International migration flows towards, within, and from Libya:

A spatial network analysis

Michele Di Maio[1], Valerio Leone Sciabolazza[2], Vasco Molini[3]

Abstract

This paper provides the first systematic and rigorous evidence on irregular migration in Libya. The source of data used in the analysis is the Displacement Tracking Matrix dataset (DTM) of the International Organization for Migration (OIM). This data provides the means to document the demographic and national composition of the migrant population crossing the Libyan territories, and to examine its impact on the local host community. Moreover, it allows us to investigate the formation and evolution of migrants' movements from, to, and within Libya by combining methodologies from both spatial statistics and network analysis. The results of the analysis are finally used to discuss the evolution of the international routes running through Libya, and identify the Libyan provinces playing a pivotal role along such routes. The ultimate goal of the paper is to obtain significant insights on migrants' behaviors in uncertain contexts, and contribute to the raising debate on the determinants and effects of international migration in circumstances characterized by high risk.

[1] University of Naples Parthenope, michele.dimaio@uniparthenope.it
[2] University of Naples Parthenope, valerio.leonesciabolazza@uniparthenope.it
[3] World Bank, vmolini@worldbank.org

Table of Contents

1. Introduction

Libya is among the African countries with the highest proportion of immigrants with respect to the total population, namely 16% (IOM; 2017).[4] At the same time, it represents a major gateway to Europe, with up to 90% of people crossing the Mediterranean Sea departing from its borders. In addition, Libya counts 217,002 people displaced inside the country (IDPs) and 278,559 people who have returned home (returnees). Libya also hosts 43,113 refugees and asylum-seekers who are registered with UNHCR. According to UNHCR (2018b), an estimated 1.3 million people are in need of humanitarian assistance in Libya.

This paper provides the first general assessment of the international migration patterns towards, within, and from Libya during the period 2016-2018. Up to now, the lack of data prevented from conducting an in-depth analytical investigation of the phenomenon. Using the most detailed data available, this paper contributes to the understanding of this important phenomenon documenting the characteristics, the location decisions, and the movements of the international migrants, the returnees, and the internal displaced population in Libya.

The source of data used in the analysis is the Displacement Tracking Matrix dataset (DTM) of the International Organization for Migration (OIM). The DTM tracks population mobility in Libya using data collected through periodic surveys. The DTM provides detailed information on international migrants and internal displaced populations (IDPs), whether on site or *en route*. To the best of our knowledge, this is the first paper using this data for a rigorous empirical analysis of international migration patterns in Libya.

The analysis proceeds as follows. First, we provide a description of the geographical distribution of international migrants in Libya and of their characteristics in terms of gender, age, country of origin and preferred destination country. We also report information on the relation between international migrants and host communities in Libya.

Second, we describe how migrants move within Libya and identify the Libyan provinces playing a pivotal role along international routes. To this end, we use spatial statistics to investigate migrants' location choices by looking at their conglomeration in specific areas, and characterize each Libyan province in terms of number of migrants with respect to the number of migrants in neighboring

[4] Other countries with high immigrant populations as a proportion of their total populations included Gabon (16%), Djibouti (13%), Côte d'Ivoire and Gambia (both 10%). In terms of the number of immigrants, South Africa is the most significant destination country in Africa with around 3.1 million international migrants residing in the country (6% of its total population).

provinces, i.e. if the number of migrants is similar in provinces that are geographically close. Next, we map the internal movements of migrants across Libyan provinces to reconstruct the international network of migrants' movements passing across Libyan provinces, by considering migrants' country of origin and destinations within each province. Finally, we identify the presence of clustered areas hosting migrants moving toward the same destinations and having the same country of origin.

Finally, we move to the analysis of the international migration flows towards and from Libya. Specifically, we investigate the direction and the composition of international migration flows passing through Libya. To this end, we track the migration flows connecting migrants' origin countries to Libyan provinces, and the Libyan provinces to migrants' preferred destinations to characterize the international migration network to and from Libya looking at migration routes within the country.

The methodologies employed in this work combine a set of tools taken from spatial statistics and network analysis. Methods from spatial statistics are used to analyze location choices and identify common patterns in migration movements as they emerge by looking at the composition of migrants in different areas. In addition, these methods allow us to identify the presence of hot spots, e.g. provinces hosting a number of migrants significantly higher than their neighboring provinces, and clusters, e.g. clumps of provinces characterized by a significantly high number of migrants, and pinpoint the major gateways for the international migration network passing through Libya. Social network analysis (SNA) is used to map the network of migratory movements, determine the level of migratory pressure in different provinces, and identify the formation of network hubs: i.e. provinces serving as a crossroad for different migration routes. To the best of our knowledge, our is the first paper which employs these techniques to characterize the formation of human movements.

The Libyan one represents a case study of particular interest to obtain significant insights on migrants' behavior in uncertain contexts. The purpose of the study is to document important stylized fact which will inform the analysis of the causes and consequences of mass South-North migration surveying IDPs and refugees in places of origin and destination. The Libya study can contribute to this global study by identifying factors that determine international and internal migration in context characterized by high risk and uncertainty.

This rigorous analysis aims at contributing to the intense debate on the determinants and effects of migration in Libya. Motivated by the high political attention received by this issue, and by the general call for a comprehensive assessment of the phenomenon, this paper to our knowledge, provides the most accurate and detailed inquiry of migration towards and within Libya up to now.

2. Background

Libya suffered from a prolonged period of conflict and instability ever since the fall of the Gaddafi regime in 2011. The uncertainty political situation characterized by the lack of a government able to control the territory has contributed to make Libya one of the most important hubs for human smuggling and refugees routes since 2011 (Cummings et al. 2015).

Before the Libyan uprising, migrants were employed in occupations that Libyans were unwilling to take up, and they represented more than 10% of the total Libyan population (World Bank, 2015). Since 2011, a significant number of migrants left Libya and there has been a large shift in the composition of migrants by nationality. The percentage of migrants from Egypt, Chad, Niger, Nigeria, and Sudan has significantly increased since 2015, while the percentage of migrants from Palestine, Iraq, and Somalia has decreased significantly.

Most migrants tracked by the International Organization for Migration (IOM) are economic migrants who plan to stay in Libya (IOM, 2017c).[5] Migrants trying to enter Europe are instead going trough Libya with the objective to reach the North of the country and a boat to the other side of the Mediterranean Sea[6] (IOM, 2017; Mixed Migration Hub, 2015; Altai Consulting and IOM, 2015a; Kelly, 2017; UNHCR, 2017d).

Although North Africa is primarily a migrant transit area, it also hosts a large number of international migrants, including refugees (see Table 1).

<< Table 1 about here >>

As remarked by IOM (2017), the North African sub-region is indeed a key hub of legal and illegal migration transit. Actually, Libya is the destination of two of the most important asylum seekers routs to Europe (see Figure 1). Between 2011 and 2016, approximately 630,000 people used the "Central Mediterranean route", the main route of arrival via irregular migration to Europe, to reach Italy

---

[5] Studies conducted by UNHCR have found similar proportions in other time periods. See https://reliefweb.int/sites/reliefweb.int/files/resources/LIB-HCR-MAS-Final-Report.pdf

[6] IOM (2017) reports serious human rights violations along these smuggling routes. Migrants often face significant violence, including extortion, exploitation, physical and sexual violence, kidnapping and robbery, with many losing their lives as a result of being transported in inhumane conditions at sea, in the desert, and in other transit locations (Frouws and Horwood, 2017). Smuggling into and outside Libya has become a very remunerative activity. Migrants smuggling is increasingly concentrated in the hands of fewer, more well-organized criminal networks, dominated by armed groups that use this activity to raise money for buying weapons and consolidate their hold on their controlled areas (Global Initiative against Transnational Organized Crime (2017). The Human Conveyor Belt). UNHCR, (2018) document an increase in smuggling costs because of the multiplication of smuggling intermediaries, as well as the liquidity and inflation crisis in Libya.

(European Commission, 2017a).[7] In 2016 alone, more than 181,000 people were detected on the Central Mediterranean route (European Commission, 2017b). The majority of these people departed from Libya (almost 90%) (European Commission, 2017b).[8]

<< Figure 1 about here >>

As emphasized by IOM (2017), conflict and violence within and in surrounding sub-regions has contributed to displacement in North Africa.[9] Migration, internal displacement, political instability and conflicts interact in complex ways in Libya. Libya had the largest number of international migrants in the sub-region, at over 770,000 in 2015 (Un DESA, 2015). According to UNHCR (2017), the unstable security and political situation in Libya contributed to a total population of more than 300,000 IDPs by the end of 2016, while also affecting the more than 38,000 refugees and asylum seekers residing in Libya.[10] According to IOM (2017b), this numbers make Libya as the third at the world level as for new displacement by conflict and violence as a proportion of the population (2,500 per 100,000 inhabitants)[11].

According to IOM data, migrants are mostly concentrated in Misrata, Tripoli and Sebha in the South. Benghazi (East) on the other hand, it has the highest number of both returnees and IDPs. Returnees are mostly present in the Northeast, close to the coast, while both migrants and conflict hotspots are mostly concentrated in the Western part of the country.

Migrants directed to Europe often settle in Libya for some time before starting their second migration journey (World Bank, 2018). Some others– including refugees –sometimes remain stranded in Libya or other countries in the Maghreb (Altai Consulting and IOM, 2015). Results from EASS (2017) indicate

---

[7] Of those who disembarked in Italy in 2016, the majority were from Western and Eastern Africa (Nigeria, Eritrea, Guinea, Côte d'Ivoire, Gambia, Senegal, Mali and Somalia) and over half applied for asylum (European Commission, 2017b); 13 per cent (approximately 24,000) were women, while 15 per cent (28,000) were children – the vast majority (91%) of whom were unaccompanied. The proportion of children, including unaccompanied children, has increased (European Commission, 2017b., IOM, 2016d).

[8] Other departure countries including Egypt, Algeria and Tunisia.

[9] For instance, migration in Eastern and Southern Africa continues to involve high numbers of irregular migrants, characterized by mixed migration flows and underpinned by multiple drivers, including socioeconomic factors, conflict and political instability (IOM, 2017). In addition to socioeconomic factors, conflict and political instability remain important drivers of irregular migration from Eastern Africa. The three major destinations for migrants from Eastern Africa are the Middle East, Europe and Southern Africa. There are four main rousts used by migrants for Eastern Africa. The first is the western route via Sudan, into Libya and across the Mediterranean. The other three main routes, include the northern route via Egypt to Israel; the southern route down the Eastern Corridor toward South Africa; and the eastern route transiting through Yemen to Saudi Arabia and beyond.

[10] Data from IOM report different numbers: while the number of migrants is the same (i.e. 700,000), they count are more than 160,000 internally displaced persons and 340,000 returnees residing in different regions of Libya (DTM Libya, Round 13, August-September 2017).

[11] The first is the Syrian Arab Republic (with 4,400 displacements per 100,000 inhabitants) and El Salvador (3,600 per 100,000 inhabitants).

that a substantial share of asylum seeker who migrated through Libya had previously worked for a prolonged period in the country. For those coming from Sub-Saharan Africa, the conflict had likely transformed Libya from a destination into a transit country. In 2010, about 2.5 million African migrants were settle in Libya. The conflict which began in 2011 had led to internal displacement of more than 434,000 Libyans by 2015 (World Bank, 2018).

3. Literature

The literature on migration has vastly grown in recent year. One of its main objectives has been identifying the supply (push) and demand (pull) factors that affect the decision to migrate. According to theory, on the supply side, relocation choices are driven by income opportunities (Borjas 1994), while on the demand side, migration flows are shaped by national policies and labor market conditions (Ortega and Peri 2012). Consistently, expected lifetime benefits from migrations are heterogeneous across individuals, and they determine how migrants self-select from specific pools of the population (Borjas 1987; Beine, Docquier, and Özden 2011).

However, over the last decades, legal channels for migration have dried up (Friebel and Guriev 2013) and violent conflicts have increasingly affected civilians in developing countries (Marshall and Elzinga-Marshall 2017). As a result, the traditional push and pull factor framework seems to not suffice anymore when analyzing modern migration trends, especially in developing countries (Clemens 2014). Whereas from a theoretical standpoint there are several common determinants between regular and irregular migration, some factors are unique to the latter. In particular, some studies have shown that uncertainty and risk situations (i.e. conflicts) alter the conditions under which individuals form their set of preferences operate, suggesting that the same pull and demand factors may influence regular and irregular migrants differently (Voors et al. 2012; Arcand and Mbaye 2013; Callen et al. 2014). At the same time, there is some evidence that self-selection and destination choices play a different role in the case of regular and irregular migrants. Specifically, the latter seems to be more risk averse than the former, and their relocation decisions depends more on the availability of diaspora networks at destination, and less on the presence of traditional pull and push factors (e.g. recruitment policies) (Ceriani and Verme, 2018; Manchin and Orazbayev 2018; Friebel et al. 2017).

Taken together, this evidence suggests that uncertainty alters the conditions under which individuals form their set of preferences and sort themselves into migrants and non-migrants. At the same time, uncertain and risky contexts like conflict and natural disasters are likely to influence the decision to become an illegal migrants and which route to use to reach the destination country.

A related set of studies are those looking at phenomenon of forced migration (Ruiz and Vargas-Silva, 2013; UNHCR 2017; Dustmann et al. 2017). In this context, two are the main relevant issues to investigate: i) the impact of forced migrations on forced migrants; ii) the impact of forced migrations on host communities. While availability of data is the major constraint to this literature, the number of studies looking at these issues is rapidly increasing.[12] Specifically, the studies on the impact of forced migration on forced migrants have looked at the access to high incomes (Sarvimäki, Uusitalo, and Jäntti 2009; Bauer, Braun, and Kvasnicka 2013) and high skilled jobs (Falck, Heblich, and Link 2011). Other studies have looked at the consequences of natives' exposure to refugees and asylum-seeker. In particular, they considered: i) changes in the host community economic structure, especially in relation to the labor market context (Braun and Mahmoud 2014; Maystadt and Verwimp 2014; Tumen 2016) and consumer prices (Balkan and Tumen 2016); ii) alterations in natives' political preferences determining a shift in local attitudes towards refugees (Lergetporer, Piopiunik, and Simon 2018) and voting behaviors (Otto and Steinhardt 2014; Dustmann, Vasiljeva, and Damm 2016; Dustmann et al. 2017; Sekeris and Vasilakis 2016; Steinmayr et al. 2016).

4. Data

Data used in this analysis come from the Flow Monitoring component of IOM's Displacement Tracking Matrix (DTM). The DTM of the International Organization for Migration (OIM) tracks and monitors the displacement and population mobility in Libya from January 2016 to April 2018. It provides detailed information on migrants and internal displaced populations (IDPs), whether on site or *en route*.

The objective of DTM is to track movement flows of migrant groups and individuals through key points of origin, transit locations and points of destination. The purpose of the monitoring is to regularly provide updated information on migration flows and profiles of migrants through specific locations (IOM; 2017).

The Flow Monitoring Point (FMP) tracking system consists of two data collection layers: 1) Baseline Assessments identify the frequency and volume of migrants in, and crossing through a specific point (referred to as Flow Monitoring Points - FMPs); 2) Profile Surveys that gather information about migrant profiles, including age, sex, areas of origin, levels of education, key transit points on their route, cost of journey, motives, and intentions. In our analysis, we only use the data from the Baseline

[12] This could be also the result of the fact that forced migration minimizes location selection (i.e. when migrants choose their destination in which their characteristics are rewarded the most) and self-selection based on economic differences, which are two of the main challenges to identify the determinants of regular migration. In fact, as showed by Kondylis (2008) and Ibáñez and Moya (2010), the nature of conflicts which usually generates forced migration are such that in most cases location choice is exogenous to forced mi grants' preferences, and unless the targeting of individuals in the conflict is economic related, it is possible to argue that the level of violence is not related to unobserved characteristics that may also affect future economic outcomes.

Assessments. Baseline Assessments identify the frequency and volume of migrants in, and crossing through the specific point, the Flow Monitoring Points (FMPs). Data are collected on a daily basis but then are quantified and reported on a monthly basis.

The Baseline Assessment survey collects information on the number of migrants, currently residing in, arriving to, and leaving from a specific FMP (see Appendix for the questionnaire). For those already present in the FMP, it records the nationality, the planned destination, the length of stay at the FMP level. In practice, what it is recorded are *the 3 first nationalities present in the FMP during the week of the assessment*, *the 3 first destination for the migrants present in the FMP during the week of the assessment*, *and percentage of migrants present in the FMP within each length of staying category* (i.e. less than wo weeks, between 2 weeks and three months, etc.) in the location during the week of the assessment. For those arriving or departing, it collects the information on the nationality and the planned destination using the same questions.

Given the way in which the questionnaire is constructed, the unit of observation in the data is the FMP. This implies that the data allow us to map and track the FMPs evolving characteristics in terms of relative presence group of individuals of given nationalities, preferred destinations, etc. Yet, the structure of the data also poses some severe limitation to the analysis. For instance, it is not possible clearly link the nationalities to the preferred destinations because both set of information are collected as share in terms of the first three nationalities and preferred destination in the FMPs.

The pool of migrants observed in the IOM flow monitoring points (FMPs) in 2017 and 2018 constitutes the population under study. In our analysis we use data from 95 FMPs that are constant across rounds. This allows us to track the movement of migrants in a consistent way and to compare flows across time in the same area. Yet, 17 additional FMPs are found throughout rounds. According to IOM, the reason is to allow data collection to cover new points that more migrants were crossing through due to security reasons.

The location of the FMPs is shown in Figure (2). While there is at least on FMP in each province the distribution in across provinces is not homogenous. While Almargeb, Aljafara, Murzuq, Tobruk, and Tripoli have 5 FMPs, Wadi Ashishati, Ghat and Nalut have only one.

<< Figure 2 about here >>

To make the results easier to interpret, the analysis is performed by aggregating the data at the province-level. The map of the provinces is shown in Figure (3). In what follows, unless differently stated, each metric is obtained by averaging the observations recorded in a province within a year (respectively 2017 and 2018).

<< Figure 3 about here >>

5. Results

5.1 Characteristics of the migrants' population

5.1.1 Demographic characteristics and spatial distribution of migrants

We begin by looking at the available information on the number of international migrants in Libya as registered in the FMPs. Figure (4a), (4b), and (4c) show the number of migrants using different geographical aggregations and time periods.

We begin by looking at the total number of migrants by province. Figure (4a) a shows the total number of migrants recorded through FMPs during the period 2017-2018 in each Libyan province. In particular, Almagerb, Alkufra, and Bengazi are the provinces in that there are more migrants registered in the FMP, while Al Jabalal Al Akhadar, Ghat and Ubari are those where the number of migrants is smallest.[13]

To explore the data more in detail, we next look at the number of migrants as recorded by the FMPs comparing 2017 and 2018 data for the same province. Data are reported in Figure (4b). What emerges from these graphs is a large increase in the presence of migrants in almost all provinces between the two years, with a huge increase in Almargeb.

Finally, Figure (4c) shows the evolution of the total number of migrants that have been recorder in each province in each round of the survey during the period 2017-2018. The data show that there is high heterogeneity in terms of migration presence across Libyan provinces. Data show a slight increase in the presence of migrants between round 5 and 16 (January 2017 – February 2018). In round 17 (March-April 2018), the data indicate a massive increase in the number of migrants in almost any province. After that, the last three rounds of 2018 included in our dataset show a reduction in the number of migrants registered in the FMPs, with the exclusion of Almagerb where the number of migrants remained very high.

<< Figure 4a about here >>

<< Figure 4b about here >>

<< Figure 4c about here >>

[13] Note that while the absolute numbers reported in these graphs have to be interpreted with much caution. In fact, since FMPs are monthly data, these numbers are likely to count the same individuals more than once.

The data allow us to recover some information on the demographic composition of migrants. These are represented in Figure (5) at the Libyan level, and in Figure (6) at the province level. Not surprisingly, the large majority of migrants are males. In 2017, females and minors are between 3% and the 5% of the migrant population, respectively. The most diverse composition of the population is found on the western regions in 2017 (e.g. Aljufra, Ghat, and Nalut). In 2018, the share of female and of minor increases significantly.

<< Figure 5 about here >>

<< Figure 6 about here >>

5.1.2 Relation of migrants with host communities in Libya

We now turn the attention to the impact that the presence of migrants has on the local host communities. The IOM collects data on answers to three different questions: i) the quality of the relation between the host community and the migrants; ii) the impact of the presence of migrants on the local labor market; iii) the impact of the presence of migrants on public services. Since answers to these questions are collected at each round of the survey, in Figures (9), (10), and (11) we report respectively the most recurrent observation registered for each of the three outcomes in a municipality for a given year.

