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RESCUE ON STAGE: BORDER ENFORCEMENT AND PUBLIC ATTENTION IN THE MEDITERRANEAN SEA

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Rescue on Stage: Border Enforcement and Public Attention in the Mediterranean Sea

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Abstract

Irregular migrants take many risks when attempting to cross borders, and border enforcement policy has to balance deterrence and humanitarian motives. Exploiting georeferenced data on the universe of sea rescue operations for migrants crossing from Libya to Europe between 2014 and 2017, this paper makes three contributions. First, it shows that a more humanitarian rescue policy increases future crossing attempts. Second, it establishes that tougher border control increases the death risk for migrants. Third, it develops and estimates a dynamic model of border enforcement with endogenous public attention, which I use to obtain attention and policy counterfactuals. According to model results, temporary increases in public attention intensify incentives for rescuing migrants, and sample years policy was suboptimal in minimizing migrants' deaths. Leveraging recent policy outsourcing border enforcement to Libyan authorities, I compute policymakers' evaluation of irregular migrants' lives; this is an order of magnitude lower than comparable estimates for citizens.

Keywords: irregular migration, border control, search and rescue, public attention
JEL Classification: F22, K42, D72, L82

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1 Introduction

Migration is increasing worldwide and represents a central issue in the politics of high-income countries. Irregular migrants to Europe and the US take serious risks; they cross borders in hostile environments—e.g., the Sahara Desert, the Mediterranean Sea, and the Rio Grande—with a high incidence of human trafficking. Destination countries engage in border enforcement, further reducing migrants' safety. Incentives for border control are compounded by high media coverage and public attention influencing the salience of humanitarian and reception costs.

In the US, the unauthorized immigrant population hovers around 10 million (Passel and Cohn, 2018); in 2019, border patrol agents apprehended 851,508 migrants trying to cross from Mexico (USBP, 2019). In Europe, unauthorized migrants were estimated to be between 4 and 5 million in 2017 (Connor and Passel, 2019) and 141,846 migrants were detected while crossing irregularly in 2019 (Frontex, 2020). From 2014 to mid-2017, around 400,000 people crossed the Mediterranean Sea from North Africa to Europe; these migration flows are bound to increase due to population growth in Africa (Hanson and McIntosh, 2016).

To reduce irregular migrants' flows, countries resort to border control activities, increasing risks for migrants. US border control activities put migrants' lives in danger at the border with Mexico by shifting their routes towards more remote crossing points (Gathmann, 2008). European countries recently pursued policies intended to prevent Syrian asylum-seekers from entering their territory along the Balkan route of migration. In the Mediterranean Sea, migrants cross from Morocco to Spain and from Libya to Italy. European authorities rescue migrants' boats, but they keep rescue operations from occurring close to North African shores to deter future migration. Between 2014 and mid-2017, more than 12,000 people drowned before reaching rescue.

Irregular migration and risk for migrants draw considerable public attention and media coverage in destination countries. In Europe, far-right populist parties exploit inflows by asylum-seekers to advance nationalistic and xenophobic rhetoric. At the same time, European and national management of irregular migration has caused public outcry in several instances. According to journalistic sources, EU member states, supported by the European Border Enforcement Agency (Frontex), have engaged in illegal operations to push back 40,000 asylum-seekers trying to cross European borders.[1] Authorities have also been accused of failing to promptly react to distress calls by migrants, ultimately putting their lives in danger. For instance, in April 2021, 130 migrants lost their lives in a shipwreck after sending a mayday call to coastguards in the Central Mediterranean.[2] In sum, countries pursue contradicting policies aiming to keep migrants out while also ensuring that they are treated humanely. Given the relevance of irregular immigration in the political debate, public attention and media coverage potentially affect how policymakers trade-off migrants' safety and deterrence.

In this paper, I make several key contributions to understanding these complex issues. My analysis exploits novel high-frequency georeferenced data on rescue operations for migrants crossing from Libya. Using this unexplored source, first, I establish a negative relation between

[1] For instance, see the article by *The Guardian* available at https://archive.ph/vOZkQ

[2] For instance, the incident is documented in an article by *The Guardian*, available at https://archive.ph/wip/ZpjLI.

the distance of rescue from Libyan shores and future crossing attempts. Second, I examine the impact of rescue distance on migrants' safety with data on deadly incidents in migration. Exploiting variation in maritime traffic as an exogenous shock to rescue operations, I find that the death risk for migrants increases with rescue distance. Third, I develop a dynamic model of border enforcement and migration, where media and public attention are explicitly modeled. I estimate it using data on migrants' rescues, migrants' deaths at sea, and public attention to migration to describe in a rich way the dynamics induced by policy changes.

In the model, migrants buy the passage from smugglers and risk being shipwrecked if coastguards do not rescue them. More precisely, the policymaker sets the mean distance of interception and migrants survive if rescue occurs before the shipwreck. Smugglers and migrants forecast future policy decisions based on present ones; hence, higher rescue distance decreases the future availability of smuggling services. The policymaker faces an intertemporal trade-off between the safety of migrants at sea and future migration pressure: lowering distances decreases the risk of shipwrecks, but it increases future migrants' departures. Shocks to public attention in the model put pressure on the government by impacting its marginal disutility from migrants' deaths and arrivals. Temporary attention shocks potentially tilt the policymaker's intertemporal trade-off toward present goals–saving lives–compared to future goals–reducing departures.

Given the present rescue distance, the realized public attention, and other shocks affecting migrants' departures, the policymaker decides on the distribution of future rescue distances. I solve numerically for the policies and estimate the model maximizing a likelihood defined on distances of the realized rescues. The estimation relies on novel data on the location of rescue interceptions in the Central Mediterranean Route of migration, provided by the European Border and Coast Guard Agency (Frontex). The dataset I employ consists of the universe of rescue interceptions for migrants departing from Libya over the period. Because of its completeness and given the frequency of operations, it gives a well-defined measure of border enforcement–rescue distance for migrants. In the estimation, I also employ a measure of the evolution of public attention to migration, based on Google searches about migration, which I cross-validate with a comprehensive dataset of newspaper articles about migration.

Jointly modeling incentives driving migrants' departures and rescue policy allows me to simulate counterfactuals on (i) how shocks to attention drive policymakers' incentives to pursue different policies and (ii) how such policies impact migrants' safety and departures. Finally, I use the estimated policy preferences to show how policymakers value migrants' safety *vis-à-vis* arrivals, and in financial terms.

I show that attention shocks reduce rescue distance; if attention increases temporarily, the policymaker accepts more future departures to diminish migrants' present death probability. By explicitly modeling the impact of policy on the evolution of public attention, my empirical strategy addresses potential endogeneity concerns.[3] The effect of shocks to attention on distance

[3] In addition, I show that the negative relation between attention and distance is robust to instrumenting attention with sports events crowding out attention to migration, in the spirit of Eisensee and Strömberg (2007). As an instrument, I use newsworthy soccer matches of Italian *Serie A*; I define a match to be noteworthy if contestants are among the three most popular teams in *Serie A*, based on Google Searches, and if their result is unexpected, based on odd-implied outcome probability. Results do not depend on the spurious seasonal correlation between migration and matches, as I show by including a fine-grained set of seasonal controls.

is persistent because of at least two reasons. First, attention shocks themselves are persistent. Second, public attention has an indirect effect on the distance of rescue from Libya through the dynamics of migrants' departures. Higher public attention leads to safer policy, which induces higher departures, thus increasing the policymaker's incentive to save migrants close to their point of departure and avoid incidents. The reaction of departures to distances induces short-run amplification in the impact of public attention on rescue distance.

Simulating the model, I illustrate that the policy stance taken from 2014 to 2017 was suboptimal in minimizing expected migrants' deaths, which could have been reduced by decreasing or increasing distance, in turn increasing safety or increasing deterrence, respectively. However, policymakers did not find it optimal to deviate, given their objectives. On the one hand, increasing rescue distance would have resulted in many migrants' deaths in the short run. On the other hand, decreasing rescue distance would have increased migrants' departures, which the policymaker wants to minimize together with deaths. Indeed, in the estimated model, the policymaker dislikes both arrivals and deaths; at the steady-state, she is willing to accept one migrant's death to avoid ten migrants' arrivals. I also cast policymakers' revealed value of saving migrants' lives in financial terms by analyzing a policy that occurred after the sample period, outsourcing border enforcement to Libyan institutions in exchange for money. I show that the revealed Value of a Statistical Life assigned by policymakers to irregular migrants is lower than comparable estimates for natives or citizens in the literature.

Previous work has drawn a connection between border enforcement and migrants' crossing attempts in Europe. Deiana et al. (2021) show that the presence of rescue operations in the Mediterranean Sea facilitates smugglers' operations.[4] Fasani and Frattini (2019) establish a negative relation between Frontex border enforcement spending and crossing attempts on land routes in Europe.[5] Hatton (2016) finds that policies limiting migrants' access to a country's territory reduce asylum applications, implying fewer migrants' entries. Other studies have shown that border closures by European countries reduce intentions to migrate to Europe, such as Aksoy and Poutvaara (2019) and Friebel et al. (2017). However, this is the first work to rely on high-frequency variation in border enforcement and migrants' departures, allowing me to obtain easier identification of the impact of policy.

An extensive literature has investigated the effect of US border enforcement on the safety of migrants trying to cross from Mexico. Cornelius (2001) and Gathmann (2008) show that US border enforcement increases the risk for irregular migrants along its border with Mexico.[6] The case of European borders is now a key dimension of the policy debate, but it has received less attention in economics so far. This work exploits the ability to measure an essential dimension of border enforcement at sea—the location of rescue for migrants—to study the relation between death probability and policy causally. Further, it provides a counterpart for sea borders to the results in the literature on border enforcement and migrants' safety.

Other studies have drawn a connection between policy outcomes and public attention–

[4] Amenta et al. (2021) highlight the difference between long-term and short-term policymaking in the Mediterranean Sea and the role of structural conditions in source countries in determining migrants' flows.

[5] They do not find such an impact on sea routes.

[6] Gathmann (2008) also shows that the US-Mexico border build-up in the late 1980s and early 1990s had a modest impact on smuggling prices. Angelucci (2012) finds a small deterrence impact for the same years but larger effects in the early 2000s.

usually in the form of media coverage–in various contexts. Eisensee and Strömberg (2007) show that higher news coverage drives the US government to increase relief response to worldwide natural disasters.[7] Durante and Zhuravskaya (2018) find that Israeli military forces strategically time attacks on Palestinians to minimize emotional press coverage abroad. The main insights of these works come from traditional media; however, recent literature has shown the internet's role in shaping political behavior. Internet access has been found to depress political turnout in Germany, Italy, and the UK–see, respectively, Falck et al. (2014), Campante et al. (2018), and Gavazza et al. (2019). However, internet has been found to contribute to other forms of political participation and oversight. Campante et al. (2018) find that the internet facilitated the establishment of local grassroots political movements in Italy. Guriev et al. (2019) show that the expansion of 3G networks reduces trust in government by exposing corruption scandals, in turn negatively affecting incumbent parties' vote share.[8,9] Besides, recent theoretical work by Matějka and Tabellini (2021) shows that, in a static setting of electoral competition, individual information acquisition alters the strategic positioning of political opponents. In sum, there is empirical and theoretical evidence of a complementarity between public attention and the public's preferred political outcomes and that the media facilitate the diffusion of policy-relevant information among voters. In this paper, I model the impact of such complementarity in a dynamic policy setting. I contribute to the literature about the impact of media on policy by showing that public attention is bound to influence policy when (i) public attention fluctuates over time and (ii) policymakers face an intertemporal trade-off between policy objectives. Further, I show that more persistent attention shocks have less impact on policymaking because they alter intertemporal trade-offs more weakly.

By building and estimating a dynamic structural model of irregular migration, I contribute to a growing literature using structural models to assess the impact of migration and migration policy. Lessem (2018) employs a discrete choice dynamic programming model to examine how wage rates and border enforcement affect migration from Mexico to the US. She finds that border enforcement reduces irregular entries and increases the length of stay of migrants, but it reduces years spent in the US in aggregate. Using a similar framework, Kovak and Lessem (2020) show that bans on legal entry for detected irregular migrants are not effective at discouraging migration. Other authors take another approach and employ static spatial equilibrium models to study migration policy. Allen et al. (2018) consider an extension of the wall at the border between the US and Mexico, finding modest impacts of the wall on migration and the US economy.[10] Piyapromdee (2021) finds that the benefits of the border wall for American citizens

[7] Other evidence suggests a link between media coverage and policy in the US. Facchini et al. (2016) establish that US representatives' voting behavior in roll call votes responds to public opinion differentially based on the level of the media coverage of their activities in their constituencies. Djourelova and Durante (2019) show that US presidents are more likely to sign executive orders on the eve of days when other important stories can crowd out their coverage.

[8] Gavazza et al. (2019) find suggestive evidence that broadband diffusion coincides with lower taxes in the UK by facilitating information diffusion among voters.

[9] In a context close to the one I study, Fasani and Frattini (2019) show that the political cycle in Europe affects border enforcement intensity. Frontex spends more on enforcement for a given route if it is close to the country holding the rotating EU presidency and in countries with incoming national elections, suggesting that policymakers benefit more from spending on routes with more political or media exposure.

[10] Feigenberg (2020) studies the effect of border walls on migration in the same context, without modeling its spatial equilibrium. The impacts on migration that he finds are considerably larger than Allen et al. (2018).

are very modest at best and lower than the cost of constructing it. Other recent works have employed structural models to examine determinants of migration choices (Albert and Monras, 2018), return decisions by migrants (Dustmann et al., 2021), and the impact of migration on economic outcomes for natives (Llull, 2018) or other migrants (Albert et al., 2020). Few works have estimated structural models to assess the determinants of migration policy, as I do. A notable exception is Görlach and Motz (2021), modeling asylum policy as a game played among European countries. In my structural framework, I jointly study the decision-making of migrants and the government in setting border enforcement, shedding light on outcomes such as migrants' safety and irregular entries.

In what follows, I first delineate the context of my study. Second, I explain the data that I employ. Third, I describe a model of border enforcement choice. Fourth, I explain my empirical approach and present results. Finally, I conclude.

2 Context

2.1 The Central Mediterranean route of migration

High-income European countries impose tight restrictions on immigration. Migrants in search of economic opportunity or political asylum try to overcome these barriers by entering European countries irregularly. In the Mediterranean Sea, migrants cross from North Africa to Europe on unseaworthy boats. In recent years, crossings in the Mediterranean Sea occurred on the Western Mediterranean route, mainly connecting Morocco to Spain, the Eastern Mediterranean route, connecting Turkey and Greece, and the Central Mediterranean route, connecting Libya and Italy. The latter route has been active since the 1990s; however, the number of migrants' crossings increased substantially in the last half of the 2000s (Fargues and Bonfanti, 2014).

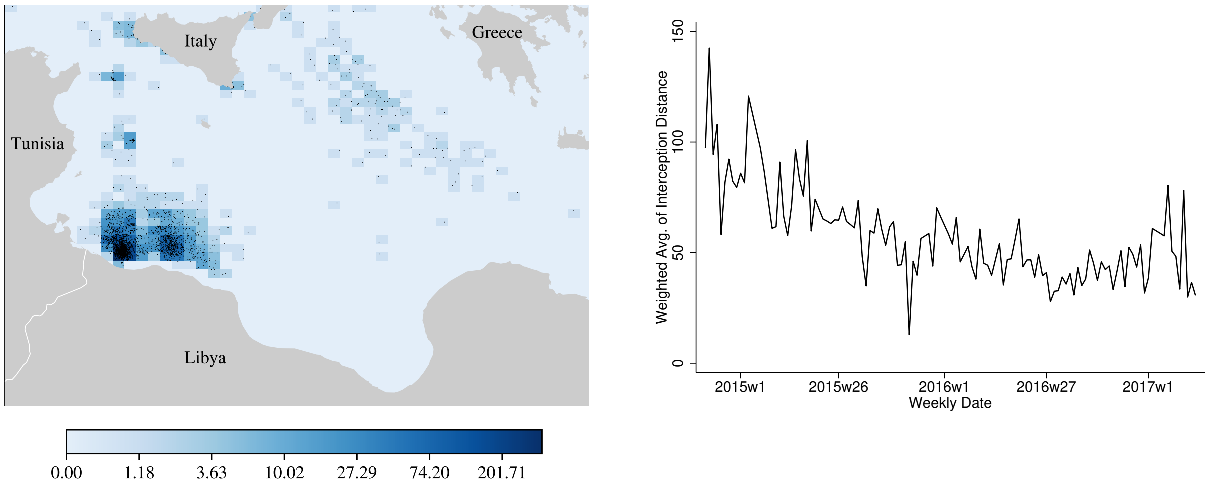
In 2014, Frontex recorded 170,664 crossings along the Central Mediterranean route, representing 60% of irregular border crossings to Europe (Frontex, 2015a). Institutional developments in Libya have certainly contributed to its centrality to the smuggling business. During Gaddafi's rule in the country, human smuggling activities started to thrive; his fall, in 2011, set them free from border controls (Tinti and Reitano, 2018). The high number of Syrian asylum-seekers fleeing the country from 2010 prompted the development of a market for crossings on a large scale (Tinti and Reitano, 2018). In response to Libya's transformation into a major human smuggling hub, European authorities established institutional Search and Rescue (SAR) operations in the Central Mediterranean such as *Hermes*, *Mare Nostrum*, and *Triton* (the focus of this study), possibly incentivizing smuggling activities (Deiana et al., 2021).

Because of the escalation in civil conflict from 2014 to 2017, Libya was incapable of rescuing boats in distress. Institutional rescuers–the Italian Navy, the Italian Coast Guard, and Frontex–and NGO actors regularly rescued migrants' traveling from Libya to Italy. However, institutional rescue did not occur near the Libyan coast, with a view of discouraging departures, as I document in Appendix Section A.3, where I summarize the main phases of the evolution of SAR. Figure 1a depicts rescues (dots) and rescue frequency (shaded squares) in the Mediterranean Sea. Rescues are heavily concentrated near Libya, in the bottom-left corner. Figure 1b shows how rescue distance for boats from Libya evolved. The average rescue took place around 50KM

Figure 1: Rescue locations and rescue distances

(a) Interception locations overlaid on 2-d histogram, frequency in IHS units

(b) Migrants-weighted mean of interception distances over time



Note: Panel (a) reports a scatter of interceptions' locations from November 1, 2014, to April 1, 2017, overlaid over 2-d histogram (50 bins on the *x-axis* and on the *y-axis*), with frequency expressed in Inverse Hyperbolic Sine units. Panel (b) shows the average distance of interceptions, weighted by number of migrants in each interception, over time (KM). Own elaboration of Frontex data. Also referenced in Appendix Section A.3.

offshore, a considerable distance for migrants typically traveling in overcrowded dinghies, but there were significant short-term and long-term changes in distances over the period. Between 2015 and 2017, around 2% of migrants lost their lives while attempting to cross. In some cases, as in April 2015, the death frequency was as high as 9%.

In roughly mid-2017, EU and Italian border enforcement policy in the Mediterranean shifted towards contracting border enforcement provision to Libyan authorities. In March 2017, Italy and the UN-backed Libyan government of Al-Sarraj reached a deal. Libyan authorities agreed to scale up migration control in exchange for financial support and naval assets. The Italian government first committed to transferring naval assets to Libyan institutions on April 21 (Interni, 2015). After a few weeks, departures started to decrease (Villa, 2015), a sign that Libyan institutions had started border enforcement activities. In my analysis below, I focus on *Triton Operation* before the deal with Libya. This allows me to focus on rescue location as the main policy instrument because other policy instruments were virtually absent over the period. In the next sections, using data on policy, arrivals, and deaths, I document a trade-off between saving migrants at sea and discouraging future departures. These policy objectives interacted with public attention to migration over the period; in what remains of this section, I give further particulars about the evolution of public attention to migration at destination and its impact on policy.

2.2 Migration and SAR: attention, coverage, and political sentiment

Migration is a central theme for European politics. In the years after the financial crisis and before the outbreak of the COVID-19 pandemic, European citizens surveyed in the Eurobarometer have consistently rated migration to be among the top two policy issues, together with terrorism.[11] Irregular migration seems to be an even higher source of worry for voters in Europe and the US (Casarico et al., 2015).

Over the years considered in my analysis, Italy has been the primary stakeholder in SAR policy along the Central Mediterranean route, both in terms of budget contribution and reception activities for disembarked migrants. As for Frontex, the other notable institutional player, the agency has claimed it needed to build political support in key stakeholders (Member States and EU bodies) to sustain its ability to perform its operations (Frontex, 2016). Based on these premises, my analysis of the political drivers of SAR will focus on Italy.

During the sample period, there was no abrupt change in the political incentives of the institutional actors involved coming from shifts in voters' attitudes toward migration. According to the Eurobarometer, 75% of Italian citizens had negative attitudes about migration from outside the EU in November 2014; the figure remained fairly stable over the next two years, registering a 69% in November 2016.[12] Also, there was no national election between 2014 and 2017, and Partito Democratico, the leading national social-democratic party, was continuously in government with the partial support of right-wing moderates in the high chamber, *Senato*. Parliament voting intentions for the main nationalist anti-immigration party in Italy, Lega, always remained between 12% and 16% from 2015 to 2017.[13]

As opposed to attitudes, public attention to migration varied considerably between 2014 and 2017, as shown in Figure 2a. The solid line reports the value for the weekly Google search volume for the word '*migranti*' (i.e., migrants). Some of the variation can be explained by large events occurring in the rescue area. This is the case, for example, of the peak in April 2015, when two migrants' boats capsized in the Strait of Sicily, causing the death of around 1,200 people.[14] Other events with a comparatively smaller death toll captured public attention in Europe and beyond due to the conditions of the victims. The death of Alan Kurdi on September 2, 2015, is a case in point. The body of the Syrian toddler washed up on a beach near Bodrum, Turkey, after he drowned with his mother and brother trying to cross at sea from Turkey to Greece. The pictures of Alan's body were widely circulated by the media, and the story caused outcry all over the world.[15] In general, as I argue in the following sections, deaths at sea, migrants' arrivals, and unrelated news competing with migration have a part in explaining the variation in attention over time.

These observations are not just limited to the measure of Google searches. The dashed line in Figure 2a reports the number of Italian news articles about migration in the Mediterranean; the evolution of searches essentially tracks news articles. Further, using the text of the articles collected, I check whether shifts in attention are driven by one particular type of voters or citizens with particular political preferences. Taking newspaper articles' sentiment as

[11] Responses can be consulted interactively at https://archive.is/JZ71S.

