Irregular Migration and the Unintended Consequences of Search and Rescue Operations in the Central Mediterranean Sea*

[Preliminary Draft - Please do not circulate]

Claudio Deiana[†], Vikram Maheshri[‡], Giovanni Mastrobuoni[§]

September 13, 2019

Abstract

The Central Mediterranean is the most dangerous crossing for irregular migrants in the world. At any given point in time, over half a million potential migrants wait in Libya to travel to Italy with the aid of human smugglers. In response to high profile shipwrecks and mounting deaths, Europe intensified search and rescue operations beginning in 2013. We develop a model of irregular migration in order to identify the effects of these operations on activity along this smuggling route. Leveraging plausibly exogenous variation from rapidly varying weather and sea conditions, we find that smugglers responded to these operations by shifting from seaworthy wooden boats to flimsy inflatable rafts. By doing so, these operations induced more crossings despite occurring during a period when overall crossings were on a downward trend. We show that this had the ultimate effect of entirely offsetting the intended safety benefits of search and rescue operations, which were captured at least in part by smugglers.

Keywords: Central Mediterranean sea crossings, international, undocumented, irregular migration, search and rescue operations, rubber boats, deaths

JEL codes: F22 (International Migration); H12 (Crisis Management).

* Opinions expressed herein are those of the authors only and do not reflect the views of, or involve any responsibility for, the institutions to which they are affiliated. Any errors are the fault of the authors only.

† University of Cagliari, claudio.deiana@unica.it.

‡ University of Houston, vmaheshri@uh.edu

§ Collegio Carlo Alberto and University of Torino (ESOMAS), giovanni.mastrobuoni@carloalberto.org

1 Introduction

Many Western countries are facing increased migratory pressure, be it over land or sea.[1] In less than a quarter of a century, annual migratory flows from Africa to Italy alone have jumped from a few hundred to almost 200,000. Indeed, the Mediterranean sea has been dubbed the New Rio Grande (Hanson and McIntosh, 2016), and these flows are expected to continue to increase because of high population growth in Africa coupled with increasing desertification.[2]

These migratory flows from the developing world have prompted a variety of reactions in destination countries: the United States has raised sanctions on migrants apprehended attempting to enter the U.S. illegally and has built barriers along the Mexican border;[3] Australia detains sea-bound immigrants, mainly Asians, in offshore facilities located on Nauru and Manus Islands; Hungary has erected a barrier on its border with Serbia and Croatia; Europe's Border and Coast Guard agency (Frontex), often in cooperation with the EU member states, patrols Europe's borders to detect (and ostensibly deter) undocumented migrants, most of whom try to cross the Mediterranean sea to reach Italy, Malta, Greece or Spain. This is far from a comprehensive enumeration of responses, nor is the demand for them abating.

One major migratory route is known as the "Central [Mediterranean] Route," on which irregular migrants board vessels along the North African coast on their way to Italy (and, to a lesser extent, Malta). In March 2015, the executive director of Frontex told the Italian Associated Press National Agency (ANSA), "Anywhere between 500,000 to a million people are ready to leave from Libya," and from 2009 to 2017 over 750,000 irregular migrants and refugees reached Italy along this route.[4] Despite it's short distance, this is now agreed to be the deadliest water crossing in the world (McAuliffe and Ruhs, 2017). In 2016 alone, roughly 8,000 people are believed to have perished in the Central Mediterranean, with countless others dying along the journey through the Sahara desert (UNODC, 2018). In comparison, annual deaths along

[1] While most international migration occurs legally, there are over 30 million irregular migrants living in the world today according to the most recent World Migration Report of the United Nations. Irregular migrants are defined by the UN as migrants who either entered, remained in, or worked in a country illegally (McAuliffe and Ruhs, 2017).

[2] Over the next 50 years population growth in sub-Saharan Africa is expected to be five times as large as the growth in Latin American population over the past 50 years (Hanson and McIntosh, 2016). The population of sub-Saharan Africa is expected to double in 30 years. Kniveton et al. (2012) model how migration will be affected by the interaction between population growth and a changing African climate.

[3] Bazzi et al. (2018) find that the increased sanctions have lowered recidivism in illegal entry, while Feigenberg (forthcoming) and Allen et al. (2018) find that the border wall reduced entry, though at a very high cost.

[4] See "Up to one million poised to leave Libya for Italy," *ANSAmed*, March 6, 2015.

the US-Mexico border range in the low hundreds.[5]

The reaction to this slowly unfolding tragedy has been inconsistent at best. In the wake of large, high profile shipwrecks, Italy and the EU established extensive search and rescue (SAR) operations at sea in the form of operations *Hermes*, *Mare Nostrum* and *Triton*. Despite intensifying efforts, some of the deadliest years on record have followed. While these well-intentioned operations ostensibly reduced the risk of death, they may have also induced greater numbers of migrants to attempt a crossing, leading to an ambiguous effect on total migrant deaths. In light of this, the EU reduced the geographic scope of their operations; however, several NGOs have recently sent rescue vessels to cover newly unpatrolled areas. Moreover, to the extent that human traffickers could respond to increased SAR operations by sending migrants on flimsier boats in a cost-saving measure, the effect of the operations on the risk of death itself may be ambiguous.

It is generally difficult to ascertain whether these policies have achieved their desired goals, as irregular migration is a difficult to observe phenomenon with several potentially conflicting interests. First and foremost, it is not obvious what the correct measure of success is, as the objectives of the EU and NGOs are neither identical nor explicitly defined. A successful operation likely reduces deaths, but it is not obvious whether it ought to reduce the total number of migrants or even the riskiness of the journey. Second, it is difficult to ascertain the counterfactual numbers of migrant crossings and deaths that would have occurred in the absence of such policies, because these are endogenously determined in a strategic equilibrium with smugglers. Third, it is difficult to estimate the risk of passage because many details of each crossing are unobserved.

In this paper, we develop a model of smuggling and rescue operations that delineates how migration, risks and death are co-determined. This model yields tests of whether smugglers strategically respond to search and rescue missions by sending more migrants on riskier journeys. We then implement our test by exploiting high-frequency data on sea conditions in the Central Mediterranean that generates plausibly exogenous variation in the risk of passage. When SAR operations are heightened, we find that smugglers grow more responsive to sea conditions, opting to send migrants only on calm days. This implies that smugglers have shifted from

[5] From 1994-2000, about 1,700 deaths were reported to Mexican Consulates along the US-Mexico border (Cornelius, 2001).

deploying seaworthy wooden boats to flimsy and cheap inflatable boats. We find direct support for this result in official, albeit incomplete, data on crossing vessels, which we complement with indirect evidence of increased imports of life-jackets and other low-cost safety materials to the Mediterranean from China, Turkey and Egypt. The shift from safe to unsafe vessels has two effects. First, we find that it entirely offsets the safety gain from SAR, so there is no net effect on the risk of passage. This implies that the safety benefits of these operations were at least partly captured by smugglers. Second, the shift to unsafe vessels likely induced more migrants to attempt a crossing as the cost of the journey decreased.

Despite the importance of this issue, there has been little empirical analysis and formal theoretical modeling of irregular migration along this important route, as pointed out by Friebel et al. (2012).[6] Friebel et al. (2017) and Aksoy and Poutvaara (2019) explore who chooses to migrate to Europe and their motivations for doing so.[7] The authors also consider some unintended effects of stricter border regulations on (negative) circular migration and (positive) demand for smugglers. Two other papers have modelled the smuggling of migrants: Woodland and Yoshida (2006) study the effects of tougher government policy for the detection, arrest, and deportation of illegal immigrants; and Tamura (2010) develop a model in which smugglers differ in their capacity to exploit their clients' labor opportunity at the destination.

Our paper also builds on a long standing literature stemming from Peltzman (1975) that argues that the potential safety benefits of new technologies or policies may be offset by the behavioral responses of different agents, be they drivers (Winston et al., 2006), drug users (Doleac and Mukherjee, 2018; Evans et al., 2019), or in this case, smugglers. Indeed, Cornelius (2001) find that the more aggressive enforcement along the US-Mexico border in the 1990s increased prices for *coyotes* and the number of deaths along the border, and Gathmann (2008) finds that in addition to a moderate price effect, aggressive border enforcement induces migrants to shift to more remote crossing points where the chances of a successful crossing are presumably higher. Because search is costly, it can lead to greater risk of death. This literature underscores the inescapable fact that the strategic responses of smugglers to search and rescue operations and the residual responses of potential migrants generate moral hazard that must be considered

[6] Orrenius and Zavodny (2015) reviews the scant literature on the determinants of illegal migration and human trafficking.

[7] In addition, Arcand and Mbaye (2013) develop a model that attempts to estimate individuals' willingness to pay to migrate using data from a survey conducted in Senegal.

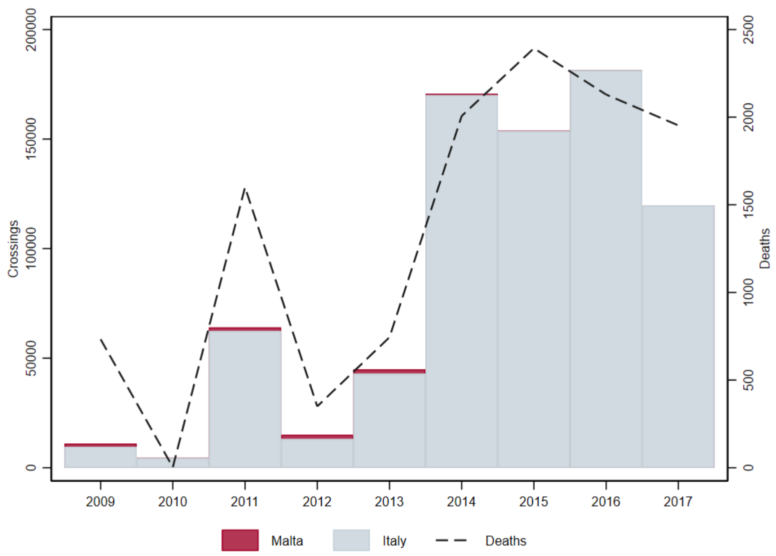
when developing enlightened policy toward such humanitarian tragedy.

The paper is organized as follows: In Section 2, we provide some background on the Central route and SAR operations that have been implemented by individual countries, the EU, and various NGOs. In Section 3, we present a simple model of human trafficking that highlights the incentives that shape the decisions of smugglers and potential migrants. In Section 4, we describe the various sources of data that we use in our analysis. In Section 5, we present an empirical approach to test the extent to which SAR operations have impacted the numbers of crossings and deaths in the Central Mediterranean and the riskiness of this passage. We present a variety of robustness checks in Section 6 before concluding in Section 7.