<< Figure 7 about here >>

<< Figure 8 about here >>

<< Figure 9 about here >>

While these measures of impact are inherently subjective and only based on individual perceptions and thus prone to different biases, still they are useful in providing at least a sense of how local communities are experiencing the migration phenomenon from their own prospective. There are three main stylized facts which emerge looking at the results. First, for each of these questions, there is significant heterogeneity in terms of answers also in relatively restricted geographical areas. Second, there is a very strong correlation between these measures. This indicates that labour market outcomes, access to and quality of public services, and - in general - the quality of relation with the local community are all aspects that should be considered simultaneously in designing policy interventions. Third, there are no detectable variations across years in any of these measures. This is not surprising given the nature of the phenomenon, but it also suggests that if one wants to mitigate the possible negative impact of the presence of migrants on host communities has to invest resources and adopt a long term perspective.

5.1.3 Top origin countries and most preferred destinations

In each survey round, for each FMP the data reports the top 3 migrants' nationalities registered, and it lists the top 3 preferred destination country for the migrants located in that FMP.

In Table (2), we show the 5 most recurrent top 1 nationalities registered in the FMPs in 2017 and 2018. The order of the names is used to signal which nationality was found more frequently than the others.

<< Table 2 about here >>

In table (3), we show the 5 most recurrent preferred arrival destinations registered in the FMPs in 2017 and 2018.

<< Table 3 about here >>

It is interesting to note that most recurrent top nationalities and preferred destinations both remain the same across different years. Notably, Egypt appears both as origin and destination place, which suggests that the pool of Libyan immigrants is partly constituted by people who decided to return to their home country. Finally, it is worth stressing that Libya represents the final destination for a large number of migrants.

5.2 Spatial and network analysis of the migration flows

In the following sections, we make use of spatial network analysis to document a set of stylized facts concerning the migration flows in Libya.

5.2.1 Hotspot provinces and clusters of provinces in Libya

As first step, we use spatial statistics to characterize each province in terms of its number of migrants with respect to the number of migrants in neighboring provinces. In practice, we test the presence of spatial autocorrelation in the migrant distribution across the Libyan provinces, i.e. if the number of migrants is similar in provinces which are geographically close (Anselin, 1995).[14] To this end, we identify *hotspot provinces* and *clusters of provinces*. A hotspot province is a province with a significantly higher (lower) number of migrants with respect to the neighboring provinces. A cluster of provinces is instead a group of provinces hosting a high (low) number of migrants.

The results of the identification of hotspots is presented in Figure (10). Two province can be characterized as hotspots in both 2017 and 2018, namely Wadi Ashshati and Almarj. In 2018, we

[14] A similar exercise in the context of asylum migration is presented in Barthel et a. (2015).

observe the emergence of four new hotspots: i.e. Ejadabia, Ghat, Murzuq, Tobruk, and Wadi Ashshati. The low number of migrants in the province of Almarj with respect to surrounding provinces might indicate that this area works as a buffer zone separating provinces with a high concentration of migrants from areas less interested by migrant's presence and passages. By contrast, the high presence of migrants in Wadi Ashshati, with respect to all the other provinces at the Libyan Western border, suggests that this area might represent a preferred point of access for the migrants arriving from the Western side of the country in both 2017 and 2018. Likewise, the emergence of hotspots in 2018 indicates a more concentrated presence of migrants in some specific provinces (i.e. Murzuq and Ejadabia), and a decreases in other adjacent provinces (i.e. Tobruk and Ghat). The fact that these are provinces located at the Libyan borders is consistent with the hypothesis on the emergence of new specific migrant routes entering Libya.

<< Figure 10 about here >>

Our analysis also reveals the presence of a cluster of provinces around Tripoli, i.e. a large group of neighboring provinces hosting a high number of migrants. The level of spatial autocorrelation in the distribution of migrants in this area increases in between 2017 and 2018, and it becomes significant at the 5% level in 2018.

5.2.2 International migrants' movements within Libya

FMPs data can also be used to map the internal movements of migrants, i.e. across different Libyan provinces. Specifically, for each FMP the data report what is the Libyan province representing the most common origin for the migrants present in the FMP. Using this information for all FMPs in our dataset, we can build the network of internal movements of migrants across all the Libyan provinces.

The results of the analysis are shown in Figure (11). In the figure, (capitals of) province i and j are connected if there is a movement from a FMP located in i to a FMP located in j. The size of the flow is proportional to the average number of migrants registered in the FMP.

Both graphs show a quite dense net of connections: each province is connected to at least other two provinces. This suggests that - in general – for each province there is not a unique migration route from or to any other province. In determining the specific migration route chose, it is thus likely that an important role is played by individual-level characteristics.

<< Figure 11 about here >>

Comparing the two graphs, we also identify a clear change in the migration internal routes between 2017 and 2018. In 2017, three major corridors run through Libya (Figure 11a): i) the eastern route, connecting Alkufra, Ejdabia, and Benghazi, and ii) the central route, going from Murzuq to Tripoli, and

iii) the western corridor, running from Ghat to Tripoli. The figure also shows that the second route was the most used at the time. By contrast, even if the eastern and central routes remain intact, paths become blurred in 2018 (Figure 11b). This might be in part due to a general reduction in the number of migrants in the countries, as suggested by the decrease in the width of the network linkages. However, it also suggests that a reorganization occurred along the corridors, with migrants more evenly distributed over all paths.

5.2.3 Clustered destinations within Libya of same-origin migrants

In the following, our main objective is to identify the possible presence within the Libyan territory of clustered destinations of migrants having the same country of origin. To this end, we analyse the movements of same-origin migrants across Libya and across time.[15]

The results are presented in Figure (12). Our analysis identifies cluster of same-origin migrants in four different cases.[16] The first one is represented by the case of the Egyptians arriving in the areas near Tripoli and near Tobruk in January 2017.[17] In other words, the results of our analysis show that two different areas of Libya attract a significantly large number of Egyptians. In particular, the graph displays the location of the FMPs where these clusters have been identified.

The second case in which a cluster of same-origin migrants is identified is the one of the Ethiopians in Tobruk in July 2017. The third is the group of migrants from Benin arriving in the area of Sebha in August 2017. In the same moth, there is also evidence of the passage of Eritreans in the provinces of Alkufra and Tobruk, approximately at 800 km from each other. Finally, the fifth reveals the arrival of

---

[15] To conduct this analysis, we follow four steps. First, we reconstruct the network of internal movements at the monthly level (similar to what was done in Figure 11). Since we are interested in the short-term dynamics, we use monthly data on migrants registered in the FMPs. Second, we identify the presence of significant spatial concentrations of migrants in FMPs located close to each other. Specifically, we test whether same-nationality migrant's clusters occur more frequently than would be expected if FMPs were distributed in a spatially random way. To this end, we use the join count test for k-coloured factors (Cliff et al. 1981; Upton et al., 1985). In our analysis, we define close FMPs all those located within a distance radius of 250 km. This value represents the minimum distance radius required to make sure that each FMP has at least a neighbouring FMP, a condition that is necessary for the implementation of the join count. Since only 5% of the FMPs are located at more than 250 km from all the others, we simply drop them from the sample. Third, for each month t, we identify the nationalities for which the test indicated significant spatial concentration. Fourth, for each of these nationalities, we plot the location of the FMPs located within 250 kilometers from each other where the majority of the arrivals corresponded to nationality i at time t.

[16] It is important to emphasise that these results emerge from the analysis of all the migration flows in Libya without imposing any a priory model of choice.

[17] The distance between these two cities is over 1000 km, exceeding four times the distance radius used to detect migrant agglomerations. This means that the test evaluated the movements in these provinces separately, and it implies that the two effects are independent.

people from Bangladesh in the area of Tripoli in January 2018. These results support the idea that same-origin migrants, moving in the same direction, sort themselves into close routes, following similar paths.

<< Figure 12 about here >>

5.2.4 Incoming and outcoming international migration flows

In this section, we investigate the direction and the composition of international migration flows to identify the backbone of the migration passing through Libya.[18]

Figure (13) reconstructs the international migration routes passing though Libya. To this purpose, we create a network where origin country *i* and destination country *j* are connected when i) country *i* was found as the major source of migrants in one of the FMPs of a province at least once in a year, and ii) country *j* was registered as the most preferred destination for the majority migrants in one of said FMPs at least once in a year. [19] In Figure (13), the circle segments represent origin and destination countries of international migration routes through Libya. Specifically, the color of the segment is uniquely associated to a country, and its size indicates the total amount of in-coming and out-coming flows in that country. The direction of the flow is encoded as follows: i.e. the flow originates from country *i* if it is adjacent to the segment circle of country *i* and it shares the same color of the segment; the flow ends to country *i* if it is adjacent to the segment circle of country *i* and it does not share the same color of the segment.[20] Similar hues of colors are used to identify larger geographical area, namely pink for East Africa, violet for North Africa, Green for West Africa, yellow for Asia, red for Americas, and blue for Europe.

The investigation of the origins of migrants flows shows that West African countries (the segments with green hues of color) represent the origin of the larger majority of migrants. Outside Africa, we observe that a major role is constantly played by Asia, specifically Bangladesh (in yellow). The analysis of the destination of migrants flows reveals that Europe (segments with blue hues of color) represents the most preferred place of arrivals for migrants. In addition, we observe that there was a second preferred destination in 2017, that is Western Asia (i.e. the segments with yellow hues of color of Kuwait, Israel, Saudi Arabia, and Turkey), but this almost disappears in 2018.

[18] This exercise requires to assume that migrants found in a FMP are all moving along the same route, and they are equally interested in reaching the top 1 preferred country of arrival recorded in that place. The assumption is instrumental to identify the backbone of the migration network passing through Libya, which is represented in Figure (13).
[19] This analysis is conducted under the assumption that migrants found in a FMP are all moving along the same route, and they are equally interested in reaching the top 1 preferred country of arrival as recorded in that FMP.
[20] For ease of interpretation, we have removed those connections signaling the case of migrants returning to their home country or intending to remain in Libya.

Comparing the plots between 2017 and 2018, it is also possible to identify changes in the direction of the flows originating from a specific area. This is the case of East Africa, namely Ethiopia, Eritrea, and Eritrea, for which we observe an expansion in the set of destinations reached, as shown by the increase in the number and the width of the flows with pink hues of color.

Finally, the figures allow to analyze the composition of the migration at destination, by looking at the different colors of incoming flows. Specifically, the figures show that for all receiving countries, the largest number of migrants originated from West Africa (flows with green hues of color). Nonetheless, we observe an increasing role played by East Africa because of a significant increase in the number of flows with pink hues of colors reaching Italy, the Netherlands, and Sweden. Less notable, but still relevant, it is also the increase in the number of flows with yellow hues of color, representing the Asian countries, reaching France and Germany.

<< Figure 13 about here >>

5.2.5 International migration flows towards and from Libya provinces

In this section we further characterize the international migration network to and from Libya looking at migration routes within the country. Using the data about origin and destination countries registered in the FMPs, we track the migration flows connecting migrants' origin countries to Libyan provinces, and the Libyan provinces to migrants' preferred destinations.

We begin by presenting the network of origin countries and Libyan provinces for both 2017 and 2018 in Figure (14).[21] In the network, origin country i is connected to Libyan province j if, at least for one round in a given year, it was found that the majority of migrants observed in a FMP located in province j departed from country i.

Looking at these graphs, it is possible to identify two important changes occurred between 2017 and 2018. First, the number of origin countries shrinks between 2017 and 2018.[22] Second, there is a notable decrease in the density of the graph, meaning that migrants from a given origin country in 2018 are

---

[21] A note on how to interpret these graphs. Suppose that – at least once in 2017 - migrants coming from country i are the majority of the hosts in one FMP of provinces A, B, and C. Now suppose that the same happens for migrants coming from country j. By construction, reproducing the network in figure 8 for i and for j will result in two figures which look exactly the same.

[22] Specifically, the top origin countries disappearing from the graph are: Benin, Cameroon, Central African Republic, Congo – Kinshasa, Guinea, Guinea – Bissau, Kenia, Malawi, Morocco, Togo, Tunisia. At the same time, we observe the appearance of Pakistan.

found in a smaller number of Libyan provinces compared to 2017. This entails a consolidation in the set of origin countries and in the routes followed by the migrants departing from these countries.[23]

<< Figure 14 about here >>

Next, we look at the network between Libyan provinces and preferred destination countries for the migrants located in each Libyan province in 2017 and 2018 in Figure (15). In the network, Libyan province *j* is connected to destination country *i* if, at least for one round in a given year, it was found that the majority of migrants observed in a FMP located in province *j* declared as first preferred destination country *i*.

Some interesting changes appear comparing the networks in 2017 and 2018. First, between the two years the number of destination countries decreased from 25 to 16.[24] Second, each of the remaining destination countries has a smaller number of connections, and the network in 2018 becomes sparser with respect to 2017. This applies to both European countries (see for instance Germany) and the African countries (see for instance Sudan). Third, some of the African countries reported as preferred destinations in 2017 disappears from the list in 2018, namely Chad, Mali, and Nigeria. While our data does not allow us to precisely identify a reason for this, one can hypothesize that migrants are reconsidering the possibility of returning to home countries. The fact that these are all conflict-affected countries suggest that – after an initial hope for being able to come back – this possibility could have been disappeared in favor of an outmigration to Europe. This would explain the drastic reduction in the number of connections between Libyan provinces with Libya. To the extent which these connections indicate migrants intending to remain in Libya, we interpret this as evidence that migrants are increasingly to leave the country.

<< Figure 15 about here >>

The information provided in Figure (14) and (15) is then combined in Figure (16), where for each province we display the top one migrants' nationality and preferred destination. The figure shows three notable facts. First, Libya represents the final destination for a number of migrants located in different provinces (e.g. Sirt and Benghazi, among the others). Second, some African countries appear both as origin and destination places (e.g. Egypt, Chad, Mali, Niger). These two findings actually complement the results in Table 2 and 3 (i.e. the 5 most recurrent top 1 nationalities and the 5 most recurrent preferred arrival destinations registered in a FMP). They indicate that - while Egypt is the only African country

---

[23] In the Appendix, we present the graphs reproducing the network for the 3 top sending country of each year, namely Egypt, Niger and Nigeria in 2017, and Egypt, Niger and Sudan in 2018.

[24] Specifically, the top destinations disappearing from the graph are: Cyprus, Kuwait, Israel, Malaysia, Mali, Nigeria, Spain, Tunisia, Turkey, and the United States. At the same time, we observe the appearance of Belgium.

both among the top five sending and the top 5 receiving ones – other African countries are the final destinations of a large number of migrants.

Third, there is a clear change in the network structure. Whereas the 2017 network is very dense, with many countries participating as origin countries, the 2018 network is far sparser.[25]

<< Figure 16 about here >>

The network represented in Figure (16) can be used to identify migration patterns exploiting the fact that not all migration linkages are equally important for a country. To this end, following a standard approach, we begin reducing the level of complexity of the network's structure by partitioning it in so called *communities*: i.e., sets of nodes densely connected with each other, and more sparsely connected with the rest of the network.[26]. In other words, a community is a group (cluster) of countries having tightly interrelated migration linkages among them while being relatively less interconnected with countries outside the group (cluster).

Figure (17) displays the communities identified based on the network of sending and receiving countries of international migrants hosted in Libyan provinces.[27] In the figure, colors are used to identify provinces belonging to the same community of the migration network: i.e. the areas where it was found the same composition of migrants and the same interests for specific destinations of arrival.

<< Figure 17 about here >>

Results indicate that provinces belonging to the same community - i.e. characterized by the presence of migrants originating in similar countries and having similar destination preferences - are located close

---

[25] There might be two concurrent reasons for this. First, a diversion in migrant routes causing a contraction in the number of countries sending migrants to Libya: i.e. some sending countries disappeared in the 2018 network because migrants coming from these places now travel across countries that are different from Libya,. Second, a stronger concentration of same-origin migrants along similar routes: i.e., migrants originating from a sending country are found in a relatively smaller number of provinces in 2018 with respect to 2017. As a consequence, the number of connections for a given sending country diminishes, and network density reduces..

[26] Community search has proven to be a valid instrument in the network analysis of migration flows (see among others Davis et al., 2013; and Peres et al., 2016).

[27] Several community detection algorithms have been proposed in the literature (see Fortunato [2010] for a complete and extensive review). The choice of one algorithm over another is usually data-driven, and it is determined by its ability to produce a meaningful community structure, with significant within-community cohesion and between-community separation (Clauset et al. 2004). A standard measure used to determine the algorithm fit to the data is modularity, a metric ranging between -1 and 1, with lower values reflecting poor community structure (many between-community edges and few within-community edges), and values closer to 1 indicating good community structure. In the case of the Libyan migration network, the algorithm producing the best partition is the spinglass algorithm (Reichardt et al., 2006), which returns a modularity value of over 0.2 for both 2017 and 2018.

to each other. This suggests the presence of specific migrant passages running across the country. For instance, consider Figure (17a). We observe the presence of at least three definite routes: i) the western route (aquamarine area), beginning in the province of Ghat and ending in the provinces of Zwara and Aljfara; ii) the eastern route (red area), passing from Alkufra up to Tobruk; and iii) a central route (green area), going from Murzuq to Tripoli. However, a major change occurs in 2018, as shown in Figure (17b). In fact, while the central and eastern routes (respectively the violet and green areas) remain almost unchanged, the western route is now split into two different corridors. The first connects the province of Wadi Ashshati to Misrata (light green area), the second connects the eastern province of Nalut with the central province of Sirt and the western provinces of Benghazi and Al Jabal Al Akhdar (red area). This might indicate that from 2017 and 2018 there was a shift in migrants' routes, and eastern cities now serve as passages to reach the other side of the country.

6. Concluding remarks

Libya's protracted conflict since 2011 has displaced significant number of Libyans. In addition, smugglers and militias have utilized security vacuum at Libyan borders, particularly in the South, to smuggle in migrants from Middle Eastern, South Asian, and sub-Saharan African countries, often selling migrants hope to enter Europe through Libya. Before 2011, migrants filled trades and occupations that Libyans were unwilling to take up; migrants have consistently made up more than 10 percent of Libya's population. Since the fall of Gaddafi, a significant number of migrants have also fled Libya and there has been a large shift in the composition of migrants by nationality. In general, most migrants currently in Libya (IOM, 2017c) are economic migrants who plan to stay in the country [28]. Those planning to go to Europe pay high amounts to smugglers to enter Libya and smuggling has become a very remunerative activity in the country; it is increasingly concentrated in the hands of fewer, more well-organized criminal networks, dominated by armed groups[29] that use this activity to raise money for buying weapons and consolidate their hold on their controlled areas.

Migration, internal displacement, political instability and conflicts interact indeed in complex ways. To analyse these phenomena, we make use of a rich toolkit that combines spatial statistics analysis and network analysis, to our knowledge a novelty in the area of human movements studies. Methods from spatial statistics are employed to analyze location choices and identify common patterns in migration

[28] Studies conducted by UNHCR have found similar proportions in other time periods. See https://reliefweb.int/sites/reliefweb.int/files/resources/LIB-HCR-MAS-Final-Report.pdf

[29] To understand the history and evolution of the smuggling networks in post-Gaddafi Libya, read "The Human Conveyor Belt" released in 2017 by the Global Initiative against Transnational Organized Crime

movements, presence of hot spots and clusters. The Social network analysis is used instead to map the network of migratory movements, determine the level of migratory pressure in different provinces, and identify the formation of network hubs.

Using the DTM dataset of the International Organization for Migration, we first provide a description of the geographical distribution of international migrants in Libya and of their main characteristics. Second, we describe how migrants move within Libya and identify the Libyan provinces playing a pivotal role along international routes. Thirdly, we analyze the international migration flows towards and from Libya by focusing on the direction and the composition of international migration. Migration flows are tracked by connecting migrants' origin countries to Libyan provinces, and the Libyan provinces to migrants' preferred destinations to characterize the international migration network to and from Libya looking at migration routes within the country.

A number of preliminary findings are noteworthy. Flow Monitoring Points data were used to build the network of internal movements of migrants across all the Libyan provinces. The results show a quite dense net of connections; it suggests thus for each province there is not a unique migration route from or to any other province. We postulate, therefore, that in the route choice an important role is played by individual-level characteristics. Comparing 2017 and 2018, we also identify a clear change in the migration internal routes between. While in 2017, the main corridors where the route connecting Alkufra, Ejdabia, and Benghazi (eastern route), the one going from Murzuq to Tripoli (central route) and the corridor connecting Ghat to Tripoli (western route), in 2018 due to the general reduction in migrants' paths become much more blurred. When looking at clustered destinations of migrants having the same country of origin, we identify five clusters. The first one is represented by the case of the Egyptians arriving in the areas near Tripoli and near Tobruk in January 2017. The second one is identified for the Ethiopians in Tobruk in July 2017. The third is the group of migrants from Benin arriving in the area of Sebha in August 2017. In the same month, there is also evidence of the passage of Eritreans in the provinces of Alkufra and Tobruk. Finally, the fifth reveals the arrival of people from Bangladesh in the area of Tripoli in January 2018. All these findings concur in showing that same-origin migrants, moving in the same direction, sort themselves into close routes, following similar paths.