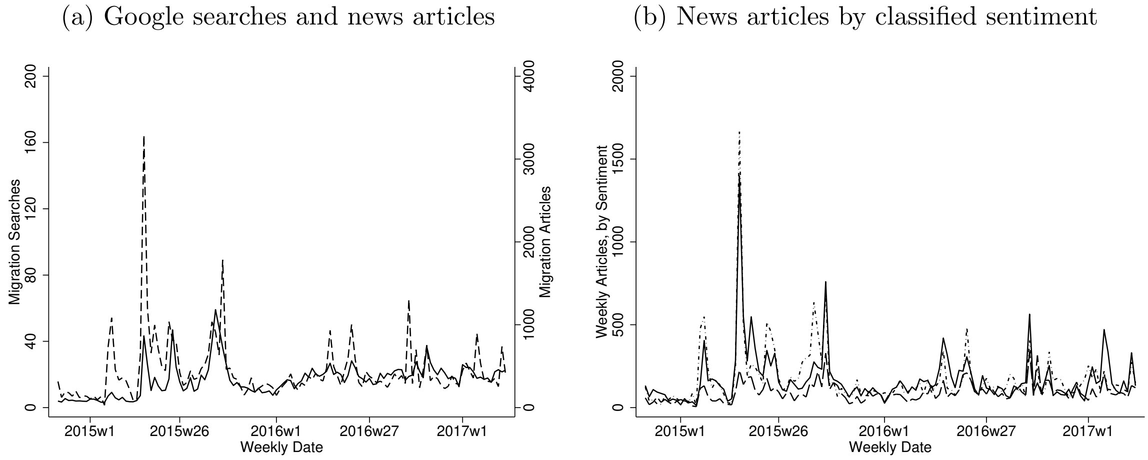
[12] 'Very Negative' or 'Fairly Negative' answers to the question '*Please tell me whether each of the following statements evokes a positive or negative feeling for you. Immigration of people from outside the EU.*' Responses can be consulted interactively at https://archive.is/0Zrhk.

[13] A visualization of aggregated polls, made by *PollofPolls*, is available on *Politico*'s website, at this https://bit.ly/35GUB8X.

[14] Two news articles about the events by *The Guardian* and the *Japan Times*, respectively, can be consulted at https://bit.ly/3lY6gYS and https://bit.ly/2QLvNch.

[15] A Washington Post article about the death of Alan Kurdi and its consequences can be consulted at https://bit.ly/39phb8D.

Figure 2: Public attention to migration over time



Note: Panel (a) reports the evolution of Google searches and news articles about migration in Italy. The solid line represents the weekly average of Google searches in Italy over time. The relative y-axis is on the LHS. Before averaging, the value is normalized, assigning 100 to the maximum. The dashed line represents weekly average articles about migration in the Italian press, retrieved by Factiva. Panel (b) reports the number of online and print newspaper articles in Italy relating to migration, over time, by sentiment classification. The solid line represents objective articles; the dashed line shows positive-sentiment articles, and the dashed-dotted line depicts negative-sentiment articles.

a (demand-driven) indicator of contemporaneous sentiment in society, I use supervised learning techniques to classify news articles as having '*Objective*,' '*Positive*,' or '*Negative*' sentiment. I defer the discussion of the classification methodology to the next section. For the moment, I show in Figure 2b that the three types of news evolved in a very similar way. The correlation between weekly objective coverage and negative and positive ones are 0.86 and 0.65, respectively, and the correlation between negative and positive coverage is 0.57. This fact further supports the idea that the substantial variation in public attention over the period did not correspond to a significant change in political attitudes towards migration.

As I argue in the rest of the paper, fluctuations in public attention affected policy. Anecdotal evidence supports this hypothesis. According to Heller and Pezzani (2016), European authorities decided to scale up the geographical extension of *Operation Triton* and launch the *Operation Sophia* in the wake of two large shipwrecks in April 2015 and the considerable public attention that ensued. As for short-term attention fluctuations, the operations of one of the non-governmental actors involved suggest a link between media pressure and policy. The activist network 'WatchTheMed Alarm Phone' provides a hotline for migrants at sea, intended to raise the alarm and put public pressure on rescuers when a migrants' boat is in distress. If migrants in distress are not promptly rescued, Alarm Phone 'inform[s] humanitarian organizations and public media to put pressure on the rescue services.'[16] For instance, in May 2019, assisting a migrants' boat in distress in the Central Mediterranean and facing uncooperative authorities, they 'launched a public pressure campaign, alerting the public to [a] case of non-assistance' (Alarm Phone, 2019). The boat in distress was subsequently rescued.[17] Institutional actors, too, suggest a possible link between attention and operations. In an interview with the Italian

[16] AlarmPhone website is available at https://bit.ly/3ajxvs3

[17] Similar stories can be read from AlarmPhone reports at https://archive.is/xgFbv, https://bit.ly/3gkCwo2, and https://bit.ly/3uYYfWW.

newspaper *Avvenire*, the Italian Retired Rear Admiral Vittorio Alessandro commented over a rescue for which Italian authorities did not want to take responsibility in 2018. In his view, if an NGO boat with journalists onboard were not present in the proximity of the event, 'nobody would have responded' to the distress call.[18] Such cases support the idea that public attention has a relevant role in shaping rescue policy in the Central Mediterranean.

3 Data

3.1 Policy and migration outcomes

To establish a link between policy and migration outcomes–migrants' deaths and departures–I collect information about the distance of rescue operations from the Libyan coast, the number of migrants rescued, and the number of deaths at sea in the area. As I explained in the previous section, I also use information about maritime traffic in the Mediterranean Sea, proxied by counts of ships entering the Mediterranean through the Suez Canal, to build an instrumental variable for policy. In my analyses on the impact of policy on outcomes, I use a measure of tidal conditions in the rescue area to consider the impact of weather on smugglers' operations.

3.1.1 Rescue operations for migrants' boats from Libya

To measure rescue distance from the Libyan coast and the number of migrants rescued, I use a dataset containing the universe of SAR operations in the Central Mediterranean from November 1, 2014, to April 1, 2017, collected by Frontex (2017). A data point in the dataset is a rescue operation, and variables collected are date, coordinates of detection and interception, type of interception (institutional, NGO, or commercial ship), type of boat used by migrants, number of migrants, and country of departure.

I focus on rescue operations for migrants coming from Libya to ensure the internal validity of my analysis.[19] In 2015 and 2016, migrants leaving from Libya constituted 91% of irregular migrants who were rescued during SAR in the Mediterranean and disembarked to Italy (CGCCP, 2017).[20] Restricting my analysis to Libya has the advantage of removing potential threats coming from undetected irregular entries not covered by my data–namely, migrants who reached Europe without being rescued at sea. According to CGCCP (2017), no migrant boat from Libya has reached Italian shores autonomously from 2015 to 2017.[21,22] In sum, the interceptions' data I use contains the universe of migrants' *departures* from Libya.

Frontex data on the type of rescuer imprecisely differentiates between NGOs and commercial ships, as I document in Section A.8.4 and A.8.5 of the Appendix. I fully address this issue in

[18] The story is available in Italian at https://bit.ly/32j63Gw.

[19] I give a complete account of my strategy in selecting boats from Libya in Section A.8.2 of the Appendix.

[20] The second most important source is the route connecting Egypt-Greece-Turkey with Calabria, in Italy, with 9% of irregular migrants.

[21] In total, less than 10,000 migrants reached Italian shores autonomously and were apprehended; they left from Algeria, Tunisia, Turkey, Greece, or Egypt (CGCCP, 2017). This figure might represent a partial account since migrants could have reached Italy without being detected; however, according to UNHCR (2018), most migrants arriving autonomously over the timeframe were intercepted near the Italian coast and directed to port by Italian authorities, undergoing identification.

[22] We can speculate that the absence of migrants reaching Italian shores autonomously from Libya is due to a combination of high traveling distances, together with the opportunity to be rescued at sea.

the data cleaning stage by complementing Frontex data with news data about interceptions and disembarkations available in the European Media Monitor website, and data about rescues by Médecins Sans Frontières, one of the prominent NGOs operating in the rescue area. To check the final data quality, I compare the number of rescues by year and actor with a report by the Italian Coast Guard (CGCCP, 2017). I only find negligible discrepancies, which I document in detail, together with all steps of data cleaning in Appendix Section A.8.

3.1.2 Missing Migrants data on deadly incidents

To measure the death risk for migrants, I complement information on migrants' arrivals with data on migrants' deaths at sea. I employ data by the Missing Migrants Project (IOM, 2017), a dataset constructed by the International Organization of Migration and accessible online. It is the most comprehensive dataset of migration incidents worldwide, and it includes information on incidents that caused one or more migrants to die or go missing. Information comes from several sources, such as media, institutions, and NGOs. It records the number of deaths and the number of missing persons per incident, indications of the incident's location, and source information. To use such data in this research, I extract only incidents that involved migrants leaving Africa from Libya. I explain how I extract the source country in Section A.9 of the Appendix.

3.1.3 Navigation reports for the Suez Canal

I retrieve monthly data about the passage of ships through the Suez Canal, collected by SCA (2017), which I use as a proxy for maritime traffic in the Mediterranean Sea. Importantly, this data includes the direction of the passage. So, I can construct a measure of shocks to commercial traffic in the Mediterranean by focusing on North-bound ships–i.e., entering the Mediterranean. Such data is only available from 2015.

3.1.4 European Centre for Medium-Range Weather Forecasts (ECMWF)

As Deiana et al. (2021), I proxy for weather conditions using tidal data by the European Centre for Medium-Range Weather Forecasts (ECMWF). I use forecast data on the significant height of combined wind waves and swell. This measure is commonly referred to as the significant wave height, an average of the heights of the highest tercile of the waves experienced by mariners in open waters as measured from the wave crest to trough of the preceding wave (Deiana et al., 2021). I retrieved this data for a location in the sea at the crossing between an imaginary line connecting Tripoli with Lampedusa and the limit of Libyan territorial waters, outside of which rescue interceptions can happen.

3.2 Attention to migration

I employ several data sources about public attention to migration in Italy to study the relation between public attention and policy. My analysis takes advantage of Google Trends data on daily searches about migration, collected with a very parsimonious word choice and data on the coverage of migration by newspapers, based on a more refined selection of terms. As I have shown in the previous section, the two measures are strongly correlated. Further, data on news articles allow me to build a measure of sentiment in media coverage of migration, useful to analyze the channel by which attention affects policy.

3.2.1 Google Trends of searches about migration

Google Trends data consist of the volume of daily searches by word, or list of words, in a given country, over time. I use such data to proxy public attention to migration in Italy; in particular, I collect the volume of searches for '*migranti*,' Italian for 'migrants,' chosen as a politically-neutral reference to the issue. Search trends are computed based on random sample of the total searches on Google, and this might produce measurement error issues. To diminish such worries, I draw the time series four times and take an average. Google Trends returns missing values when search volume is too low to give a precise estimate. I set those observations to 0. However, this is a minimal issue for this series. Due to the high attention to the issue, missing observations are only the 0.7% of daily observations for two series and the 1.1% in the remaining two. When averaging over weeks, I have no zero-observations.

3.2.2 News articles about migration from Factiva and data on diffusion

Dow Jones Factiva is an online repository of digitalized news text. Its Italian chapter contains news articles from an extremely comprehensive list of printed and online sources.[23] I retrieve articles covering irregular migration to Europe through the Mediterranean based on the presence of at least one string referring to migration as well as a string among a list of Mediterranean toponyms.[24] In this way, I extract 82,691 articles dated October 1, 2014, to August 31, 2017.

After collecting articles, I create a sentiment classification based on Kaal et al. (2014), employing supervised machine learning. The classification, detailed in Appendix Section A.10, distinguishes objective from subjective articles; further, it classifies subjective articles as either positive-sentiment or negative-sentiment.[25]

To complete my press data, I gather information about the diffusion of various sources employed. To this end, I employ data by *Accertamenti Diffusione Stampa* and *Audiweb*. These agencies research the diffusion of media sources. *Accertamenti Diffusione Stampa* obtains and audits data on the diffusion of traditional newspapers prepared by publishers, making them available in monthly chapters. Their measure of diffusion merges sales of newspapers and subscriptions. *Audiweb* researches diffusion of online sources, in partnership with the Nielsen corporation, using a representative panel of the Italian population and website usage data. For a given month, *Audiweb* collects the total estimated digital audience of a given digital source, represented by single users. Using diffusion data for print and online media, I match 76% of the articles collected through Factiva–28% are in the printed press, and 48% are online.

As I showed in the previous section, Google searches based on the word '*migranti*' correlate well with news articles about migration in the Mediterranean. However, Google search volume

[23]A complete list of newspapers in Factiva's database is available upon request to the author.

[24]The specific list of strings is available in Appendix Section A.10 of the Appendix, together with further description of data cleaning procedures.

[25]The classification allows further data cleaning by identifying articles not covering migration.

as a measure of public attention measure has some advantages. First, it likely responds less to supply shocks in the media market, which I am not interested in tracking, than news articles. Second, it may respond more quickly to shifts in public attention to events that have yet to materialize in newspaper contents, e.g., waves of attention starting in social networks.

In Appendix Table A.1, I list the main summary statistics from the data explained in this section.

4 Model

Time is infinite and discrete. Smugglers and migrants trade on the market for crossings, forecasting future rescue policy based on the present one. An impatient policymaker sets migrants' safety taking into account their policy forecast; she cares more about outcomes in periods of high public attention. Attention evolves in response to policy outcomes and shows persistence.

The timeline of the model areound period (week) t is as follows:

i. The policymaker observes $t-1$ arrivals, deaths, and attention and uses them to form an expectation for future attention.

ii. A measure of migrants and smugglers observe $t-1$ distance of rescues from Libyan shores and use it to forecast rescue distance at time t.

iii. Given t distance, t weather, $t+1$ expected attention, a law of motion for expected attention, and migrants' forecasting process for policy, the policymaker chooses rescue distance at time $t+1$.

iv. Given smugglers' cost-structure heterogeneity and migrants' and smugglers' forecast for distance, a measure of migrants leaves the Libyan coast and travels on a segment at a constant speed, encountering shipwreck according to a Poisson process, with arrival rate λ, and rescue, with arrival rate $1/\hat{\mu}_t$ chosen by policymakers.

v. Time t arrivals, deaths, and attention realize.

In the next paragraphs, I turn to a more precise definition of the model. I start by characterizing crossings. Then, I describe the behavior of migrants and smugglers. Finally, I deal with the evolution of public attention and the problem of the policymaker.

4.1 Death probability and rescue distance

A smuggler can offer a crossing to a migrant who travels on a line connecting Africa and Europe. Deadly incidents occur over this line according to a Poisson process with arrival rate λ. Rescue happens according to a Poisson process, too. It can only occur from the end of Libyan territorial waters, b, onwards. The policymaker sets the arrival rate of rescue, or the inverse of mean rescue distance $\bar{\mu}_t$, for the migrant. Further, the arrival rate of shipwreck within territorial waters is λ_b, possibly different from λ. As shown in Section A.11.1 of the Appendix, the probability of rescue π_t as a function of μ_t is given by:

$$\pi_t = \frac{\exp(-\lambda_b b)}{\lambda \bar{\mu}_t + 1}. \tag{1}$$

The probability of survival decreases in the arrival rate of shipwreck, λ, and in the size of the no-rescue area, b. Also, it decreases in the mean rescue-interception distance, $\bar{\mu}_t$. Taking the model to the data will require expressing survival probability in terms of the mean observed distance for the rescued, μ_t. Mean observed distance will be lower than mean distance, as interceptions 'assigned' higher distances are more likely to result in a shipwreck and not being observed. In equation 17, I derive the following:

$$\bar{\mu}_t = \frac{1}{\mu_t^{-1} - \lambda}. \tag{2}$$

Since there is a one-to-one correspondence between μ_t and $\bar{\mu}_t$, I can define the former as the planner's policy, with no loss of generality. Equations 1 and 2 give:

$$\pi_t = \exp(-\lambda_b b) - \exp(-\lambda_b b)\lambda \mu_t. \tag{3}$$

This relates survival probability and policy.

4.2 Departures and past distance

Consider a crossings smuggling market, with homogenous migrants having a higher marginal utility of consumption in Europe and smugglers with a heterogeneous cost structure. In particular, assume that smugglers pay a fixed cost for offering a crossing. Also, suppose that migrants and smugglers approximate policy at time t by:

$$\mu_t = \kappa_0 + \kappa_1 \hat{\mu}_{t-1}, \tag{4}$$

where $\hat{\mu}_t$ is the average observed distance from rescues occurring in the week t.

Later, I discuss why past policy enters the approximation. Assuming, as a simplification, that N_s does not vary by week, $\hat{\mu}$ is Gamma-distributed with shape N_s and scale μ_t. In addition, I impose that crossing costs are increased by a positive constant in days of bad weather. In Section A.11.1 of the appendix, I show that under distributional assumptions on the fixed cost parameters for smugglers, departures at time t follow:

$$\log \ell_t = \omega_0 - \omega_1 \hat{\mu}_{t-1} - \omega_2 w_t + \varepsilon_{\ell,t}, \tag{5}$$

where ℓ_t is the number of migrants leaving at time t, and w_t takes value one for bad weather, and ω_0, ω_1, and ω_2 are positive, and $\varepsilon_{\ell,t}$ is normally distributed with mean zero and variance σ_ℓ^2.

4.3 Evolution of public attention

Past policy outcomes should influence the level of present public attention. Also, attention shocks should be persistent, e.g., due to the inclusion of the issue in parties' platforms or via the circulation of content on social media. I assume the following law of motion for attention:

$$g_t = \alpha_0 + \alpha_1 s_{t-1} + \alpha_2 d_t + \varepsilon_{g,t}, \tag{6}$$

where g_t stands for attention, d_t for deaths, and $\varepsilon_{g,t}$ evolves according to $\varepsilon_{g,t+1} = \rho_g \varepsilon_{g,t} + \nu_{g,t}$. The variable s_{t-1} represents a stock of accumulated arrivals. I defer the discussion of its evolution to the following subsection. For the moment, I only stress that arrivals affect the evolution of attention with a week lag, while deaths affect contemporaneous attention. This formulation, other than being convenient for reducing the state space and simplifying the numerical implementation, agrees with the empirical regularities I show in Section 5.4. I work under the assumption that departures do not influence attention *per se*, but only through arrivals and deaths.[26]

4.4 Policymaker

The policymaker faces a dynamic problem. She has to set policy μ_t by taking into account the current risk for migrants at sea and the impact on future departures. The flow loss from arrivals and deaths at sea is given by:

$$L(s_t, d_t, g_t, n_t) = g_t^{\theta_3} \left(\theta_2 s_t^{\theta_4} + (1-\theta_2) d_t^{\theta_4} + \theta_5 n_t \right). \tag{7}$$

The first two addends in brackets are increasing and convex in deaths d_t and the stock of arrivals s_t, given by:

$$\forall t, \quad s_t = (1-\theta_1) s_{t-1} + a_t, \qquad \theta_1 \in [0,1], \tag{8}$$

where a_t represents weekly arrivals. The depreciation parameter θ_1 is meant to simultaneously capture time-decreasing costs of migrants' reception and voters' memory depletion. The parameter θ_2 determines the relative importance of migrants' arrivals and deaths in the loss function, and θ_4 controls the convexity of the loss function. The first term in the flow loss captures the complementarity between policy outcomes and attention, whose degree is determined by θ_3.

The variable n_t is a dummy for high NGO presence, which I assume to follow a Markov process. As I document in Appendix Section A.7, high NGO presence does not imply that institutional actors are incapable of setting their preferred policy. However, to the extent that NGOs engage in rescue activities close to Libyan shores, it is possible that they impose a cost of increasing rescue distance. For this reason, the variable θ_5 should a priori be positive.[27]

The variable g_t is public attention to migration in a given week. This can capture (i) salience

[26] This is more than plausible over the sample period since refoulements were scarcely present in the news.

[27] In specifying the model, I interact the NGO cost variable with attention, like all other terms in the loss function, because the cost of deviating from NGO-preferred policy can be conceived as political. Indeed, SAR NGO actors are highly visible in the Italian and European media and the subject of political debate.

of the migration policy dimension in the eyes of voters or (ii) the extent to which voters are informed about its outcomes. The former interpretation is coherent with the modeling framework in Hatton (2021), where the policymaker wants to maximize the median voter's utility, defined as a sum over policy dimensions weighted by their salience in the eyes of voters. The latter interpretation is in line with Matějka and Tabellini (2021), where weights represent voters' level of information on a particular dimension.[28] No notion of sentiment enters the definition of g_t. More precisely, I do not distinguish between public attention about the humanitarian goal–reducing shipwrecks and migrants' deaths–or the deterrence one–avoiding irregular migrants' arrivals. In Appendix Section A.6, I exploit newspaper articles to assess this modeling assumption. I regress rescue distance on different types of attention–objective, positive-sentiment, and negative-sentiment. Only 'objective' attention correlates with rescue distances. This is consistent with my modeling choice and with the interpretation of g_t as a measure of citizens' information on migration outcomes.

The policymaker takes her decision before the realization of g_{t+1}, but she can condition on past policy, stock of arrivals, weather, NGO presence, and shocks to attention. Then, I can describe the policymaker's problem as:

$$
\begin{aligned}
V(s, \varepsilon_g, \hat{\bar{\mu}}, w, n) = \max_{\bar{\mu}'} & - \mathbb{E}_{w'|w} g_t^{\theta_3} \left((1-\theta_2) s'^{\theta_4} + \theta_2 d'^{\theta_4} - n'\theta_5 \right) + \beta \mathbb{E} V(s', \varepsilon_g', \hat{\mu}', w', n' | \bar{\mu}) \\
\text{s.t. } & \log \ell' = \omega_0 + \omega_1 \bar{\mu} - \omega_2 w + \varepsilon_\ell, \\
& \hat{\mu}' \sim \Gamma(N_s, \mu^{-1}), \\
& \pi' = \exp(-\lambda b) - \exp(-\lambda b) \hat{\bar{\mu}}' + \varepsilon_d \\
& a' = \ell' \pi', \\
& d' = \ell'(1 - \pi'), \\
& \hat{g}' = \alpha_0 + \alpha_1 s + \alpha_2 d' + \varepsilon_g', \\
& \varepsilon_g' = \rho_g \varepsilon_g + \nu_g \\
& s' = (1 - \theta_1) s + a', \\
& w' \sim \text{Markov with transition matrix } \Pi_w, \\
& n' \sim \text{Markov with transition matrix } \Pi_n.
\end{aligned} \tag{9}
$$

Assuming that migrants are not informed about attention, it is intuitive that μ_{t-1} should enter the migrants' approximation for the evolution of policy. Present attention correlates with past attention; for this reason, current policy will correlate with past policy. If migrants can observe the past distance, they can rely on its persistent structure to infer the policymaker's behavior.

[28] Although the two interpretations are not mutually exclusive and they are coherent with my modeling framework, I favor the latter since I will ultimately measure g_t with Google searches and media coverage of migration. Despite finding a link between salience and media coverage of migration on cross-country data, Hatton (2021) warns that such correlation is not always strong.

5 Estimation

5.1 Arrival rate of an incident

5.1.1 Methodology

Investigating the impact of rescue distance on safety requires constructing a measure of survival probability for migrants. Using IOM (2017) data, I construct d_t, counting total deaths for a given week t, summing dead and missing migrants.[29] I obtain the total number of arrivals in a given week, a_t, by summing over rescue operations in Frontex (2017). I measure survival frequency, $\bar{\pi}_t$, for migrants leaving the Libyan coast in a given week by dividing the number of arrivals by the sum of arrivals and deaths.

I measure $\hat{\mu}_t$ as the average observed distance from Libyan territorial waters for rescues occurring in a week, weighted by the number of migrants in the rescue. In math notation,

$$\hat{\mu}_t = \sum_{i \in I_t} \frac{dist_{i,t} * a_{i,t}}{a_t} - b, \tag{10}$$

where I_t represents the set of rescue interceptions in the week t, i indexes a given rescue interception, and $dist_{i,t}$ is the rescue distance. The constant b is the limit of territorial waters, 12 Nautical Miles $\approx$ 22.224 KM from the coast, and $a_{i,t}$ is the number of migrant arrivals for interception i in the week t. SAR activities by international assets cannot occur within Libyan territorial waters.[30]

The variable $\hat{\mu}_t$ represents a biased estimate of the mean distance set by policymakers because it does not take into account distances for dead and missing migrants in a week. Here and in the previous section, I present all outcomes as functions of the observed mean–rather than the unconditional mean–distance. Since there is a one-to-one mapping between the two, as shown in the previous section, this does not threaten the model's estimation. Further, when assessing the impact of rescue distances on migrants' safety, I use Equation 1 to obtain an unbiased estimate of the effect of mean distance.

