Can violent conflicts explain the recent increase in asylum seekers from Africa to Europe?

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Hannes Weber, University of Tuebingen[1]

Abstract

The “refugee crisis” is currently one of the most salient issues in European public discourse. While much attention has been given to migrants fleeing the civil war in Syria, the number of asylum seekers from Africa entering the European Union has also seen considerable increases recently: Between 2010 and 2015, their number has tripled. In this paper, we address the question if this considerable increase can be explained by changes in political violence within the countries of origin. We use quarterly data on bilateral flows of asylum seekers from 38 African into 19 European countries from 2011 to 2015, resulting in roughly 14,000 observations. These data were amended by aggregated real-time data on conflict events and violent deaths as well as several other known predictors of migratory movements. We find that an increase in the number of violent incidents leads to an increase in the number of asylum seekers which can be felt around 9 months before leveling off. On the other hand, changes in the level political violence cannot explain the increase in refugee migration since late 2013, when the Italian Navy launched the sea rescue mission “Mare Nostrum”. In fact, violent conflict appears to be much stronger correlated with refugee flows before “Mare Nostrum”, when total monthly inflows to Europe oscillated around an equilibrium number of ca. 5,000. Since then, however the statistical association is greatly reduced.

Key words: Migration, refugees, asylum, Africa, European Union.

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[1] Contact: Dr. Hannes Weber, Department of Sociology, University of Tuebingen, Germany. Mail: hannes.weber@uni-tuebingen.de

Introduction

One of the most salient issues in contemporary Europe is the large number of refugees[2] and migrants coming to the European Union (EU) from other world regions. Between September 2013 and September 2015, the monthly inflow of asylum seekers to the EU increased fourfold (Eurostat 2016). By mid-2015, immigration had become the number one concern for European citizens when asked about the most important issues facing the EU at the moment (European Commission 2015). The public discourse largely focuses on refugees from the Middle East, particularly from civil war-ridden Syria. However, asylum migration from Africa has also tripled from 69,000 registered refugees in 2010 to 202,000 in 2015.

Figure 1 plots the monthly asylum application rates from all African countries in Europe[3] between January 2008 and April 2016. As the graph shows, the time series appears rather stationary in the beginning, fluctuating around an average of ca. 5,000 asylum applications per month. In early 2011, the number of refugees from North Africa modestly increased during the events of the "Arab Spring", but this quickly leveled off. However, since around 2013, an obvious upward slope in the asylum migration rate can be noted in the data. As the Mediterranean routes to the shores of Spain, Greece, and particularly Italy are the main ways for African refugees to enter the European Union, seasonal differences in the number of arrivals are of significant size. Crossings by boat typically become more numerous in late summer and decrease sharply in winter. In 2015, monthly asylum applications from African citizens rose to more than 15,000 on average (or three times the quasi-equilibrium of 2008–2012).

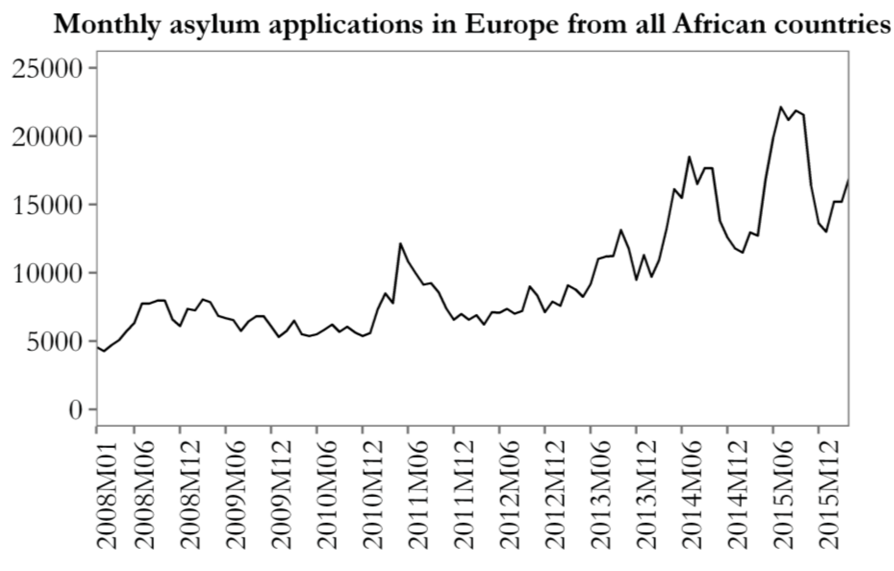


Figure 1: Monthly asylum applications from African citizens in Europe, 2008–2016
Source: Eurostat (2016), own calculations.

[2] The terms "refugees" and "asylum seekers" are used interchangeably in this article denoting people who formally apply for asylum without normative implications about motives for migrating or legal considerations.
[3] For reasons of data availability, "Europe" refers to the EU-28 countries in addition to Norway, Switzerland, and Iceland in this article.

The geographic distribution of refugees shows considerable differences with regard to both countries of origin as well as countries of destination. In Figure 2, European countries are shaded according to the number of asylum seekers from Africa they took in, while for African countries numbers represent outflows of asylum seekers migrating to Europe. Italy (154,000 asylum applications between 2011 and 2015), Germany (122,000), and France (119,000) have been the preferred destinations in recent years for African refugees.