The investigation of the origins of migrants flows indicates that West Africa is the first source. Outside Africa, we observe that a major role is by specifically Bangladesh. The comparison between 2017 and 2018 also indicates an increasing role played by East Africa. When looking at the most common destination, Europe ranks first, while the second one is represented by a Middle Eastern group of countries including Kuwait, Israel, Saudi Arabia, and Turkey.

In the final section, using the data about origin and destination countries, we track the migration flows connecting migrants' origin countries to Libyan provinces, and the Libyan provinces to migrants' preferred destinations. Between 2017 and 2018, we find that the number of destination countries decreased from 25 to 16. Each of the remaining destination countries has a smaller number of connections, and the network in 2018 becomes sparser with respect to 2017. This applies to both European and African countries. Also, some of the African countries reported as preferred destinations in 2017 disappears from the list in 2018, namely Chad, Mali, and Nigeria. The fact that these are all conflict-affected countries suggest that – after an initial hope for being able to come back – this possibility could have been disappeared in favor of an outmigration to Europe. This would explain the drastic reduction in the number of connections between Libyan provinces with Libya. To the extent which these connections indicate migrants intending to remain in Libya, we interpret this as evidence that migrants are more inclined to leave the country.

The present paper provides a first general assessment of migration flows in Libya from 2017 to 2018 using a rich but much unexplored dataset on migrants flows collected by IOM. As first a first step of broader analytical work on migration in Libya we provided evidence on the spatial distribution of migrants at the most disaggregated level (i.e., provinces); we reconstructed the network of human corridors connecting Libyan provinces and preliminary identified the destination choice patterns. Having mapped the flows, further research on the topic will focus on the impact of policy decisions and on the costs and impact of Libyan conflicts on within country movements.

References

Alix-Garcia, Jennifer, and David Saah. 2009. "The Effect of Refugee Inflows on Host Communities: Evidence from Tanzania." *The World Bank Economic Review* 24 (1): 148–70.

Alix-Garcia, Jennifer, Sarah Walker, Anne Bartlett, Harun Onder, and Apurva Sanghi. 2018. "Do Refugee Camps Help or Hurt Hosts? The Case of Kakuma, Kenya." *Journal of Development Economics* 130: 66–83

Altai Consulting and International Organization for Migration (IOM) 2015a. Migration Trends Across the Mediterranean: Connecting the Dots. Prepared by Altai Consulting for IOM, MENA Regional Office. Available from https://publications.iom.int/system/files/altai_migration_trends_accross_the_mediterranean.pdf

Anselin, Luc. 1995. "Local Indicators of Spatial Association—LISA." *Geographical Analysis* 27 (2): 93–115.

———. 2003. "Spatial Externalities, Spatial Multipliers, and Spatial Econometrics." *International Regional Science Review* 26 (2): 153–66.

Arcand, Jean-Louis, and Linguère Mously Mbaye. 2013. "Braving the Waves: The Role of Time and Risk Preferences in Illegal Migration from Senegal." 7517. IZA Discussion Paper.

Balkan, Binnur, and Semih Tumen. 2016. "Immigration and Prices: Quasi-Experimental Evidence from Syrian Refugees in Turkey." *Journal of Population Economics* 29 (3): 657–86.

Barthel, Fabian, and Eric Neumayer. 2015. "Spatial Dependence in Asylum Migration." *Journal of Ethnic and Migration Studies* 41 (7): 1131–51.

Bauer, Thomas K, Sebastian Braun, and Michael Kvasnicka. 2013. "The Economic Integration of Forced Migrants: Evidence for Post-war Germany." *The Economic Journal* 123 (571): 998–1024.

Beine, Michel, Frédéric Docquier, and Çağlar Özden. 2011. "Diasporas." *Journal of Development Economics* 95 (1): 30–41.

Bertoli, Simone, and Jesús Fernández-Huertas Moraga. 2013. "Multilateral Resistance to Migration." *Journal of Development Economics* 102 (May): 79–100.

Borjas, George J. 1987. "Self-Selection and the Earnings of Immigrants." *National Bureau of Economic Research*.

———. 1994. "Ethnicity, Neighborhoods, and Human Capital Externalities." *American Economic Review* 85 (3): 365–90.

Borton, John, Emery Brusset, and Alistair Hallam. 1996. "The International Response to Conflict and Genocide: Lessons from the Rwanda Experience: Humanitarian Aid and Effects." Joint Evaluation of Emergency Assistance to Rwanda.

Bove, Vincenzo, and Tobias Böhmelt. 2016. "Does Immigration Induce Terrorism?" *The Journal of Politics* 78 (2): 572–88.

Braun, Sebastian, and Toman Omar Mahmoud. 2014. "The Employment Effects of Immigration: Evidence from the Mass Arrival of German Expellees in Postwar Germany." *The Journal of Economic History* 74 (1): 69–108.

Brekke, Jan-Paul, and Grete Brochmann. 2015. “Stuck in Transit: Secondary Migration of Asylum Seekers in Europe, National Differences, and the Dublin Regulation.” *Journal of Refugee Studies* 28 (2): 145–62.

Callen, Michael, Mohammad Isaqzadeh, James D Long, and Charles Sprenger. 2014. “Violence and Risk Preference: Experimental Evidence from Afghanistan.” *American Economic Review* 104 (1): 123–48.

Ceriani, Lidia, and Paolo Verme. 2018. “Risk Preferences and the Decision to Flee Conflict.” 8376. Policy Research Working Paper. The World Bank.

Charbonneau, Karyne B. 2014. “Multiple Fixed Effects in Binary Response Panel Data Models.” *The Econometrics Journal*.

Clauset A., M. E. J. Newman, and C. Moore (2004), "Finding community structure in very large networks," *Physical Review E*, 70, 066111.

Clemens, Michael A. 2014. “Does Development Reduce Migration.” In *International Handbook on Migration and Economic Development*, 152–85. Edward Elgar Publishing.

Cliff, A. D., and J. K. Ord (1981), *Spatial processes*, Pion.

Collyer, Michael, and Hein De Haas. 2012. “Developing Dynamic Categorisations of Transit Migration.” *Population, Space and Place* 18 (4): 468–81.

Cummings, Clare, Julia Pacitto, Diletta Lauro, and Marta Foresti. 2015. “Why People Move: Understanding the Drivers and Trends of Migration to Europe.” *London: Overseas Development Institute*.

Davis, K. F., P. D’Odorico,, F. Laio, and L. Ridolfi, (2013), “Global spatio-temporal patterns in human migration: a complex network perspective,” *PloS one*, 8(1), e53723.

Dolfin, Sarah, and Garance Genicot. 2010. “What Do Networks Do? The Role of Networks on Migration and ‘Coyote’ Use.” *Review of Development Economics* 14 (2): 343–59.

Dustmann, Christian, Francesco Fasani, Tommaso Frattini, Luigi Minale, and Uta Schönberg. 2017. “On the Economics and Politics of Refugee Migration.” *Economic Policy* 32 (91): 497–550.

Dustmann, Christian, Kristine Vasiljeva, and Anna Piil Damm. 2016. “Refugee Migration and Electoral Outcomes.” *CReAM DP* 19: 16.

European Commission 2017a Irregular Migration Via the Central Mediterranean: From Emergency Responses to Systemic Solutions. EPSC Strategic Notes, Issue 22. Available from https://ec.europa.eu/epsc/sites/epsc/files/strategic_note_issue_22_0.pdf.

European Commission (2017b) Migration on the Central Mediterranean: Managing Flows, Saving Lives. Joint Communication to the European Parliament, the European Council and the Council, 25 January. Available from https://ec.europa.eu/home-affairs/sites/homeaffairs/files/what-we-do/policies/european-agenda-migration/proposal-implementation-package/docs/20170125_migration_on_the_central_mediterranean_route_-_managing_flows_saving_lives_en.pdf.

Falck, O., S. Heblich, and S. Link. 2011. “The Evils of Forced Migration: Do Integration Policies Alleviate Migrants’ Economic Situations?” 5829. IZA Discussion Paper.

Fortunato, S. (2010), “Community detection in graphs,” *Physics reports*, 486(3-5), 75-174.

Friebel, Guido, and Sergei Guriev. 2013. “Human Smuggling.” In *International Handbook on the Economics of Migration*, edited by A. F. Constant and K. F. Zimmermann, 121–33. Edward Elgar.

Friebel, Guido, Miriam Manchin, Mariapia Mendola, and Giovanni Prarolo. 2017. “Human Smuggling and Intentions to Migrate: Global Evidence from a Supply Shock along Africa-to-Europe Migration Routes.”

Frouws, B. and C. Horwood 2017 Smuggled South. Danish Refugee Council and Regional Mixed Migration Secretariat (RMMS), March. Available from http://regionalmms.org/images/briefing/Smuggled_South.pdf)

Gathmann, Christina. 2008. “Effects of Enforcement on Illegal Markets: Evidence from Migrant Smuggling along the Southwestern Border.” *Journal of Public Economics* 92 (10–11): 1926–41.

Global Initiative against Transnational Organized Crime (2017). The Human Conveyor Belt.

Graham, Bryan S. 2015. “Methods of Identification in Social Networks.” *Annual Review of Economics* 7: 465–85.

Haas, H. De. 2011. “The Determinants of International Migration: Conceptualising Policy, Origin and Destination Effects.” 32. IMI/DEMIG Working Paper.

Hammersley, John M, and Peter Clifford. 1971. “Markov Fields on Finite Graphs and Lattices.”

Hanson, Gordon H, and Antonio Spilimbergo. 1999. “Illegal Immigration, Border Enforcement, and Relative Wages: Evidence from Apprehensions at the US-Mexico Border.” *American Economic Review* 89 (5): 1337–57.

Henderson, J Vernon, Adam Storeygard, and David N Weil. 2012. “Measuring Economic Growth from Outer Space.” *American Economic Review* 102 (2): 994–1028.

Ibáñez, Ana María, and Andrés Moya. 2010. “Vulnerability of Victims of Civil Conflicts: Empirical Evidence for the Displaced Population in Colombia.” *World Development* 38 (4): 647–63

IOM (2016d). The Central Mediterranean Route: Deadlier Than Ever. Data Briefing Series Issue No. 3. IOM GMDAC, Berlin. Available from https://publications.iom.int/system/files/pdf/gmdac_data_briefing_series_issue3.pdf.)

IOM 2017 Missing Migrants Project. Latest Global Figures. International Organization for Migration, Geneva. Available from ttps://missingmigrants.iom.int/latestglobal-figures

IOM (2017b). World Migration Report 2018. International Organization for Migration, Geneva.

IOM (2017c) *Analysis: Flow Monitoring Surveys. The Human Trafficking and Other Exploitative Practices Prevalence Indication.* International Organization for Migration, Geneva.

Jackson, Matthew O. 2010. *Social and Economic Networks*. Princeton: Princeton University Press.

Kondylis, Florence. 2008. “Agricultural Outputs and Conflict Displacement: Evidence from a Policy Intervention in Rwanda.” *Economic Development and Cultural Change* 57 (1): 31–66.

Krivitsky, Pavel N, and Mark S Handcock. 2014. “A Separable Model for Dynamic Networks.” *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 76 (1): 29–46.

Leone Sciabolazza, Valerio. 2018. “A Net of Moving People: Network Analysis of International Migration Flows.” In *Networks of International Trade and Investment*, edited by A. Amighini, S. Gorgoni, and Smith M., Vernon Pre.

Lergetporer, Philipp, Marc Piopiunik, and Lisa Simon. 2018. “Do Natives’ Beliefs About Refugees’ Education Level Affect Attitudes Toward Refugees? Evidence from a Randomized Survey Experiments.” 6832. CESifo Working Paper Series.

Lusher, Dean, Johan Koskinen, and Garry Robins. 2012. *Exponential Random Graph Models for Social Networks: Theory, Methods, and Applications*. Cambridge University Press.

Manchin, Miriam, and Sultan Orazbayev. 2018. “Social Networks and the Intention to Migrate.” *World Development* 109: 360–74.

Marshall, Monty G., and Gabrielle Elzinga-Marshall. 2017. “Global Report 2017: Conflict, Governance, and State Fragility.”

Maystadt, Jean-François, and Philip Verwimp. 2014. “Winners and Losers among a Refugee-Hosting Population.” *Economic Development and Cultural Change* 62 (4): 769–809.

Micallef, Mark. 2017. “The Human Conveyor Belt: Human Smuggling and Trafficking in Post-Revolution Libya.” *Global Initiative against Transnational Organised Crime*.

Michalopoulos, Stelios, and Elias Papaioannou. 2013. “Pre-colonial Ethnic Institutions and Contemporary African Development.” *Econometrica* 81 (1): 113–52.

Mixed Migration Hub 2015 Detained Youth: The Fate of Young Migrants, Asylum-Seekers and Refugees in Libya Today. Study 1, July 2015. MHUB. Available from www.mixedmigrationhub.org/wp-content/uploads/2015/07/MHUB_2015_Detained-Youth_Exec-Summary_EN.pdf

Moran, P. A. P. (1950), “Notes on Continuous Stochastic Phenomena,” *Biometrika*, 37 (1), pp. 17–23.

Ortega, Francesc, and Giovanni Peri. 2012. “The Role of Income and Immigration Policies in Attracting International Migrants.” *IZA Discussion Paper*, no. 6655.

Otto, Alkis Henri, and Max Friedrich Steinhardt. 2014. “Immigration and Election Outcomes—Evidence from City Districts in Hamburg.” *Regional Science and Urban Economics* 45: 67–79.

Peres, M., H. Xu, and G. Wu (2016), “Community Evolution in International Migration Top1 Networks,” *PloS one*, 11(2), e0148615.

Raleigh, Clionadh, Andrew Linke, Håvard Hegre, and Joakim Karlsen. 2010. “Introducing ACLED: An Armed Conflict Location and Event Dataset: Special Data Feature.” *Journal of Peace Research* 47 (5): 651–60.

Reichardt J., and Bornholdt S. (2006), “Statistical Mechanics of Community Detection,” *Physical Review E*, 74, 016110.

Robins, Garry, Pip Pattison, Yuval Kalish, and Dean Lusher. 2007. “An Introduction to Exponential Random Graph (P*) Models for Social Networks.” *Social Networks* 29 (2): 173–91.

Ruiz, Isabel, and Carlos Vargas-Silva. 2013. “The Economics of Forced Migration.” *The Journal of Development Studies* 49 (6): 772–84.

Sarvimäki, M., R. Uusitalo, and M. Jäntti. 2009. “Long-Term Effects of Forced Migration.” 4003. IZA

Discussion Paper.

Sekeris, Petros, and Chrysovalantis Vasilakis. 2016. "The Mediterranean Refugees Crisis and Extreme Right Parties: Evidence from Greece." 72222. MPRA Paper.

Skillikorn, David B, and Olivier J Walther. 2017. "Spatial and Temporal Diffusion of Political Violence in North and West Africa." In *African Border Disorders*, edited by Olivier J. Walther and William F.S. Miles, 107–32. Routledge.

Steinmayr, A., Ana María Ibáñez, Andrés Moya, Florence Kondylis, Christian Dustmann, Kristine Vasiljeva, Anna Piil Damm, Jean-François Maystadt, and Philip Verwimp. 2016. "Exposure to Refugees and Voting for the Far-Right: (Unexpected) Results from Austria." *CReAM DP*, IZA Discussion Paper, 38 (4): 31–66.

Trémolières, Marie, and Olivier Walther. 2017. *Cross-Border Co-Operation and Policy Networks in West Africa*. OECD Publishing.

Tumen, Semih. 2016. "The Economic Impact of Syrian Refugees on Host Countries: Quasi-Experimental Evidence from Turkey." *American Economic Review* 106 (5): 456–60.

UN DESA 2015 *International Migrant Stock: The 2015 Revision*. United Nations, New York. United Nations Department of Economic and Social Affairs. Available from www.un.org/en/development/desa/population/migration/data/estimates2/index.shtml.

UN DESA, 2015. Datasets. United Nations Department of Economic and Social Affairs. Available from www.un.org/en/development/desa/population/migration/data/estimates2/estimates15.shtml (i.e. Figure 3. Estimated regional migration flows, 2010–2015

UN DESA 2016. *International Migration Report 2015*. United Nations Department of Economic and Social Affairs Available from www.un.org/en/development/desa/population/migration/publications/migrationreport/docs/MigrationReport2015_Highlights.pdf.

UNHCR. 2017. "UNHCR Statistical Online Population Database." UNHCR Geneva. http://popstats.unhcr.org.

UNHCR 2017a Global Trends: Forced Displacement in 2016. UNHCR, Geneva. Available from www.unhcr.org/5943e8a34

UNHCR 2017d Desperate Journeys: Refugees and Migrants Entering and Crossing Europe via the Mediterranean and Western Balkan Routes. UNHCR Bureau for Europe. Available from www.unhcr.org/58b449f54.pdf.

UNHCR, 2018. Mixed Migration Trends in Libya.

UNHRC (2018b). *Global Focus.* United Nations Human Rights Council. Geneva, Switzerland

Upton, G., and B. Fingleton (1985), *Spatial data analysis by example: point pattern and quatitative data*, Wiley.

Van der Loo, M. P. J. (2014), "The stringdist package for approximate string matching," *The R Journal*, 6(1): 111-122.

Voors, Maarten J, Eleonora E M Nillesen, Philip Verwimp, Erwin H Bulte, Robert Lensink, and Daan P Van Soest. 2012. "Violent Conflict and Behavior: A Field Experiment in Burundi." *American Economic Review* 102 (2): 941–64.

Walther, Olivier J. 2017. “Wars and Conflicts in the Sahara-Sahel.” 10. OECD West African Papers.

Whitaker, Beth Elise. 1999. *Changing Opportunities: Refugees and Host Communities in Western Tanzania*. Centre for Documentation and Research, United Nations High Commissioner for Refugees.

World Bank (2018). Asylum seeker in the European Union: Building Evidence for Policy Making. Washington D.C

Tables

Table 1: International migrants in Libya (2000 and 2017)

Number of international migrants (thousands)		International migrants percentage of total population		Females among international migrants (percentage)		Median age of international migrants (years)	
2000	2017	2000	2017	2000	2017	2000	2017
567	788	10.6	12.4	35.0	28.8	29.6	32.2

Source: International Migration Report 2018 (Highlights).

Table 2: 5 most recurrent top 1 nationalities registered in a FMP

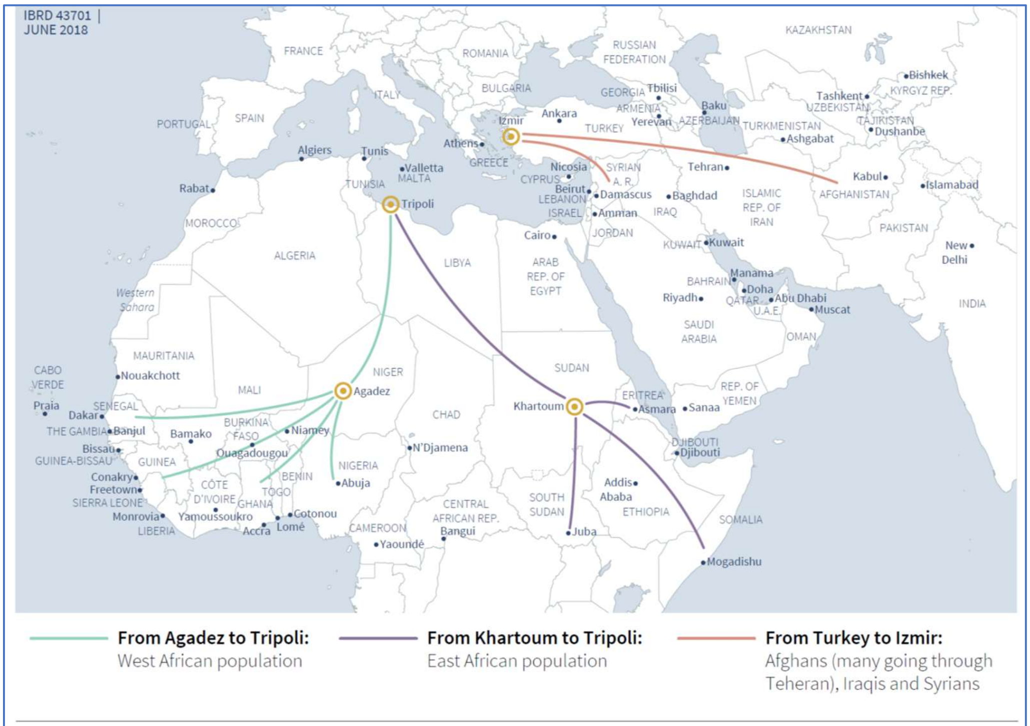
2017	**2018**
Egypt	Egypt
Niger	Niger
Nigeria	Sudan
Sudan	Nigeria
Chad	Chad

Table 3: 5 most recurrent preferred arrival destinations registered in a FMP

2017	**2018**
Libya	Libya
Italy	Italy
Germany	France
France	Germany
Egypt	Egypt

Figures

Figure 1: The three main asylum seekers routes to the EU



Source: Data from the EASS 2017.