I am interested into how observed distance $\hat{\mu}_t$ affects survival frequency $\bar{\pi}_t$. I first investigate the issue with OLS, controlling for weather conditions (swell) w_t, year FEs, and quarter-of-the-year or week-of-the-year FEs; FEs capture changes in policy or smuggling practices, possibly correlated with interception distances and seasonality not captured by weather. I use HAC standard errors, allowing for arbitrary heteroskedasticity and autocorrelation up to lag 3.

OLS is prone to some endogeneity concerns. The most pressing issue is that the policymaker might have information unknown to the econometrician about the risk features of crossings

[29] The procedure agrees with IOM methodology registering migrants as 'dead' only if a body is found and 'missing' when a shipwreck happens and a body is not found.

[30] There have been very few exceptions to this principle during the sample period. Indeed, I find only 2.4% of rescue observations below the territorial waters limit. For this reason, only one of the 117 weekly observations in the dataset with a rescue has a negative value. This value is exceptional and is problematic for two reasons. First, the mean rescue distance in the model is the empirical counterpart of the inverse of an arrival rate of interception from the limit of international waters; both have to be positive. Second, I suppose and empirically assess that smugglers and migrants make departure decisions based on persistence. In that case, migrants should partially disregard the informative content of this observation. For this reason, I *winsorize* observations at the 1^{st} percentile, effectively replacing the value of the only negative observation with the second-to-lowest.

within a particular week. Knowing that migrants face particularly risky conditions in a given week, the policymaker might adjust distance downwards to avoid tragedies, inducing a bias towards zero in the negative coefficient on distance. Then, in estimating parameters for the model, I resort to 2SLS estimation relying on ship crossings of the Suez Canal.

The rationale for Suez Canal ship crossings' relevance is that authorities may take trade into account and 'protect' commercial ships from rescue duties when commercial traffic is high North of the rescue area. We would expect that authorities react to higher Suez crossings by intercepting migrants closer to Libyan coasts to ensure they do not reach commercial vessels' transit areas. Higher maritime traffic would then translate into reduced rescue distance and the probability of interceptions by commercial ships overall. In Appendix Section A.4, I further argue for the relevance of my instrument with anecdotal evidence.

To construct my instrument, I match monthly data on Suez crossings with weekly information on rescues and shipwrecks. I construct variable $suez_t^{nb}$, representing the average daily number of ships crossing the Suez Canal South to North in a given week. Finally, I create my instrument as the sum of the past values of $suez_t^{nb}$ for a given time window of T weeks:

$$suez_{t,T}^{nb} = \sum_{i=1}^{T} suez_{t-i}^{nb}. \tag{11}$$

Constructed in this way, the instrument allows for policy inertia and lag in adjusting to new traffic conditions. When using $suez_{t,T}^{nb}$ as an instrumental variable, I rely on 2SLS, with a first stage of the following form:

$$\hat{\mu}_t = \beta + \beta_S suez_{t,T}^{nb} + \beta_Y Y_t' + \beta_Q Q_t' + \nu_t, \tag{12}$$

where Y_t and Q_t are, respectively, a vector of year and quarter-of-the-year (or week-of-the-year) FEs. I estimate the 2SLS specification using HAC standard errors, robust to arbitrary heteroskedasticity and autocorrelation up to the $T+1$ lag, as my transformation could introduce autocorrelation concerns; I set $T = 8$, to allow sufficient time for policy to adjust in response to traffic. Using the estimates from this procedure and 3, I back $\hat{\lambda}_b$ out from the constant. The arrival rate of shipwreck, $\hat{\lambda}$, will be given by the coefficient on distances divided by $\hat{\lambda}_b$.

Three possible violations of the exclusion restriction are worth addressing here. First, shipping companies might consider migrant flows in their operations. Using North-bound Suez crossings reduces this source of worry. A fraction of 87% to 88% of the cargo volume crossing Suez North-Bound comes from outside the Red Sea (SCA, 2017), with traveling distances going from 4,000 to over 10,000 KM before reaching the rescue area; so, shipping companies can hardly plan their routes accounting for frequent changes in migrants' safety. Also, using lagged crossings strengthens the instrument's credibility because it reduces the concern that maritime traffic reacts to contemporaneous traveling conditions of migrants. Further, obtaining timely information about migrants' safety in a given week is certainly not easy for external observers. Still, departures might be easier to forecast given media coverage of migration, and they could correlate with crossings' safety. A second possible threat to the exclusion restriction comes from migrants taking into account the opportunity to be saved by commercial ships. If this is the case, migrants and smugglers could exploit maritime traffic by increasing departures, inducing more crowded and possibly dangerous crossings. I check that both of the previous concerns do not affect my results by showing that controlling for departures does not change them. A third threat comes from the spurious correlation between trade and migrants' safety through weather, season, and long-term shifts in policy. I account for such confounders by checking that results are robust to controlling for weather, year, and quarter-of-the-year or week-of-the-year FEs.

Before proceeding to results, another caveat is in order. Despite the completeness of Missing Migrants data, some migrants' deaths could go undetected, especially when distances are high; in this case, the effect estimated above would be a lower bound on the actual one. When making normative statements about the optimal policy to be taken, I will take this into account. However, this issue does not hamper the estimation strategy for the present structural model. Indeed, in the theoretical framework presented above, the policymaker cares about *observable* outcomes, as it is apparent from how public attention enters the analysis. For this reason, I assume that shipwrecks that are not observed do not represent political harm for the policymaker and thus do not enter the loss function.

5.1.2 Results

Table 1 reports OLS estimates in the first four columns and 2SLS estimates in the last four. Couples of columns alternate the presence of year FEs and quarter-of-the-year FEs with year FEs and week-of-the-year FEs. Within each couple, the first row does not control for swell while the second does.

OLS results suggest that rescue distance reduces crossings' safety; however, the result is not significant for the OLS specification when not controlling for week-of-the-year FEs. Higher observed average distance of interceptions results in higher death risk for migrants. In the OLS regression including year and week fixed effects, a 10 KM increase in observed distance corresponds to a rise in death probability by 1 percentage point, a sizable impact if compared to an average death frequency of 4% over the period analyzed. The impact of weather is somewhat non-robust.

The Kleinbergen-Paap F-Stat for the instrument is larger than 10 for both specifications including week-of-the-year FEs. I report the results of the first stage in Table A.2 in the Appendix, in a specification with year and quarter-of-the-year FEs, and one including week-of-the-year instead of quarter-of-the-year FEs, in the first two columns. Higher North-bound Suez crossings reduce distances of interceptions. In the second two columns, I run a placebo test and check that future Suez crossings do not predict rescue distance when I control for past ones. The last two columns display the instrument's impact on the proportion of migrants intercepted by commercial ships. Higher maritime traffic reduces the proportion of migrants intercepted by commercial ships. This finding supports the idea that authorities wish to avoid disruptions to the maritime route passing North of the interception area.

In IV estimates, distance becomes significant across specifications. In my preferred specification, with quarter-of-the-year FEs, an increase in observed distance by 10 KM increases death probability by 2.2 percentage points. The results are very similar in other specifications. The

Table 1: Impact of distance and weather on risk

	$\bar{\pi}_t$							
	OLS	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS
$\hat{\mu}_t$	-0.000953	-0.000939	-0.000733*	-0.000890**	-0.00222**	-0.00208**	-0.00229***	-0.00232***
	(0.000622)	(0.000599)	(0.000394)	(0.000392)	(0.000923)	(0.000876)	(0.000571)	(0.000626)
Bad Weather		-0.0180		-0.0192**		-0.00874		-0.0139*
		(0.0122)		(0.00822)		(0.00686)		(0.00716)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-o-y FEs	Yes	Yes	No	No	Yes	Yes	No	No
Week-o-y FEs	No	No	Yes	Yes	No	No	Yes	Yes
N	117	117	117	117	103	103	103	103
$KP\ F$					5.844	5.732	12.784	11.243

Note: All variables are weekly aggregates. The dependent variable is survival frequency, the ratio of arrivals to departures–arrivals, deaths, and missing in the rescue area. Arrivals represent all migrants who arrived during rescue operations involving migrant boats leaving the North African coast from Libya, obtained from Frontex data. I retrieve Deaths and missing data from Missing Migrants Project. The main independent variable is the average distance of interceptions (KM), weighted by the proportion of migrants saved, obtained from Frontex data. The first four columns are estimated with OLS, the last four with 2SLS, using an 8-week rolling sum over lags of North-bound Suez Crossings as an instrument. I partial out a varying set of season and time controls in each specification and control for weather, defined as swell. HAC standard errors (in parentheses), robust to arbitrary heteroskedasticity up to 3 lags in the first four columns, and up to 9 lags for the last two. P-values are denoted as follows: * $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$.

2SLS estimate is more than twice the OLS one, supporting the idea that the policymaker has information unknown to the econometrician about the risk of specific crossings and decreases distance in response to unsafe conditions.

As I pointed out above, shipping companies might be able to forecast departures; this might threaten my identification strategy if departures are correlated with safety, e.g., because crossings with more people per boat are riskier. As I show in Appendix Table A.3, controlling for log departures, my results remain unaffected.

Given that the estimated constant is not statistically different from 1–and that it is actually estimated to be higher than 1–I estimate $\hat{\lambda}_b = 0$. Consequently, I read $\hat{\lambda}$ off the coefficient on distance. Using $\hat{\lambda}_b$, $\hat{\lambda}$, and Equation 2, I can obtain an estimate of the increase in the probability of death coming from an increase in the mean distance of rescue from average values, μ_t, instead of the observed one, $\bar{\mu}_t$. Increasing the mean distance of interception by 10 KM reduces survival probability by 2 percentage points, roughly 90% of the 2.2-percentage-points of my preferred estimate in Table 1.

5.2 Rescue Distances and Departures

5.2.1 Methodology

To investigate the relationship between the present rescue distance set by policy and future departures, I test whether a lower rescue distance invites higher future migration. I regress the log of one plus departures on contemporaneous and lagged distances.[31] To measure departures (ℓ_t), the total number of attempted crossings, I sum arrivals, deaths, and missing migrants in a given week. I control for significant wave height. In different specifications, I control for year and quarter-of-the-year fixed effects or quarter-by-year fixed effects. I include contemporaneous distance and four weekly lags; this allows me to retain a large enough sample while testing the

[31] I choose to work with log-departures to be consistent with the framework of my model. Then, I add 1 to arrivals to take care of weeks with 0 arrivals–6% of observations in the sample.

potentially heterogeneous effects of different weekly lags. However, I also experiment with other lag configurations for robustness. I use standard errors robust to arbitrary heteroskedasticity and autocorrelation up to the 3^{rd} lag. I expect past distance to matter if migrants and smugglers forecast future policy based on the present. After showing that the first weekly lag drives the effect, I estimate a specification including only such lag, which I use to estimate my structural model's parameters.

Higher expected departures might lead the policymaker to move rescue interceptions nearer to the Libyan coast to avoid shipwrecks, biasing the coefficient on contemporaneous distance negatively–away from 0. Finding only lags to be significant would make exogeneity more credible in this context. In the baseline specification, I include present distance and four lags; to assess robustness, I experiment with other sets of lags and quarter-by-year FEs.

The estimated coefficients likely do not suffer from detection bias, as studied by Hanson and Spilimbergo (1999) for land borders. Such a bias would arise if lower distances increased the likelihood of detecting attempted crossings. According to policy sources, all migrants arriving in Italy from Libya over the sample period were rescued at sea, as documented in Section 3.

5.2.2 Results

Table 2 confirms that past policy has an impact on future departures. In the first four columns, I estimate the impact of contemporaneous and lag distance on log-departures by progressively including controls. Only the first lag matters across specifications, suggesting that smugglers and migrants forecast the following week's rescue distance based on the present one and that higher forecasted distances lower departures.

The fact that present distances do not have a statistically significant effect reduces worries of potential reverse causality–policy adjusting in response to expectations in departures. Further, this should solve any remaining worry about rescue distance reducing detection: such an effect, if present, would negatively bias the coefficient on same-time distance. In the last four columns, I only include the first lag of distance. A 1-KM increase of observed distance corresponds to a reduction in departures by 2 percent. Weather conditions have a significant and large effect in all specifications: a 1-sd deviation increase in swell results in a 130% decrease in migration. As I show in Table A.4 in the Appendix, this result is not limited to the specific number of lags chosen; the statistical significance of the first lag of distance and weather holds across specifications. Even though the estimate becomes noisier for $T = 1$, it retains a p-value below 10%.

It is not surprising that smuggling practices quickly adjust to rescue policy. According to Porsia (2015) and Micallef (2017), smugglers can use web-based trackers of the Automatic Identification System (AIS) of rescue vessels to collect information about the location of rescues. Further, there is evidence of smugglers equipping migrants' boats with GPS technology, which can also be used by smugglers to manage crossings.(Jacquemet, 2020).[32]

[32]See, for instance, the article by *The Independent*, available at https://archive.is/8y1Xr.

Table 2: Impact of Distance and Weather on Departures

	$\log(1+dep_t)$							
$\hat{\mu}_t$	0.00357	0.00527	0.00247	-0.00430				
	(0.00943)	(0.00893)	(0.00844)	(0.00881)				
$\hat{\mu}_{t-1}$	-0.0168**	-0.0133**	-0.0167**	-0.0249***	-0.0157**	-0.0198**	-0.0217**	-0.0329***
	(0.00682)	(0.00662)	(0.00743)	(0.00803)	(0.00733)	(0.00929)	(0.0100)	(0.0106)
$\hat{\mu}_{t-2}$	0.00304	0.00682	0.00401	-0.00308				
	(0.00681)	(0.00682)	(0.00732)	(0.00649)				
$\hat{\mu}_{t-3}$	-0.00639	-0.000733	-0.00294	-0.00762				
	(0.00849)	(0.00857)	(0.00869)	(0.00797)				
$\hat{\mu}_{t-4}$	0.00537	0.0136	0.0117	0.0119				
	(0.00810)	(0.0116)	(0.0114)	(0.0111)				
$Bad\quad weather_t$	-0.708***	-0.721***	-0.732***	-0.738***	-1.292***	-1.340***	-1.339***	-1.403***
	(0.0845)	(0.0990)	(0.117)	(0.125)	(0.185)	(0.196)	(0.226)	(0.217)
Quarter-by-y FEs	No	No	No	Yes	No	No	No	Yes
Year FEs	No	Yes	Yes	No	No	Yes	Yes	No
Quarter-o-y FEs	No	No	Yes	No	No	No	Yes	No
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	83	83	83	83	116	116	116	116

Note: All variables are weekly aggregates. The dependent variable is the logarithm of one plus departures, defined as the sum of arrivals, deaths, and missing in the rescue area. Arrivals represent all migrants who arrived during rescue operations involving migrant boats leaving the North African coast from Libya, obtained from Frontex data. I retrieve deaths and missing migrants' data from the Missing Migrants Project. The main independent variable is the average distance of interceptions (KM), weighted by the proportion of migrants saved, obtained from Frontex data. The first three columns include weekly lags for distance, with a varying set of controls (no control, year FEs, year and quarter-of-the-year FEs). Specifications include a varying set of year and season controls, reported in the table. All regressions include weather as a control, defined as swell. HAC standard errors (in parentheses), robust to both arbitrary heteroskedasticity and arbitrary autocorrelation up to 3 lags. P-values are denoted as follows: * $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$.

5.3 Frequencies for Markov processes on weather and NGO presence

The estimations of Π_w and Π_n require evaluating the probability of a given transition. For a generic Markov process, define the sample as the set of transitions represented by couples of adjacent weeks. Define the variable $x_{ij,t}$ taking value 1 if a transition from i to j at time t. An estimate for the probability of transition from i to j, π_{ij}, is given by:

$$\pi_{ij} = \frac{\sum_t x_{ij,t}}{\sum_{z\in\{i,j\}} \sum_t x_{iz,t}}. \tag{13}$$

In this way, I separately estimate Markov transition matrices for NGO and weather transitions. I summarize both variables with a dummy counterpart, taking value 1 whenever the relative variable is higher or equal to its median value.

I report results for both processes in Table 3. Both weather and NGO presence display some persistence. On average, after observing no NGO presence in a week, it takes 2.8 weeks to observe NGO operations in the rescue area; if instead, rescue operations by NGOs occur in a week, it takes another 3.4 on average to have a week of no NGO operations. The persistence of weather conditions is slightly lower. Starting from a week with good weather, it takes on average 2.3 weeks to reach a week with bad weather; on the converse, it takes on average 2.9 weeks to go from bad weather to good weather.

5.4 Evolution of Public Attention

I estimate the evolution of attention given outcomes, as in Equation 6. Attention, g_{t+1}, is measured by the weekly average of Google searches and deaths and arrivals. Below I report GLS estimated parameters with standard errors in parentheses:

$$\begin{aligned} \ln g_t = &\ 2.517 + 0.028 s_{t-1} + 0.474 d_t + \varepsilon_{g,t} \\ &(0.125) \quad (0.196) \qquad (0.008) \end{aligned} \tag{14}$$

Here, I express deaths and arrivals in thousands. Outcomes and past attention have a positive effect on future attention. An increase in deaths by 1,000 increases attention by 40%; an increase in arrivals by 1,000 increases attention by 3%.

Before estimating the AR1 process for the error term, I run an Augmented Dickey-Fuller test, and I reject the null of a unit root, with a p-value lower than 1%. Then, I perform the estimation using OLS.

$$\hat{\varepsilon}_{g,t+1} = 0.776 \hat{\varepsilon}_{g,t} + \nu_{g,t} \tag{15}$$

And $\sigma_g = 0.363$. I find the process of the error term to be very persistent.

As a robustness check, in Appendix Table A.5 I show that the convenient assumption that only past arrivals affect attention agrees with the dynamics of attention in the data. A possible explanation is that the press covers arrivals on the day migrants are transferred to Italy from the rescue area, hours or days after the rescue operation.

5.5 Preference Parameters

5.5.1 Methodology

Define as follows the vector of states:

$$X_t = [\mu, s, n_t, \varepsilon_g, w_t]. \tag{16}$$

Define by $\bar{\mu}(x)$ the policy function for mean distance, and by R the event *rescue* for the observed unit (boat). The distribution of distances, given that I only observe rescued boats, and given states is:

$$\begin{aligned} f(dist|R, \bar{\mu}(X_t)) &= \frac{\mathbb{P}(R|dist, \bar{\mu}(X_t)) f(dist)}{\mathbb{P}(R)} = \\ &= \frac{\exp(-\lambda b) \exp(-\lambda dist) \bar{\mu}^{-1} \exp(-\bar{\mu}^{-1} dist)}{\exp(-\lambda b)(\lambda \bar{\mu} + 1)^{-1}} = \\ &= \left(\lambda + \bar{\mu}^{-1}\right) \exp\left(-\left(\lambda + \bar{\mu}^{-1}\right) dist\right) \end{aligned} \tag{17}$$

Notice that the previous equation represents the density of an exponential random variable with a mean corresponding to our definition of μ, mean distance conditional on rescue, and such that:

$$\mu = \frac{1}{\lambda + \bar{\mu}^{-1}} \tag{18}$$

Also, with this I can write the following log-likelihood exploiting distance data:

$$\begin{aligned} ll(Y;\theta) &= \sum_{t:t\in T} \sum_{i:i\in I_t} \log f((dist_{i,t} - b)|\bar{\mu}_t(X_t)) = \\ &= \sum_{t:t\in T} \sum_{i:i\in I_t} \log \mu - \mu(dist_{i,t} - b). \end{aligned} \tag{19}$$

Since retrieving the likelihood value for a given vector of parameters requires first computing the policy function through Value Function Iteration (VFI), the model's estimation is computationally cumbersome. For this reason, I implement VFI by parallelizing over states on GPU. I also impose some simplification to shorten computation time. I estimate the model disregarding uncertainty over deaths, arrivals, and realized distances–focusing instead of mean distance set by policy. I use coarse grids on states (14 points for present distance, 7 for arrivals and attention). Further, I assume $\theta_1 > 0.25$ to exclude explosive dynamics on the arrivals stock variable, which I could not manage with my arrivals grid. This approach allows me to estimate the standard errors on utility parameters using bootstrap. In doing so, I account for the autocorrelation introduced by my instrument for policy, using the Non-Overlapping Block Bootstrap scheme introduced by Carlstein et al. (1986).

It is helpful to clarify, intuitively, what variation allows to estimate each parameter in the model. I identify θ_1 (the depreciation of the arrival stock) by the cross-variation of arrivals at different time lags and policy, and θ_2 (the relative weight on deaths) by the mean distance set by policy. I recover θ_3 (the coefficient on attention) by the cross-variation of distance and public attention. The estimation of θ_4 (the curvature parameter) intuitively relies on the correlation between distances and attention at differing levels of past arrivals. I pin down θ_5 (the cost-shifter induced by NGOs) with the cross-variation of distance and NGO presence.

I set the discount factor β as the product of two elements. First, a discount factor based on estimates in the social time preference rate literature–a 4.7% annual discount rate for Italy according to Evans and Sezer (2005). Second, a 0.989 probability that the government does not change from one period to the next, chosen to match the frequency of changes in Italian prime ministers between 2000 and 2020.[33] The resulting discount factor β of 0.990 captures patience and the time horizon of the main political actors involved.

5.5.2 Results

Policymakers' utility parameters are reported in Table 3. The estimate for θ_1 is very close to one, implying that the policymaker bears the political cost of migrants' inflows on the week when arrivals realize. Since the bulk of the financial cost of irregular entries consist of reception costs occurring in the months after arrivals rather than the funding ot rescue operations, this result

[33] A complete timeline of Italian prime ministers can be found at https://archive.is/Tv1nx.

suggests that the political cost of rescues is largely non-financial.[34] Alternatively, policymakers could view public opinion as having a relatively short memory of past events after accounting for the evolution of public attention and its persistence.

Table 3: Estimated Parameters

Est. Strategy	**Par.**	**Description**	**Estimate**	**90% Conf. Int.**
IV	$-\lambda$	arrival rate of incident	-0.00222	$[-0.00374, -0.000702]$
OLS	ω_0	intercept of migrant arrivals	8.60	$[8.06, 9.13]$
	ω_1	coefficient on distance	-0.0188	$[-0.034, -0.00359]$
	ω_2	coefficient on bad weather	-1.87	$[-2.41, -1.33]$
GLS	α_0	intercept of attention eq.	2.517	$[2.312, 2.722]$
	α_1	coefficient on deaths	0.474	$[0.152, 0.797]$
	α_2	coefficient on arrivals	0.028	$[0.014, 0.042]$
	ρ_g	AR1 coefficient for error	0.776	
Freq.	Π_n	transition matrix for NGOs	(0.642,	$[0.535, 0.748]$
			0.709)	$[0.583, 0.835]$
Freq.	Π_w	transition matrix for weather	(0.571,	$[0.464, 0.679]$
			0.652)	$[0.536, 0.769]$
MLE	θ_1	stock depreciation	0.981	$[0.860, 0.999]$
	θ_2	relative importance of deaths	0.999	$[0.659, 1.000]$
	θ_3	coefficient on attention	1.293	$[0.988, 1.481]$
	θ_4	curvature on deaths and arrivals	3.176	$[2.374, 3.247]$
	θ_5	NGO cost	0.552	$[0.019, 0.635]$
Ass.	β	discount factor	0.990	

Note: Estimated parameters, along with the relative estimation strategy, and estimated value. The value for the discount factor is assumed. Errors for the utility parameters obtained with bootstrap (1000 draws).