2 Background

The Mediterranean Sea has been the home of myriad trade and migration routes for millennia. Italy, with its strategic central position and proximity to African shores, has always been an important trading hub as a well as a major port of entry into Europe. One of the most important migratory routes goes from Libya to the Italian island of Lampedusa, which is closer to Africa

Figure 1: Crossings and Deaths Along the Central Route, 2009-2017



Note: Left axis corresponds to crossings to Malta and Italy respectively. Right axis corresponds to deaths in transit. Italian and Maltese data are available from UNHCR at `http://data.unhcr.org/mediterranean` and `http://www.unhcr.org.mt/charts/category/12`, respectively.

(103 miles from Ras Kaboudja, Tunisia and 184 miles from Tripoli, Libya) than to Italy (174 miles to Sicily and 246 miles to continental Italy).

Between 1997 and 2008, the number of irregular crossings from North Africa to Italian shores was stable at around 20,000 per year. On August 30, 2008, the Italian Prime Minister Berlusconi flew to Benghazi to sign a treaty with Libya to reduce migratory pressure. As a result, Libyan arrivals to Italian shores dropped to about 9,500 in 2009 and 4,500 in 2010.

Pro-democracy uprisings during the "Arab Spring" of 2011 sharply increased migratory pressure.[8] The instability that spread across the Arab world, especially in North Africa, led to a marked increase in refugee crossings across the Central Mediterranean that reached particularly high levels between February and June 2011. Unsavoury actors with ties to Al Qaeda quickly controlled parts of the market for human smuggling into Europe, which was largely organized out of Libya. By the end of 2011, more than 50,000 immigrants from North Africa had reached European shores, and Italy became the main port of disembarkation on the Central Mediterranean route.[9]

Table 1: EU Operations

EU Operations	Dates	Maritime SAR Distance from Italian shores	Budget per month	Budget total
Hermes (Main operation)	16 Apr - 16 Oct 09	24	0.9	5.2
	14 Jun - 29 Oct 10	24	0.8	3.3
	20 Feb - 31 Aug 11	24	2.5	15.0
	02 Jul - 30 Oct 12	24	1.0	4.1
	06 May - 07 Oct 13	24	1.5	9.0
Hermes (Extension)	01 Sep 11 - 31 Mar 12	12*		
	01 Nov 12 - 31 Jan 13	12*		
Mare Nostrum	18 Oct 13 - 31 Oct 14	138	9.5	113
Triton I	01 Nov 14 - 30 Apr 15	30	2.9	27.5
Triton II	01 May 15 - 31 Dec 17	138	10	320

NGO Operations	Dates	Maritime SAR Distance from Italian shores	Fundraising per month	Fundraising total
MOAS	25 Aug - 15 Oct 14	Libya	2.1	4
MOAS	01 May - 01 Oct 15	Libya	1.1	5.7
MOAS	06 Jun - 31 Dec 16	Libya	0.86	6
MOAS	01 Apr - 01 Sep 17	Libya	0.55	3.3

Note: Budget numbers are in million Euro. Information on the size of the SAR has sometimes been hidden in the official Operational Plans. In these instances values have been assumed from various evidence and are indicated by a *. For example, in the absence of additional resources allocated to the extended operations, we assume that the surveillance occurs within the territorial sea, as defined by the 1982 United Nations Convention on the Law of the Sea, which is at most 12 nautical miles from the coastal state.

[8] In January 2011, following a month of protests against his rule, the President of Tunisia, Ben Ali, was forced to flee to Saudi Arabia. Tripoli fell in August 2011 and Muammar Gaddafi was captured and killed on October 20, 2011 as for other North African leaders. Additional unrest took place in Egypt, where President Hosni Mubarak was ousted, arrested, and charged (he later died in prison).

[9] The Libyan Army and the police often worked together to force migrants that had been living and working

After two relatively calm years, attempted crossings to Italy further skyrocketed and reached close to 200,000 in 2016. This escalation was accompanied by a sharp increase in the number of people dying along the sea route from North Africa with death rates of about 2 percent. We summarize these aggregate trends in Figure 1.

While irregular migration in the Central Mediterranean surged and becoming more deadly, Italy and the EU launched a number of search and rescue (SAR) operations with specific objectives. We summarize their operating dates, jurisdiction and budgets in Table 1.

Hermes

In the years preceding the Arab Spring, EU planes, helicopters and naval assets patrolled Italian shores from North Africa as part of *Operation Hermes*, which had a monthly budget of less than a million Euro (Frontex, 2009, 2010). In response to the surge following the Arab Spring, the Joint Operation European Patrol Network (EPN) *Hermes* was launched in February 2011 and lasted until August along with a near tripling of the operational budget.

The main objectives of *Hermes* as laid out by Frontex were (i) border surveillance, (ii) early detection of crossings to inform third countries and seek cooperation (iii) information gathering on crossings, (iv) identification and return of third country nationals, and (v) prevention and fight of smuggling of migrants and trafficking of human beings. Its geographical operational area extended up to 24 nautical miles from Sicily, which corresponds to Italian territorial waters plus contiguous zones. Frontex extended the operations twice.

Mare Nostrum

Large scale sea accidents led to important changes at the end of 2013. On October 3, a boat carrying migrants from Libya to Italy sank off of the Italian island of Lampedusa. The death toll after an initial search was 359 (it was later revised upward). Later in the week, a second shipwreck near Lampedusa led to an additional 34 deaths. In response to these twin tragedies, the Italian government initiated *Mare Nostrum* on October 18, 2013, the first military operation with an explicit humanitarian aim in the Central Mediterranean Sea.

Unlike Hermes, *Mare Nostrum* had the explicit goal of safeguarding human life at sea. The force included personnel as well as sea and air assets of the Navy, the Air Force, the Carabinieri,

in Libya to leave for Italy (Frontex, 2012).

the State and the Financial Police, and the Coastal Guard (Ministry of Defense, 2013). Once rescued, migrants were generally channeled to the existing reception system for asylum seekers (Bratti et al., 2017). Operationally, *Mare Nostrum* consisted of permanent patrols in the search and rescue zones of Libya and Malta as well as Italy. This extended 138 miles south of Sicily and included naval and aircraft deployments that were carried out by military personnel. The monthly cost of the operation was around €9.5 million, dwarfing that of Hermes. Despite seemingly broad public support, the operation was criticized as an unfair burden for Italy to bear alone.*Mare Nostrum* was also criticised by UK's former foreign office minister, Lady Anelay, who described it as, "an unintended 'pull factor,' encouraging more migrants to attempt the dangerous sea crossing and thereby leading to more tragic and unnecessary deaths."

Triton

In spite of opposition from the UK, patrolling activities were taken over by the Frontex-led Operation *Triton* on November 14th 2014, which officially superseded *Mare Nostrum* (Frontex, 2014).The European Commission specified that the *Triton* mission would differ from *Mare Nostrum* since its primary objective was not the search and rescue of migrant boats in distress but rather surveillance of the external borders of the European Union. However, the European Parliament and of the Council of the European Union clarified that the operation would not escape the obligations of international and European law, which required intervention where necessary to rescue migrants in difficulty (Regulation EU 656/2014).

Triton's initial operational SAR area shrunk to only 30 miles from the Italian and Maltese coasts. However, after two more high profile shipwrecks in a single week in April 2015 resulted in over one thousand migrant deaths, the funding and operational power of *Triton* expanded dramatically. The second phase of *Triton* expanded the SAR area up to 138 miles south of Sicily and tripled its operational budget. In addition, Frontex began to destroy migrant smuggler vessels to prevent them being reused.[10]

[10] On May 2015, the EU launched a military operation known as European Union Naval Force Mediterranean (EUNAVFOR Med) Operation Sophia. The main mandate was to take systematic measures to identify and stop boats used or suspected of being used by human traffickers in the Central Mediterranean. On 20 June 2016, the Council added two additional tasks to the mission's mandate: (i) training the Coast Guard and the Libyan Navy and (ii) contributing to the implementation of the UN arms embargo on the high seas off the coast of Libya. On December 21, 2018, the European Council extended the mandate of the operation until March 31, 2019. The Operational budget until 27 July 2016 was 11.82 million (12 months) while for the period 28 July 2016 to 27 July 2017, the reference amount for the common costs of EUNAVFOR MED operation SOPHIA was 6.7 million.

Figure 2: Timeline of Major Search and Rescue Operations in the Central Mediterranean Sea

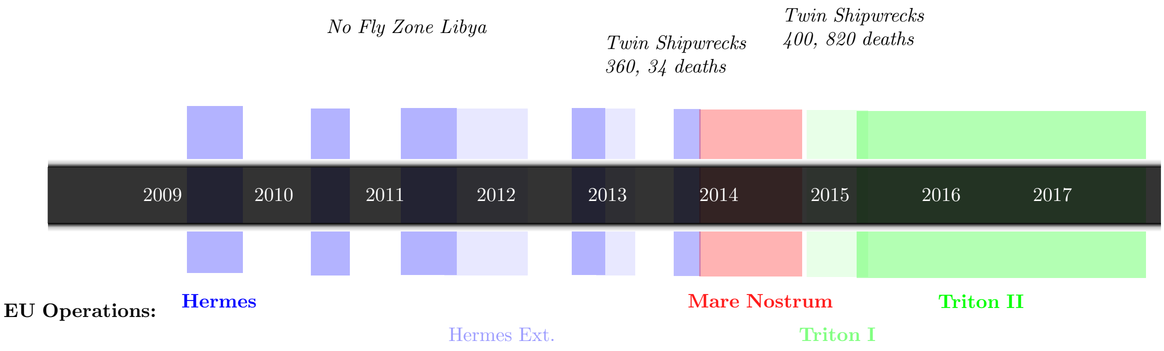


Figure 2 summarizes the timeline of all SAR operations along the Central route. Non Governmental Organizations have also participated in SAR operations, which we discuss in more detail in Section 6.3. Maps of operational areas are provided in the Appendix (Figure A.1).

3 Model

We present a model of irregular migration that highlights the important incentives faced by smugglers and potential migrants. Importantly, it provides a useful guide for empirical analysis of irregular migration. In particular, because many features of this market are either unobserved or incompletely observed (e.g., prices, vessel types), the implications of our model allow us to draw inferences on the incidence of search and rescue operations on the various agents involved.