Figure 2: Map of Flow Monitoring Points (FMPs)

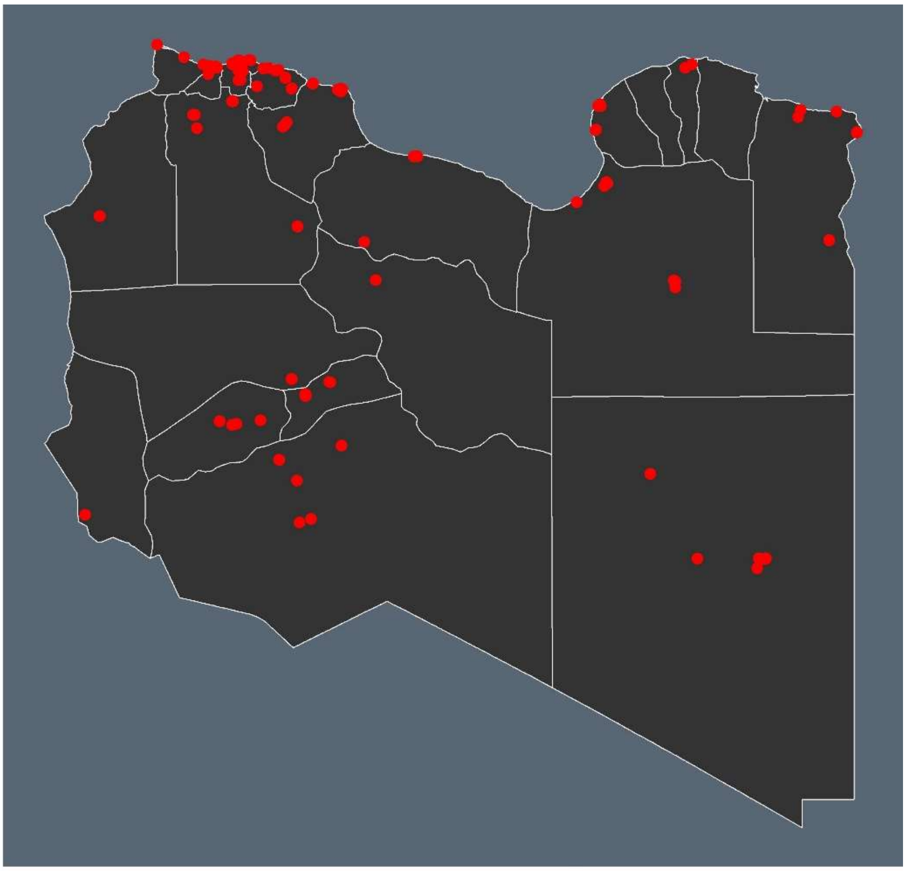


Figure 3: Map of Libyan Provinces

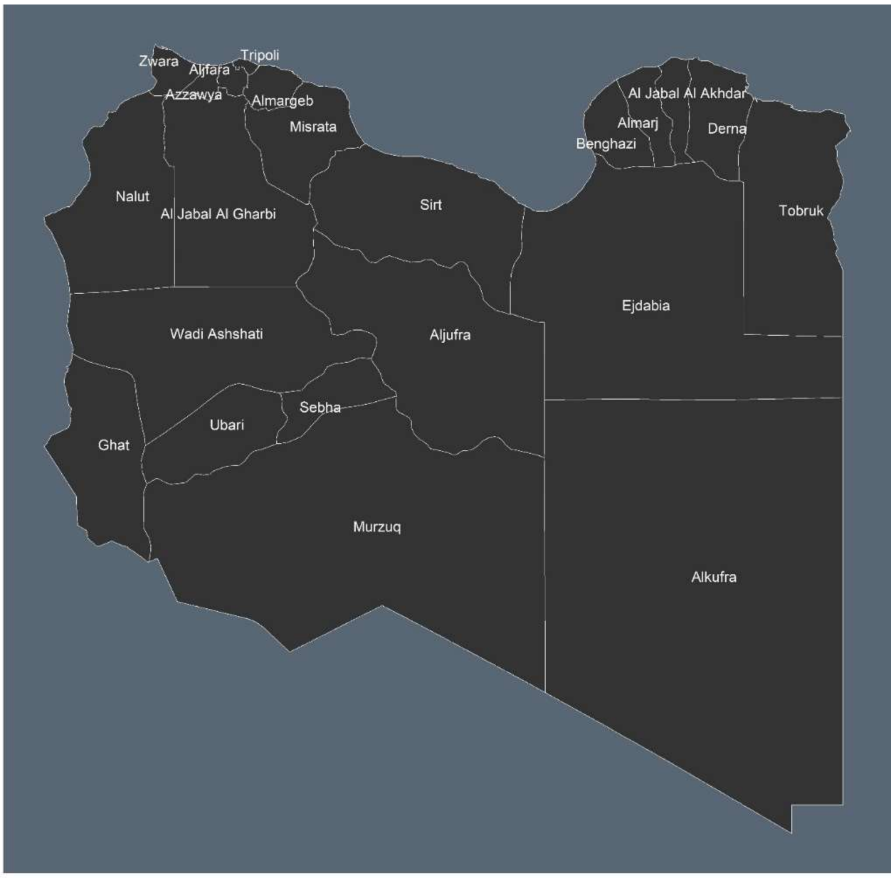
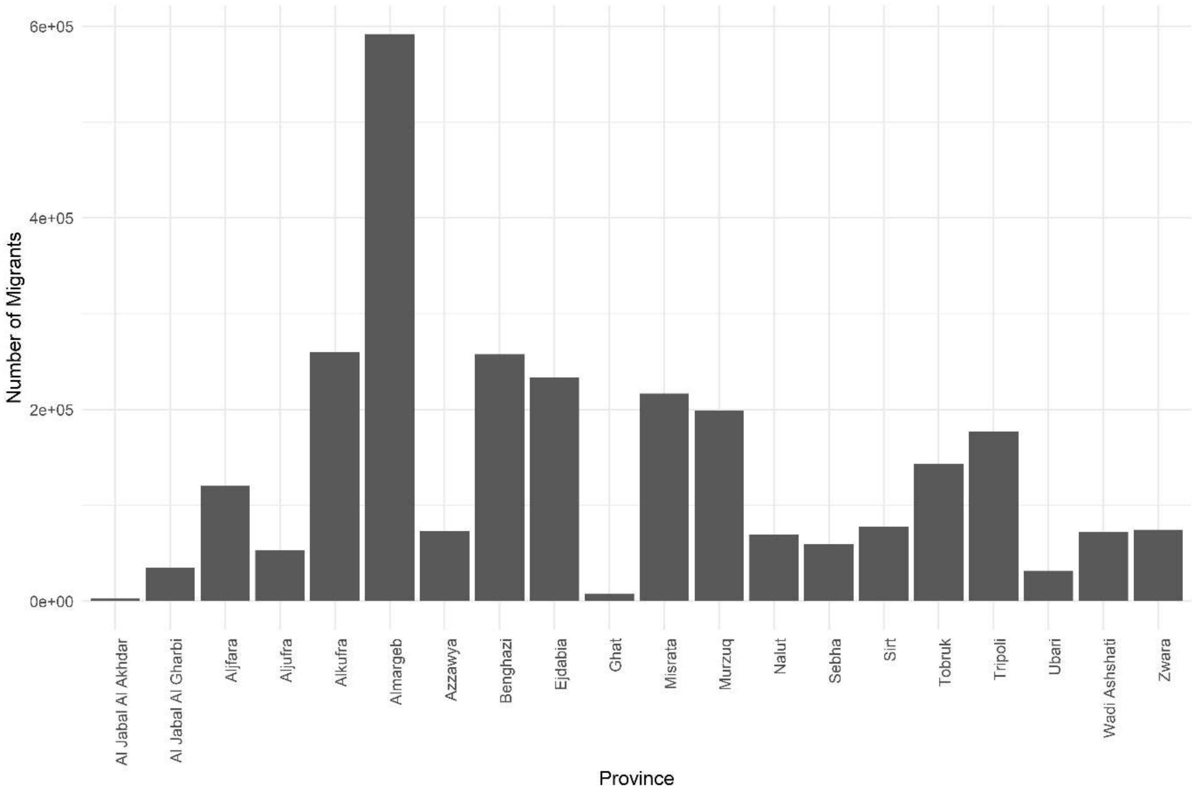


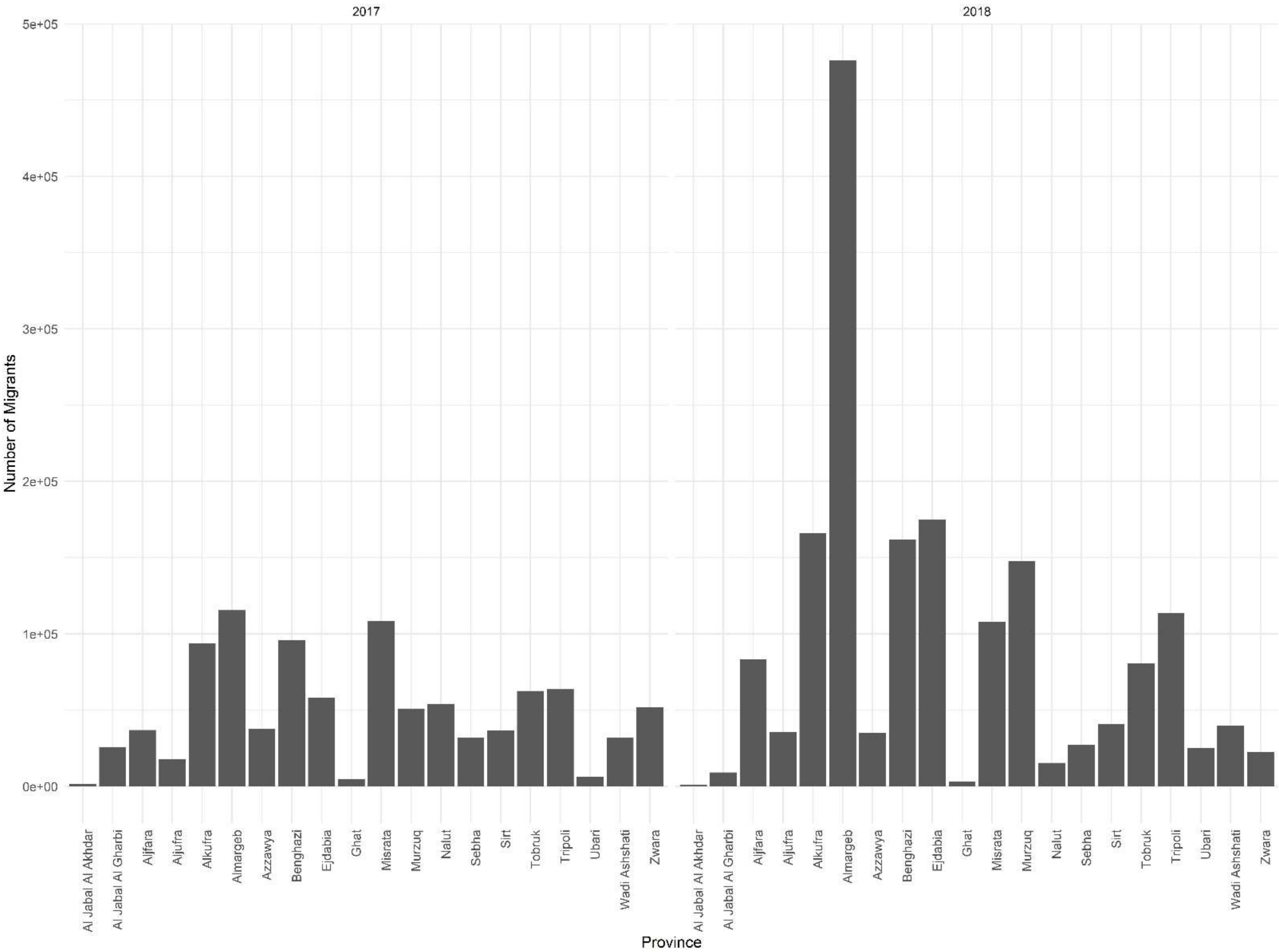
Figure 4: Number of Migrants

Figure 4 a: Number of Migrants registered in the FMPs (all rounds 2017 and 2018)



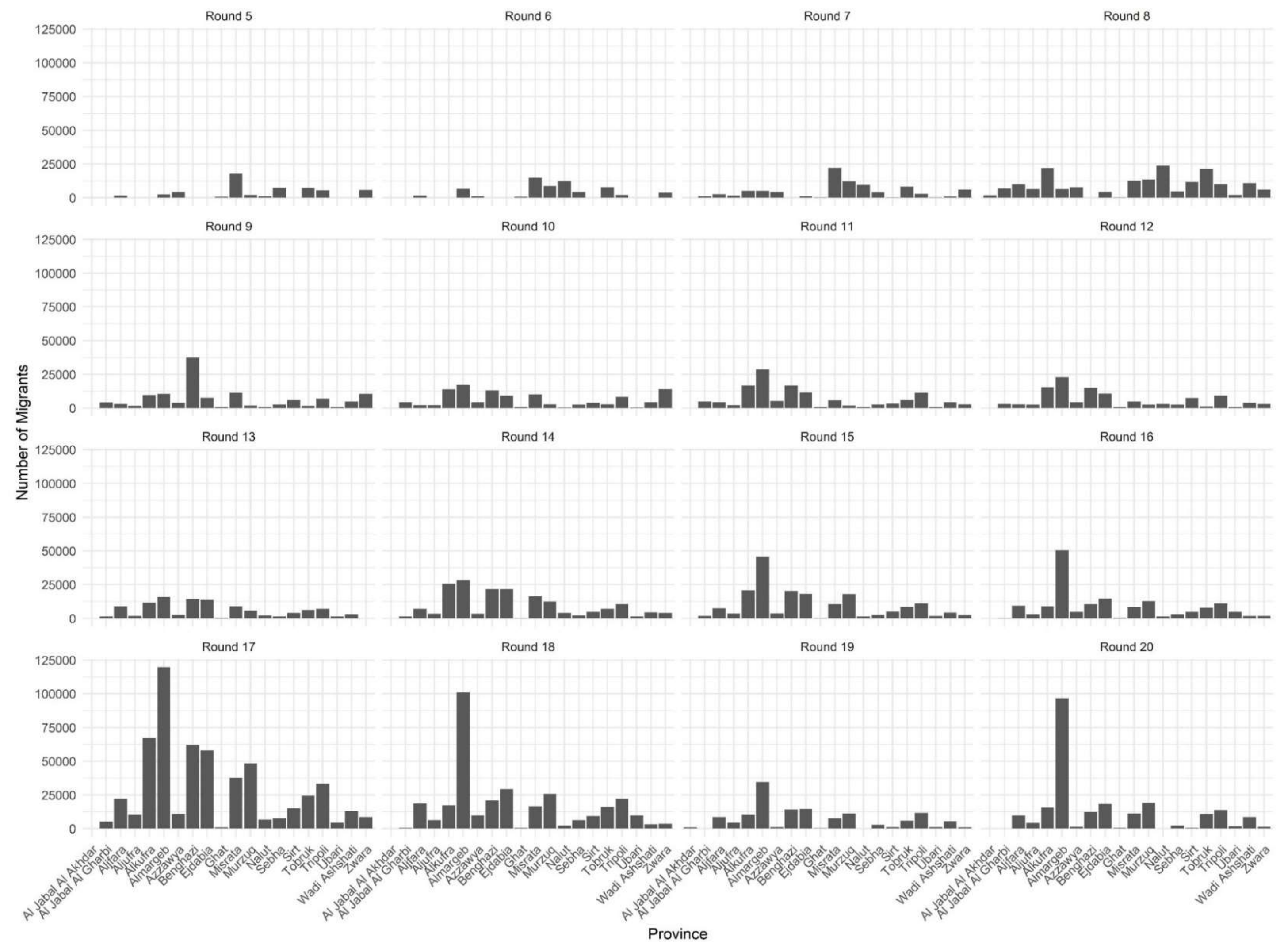
Note: bars indicate the number of migrants in Libyan provinces in all rounds Souce: IOM.

Figure 4 b: Number of Migrants registered in the FMPs – by year and by province



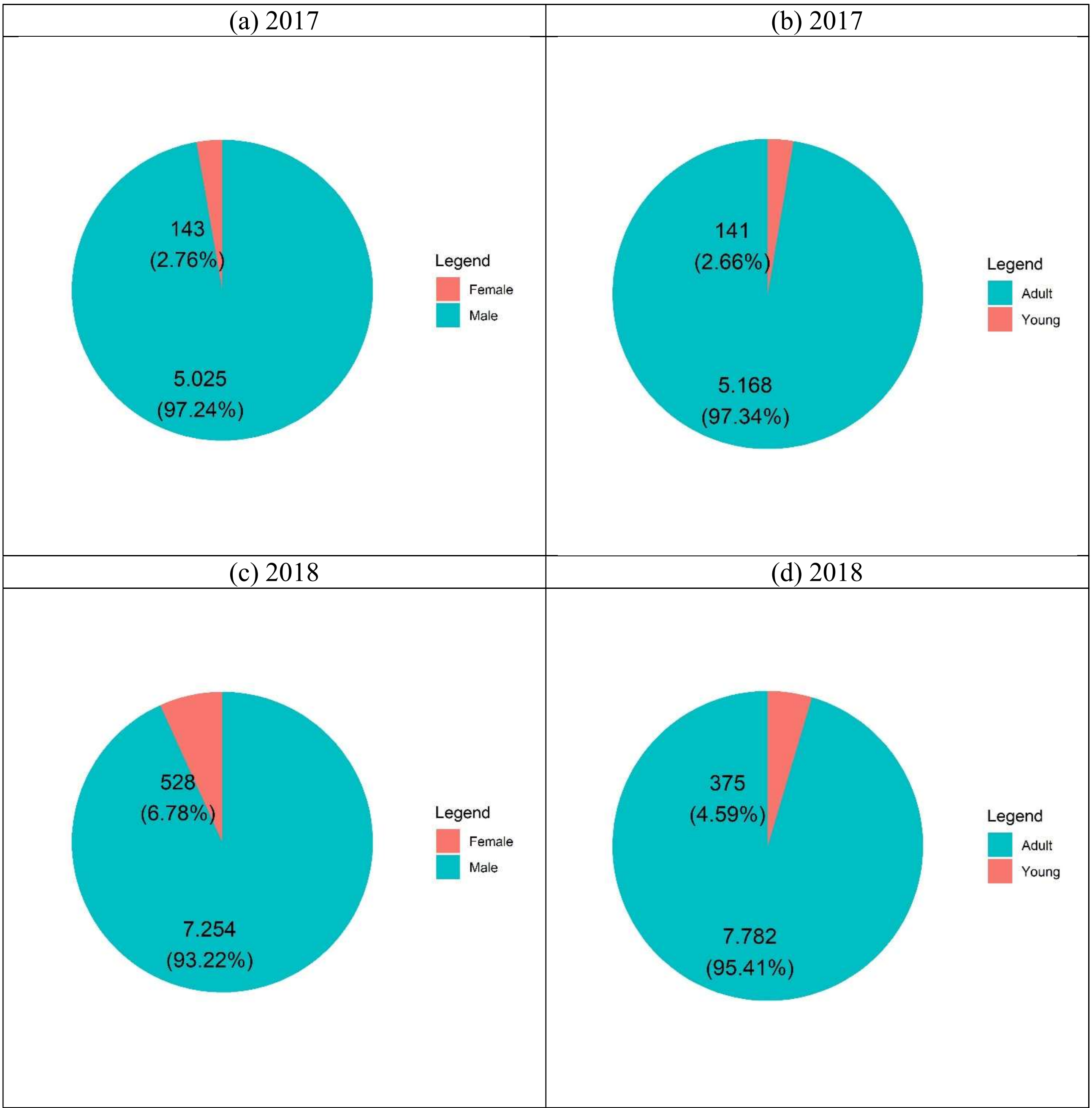
Note: bars indicate the number of migrants in Libyan provinces in 2017 (left panel) and 2018 (right panel). Source IOM