The estimate for θ_5 is positive and significantly different from zero; so, NGO presence increases the cost of setting a high distance. This result is consistent with the idea that non-institutional actors in the rescue area reduce the ability of the policymaker to set the preferred distance, possibly explaining policymakers' attempt to restrict NGO operations in the rescue area, e.g., through the NGO Code of Conduct of July 2017 documented in Appendix Section A.7.[35]

The estimated θ_3 is positive and significant, supporting the explanation that periods of higher attention are more relevant for policymakers. The estimates of θ_2 and θ_4 displayed in Table 3 jointly determine the policymakers' willingness to accept deaths in exchange for a reduction in arrivals. Define $\Delta U^d(1; X)$ as the policymakers' welfare loss from one more migrants' death, for the realized vector of states and policy outcomes X, and $\Delta U^a(1; X)$, as the loss from one more arrival. As I discuss below, this model converges to a stochastic steady-state, which I approximate by simulating model outcomes over several periods. Evaluating steady-state policy and averaging over realizations of weather and attention, I obtain an estimate of

[34] In 2015, 71% of the €2.7 billion sustained for the migrants' crisis went into reception, healthcare, and education. The remaining 29% went in rescue operations (MEF, 2017).

[35] I am not modeling the impact of the 2017 Code of Conduct as it entered into effect months after the end of my sample.

the relative loss from deaths and arrivals as:

$$\mathbb{E}\left(\frac{\Delta U^d(1;X)}{\Delta U^a(1;X)}\right) \simeq 9.662. \tag{20}$$

At the steady-state, the policymaker is willing to accept roughly 1 death for a reduction of 10 arrivals. This estimate is consistent both with a steady-state survival probability of around 90% and with the average survival probability at the end of my sample, computed to be about 89%.

6 Model fit, policies, and base model dynamics

6.1 Model fit

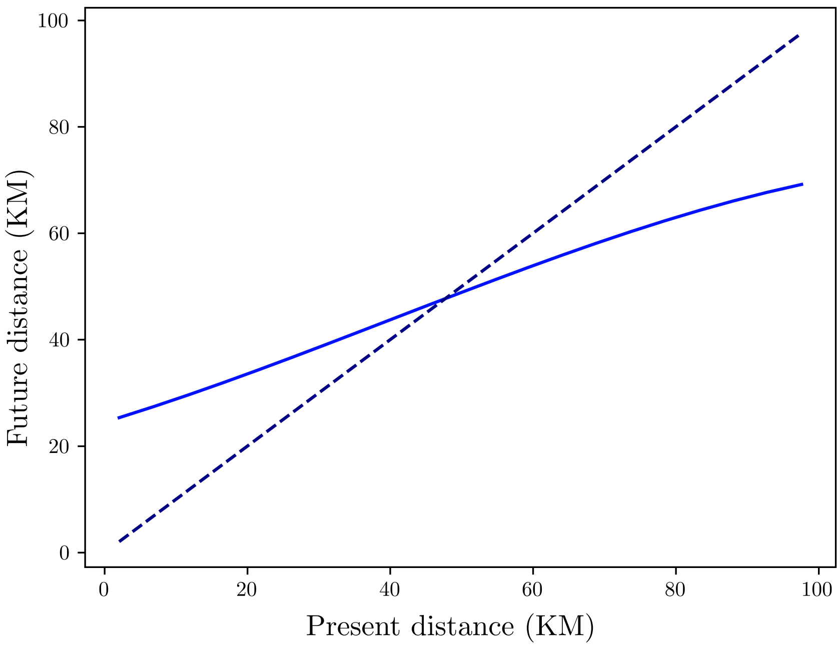
Table 4: Model and data moments

Moment	**Model**	**Data**	**95% Data CI**
β in $\mu_t = \alpha + \beta g_{t-1} + \varepsilon_t$	-14.7	-17.5	$[-25, -9.98]$
β in $\mu_t = \alpha + \beta \mu_{t-1} + \varepsilon_t$	0.779	0.671	$[0.507, 0.835]$
β in $\mu_t = \alpha + \beta \ell_{t-1} + \varepsilon_t$	-0.00113	-0.00147	$[-0.00265, -0.000299]$
β in $\mu_t = \alpha + \beta d_{t-1} + \varepsilon_t$	-0.00281	-0.0111	$[-0.0428, 0.0205]$
β in $\mu_t = \alpha + \beta mig_{t-1}^{ngo,high} + \varepsilon_t$	-15.1	-16.032	$[-25.3, -6.77]$
β in $\mu_t = \alpha + \beta swell_{t-1}^{high} + \varepsilon_t$	3.883	5.69	$[-2.34, 13.7]$
β_Q^2 in $\mu_t = \alpha + \beta_Y' Y_t + \beta_Q' Q_t + \varepsilon_t$	-8.5	-4.68	$[-13.7, 4.35]$
β_Q^3 in $\mu_t = \alpha + \beta_Y' Y_t + \beta_Q' Q_t + \varepsilon_t$	-15.7	-16.3	$[-24.3, -8.22]$
β_Q^4 in $\mu_t = \alpha + \beta_Y' Y_t + \beta_Q' Q_t + \varepsilon_t$	-14.7	-17.7	$[-27.2, -8.19]$
β_Y^{2015} in $\mu_t = \alpha + \beta_Y' Y_t + \beta_Q' Q_t + \varepsilon_t$	-26.3	-34.7	$[-52.2, -17.1]$
β_Y^{2016} in $\mu_t = \alpha + \beta_Y' Y_t + \beta_Q' Q_t + \varepsilon_t$	-38.6	-56.1	$[-73.1, -39.2]$
β_Y^{2017} in $\mu_t = \alpha + \beta_Y' Y_t + \beta_Q' Q_t + \varepsilon_t$	-46.2	-60.3	$[-80.9, -39.6]$

Note: Table comparing moments obtained from model-predicted distances and the true data. $mig_t^{ngo,high}$ is a dummy taking value 1 if the proportion of rescues performed by NGOs in a given week is higher than median. The variable $swell_t^{high}$ is a dummy taking value 1 swell in a given period is higher than median. The vectors Y_t and Q_t are year and quarter-of-the-year FEs. The variable g_t represents log Google searches, μ_t is average rescue distance, ℓ_t are migrants' departures, and d_t are dead and missing migrants.

Table 4 reports a list of moments from the model, compared to the same moments estimated through regressions on the actual data, with HAC robust confidence intervals. The model replicates the magnitudes and signs of the correlations between distances and past attention, past distances, and departures. The correlation between past deaths and distances has the same sign in the actual and the model-simulated data, but the model's one is lower. However, the correlation for the model-simulated data falls within the confidence interval of the estimate in the actual data. The model also replicates well the relation between distances and past NGO presence and weather. Finally, I test how the model matches seasonal and long-term trends in the data by comparing the results of a regression of distances on year and quarter-of-the-year FEs for the model-simulated and the actual data. The model significantly under-predicts the decrease in average distances in 2016, possibly due to non-modeled long-term policy shifts; however, it replicates seasonal variation. Further, as it is apparent from Figure A.1 in the Appendix, showing realized mean distances (solid line) and model-predicted ones (dashed line), the model's results replicate the long-term trend in distances.

Figure 3: Optimal future distance given present distance



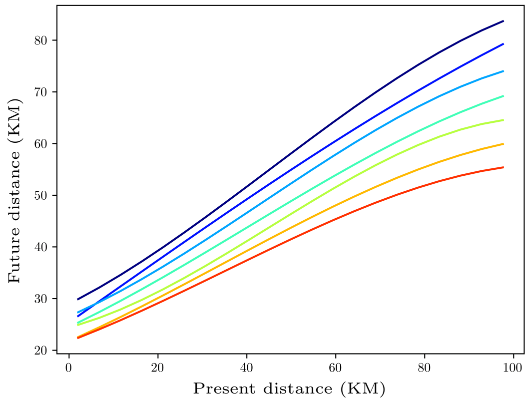
Note: Optimal future distance (KM) given present distance (KM), solid line, with attention shock fixed to mean, good weather, low NGO presence, and past arrivals' stock fixed to 2,000. The dashed line is the 45-degree line. The policy is obtained by VFI using fixed grids, as explained above, and then a 4-degree polynomial is fit through grid points.

6.2 Policies

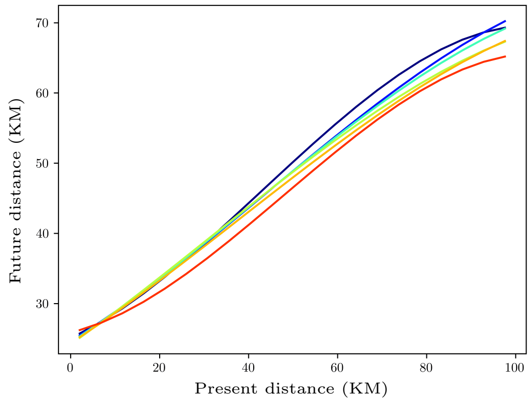
The solid line in Figure 3 depicts optimal future distance chosen by the policymaker as a function of present distance, holding attention, weather, NGO presence, and stock of arrivals fixed. I obtain the policy by VFI on a pre-specified grid; I plot it after fitting a 4-degree polynomial through it. Optimal future distance is increasing in the present one because, for lower present distance, the policymaker expects more departures, which raises the stakes of ensuring safety for migrants. Also, the relationship is less steep than the dashed 45-degree line, which suggests that, for given states, policy stabilizes at an interior point. Indeed, the simulated model quickly converges to a distance of 43 KM, on average, irrespective of the starting points used. Figure 4 shows the future distance as a function of past distance again; however, each of the panels shows how such policy varies by other states: attention, past arrivals stock, weather, and NGO presence. Figure 4a shows the past distance-policy relation by values of attention; warmer

Figure 4: Optimal future distance given present distance, by other states

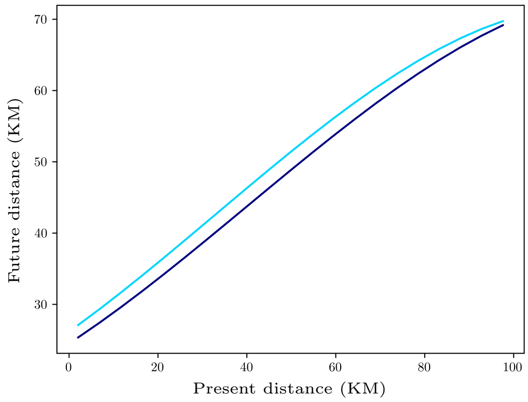
(a) Attention



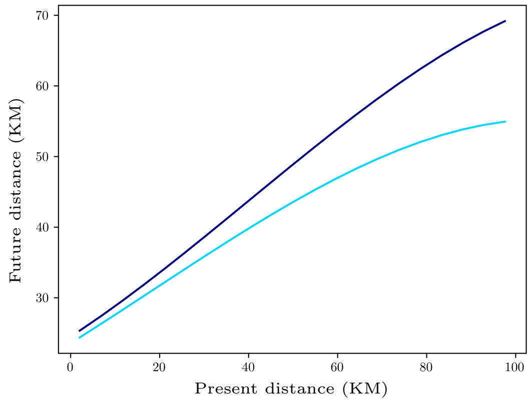
(b) Arrivals



(c) Weather



(d) NGO Presence



Note: Optimal future distance (KM) given present distance (KM), by attention (Figure 4a, warmer colors for higher attention), past arrivals stock (Figure 4b, warmer colors for higher arrivals), weather (Figure 4c, darker color is good weather), NGO presence (Figure 4d, darker color is low NGO presence). Policies are obtained by VFI using fixed grids, as explained above, and then a 4-degree polynomial is fit through grid points.

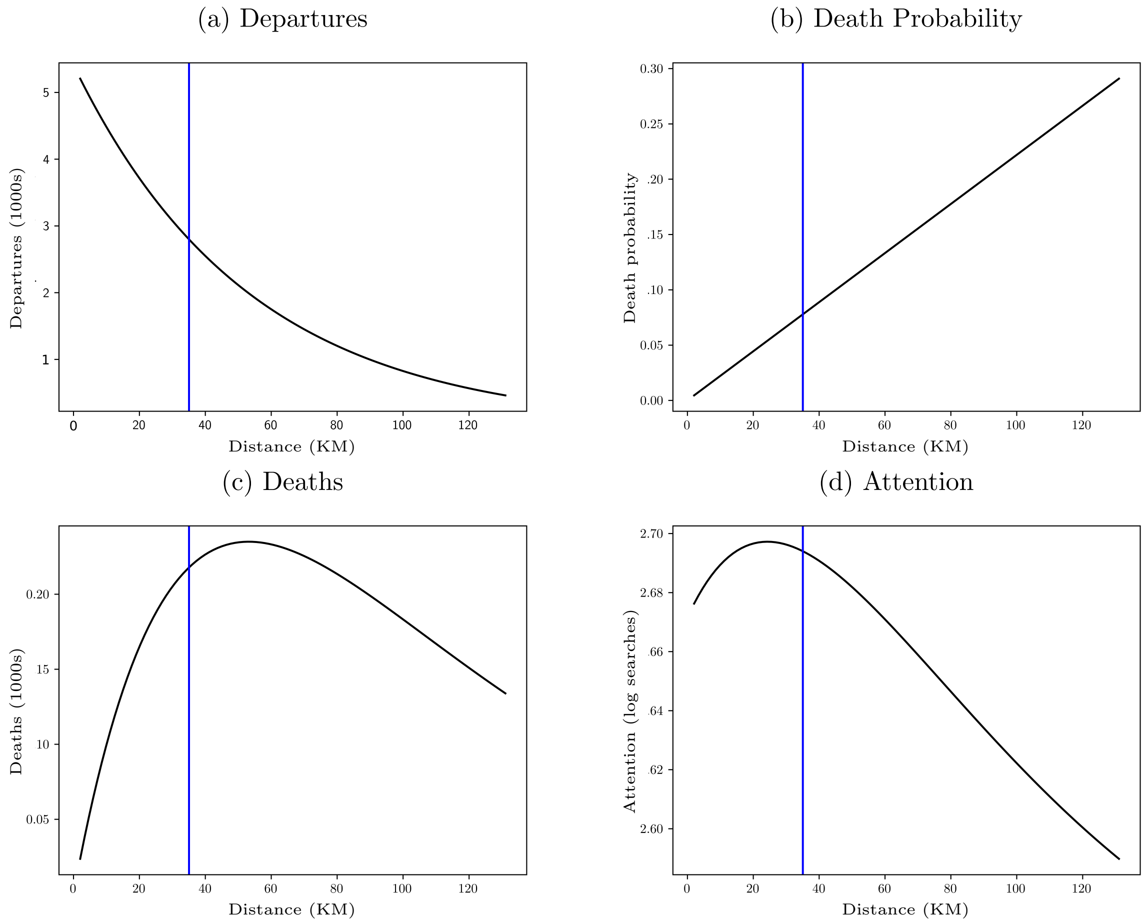
colors represent higher attention. Attention increases the incentive to save migrants at sea, compared to reducing future departures. As attention grows, rescue operations move closer to the Libyan coast. As it is clear from Figure 4b, the role of previous arrivals, instead, is quite limited, consistent with the very high estimate of θ_1. Higher past arrivals (warmer colors) have two effects: on the one hand, they increase the marginal utility of decreasing arrivals by convexity; on the other hand, they reduce the scope for decreasing the arrivals stock. The latter effect seems to prevail so that a higher arrival stock leads to a decrease in distance. In Figure 4c, good weather is depicted in darker blue. Bad weather increases distances by decreasing the expectation over the number of migrants leaving, given past policy, reducing incentives for rescue. This idea is consistent with the regularity in the data that distances increase in winter. Finally, in Figure 4d, lighter blue represents a high NGO presence. A higher NGO presence increases the cost of increasing distance, which then has to decrease.

6.3 Fixing distance

It is helpful to compare historic and steady-state policy to the outcomes of a policy fixing distance to a level, depicted by distance level in Figure 5. Upper panels represent the fundamental trade-off of the problem. As Figure 5a shows, departures decrease with distance; instead, results in Figure 5b show that death probability decreases with distance. Due to the composition of the two effects, expected deaths are inverse-u shaped in rescue distance set by the policymaker, as shown in Figure 5c. Deaths are minimized for very low distances and low for high distances; they peak around 40 KM.[36]

Since deaths and arrivals are lower when distance is high, it is then natural to ask why the distance chosen by the policymaker stabilizes at an interior point around 43KM, close to the historical average distance set by policy, as depicted by the blue vertical line. This is not due to the policymaker taking into account the policy's impact on attention, which would actually be reduced by higher distances. Instead, the policymaker prefers an interior equilibrium because increasing distance is bound to increase deaths in the short term.

Figure 5: Fixed-distance policy impact on arrivals, death probability, and deaths



Note: Outcomes of a fixed-distance policy on arrivals, in thousands, Figure 5a, death probability, Figure 5b, deaths, in thousands, Figure 5c, and attention, Figure 5d. Distance on the x-axis.

[36]The fact that deaths underreporting may be higher when distances are higher does not challenge the result on deaths-minimization presented here. Indeed, if the estimated arrival rate of shipwrecks is a lower bound on the death probability, deaths would still be minimized for low distances.

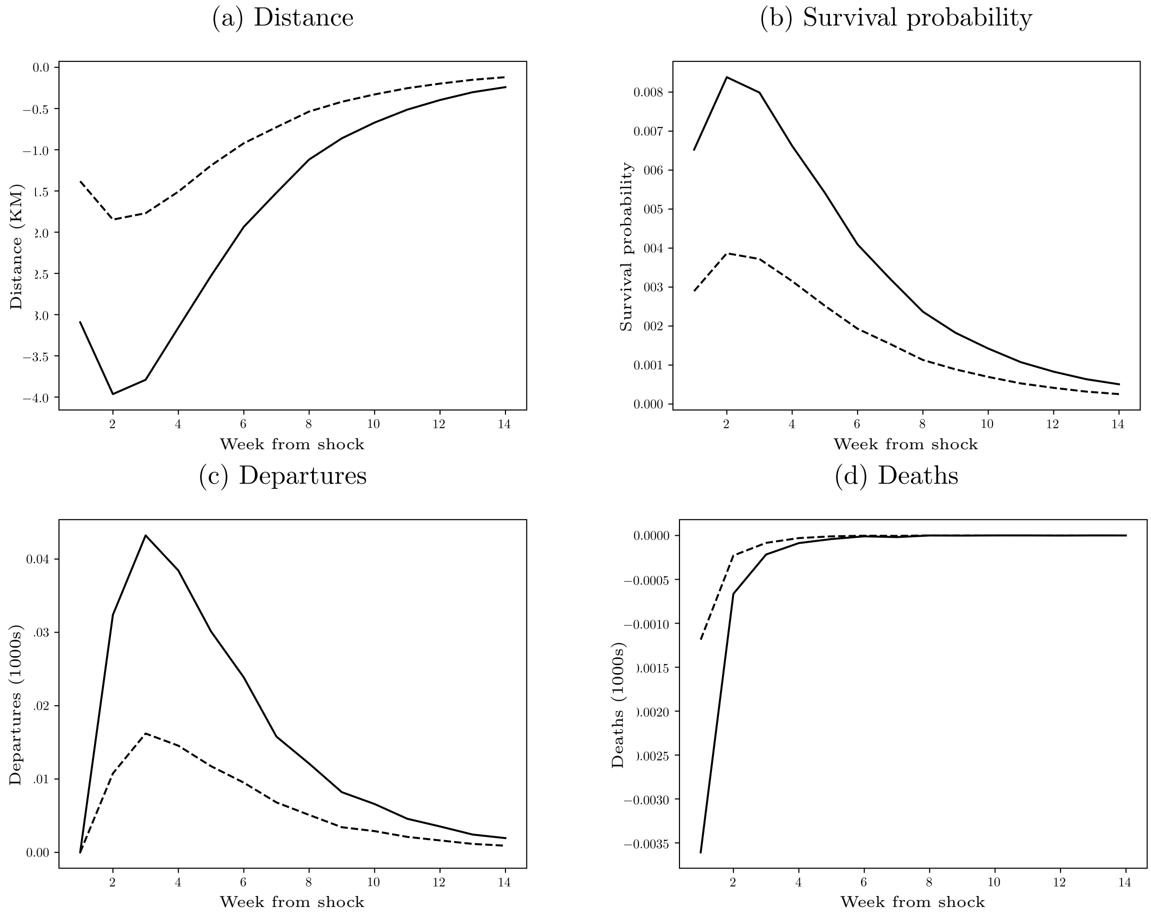
7 Effects of attention

Figure 6 shows the impact of a shock to attention. To construct it, I first simulate the model for 100 periods starting from average states, good weather, and no NGO presence. Then, I shock attention in the 100^{th} period by one and two times the attention noise standard deviation, register its evolution for 15 periods, and compute the difference with baseline evolution without the shock for every period. I simulate the model 10,000 times and plot the evolution of median differences. The upper LHS panel shows the effect of a shock in attention on distances. Shocks to attention persistently decrease distances; impacts take about 9 periods to go below 25% of the effect at peak. The intuition on the sign is the same given above. A shock to attention will depreciate eventually, and because policy outcomes are complementary to contemporaneous attention, the policymaker will be willing to take more future arrivals to decrease deaths today. Two factors can explain persistence. First, the attention shock itself is persistent. Second, by decreasing distance in reaction to an attention shock, the policymaker induces higher future departures–as shown in the lower LHS panel–and a higher benefit of setting a safer policy. This effect also induces amplification over time, and it leads to a lagged peak in attention's impact on policy, reached around the second or third week. Since the policymaker's loss is convex in arrivals, she will find it optimal to gradually decrease distance, which will eventually converge to the non-shocked level. Considering the magnitude of the effect at the peak and the shock to log-attention (0.363), a one-unit increase in log-attention in the model leads to a 5.2 KM median decrease in the distance of rescues. The overall effect on deaths is given by the composition of the effect on departures and the impact on rescue probability–as shown in the upper RHS panel. A one-unit increase in log-attention increases departures by about 17 persons at the peak, medianly, and it increases rescue probability by 0.5 percentage points. However, the effect on departures is lagged. Deaths decrease in the first period, due to the reduction in distances not matched by an increase in departures, but this effect reverts to zero in the third week. At that point, distances are already increasing, thereby pushing down departures, so any positive impact on deaths fades away. Hence, the net effect on deaths is negative.

Model results also deliver relevant predictions as to how the persistence of policy shocks affects policy responses. Figure 7 shows the impact of a 2-sd shock to attention as described above, but assuming now that the policymaker expects a higher shock persistence. In particular, I re-evaluate policies for attention persistence $\rho_g = 0.9$, and $\rho_g = 0.999$, other than the baseline $\rho_g = 0.776$. Increasing persistence has two effects. On the one hand, it increases the informativeness of the present attention shock on next-period distance (when rescues take place), which should make for a comparatively more substantial effect of attention shocks. On the other hand, it increases the expectations of $t+2$ attention, increasing the incentive to limit departures. The second effect prevails: an increase in persistence reduces the impact of attention on policy, so much so that for persistence $\rho_g = 0.999$, attention shocks have virtually no effect on distance.