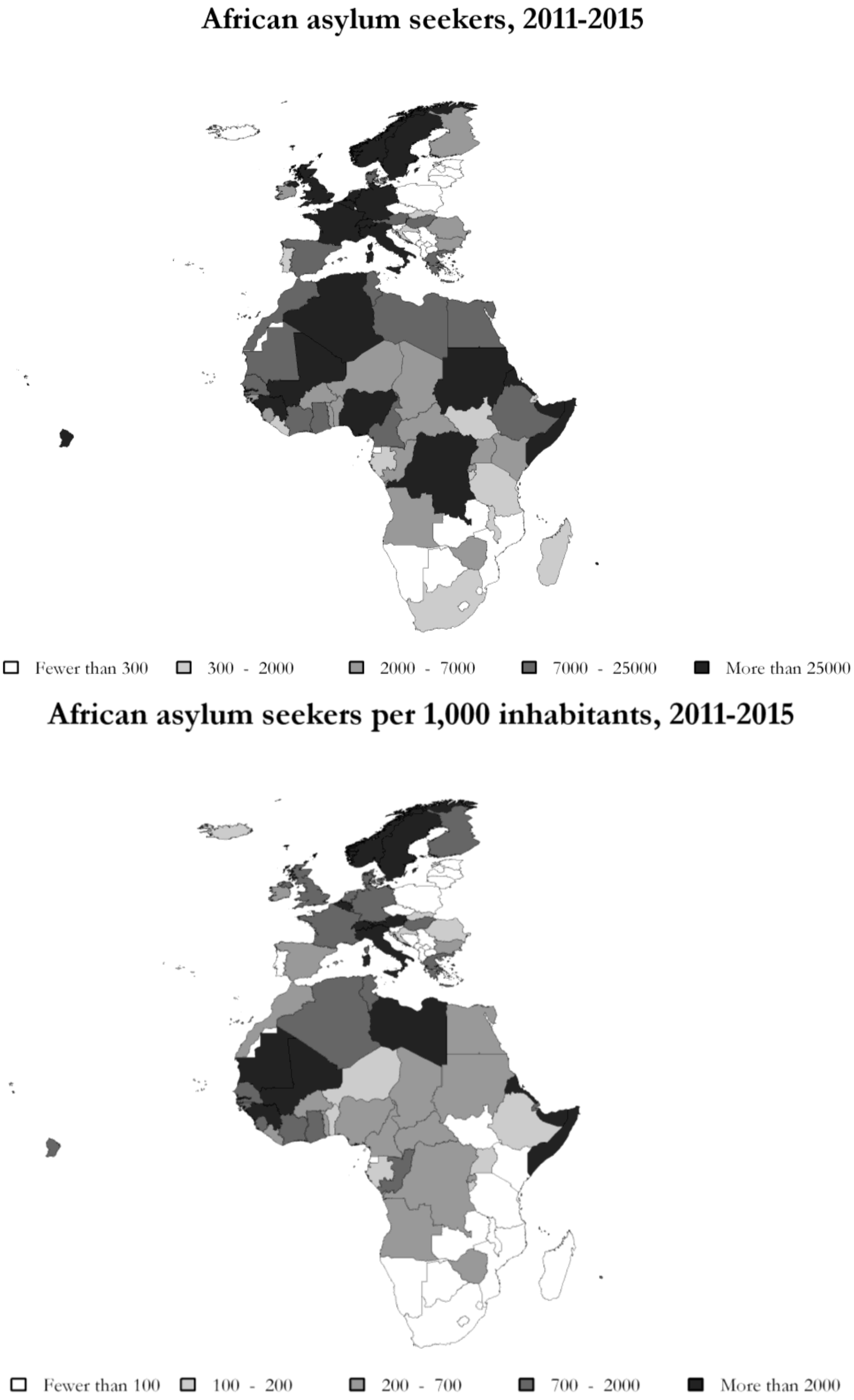


Figure 2: Monthly asylum applications from African citizens in Europe, 2008–2016

Source: Eurostat (2016), own calculations.

By contrast, very few people sought refuge in a Central-Eastern European country, exceptions including Hungary, where a sizeable number of Africans arrived in mid-2015 before several countries along the so-called "Balkan route" closed their borders.

When the number of refugee inflows is expressed as a proportion of the total resident population, a slightly different picture emerges (see bottom panel of Figure 2). Malta, with 18 new asylum applications from African citizens for every 1,000 inhabitants between 2011 and 2015, has received by far the most refugees from across the Mediterranean as a share of its small population. In Switzerland, the number of recently arrived Africans within the five years under study (72,000 or 9 per 1,000 inhabitants) amounts to almost 1% of the total population. Sweden and Norway follow with 8 and 6 refugees per 1,000 residents, respectively. Contrast this with 300 Africans who applied for asylum in Poland (8 per 1 Million inhabitants) and 150 in the Czech Republic (14 per 1 Million). Spain, which was targeted by a considerable number of refugee boats in previous years, received a modest 10,000 African refugees (or 0.2 per 1,000 inhabitants) since 2011.

Eritrea has been the number one country of origin for asylum seekers with close to 100,000 Eritreans applying for asylum in Europe between 2011 and 2015. This translates to almost 2% of the population who fled to Europe in only five years. The Gambia has seen a similarly high level of emigration to Europe as a share of the total population (15 refugees for every 1,000 inhabitants). Somalia has seen 81,000 or 0.8% of its population seeking refuge in Europe. Nigeria (83,000) and the Democratic Republic of the Congo (DRC, 37,000) also sent sizeable numbers of asylum seekers, while in terms of per-capita flows emigration was higher in sparsely populated Mauritania and Libya. By contrast, citizens of Southern African countries only rarely apply for asylum in Europe. This might be attributed to the fact that South Africa is a closer destination for refugees from, say, Zimbabwe, but arguably also to political stability in countries such as Botswana and Namibia.

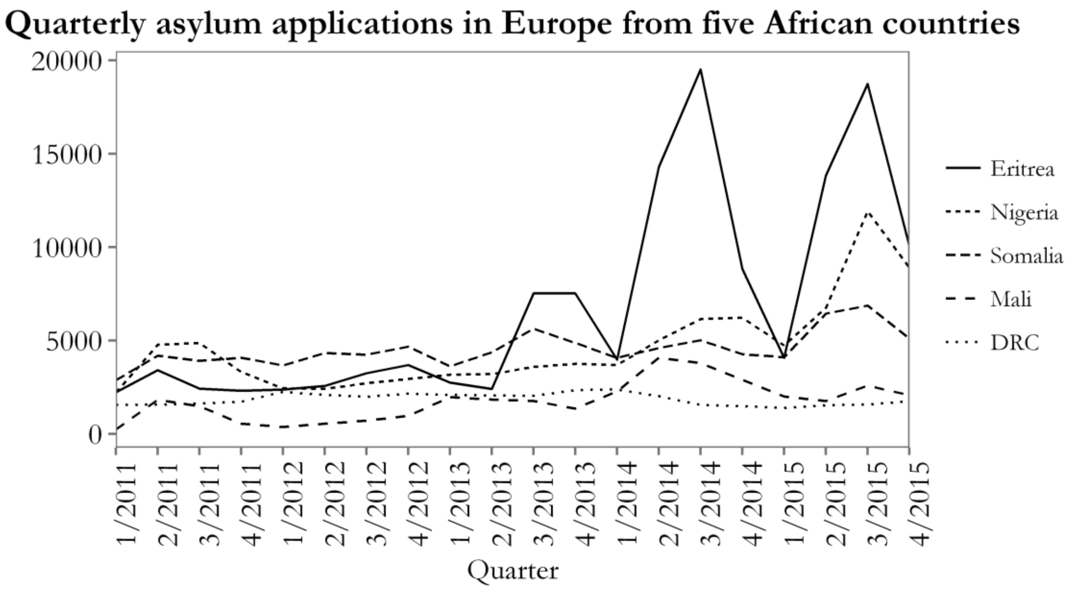


Figure 3: Quarterly asylum applications from five African countries in Europe
Source: Eurostat (2016), own calculations.