On the demand side of the market for passage across the Mediterranean we assume a unit mass of potential migrants. Migrant i has utility

$$u_i = \alpha_i \sigma_b - p_b$$

where σ_b is the probability of safe passage on a boat of type b, and p_b is the price charged by the smuggler for passage on that boat. We assume that there are two types of boats: safe boats ($b = S$; e.g., a sturdy wooden fishing boat or motorized speedboat) and unsafe boats ($b = U$; e.g., an inflatable raft with under-powered outboard motor, see Figure B.1 in the Appendix), and these are distinguished in the model by the fact that $\sigma_S > \sigma_U$. α_i is an individual specific parameter that reflects the intensity of i's desire to cross and is distributed according to the

Figure 3: Migrant's Crossing Decisions

continuous cumulative density F_α. For a given set of prices, if neither boat option provides migrant i with positive utility, they will decline to cross.

On the supply side, we assume that there is a monopolist smuggler who offers passage to migrants at a price of p_b and at a cost of c_b.[11] We assume that seats on safe boats are more costly to provide than seats on unsafe boats (i.e., $c_S > c_U$).[12] For a given menu of prices, some fractions M_S and M_U of migrants will attempt to cross on safe and unsafe boats respectively. The smuggler's problem can thus be written as

$$\max_{p_S, p_U} M_S \cdot (p_S - c_S) + M_U \cdot (p_U - c_U)$$

where M_S and M_U now correspond to the fraction of potential migrants that choose the safe and unsafe options respectively. Because the M_b are endogenously determined, solving for equilibrium prices and quantities in this market is both difficult and offers little descriptive insight without imposing considerable additional structure on the model. Instead, we characterize a few key aspects of the market that can be empirically testable with limited data.

We begin our analysis by noting that smugglers will never set prices such that a less motivated migrant (lower α_i) would choose a safer boat than a more motivated migrant.

Lemma 1. *If $\alpha_i < \frac{p_U}{\sigma_U}$, then i will not cross. If $\frac{p_U}{\sigma_U} \le \alpha_i < \frac{p_U - p_S}{\sigma_U - \sigma_S}$ then i will cross on an unsafe boat. Otherwise, i will cross on a safe boat.*

Proofs may be found in the Appendix. Lemma 1 imposes an ordering on migrants' α_i that allow us to pin down the number of attempted crossings M_S and M_U, which we illustrate in Figure 3.

[11] It is unclear how much different militias and different criminal networks compete with each other. For local, tribal, and community interests, smuggling is sometimes perceived as a way to finance their security in times of civil unrest (Micallef, 2017). This is likely to generate some local monopoly power.

[12] According to Libyan smugglers that have been interviewed by investigative reporters a ticket to cross the Mediterranean would cost at least USD500, and the price would increase for a safer place on the wooden boats (Mannocchi, February 12, 2018).

We are particularly interested in understanding what happens when search and rescue operations are instituted. In the model, these can be thought of as increases in σ_U.[13] In order to derive comparative statics on σ_U, we make the following technical assumption on F_α:

Assumption 1. *Let f_α be the PDF associated with the density F_α, and define $g = \frac{d \log f_\alpha}{d\alpha}$. Then $g\left(\frac{p_U}{\sigma_U}\right) + \frac{\sigma_U}{p_U}$ cannot lie between $\frac{1}{\sigma_U^2 p_U}$ and $\frac{1}{\sigma_U^2 (p_U - c_U)}$.*

In simple English, Assumption 1 states that the curvature of F_α at a particular point cannot lie between two bounds that are based on the price-cost margin of unsafe travel. These bounds are narrowly defined, and the assumption is made only on the second derivative (rather than the first derivative) of F_α, so it is likely to be much weaker than a monotone likelihood ratio condition that is often imposed in similar models of price discrimination. Finally, we define the crossing risk, or the probability that a migrant is observed to die as:

$$R = 1 - \frac{\sigma_S M_S + \sigma_U M_U}{M_S + M_U} \tag{1}$$

Under Assumption 1, we obtain the following result:

Proposition 1. *In equilibrium, an increase in σ_U will result in*

1. *An increase in the number of migrants who attempt crossings (i.e. $M_S + M_U$).*
2. *Increases in p_U, p_S and $p_S - p_U$.*
3. *An increase in smuggler's profits.*
4. *An ambiguous effect on R.*

We can illustrate the effects of search and rescue operations and their incidence on migrants in Figure 4. In the presence of such operations, the first result of the proposition implies that the migrant who is indifferent between passage on an unsafe boat and no passage at all now has a lower α_i. Intuitively, the increased safety of the journey offset the increased price. All migrants close to this threshold are made better off by search and rescue operations (indicated in blue). In this region, migrants with greater α_i enjoy greater benefits from the search and rescue operations since they value safety more.

[13] In practice, search and rescue operations may also increase σ_S. As long as the proportional increase in σ_U is greater than the proportional increase in σ_S, all of our results still hold.

Figure 4: Incidence of Search and Rescue Operations on Migrants

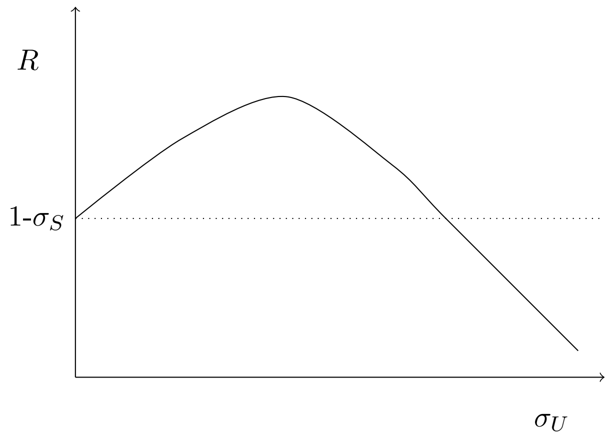
Note: The blue region contains migrants who are made better off by search and rescue operations, and the red region contains migrants who are made worse off by search and rescue operations. A greater intensity of color reflects a greater (positive or negative) incidence.

The second result of the proposition implies that the migrant who is indifferent between passage on a unsafe boat and a safe boat now has a higher α_i since there is less of a safety premium to taking the safe boat and it has gotten more expensive as well. All migrants who still take the safe boat are made worse off by search and rescue operations since they pay a higher price but get no added benefit. Moreover, those migrants who are just to the left of this new threshold are also worse off since they highly value safety but are now priced out of safe boats.

Search and rescue operations make smugglers unambiguously better off (result 3), as they are able to capture, at least partially, the safety benefits of the operations. However, it is ambiguous as to whether migrants will on net be better off since search and rescue operations may make the journey *more* treacherous by driving a large enough share of migrants to now cross on unsafe boats instead of safe boats (result 4). Perhaps surprisingly, when σ_U is small, it is more likely that search and rescue operations will increase the crossing risk, and only when σ_U is large will the crossing risk decrease. The intuition for this is conveyed in Figure 5. When $\sigma_U = 0$, all travel occurs on safe boats, hence $R = 1 - \sigma_S$. As σ_U grows larger, an increasing amount of travel occurs on unsafe boats, so R increases. When $\sigma_U \geq \sigma_S$, all travel occurs on unsafe boats, so $R = 1 - \sigma_U$. The continuity of the objective implies that in some range of large but not too large σ_U, R will be decreasing. Whether we are on the increasing or decreasing portion of the curve in Figure 5 (and hence whether search and rescue operations increase or decrease crossing risk) is thus an empirical question.

The key feature of search and rescue operations in this model is their ability to manipulate σ_U by making passage on unsafe boats more likely to succeed. It follows that any other policy or environmental change that manipulates σ_U should systematically affect the market for smuggling in an analogous manner. As a result, we might seek to understand how search and rescue

Figure 5: Net Crossing Risk and Unsafe Boat Crossing Risk



operations would affect crossings, deaths and risks even if we never observed such operations provided that we did observe how the market responded to other environmental changes that affected σ_U. We leverage this logic in our empirical approach.

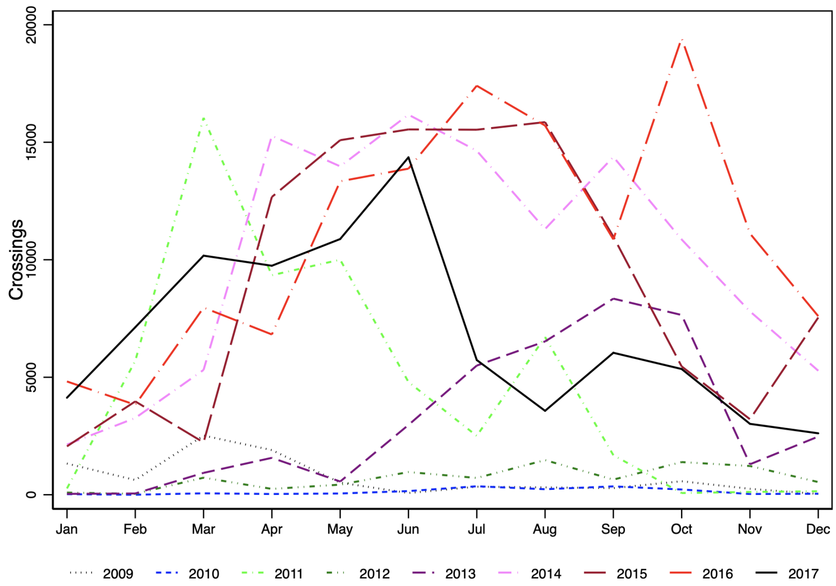
4 Data

We combine data from different sources that focus on the migration along the Central Mediterranean route from 2009 to 2017. Extralegal behavior is by its very nature often difficult to observe. As such, we always rely on multiple sources for those variables that are least well documented in official statistics. Our final dataset contains daily information on irregular crossings, deaths, tidal conditions and search and rescue operations.

4.1 Data on Crossings

We obtained a novel database on the number of daily irregular migrants to Italy from the *Polizia di Stato* (State Police) who operate under the control of the Department of Public Security (Ministry of Interior). The Department oversees all activities related to public order, which includes operational support for search and rescue missions. In addition to collecting information on irregular migration, they are tasked with controlling the flow of migrants into Italy and enforcing regulations regarding the entry of and stay of migrants. We use their data to construct our measure of daily arrivals to the Italian shores, which constitutes the bulk (over

Figure 6: Arrivals by years



Note: Monthly arrivals.

75%) of all arrivals along the Central route.[14] We then compute total daily crossings as the sum of arrivals and deaths in transit.

Attempted crossings have increased over the sample period, peaking in 2016 (see Figure 1) There are on average 170 attempted crossings per day along the Central route, and they follow a strong seasonal pattern as shown in Figure 6. Nevertheless, there is significant variation in seasonality across the different years of our sample.