Figure 4 c: Number of Migrants registered in the FMPs – by round and by province



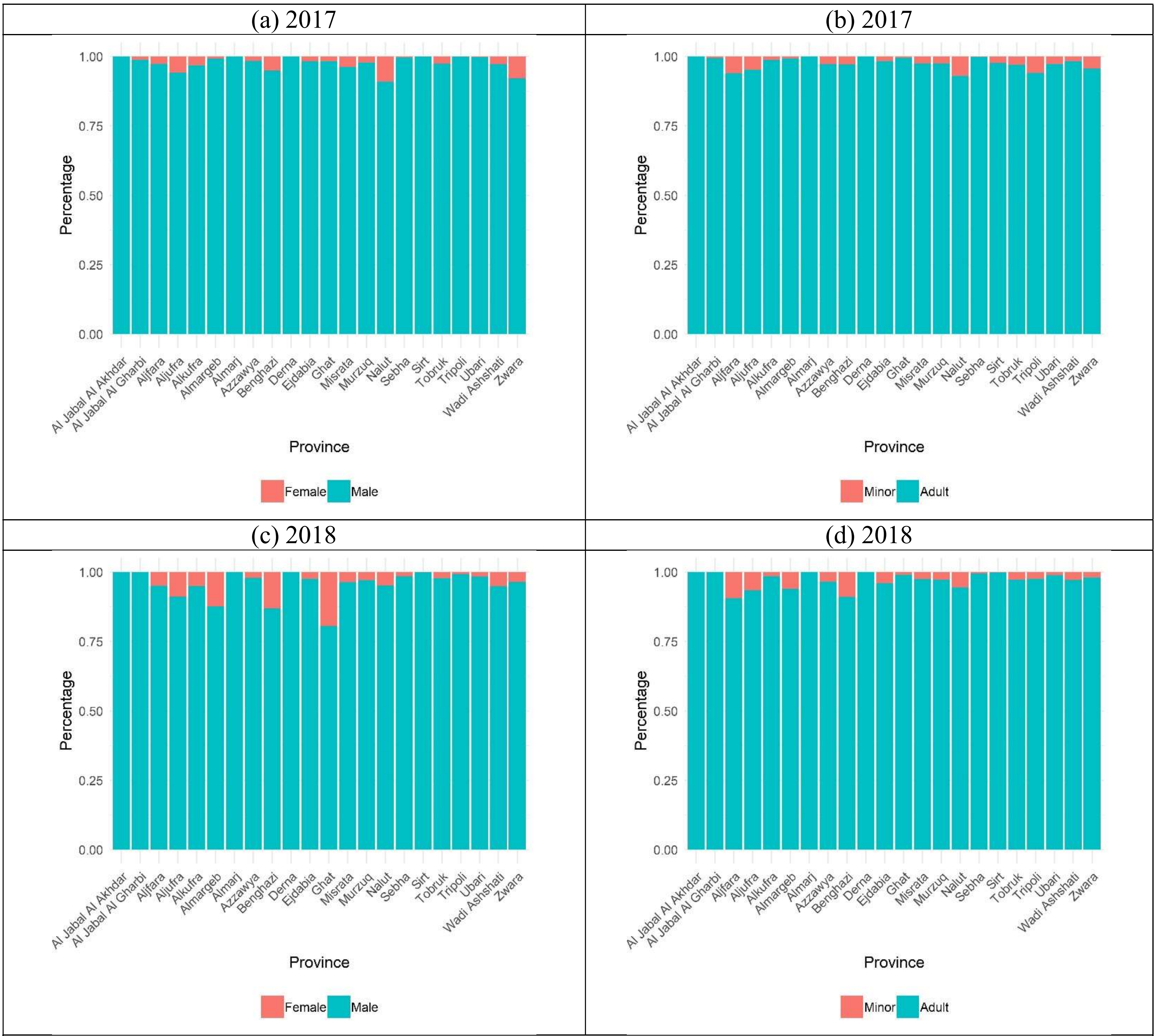
Note: For each round, bars indicate the number of migrants in Libyan provinces. Source IOM.

Figure 5: Demographic Composition of Migrants



Note: pie slices indicate the percentage of of males and females (panel a and c) or minors and adults (panel b and d) in Libya, respectively in 2017 (panel a and b) and in 2018 (panel b and c). Displayed results are yearly averages of monthly data. Source: IOM.

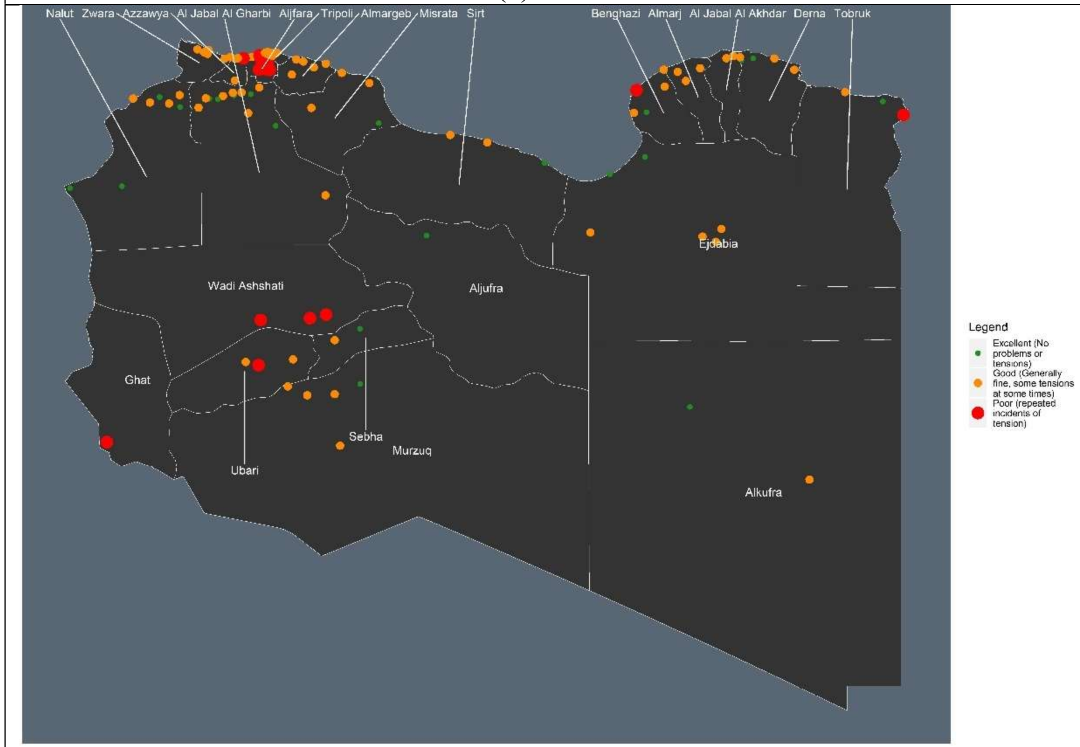
Figure 6: Demographic Composition of Migrants by Province



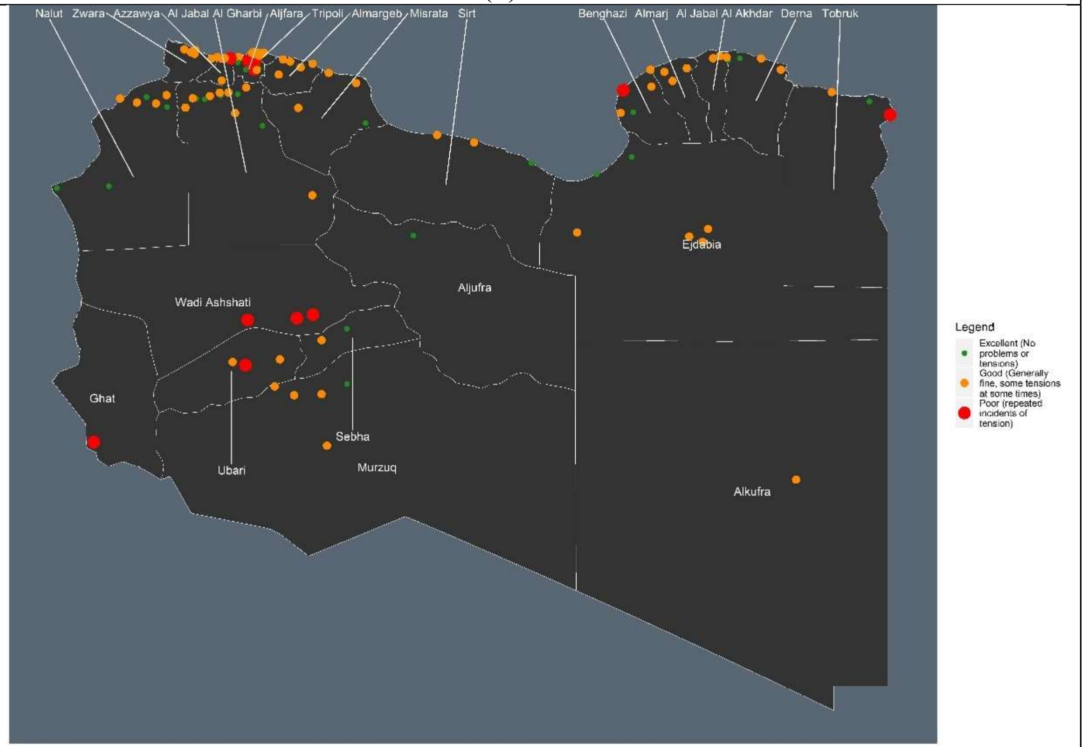
Note: Bars indicate the percentage of males and females (panel a and c) or minors and adults (panel b and d) in Libyan provinces, respectively in 2017 (panel a and b) and in 2018 (panel b and c). Displayed results are yearly averages of monthly data. Source: IOM.

Figure 7: Relation with host community

(a) 2017



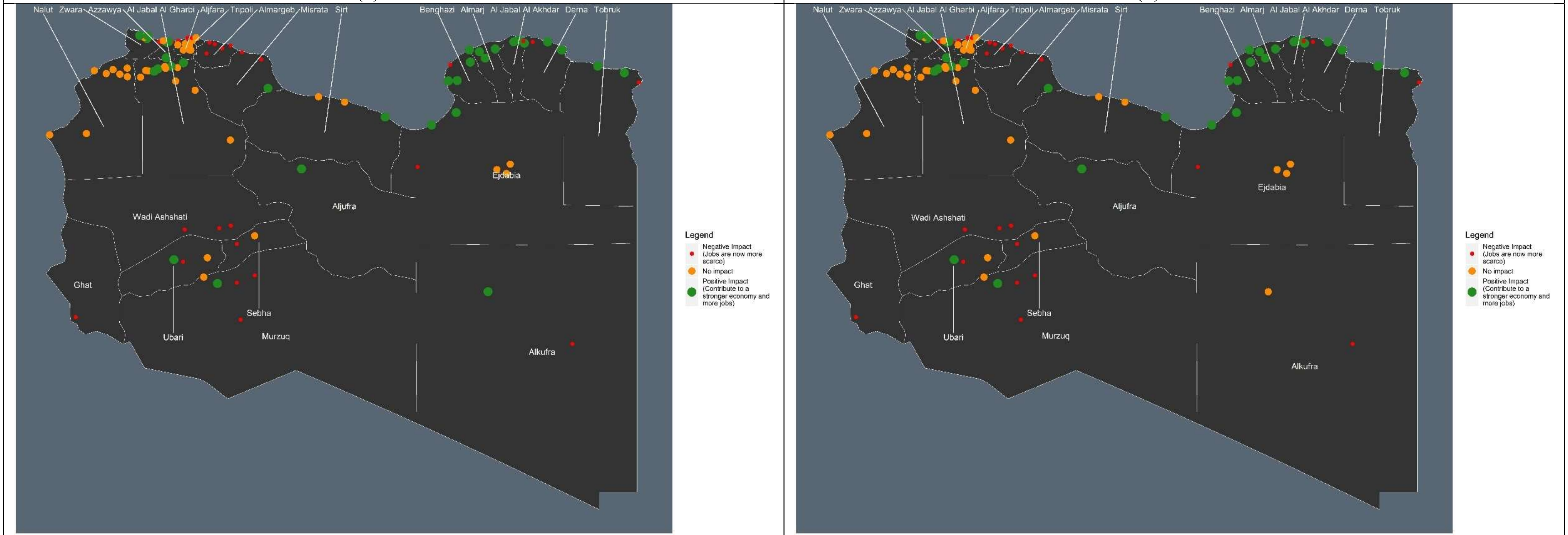
(b) 2018



Note: Dots are used to identify Libyans municipalities. The color and the size indicate the most recurrent observation registered in the municipality a given year.

Figure 8: Impact on labor market

(a) 2017 | (b) 2018



Note: Dots are used to identify Libyans municipalities. The color and the size indicate the most recurrent observation registered in the municipality in a given year.

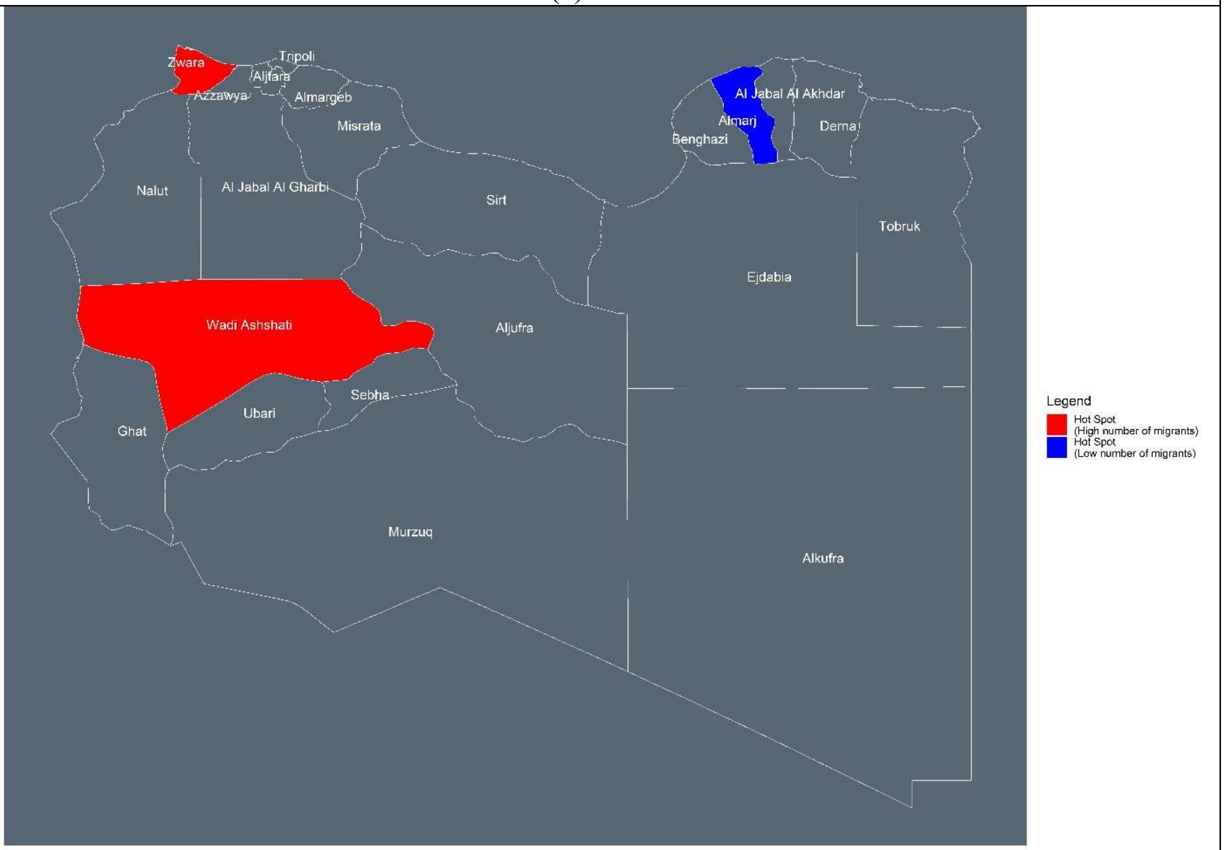
Figure 9: Impact on public services

(a) 2017	(b) 2018

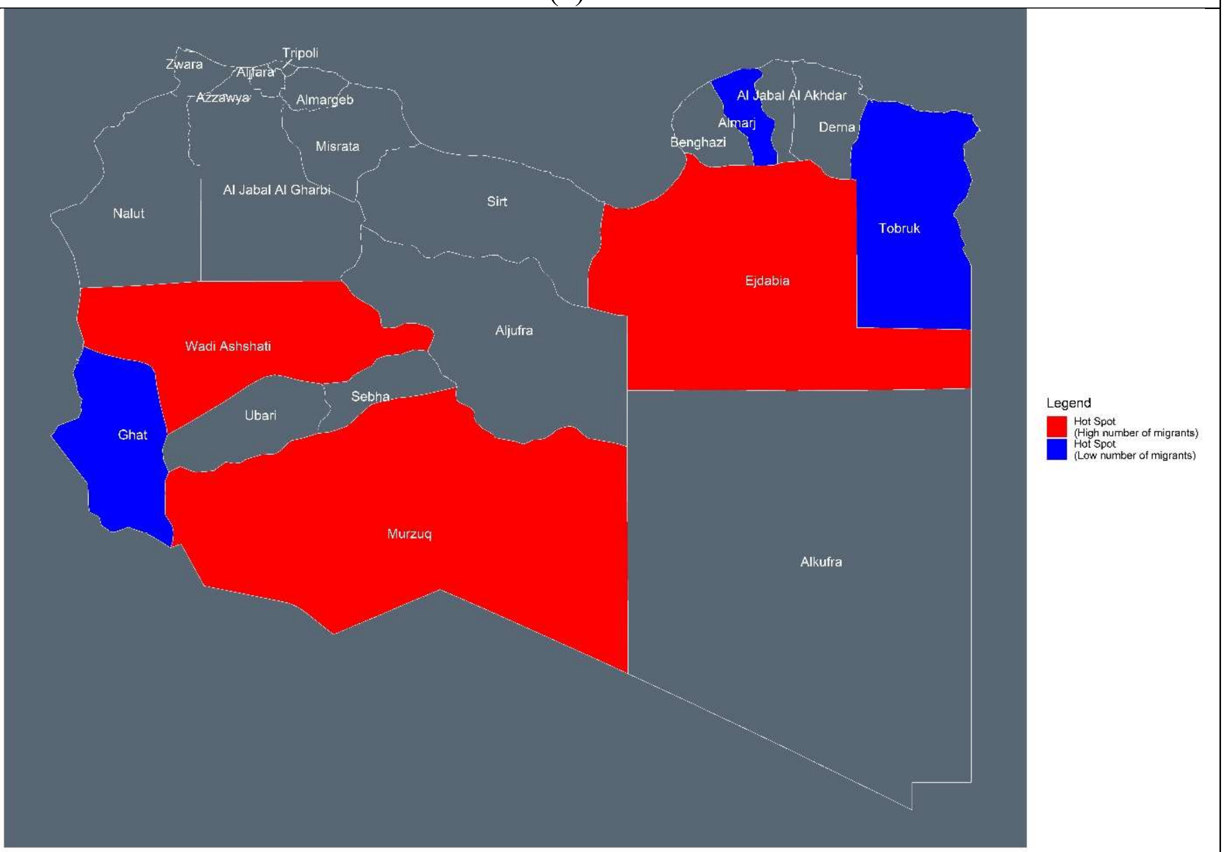
Note: Dots are used to identify Libyans municipalities. The color and the size indicate the most recurrent observation registered in the municipality in a given year.