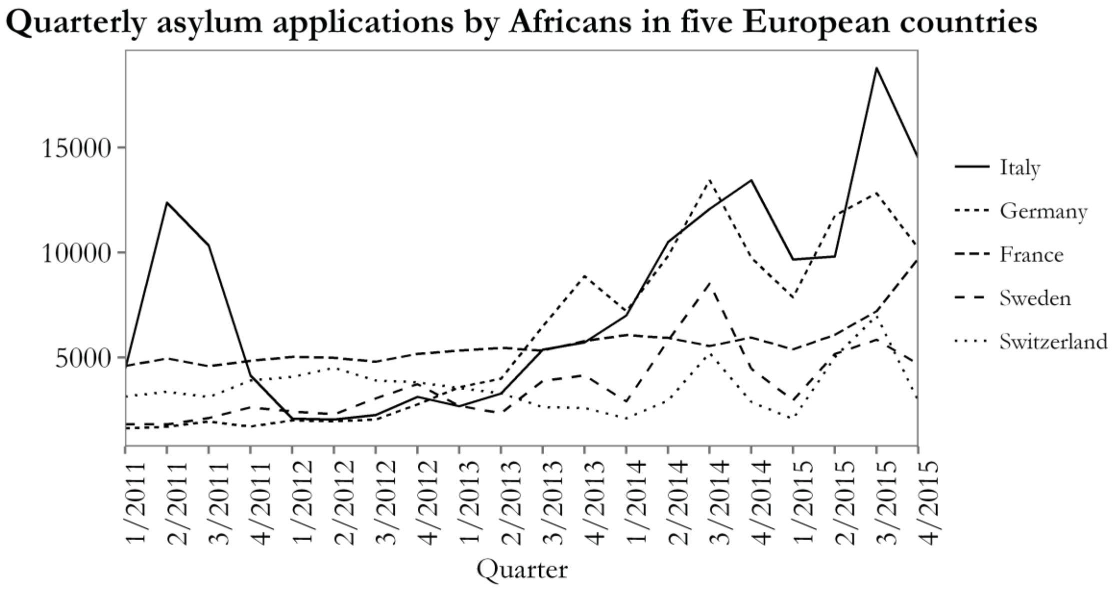


Figure 4: Quarterly asylum applications from Africa in five European countries
Source: Eurostat (2016), own calculations.

Disentangling these aggregate numbers, Figures 3 and 4 visualize trends in outflows from the five most important sending countries in Africa and inflows into the five most important receiving countries in Europe, respectively. The first graph shows that not all countries are responsible for the recent increase in refugee movements. Notably, numbers from the DRC remain constant over the observed period of time, while a huge increase in inflows can be noted from Eritrea. In total, a two-partite pattern is obvious in Figure 3, with the first half showing five rather stationary time series, followed by disruptive outbreaks and an upward trend for at least Eritrea and Nigeria in the second half. A similar pattern can be observed in the receiving countries (Figure 4). With the exception of a brief episode of "Arab Spring" refugee movements to Italy in mid-2011, levels were stable in the countries under study with France attracting most African refugees according to the de-facto equilibrium values. Remarkably, asylum migration from Africa to Germany had been low before 2013. From late 2013 on, however, the number of applications rose sharply, in particular in Italy and Germany; but the other three countries' trends show notable peaks as well.

The considerable increase in asylum seekers from several African countries since late 2013 coincides with the launch of "Mare Nostrum", a search-and-rescue operation in the Mediterranean led by the Italian Navy. Other countries joined and the operation was succeeded by a program under the auspices of the European Union's border control agency, Frontex. "Mare Nostrum" was triggered by one of the hitherto greatest tragedies involving refugee boats when more than 300 people died off the coasts of the Italian island of Lampedusa in October 2013. Since then, the Italian Navy and their partners have rescued countless of lives and the number of people risking their lives in boats that are hardly seaworthy has markedly increased. Naturally, cause and effect are difficult to disentangle in this descriptive observation. It might be that refugee numbers would have increased anyway, with or without an intensification of rescue missions. Or, as an alternative view, the fact that more people were rescued and brought to Europe encouraged more migrants to risk the passage because the perceived likelihood of reaching the continent increased.

Proponents of the former argument point to high levels of political violence in many countries and suggest that most people would have fled their country in any case. Accordingly, contemporary public discourse often attributes the increase in refugees to conflicts and human rights violations in African countries (e.g., Le Monde 2014, NYTimes 2015, Die Zeit 2015). In fact, the number of violent incidents in many African countries has increased within the observed period of time. On the other hand, many of these conflicts have been ongoing for years, but the number of people coming to Europe from African war zones had been comparatively low throughout the previous decade.

In this paper, we seek to address the question of whether violent conflicts in African countries of origin can explain the increase in asylum migration to Europe observed in recent years. We compare pre- and post-"Mare Nostrum" data, investigating whether violent incidents and casualties have become more important in determining refugee flows over the course of the past years. Contrary to most previous studies on the topic (e.g., Neumayer 2005, Moore & Shellman 2007, Hatton 2009, Keogh 2013), our quarterly measurement of conflicts and asylum emigration allows a more fine-grained study of how political violence affects refugee flows, including the time lag between an intensification of a conflict and an increase in emigrants from a country.

Theoretical considerations

Violent conflicts have long been recognized as a major predictor of asylum movements (e.g., Schmeidl 1997; Vogler and Rotte 2000; Moore and Shellman 2007; Neumeyer 2005). In the usual terminology of "push- and pull-factors" (Lee 1966), political violence is a factor that pushes people out of their country or residence. However, some studies do not find any association between levels of violence and the number of asylum seekers arriving in European countries (e.g., Holzer et al. 2000). Thus, although the association between violence and flight is apparent, the theoretical mechanism is not straightforward. In particular, it has to be considered that many refugees fleeing from violent conflicts find refuge in other parts of their country of origin or in neighboring countries, and only a fraction applies for asylum in Europe. Migrating to Europe is therefore usually conceived of as a rational decision considering the costs and benefits of migration (e.g., Neumayer 2005; Mayda 2010).

Several factors have long been known to affect decisions for or against migration (for an overview see, e.g., Massey et al. 1993). Economic factors are most commonly referred to when analyzing the causes of migration. For instance, in a classic study, Ravenstein (1885) found that people tend to move where employment possibilities are available. Neoclassical theory accordingly assumes that migration between regions or countries will take place as long as wage differences persist (which are due to differences in the supply with capital and labor). Accordingly, given the strong and persisting differences between Africa and Europe regarding income and standard of life, we should expect strong motives for migration for large parts of the population. Critics of neoclassical theory posit that people usually do not make decisions alone but rather are embedded in social contexts of family and other networks which need to be considered (Stark and Blum 1985). For instance, for migratory movements with the purpose of family reunion, economic considerations about available jobs or income level are usually less important. Many studies have accordingly found evidence for migration networks (Pedersen et al. 2008, Mayda 2010), such that family reunion and other mechanisms generate "chain migration" which is less impacted by the economic context or migration policies. Moreover, there is consistent evidence that emigration rates increase rather than decrease if wages and income levels rise in developing countries (e.g., Moore and Shellman 2007), or that an inverted U-shaped relationship exists between the two variables (Vogler and Rotte 2000). A plausible explanation for this lies in the fact that the costs of migrating can be more often afforded if income levels increase.

As a consequence, migrants to Europe often come from countries with an intermediate level of socio-economic development (e.g. in North Africa), while the poorest world regions have so far sent fewer people to Europe (de Haas 2007). These findings must be considered when theorizing the impact of violence on asylum migrations. For instance, being affected by political violence might negatively affect the monetary resources needed to migrate to Europe. In many cases, fleeing to Europe needs savings and preparations. Hence, while motives to emigrate might increase during civil wars or other crises, opportunities might decrease. It is therefore also important to consider the possibility that an intensification of violence triggers an increase in refugee movements with some time lag.