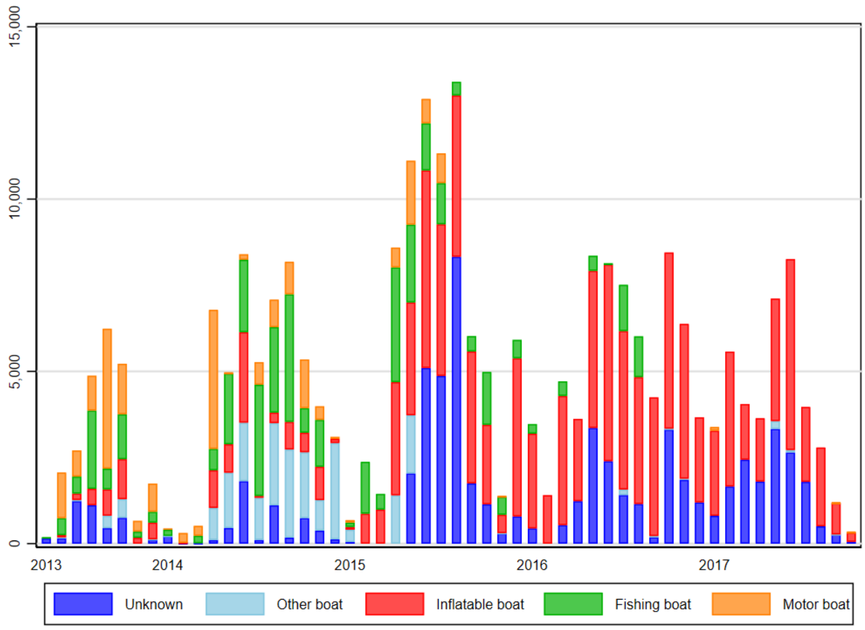
We also gathered information on the type of vessel used from 2013-2017 from Frontex, though many crossing vessels in that sample period are unknown. We summarize these data in Figure 7. It is immediate that over time, especially at the start of *Triton II* operations in mid-2015, inflatable boats become the main vessel used by smugglers.

4.2 Data on Deaths

Although official statistics on deaths in transit are difficult to come by, a number of well-funded transnational organizations, some of which are supported by governments, make great efforts to document these deaths. We cross reference these data sets to create a comprehensive single

[14] Most of the migrants arrive on the Lampedusa shores (22%), Augusta (20%) and Pozzallo (14%) in Sicily.

Figure 7: Types of Vessels Used, 2013-2017



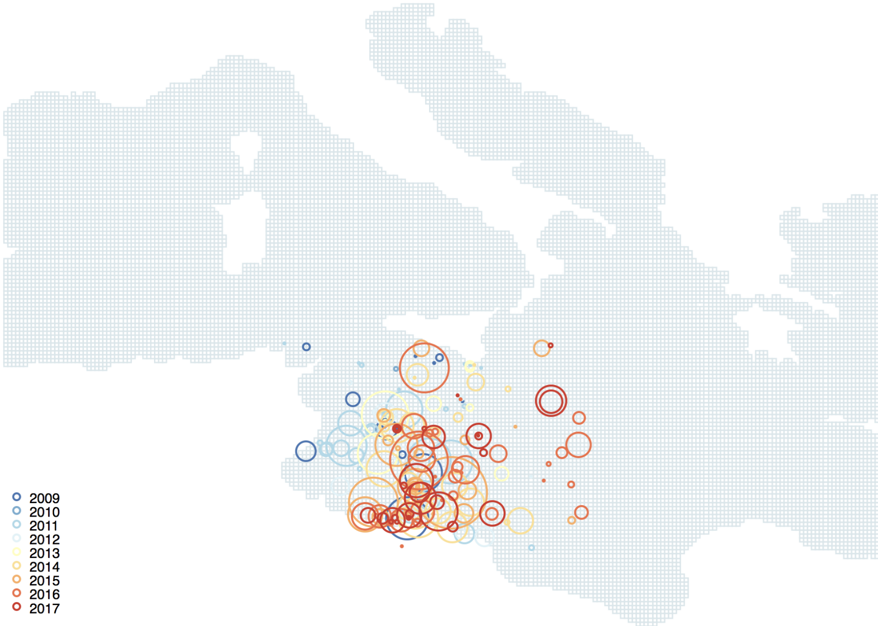
Source: Frontex.

measure of daily deaths. The average number of daily deaths is 3.6, which corresponds to a crossing risk that ranges between 2.7 to 5.5 percent depending on how it is calculated (see below).

Our primary source is UNITED for Intercultural Action, the European network in support of migrants, refugees and minorities. The organization has monitored the deaths at sea since 1993 with the support of more than 560 organisations and institutions from 46 European countries (including the European Commission, the Council of Europe, OSCE-ODIHR and Heinrich-Böll-Stiftung). UNITED monitors the number of deaths during border crossing attempts around the world and counts refugees, asylum seekers and undocumented migrants who have died through their attempts to enter Europe. To produce the *List of Deaths* dataset, UNITED conducts research using information from field organizations, institutional sources, and the migrants' protection systems of various European countries. This dataset contains information on where, when and under which circumstances a migrant died, importantly including whether it happened during an attempted border-crossing. UNITED also tabulates deaths that occurred via human trafficking or as a consequence of medical, psychological or security neglect.

Although the *List of Deaths* database is considered to be the largest and most comprehensive

Figure 8: Deaths by Location and Type of Transport



Source: Authors calculations from UNITED, Missing Migrants Project, IOM, and Frontex.

source on deaths at sea, we augment it with information provided by the Missing Migrants Project that covers the portion of our sample period in 2017.[15] For robustness, we also cross-reference our data with data from Frontex that spans 2014-2016 and the *Migrants File* dataset that spans 2009-2016.[16]

In Figure 8, we present a map of sea accidents during our sample period. Larger circles correspond to more deadly shipwrecks. Not only does the number of deaths increase over time, deaths also appear to occur closer to the Libyan shore. This is consistent with the increasing use of unsafe boats for attempted crossings.

Calculating Daily Crossing Risk

The crossing risk in equation (1) is an aggregate function of all crossings and deaths. Our goal is to construct a daily measure of crossing risk for departures based on observed daily arrivals and daily deaths. If all attempted crossings concluded in a single day, then daily crossing risk

[15] UNITED has not geolocalized more recent data; as such our last extraction was on May, 30 2017. The Missing Migrants Project, which fills this gap, is supported by UK Aid from the Government of the United Kingdom and International Organization for Migration (IOM).)

[16] The *Migrants File* database collects information from Puls, a project run by the University of Helsinki, Finland and commissioned by the Joint Research Center of the European Commission. (See `http://www.themigrantsfiles.com/`.) Relative to other official sources, this seems to under-count deaths.

could simply be calculated as

$$R_t = \frac{\text{Total Deaths}_t}{\text{Total Attempted Crossings}_t} \tag{2}$$

In practice, the journey may take up to three days, so daily departures do not necessarily correspond to daily arrivals. As a result, we calculate crossing risk in a variety of different but complementary ways. Specifically, we generalize equation (2) and define

$$R_t^{c,d} = \frac{(\text{Total Deaths}_t + ... + \text{Total Deaths}_{t+d})/(d+1)}{(\text{Total Attempted Crossings}_t + ... + \text{Total Attempted Crossings}_{t+c})/(c+1)} \tag{3}$$

where $R_t^{c,d}$ represents the crossing risk as calculated using an average of deaths during a d day period and arrivals (total attempted crossings) over a c day period. Note that $R_t^{0,0}$ corresponds to the naive calculation of crossing risk defined in equation (2).

4.3 Data on Crossing Conditions

We proxy for crossing conditions with data on the significant height of combined wind waves and swell, which is commonly known as the significant wave height ($H^{1/3}$). The combined height of the sea and swell is 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.[17] We obtained detailed tidal data from the European Centre for Medium-Range Weather Forecasts (ECMWF), an independent intergovernmental organization that is supported by 34 mostly European states.

The ECMWF provides high quality re-analysis datasets (ECMWF ERA-Interim) that incoprate high frequency readings from weather stations, satellites and sondes (Dee et al., 2011). We also collected data on wave forecasts. According to the ECMWF, these forecasts tend to overestimate actual wave conditions because the model is not calibrated for the Libyan region. For this reason we computed unbiased forecasts by recentering the published forecasts of $H_{1/3}$ to ensure that forecast error was mean zero.[18] We measure tidal conditions at a variety of

[17] Appendix Table B.1 describes wave and swell in terms of height and length. Waves can vary from zero (calm) with no waves breaking) to very high (towering seas) or phenomenal which is a rare case as for hurricanes or cyclones.

[18] Scatter plots of biased and unbiased forecasts of $H^{1/3}$ against observed realizations of $H^{1/3}$ are presented

Table 2: Summary

Variables	Count	Mean	SD	Min	Max
Crossings	3287	170.4411	397.2276	0.0000	4001
Hyp. Crossings	3287	2.4855	2.9991	0.0000	8.9874
Deaths	3287	3.6240	29.9519	0.0000	846
Crossing Risk	1521	0.0471	0.1909	0.0000	1.0000
Crossing Risk Type 1A	2017	0.0408	0.1673	0.0000	1.0000
Crossing Risk Type 2A	2036	0.0553	0.1951	0.0000	1.0000
Crossing Risk Type 1B	2305	0.0275	0.1286	0.0000	1.0000
Crossing Risk Type 2B	2315	0.0357	0.1476	0.0000	1.0000
Wave Tripoli	3287	0.8205	0.5058	0.1077	4.4130
Max Wave Tripoli	3287	1.0811	0.6136	0.2003	4.4130
Wave Bengazi	3287	1.2118	0.7316	0.2152	4.8480
Wave Al Huwariyah	3287	1.4782	0.9104	0.1284	5.2737
Wave Annaba	3287	1.4001	0.9152	0.2086	5.5798
Unbiased Wave Forecast	3287	0.8202	0.6048	0.0205	4.4431
Fr. Unkown	766	0.2002	0.3414	0.0000	1.0000
Fr. Other	766	0.0689	0.2292	0.0000	1.0000
Fr. Inflatable	766	0.4822	0.4477	0.0000	1.0000
Fr. Fishing	766	0.1282	0.3006	0.0000	1.0000
Fr. Motor	766	0.1205	0.3007	0.0000	1.0000

potential departure points along the North African coast: Tripoli, Libya; Benghazi, Libya; Al Huwariyah, Tunisia; and Annaba, Algeria. Average wave height varies between 1.08 and 1.47 meters depending on where it is measured.

We summarize all of our main variables in Table 2.

5 Empirical Approach and Results

Our model generates predictions of how the market for irregular migration is affected by changes in the probability of successful passage on unsafe boats (σ_U). The fraction of potential migrants who attempt to cross is given by $1 - F[p_U/\sigma_U]$.