Figure 10: Hotspot provinces

(a) 2017



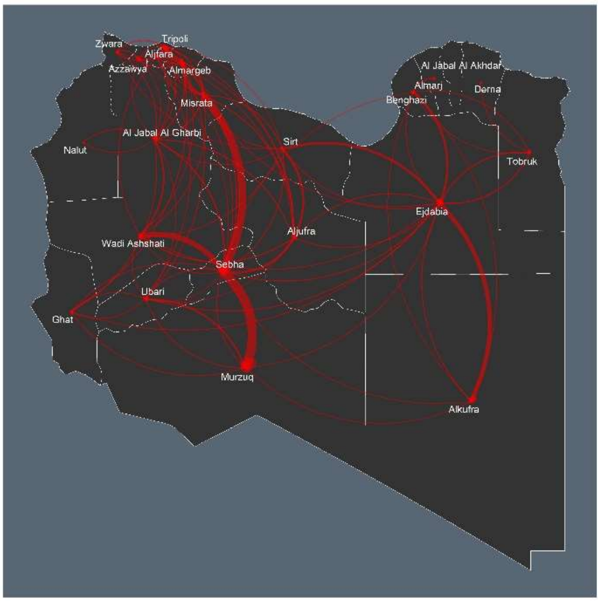
(b) 2018



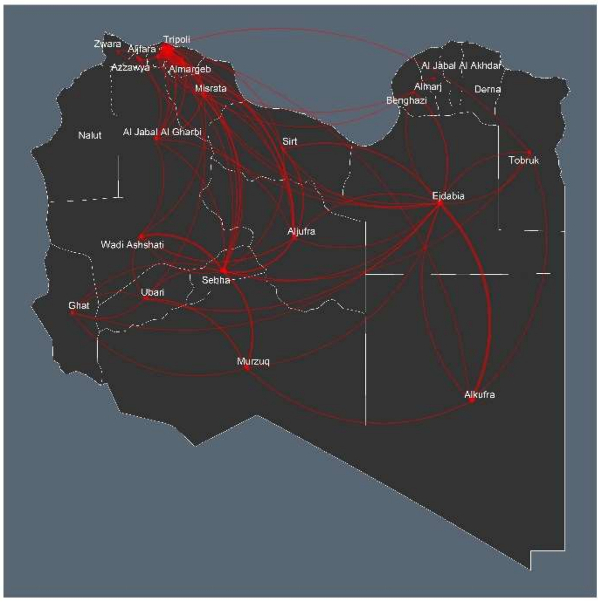
Note: Provinces with a high/low number of migrants adjacent to provinces with a low/high number of migrants are indicated in red/blue.

Figure 11: Network of migrants' movements within Libya

(a) 2017



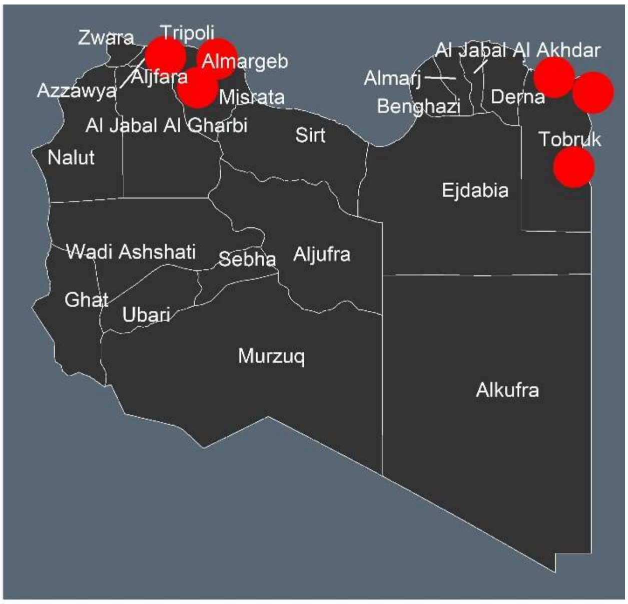
(b) 2018



Note: each link indicates a movement from a FMP located in province *i* to a FMP located in province *j*. The width of the link is proportional to the number of people who moved from one province to the other in 2017 (panel a) and in 2018 (panel b).

Figure 12: Clustered movements of same-origin migrants

Country of origin Egypt (January 2017)



Country of origin Ethiopia – July 2017

Country of origin Benin (August 2017)

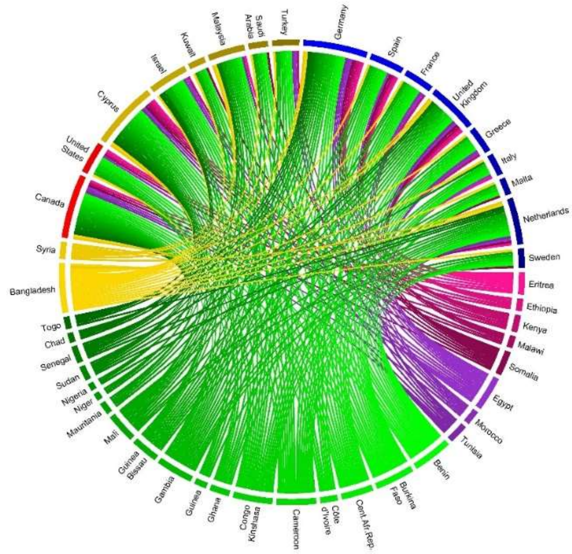
Country of origin Eritrea (August 2017)

Country of origin Bangladesh (January 2018)

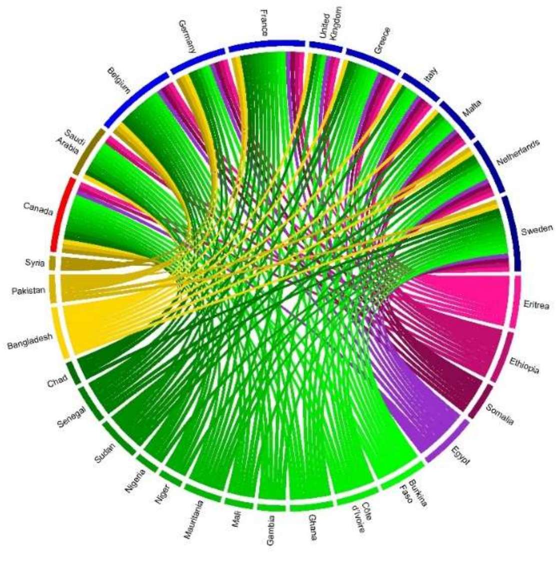

Zwara
Tripoli
Almargeb
Al Jabal Al Akhdar
Azzawya
Aljfara
Almarj
Misrata
Derna
Benghazi
Al Jabal Al Gharbi
Nalut
Sirt
Tobruk
Ejdabia
Aljufra
Wadi Ashshati
Sebha
Ghat
Ubari
Murzuq
Alkufra

Figure 13: the backbone of the Libyan migration network

(a) 2017



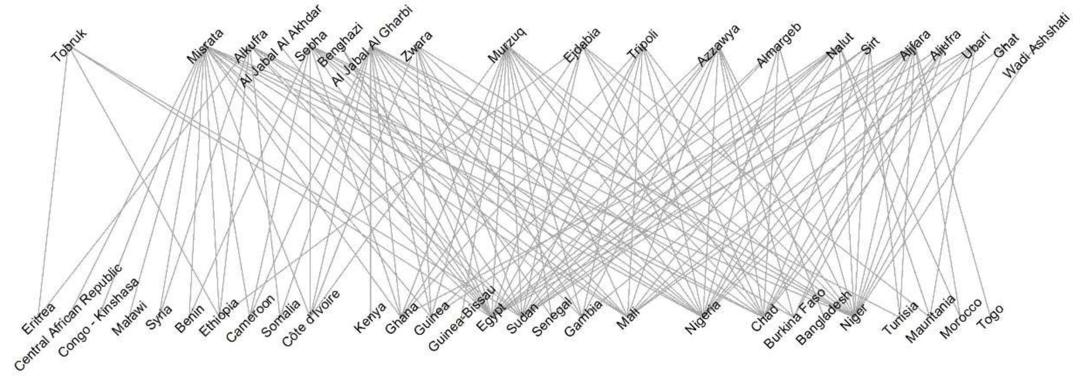
(b) 2018



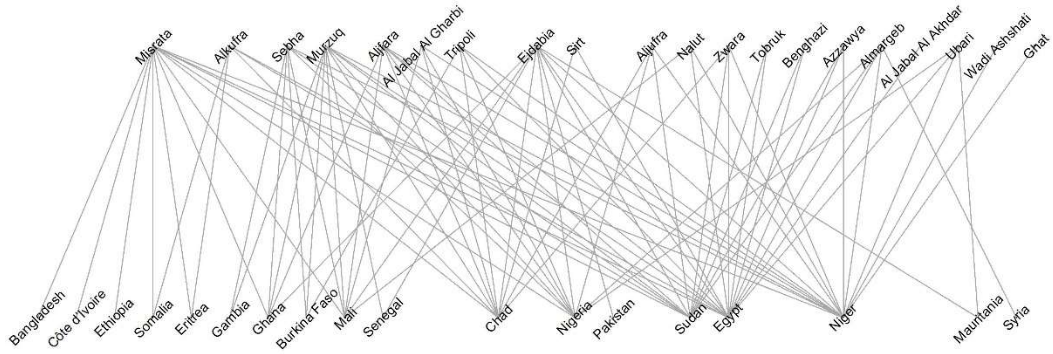
Note: circles segments represent the origins and destinations of migration flows. The direction of the flow is encoded both by the origin colour and by the gap between link and circle segment at the destination. The size of the segments indicates the total amount of incoming and outcoming flows in one country. Similar hues of colors are used for countries located in nearby regions: i.e. pink for East Africa, violet for North Africa, Green for West Africa, yellow for Asia, red for Americas, blue for Europe, and grey for Oceania.

Figure 14: Origin countries

2017 – Top 1 origin countries



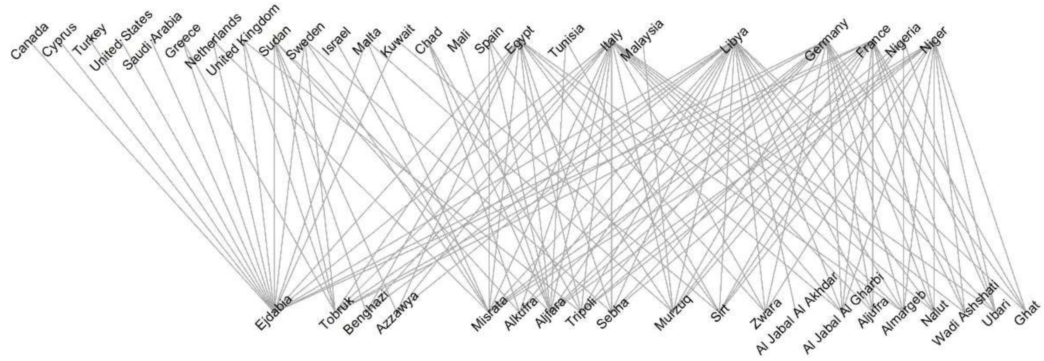
2018 – Top 1 origin countries



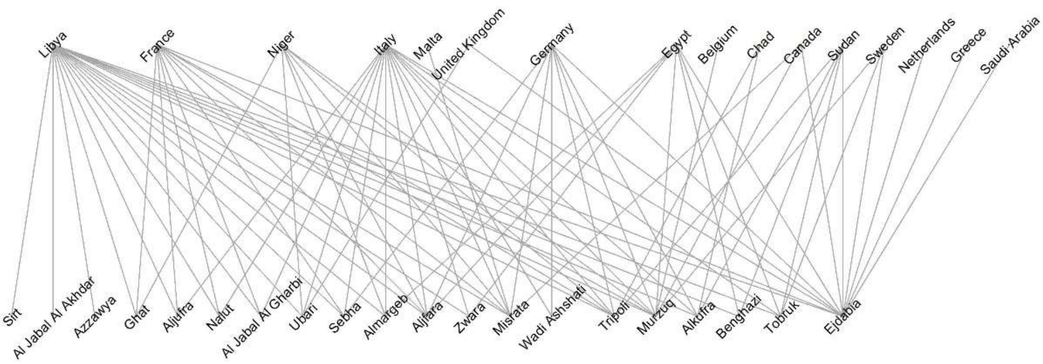
Note: A connection is drawn between a country name and a Libyan province when - at least for once - migrants found in the FMPs of said province mainly belongs to that country (connections on the bottom of the plot. Panel (a) and (b) aggregates this information for respectively 2017 and 2018.

Figure 15: Receiving countries

2017 – Top 1 receiving countries



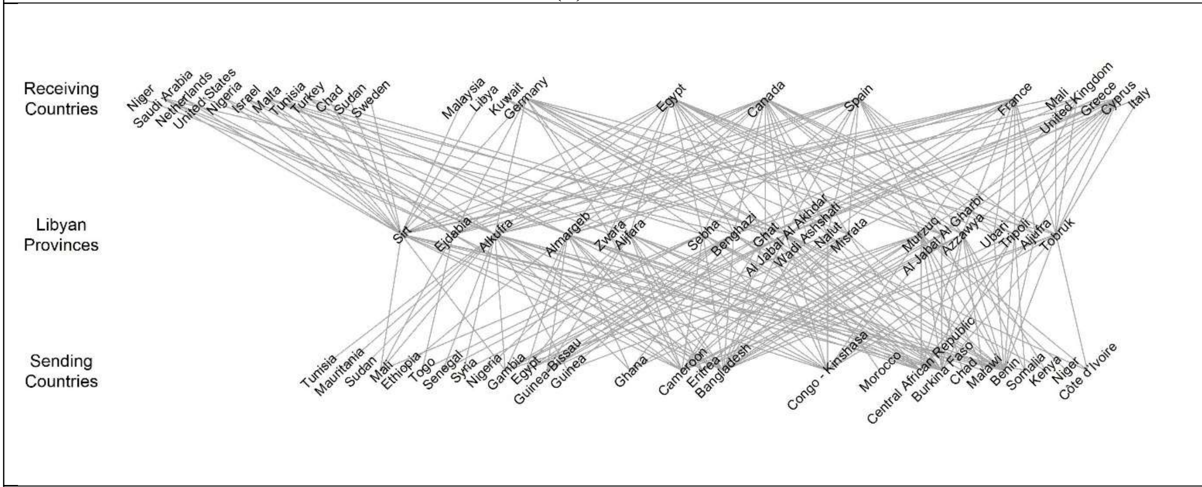
2018 – Top 1 receiving countries



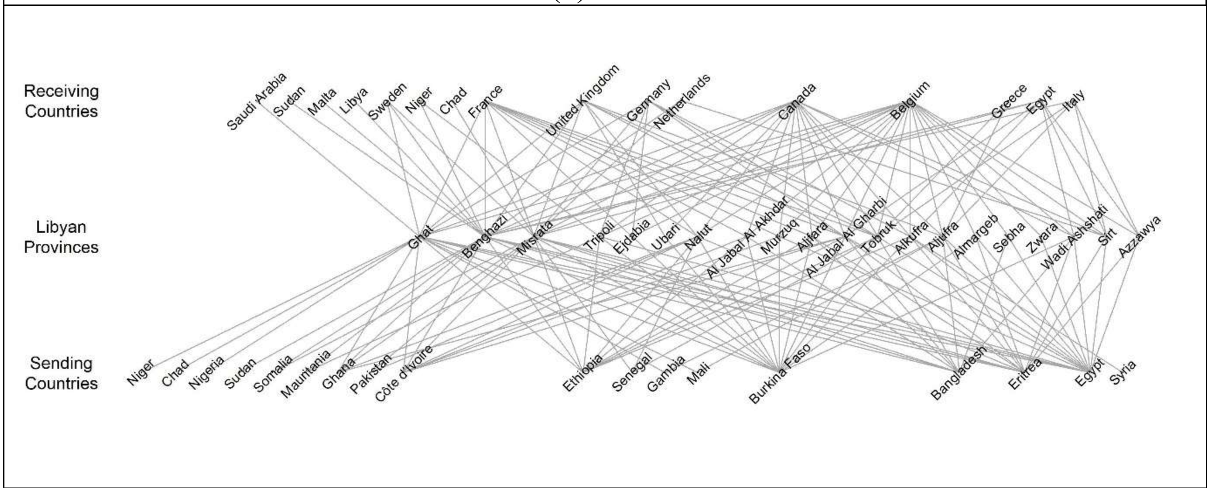
Note: A connection is drawn between a country name and a Libyan province when - at least for once - migrants found in the FMPs of said province have a major preference for moving towards that country. Panel (a) and (b) aggregates this information for respectively 2017 and 2018.

Figure 16: Libyan top in and out coming migration flows

(a) 2017

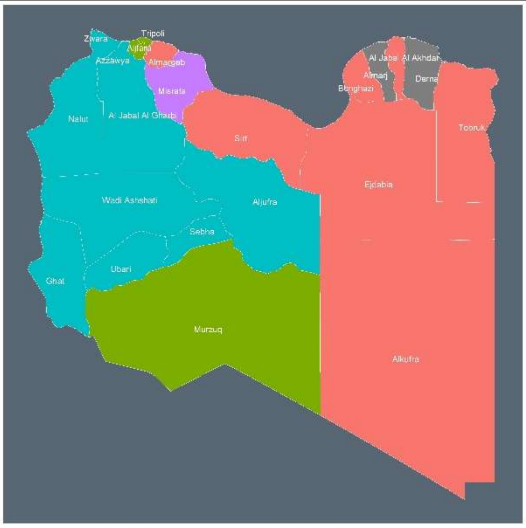
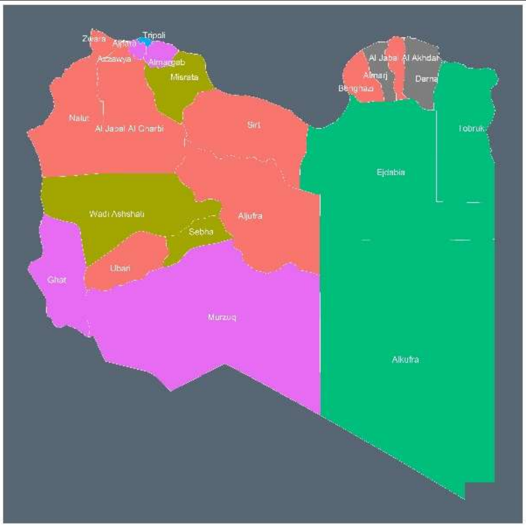


(b) 2018



Note: A connection is drawn between a country name and a Libyan province when - at least for once - migrants found in the FMPs of said province mainly belongs to that country (connections on the bottom of the plot), or they have a major preference for moving towards that country (connections on the top of the plot). Panel (a) and (b) aggregates this information for respectively 2017 and 2018.

Figure 17: Spatial distribution of Libyan migration network communities – Libyan provinces

<table>
<tr><td>(a) 2017</td><td>(b) 2018</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td colspan="2">Note: all provinces denoted with the same colors belongs to the same network community. The color grey is used to identify the provinces for which data was not available.</td></tr>
</table>

Appendixes

A.1 Data cleaning and geo-processing of the data

The spatial analysis performed in this paper required to exactly pinpoint the location of FMPs and municipalities within a province, and associate a longitude and a latitude to them. Unfortunately, raw data were often corrupt or inaccurate, and it required an intense process of data cleaning.

Many are the issues that had to be solved. Each location was not uniquely associated to a Muhazafat (the first-level administration subdivision of Libya), a Baladiyah (the second-level administration subdivision of Libya), and a Muhalla (the third-level administration subdivision of Libya). Some records reported only the location name. Because of well-known problems of transliterations of Arabic to Latin characters, an effort was required to disambiguate those names and match them across different rounds. Finally, many records were only associated to a pair of coordinates, and it was necessary to associate these coordinates to the name of the location to which they referred, in order to match the record with the records reporting only the location name. To complicate things, sometimes coordinates were incorrectly reported: latitude and longitude were either inverted, or they had the same value.

When the records only reported the name of the location, a disambiguation process combining text analysis, network analysis, and manual disambiguation was used in order to correctly associate each location to the name of its administrative subdivisions, and match FMP names across different rounds. Specifically, data processing required the following steps. First, each Muhazafat name found in the dataset was paired with all the other Muhazafat names recorded in the data. Second, each pair of names was compared by using different metrics of string distance made available by the R package *stringdist*: namely full and restricted Damerau-Levenshtein distance, Hamming distance, Q-gram distance, Cosine distance, Jaccard distance, Jaro-Winker Distance, and Longest common substring distance.[30] Third, each Muhazafat name *i* was associated to the Muhazafat name *j* for which the majority of the distance metrics reported the minimum string distance. We refer to the matches resulting from this third step as *temporary matchings*. Fourth, a network was created where nodes are Muhazafat names, and a link between the Muhazafat name *i* and *j* signals that a *temporary matching* was found between them. Fifth, each network component - i.e. a subset of nodes connected to each other, and not connected with the rest of the network – was extracted to be separately examined. Sixth, names within a component embedded in a triangle (i.e. name *i*, *j*, and *k* were mutually connected) were assigned to the same ID. All names left without an ID after this process were manually checked. When a plausible matching was

[30] See for an extensive review of this methods Van der Loo (2014).

found between a name without ID and a name with an ID, the former was associated to the ID of the latter. Alternatively, it was assigned to a new ID.