Apart from the socioeconomic context, geographic factors have long been known to facilitate or impede migration (e.g., Zipf 1946). Cohen et al. (2008) are able to explain up to 64% of differences in global migratory movements based on a model of geographic and demographic factors only. Population size and growth (Kim and Cohen 2010) as well as age structure (Mayda 2010) are also known determinants of gross outflows: Migrants are typically in their twenties and if young cohorts dominate a country's age structure, the pool of possible emigrants is larger. Considering these demographic factors is especially relevant since Africa is the only continent where the population is still growing at a substantially large rate. Accordingly, population projections for Africa have consistently been corrected upwards in the past two decades because contrary to expectations, fertility has not decreased significantly in many countries. In addition, environmental factors and climate change have been discussed as possible reasons for why emigration from Africa will increase (Piguet 2013).

Finally, asylum-related and other policies can obviously affect the number of refugees entering the European Union or a specific European country (e.g., Neumeyer 2004; Mitchell et al. 2011, Toshkov 2014). Despite a Europeanization of asylum laws, national-specific differences persist (Toshkov and de Haan 2013). As a result, countries might be targeted specifically for their liberal policies or, conversely, countries might adjust their policies to the rate of asylum applications. For instance, Toshkov (2014) finds that more asylum seekers lead to a lower recognition rate, while a higher recognition rate attracts more asylum seekers. While the formal recognition rate can be measured, administrative practice (e.g., regarding deportations) can differ and are hard to measure. In addition, perceptions of asylum policies in refugees' countries of origin might differ from reality.

Data and methods

Definitions and data sources

Our dependent variable of interest is the quarterly number of asylum applicants from Africa (whose country of citizenship is referred to as "country of origin") in a European country ("country of destination"). It is important to note that we analyze aggregate data and cannot make inferences about individuals, e.g. whether it is "justified" that individuals from a particular country flee to Europe, since this would represent an ecological fallacy (although violence and human rights violations are on the rise in a country, an individual asylum seeker might not have been affected, and conversely, a particular individual might come from a relatively stable country and nonetheless have experienced prosecution or violence). Our units of analyses are thus flows between two countries at a given time point; for instance, the number of Algerians applying for asylum in Austria in the first quarter of 2011.

We analyze quarterly data covering the period from 2011 to 2015, during which the recent increase in asylum migration from Africa to Europe could be observed. All African countries with a total net asylum migration rate of at least 1,000 persons to Europe, and all European countries where at least 1,000 Africans applied for asylum in the period of study were selected for the analysis. This selection results in 722 dyads of 38 source and 19 destination countries which are each measured in 20 three-months-periods from the first quarter of 2011 until the fourth quarter of 2015, resulting in 14,440 observations.[4] Monthly data from Eurostat (2016) on asylum applications were aggregated to quarterly data. We take the logarithm of bilateral flows since the original variable is heavily skewed in its distribution. Our main independent variable of interest is the level of political violence in countries of origin. Information on conflict events and violent deaths in the source countries come from the Armed Conflict Location & Event Data Project (ACLED, see Raleigh et al. 2010). ACLED collects geo-coded real-time data on violent protests and deaths related to political violence in Africa. We aggregated these data to quarterly measures on the number of violent incidents and the number of fatalities from politically motivated violence. Since the distributions of both the number of incidents as well as the death toll from political violence are skewed, the log of both variables is taken as well.

A number of other variables were compiled for the dataset. As a measure of country-specific asylum policy, we calculated the quarterly rejection rate of African asylum seekers for each European country. This variable is defined as the percentage of negative decisions on asylum applications from African citizens as a share of all decisions on Africans in the respective quarter (calculated from Eurostat 2016). Quarterly time-variant economic variables include unemployment and gross domestic product (GDP) growth rates in the countries of destination. In addition, several time-invariant or near-invariant (i.e. slowly changing or "sluggish") variables

[4] The following African countries sent at least 1,000 refugees to Europe between 2011 and 2015 and are included in this study: Algeria, Angola, Benin, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Comoros, Côte d'Ivoire, Djibouti, Democratic Republic of the Congo, Egypt, Eritrea, Ethiopia, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Liberia, Libya, Malawi, Mali, Mauritania, Morocco, Niger, Nigeria, Republic of the Congo, Rwanda, Senegal, Sierra Leone, Somalia, Sudan, Tanzania, Togo, Tunisia, Uganda, and Zimbabwe. European countries where at least 1,000 Africans applied for asylum between 2011 and 2015 are: Austria, Belgium, Bulgaria, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Malta, Netherlands, Norway, Romania, Spain, Sweden, Switzerland, and the United Kingdom.

are considered. If a time-invariant variable is correlated with both the dependent as well as the independent variable of interest, its exclusion might bias the results. For instance, if political violence happened to be more intense in more distant countries, and greater distance to Europe impeded asylum migration, the effect of violence on asylum flows might be underestimated without including distance as a control. This becomes relevant for models that do not eliminate time-constant heterogeneity between units. As bilateral time-constant variables, we include capital-to-capital distance (in 1,000 kilometers) and past colonial rule. A time-variant but (in most cases) only marginally changing factor is the diaspora size, i.e. the stock of migrants (defined by country of birth) from the respective source country already living in the destination country at the beginning of our time series. Other factors that only marginally changed during the observed five-year period include population size and growth rate, level of socio-economic development, and political regime type, which can all be important predictors of migratory movements. As a downside to the short timeframe analyzed in this study, these effects cannot be identified in a unit fixed-effects model due to the small amount of variance empirically observable over time. However, precisely since these highly path-dependent factors hardly changed in recent years, they cannot be responsible for the strong increase in asylum seekers evident over the same period of time which is what we seek to explain. Our focus is therefore on a fine-grained analysis of variables such as political violence that can change abruptly.

While the main variables of interest have complete information, there is some amount of missing data for several control variables. We used Amelia II (Honaker et al. 2011) for R (R Core Team 2013) to impute missing data based on all information in the dataset. Each statistical model was estimated separately in ten multiply imputed datasets and the results (coefficients and standard errors) were averaged using Rubin's rules. A list of all variables and data sources is given in the appendix.

Statistical models

With T = 20 (quarters) and n = 722 (country-country dyads), our time-series cross-section (TSCS) data are a case of "small-T, large-N". Four methods suitable for this type of data are considered: a fixed-effects (FE) model, a random-effects (RE) model, a first-differenced (FD) model, and a dynamic panel model including a lagged dependent variable (LDV). All of these models try to address the issue of unobserved heterogeneity in the data which exists because multiple measurements of the same unit are usually similar to each other. Thus, in our case where units are pairs of country of origin and country of destination, multiple observations of "Algeria-Austria" will likely be correlated and systematically differ from all observations of, say, "Nigeria-Italy". Most often, not all of these systematic differences can be explained by the observed variables, and it is usually suspected that historical, cultural, or other latent factors account for part of the autocorrelation among the errors.