In Appendix Section A.5, I investigate how the dynamics of attention and policy predicted by the model compare with the data in two ways. First, I regress rescue distance on lags and leads of attention, controlling for year and quarter of the year fixed effects in each regression. Consistently with the model, I show that only lags of attention significantly reduce rescue

Figure 6: Impact of a shock to attention over time (median)



Note: IRF of a positive log-attention shock of 2-sd (solid line) and 1-sd (dashed line) with $\rho_g = 0.776$, in differences with base case, after simulating the model for 100 weeks starting from average values, good weather, and no NGO presence. One standard deviation corresponds to 0.363 log-attention. Upper LHS is variation in median distance set by policy, upper RHS is variation in median probability of rescue, lower LHS is variation in median departures, in thousands, lower RHS is variation in median deaths, in thousands. Montecarlo simulation for 10,000 draws of random vectors of shocks and 15 weeks. The figure is obtained by differentiating the path of the variable in the un-shocked case from that in the shocked case.

distance and that the effect displays amplification and persistence. Second, I conduct the same analysis instrumenting attention with *noteworthy* soccer matches in *Serie A*, in the spirit of Eisensee and Strömberg (2007), and controlling for a fine-grained list of seasonal controls. After establishing that the instrument is not weak, I show that IV results qualitatively match model simulations.

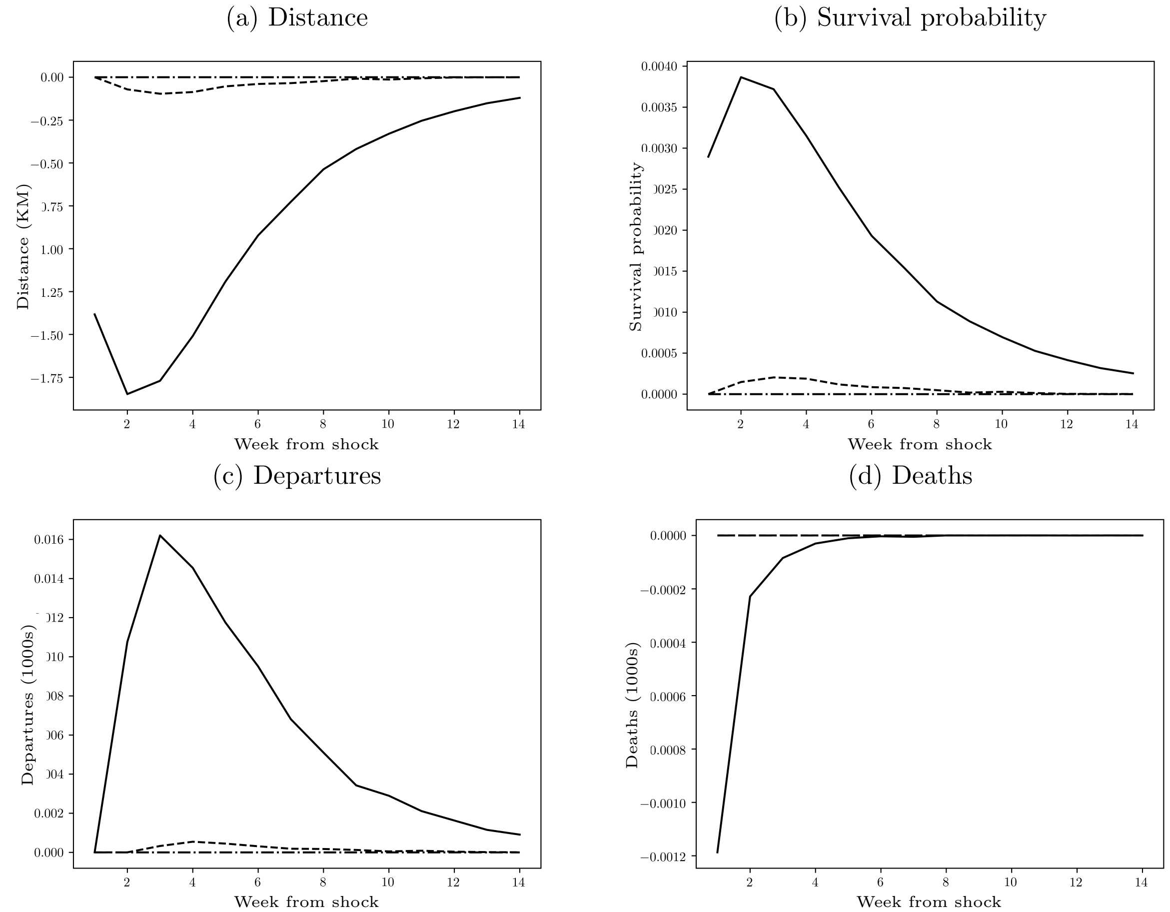
8 Externalization of border enforcement and the Value of a Statistical Life

8.1 Externalization of border enforcement in Libya

Italian and European authorities have been increasingly relying on agreements with transit countries to curb irregular migration in recent years.[37] In mid-2017, after my sample period,

[37]In March 2016, Turkey agreed to limit the influx of Syrian asylum-seekers to the EU in exchange for migrants' resettlement, easier procedures for Turkish migration to Europe, and a financial transfer to the Turkish

Figure 7: Impact of a 2-sd shock to attention over time (median), by persistence



Note: IRF of a positive log-attention shock of 2-sd with $\rho_g = 0.776$, differences with base case, after simulating the model for 100 weeks starting from average values, good weather, and no NGO presence. One standard deviation corresponds to 0.363 log-attention. Different styles represent different degrees of persistence of attention shocks: (1) solid line represents baseline persistence $\rho_g = 0.776$, dashed line represents (2) $\rho_g = 0.9$, and dashed-dotted line represents (3) $\rho_g = 0.999$. Upper LHS is variation in median distance set by policy, upper RHS is variation in median probability of rescue, lower LHS is variation in median departures, in thousands, lower RHS is variation in median deaths, in thousands. Montecarlo simulation for 10,000 draws of random vectors of shocks and 15 weeks. The figure is obtained by differentiating the path of the variable in the un-shocked case from that in the shocked case.

Italy externalized border enforcement policy to Libyan authorities in exchange for financial support, after signing a Memorandum of Understanding with the Libyan Government of National Accord at the beginning of 2017. In the year following the start of the policy, arrivals decreased by 87% compared to the previous year, and deaths at sea decreased by 82% (Villa, 2015). The extent of the financial support provided by Italian and European institutions to Libyans is not transparent. However, a recent journalistic investigation suggests it was around €475 million, partially channeled through equipment for the so-called Libyan Coast Guard.[38]

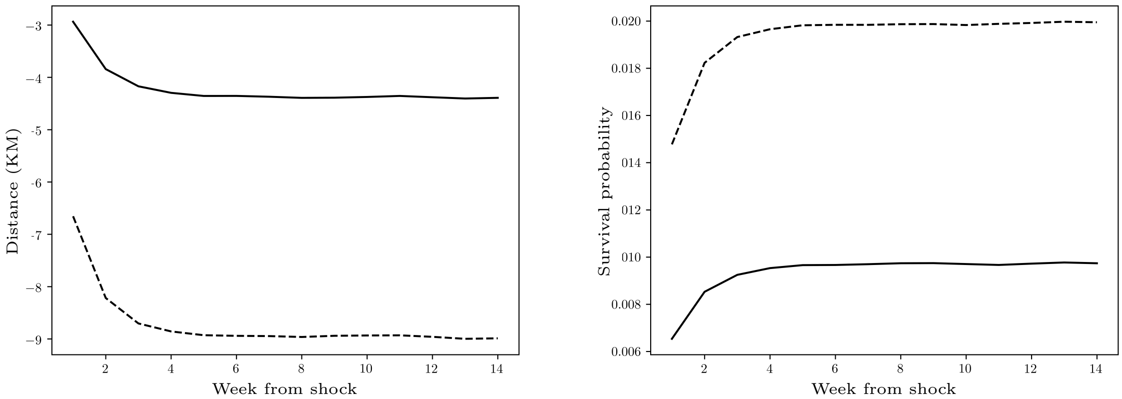
We can use the model to analyze the externalization policy undertaken by European and Italian authorities in Libya. Externalization of border enforcement can be thought of in different ways, depending on how it effectively reduced migrants' flows. On the one hand, policing activities on land or reduced support to smuggling networks may have caused a reduction in the

government.

[38]The investigation appeared on *Euronews* and it is available at https://bit.ly/2HHgKfn in Italian. I can provide an English summary upon request.

Figure 8: Impact of an unexpected permanent shock to ω_0 over time (mean)

(a) Distance (b) Survival probability



Note: IRF of an unexpected permanent reduction of ω_0 by 5% (solid line), and 10% (dashed line) in differences with the base case, after simulating the model for 100 weeks starting from average values, good weather, and no NGO presence. The LHS panel displays the variation in the mean distance set by policymakers; the RHS panel shows the variation in the mean probability of rescue. Montecarlo simulation for 100,000 draws of random vectors of shocks and 15 weeks. I obtain the figure by differentiating the path of the variable in the un-shocked case from that in the shocked case.

overall profitability of smuggling.[39] We can frame this effect as a reduction in ω_0 in Equation 5, implying an overall decrease in departures. On the other hand, the externalization policy may have reinforced the ability of the Libyan Coast Guard to apprehend migrants trying to reach Europe. In this case, the externalization policy would have particularly reduced the profitability of smuggling activities for high rescue distances, as a lower distance implies a lower probability of apprehension. In the language of the model, this would represent a reduction of ω_1, causing a downward shift of departures as a function of past distance, keeping the intercept fixed. The two possible effects–a reduction in ω_0 and ω_1–have opposite impacts on the dynamics of the model. As shown in Figure 8 and 9, respectively, a decrease in ω_0 reduces the steady-state rescue distance while an increase in ω_1 increases it. Effects on the rescue probability for migrants are the opposite.

8.2 Deaths, arrivals, policymaker's welfare, and VSL

Leveraging the model, I can compute the variation in policymakers' welfare produced by the deal. As I noted above, the agreement could have changed both ω_0 and ω_1, influencing how distance turns into future departures. Define $\bar{\omega}_{deal} = [\omega_{0,deal}, \omega_{1,deal}]$. We can think about the deal as shifting the relation between distance and departures to:

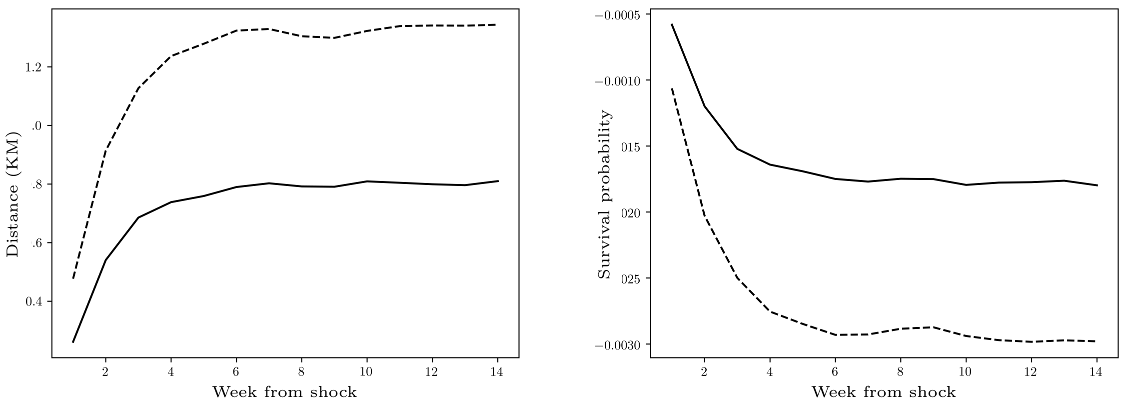
$$\log \ell_{t+1} = \omega_{0,deal} + \omega_{1,deal}\mu_t + \omega_2 w_{t+1}. \tag{21}$$

Knowing $\bar{\omega}_{deal}$, I back out the willingness-to-pay for welfare dividing the increase in policy-maker's welfare from the deal, $V(\bar{\omega}_{deal}) - V(\bar{\omega})$, by the financial cost of the deal, P_{deal}. Ideally,

[39]The idea that the deal affected the overall profitability of smuggling relative to alternative businesses is consistent with widespread evidence that the negotiations involved exponents of criminal organizations and traffickers. See, for instance, the following articles by the Italian newspapers *Avvenire*, *L'Espresso*, *Internazionale*, and the news agency *Reuters*, respectively at https://archive.is/tW7Fu, https://archive.is/WIq6V, https://archive.is/WIq6V, and https://archive.is/Q66zO.

Figure 9: Impact of an unexpected permanent shock to ω_1 over time (mean)

(a) Distance (b) Survival probability



Note: IRF of an unexpected permanent reduction of ω_1 by 5% (solid line), and 10% (dashed line) in differences with the base case, after simulating the model for 100 weeks starting from average values, good weather, and no NGO presence. The LHS panel displays the variation in the mean distance set by policymakers; the RHS panel shows the variation in the mean probability of rescue. Montecarlo simulation for 100,000 draws of random vectors of shocks and 15 weeks. I obtain the figure by differentiating the path of the variable in the un-shocked case from that in the shocked case.

I could estimate $\bar{\omega}_{deal}$ by regressing departures on distance under the new policy. Unfortunately, a time-series of distances after the policy was implemented is not available. Instead, to obtain an estimate of the policy impact, I use aggregate data on departures and death probability in the year following the deal, together with my model, in the following way. First, I express $\omega_{0,deal}$ as a function of new log average departures and $\omega_{1,deal}$, using Equation 21. Second, I define $\mu_{ss}(\omega_{1,deal})$ as the steady-state distance as a function of the new parameters. Third, I back out the new average distance by using the death probability observed after the deal, together with the OLS-estimated relation between death probability and distance, and call it μ_{deal}. Finally, I numerically solve $\mu_{ss}(\omega_{1,deal}) = \mu_{deal}$ for the new $\omega_{1,deal}$, and use the latter to get $\omega_{0,deal}$. I obtain two solutions, $\omega_{1,deal} = 0.0399$ and $\omega_{1,deal} = 0.257$, but I discard the latter since it would result in implausibly high departures for zero-distance–roughly 13 million people per week, more than 30 times the migrant flow in the whole sample period. Consequently, I back out $\omega_{0,deal} = 1.890$. This result is consistent with the policy having increased ω_1 and reducing ω_0.

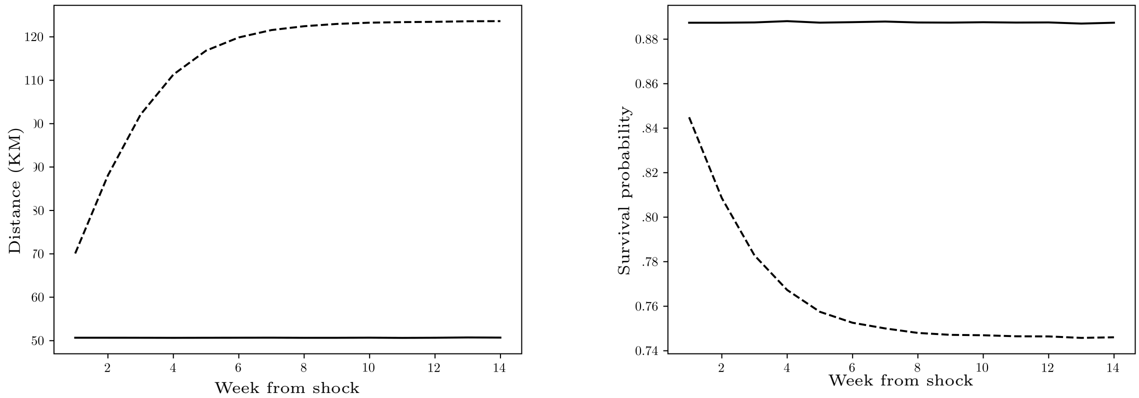
Comparing these effects with the financial transfer paid to Libyan institutions, I obtain an estimate of the average willingness-to-pay of the policymaker for saving one migrants' life from a shipwreck involving D deaths at steady-state expected outcomes, averaging over weather and attention. Setting D to the standard deviation of deaths, 128, I get an average willingness to pay of €78 000; given convexity of the policymaker's preferences, this estimate goes up to €146 000 for D equal to two times the standard deviation of deaths, and €250 000 for three times the standard deviation. It is insightful to weigh these figures against the estimate in Ashenfelter and Greenstone (2004) that the US government is willing to pay at most \$ 1.54 million to prevent one citizen's death. We cannot be sure that the same estimate applies to European authorities; however, it can provide a useful proxy. Results suggest that the evaluation of migrants' lives is much lower compared to citizens' ones.

9 NGO actors and NGO ban

Non-Governmental Organizations are active rescue actors in the Mediterranean alongside institutional ones–Frontex, the Italian Navy, and the Italian Coast Guard. NGO presence in the Mediterranean rests on long-term investments in capital equipment–ships–by a wide range of established organizations.[40] As I document in Figure A.4, these organizations have taken up a non-negligible share of rescues over time. At the same time, their objectives do not entirely align with policymakers'. NGOs aim to save migrants at sea rather than pursue deterrence, resulting in conflict between them and institutions.[41]

Figure 10: Impact of an unexpected permanent NGO ban

(a) Distance (b) Survival probability



Note: Simulated evolution of distances and death probability from steady state after an unexpected NGO ban. Solid line represents mean evolution without NGO ban; dashed line represents mean evolution with NGO ban. I simulate the model for 100 weeks starting from average values, good weather, and no NGO presence, then I simulate the model for 15 additional weeks with and without the ban. The LHS panel displays the variation in the mean distance set by policymakers; the RHS panel shows the variation in the mean probability of rescue. Montecarlo simulation for 100,000 draws of random vectors of shocks.

As shown in Figure A.6, reporting the evolution of rescue distance by actor type, NGOs conduct rescues closer to the Libyan coast, reducing policymakers' ability to set high rescue distances. Thus, NGO rescues affect policy in two ways. First, they reduce the ability of policy to react to attention shocks. As I document in Appendix Section A.7.2, the reduced-form impact of attention on rescue distance is lower when NGO presence is high, reinforcing the idea that institutional actors—rather than NGOs—react to attention shifts. Second, they decrease rescue distance overall, directly, by saving migrants close to the coast, and, indirectly, by shifting expectations about the future rescue distance. In the eyes of the policymaker, higher present rescue distances are complementary to future higher rescue distances, as lower future distances are more beneficial to the policymaker when expected departures are low. The effect of NGO presence on distances overall is substantial. In Figure 10, I show the impact of an unexpected permanent NGO ban at time zero on rescue distances. In roughly two months, such policy would push rescue distances to the upper boundary of rescue distances from Libya

[40] *Médecins Sans Frontièrs* and *Sea Watch* were the first to start operations and were already active in 2015. From 2016 *SOS-Méditerranée*, *Sea-Eye*, *Pro-Activa Open Arms*, *Jugend Rettet*, the *Lifeboat Project*, the *Boat Refugee Foundation*, *Save the Children* and *Mission Lifeline* started operating (Cusumano and Pattison, 2018).

[41] Nonetheless, NGO actors destroy smugglers' boats after conducting rescues, as all actors are required to do in the rescue area.

(the island of Lampedusa in Italy), reducing survival probability for migrants by 15 percentage points. These results suggest that the presence of NGOs keeps authorities from choosing a corner solution where they rescue migrants close to Italian coasts.

10 Conclusion

Irregular migration and border enforcement are at the forefront of the political debate in high-income countries, particularly Europe and the US. Despite the relevance of the policy issue, the literature has devoted relatively little attention to understanding the main incentives driving policy in this domain. Past work has shown that US border enforcement along the Mexican frontier reduces migrants' flows but puts their lives in danger. The same holds in the Mediterranean Sea, dividing Europe from Africa. Border enforcement decisions involve a trade-off between deterrence and safety conditions for migrants' crossings.

In the context of the Central Mediterranean Route of migration, policymakers decide where to save migrants' boats in distress and disembark them in Europe. Saving migrants close to the Libyan shores, where they leave from, would reduce shipwreck risk. However, a low rescue distance increases future departures. I model the ensuing dynamic problem and estimate it using high-frequency georeferenced data of rescue operations in the Mediterranean. The policymaker sets the distance of rescues from the Libyan coast; she faces a trade-off between risk for migrants at sea today and future arrivals. I use the estimated parameters to show that policymakers are willing to accept one death in exchange for ten fewer arrivals at steady-state. I also show that European policy between 2014 and 2017 was suboptimal in minimizing migrants' deaths at sea.

Because of their political relevance, irregular migration and border enforcement outcomes receive high visibility in high-income countries. The estimated model considers the effects of public scrutiny on the policymaker's decisions, as measured by Google-searches volume about migration. Temporary attention shocks tilt policymaker's goals towards short-term outcomes. Then, the policymaker accepts higher future arrivals to reduce the current risk for migrants. This idea on how public attention influences policy potentially generalizes to all policy contexts in which (i) policymakers' trade-off is intertemporal and (ii) public attention to policy outcomes changes over time.

Finally, the mechanism proposed suggests a potential avenue for future research. In the framework presented above, the evolution of public attention is not directly under the control of actors involved; however, future work could explore the possibility. In the context of this study, several political agents take into account the effect of their actions on the dynamics of public attention. Humanitarian organizations in the Mediterranean Sea aim to increase transparency on the outcomes of border enforcement in the Mediterranean. Politicians in government may try to influence the evolution of attention by strategically timing communication or policies competing for coverage. In this or other policy domains, future research should consider the strategic behavior of stakeholders in trying to influence public attention to and the salience of policy outcomes and how these ultimately impact policymaking.

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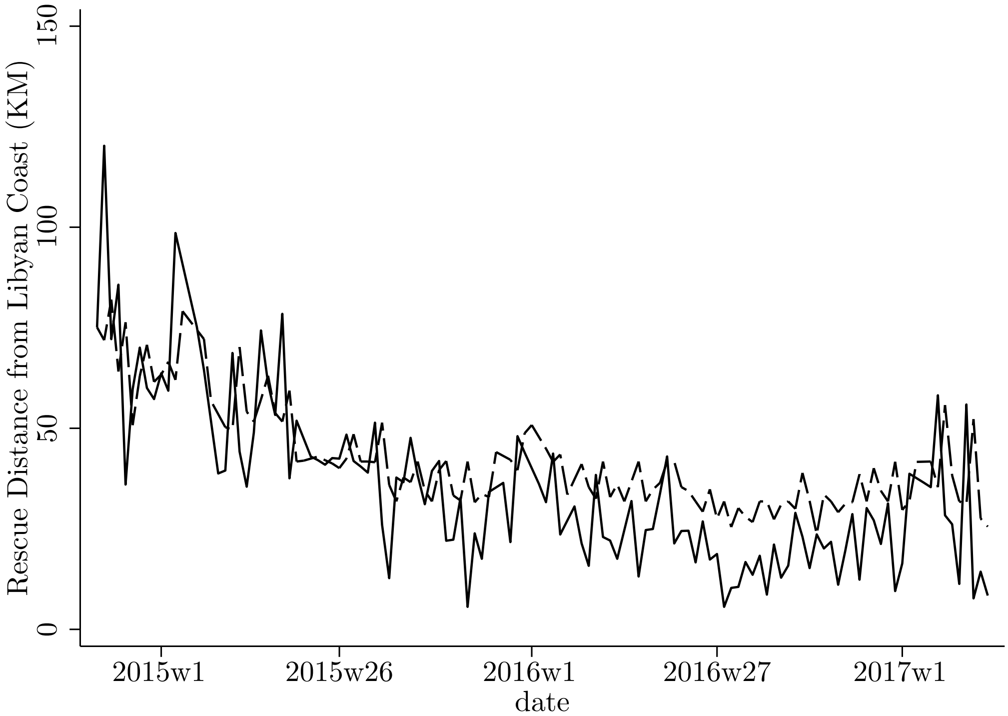
Appendix

A.1 Figures

Figure A.1: Evolution of actual and model-predicted distances



Note: Evolution of model-predicted distances (dashed line) and distances in the data (solid line). Referenced in Section 6.1.