The same process was then applied to disambiguate Baladiyah names, using an additional rule in the creation of the network of *temporary matchings* (step four): a link between the Baladiyah name *i* and *j* was drawn if a *temporary matching* between them was found, and if they were associated to the same Muhazafat. In the same fashion, also Muhalla names were disambiguated. In this case, a new rule was imposed in the creation of the network of *temporary matchings*: a link between the Muhalla name *i* and *j* was drawn if a *temporary matching* between them was found, and if they were associated to the same Muhazafat and Baladiyah. Finally, the disambiguation method was used to match FMP names. This time, the creation of the network of *temporary matchings* required that a link between the FMP names *i* and *j* was drawn if a *temporary matching* between them was found, and if they were associated to the same Muhazafat, Baladiyah, and Muhalla. The entire process of name disambiguation discussed so far represents the *first step* of our data cleaning procedure. The set of records uniquely associated to an ID after this step are referred to as *set 1*.

When the records only reported the coordinates of the location, the following method was adopted. First, we examined the case when latitude and longitude reported the same value for location *i*. In this context, we looked for a match at the fourth decimal digits between the latitude of location *i* with either the latitude and the longitude of all the locations associated to a non-equal pair of coordinates. When a match was found between the latitude (longitude) of location *i* and *j*, the longitude (latitude) of location *j* was also assigned to location *i*. A match for locations with same latitude and longitude values was obtained for approximately 90% of the cases. Second, we addressed the case when coordinates referred to points falling outside the Libyan borders. In such situations, latitude and longitude were switched. In c.a. 99% of the cases, this allowed to identify a location within Libya. Third, we have calculated the spatial distance between each pair of locations using their coordinates. Whenever two points felt within a distance radius of 10 KMs, these were associated to the same ID. This process of geo-localization of the records represents the *second step* of our data cleaning procedure. The set of records uniquely associated to an ID after this step are referred to as *set 2*.

In the *third step* of our data cleaning procedure, we worked with the set of records reporting both the name and the coordinates of the locations (*set 0*). These were passed through both the process of name disambiguation (*first step*) and geo-localization (*second step*) in order to uniquely associate them to a ID. Successively, the location name was used to match set *0* and *1*. Whenever a record in *set 1* matched with a record in *set 0*, all the records associated to the same ID in *set 1* were assigned to the ID of the matching record in *set 0*. The same was done to associate the records in *set 2* with the IDs in *set 0*.

The records that remained unmatched after the *third step*, were further processed by using the R package *nominatim*[31] to access the OpenStreetMap API in the following way. The unmatched location names were searched on the OpenStreetMap database to retrieve their coordinates. Whenever multiple values were returned, the location falling within the Muhazafat, Baladiyah, and Muhalla names associated to the record was selected. In the cases when no results were returned, the location name was manually search on Google maps to identify its coordinates. Similarly, the OpenStreetMap database was searched to obtain the names of the locations associated only to a pair of coordinates. This process corresponds to the *fourth step* of our data cleaning procedure.

Finally, the records obtained after the *fourth step* were passed through the procedures described in the *first* and *second step* of the data cleaning procedure. Then, the record names and locations obtained in this way were matched with the names and locations obtained after the *third step*. As a result, we were able to identify 95 FMPs uniquely associated to an ID which are constant across rounds.

A.2 Methodology to identify hotspot provinces and cluster provinces

For testing the presence of spatial autocorrelations across provinces in terms of number of migrants, we use the Moran (1950)'s I index.[32]

To identify hotspot provinces and cluster provinces we combine two pieces of information which are reported Figure (A2) Panel (1) and in Panel (2). In Panel (1), we categorize provinces according to the number of migrants in the province and in the adjacent provinces. In particular, the provinces with a low number of migrants which are adjacent to provinces with a low number of migrants are indicated in deep blue; provinces with a low number of migrants adjacent to provinces with a high number of migrants are indicated in blue; provinces with a high number of migrants adjacent to provinces with a low number of migrants are indicated in red, and provinces with a high number of migrants adjacent to provinces with a high number of migrants are indicated in dark red.

Panel (2) report the same information in another form. The X and Y axis indicates respectively the number of migrants found in province i, and the average number of migrants found in the provinces

[31] Available at https://github.com/hrbrmstr/nominatim

[32] The Moran's I index is computed as $I_i = \frac{(x_i - \bar{x})(\sum_i \sum_j w_{ij})}{\sum_i (x_i - \bar{x})^2 / N}$, where x_i is the average number of migrants in FMP i, $\bar{x}$ is the average number of migrants in FMPs, and w_{ij} is the distance between FMP i and FMP j. The Moran's I index ranges between $\{-1; 1\}$. A value close to 1 indicates positive spatial autocorrelation. A value approaching -1 signals negative autocorrelation. A value of 0 suggest the absence of any spatial auto-correlation.

adjacent to i. This implies that deep blue provinces are in the bottom-left quadrant, blue provinces in the upper-left, red provinces in the bottom right, and the deep red provinces in the upper-left.

We can use these graphs to identify hotspots and clusters as follow.

Cluster provinces are groups of provinces hosting a high (low) number of migrants. In order to identify a cluster, we use the graph in Panel

Panel (a) can be read as follow.

On the right quadrants are located those provinces hosting a high number of migrants. Specifically, it shows those provinces contiguous to other provinces with a high number of migrants - top right quadrant – and those provinces adjacent to provinces with a low number of migrants – bottom right quadrant. Provinces in the top right quadrant are associated to the color dark red in the map. Provinces in the bottom right quadrant are associated to the color red in the map.

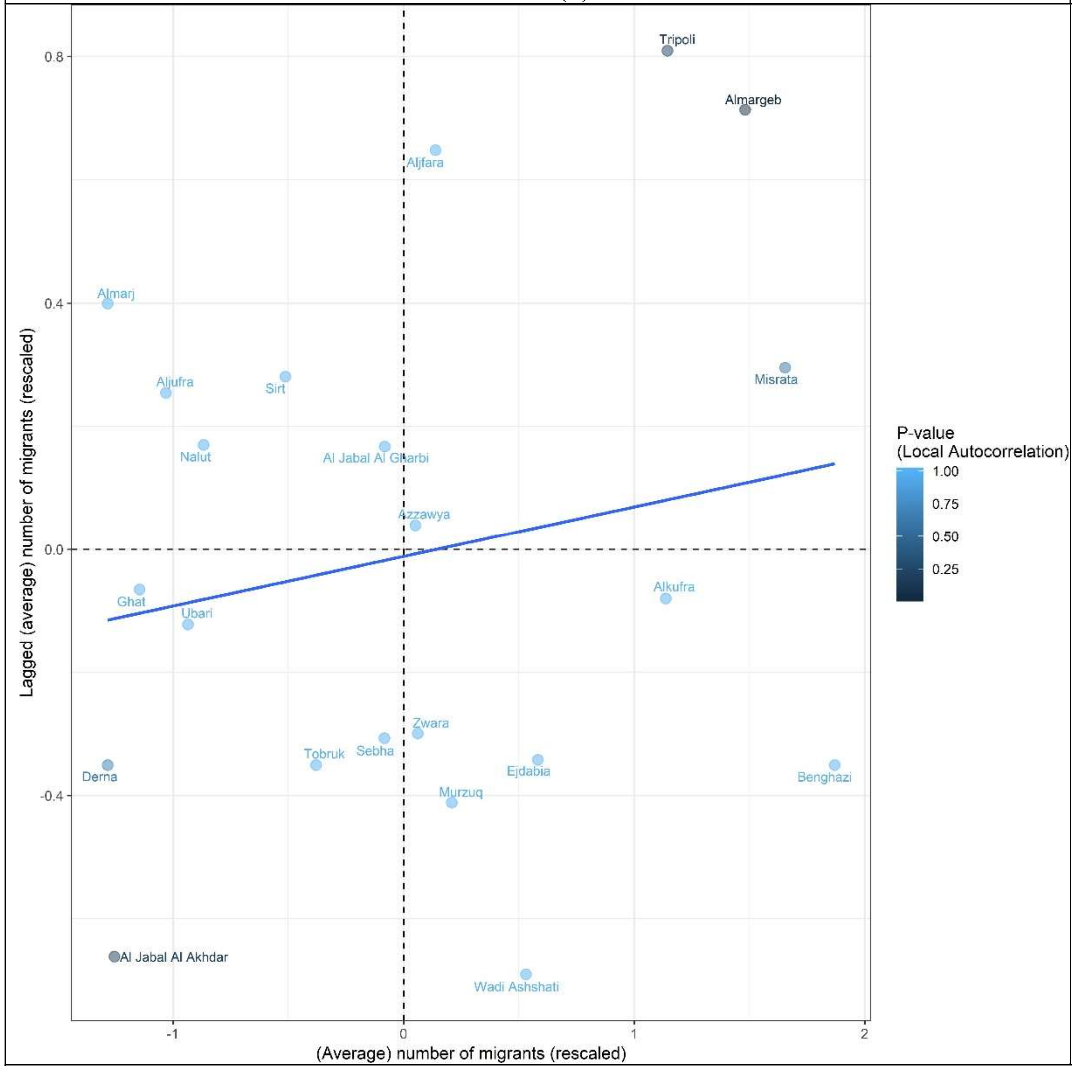
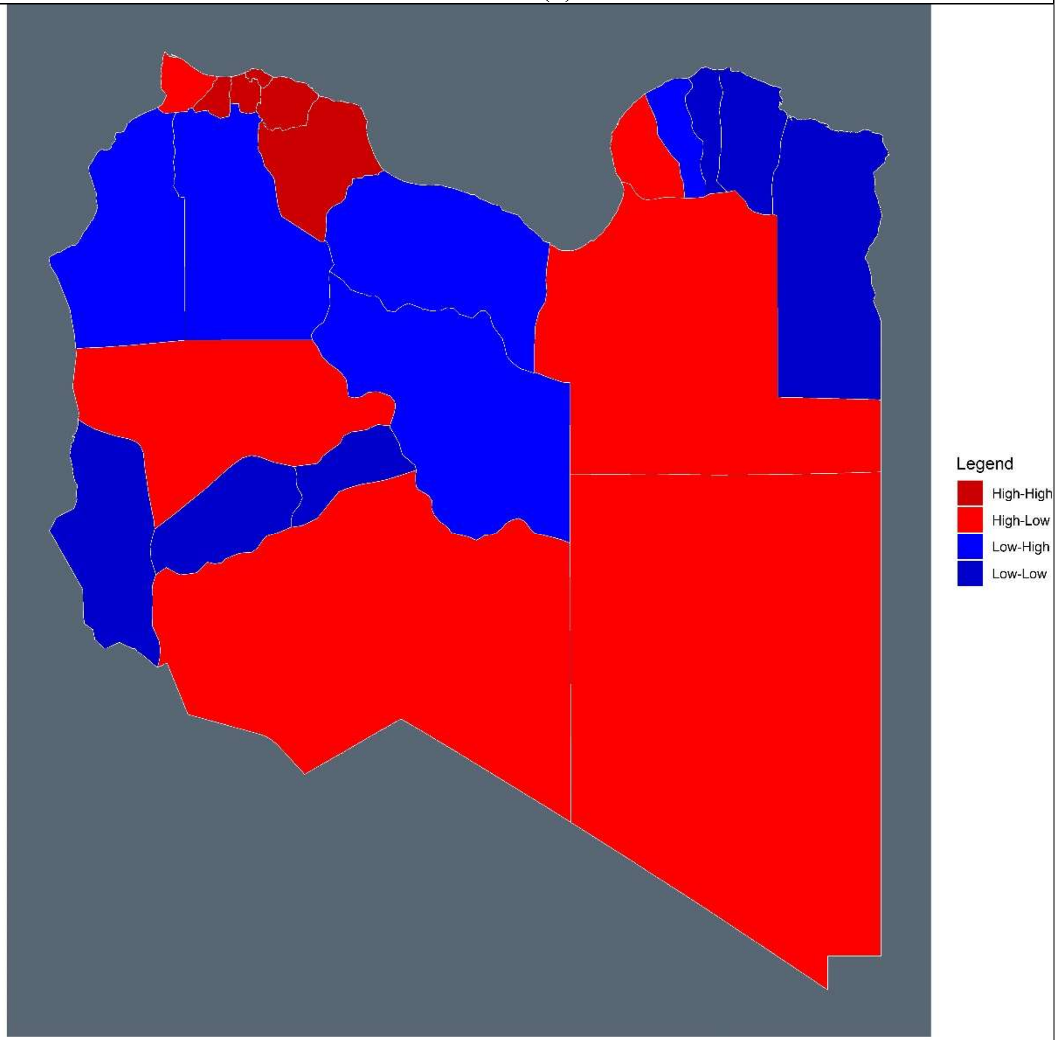
On the left quadrants are found those provinces featuring a low number of migrants. Specifically, it shows those provinces contiguous to other provinces with a high number of migrants - top left quadrant – and those provinces adjacent to provinces with a low number of migrants – bottom left quadrant. Provinces in the top left quadrant are associated to the color blue in the map. Provinces in the bottom left quadrant are associated to the color deep blue in the map.

A cluster is either:

i. a group of contiguous provinces located in the right quadrants: if the cluster is associated to an area featuring a high number of migrants. This cluster is associated to areas featuring red hues of color in the map.
ii. a group of contiguous provinces located in the left quadrants (if the cluster is associated to an area featuring a low number of migrants). This cluster is associated to areas featuring blue hues in the map.

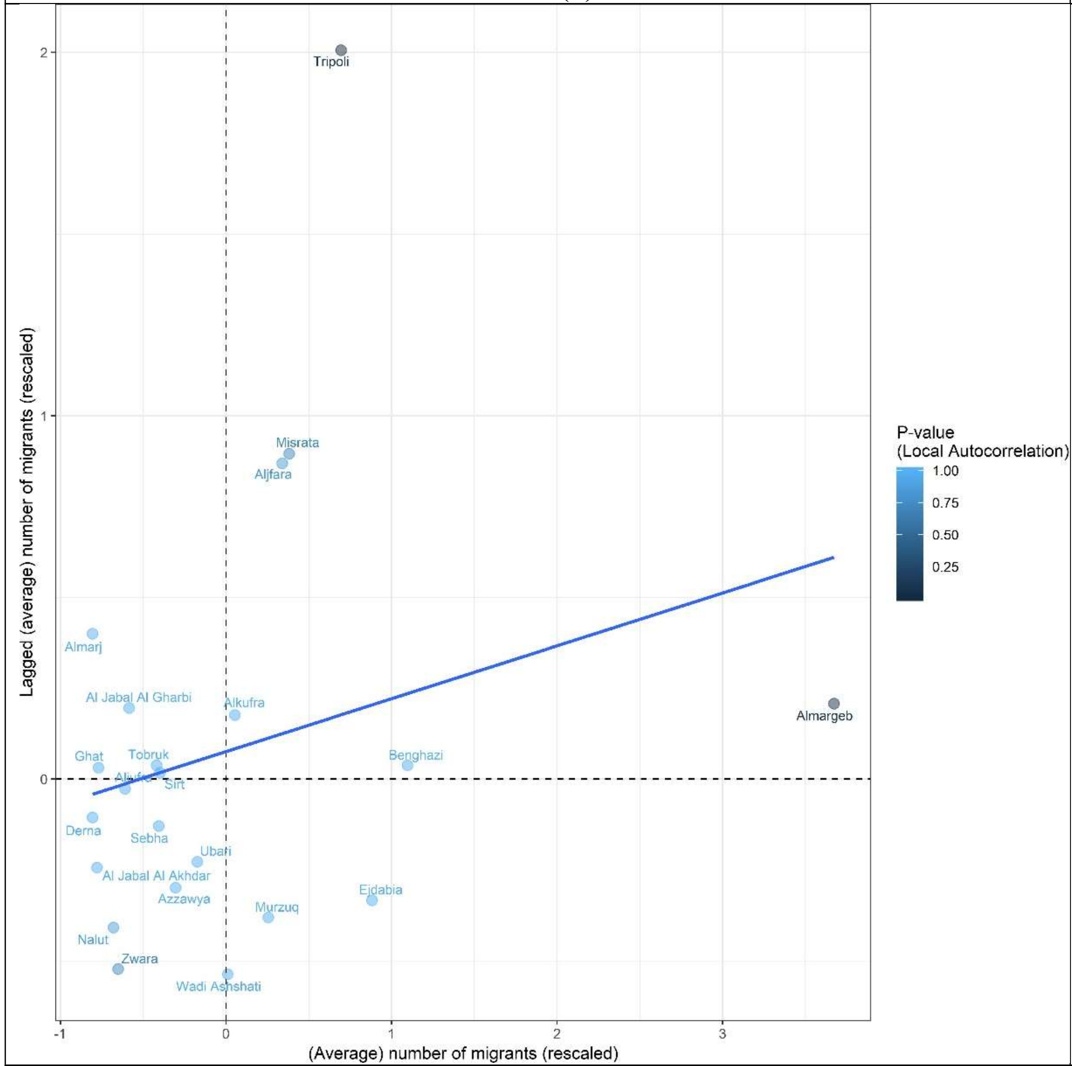
A hotspot is either:

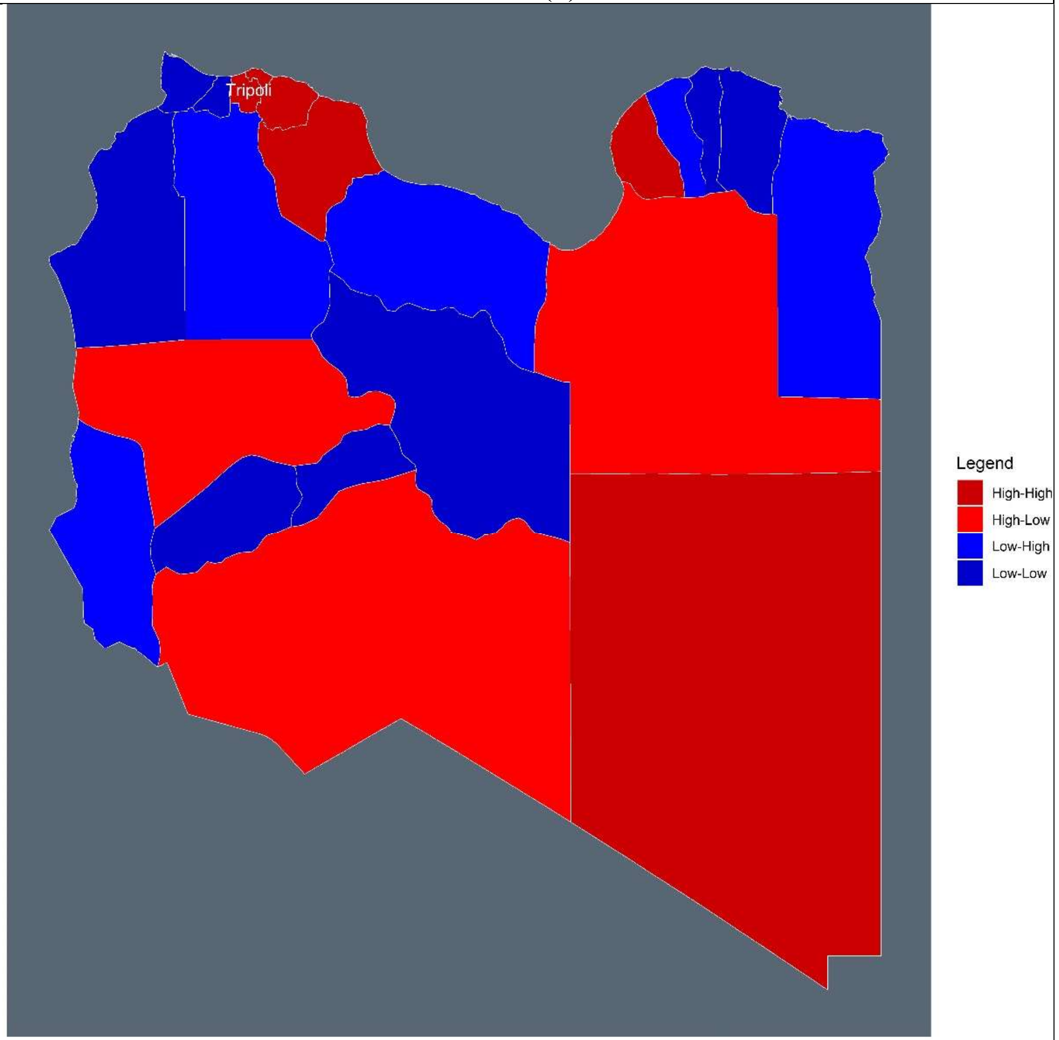
i) a province located in the bottom right quadrant, which is spatially adjacent to provinces located in the bottom quadrants. It corresponds to a province with red color surrounded by provinces with blue color in the map.
ii) a province located in the top left quadrant, which is spatially adjacent to provinces located in the top quadrants. It corresponds to a province with blue color surrounded by provinces with red color in the map.