The fixed-effects model alters the standard linear model by splitting up the error term into an idiosyncratic and a unit-specific time-constant term. It can be written as

$$y_{i,t} = \beta X_{i,t} + \eta_i + \varepsilon_{i,t} \quad (1)$$

where $y_{i,t}$ is the outcome for country-pair *i* in quarter *t*, $X_{i,t}$ is a vector of explanatory variables with regression weights β, η_i is a time-constant error term varying across units only and $\varepsilon_{i,t}$ denotes the idiosyncratic error for each observation with mean zero and constant variance. In the FE model, η_i may be correlated with the other predictors and are treated as "fixed" or equivalent to a set of n-1 dummy variables for each unit, thereby eliminating all variance between units. Only differences within country-pairs are relevant in this model. For instance, if we look at all 20 observations for unit "Nigeria-Italy", are those observations with an above-average number of deaths from violent conflict also characterized by higher rates of asylum migration? We cannot explain why migration from Nigeria to Italy has been higher than migration from Algeria to Austria, and all time-invariant predictors are disregarded by the analysis. But these consequences are in fact intended since we want to identify an effect responsible for the observed changes over time instead of some cross-sectional correlation (see, e.g., Halaby 2004, p. 523). Moreover, both the dependent as well as the independent variable of interest show considerable variance over time, including sharp increases and abrupt decreases. Therefore, the problems associated with slowly-changing path-dependent variables in FE models described by, e.g., Pluemper and Troeger (2007), do not apply here.

Since the aggregated time series shown in Figure 1 is obviously non-stationary at least since around 2013, the danger of spurious regression exists since even two purely stochastic non-stationary time series (random walks) are known to be significantly correlated in most instances (Granger and Newbold 1974). The shift in mean asylum flow over time might be attributed to "common shocks" (such as changes in European asylum policies in the Mediterranean) and can be captured by a time-specific error term δ_t, which is equivalent to a set of dummy variables for each quarter (also denoted as time or period fixed-effects). We estimate a model with period effects and include seasonal dummies in all other models.

The random-effects (RE) model can also be expressed by equation (1), but contrary to the FE model, in the RE model the time-constant error term η_i is uncorrelated with the other regressors. As a result, it only accounts for the serial correlation in the errors and there is still variance between units that can be explained by other unit-specific characteristics. The RE model (or random-intercept model in the terminology of multi-level models) can therefore take effects of time-invariant variables such as geographic distance into account which is not possible with FE. However, the central assumption that unit-specific errors are not correlated with the regressors is, as in most applications, not very plausible.

Another approach to tackle unobserved heterogeneity is presented by the first-difference estimator which wipes out any differences in the levels of our variables of interest (which might be affected by past uncontrolled factors) and only looks at changes during the observed period of time. For instance, we are interested in knowing whether increases (decreases) in political violence are usually associated with increases (decreases) in asylum emigration. Since we suspect our time-series to be trend-stationary, first-differencing the data can eliminate some of the problems associated with this kind of data. On the other hand, FD only considers short-term changes and not the deviation of the current observation from the long-term mean (as in the FE model, a difference that obviously only becomes relevant for $T > 2$) which might be relevant if, for instance, there are ceiling effects or a regression to the mean for very large values of y. The FD model can be written as:

$$\Delta y_{i,t} = \beta \Delta X_{i,t-1} + \Delta \varepsilon_{i,t} \tag{2}$$

Finally, following Beck's and Katz' (1995; 2011) highly influential articles, many studies have analyzed panel data using a lagged dependent variable (LDV) in addition to the "panel-corrected standard errors" proposed by Beck and Katz. The LDV is included to capture all effects that led to a specific level of the dependent variable at the previous time point. Similar to the other approaches described above, the LDV model aims at capturing unobserved heterogeneity between the units under study, i.e. the undisclosed reasons for why bilateral asylum flows are generally higher between one pair of countries compared with another pair. In the longer run, however, given sufficient variation over time and between units, different units might converge to different levels which cannot be explained by the LDV (see, e.g., Wilson and Butler 2007, p. 107). Contrary to the FE and FD models, the Beck-Katz specification with LDV is therefore open to time-invariant covariates. A formal expression of this model can take the following form:

$$y_{i,t} = \alpha + \gamma y_{i,t-1} + \beta X_{i,t} + \varepsilon_{i,t} \tag{3}$$

We estimate LDV, RE, FE, and FD models for specifications including time-variant variables only. All models are estimated using the plm package for R (Croissant & Millo 2008). For more extensive models including also time-invariant and near-time-invariant regressors, we use Beck-Katz-type specifications with an LDV and panel-corrected standard errors. Since a sizeable number of potential control variables were suggested in the literature and compiled for this study (see Appendix), an important question concerns which of these to include in the respective model. A well-known issue with aggregate cross-country data is the usually high level of multicollinearity. For instance, level of socio-economic development, political regime type, population growth rates, unemployment, and political violence might all be correlated in the countries of origin. Throwing all of these variables simultaneously into a multivariate model, we would likely not be able to figure out which of these variables is responsible for the observed differences in asylum emigration. A key issue with these "garbage-can models", as they are often referred to (see, e.g., Schrodt 2014), is the fact that coefficients of independent variables of interest might be heavily sensitive to the inclusion or exclusion of one or two variables from the long list of controls without a plausible theoretical mechanism behind this finding. In other words, results from such analyses might be "model-dependent" (Ho et al. 2007). In a final step, we use simulations in order to assess the degree of model dependency. We estimate 1,000 models regressing bilateral asylum flows on the independent variable of interest – the number of conflict deaths – in addition to an LDV, time dummies, and a set of randomly drawn control variables. While being atheoretical, this procedure can inform about the sensitivity of the results to slightly different specifications of the model and we therefore regard this approach as preferable to only reporting a handful of selected model specifications.

Results

For how long does an increase in political violence affect refugee flows to Europe? We conduct an exploratory analysis to find out which time lag is appropriate to use in the subsequent models. As Table 1 shows, the number of conflict deaths is significantly associated with the volume of bilateral asylum flows in a bivariate model including fixed effects for country-pairs and periods. The effect decays over time and disappears from a lag of four quarters onwards. This is an important finding, suggesting that yearly (or less often) observations of asylum migration dynamics may miss this relationship. As a consequence of these results, we measure conflict fatalities and asylum flows at the same time in the following analyses.