A.2 Tables

Table A.1: Main summary stats from data

	Mean	sd	Min	Median	Max	N
Arrivals	2584	2797	0	1705	15373	126
Deaths and Missing	55.4	128	0	5	825	126
Survival Frequency	0.957	0.143	0	0.998	1	119
Distance from Ter. Waters.	35.1	20.6	5.6	31.6	120.3	117
Swell	0.133	1.03	-1.32	-.265	3.0	126
Migration Searches	16.8	9.66	3.15	17.2	59.1	126
Obj. Articles	171	162	13	130	1398	126
Obj. Art. (Weighted Online)	0.681	0.6	0.0581	0.529	5.0	126
Obj. Art. (Weighted Print)	0.307	0.28	0	0.222	1.5	126
Pos. Sent. Articles	93.2	59.1	6	83	338	126
Obj. Art. (Weighted Online)	0.371	0.238	0.000552	0.329	1.2	126
Obj. Art. (Weighted Print)	0.251	0.148	0.00819	0.239	0.8	126
Neg. Sent. Articles	177	185	10	125	1665	126
Obj. Art. (Weighted Online)	0.626	0.657	0.0343	0.438	5.6	126
Obj. Art. (Weighted Print)	0.801	0.719	0.0221	0.582	5.1	126
Number of Matches	0.119	0.325	0	0	1	126
Noteworthy Matches	0.0635	0.245	0	0	1	126
Avg. Ships by Suez (8 weeks)	185	7.72	174	184	210.8	109

Note: Main summary statistics about migration outcomes, weather, attention, searches, articles, and maritime traffic. All variables are weekly aggregates, except for trade variables, displaying monthly values for the 126 weeks in the sample. Arrivals represent all migrants arrived during rescue operations involving migrant boats leaving the North African coast from Libya, obtained from Frontex data. Survival frequency is the ratio of arrivals to departures–arrivals, deaths, and missing in the rescue area. Deaths and missing data are retrieved from Missing Migrants Project. The average distance of rescue operations from territorial waters is reported in KM, obtained from Frontex data. Swell is defined as 4 times the square root of the integral over all directions and all frequencies of the two-dimensional wave spectrum; the integration is performed over all frequencies up to infinity. Swell data was downloaded from the ECMWF database, and it refers to the sea at the crossing of territorial waters around Tripoli and a line connecting the center of Tripoli to the island of Lampedusa–the closest Italian territory. Migration searches on Google refer to Italy. In the same way, objective, positive-sentiment, and negative-sentiment articles about migration are counted among Italian newspapers. The two weighted measures of articles weigh them by a measure of the audience of the newspaper or newspapers' website, using data from *Audiweb* and *Accertamenti Diffusione Stampa*. A noteworthy match is a dummy taking value one if a noteworthy match occurred over a week. The latter is defined as a *Serie A* match respecting the following two criteria: (i) it was played between two of the three teams in Italy that were most searched on Google during the year starting on October 2013, and (ii) the ex-ante probability of its outcome, based on odds data from Bet365, is below the median probabilities. The number of ships crossing Suez Northbound, obtained by Suez Canal Authority, is summed over the 8 weeks before the observation.

Table A.2: Distance, interceptions by commercial ships and Suez crossings

	$\hat{\mu}_t$				mig_t^{com}	
$suez_{t,8}$	-0.553**	-0.730***	-0.495**	-0.718***	-0.00774***	-0.0121***
	(0.221)	(0.139)	(0.197)	(0.153)	(0.00272)	(0.00344)
$suez_{t+8,8}$			-0.184	0.00980		
			(0.168)	(0.111)		
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-o-y FEs	Yes	No	Yes	No	Yes	No
Week-o-y FEs	No	Yes	No	Yes	No	Yes
N	103	103	95	95	103	103

Note: All variables are weekly aggregates. The dependent variable in the first four columns is the average distance of interceptions (KM), weighted by the proportion of migrants saved, obtained from Frontex data. The first two columns have the daily average of Suez North-bound crossings, summed over the previous 8 weeks, as the main independent variable; partialed-out controls include year and quarter-of-the-year FEs, and year and week-of-the-year FEs. Estimations in the third and fourth columns add the main dependent variable forwarded by 8 weeks. In the last two columns, the dependent variable is the proportion of migrants rescued by commercial ships in a given week. The main independent variable is average Suez crossings summed over the previous 8 weeks; controls include year and quarter-of-the-year FEs, and year and week-of-the-year FEs. HAC standard errors (in parentheses), robust to both arbitrary heteroskedasticity and arbitrary autocorrelation up to 9 lags. Table referenced in Section 5.1.2. P-values are denoted as follows: * $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Impact of distance and weather on risk, controlling for log-departures

	$\bar{\pi}_t$			
	2SLS	2SLS	2SLS	2SLS
$\hat{\mu}_t$	-0.00225**	-0.00213**	-0.00226***	-0.00218***
	(0.000915)	(0.000927)	(0.000543)	(0.000595)
$log(1 + departures)$	0.00577	0.00315	-0.00193	-0.00971**
	(0.00381)	(0.00486)	(0.00438)	(0.00427)
$Bad \quad weather_t$		-0.00656		-0.0198***
		(0.00847)		(0.00588)
Year FEs	Yes	Yes	Yes	Yes
Quarter-o-y FEs	Yes	Yes	No	No
Week-o-y FEs	No	No	Yes	Yes
N	103	103	103	103
$KP\ F$	5.715	5.629	14.336	11.454

Note: All variables are weekly aggregates. The dependent variable is survival frequency, the ratio of arrivals to departures–arrivals, deaths, and missing in the rescue area. Arrivals represent all migrants arrived during rescue operations involving migrant boats leaving the North African coast from Libya, obtained from Frontex data. Deaths and missing data are retrieved from Missing Migrants Project. The main independent variable is the average distance of interceptions (KM), weighted by the proportion of migrants saved, obtained from Frontex data. All columns report 2SLS estimations, using a 12-week rolling sum over lags of North-bound Suez Crossings as an instrument. A varying set of season and time controls (partialled out), and weather, defined as swell, is used in each specification, as indicated in the table. HAC standard errors (in parentheses), robust to arbitrary heteroskedasticity up to 3 lags in the first four columns, and up to 9 lags in the last two. Table referenced in Section 5.1.2. P-values are denoted as follows: * $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Impact of distance and weather on departures, other lags

	$\log(1+dep_t)$				
$\hat{\mu}_t$	0.00111	0.000722	-0.00383	-0.00430	-0.00365
	(0.00661)	(0.00785)	(0.00833)	(0.00881)	(0.00943)
$\hat{\mu}_{t-1}$	-0.0125*	-0.0144**	-0.0237***	-0.0249***	-0.0177**
	(0.00689)	(0.00703)	(0.00720)	(0.00803)	(0.00887)
$\hat{\mu}_{t-2}$		-0.000142	-0.00122	-0.00308	0.000248
		(0.00544)	(0.00529)	(0.00649)	(0.00789)
$\hat{\mu}_{t-3}$			-0.00774	-0.00762	0.00266
			(0.00849)	(0.00797)	(0.00586)
$\hat{\mu}_{t-4}$				0.0119	0.0126
				(0.0111)	(0.0114)
$\hat{\mu}_{t-5}$					-0.00191
					(0.00807)
$Bad \quad weather_t$	-0.759***	-0.742***	-0.731***	-0.738***	-0.771***
	(0.0890)	(0.107)	(0.103)	(0.125)	(0.114)
Quarter-by-y FEs	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes
N	108	99	91	83	77

Note: All variables are weekly aggregates. The dependent variable is the logarithm of one plus departures, defined as the sum of arrivals, deaths, and missing in the rescue area. Arrivals represent all migrants arrived during rescue operations involving migrant boats leaving the North African coast from Libya, obtained from Frontex data. Deaths and missing data are retrieved from Missing Migrants Project. The main independent variable is the average distance of interceptions (KM), weighted by the proportion of migrants saved, obtained from Frontex data. All regressions include year by quarter-of-the-year FEs and weather as a control, defined as swell–4 times the square root of the integral over all directions and all frequencies of the two-dimensional wave spectrum; the integration is performed over all frequencies up to infinity. Swell data refers to the sea at the crossing of territorial waters around Tripoli and a line connecting the center of Tripoli to the island of Lampedusa–the closest Italian territory. HAC standard errors (in parentheses), robust to both arbitrary heteroskedasticity and arbitrary autocorrelation up to 3 lags. Table referenced in Section 5.2.2. P-values are denoted as follows: * $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Impact of Arrivals on Attention, Other Lags

	g_t				
mig_t	0.00978	0.0116	0.0101	0.00963	0.00714
	(0.0151)	(0.0146)	(0.0142)	(0.0145)	(0.0142)
mig_{t-1}	0.0364**	0.0388**	0.0415**	0.0411**	0.0400**
	(0.0168)	(0.0196)	(0.0200)	(0.0197)	(0.0202)
mig_{t-2}		0.0118	0.0146	0.0169	0.0155
		(0.0178)	(0.0185)	(0.0180)	(0.0182)
mig_{t-3}			0.0108	0.0134	0.0153
			(0.0132)	(0.0138)	(0.0135)
mig_{t-4}				0.0108	0.0130
				(0.0114)	(0.0122)
mig_{t-5}					0.0101
					(0.0111)
Year FEs	Yes	Yes	Yes	Yes	Yes
Quarter-o-y FEs	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes
N	125	124	123	122	121

Note: All the variables are weekly aggregates. The dependent variable is log Google searches about migration in a given week. The main dependent variables are lags of migrants' arrivals (in thousands)–representing all migrants arrived during rescue operations involving migrant boats leaving the North African coast from Libya, obtained from Frontex data. All regressions include year FEs and quarter-of-the-year FEs as a control. HAC standard errors (in parentheses), robust to both arbitrary heteroskedasticity and arbitrary autocorrelation up to 3 lags. Table referenced in Section 5.4. P-values are denoted as follows: * $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$.

A.3 Recent rescue policy on the central Mediterranean route of migration

The risk for migrants encouraged an institutional effort to conduct rescue operations at sea, which reduced barriers to entry in the smuggling scheme; at the same time, deterrence emerged as a policy issue. Figure A.2 summarizes the main phases of rescue policy in the Central Mediterranean route as established by this section. In 2012 and 2013, Libyan smugglers relied on wooden vessels capable of reaching the Italian shores 300 KM away. Shipwrecks were not absent; in October 2013, a migrants' ship sank off the coast of Lampedusa, causing the death of 366 African migrants, most of whom were Eritreans. The tragedy led Italian authorities to launch the SAR operation Mare Nostrum, managed by the Italian Navy. It is possible that institutional SAR operations reaching into the Maltese and Libyan rescue areas opened the opportunity for smugglers to enter business with cheaper boats. Deiana et al. (2021) show that in periods where rescue operations are present in the Mediterranean Sea, weather conditions have more of an impact on departures since smugglers switch to less safe and cheaper technologies, inducing a higher number of crossings. In October 2014, Italy discontinued Mare Nostrum because of the uneven burden-sharing among European Nations. The European Border Enforcement Agency (Frontex) launched *Triton Operation* on November 1, 2014, and took over patrolling activities (EPSC, 2017). Officially, this was a border enforcement operation. Still, international conventions–such as the 1982 United Nations Convention on the Law of the Sea (UNCLOS) and the 1974 International Convention for the Safety of Life at Sea (SOLAS)–require assets employed in these operations to engage in SAR. *Triton* 's operational area was reduced to roughly 220 KM away from the Libyan coast with a view of discouraging migration. Indeed, deterrence motives are apparent both in external and internal communication on rescue operations by the agency–see, for example, Frontex (2015b), a disclosed internal document compiled by the EU border enforcement agency.[A.1] However, EU authorities would soon have to adjust their policy to decrease the risk for migrants.

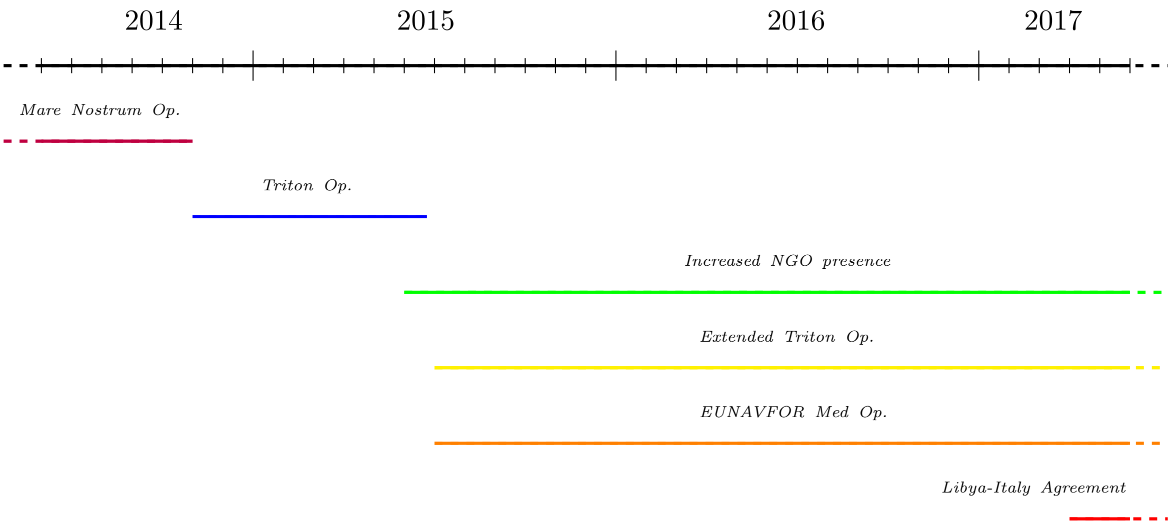
EU policy saw a significant turn in favor of migrants' safety in April 2015, after two shipwrecks involving 1,200 migrants and garnering large attention (Heller and Pezzani, 2016). First, the mandate for *Triton Operation* increased to cover a larger area. Second, the EU started European Operation Sophia, conducting SAR activities inside the Libyan SAR zone (EPSC, 2017), just outside Libyan territorial waters, 22.224 KM from the Libyan coast.

A.4 Commercial ships' rescues and exogenous variation in distance

To investigate the relation between rescue distance and migrants' risk, I employ variation in commercial sea traffic, proxied by the number of ships entering the Mediterranean through the Suez Canal, as an exogenous shock to rescue distance. Commercial ships are obliged to provide

[A.1] The document was collected by Forensic Oceanography, a research team based within the Forensic Architecture Agency at Goldsmiths (University of London), for the project 'Death by Rescue,' available at https://archive.is/5NjTU.

Figure A.2: Chronology of operations and main events



Note: Source: own elaboration of EPSC (2017).

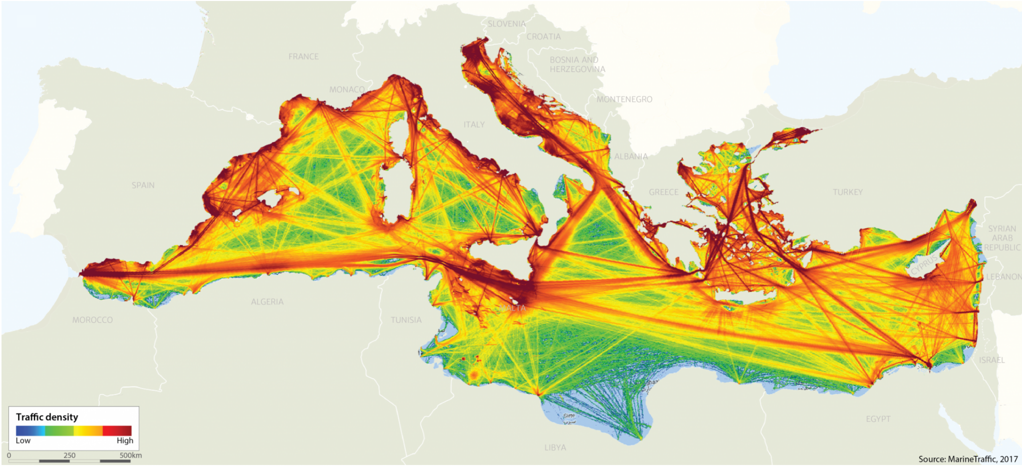
rescues to boats in distress if requested. As shown in Figure A.3, the Mediterranean rescue area is located just south of a major maritime shipping hub, connecting the East and West Mediterranean, and notably routes connecting the Suez Canal with the West Mediterranean and Gibraltar. Rescue distance set by policymakers directly impacts the proportion of rescues taken up by commercial ships. Higher distances make it more likely for migrants' boats to reach the commercial route passing South of Sicily. The dashed line in Figure A.4 shows a kernel regression of the proportion of migrants saved by merchant or fishing vessels over time. In the first months of 2015, when rescue distances were high, commercial ships took up around 30% of rescues. Then, rescues imposed a significant financial burden on commercial shipping, mainly in terms of delays for large shipments, leading shipowners to voice requests for intervention to EU authorities in 2015.[A.2] After the geographical expansion of rescue activities, the proportion of rescues by merchant ships reverted to 3-4%.

We can hypothesize that the EU and Italian authorities consider the impact of rescue operations on trade when setting policy. Shipping delays caused by rescues can create economic damage by negatively affecting trade. Further, they can represent a considerable cost item for the shipping industry, widely consisting of European companies: four of the five largest liner companies by cargo capacity are European (Asariotis et al., 2018). According to the European Community Shipowners' Association (ECSA, 2015), Italian and EU authorities have recognized the problem and helped reduce the burden for shipowners. Indeed, 'mitigat[ing] the risk to maritime industry activities' was among the themes discussed in 2016 at the Shared Awareness and De-confliction in the Mediterranean (SHADE MED) forum. SHADE MED was organized by NATO and European and Italian authorities; it brought together representatives of military and civilian organizations engaged in maritime security and rescue, including members of the shipping industry.[A.3] Authorities are likely to take these concerns more seriously when stakes

[A.2] A letter by the European Community Shipowners' Association and International Chamber of Shipping, addressed to the EU Member States and EU authorities in copy, is available at https://bit.ly/3jD46La.

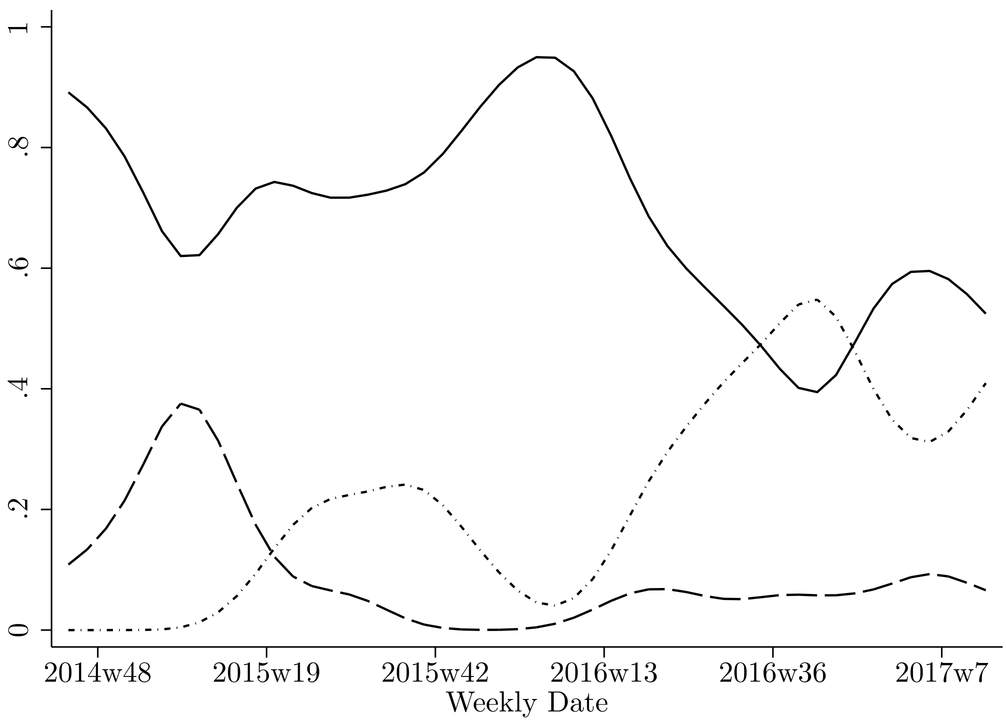
[A.3] See https://bit.ly/3mtgE9U for an account of the event.

Figure A.3: Maritime traffic density in the Mediterranean Sea



Note: Source: MarineTraffic (2017) as in UNEP (2017). Referenced in Section A.4.

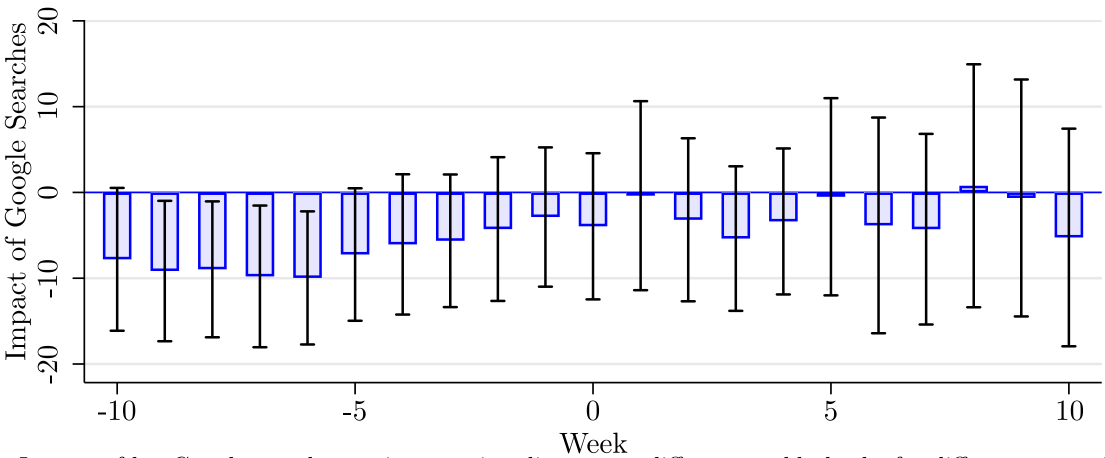
Figure A.4: Migrants' share intercepted by actor, over time



Note: Proportion of migrants intercepted by different actors over time; kernel regression with Gaussian kernel. Polynomial used for smoothing has degree 3, bandwidth is 5 weeks. The dashed line represents commercial ships, the dashed-dotted line represents NGOs, and the solid line represents residual institutional interceptions. Referenced in Section A.7.

are high; rescue practices should then adjust in response to variation in maritime traffic in the Mediterranean basin. In Table A.2, I show that this is the case by proxying maritime traffic over time with the count of ship crossings from the Red Sea to the Mediterranean Sea through the Suez Canal, an international trade hub connecting the Red Sea and the Mediterranean. Importantly, it provides a much faster sea route from South Asia to Europe than its best counterpart–circumnavigating Africa. For this reason, the Suez Canal traffic virtually consists

Figure A.5: Impact of searches on distance over time



Note: Impact of log Google searches on interception distance at different weekly leads, for different regressions. Controls include year and quarter-of-the-year fixed effects. Plot includes Bonferroni-corrected confidence intervals for $\alpha = 5\%$. HAC standard errors robust to arbitrary heteroskedasticity and autocorrelation up to lag 3.

of goods transportation only (ALEXBANK, 2018), and between 7 and 10% of world sea trade (in volume) passes through it (De Waal, 2019).