We observe two sources of variation in σ_U. First, the probability of passage on an unsafe boat depends on whether there is a search and rescue (SAR) operation in place and, if so, its intensity. This varies at low frequency because SAR operations are initiated infrequently and often last many months if not years. Second, the probability of passage on an unsafe boat varies at high-frequency depending on the daily weather and wave conditions on the Libyan shore. Rough winds and seas can dramatically affect the probability of safe passage on an inflatable boat, but sturdier boats are largely impervious to all but the worst conditions.

We first leverage the low-frequency variation in SAR operations to analyze how the numbers of crossings, deaths and crossing risk vary with SAR operations in three sets of monthly

in Figure A.2 in the appendix.

regressions:

$$Y_t = \sum_k \beta^k \mathrm{SAR}_t^k + f(t) + \epsilon_t. \tag{4}$$

Y_t corresponds to one of the three outcomes, the subscript k indexes each search and rescue operation that was implemented during our sample period. f(t) is a function of time and includes a cubic polynomial in t to control for the long term trends and week of the year fixed effects to control for seasonality. Estimation results are presented in Table 3. Consistent with our model, all SAR operations are associated with greater numbers of crossings. Despite the increase in crossings, we find no statistically significant effects on deaths or crossing risk.

Relying solely on low-frequency variation in σ_U has two main drawbacks. First, it may be correlated to other changes in the market environment that affect the decisions of traffickers and migrants. Second, the variation is limited, by construction. In order to circumvent these issues, we explore how crossings, death and crossing risk respond to plausibly exogenous high-frequency variation in daily crossing conditions.

We proxy for these conditions with a measure of significant wave height $H^{1/3}$, which is a widely used measure in navigation that corresponds to the average height of the largest third of the waves in the open sea. Significant wave height is commonly modeled using the Rayleigh distribution (Battjes and Groenendijk, 2000), which allows the calculation of average wave heights above given percentiles. This is particularly relevant to our analysis, as shipwrecks are most likely to be caused by only the very largest waves. For example, 1 in 10 waves have

Table 3: Irregular Migration During Search and Rescue Operations

	(1) Crossings	(2) Deaths	(3) Crossing Risk
Hermes	-30.0001	0.9339	-0.0001
	(56.8922)	(2.5608)	(0.0262)
Hermes Ext	6.4691	1.1978	0.0544
	(27.3405)	(1.5827)	(0.0426)
Mare Nostrum	238.9778***	3.9932	-0.0166
	(56.9587)	(2.6398)	(0.0270)
Triton I	190.4897***	8.4022	-0.0226
	(52.6080)	(5.1816)	(0.0275)
Triton II	276.0192***	3.4329	-0.0642*
	(90.9075)	(3.7806)	(0.0359)
Observations	3,287	3,287	1,521
R-squared	0.0904	0.0059	0.0188

Note: All effects are estimated relative to a baseline in which Hermes was in place. Crossing Risk is defined as $R_t^{c,d}$. We control for a cubic polynomial in day t and for week of the year fixed effects.
* p<.10 ** p<.05 *** p<.01.

an average height of $H^{1/10} = 1.27H^{1/3}$. Given J waves, the maximum wave height can be approximated as $\sqrt{0.5ln(J)}H^{1/3}$, which, for large J, is about twice the significant wave height $2H^{1/3}$. This means that with a significant wave height of 1.5 meters, a vessel crossing the Central Mediterranean sea would most likely encounter waves of up to 3 meters of height. The linearity of H (in its exponent) implies that modelling crossing, deaths and risk of death as a linear function of significant wave height $H^1/3$ is empirically equivalent to choosing any other wave height (with coefficients appropriately).

Figure A.3 presents scatter plot of the total number of daily (t =day) crossings against wave height. We model the crossings, deaths, and death rates as a function of current and potentially lagged waves after controlling for interacted week/year fixed effects (λ_w, which also capture all our SAR periods):[19]

$$Y_t = \omega_0 H_t^{1/3} + \omega_1 H_{t-1}^{1/3} + ... + \lambda_w + \epsilon_t. \tag{5}$$

As Tripoli and Lampedusa are 184 miles apart, the journey takes 61 hours at a speed of 2.5 knots, a typical speed for fishing boats and fully cramped rubber boats.[20] Hence smugglers expecting a 2 or 3-day trip what may matter is the maximum wave condition over the following few days ($\mathbf{H}_t^{1/3} = \max(H_t^{1/3}, H_{t-1}^{1/3}, ...)$). Our model suggests that smugglers may respond to SAR operations by substituting away from safe vessels towards unsafe ones. Hence, in order to leverage both the low frequency variation in operations and high frequency variation in crossing conditions, we specify the following regression equation:

$$Y_t = \sum_k \omega_k \text{SAR}_t^k \mathbf{H}_t^{1/3} + \omega_0 \mathbf{H}_t^{1/3} + \lambda_w + \epsilon_t. \tag{6}$$

We present our results in Table 4. Adverse conditions reduce the numbers of crossings (column 1) and matter for up to three days, which is consistent with the typical duration of the journey. One additional meter of wave height reduces the daily number of people crossing the sea by between 70 (40 percent) and 110 (64 percent). Column 2 shows that during well-funded operations adverse conditions suppress crossings more than periods when no operations are in

[19] Starting from the fraction of potential migrants crossing the sea, a uniform distribution of α_i and an inverse relationship between wave height and p_U/σ_U would lead to a linear specification. Later we test whether the results are robust to choosing a different functional form.

[20] In our sample period, 22% of disembarkments occurred in Lampedusa. Faster boats may attempt to reach mainland Sicily in three days. Pozzallo, where 14% of the disembarkments took place is 282 miles away from Tripoli.

Table 4: Wave Height, Crossings, Deaths and Crossing Risk

	(1)	(2)	(3)	(4)	(5)	(6)
	Crossings		Deaths		Crossings Risk	
Wave Tripoli	-110.4420***		-3.7814***		0.0190	
	(18.3236)		(1.4097)		(0.0273)	
Lag 1 Wave Tripoli	-84.7044***		-0.6047		0.0068	
	(16.4332)		(0.9391)		(0.0197)	
Lag 2 Wave Tripoli	-70.7536***		-1.6416		0.0026	
	(18.0249)		(1.4454)		(0.0227)	
Lag 3 Wave Tripoli	-14.5225		-2.8174*		-0.0082	
	(13.9124)		(1.4791)		(0.0206)	
Max Wave Tripoli * No Operation		-56.3187**		-0.7093**		0.0296
		(22.6694)		(0.3492)		(0.0333)
Max Wave Tripoli * Hermes		-41.4040*		-1.8482*		-0.0262
		(21.9062)		(1.0880)		(0.0407)
Max Wave Tripoli * Hermes Ext		-17.5742**		0.0212		-0.0432
		(8.5916)		(0.1712)		(0.0441)
Max Wave Tripoli * Mare Nostrum		-147.9749***		-0.5868		-0.0032
		(55.4899)		(0.5558)		(0.0149)
Max Wave Tripoli * Triton I		-241.1372***		-6.6480*		-0.0253
		(75.0366)		(3.5170)		(0.0278)
Max Wave Tripoli * Triton II		-309.5341***		-8.6793**		0.0592
		(60.3643)		(4.3045)		(0.0394)
Observations	3,284	3,287	3,284	3,287	1,521	1,521
R-squared	0.0478	0.0565	0.0047	0.0057	0.0016	0.0056
Mean Crossing	170.4411	170.4411	170.4411	170.4411	170.4411	170.4411
Mean Wave Tripoli	0.8205	0.8205	0.8205	0.8205	0.8205	0.8205
Week-Year FE	X	X	X	X	X	X

Note: We include dummy for Hermes, Hermes Ext, Mare Nostrum, Triton I and II Operations while the baseline dummy is No Operation period. Max Wave variable takes the maximum between Wave value at time t, t-1 and t-2. Crossing Risk is defined as $R_t^{0,0}$.
* p<.10 ** p<.05 *** p<.01.

place. This difference is particulary large starting with *Mare Nostrum*, and then grows further during *Triton II*.[21] These results suggest that during periods of SAR operations, smugglers shift from safe boats to unsafe boats, as safe boats should be less responsive to short-run fluctuations in crossing conditions. Moreover, this substitution pattern is weaker during periods of lower intensity SAR (e.g., *Hermes* and *Hermes* Extension), which is consistent with such operations generating a smaller increase in σ_U than their better funded counterparts.

These findings are also consistent with the evolution in the share of inflatable boats as shown in Figure 7. Inflatable dinghies purchased online (see Appendix Figure B.1) were used in greater numbers starting in the summer of 2014 towards the end of the *Mare Nostrum* operation.[22]

Adverse conditions also reduce the total number of deaths (column 3), and these reductions are larger during periods of SAR (column 4) though this difference is not statistically significant. However, as shown in columns 5 and 6, this reduction in deaths is driven by a reduction in crossings rather than a reduction in crossing risk. Again, this is consistent with the prediction

[21] This is in line with smugglers admitting in Porsia (2015) that they soon understood the humanitarian aim of *Mare Nostrum* and "... quickly took the advantages from that, adapting the amount of fuel and supply's to cover the shorter distance up to coordinates where Italian forces were."

[22] See details in `https://wikileaks.org/eu-military-refugees/EEAS/EEAS-2016-126.pdf`. The European External Action Service (EEAS) acknowledges different interceptions "by Maltese customs of 20 packaged rubber boats in a container destined to Libya. As there are no legal grounds for holding such shipments, it was released for delivery to the destination" as clearly stated in pg. 7/22.

Table 5: Vessel Types During Search and Rescue Operations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Boat Type	Fr. Inflatable		Fr. Fishing		Fr. Motor		Fr. Other		Fr. Uknown	
Max Wave$_{(t,t-1,t-2)}$	-0.1265***		0.0597**		0.0390		0.0239		0.0039	
	(0.0323)		(0.0304)		(0.0274)		(0.0224)		(0.0312)	
Max Wave Tripoli * Hermes		-0.1744**		-0.0027		0.0767		-0.0611		0.1615
		(0.0714)		(0.0823)		(0.0582)		(0.0493)		(0.1010)
Max Wave Tripoli * Mare Nostrum		-0.1426***		0.1799**		-0.0487		0.0447		-0.0333
		(0.0533)		(0.0833)		(0.0629)		(0.0650)		(0.0473)
Max Wave Tripoli * Triton I		-0.1913***		0.0022		0.1624**		0.0753		-0.0486
		(0.0517)		(0.0466)		(0.0742)		(0.0697)		(0.0597)
Max Wave Tripoli * Triton II		-0.0696		0.0515*		-0.0027		0.0026		0.0183
		(0.0583)		(0.0298)		(0.0165)		(0.0140)		(0.0529)
Observations	766	766	766	766	766	766	766	766	766	766
R-squared	0.0194	0.0331	0.0065	0.0258	0.0033	0.0233	0.0018	0.0252	0.0000	0.0106
Mean Wave Tripoli	0.8119	0.8119	0.8119	0.8119	0.8119	0.8119	0.8119	0.8119	0.8119	0.8119
Mean dep. var.	0.4822	0.4822	0.1282	0.1282	0.1205	0.1205	0.0689	0.0689	0.2002	0.2002
Month-Year FE	X	X	X	X	X	X	X	X	X	X
Week FE	X	X	X	X	X	X	X	X	X	X

Note: We include dummy for Hermes, Mare Nostrum, Triton I and II Operations while the baseline dummy is Hermes period. Max Wave variable takes the maximum between Wave value at time t, t-1 and t-2.
* p<.10 ** p<.05 *** p<.01.

of our model whereby smugglers would shift from safe to unsafe vessels.