Table 1: Exploratory analysis of time-lags in the effect of conflict deaths on asylum flows

	Dependent variable: Log of bilateral asylum flows								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(fatalities)	.035***								
	(.006)								
lag(log(fatalities), 1)		.028***							
		(.006)							
lag(log(fatalities), 2)			.022***						
			(.006)						
lag(log(fatalities), 3)				.023***					
				(.007)					
lag(log(fatalities), 4)					.014				
					(.007)				
lag(log(fatalities), 5)						-.003			
						(.007)			
lag(log(fatalities), 6)							-.019*		
							(.008)		
lag(log(fatalities), 7)								-.030***	
								(.008)	
lag(log(fatalities), 8)									-.032***
									(.008)
Observations	14,440	13,718	12,996	12,274	11,552	10,830	10,108	9,386	8,664
R^2	.023	.019	.020	.020	.019	.014	.012	.009	.008

Note: Fixed-effects models (country of origin - country of destiny pairs) with period dummies. Data sources: see text. *p<.05, **p<.01, ***p<.001

Table 2: Time-variant predictors of quarterly bilateral refugee flows from Africa to Europe

	Method:					
	OLS	LDV	RE	FE	FE de-trended	FD
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	1.267***	.115***	1.611***			
	(.061)	(.030)	(.084)			
Log(Asylum flow, t-1)		.895***				
		(.004)				
Log(Conflict deaths)	.151***	.025***	.027***	.021**	.025***	.017*
	(.011)	(.005)	(.007)	(.007)	(.007)	(.007)
Log(Violent incidents)	.148***	.008	.080***	.073***	.030**	.007
	(.016)	(.007)	(.011)	(.011)	(.011)	(.011)
Unemployment rate in destination	-.040***	-.003*	-.034***	-.036***	-.047***	-.005
	(.003)	(.001)	(.005)	(.005)	(.005)	(.012)
GDP growth in destination	-.283***	-.031**	.028**	.035***	-.005	-.012
	(.020)	(.010)	(.010)	(.010)	(.011)	(.008)
African asylum rejection rate	.002**	-.00003	.002***	.002***	.003***	.001*
	(.001)	(.0003)	(.0004)	(.0004)	(.0004)	(.0004)
Seasonal dummies	Yes	Yes	Yes	Yes	No	Yes
Period dummies	No	No	No	No	Yes	No
Observations	14,440	13,718	14,440	14,440	14,440	13,718
R^2	.102	.813	.018	.016	.033	.004

Note: Data sources: see text. OLS = ordinary least squares, LDV = lagged dependent variable, RE = random effects, FE = fixed effects, FD = first difference. *p<.05, **p<.01, ***p<.001

Table 2 presents panel regressions of bilateral asylum flows on time-variant predictor variables. The number of fatalities from violent conflicts in a quarter is significantly associated with the volume of asylum flows in all models. The evidence is less clear regarding the number of incidents (such as violent protests or clashes) which are significant in four out of six models. As expected, unemployment in the country of destination tends to negatively affect asylum migration. With regard to GDP growth in the destination, the correlation is negative in the pooled models, suggesting that countries with higher growth attract fewer migrants. It has to be noted, however, that Central-Eastern European countries tend to have higher growth rates but fewer asylum applications which is likely due to factors other than economic growth. When unit-specific peculiarities are taken into account (RE and FE models), the sign turns positive, suggesting that within the time series of a specific country pair, quarters with higher growth rates in the destination are on average also quarters with higher inflows. This association disappears when time fixed-effects are taken into account, however. Finally, the share of negative decisions on Africans' asylum applications in the destination is positively related to asylum inflows in most models. The direction of causality is obviously unclear here. A plausible interpretation of this result could be that countries accept less Africans as soon as they notice their number going up.

While the question of endogeneity is difficult with regard to policies, we can be more confident that the effect of violent deaths is identified in the FE and FD models with the direction of causality as postulated by theory. Although it is not beyond imagination that, for instance, an increase in out-migration might trigger an intensification of violence among the remaining forces of a civil war, the mechanism of violence as a "push-factor" is likely to dominate.

Regarding the question of model selection, we performed several tests to decide which specification is appropriate. Clustering of errors within units can be detected in various ways. We used an F-test which revealed that the random-effects (RE) model is preferable over the otherwise identically specified pooled model. As is common when deciding between RE and FE models, a Hausman-test was carried out which suggested that the RE model is inconsistent and FE is preferable. Another F-test shows that the inclusion of period dummies (Model 5) improves the explanatory power of the model compared with a model with seasonal dummies only.

Thus, there is consistent evidence that political violence causes asylum emigration. However, to what extent can the huge increase in asylum seekers observed during the study period be attributed to intensifications of political violence? Conventional measures of model fit such as R^2 suggest the overall explanatory power of this predictor is rather low. In addition, we use a split-sample design to evaluate whether the effect of violence has become more pronounced during the second half of the study period which saw a departure from the previous stationary trend in the total number of inflows which has since shown an upward tendency (see Figure 1). We refer to these two periods as "pre- and post-Mare Nostrum" after the sea-rescue mission led by the Italian navy that started in late 2013. The results are plotted in Figure 5. It turns out that the coefficients for conflict deaths are greatly reduced during 2013 to 2015 compared with the preceding period. The number of deaths from violent conflicts has only a small and sometimes even statistically insignificant bivariate effect on the rate of asylum seekers which surged during this period. This is unexpectedly strong evidence against the assumption that an increase in political violence can explain the rising number of refugees coming to Europe.