Figure A2.1a: Local Moran Test of Spatial Autocorrelation in Migrants Distribution - 2017	
Panel (1)	Panel (2)
	
Note: The figures refer to the year 2017. Provinces with a low number of migrants adjacent to provinces with a similar low number of migrants are indicated in deep blue in Panel (1) and positioned in the bottom left quadrant in Panel (2). Provinces with a low number of migrants adjacent to provinces with a high number of migrants are indicated in blue in Panel (1) and positioned in the top left quadrant in Panel (2). Provinces with a high number of migrants adjacent to provinces with a low number of migrants are indicated in red in Panel (1) and positioned in the bottom right quadrant in Panel (2). Provinces with a high number of migrants adjacent to provinces with a similar high number of migrants are indicated in dark red in Panel (1) and positioned in the top right quadrant in Panel (2). The x and y axis in Panel (2) indicates respectively the number of migrants found in province *i*, and the average number of migrants found in the provinces adjacent to *i*. Only the names of the provinces for which the test returned a 5% significant level of autocorrelation are shown in Panel (1).	

A2.1b: Local Moran Test of Spatial Autocorrelation in Migrants Distribution - 2018

Panel (1)	Panel (2)



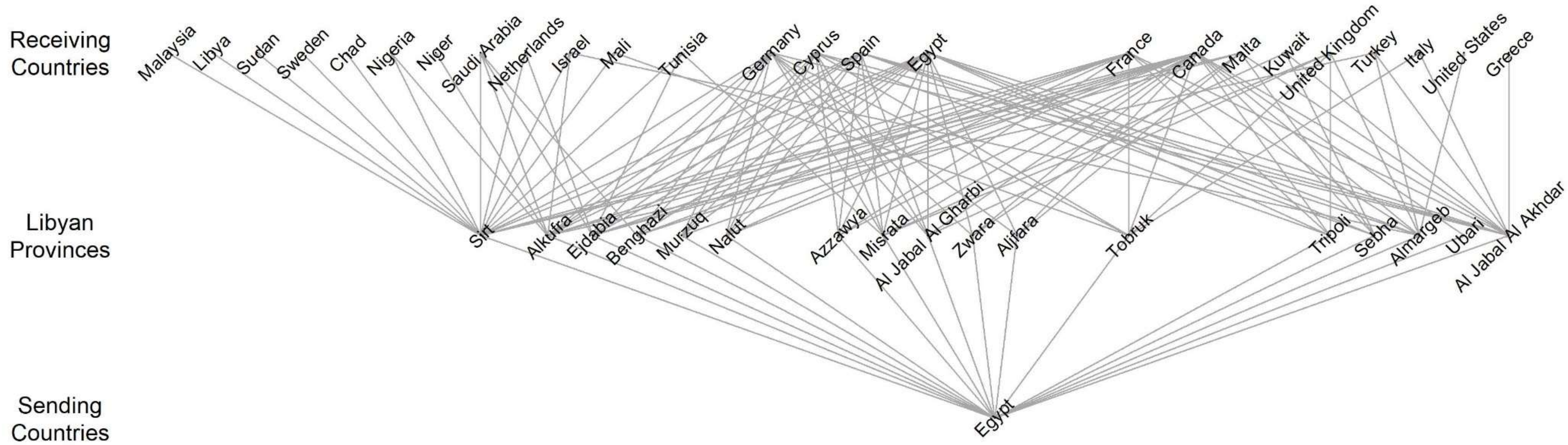


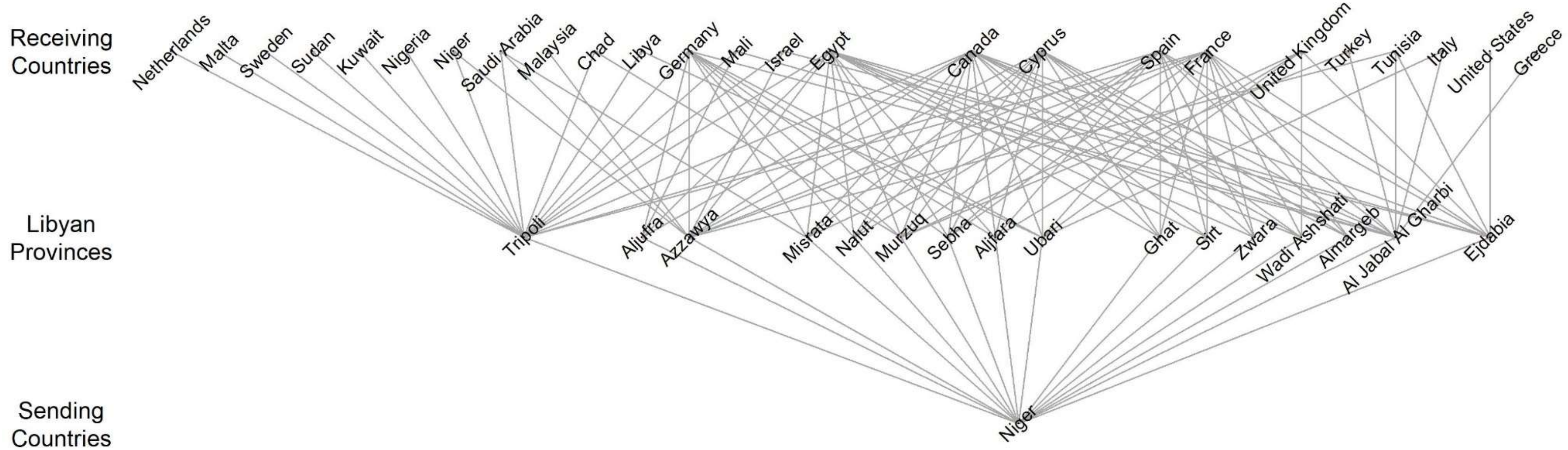
Note: The figure refers to the year 2018. Provinces with a low number of migrants adjacent to provinces with a similar low number of migrants are indicated in deep blue in Panel (1) and positioned in the bottom left quadrant in Panel (2). Provinces with a low number of migrants adjacent to provinces with a high number of migrants are indicated in blue in Panel (1) and positioned in the top left quadrant in Panel (2). Provinces with a high number of migrants adjacent to provinces with a low number of migrants are indicated in red in Panel (1) and positioned in the bottom right quadrant in Panel (2). Provinces with a high number of migrants adjacent to provinces with a similar high number of migrants are indicated in dark red in Panel (1) and positioned in the top right quadrant in Panel (2). The x and y axis in Panel (2) indicates respectively the number of migrants found in province *i*, and the average number of migrants found in the provinces adjacent to *i*. Only the names of the provinces for which the test returned a 5% significant level of autocorrelation are shown in Panel (1).

A.3 The network of top 1 sending countries

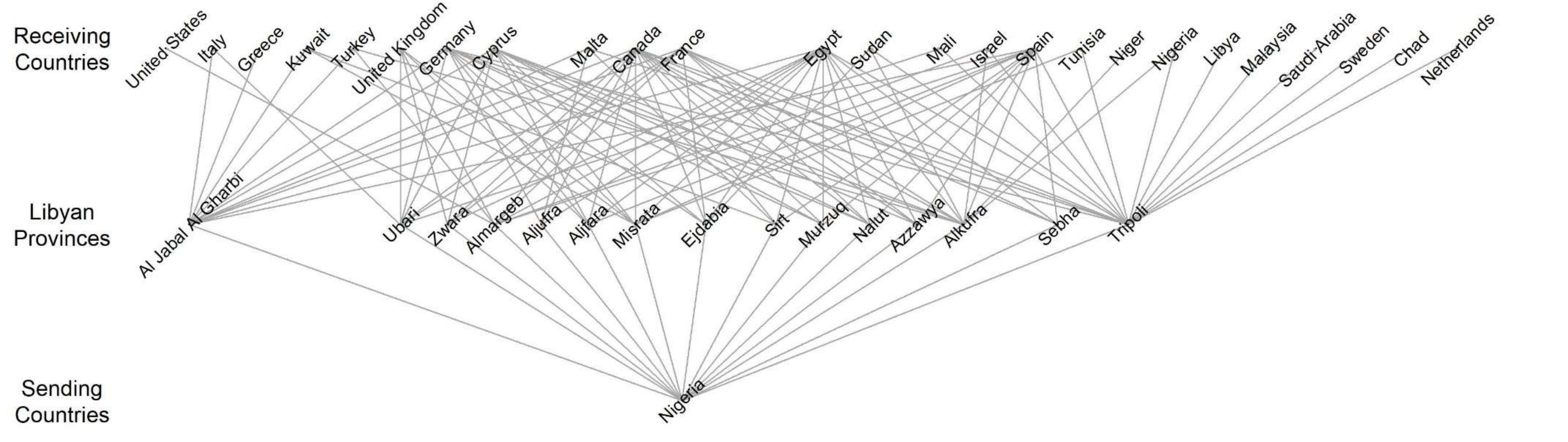
Figure A3 1: Top senders – 2017

EGYPT



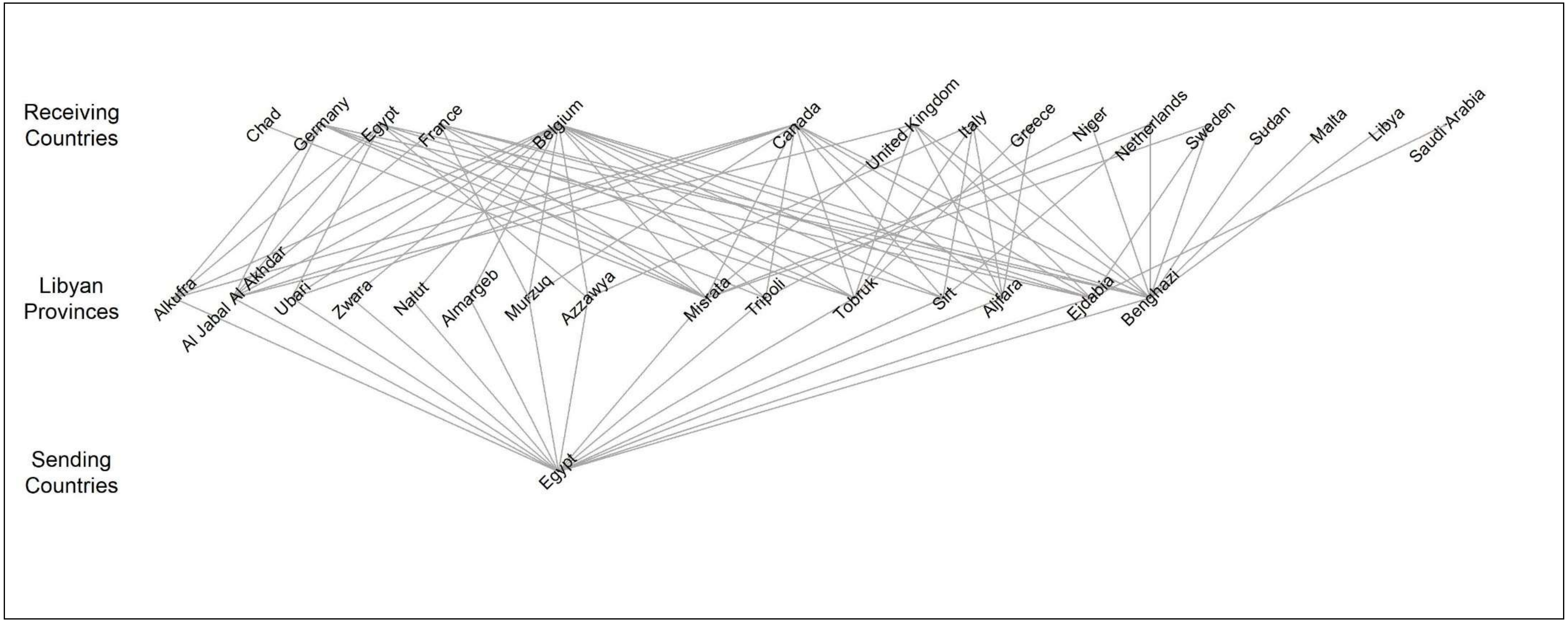

Receiving Countries
Netherlands
Malta
Sweden
Sudan
Kuwait
Nigeria
Niger
Saudi Arabia
Malaysia
Chad
Libya
Germany
Mali
Israel
Egypt
Canada
Cyprus
Spain
France
United Kingdom
Turkey
Tunisia
Italy
United States
Greece
Libyan Provinces
Tripoli
Aljufra
Azzawya
Misrata
Nalut
Murzuq
Sebha
Aljfara
Ubari
Ghat
Sirt
Zwara
Wadi Ashshati
Almargeb
Al Jabal Al Gharbi
Ejdabia
Sending Countries
Niger

NIGER

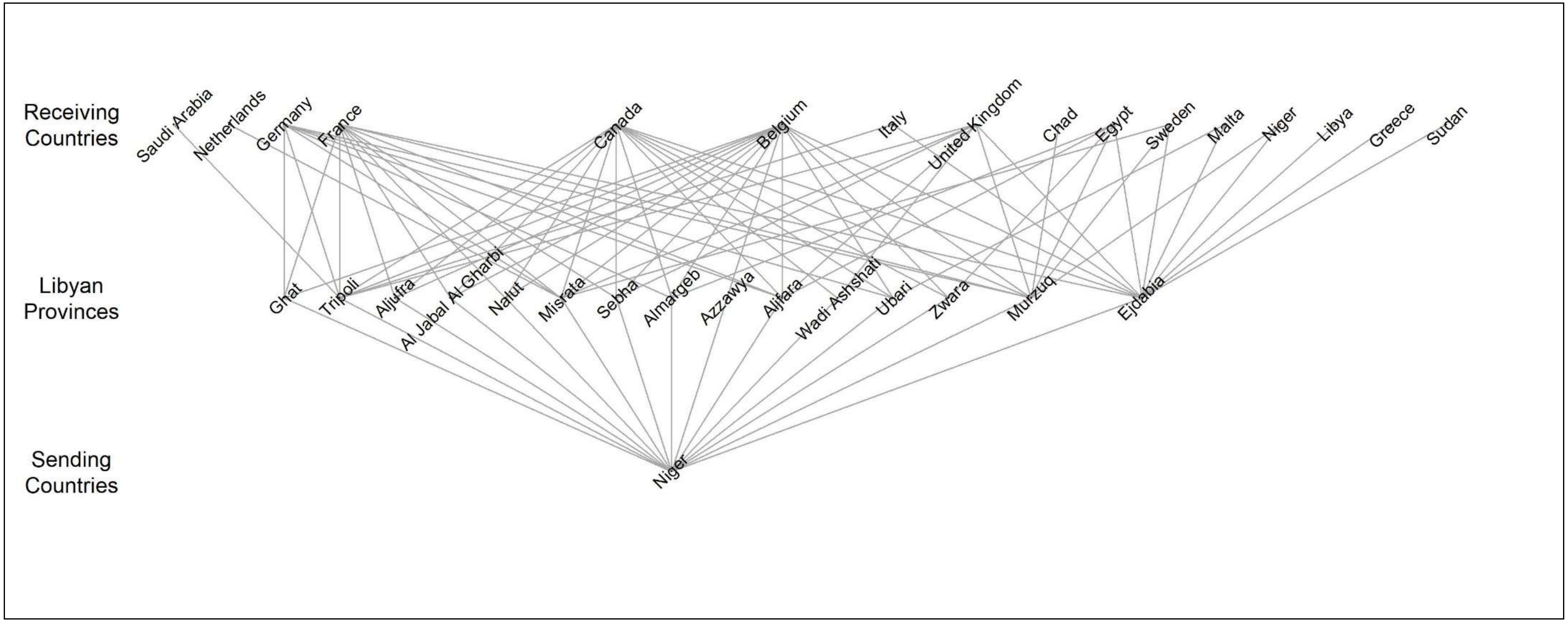


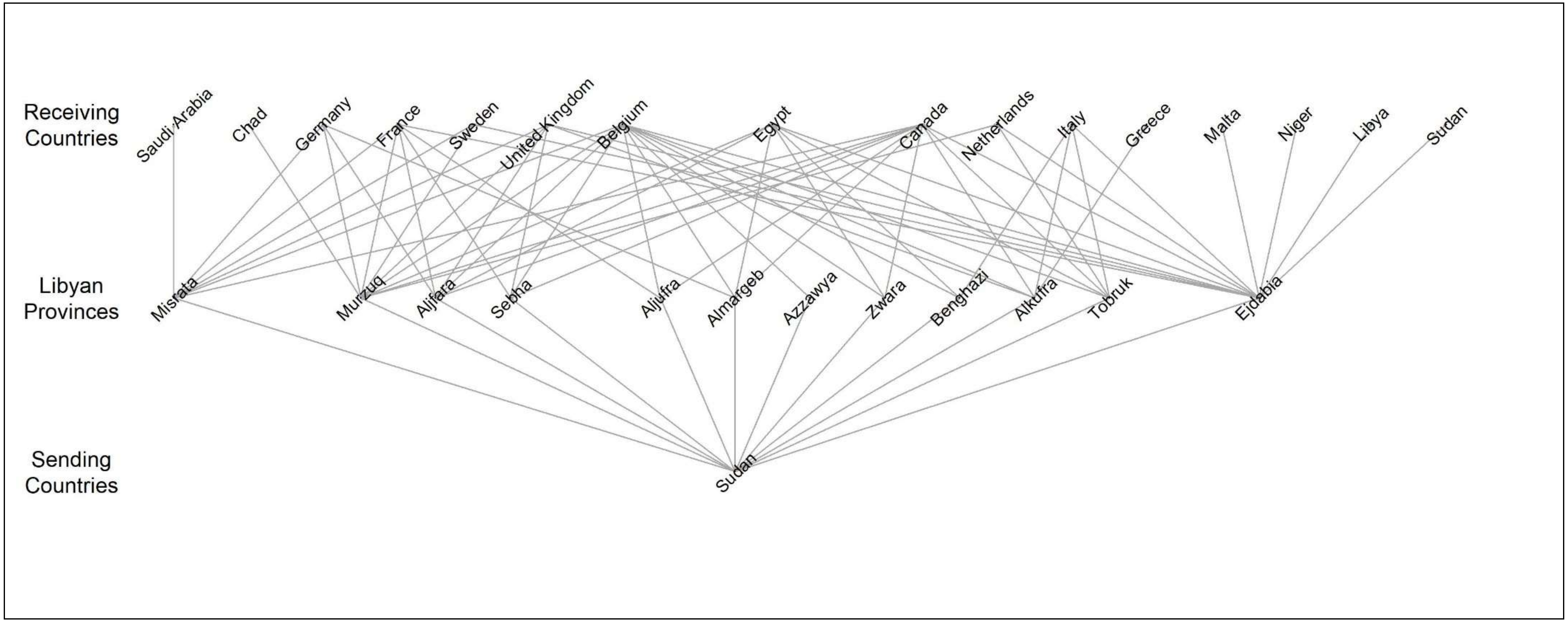
NIGERIA

TOP SENDERS 2018
EGYPT



Receiving Countries
Chad
Germany
Egypt
France
Belgium
Canada
United Kingdom
Italy
Greece
Niger
Netherlands
Sweden
Sudan
Malta
Libya
Saudi Arabia
Libyan Provinces
Alkufra
Al Jabal Al Akhdar
Ubari
Zwara
Nalut
Almargeb
Murzuq
Azzawya
Misrata
Tripoli
Tobruk
Sirt
Aljfara
Ejdabia
Benghazi
Sending Countries
Egypt


Receiving Countries
Saudi Arabia
Netherlands
Germany
France
Canada
Belgium
Italy
United Kingdom
Chad
Egypt
Sweden
Malta
Niger
Libya
Greece
Sudan
Libyan Provinces
Ghat
Tripoli
Aljufra
Al Jabal Al Gharbi
Nalut
Misrata
Sebha
Almargeb
Azzawya
Aljfara
Wadi Ashshati
Ubari
Zwara
Murzuq
Ejdabia
Sending Countries
Niger


Receiving Countries
Libyan Provinces
Sending Countries
Saudi Arabia
Chad
Germany
France
Sweden
United Kingdom
Belgium
Egypt
Canada
Netherlands
Italy
Greece
Malta
Niger
Libya
Sudan
Misrata
Murzuq
Aljfara
Sebha
Aljufra
Almargeb
Azzawya
Zwara
Benghazi
Alkufra
Tobruk
Ejdabia
Sudan