We attempt to test for substitution across vessel type more directly by re-estimating Eq. 5 and specifying the fraction of attempted crossings on different types of vessels as dependent variables. Results are presented in Table 5. With the caveat that these dependent variables are noisy (Frontex classifies 6.8% of vessels as "other" and 20% of vessels as unknown), our results are consistent with strategic smuggler responses as predicted by the model. Because these regressions include fixed effects at the month/year and week of the year level (there is not enough variation to control for week/year FEs), they reveal that smugglers shift between different types of vessels at a very high frequency.

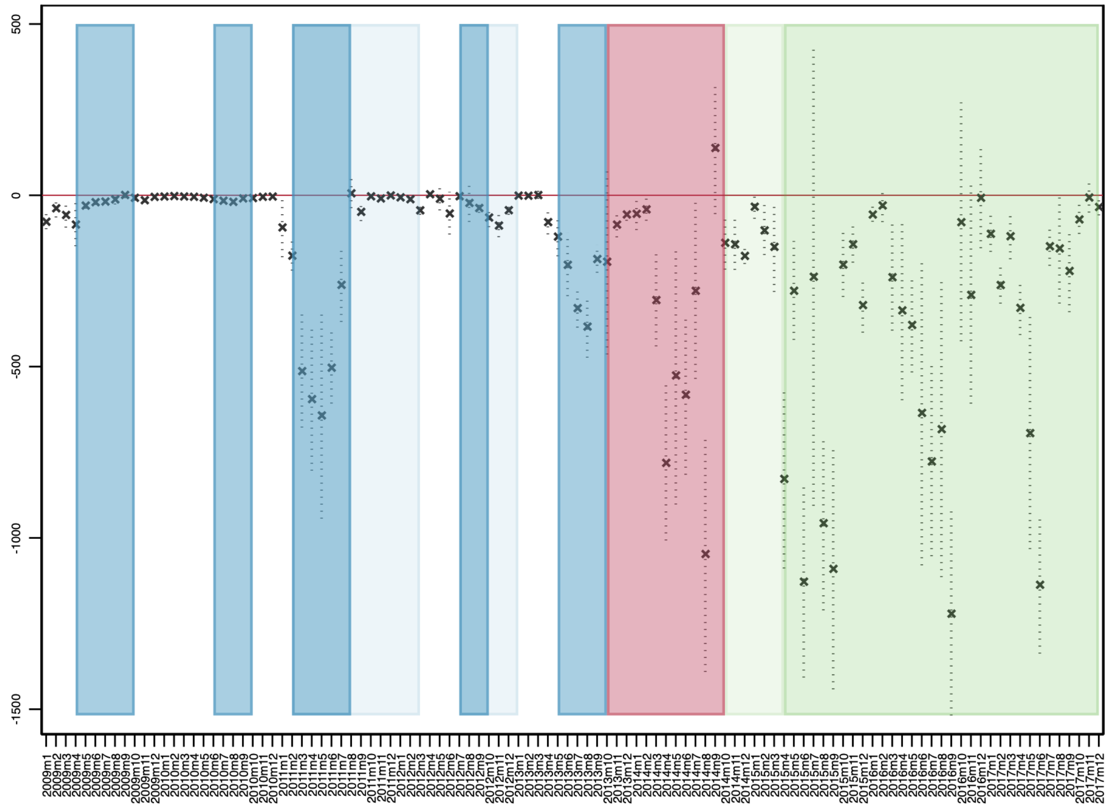
The evidence presented above broadly supports the notion that various SAR operations had the unintended consequences of (1) increasing crossings and (2) diverting crossings from safer boats to less safe boats. We further analyze the behavioral responses of smugglers and migrants by estimating month-specific responses to crossing conditions with the following regression equation:

$$Y_t = \omega_m H_t^{1/3} + \lambda_w + \epsilon_t \tag{7}$$

The key modification in equation (7) is that the coefficient on $H_t^{1/3}$ is allowed to vary by year/month of the sample. Hence we can directly estimate changing responses over time and assess the extent to which they correspond to periods of SAR operations.

In Figure 9 we specify Y_t as daily crossings and present estimates of ω_m over time along with 95% confidence intervals. When there are no operations, $\hat{\beta}_m$ is effectively zero. Only during

Figure 9: Crossings and Wave Conditions



Note: Each "X" corresponds to an estimate of ω_m, along with 95% confidence intervals (i.e., the responsiveness of crossings to weather conditions). The dark and light blues, the red and the green shaded backgrounds indicate when Hermes and its Extension, Mare Nostrum and Triton were operating, respectively. Year$\times$Week fixed effects included.

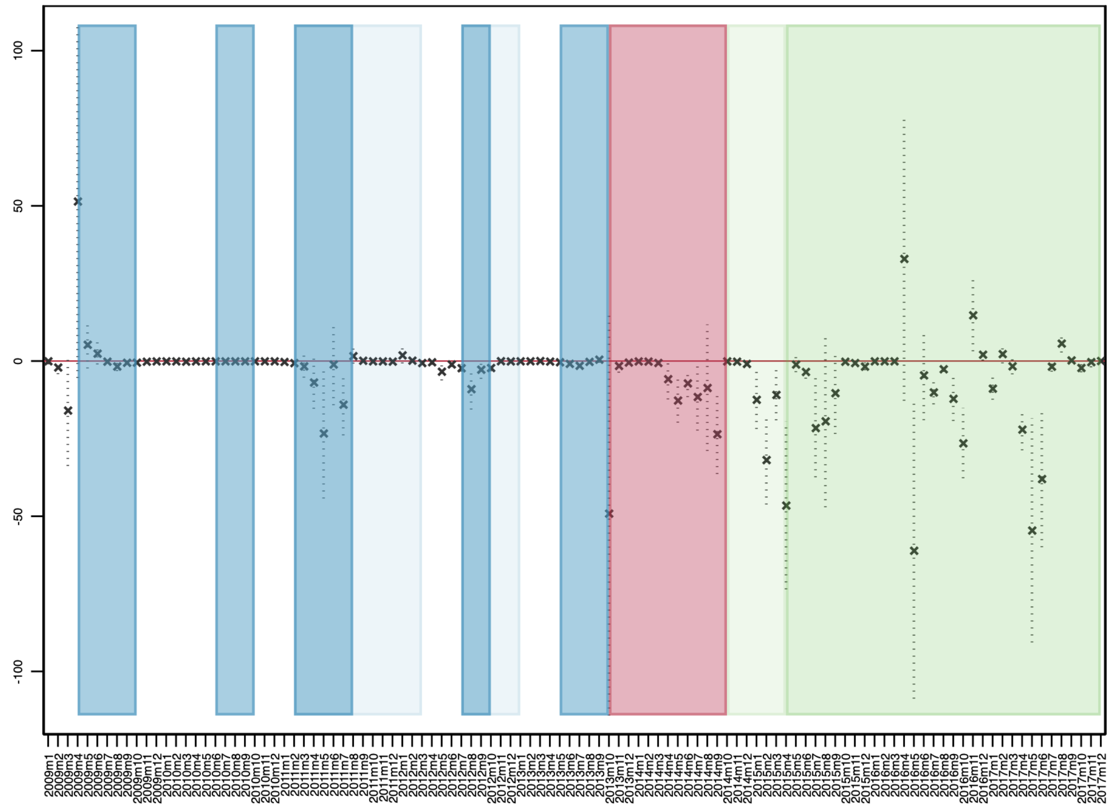
periods of SAR do the number of crossings vary with weather conditions, which reflects the use of unsafe boats. These responses are greatest during the periods of highest intensity SAR operations corresponding to Hermes 2011, Hermes 2013, Mare Nostrum and Triton II (see Table 1).

As seen in Figure 10, deaths are also more responsive to weather conditions during periods of SAR. As argued before, this is likely due to changes in the numbers of crossings rather than reductions in crossing risk, as Figure 11 reveals no systematic relationship between crossing risk and SAR operations.[23]

To what extent are the relationships between crossing conditions and attempted crossings truly a decisive response to changes in σ_U as opposed to a mere correlation? We present

[23] Figures A.4, A.5 and A.6 show similar graphs using max wave conditions as main regressor.