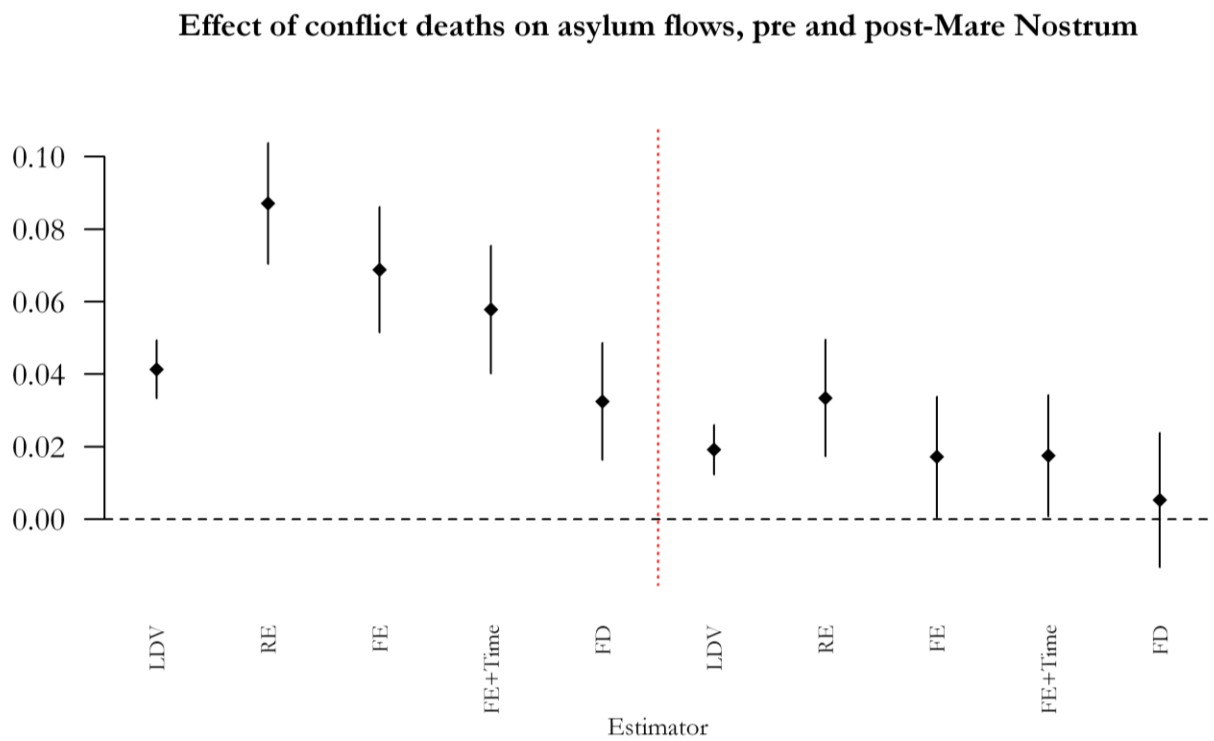


Figure 5: Effect of conflict deaths on asylum flows, pre and post-Mare Nostrum

Note: Left side reports effects before (January 2011 – September 2013), right side after "Mare Nostrum" (October 2013 – December 2015). Graph shows unstandardized regression coefficient and 95% confidence intervals. LDV = lagged dependent variable, RE = random effects, FE = fixed effects, FD = first difference. Models include seasonal dummies except for models labeled "FE + Time" which include period dummies. For LDV model, Beck-Katz "panel-corrected standard errors" are calculated. Data source: see text, own calculations.

Finally, as robustness check, we report simulation results were models specified as in equation (3) were repeatedly estimated with a random set of control variables. The latter included both time-variant as well as time-invariant or near time-invariant variables such as geographic distance, past colonial experience, diaspora size, affectedness by climate change, as well as various economic and demographic indicators. Figure 6 compares the resulting unstandardized coefficients before and after the start of "Mare Nostrum". As the plots show, coefficients are more than halved in most cases for the second half of our study period. No matter which controls are added to the respective model, coefficients pre-"Mare Nostrum" are always greater than their later counterparts.

Accordingly, Figure 7 shows that regardless of which control variables are added to the model, the number of deaths from political violence is always significantly associated with asylum emigration before late 2013. Since then, however, evidence is considerably less compelling. In fact, in 21% of all models for the later period, the association is not statistically significant.

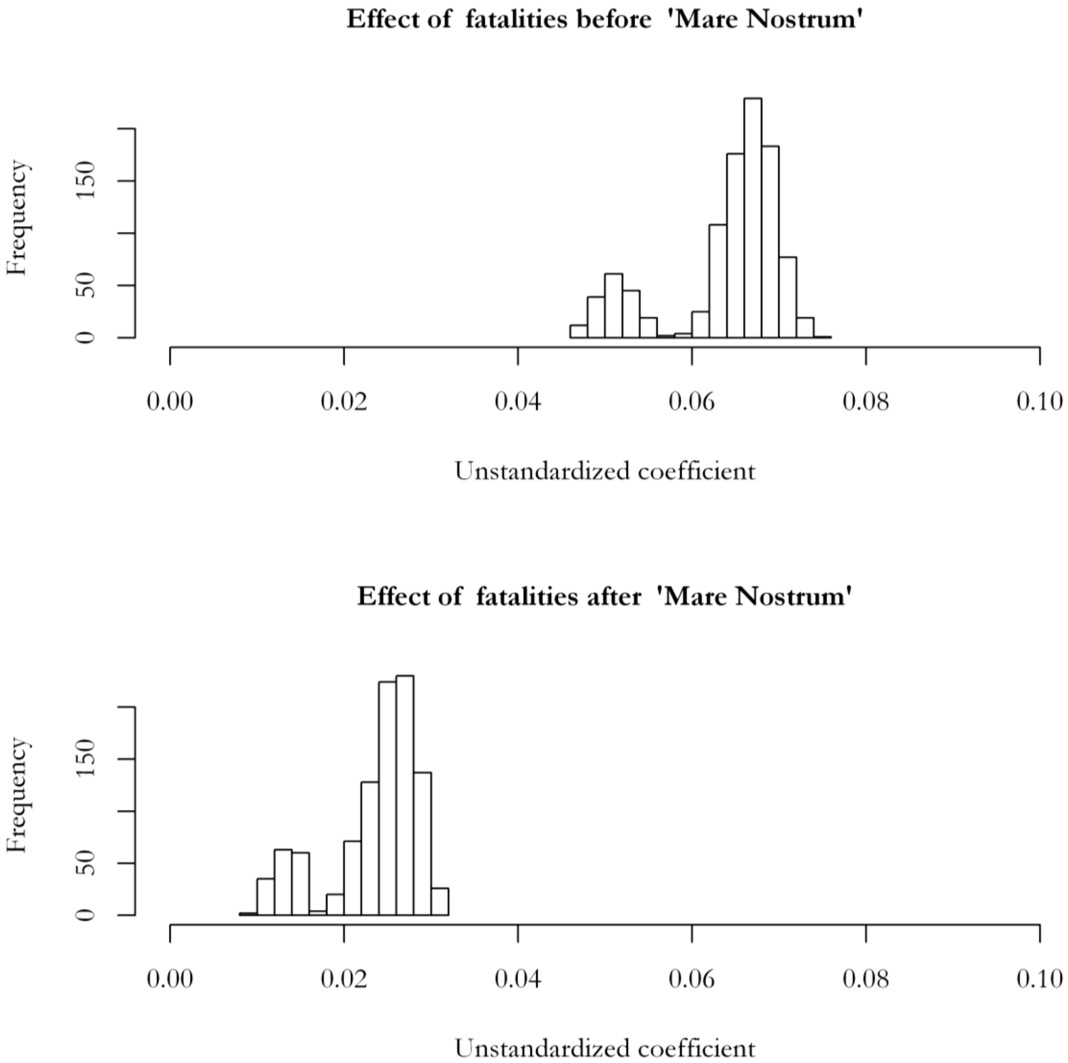
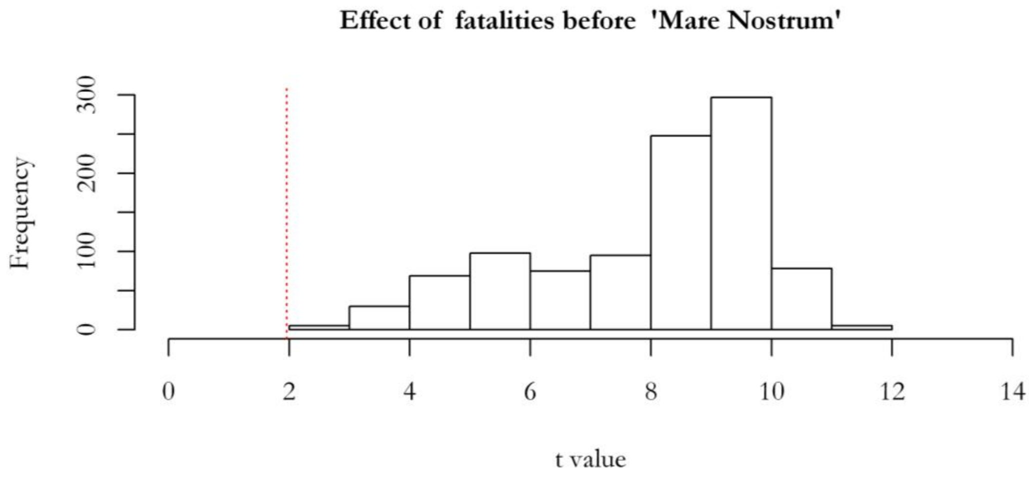