A.5 Effects of attention: OLS and 2SLS

As a robustness check to the structural methodology employed, it is helpful to see whether reduced-form strategies qualitatively replicate the effects of attention found with the model. To do that, I regress observed mean distance μ_t on lags and leads of attention g_t, representing weekly average Google searches about migration, in logs. I estimate one specification for each lag or lead separately to assess each lag's composite effect. I allow for arbitrary heteroskedasticity and autocorrelation up to lag 3. Then, I graphically inspect results by looking at a bar plot of coefficients, with their confidence intervals, and correcting for multiple-hypothesis testing 'a la Bonferroni. Figure A.5 reports the impact of attention on distance for leads between -10 and 10. Past attention has a negative effect from the first lag, increasing in magnitude and becoming significant at the 10% significance level on the 5^{th} lag, peaking at the 6^{th}, and then fading away. Leads have no effect whatsoever. Results qualitatively support the idea that the dynamics of attention and policy generate persistence and amplification. An increase in attention by about 10% on the 6^{th} lag decreases observed average distances by 1 KM. In terms of the previous impulse-response functions, a one-unit increase in log-attention leads to a 10-KM decrease in distances at peak. This effect is almost twice the effect found in the model, although the difference is not significant. On the one hand, this may indicate that the model structure helps specify the dynamics of potentially endogenous variables; on the other hand, effects may be heterogeneous across states. Indeed, model-simulated and data moments are quite similar in Table 4, where I use actual states to predict future distances.

To further explore the robustness of my findings, I instrument attention with important sports events in Italy–*noteworthy* matches in *Serie A*. In principle, the occurrence of relevant sports events crowds out attention to migration as in Eisensee and Strömberg (2007), by competing for public attention, space in newspapers, and social media space. The effect of matches on migration searches can be direct if unexpected matches decrease the time people devote to acquiring information about migration. The effect can also be indirect if sports events crowd out news about migration in newspapers due to limited space or reduce the salience of migration content in social media.

I define a match to be *noteworthy* if it respects the following two criteria: (a) the two teams participating in it are among the most popular, and (b) its result is unexpected. As for (a), I restrict to matches between the three teams ranking highest in Google searches during the twelve months until the start of the sample of interceptions (October 2013 to October 2014)–Juventus, Inter, and Napoli. As for (b), I define unlikely victories as those displaying the probability of occurred events–implied by odds–lower than the 50^{th} percentile. To retrieve probabilities implied by odds, I use a simple and usual model of the behavior of a betting agency and public data collected by the agency *Bet365*. In the first stage, I use newsworthy matches as an instrument, controlling for year and week-of-the-year fixed effects, eliminating the potentially confounding role of seasonality in driving policy and match results.

I report estimates for the first stage in Appendix Table A.6. The first three columns show the impact of *noteworthy* matches at different lags and leads, with different sets of controls, indicating that only the first lag has a statistically significant effect; the latter is negative, implying crowding out of attention. The fourth column shows the specification with only one lag, as in the first stage of the 2SLS estimation; the effect is still negative and significant. The last two columns show the impact of the presence in a week of a match respecting only criterion (a), namely that playing teams are among the three most popular in Italy. Effects point in the same direction, but they are more imprecise and lower in magnitude. Results suggest that migration and sports are competing issues in terms of attention. When matches are less newsworthy, they arguably circulate less in social media and newspapers, taking less space from migration as an issue. Choosing matches respecting both (a) and (b) as an instrument increases the relevance of the matches instrument.

I show the result of the 2SLS estimation for different lags, separately, in Appendix Table A.7, together with KP F statistics. F-stats are all above the 10-threshold. Consistent with the results in Figure, I find a negative and significant effect only from lag 4 to lag 6. Effects are larger than OLS estimates for the 5^{th} lag: an increase in attention by 10% decreases distance by 2 KM, double the OLS estimate–although the confidence intervals overlap. Coefficients on the 4^{th} and 6^{th} are still larger than OLS estimates but far closer in magnitude. Then, the effects of attention found in the impulse response functions are considerably lower than the 2SLS-estimated impact of attention. The previous discussion on shocks' persistence offers a possible explanation. As I highlight above, low-persistence shocks tend to have a larger impact on policy than high-persistence ones because they strongly affect the intertemporal incentives of the policymaker. Soccer matches might be able to shift attention in the short run. Still, since they do not directly influence the migration debate, their effect dissipates quickly.[A.4]

Despite both OLS and IV display amplification and persistence, the dynamics of the effects unfold with a different timing with respect to model results. In model impulse-response func-

[A.4]Indeed, I check that the impact of matches is never significant after the second weekly lag. Tables are available upon request.

tions, the effect peaks at the second or third week; in OLS and 2SLS results, this happens around the fifth or sixth week. The discrepancy may be due to two assumptions of the model. First, the policymaker has to make weekly decisions. In the real world, the timeframe for decisions might be slightly longer; if this were the case, the whole dynamics presented with impulse-response functions would mechanically take more time to unfold. Second, only past week distances affect departures. As Table A.4 indicates, this is a sensible assumption; however, policymakers may believe other lags to have an impact.

Table A.6: Impact of sports events on attention to migration

			g_t			
$noteworthy_{t+1}$	-0.363	-0.155	-0.105			
	(0.246)	(0.167)	(0.183)			
$noteworthy_t$	-0.131	-0.128	-0.222			
	(0.147)	(0.150)	(0.141)			
$noteworthy_{t-1}$	-0.467**	-0.395**	-0.614***	-0.651***		
	(0.212)	(0.179)	(0.0793)	(0.0760)		
$matches_{t+1}$					-0.0285	0.0663
					(0.130)	(0.0861)
$matches_t$					-0.0615	-0.0541
					(0.123)	(0.0849)
$matches_{t-1}$					-0.235*	-0.260***
					(0.120)	(0.0816)
Year FEs	No	Yes	Yes	Yes	Yes	Yes
Week-o-y FEs	No	No	Yes	Yes	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
N	124	124	124	125	124	124

Note: All variables are weekly aggregates. The dependent variable is log migration searches. Impact of *noteworthy matches* and *matches* dummies on attention. A *noteworthy* match as a *Serie A* match respecting the following two criteria: (a) it was played between two of the three teams in Italy that were most searched on Google during the year starting on October 2013, and (b) the ex-ante probability of its outcome, based on odds data from Bet365, is below the median of probabilities. The variable *matches*, instead, only preserves criterion (a). The first three columns include one lag and one lead for *noteworthy matches* dummy, with a varying set of controls (no control, year FEs, year and week-of-the-year FEs). The fourth column reports the estimation only for the first lag, with year and week-of-the-year FEs. The last two columns report results for *matches* dummy, with year FEs and then year and week-of-the-year FEs. HAC standard errors (in parentheses), robust to both arbitrary heteroskedasticity and arbitrary autocorrelation up to 3 lags. P-values are denoted as follows: * $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$.

A.6 Effects of attention: slanted or objective coverage

In the model, attention shifts only affect policy by influencing the visibility of policy outcomes; attention does not directly influence the political cost of migrants' deaths *vis-à-vis* arrivals.

Table A.7: Impact of attention on distance, 2SLS

	$\hat{\mu}_t$							
	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 6$	$\tau = 7$	$\tau = 8$
g_τ	4.177	-5.480	3.008	-8.189***	-20.95***	-8.644**	-5.031	0.201
	(8.893)	(5.293)	(8.098)	(2.989)	(3.458)	(3.758)	(8.683)	(5.253)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week-o-y FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	115	114	113	112	111	110	109	108
$KP\ F$	35.635	26.618	53.122	26.913	20.382	33.360	33.789	28.872

Note: All variables are weekly aggregates. The dependent variable is the average distance of interceptions (KM), weighted by the proportion of migrants saved, obtained from Frontex data. The instrument is lag noteworthy matches, a dummy taking value one if a noteworthy match occurred over a week. The latter is defined as a *Serie A* match respecting the following two criteria: (a) it was played between two of the three teams in Italy that were most searched on Google during the year starting on October 2013, and (b) the ex-ante probability of its outcome, based on odds data from Bet365, is below the median of probabilities. The table reports the coefficient for separate specifications, each including only one lag for attention at the week τ. All regressions include year and week-of-the-year fixed effects, partialled out. I report a KP F-stats for every estimation. HAC standard errors (in parentheses), robust to both arbitrary heteroskedasticity and arbitrary autocorrelation up to 3 lags. P-values are denoted as follows: * $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$.

In this section, I check the robustness of this assumption by checking whether the effects of attention are driven by slanted or objective coverage. To do it, I construct a measure of slant in my analysis. We have seen that news articles and Google searches are highly correlated; for this reason, I consider them to be two consistent measurements of public attention to migration. Then, I use the sentiment classification explained above to construct weekly counts of objective, positive-sentiment, and negative-sentiment news articles.[A.5] In doing so, I reproduce the OLS estimation strategy used to investigate the impact of attention on distance in Appendix Section A.5; however, I now employ the weekly number of sentiment-classified articles as the independent variable.

I estimate specifications with an unweighted count of articles and specifications where I weigh articles in the dependent variable by the diffusion of their source. I assign each source a weight equal to the share of source diffusion before the sample period–in October 2014. I do so for print and online media separately, in the absence of a clear concept on how to weigh online diffusion against print diffusion. I also show results for unweighted online and print articles summed together. Since I test my hypotheses for different lags and different definitions of the dependent variable–unweighted count, weighted print count, weighted online count–I show the significance for both baseline p-values and Bonferroni-adjusted ones. The number of hypotheses is given by the number of lags tested times weighing type. I include all three types of classified articles counts in regressions, objective obj_t, positive-sentiment pos_t, and negative-sentiment neg_t, as they are strongly correlated. Again, I estimate one specification for every lag and lead separately and look at the composite effect of each lag, allowing for arbitrary heteroskedasticity and autocorrelation up to lag 3.

Appendix Table A.8 reports results. The table displays the impact of the 4^{th}, 5^{th}, and 6^{th}

[A.5] Alternatively, I could build three dictionaries of positive-, negative-charged positive, and neutral words to be looked up on Google Trends. However, this strategy would pose two methodological challenges. First, it would give me strong freedom in selecting words. Second, other words would lead to searches series with more zeros in Google search volume over time, which I have explained to be problematic above.

Table A.8: Impact of news attention on distance

	Count			Weighted (Print)			Weighted (Online)		
	$\tau = 4$	$\tau = 5$	$\tau = 6$	$\tau = 4$	$\tau = 5$	$\tau = 6$	$\tau = 4$	$\tau = 5$	$\tau = 6$
$\sin^{-1} obj_\tau$	0.53	-9.32***	-5.76*	-2.93	-15.6***	-20.7***	-8.99	-12.3**	-10.4*
	(3.21)	(3.01)**	(3.08)	(6.40)	(6.03)	(6.85)**	(5.98)	(6.04)	(5.54)
$\sin^{-1} pos_\tau$	-4.63	0.49	0.57	-6.56	9.30	11.6	-2.39	-7.28	1.13
	(3.06)	(3.54)	(2.69)	(9.71)	(10.7)	(11.4)	(5.68)	(6.46)	(7.74)
$\sin^{-1} neg_\tau$	-0.34	6.40**	-0.63	0.12	4.78	-1.09	3.87	11.4**	-1.47
	(2.59)	(2.80)	(2.28)	(3.71)	(4.39)	(4.03)	(4.14)	(5.03)	(4.65)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-o-y FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	113	112	111	113	112	111	113	112	111

Note: All the variables are weekly aggregates. The dependent variable is the average distance of interceptions (KM), weighted by the proportion of migrants saved, obtained from Frontex data. The independent variable is news articles by classification type and counting strategy. Columns 1 to 3 use articles count; estimations in columns 4 to 6 use only print articles and weigh them by the reach of newspapers in September 2018, according to *Accertamenti Diffusione Stampa*; estimations in columns 7 to 9 use only online articles and weigh them by the proportion of website users in September 2018, according to *Audiweb*. For each of the three subgroups, the first, second, and third columns report results when using the 4^{th}, 5^{th}, and 6^{th} lag, respectively. All regressions include year and quarter-of-the-year fixed effects. HAC standard errors (in parentheses), robust to both arbitrary heteroskedasticity and arbitrary autocorrelation up to 3 lags. Significance stars on coefficients refer to baseline significance levels; significance stars on standard errors refer to Bonferroni adjusted significance levels, for nine hypotheses; P-values are denoted as follows: * $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$.

lag of news articles on distance for different types of news articles weighting: count, diffusion-weighted for print, and diffusion-weighted for online media. I use the Inverse Hyperbolic Sign instead of the logarithm in this table to accommodate one zero observation in the weighted-print objective attention. Stars on coefficients report significance levels according to baseline tests, and stars on standard errors report significance according to Bonferroni-adjusted p-values, accounting for the nine hypotheses tested. The effect of objective coverage is always negative and significant for 5^{th} and 6^{th} lags for the baseline test. Coefficients are larger when using weighted measures. However, the effect is concentrated on print media; indeed, coefficients on online media are 80% to 50% of those on print media, and insignificant according to Bonferroni p-values. Positive coverage is nowhere significant, and signs flip across specifications. Negative coverage signs are inconsistent across specifications, but there is a significant and positive effect for the baseline and online weighted measure. However, the effect is not significant when using the corrected p-values. Overall, objective coverage is the only one to show a robust effect, magnified when considering diffusion-weighted print media. Also, the effect of negative coverage on distance is positive, suggesting that policy responds to disadvantageous migration policy coverage by increasing risk for migrants, if it responds at all. Even if an effect of negative coverage is present, the objective coverage effect arguably prevails, as shown when considering the composite impact of attention on distance above.

A.7 NGO search and rescue actors

A.7.1 Background

The severe danger for migrants crossing the Mediterranean pushed humanitarian organizations to engage in migrant interceptions at different stages of the *Triton Operation*, especially after the twin shipwrecks of April 2015. All of them focused on saving lives as their only stated objective.

Even if they disagreed over deterrence objectives with NGOs, authorities could steer operations in their preferred direction in many ways. First, the responsibility to assign rescues rests with the Maritime Rescue Coordination Center of Rome, at the Italian *Ministero delle Infrastrutture*. NGO and the MRCC have worked together to manage SAR, but tension has emerged at times. In 2018, for example, NGOs accused the Italian MRCC of intentionally not sharing information with them about migrants' boats in distress to prevent non-institutional players from interfering in operations.[A.6] Second, as suggested in Cusumano and Pattison (2018), authorities could ask NGOs to transfer migrants from the rescue area to an Italian port, with the consequence that they had to leave the area instead of using for that aim faster governmental assets. Third, SAR actors influence each other indirectly because if an actor forgoes its search duties in an area, another actor has to take up the task. During several operations, NGOs and their supporters have lamented the absence of institutional SAR actors needed in the rescue area and the consequent need to take action in their place.[A.7] Fourth, and most importantly, although strong at times, NGO interceptions almost always remained a minority fraction; Figure A.4 supports this idea, showing a kernel regression of proportion intercepted by NGOs over time, in the dashed-dotted line. Therefore, NGO involvement did not make institutions incapable of conducting their preferred policy altogether; instead, NGO presence acted as increasing the cost of making policy less safe for migrants.

While it is clear that institutional actors had the opportunity to affect policy even during high NGO involvement, the misalignment of their objectives between the two is apparent. In the summer of 2017, the Italian government drafted a code of conduct for NGOs backed by the EU and documented in Cusumano (2019). The code's objective was to regulate their activities in the Central Mediterranean, and it posed requirements on NGO vessels in exchange for their opportunity to disembark migrants in Italy. Among 13 provisions, the code required NGO vessels to 'not to make communications or send light signals to facilitate the departure and embarkation of vessels carrying migrants,' forbid them from entering Libyan territorial waters unless in exceptional circumstances, and compel them to execute the instructions of the MRCC.

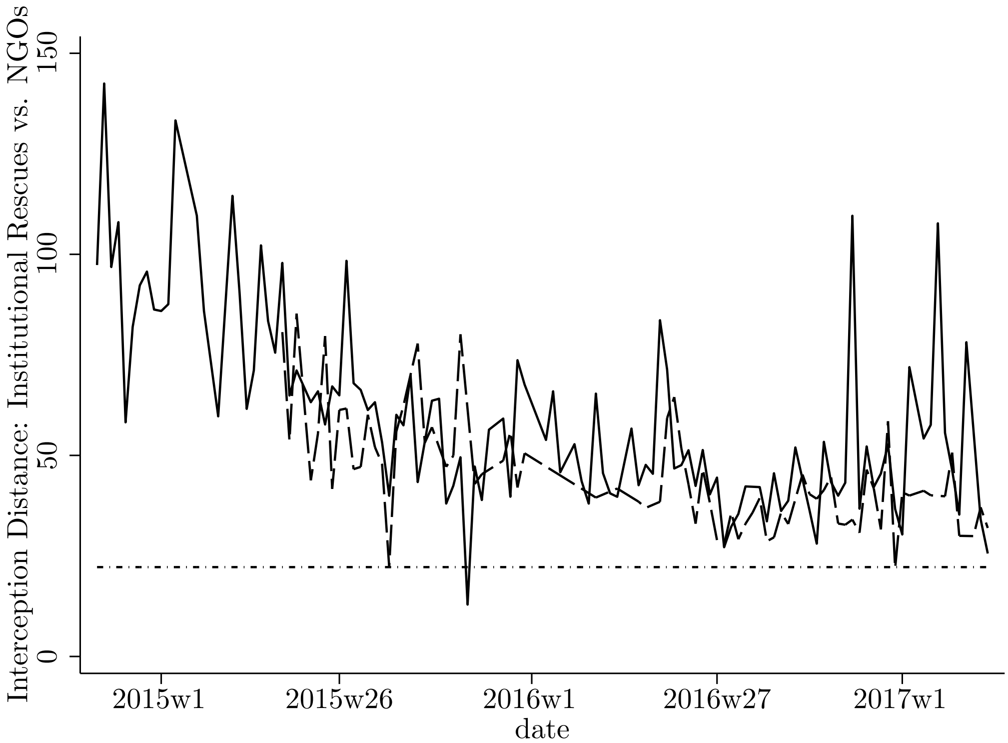
A.7.2 Robustness of NGO modeling strategy

In setting up the model, I have defined institutional actors as the primary decision-makers and modeled NGO presence as hindering their ability to set the preferred distance. To further

[A.6]The following newspaper articles document the issue: https://archive.is/tQoFU and https://archive.vn/8ds2B. They are in Italian, but I can provide an English summary if requested.

[A.7]The following tweets by MSF and one of its employees are examples: https://archive.vn/0yepl and https://archive.is/V4Rid.

Figure A.6: Average rescue distance by actor over time



Note: Average rescue distance by actor over time: the solid line represents institutional rescues; the dashed line represents NGOs. The dashed-dotted line defines the limit of territorial waters. Referenced in Section 9.

explore the issue, I investigate whether institutional or non-institutional players drive the effect of attention on distance. More precisely, I explore how NGO presence moderates the impact of public attention. I regress distance on attention at different lags in separate estimations, interacting attention with mig_t^{ngo}, a variable measuring the percentage of migrants intercepted by NGOs in a given week. I estimate one specification for every τ for several lags, Again, I allow for arbitrary heteroskedasticity and autocorrelation up to lag 3. Then, I turn to an auxiliary analysis of NGO rescues to clarify their interaction with institutions.

Appendix Table A.9 shows how NGO presence affects the impact of attention on distance. An increase in attention by 10% decreases distance by 1.4 KM on the 5^{th} lag. NGO presence, too, diminishes distances. An increase in NGO presence by 10 percentage points decreases interception distance by 3 to 13 KM. NGO presence also decreases the influence on attention on policy.

Appendix Figure A.6 further sheds light on the issue, comparing the evolution of institutional (solid line) and NGO rescue distances (dashed line). The graph suggest that NGOs consistently keep a lower distance–the mean for NGOs is 44.9KM versus 60KM for institutions. Their position varies less over time, too–the standard deviation for NGOs is 13.6 versus 23.8 for institutions. We observe some correlation between NGOs and institutional rescues, becoming less apparent as time passes and NGO presence in the rescue area becomes stronger. Two factors can partially explain it. First, some long-term covariance arguably comes from long-term policy changes and seasonal variation affecting interception distance over time. Second, short-term correlation can be due to coordination and, in particular, the fact that interceptions

Table A.9: Impact of attention on distance: interaction with NGO presence

	$\hat{\mu}_t$					
	$i = 1$	$i = 2$	$i = 3$	$i = 4$	$i = 5$	$i = 6$
g_{t-i}	-3.844	-6.466*	-10.06***	-9.360***	-14.09***	-12.87***
	(3.362)	(3.513)	(2.588)	(3.037)	(2.292)	(3.075)
mig^{ngo}_{t-i}	-29.43	-73.44**	-125.9***	-69.65	-136.1***	-74.74*
	(32.86)	(33.02)	(43.87)	(43.41)	(29.49)	(38.53)
$g_{t-i} * mig^{ngo}_{t-i}$	11.25	23.70**	42.79***	25.79*	47.17***	25.34**
	(11.07)	(11.24)	(14.22)	(14.42)	(10.55)	(12.52)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-o-y FEs	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
N	108	106	106	105	105	102

Note: All variables are weekly aggregates. This table reports the impact of searches on rescue distance in interaction with NGO migrant share of rescues. Each specification has a different lag of searches and NGO presence (1 to 6) as dependent variables. All of the specifications control for year and quarter-of-the-year FEs. HAC standard errors (in parentheses), robust to both arbitrary heteroskedasticity and arbitrary autocorrelation up to 3 lags. P-values are denoted as follows: * $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$.

often involve different actors. Appendix Table A.10 shows the result of regressing NGO rescue distance on the institutional actors' one while progressively introducing year and quarter-of-the-year fixed effects (columns one to three). We observe a positive and significant relation between NGO and institutional rescue distance in the specification with no controls. A one-KM increase in institutional distance increases NGO distance by 0.37. However, introducing year and quarter-of-the-year fixed effects more than halves the coefficient and makes it only significant at a 10% level. Then, policy changes and season seem to explain a good part of the relation between the two distances. The remaining correlation does not come from the role of attention; indeed, searches (5^{th} lag), added in the last specification, are insignificant, and the coefficient on institutional distance displays little change. This result is not specific to the chosen lag in attention.

As an alternative strategy, I replicate the Figure reporting OLS estimates for attention only considering NGO rescues. Appendix Figure A.7 shows no evidence of a relationship between attention and distance for NGO actors.

These results support my modeling assumptions. NGOs focus on humanitarian motives, and they save migrants as close as possible to Libyan shores. In so doing, they do not need to react to attention, and their presence makes it less easy to do the same for policymakers.