Figure 10: Deaths and Wave Conditions



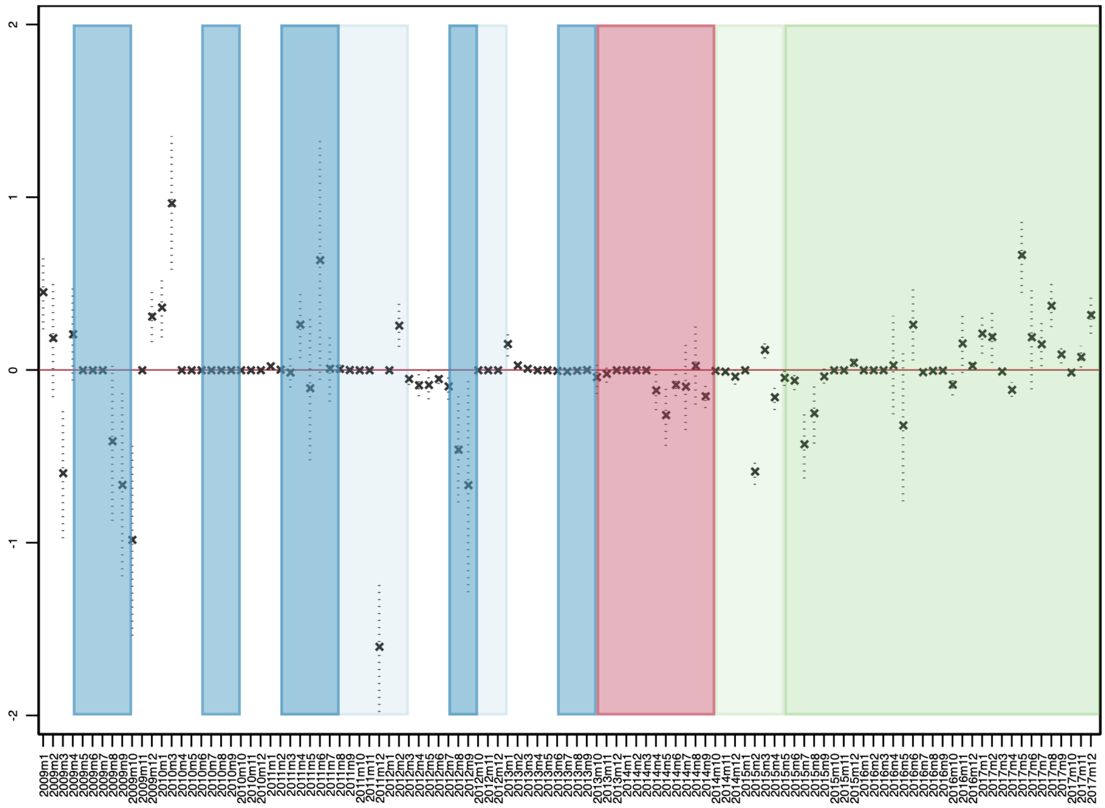
Note: Each "X" corresponds to an estimate of ω_m, along with 95% confidence intervals (i.e., the responsiveness of crossings to weather conditions). The dark and light blues, the red and the green shaded backgrounds indicate when Hermes and its Extension, Mare Nostrum and Triton were operating, respectively. Year×Week fixed effects included.

suggestive evidence that smuggler and migrant behavior is shaped by changing incentives by estimating how our outcome variables respond to contemporaneous forecasts of future weather conditions. A systematic response to expected crossing conditions (conditional on currently observed crossing conditions) would constitute evidence of sophisticated behavior in this market. We estimate regression equations of the form:

$$Y_t = \sum_k \omega_k \mathrm{SAR}_t^k \omega_k \mathbb{1}(H_t^{1/3} < E_t[H_t^{1/3}]) + \lambda_w + \epsilon_t \tag{8}$$

where $\mathbb{1}(H_t^{1/3} < E_t[H_t^{1/3}])$ is an indicator variable that is equal to 1 if contemporaneous wave height is lower than an unbiased forecast of future wave height, i.e,. if crossing conditions are better today than tomorrow.

Figure 11: Crossing Risk and Wave Conditions



Note: Each "X" corresponds to an estimate of ω_m, along with 95% confidence intervals (i.e., the responsiveness of crossings to weather conditions). The dark and light blues, the red and the green shaded backgrounds indicate when Hermes and its Extension, Mare Nostrum and Triton were operating, respectively. Year×Week fixed effects included.

We present our estimation results in Table 6. When crossing conditions are more favorable today than tomorrow, smugglers send more migrants (column 1), and this strategic decision is more pronounced during the most intense periods of search and rescue operations (column 2). Deaths are lower when crossing conditions are more favorable today than tomorrow (columns 3 and 4), and the risk of crossing is also lower at those times (columns 5 and 6). This is consistent with the fact that crossing conditions matter, smugglers are aware of this, and they use this information in a strategic manner.

Given the anecdotal evidence of Chinese rubber boats reaching Libya through neighboring countries, as a final piece of indirect evidence of he substitution across boat types, we track the total number of rubber boats (and similar vessels) that were imported (mainly from China) by Malta, Egypt and Turkey. As a control group we use the total number of ferries, and we

Table 6: Trafficker Responses to Weather Forecasts

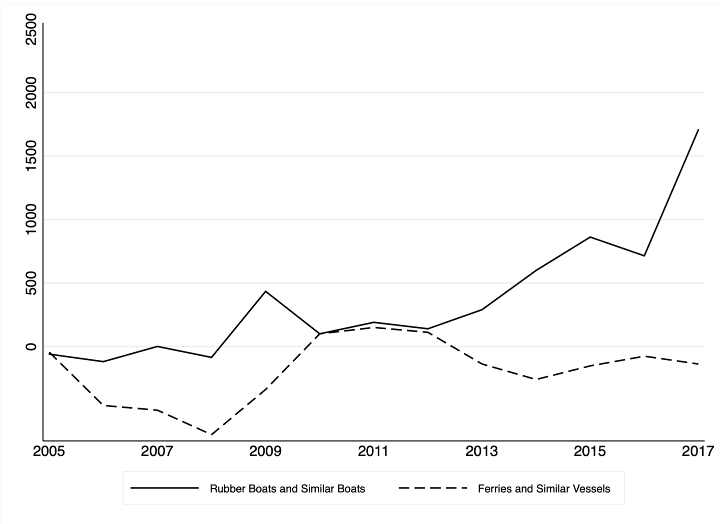
	(1)	(2)	(3)	(4)	(5)	(6)
	Crossings		Deaths		Crossing risk	
I(Max $Wave_t < UForecast_{t+1}$)	60.9989***		-1.9507*		-0.0153	
	(19.6773)		(1.0627)		(0.0152)	
I(Max $Wave_t < UForecast_{t+1}$) * No Operation		-2.0458		-0.8099		-0.0193
		(12.5674)		(0.6881)		(0.0118)
I(Max $Wave_t < UForecast_{t+1}$) * Hermes		-46.2060*		-1.2395		0.0605**
		(26.5724)		(2.0040)		(0.0273)
I(Max $Wave_t < UForecast_{t+1}$) * Hermes Ext		-8.0018*		-0.4772		0.1481
		(4.8602)		(0.4088)		(0.1188)
I(Max $Wave_t < UForecast_{t+1}$) * Mare Nostrum		114.7730***		-6.8574**		-0.0630**
		(35.8652)		(2.9484)		(0.0274)
I(Max $Wave_t < UForecast_{t+1}$) * Triton I		33.0788		-10.5347		-0.0597***
		(44.2907)		(8.1757)		(0.0231)
I(Max $Wave_t < UForecast_{t+1}$) * Triton II		193.1539***		-0.3497		-0.0364
		(46.3223)		(2.3397)		(0.0234)
Observations	3,287	3,287	3,287	3,287	1,521	1,521
R-squared	0.0060	0.0268	0.0008	0.0027	0.0014	0.0162
Week-Year FE	X	X	X	X	X	X

Note: We include dummy for Hermes, Hermes Ext, Mare Nostrum, Triton I and II Operations while the baseline dummy is No Operation period. Max Wave variable takes the maximum between Wave value at time t, t-1 and t-2. Crossing Risk is defined as $R_t^{0,0}$. Unbiased forecast of Tripoli is used.
* p<.10 ** p<.05 *** p<.01.

normalize the numbers to be 100 in 2010. Figure 12 shows that in the period prior to operations, these crossings displayed little trend. However, they begin to diverge after the introduction of *Mare Nostrum* in 2014, and this divergence is exacerbated after *Triton* in 2015. By the time of *Triton II* the imports had increased by more than 15 times.[24]

This pattern is further supported by trends in imports of life-jackets to Egypt, Libya and Malta, which we present in Figure 13. Indeed, a sharp increase in imports of these inexpensive

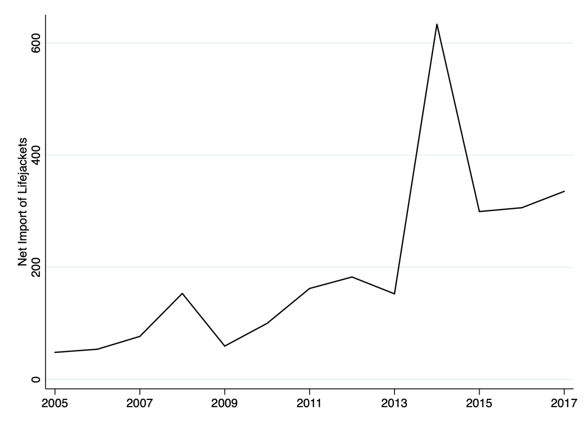
Figure 12: Rubber Boats vs. Wooden Ferries

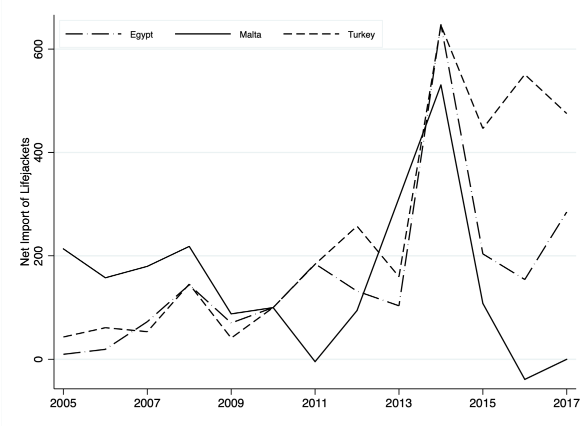


Note: Both series are normalized to zero in 2010.

[24] In July 2017 the EU introduced an export ban on inflatable boats and outboard motors to Libya.

Figure 13: Net Import of Lifejackets and By Countries





Note: Both series are normalized to 100 in 2010.

safety devices, whose benefits would effectively only accrue to passengers on unsafe, inflatable vessels, is indirect evidence that traffickers offset the safety benefits of search and rescue operations.[25]

To summarize, we find that in periods when SAR operations are in place, irregular migration along the Central route increases, though the probability of perishing on this crossing does not. These increases are largest when SAR operations are most intense. Moreover, traffickers respond strategically to adverse weather and tidal conditions. The fact that these responses are largest when SAR is in place is evidence that the operations have induced traffickers to shift from safer wooden boats to less seaworthy inflatable craft. This is supported by direct, albeit incomplete, data on the types of vessels used by migrants and indirect data on alternative safety measures such as life jackets. The implication of these findings, interpreted through the lens of our model, suggest that SAR operations have increased irregular migration along the Central route, and the potential safety benefits of these operations have been offset by the greater use of unsafe boats, which has allowed smugglers to capture the benefits of these operations.

[25] The conjectured use of life-jackets on unsafe boats is also evidence that traffickers are constrained by the safety concerns of migrants through competition.

6 Robustness

6.1 Alternative Specifications of Crossing Conditions

In our main results, we proxy for crossing conditions with tidal conditions measured outside of Tripoli, Libya, which is the main embarkation point for irregular migrants. However, not all crossings originate from the same location in North Africa. In Table A.1 we conduct a horse race between significant wave height in four different locations (Tripoli and Benghazi, Libya; Al Huwariyah, Tunisia; and Annaba, Algeria). The results are broadly consistent with our previous results, though direct comparisons are inadvisable since sea conditions at each of these locations are are highly correlated to one other. Nevertheless, crossings consistently respond most strongly to conditions outside of Tripoli.