Figure 6: Coefficients from simulations with random sets of control variables

Note: Histograms show unstandardized regression coefficients from 1,000 models estimating the effect of political violence on asylum flows for the period of January 2011 to September 2013 (upper panel) and October 2013 to December 2015 (lower panel), respectively. Model specifications include a lagged dependent variable, time dummies, a randomly drawn set of control variables, and panel-corrected standard errors. Data sources: see text, own calculations.

Conclusion

The number of asylum seekers from Africa entering the European Union has oscillated around a quasi-equilibrium of 5,000 per month between 2008 and 2012. However, since then, asylum migration from Africa has increased threefold within a short period of time. While political violence and conflicts were intense in many countries, this factor cannot explain the recent increase in refugees. On the contrary, we find that since late 2013, the statistical association between political violence and asylum migration is greatly reduced compared with previous years. Accordingly, countries that send more migrants do not on average witness more conflicts. Levels of political violence are high in many of these countries, but have been high already before the emigration waves started, so it is hard to causally attribute the increase in asylum seekers to violent conflicts.



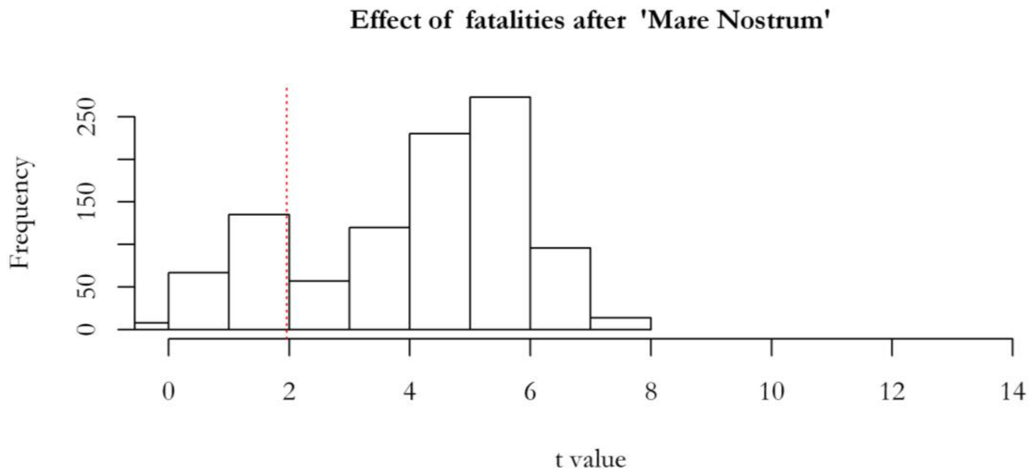


Figure 7: T-values from simulations with random sets of control variables

Note: Histograms show t-values from 1,000 models estimating the effect of political violence on asylum flows for the period of January 2011 to September 2013 (upper panel) and October 2013 to December 2015 (lower panel), respectively. Model specifications include a lagged dependent variable, time dummies, a randomly drawn set of control variables, and panel-corrected standard errors. Data sources: see text, own calculations.

While we offer evidence against the assumption that changes in political violence triggered the recent increase in asylum seekers, we cannot determine what did. A possible ad-hoc explanation might describe this increase as a result of changing opportunity structures: While the motives to emigrate had been there even in previous years, the perceived likelihood of success increased recently. A reason for this might be the intensification of sea-rescue missions in combination with the de-facto breakdown of the "Dublin" regulations. These regulations state that asylum applications have to be filed in the country where the applicant first set foot in the EU, but enforcement varies between countries and over time. For instance, while the total number of asylum applications in Germany increased tenfold between 2010 (48,000) and 2015 (477,000), the reported number of "Dublin transfers" to other European countries actually decreased from 2,400 to 2,000 or 0.4% as a proportion of total inflows (Eurostat 2016). As a result, refugees entering the European Union have improved chances of reaching and staying in the preferred country of destination (where, e.g., relatives already live). On the other hand, we did not find evidence for a negative effect from the formal acceptance rate of African asylum applications on the number of newcomers. However, formal rejections need not translate into deportations, reliable data are scarce, and hence the opportunity structure presented by laws, policies, and administrative practice is difficult to model in quantitative studies.

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Appendix: Variables and data sources

Variable	N	Mean	St. Dev.	Min	Max	Source
asylumflow_quarter	14,440	52.794	225.720	0	7,690	Eurostat (2016)
incidents	14,440	71.366	137.302	0	1,016	ACLED
fatalities	14,440	158.632	447.123	0	6,109	ACLED
unempl_dest	14,440	9.219	5.686	3.100	27.867	World Bank (2015)
growth_dest	14,440	0.302	0.818	-3.800	4.703	World Bank (2015)
reject_rate_dest	14,440	62.082	25.466	0.000	100.000	Eurostat (2016)
season	14,440	2.500	1.118	1	4	
PopGrowth	14,440	2.517	0.726	-0.027	3.993	UN (2016)
ClimateRiskIndex	14,060	109.320	26.574	40.170	156.670	Kreft et al. (2014)
YouthRatio	14,440	47.438	4.694	33.051	53.555	UN (2016)
Pop_size	14,440	26,559	33,734	876	177,476	UN (2016)
FH	14,440	9.711	2.955	3	14	Freedom House (2015)
GDP_cap	13,680	3,451.1	3,526.1	594.16	15,590	World Bank (2015)
YearsSchooling	14,060	4.203	1.793	1.300	7.600	World Bank (2015)
InfMort	14,440	88.368	40.670	15	182	World Bank (2015)

PhysPopDens	14,440	17.268	69.398	-2.314	438.176	World Bank (2015)
Urban	14,440	41.960	17.054	11.761	78.359	World Bank (2015)
UnempTot	14,060	7.595	5.433	0.600	31.000	World Bank (2015)
UnempYouth	14,060	13.549	11.130	0.700	51.200	World Bank (2015)
TFR_t_20	14,440	5.962	1.175	2.900	7.771	UN (2016)
Pop_dest	14,440	23,345.630	25,267.050	429	81,197	UN (2016)
GDP_dest	14,440	31,736.840	17,051.510	5,500	75,900	OECD (2016)
distance	14,440	4.910	1.557	0.357	8.846	
colonialhistory	14,440	0.062	0.242	0	1	
diaspora	13,660	7,039.174	44,440.500	0	788,563	Eurostat (2016)