A.8 Frontex data

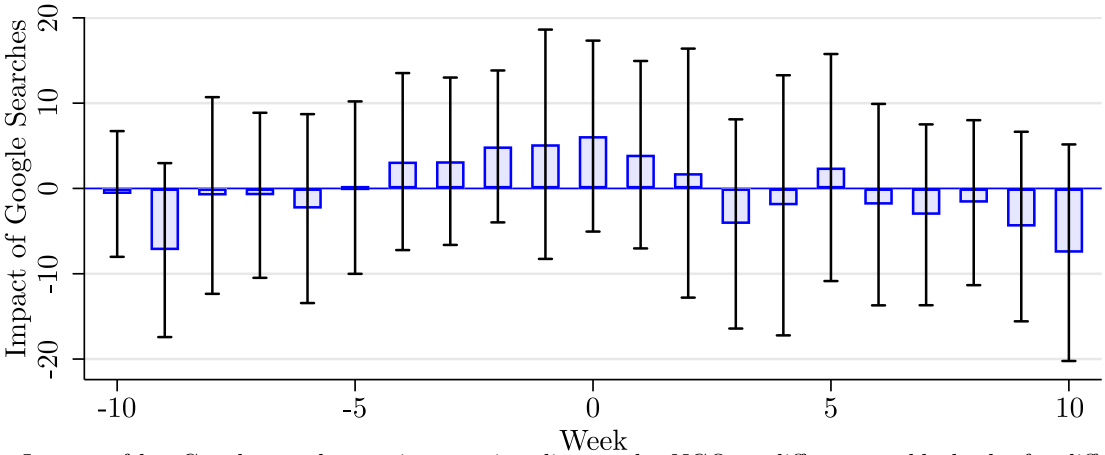
In this section, I give an account of the procedures followed for constructing the interceptions dataset used in the paper.

Table A.10: NGO and institutional distances

	$\hat{\mu}_t^{ngo}$			
$\hat{\mu}_t^{inst}$	0.373***	0.205**	0.137*	0.144*
	(0.121)	(0.0994)	(0.0817)	(0.0814)
Year 2016		-14.17***	-15.44***	-15.71***
		(3.395)	(2.906)	(2.915)
Year 2017		-13.45***	-16.07***	-16.46***
		(2.976)	(3.998)	(4.109)
2^{nd} quarter			4.354	4.295
			(3.462)	(3.480)
3^{rd} quarter			-4.740*	-4.968*
			(2.651)	(2.774)
4^{th} quarter			-2.864	-3.244
			(3.120)	(3.242)
g_{t-5}				1.152
				(3.019)
Constant	12.01***	25.50***	29.70***	26.54***
	(3.349)	(4.509)	(5.201)	(9.496)
N	74	74	74	74

Note: All the variables are weekly aggregates. This table reports the relation between institutional average rescue distance and NGO operations average rescue distance. The first three specifications progressively introduce controls (no control, year FEs, and quarter-of-the-year FEs). The last specification introduces the 5^{th} lag of attention as an independent variable. HAC standard errors (in parentheses), robust to both arbitrary heteroskedasticity and arbitrary autocorrelation up to 3 lags. P-values are denoted as follows: * $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.7: Impact of leads of searches on NGO distance



Note: Impact of log Google searches on interception distance by NGO at different weekly leads, for different regressions. Controls include year and quarter-of-the-year fixed effects. Plot includes Bonferroni-corrected confidence intervals for $\alpha = 5\%$. HAC standard errors robust to arbitrary heteroskedasticity and autocorrelation up to lag 3.

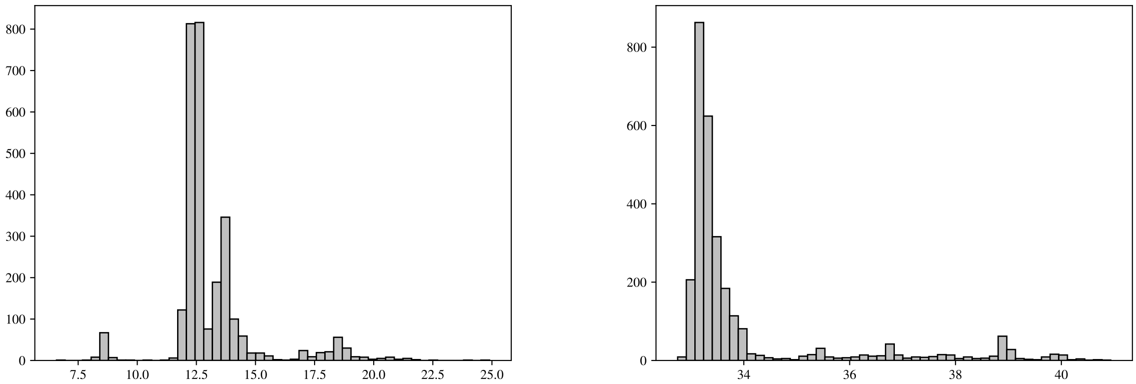
A.8.1 Construction of the dataset

I obtained Frontex data on interception locations through a FOIA request under Regulation (EC) No 1049/2001 of the European Parliament and of the Council of 30 May 2001, using the portal AskTheEU. The request can be consulted at https://archive.ph/wip/cJbbZ. With a subsequent request, available at https://archive.ph/wip/tIurr, I obtained country of departure. These two datasets list incidents–interceptions–involving irregular migrants. They show the number of same-day incidents, along with the covariates listed above. Importantly, coordinates in the data seem to have been multiplied by the number of incidents on that day. For this reason, I made an inquiry with Frontex via email and received a corrected dataset. In the first two requests, Frontex had not agreed to publish the location of interceptions within *Triton* 's Operational Area–a few operations occurring unusually far from the Libyan coast. However, in the subsequent email exchange, Frontex made locations for these operations available. The dataset received during the private exchange did not include the type of transport and country of departures as variables. Luckily, it was possible to match this information later. For days in which only one operation had occurred, the matching was based on the date. For days with more than one operation, I matched observations based on the number of migrants, type of detection, and type of interception. The matching process was effective, leaving out only 45 interceptions–for them, I lack Frontex information on country of departure and type of transportation. However, this number was reduced to 3 when applying the procedure to retain only rescues for boats from Libya, explained below.

A.8.2 Selection of interceptions from Libya

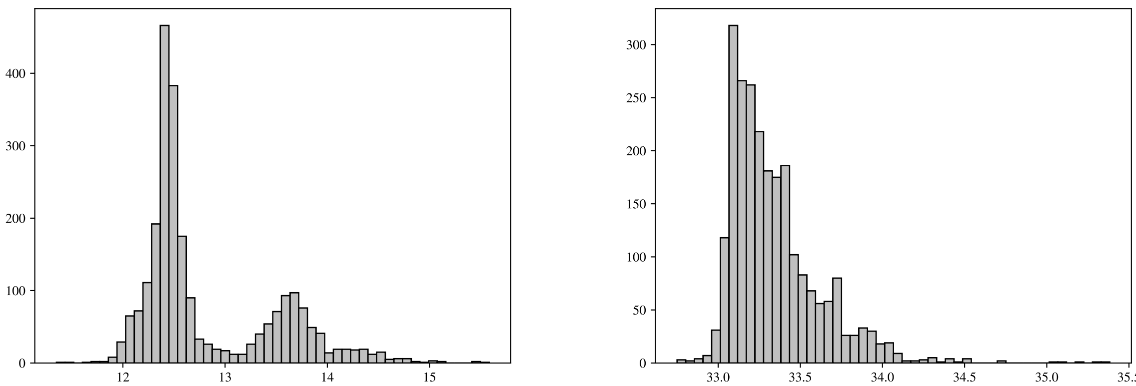
As it is apparent from Figure 1a, rescue operations during the period were concentrated in the Mediterranean Sea area enclosed between Tunisia and the West coast of Libya. Also, operations outside this area are geographical outliers, given their position. For the sake of internal validity, I drop these outliers in two ways. First, upon observing the skewness of interception longitudes

Figure A.8: Interception longitudes and latitudes histograms



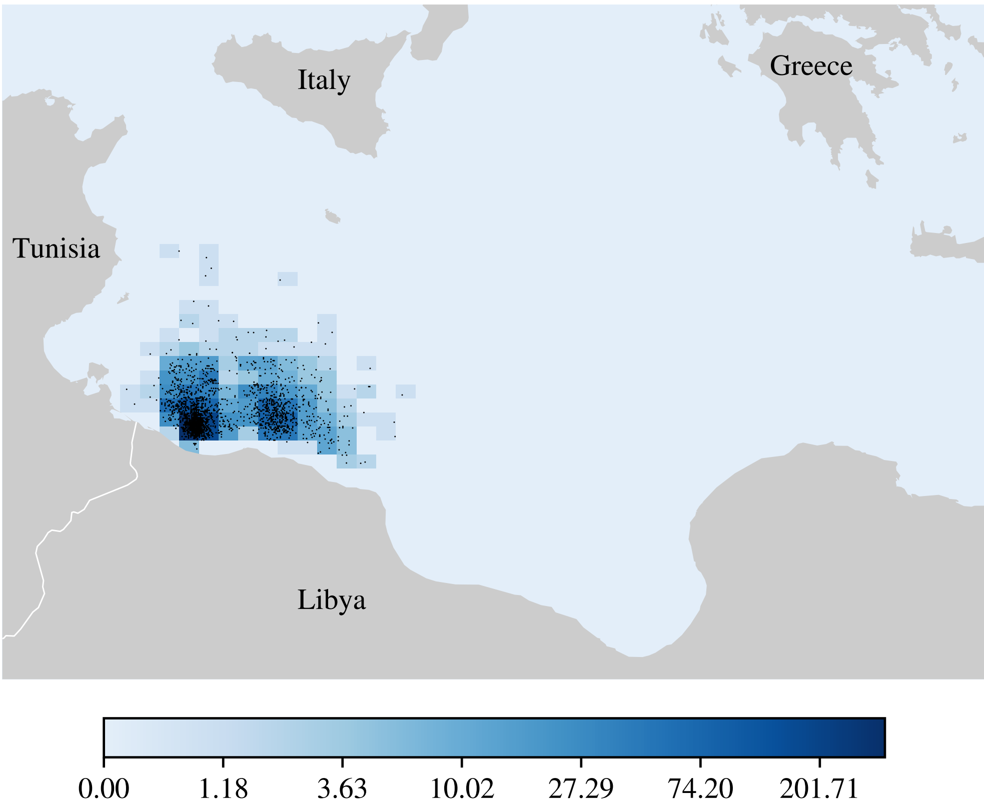
Note: Histograms of interception longitudes (LHS) and latitudes (RHS) from November 1, 2014, to April 1, 2017. Own elaboration of Frontex data.

Figure A.9: Interception longitudes and latitudes histograms for final sample



Note: Histograms of interception longitudes (LHS) and latitudes (RHS) from November 1, 2014, to April 1, 2017, restricting to the final sample. Own elaboration of Frontex data.

Figure A.10: Interception loc. of final sample overlaid on 2-d histogram, frequency in IHS units



Note: Scatter of interceptions' locations from November 1, 2014, to April 1, 2017, restricting to the final sample, overlaid over 2-d histogram (50 bins on the *x-axis* and on the *y-axis*), with frequency expressed in Inverse Hyperbolic Sine units. Own elaboration of Frontex data. Referenced in Section A.8.2.

and latitudes in Figure A.8, I use the matched observations–having country of departure–to extract the 99.5^{th} percentile. Second, for all matched observations, I retain only interceptions with Libya as the source country. The resulting distribution of longitudes and latitudes can be observed in Figure A.9. Finally, the geographical distribution of interceptions available in the sample is displayed in Figure A.10, showing a scatter of interceptions locations overlaid over a 2-d histogram of interception frequencies in Inverse Hyperbolic Sine units.

A.8.3 Comparison of aggregates to Italian Coast Guard data

The Italian Coast Guard produces aggregate data on rescue operations, reporting operations per year, and actor (CGCCP, 2017). I used it to check for inconsistencies in the aggregate number of migrants saved. For example, in 2015, Frontex data contains 134,073 migrants rescued in boats from Libya against 139,777 in Italian data; in 2016, the former includes 158,338 and the latter 162,732. These differences may be due to one of the following reasons. First, there might be discrepancies in how the data deals with migrants who lost their lives during operations or whose corpses were found by rescuers. Frontex data classifies these cases among total migrants and also collects them as deaths during the operation. For this reason, the number of migrants in the data I use is the number of total migrants minus the number of deaths. The Italian Coast Guard might use different conventions. Second, I use a 'conservative' way of assigning departures to Libya. Third, very few NGO operations might be missing from the data. Indeed, Frontex data lacked the NGO classification in 2015. As I document in the following sections of the Appendix, I manually matched operations in my dataset to rescue data published by one NGO, complete with location and number of migrants, and news data about interceptions and disembarkations. Using this strategy, matched Frontex data counts 18,229 migrants intercepted by NGOs against 20,063 in Italian aggregate data; in 2016, the former has 43,604 intercepted by NGOs, and the latter 46,796. There, part of the mismatch can likely be attributed to the fact that data on NGO interceptions in CGCCP (2017) also includes non-Libyan interceptions; however, another part can be explained by a minimal number (12) of interceptions not present in Frontex data.

A.8.4 NGO operations in 2015

In the matched Frontex dataset, according to the type of interception classification, migrants rescued during NGO operations were only 2,840 in 2015, against 20,063 in CGCCP (2017). Instead, in 2016 the former was 43,602 and the latter 46,796. MSF (in partnership with MOAS) was virtually the only NGO actor performing interceptions during the spring and summer of 2015 and having naval assets in place able to take migrants on board and disembark them in Italy.[A.8] Then, I corrected the information available in Frontex (2017), using data about NGO interceptions by MSF, publicly available on their website. I matched based on location and number of migrants, encountering no or negligible discrepancies–all documented. In a few cases, I had to complement my strategy with news data on operations available through the European Media Monitor website. In the end, I was unable to match only 12 MSF interceptions with Frontex data. As explained above, matched Frontex data counts 18,229 migrants

[A.8] Sea-Watch was involved, too, but it mostly performed few complementary actions during the period.

intercepted by NGOs against 20,063 in Italian aggregate data in 2015; in 2016, the former has 43,604 intercepted by NGOs, and the latter 46,796. Again, part of the discrepancy can be explained by the fact that data on NGO interceptions in CGCCP (2017) also includes non-Libyan interceptions.

A.8.5 Commercial ships

There is a considerable amount of misreporting of the type of actor for commercial ships' interceptions in Frontex data. Indeed, the agency classified several interceptions by commercial ships as 'Other.' An inspection of news articles revealed that this code, at times, is applied to Frontex assets' interceptions. Using news data from the European Media Monitor website I check, for every interception classified as 'Other,' if it was an interception by a commercial vessel. For each date where an interception classified as 'Other' was present, I checked for the presence of articles about the rescue in main Italian news agencies (ANSA, Adnkronos, AGI) in the next three days after the operation, among articles including one of the following words: `migrant* migraz* immigra* rifugiat* clandestin*`. If the article was not present, I increased the number of sources to include all Italian news websites or the number of days. I document this process in the notes of the dataset I compiled. Following this procedure, I was able to match a considerable number of operations. Now, matched Frontex data has 13,593 migrants intercepted by commercial ships against 16,158 in Italian data in 2015; in 2016, the former counts 10,152 intercepted by commercial ships, and the latter 13,888. In this case, unmatched operations can still be classified as 'Other.' However, part of the difference can still be explained by the fact that the aggregate number of interceptions by commercial vessels in CGCCP (2017) does not only include interceptions for boats from Libya. This is even more of an issue for commercial ships because their interceptions tend to occur north of the usual rescue area, closer to the routes from Tunisia or Egypt.

A.9 Missing Migrants

To use Missing Migrants data, I need to extract deadly incidents involving migrants leaving Africa from Libya. The country of departure is not a variable in the dataset, as this information is not readily available in most cases. Nonetheless, Missing Migrants data contains two geographical variables that can be used to this end. First, it contains a variable indicating the route followed by migrants. Second, it contains a location description in words. I use the first variable to drop all observations not included in the Central Mediterranean Route. I select all incidents containing Libyan toponyms, Also, I include incidents displaying general toponyms of the Strait of Sicily and cases of unknown locations in the Central Mediterranean, since migrants from Libya are 91% of migration in the Central Mediterranean route during my sample period.

A.10 News articles from Factiva

As I explained in Section 3.2.2, I retrieved articles based on the presence of at least one string referring to migration as well as a string among a list of Mediterranean toponyms. The list of strings used in retrieving articles, complete with logical operators, is: (`migra*` OR `immigra*` OR `rifugiat*` OR `clandestin*` OR `richiedent* asilo`) AND (`Canale di Sicilia` OR `Sicilia` OR `Libia` OR `Lampedusa` OR `Mediterraneo`).

To focus on news about migration and migration coverage, I excluded news items about movies, books, cultural events relating to migration. Then, I excluded articles containing one or more of the following strings: `film` OR `lungometraggio` OR `cortometraggio` OR `cinema` OR `rappresentazione` OR `spettacolo` OR `premiere` OR `librr*` OR `la mostra` OR `le mostre` OR `delle mostre` OR `sulla mostra` OR `sulle mostra` OR `dalla mostra` OR `dalle mostra`.

Finally, Factiva data also contains newswires. These are available to the public online. However, newswires also give aggregations used in redacting newspapers. I exclude these since they only repeat pieces of news from elsewhere. I do so by deleting articles containing one of the two following strings: `caporedattori` OR `notizie del giorno`.

I classified news articles as 'Objective,' 'Positive-Sentiment,' 'Negative-Sentiment,' or 'Unrelated to migration,' using supervised machine learning. I built the training sample as a random subset of 2,236 articles, asking an external rater to classify a training set of articles based on sentiment. I asked to say whether articles were covering the news objectively or subjectively, or unrelated to migration. If articles were selected to be subjective, I asked to report whether they had a negative or positive sentiment. Further, I asked a second external rater to perform a similar rating on a random subset of 802 to check inter-rater agreement. Percentage agreement occurs for 82% of articles in the subset, and Cohen's agreement equals 0.73. Then, I proceeded to classify articles out of the training sample using a logistic regression classifier. Out of the 2,236 rated articles, 80% of which make the training set; I use the other 20% for testing. I set hyperparameters using cross-validation and attained balanced accuracy of the model is about 59%.

A.11 Analytical appendix

A.11.1 Probability of survival

By the memoryless property of the exponential distribution, I write the probability of survival as the product of the likelihood of surviving in the Libyan territorial waters and the probability of surviving beyond. Call a the rescue distance for a migrant's rescue. We can write the following

$$\begin{aligned} \pi_t &= exp\left(-\lambda_b b\right) \int_0^{+\infty} \int_a^{+\infty} \lambda e^{-\lambda x} dx \frac{1}{\mu_t} \exp\left(-\frac{1}{\mu_t} a\right) da = \\ &= \exp\left(-\lambda_b b\right) \int_0^{+\infty} e^{-\lambda a} \frac{1}{\mu_t} \exp\left(-\frac{1}{\mu_t} a\right) da = \\ &= \frac{\exp\left(-\lambda_b b\right)}{\lambda \mu_t + 1} \end{aligned} \tag{A.1}$$

A.11.2 Departures

Consider a measure of homogeneous migrants deciding whether to cross to Europe paying crossing price p_t and facing expected probability of survival $\mathbb{E}\pi_t$.[A.9] Migrants live two periods. In period 0, they decide whether to migrate, paying p; in period 1, they receive income y_j with $j \in \{e, h\}$ indexing the location–Europe or Libya, respecitvely–and $y_e > y_h$. Suppose that migrants can finance consumption and the crossing with wealth k and debt with interest $(1+r)$. Their consumption, depending on the location, is given by:

$$\begin{cases} c_e = y_e + (k-p)(1+r) \\ c_h = y_h \end{cases}$$

Suppose that migrants are linear in utility from consumption, with marginal utility normalized to one, and they face a disutility of dying during the crossing $d > 0$. In addition, they enjoy an additive idiosyncratic shock from migrating, $\nu_{i,t}$, I.I.D. across time, exponentially-distributed with rate η.

Assuming that smuggling services are controlled by a monopolisitic firm, thus reaping all the benefits from trade, the price paid by migrants is a linear function of the rescue probability:

$$p_{i,t} = \frac{y_e}{1+r} + k + d - \frac{y_h + d - \nu_{i,t}}{(1+r)\mathbb{E}\pi_t}. \tag{A.2}$$

Smugglers' cost from offering the journey is $c_0 + c_1 w_t$, where $c_0, c_1 > 0$ and w_t takes value one when weather at time t is bad. Since migrants and smugglers can forecast the weather only in expectation, they know the expectation of this cost, based on the previous weather realization w_{t-1}; this is given by

$$\mathbb{E}\left(c_0 + c_1 w_t\right) = c_0 + c_1 \pi^w_{01} + c_1 \left(\pi^w_{11} - \pi^w_{10}\right) w_{t-1}, \tag{A.3}$$

with π^w_{ij} representing the ij^{th} entry on the transition matrix for weather, Π_w. Assume that the price of the journey is paid upon successful completion.[A.10] Smugglers engage in trade as long as

$$\begin{aligned} \Pi_t = \left(\frac{y_e}{1+r} + k + d\right)&\left[\exp(\lambda_b b) - \exp(\lambda_b b)\lambda\left(\kappa_0 + \kappa_1 \mu_{t-1}\right)\right] + \\ &- \frac{y_h + d - \nu_{t,i}}{(1+r)} - c_0 - c_1 \pi^w_{01} - c_1 \left(\pi^w_{11} - \pi^w_{10}\right) w_{t-1} \geq 0. \end{aligned} \tag{A.4}$$

The measure of smugglers present in the market in a given week is given by the random

[A.9] Migrants do not know the actual probability of survival because they do not know the distance policymakers will choose at time t; they can only form an expectation based on previous average distance $\hat{\mu}_{t-1}$, as described in Equation 4.

[A.10] This is not a key assumption; indeed the fundamental driver of the result below is that the profit of smugglers increase in the probability of survival, which is true both under the assumption that the price is paid upon completion but also if it is not (since the price increases in survival probability. Nonetheless, I prefer this forumulation since it agrees with evidence from the sample period on smugglers and migrants employing payment schemes mediated by third parties (Szumski, 2016); these could be enforced by the transcontinental nature of smugglers networks (Micallef, 2017). In addition, as a further interpretation, we could view payments for completed journeys as a reduced form for reputation-driven profits.

variable $S\varepsilon_{t,\ell}$, defined as the product of the constant S, and the random term $\xi_{\ell,t}$, whose log, $\varepsilon_{\ell,t}$, is distributed with mean 0. The migration flow in a given week is given by the portion of migrants who are willing to engage in trade for a price high enough to offset the cost of smugglers' services, based on the realization of ν_t This implicitly defines the measure of migrants leaving Libya at a given time t, ℓ_t, as a function of the previous average distance observed:

$$\ell_t = S\xi_{t,\ell} \exp\left(A - B\hat{\mu}_{t-1}\right), \tag{A.5}$$

where A and B are as follows:

$$\begin{cases} A = \eta\left(y_h + d + c_0 + c_1\pi_{01}^w + c_1\left(\pi_{11}^w - \pi_{10}^w\right)w_{t-1} + \left(\exp(\lambda_b b) - \kappa_0\right)\left(y_e + (k+d)(1+r)\right)\right) \\ B = \eta\left(y_e + (k+d)(1+r)\right)\exp(\lambda_b b)\kappa_1 \end{cases}$$

where κ_0 and κ_1 are the coefficients in the forecast Equation 4. Since past and present rescue distances are correlated, we have $\kappa_1 > 0$ and $B > 0$; so, departures are decreasing in past rescue distance. We can write the following estimating equation:

$$\log \ell_t = \log S + A - B\hat{\mu}_{t-1} + \varepsilon_{t,\ell}. \tag{A.6}$$