0.0901 | -0.119 | -0.125 | -0.117 |
| | (0.141) | (0.142) | (0.141) | (0.141) | (0.141) | (0.141) |
| Refugee Camps at Destination | -0.509*** | -0.505*** | -0.558*** | -0.535*** | -0.565*** | -0.478*** |
| | (0.124) | (0.130) | (0.120) | (0.121) | (0.120) | (0.125) |
| Constant | -13.56*** | -13.65*** | -13.56*** | -13.73*** | -13.71*** | -13.56*** |
| | (0.771) | (0.775) | (0.755) | (0.751) | (0.738) | (0.762) |
| Observations | 64,800 | 64,800 | 64,800 | 64,800 | 64,800 | 64,800 |
| R-squared | 0.151 | 0.154 | 0.150 | 0.152 | 0.152 | 0.154 |

**Summary**: This table corresponds to the mobility of non-refugees in Turkey and is the counter-factual in our analysis. Our analysis controls for month fixed effects and includes dummy variables to control for the presence of *refugee camps at the origin* and *refugee camps at destination*. Columns (1) to (6) show the coefficients or our empirical specification 2. Each column corresponds to a new specification with the addition of events which respectively relate to rallies for leadership change, boycotts, violent protests, economic aid, humanitarian aid and asylum grants. Each event is considered both at the origin and destination districts.

**Notes**: (i) Our dependent variable is measured by a migration rate, which is of the form *Migration Rate_'r'_'i'* where *'r'* refers to the non-refugee (resp. refugee) 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 10 calls); (ii) Robust standard errors are reported in parentheses; (iii) *** 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.

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