6.2 Alternative Specifications of Crossing Risk and Functional Form

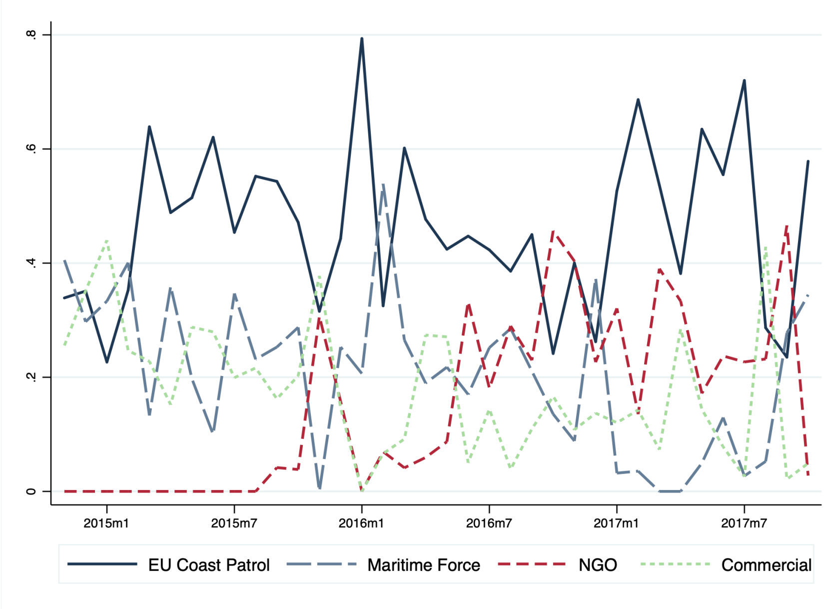
As discussed in Section 4, it is difficult to precisely measure crossing risk in our data since crossings are measured at the time of arrival while deaths occur during a multi-day journey. In Table A.2 we re-estimate equation (6) with several alternative measures of crossing risk.[26] There are two operational periods in which larger waves increase crossing risk: when no operations are in place and during Triton II. Because these are the two periods with the least potential substitution across types of vessels, this is consistent with our model.

6.3 NGO Operations

In addition to official operations by the EU and Italian government, several humanitarian operations were conducted by NGOs during our sample period; however these were much smaller in scope and intensity than official operations. The most active NGO, Malta-based Migrant Offshore Aid Station (MOAS), deployed fishing vessels and two drones.(MOAS, 2014, 2015, 2016, 2017) MOAS offered an example that was later been imitated by other NGOs. In 2015, the Brussels and Barcelona branches of Médecins Sans Frontiéres (MSF) developed their own SAR capabilities using their own vessels; German NGO Sea-Watch also purchased a vessel to search for migrant boats in distress in 2015. In February 2016, SOS Mediterranee chartered a

[26] Alternative results are shown in Figures A.7, A.8 , A.9 and A.10 using Crossing Risk defined as $R_t^{1,2}$, $R_t^{2,2}$, $R_t^{1,1}$ and $R_t^{2,1}$, respectively.

Figure 14: Rescue Activity by Organization 2014-2017



Note: We present the fraction of monthly crossing attempts that are intercepted by various organizations. Monthly attempts are measured as the sum of crossings and deaths.

77 meter ship to conduct operations in partnership with the Amsterdam branch of MSF.

All of these organizations usually initiate rescues between 10 and 30 nautical miles off the coast of Libya upon authorization of the Italian Maritime Rescue Coordination Centre (MRCC). NGOs follow one of two different operating models. MOAS, MSF, and SOS-Mediterranee conduct extensive SAR operations that involve the rescuing of migrants with larger vessels that can transport them to Italian ports. Smaller NGOs such as Sea-Watch and Pro-Activa focus on rescue and the distribution of life preservers and emergency medical care while waiting for larger ships to transport migrants to Italian port.

In Figure 14, we see that NGO activity only constituted a substantial portion of all SAR activity starting in June 2016 during *Triton II*. Hence our estimates of responsiveness to crossing conditions during early SAR operational periods are likely to be unaffected by NGO activity. Nevertheless, in Table 7 we reestimate our main regressions controling explicitly for MOAS operations. The coefficient on MOAS activity is negative is fairly large in column 1, which may indicate that NGO vessels induce substitution towards unsafe boats. And again we find that deaths and crossing risk do not respond to crossing conditions (columns 2 and 3). Our results are also robust to alternative functional form specifications (columns 4-6).

Table 7: Robustness Checks

	(1) Crossings	(2) Deaths	(3) Crossing Risk	(4)	(5) Hyperbolic Crossings	(6)
Max Wave Tripoli * No Operation	-45.6019*	-0.6741	0.0329	-1.1183***	-1.0357***	
	(23.7139)	(0.6041)	(0.0418)	(0.2923)	(0.2715)	
Max Wave Tripoli * Hermes	-43.7334*	-2.0538	-0.0264	-1.4118***	-1.4078***	
	(25.2692)	(1.3038)	(0.0419)	(0.1928)	(0.1924)	
Max Wave Tripoli * Hermes Ext	-15.1758*	0.0065	-0.0442	-0.6733***	-0.6735***	
	(9.1659)	(0.1926)	(0.0475)	(0.2384)	(0.2385)	
Max Wave Tripoli * Mare Nostrum	-134.3143**	-0.3699	-0.0007	-1.5640***	-1.5160***	
	(57.8305)	(0.6001)	(0.0177)	(0.2478)	(0.2422)	
Max Wave Tripoli * Triton I	-229.2326***	-6.7730*	-0.0305	-1.9175***	-1.9184***	
	(69.1965)	(3.5598)	(0.0322)	(0.2573)	(0.2575)	
Max Wave Tripoli * Triton II	-212.1369***	-8.8804	0.0682	-2.2751***	-1.9600***	
	(46.5248)	(5.5740)	(0.0531)	(0.2667)	(0.2647)	
Max Wave Tripoli * MOAS	-314.9949***	0.7336	-0.0147		-1.0704**	
	(111.7766)	(5.9464)	(0.0656)		(0.5060)	
I($MaxWave_t < UForecast_{t+1}$) * No Operation						-0.2474
						(0.1731)
I($MaxWave_t < UForecast_{t+1}$) * Hermes						-0.7019***
						(0.2629)
I($MaxWave_t < UForecast_{t+1}$) * Hermes Ext						-0.2840
						(0.2368)
I($MaxWave_t < UForecast_{t+1}$) * Mare Nostrum						0.6649**
						(0.3016)
I($MaxWave_t < UForecast_{t+1}$) * Triton I						0.2638
						(0.3697)
I($MaxWave_t < UForecast_{t+1}$) * Triton II						1.0519***
						(0.2117)
Observations	3,287	3,287	1,521	3,287	3,287	3,287
R-squared	0.0717	0.0063	0.0058	0.0850	0.0886	0.0190
NGOs	X	X	X	X	X	
Week-Year FE	X	X	X	X	X	X

Note: We include dummy for Hermes, Hermes Ext, Mare Nostrum, Triton I and II Operations while the baseline dummy is No Operation period. Max Wave variable takes the maximum between Wave value at time t, t-1 and t-2. Crossing Risk is defined as $R_t^{0,0}$. Unbiased forecast of Tripoli is used.
* p<.10 ** p<.05 *** p<.01.

7 Conclusion

Irregular migration is a large and growing issue that concerns the governments of rich and poor countries alike. In the Central Mediterranean, the large humanitarian toll of irregular migration is borne directly by migrants from the Middle East and Sub-Saharan Africa, but also indirectly by European countries who conduct costly search and rescue operations and whose internal politics have been shaken to the core by this issue.

Looking back at nearly a decade of data on crossings, we find that while these search and rescue operations have no doubt saved lives directly, they may have had adverse unintended consequences that must be considered. First, by reducing the risk of crossing, these operations likely induced more migrants to attempt to cross, which exposes more people to the risk of death along the passage. Second, by reducing the costs to traffickers of using unsafe boats, these operations induced a large substitution away from seaworthy wooden vessels and towards flimsy, inflatable boats. Thus, the benefits of search and rescue operations have been, to some extent, captured by human traffickers. The fact that these agents often work under the auspices of unsavory organizations such as ISIS is troubling for obvious reasons.

Well-intentioned policymakers who are motivated to take action face a genuine dilemma. By failing to act, it is likely crossings would continue and deaths would continue to mount. But by intervening along the route, it is likely that more migrants would attempt an extremely dangerous undertaking. Perhaps there is a third choice. Ultimately, addressing this issue will require interventions that reduce demand for irregular migration, the two obvious substitutes for it being better conditions in home countries and safe, legal migration. In all regions where irregular migration has emerged as a burning issue, such as Southeastern Europe, Turkey and the Middle East, and the US-Mexico border, politicians and policymakers would be well advised to heed these lessons.

References

Aksoy, C.G., Poutvaara, P., 2019. Refugees' Self-selection into Europe: Who Migrates Where? Technical Report.

Allen, T., Dobbin, C.d.C., Morten, M., 2018. Border Walls. Technical Report. National Bureau of Economic Research.

Arcand, J.L., Mbaye, L., 2013. Braving the waves: the role of time and risk preferences in illegal migration from Senegal. IZA Discussion Papers 7517. Institute for the Study of Labor (IZA).

Battjes, J.A., Groenendijk, H.W., 2000. Wave height distributions on shallow foreshores. Coastal engineering 40, 161–182.

Bazzi, S., Burns, S., Hanson, G., Roberts, B., Whitley, J., 2018. Deterring Illegal Entry: Migrant Sanctions and Recidivism in Border Apprehensions. Technical Report. National Bureau of Economic Research.

Bratti, M., Deiana, C., Havari, E., Mazzarella, G., Meroni, E.C., 2017. What Are You Voting For? Proximity to Refugee Reception Centres and Voting in the 2016 Italian Constitutional Referendum. IZA Discussion Papers 11060. Institute for the Study of Labor (IZA).

Cornelius, W.A., 2001. Death at the border: Efficacy and unintended consequences of us immigration control policy. Population and development review 27, 661–685.

Dee, D.P., Uppala, S., Simmons, A., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M., Balsamo, G., Bauer, d.P., et al., 2011. The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. Quarterly Journal of the royal meteorological society 137, 553–597.

Doleac, J., Mukherjee, A., 2018. The Moral Hazard of Lifesaving Innovations: Naloxone Access, Opioid Abuse, and Crime. IZA Discussion Papers 11489. Institute for the Study of Labor (IZA).

Evans, W.N., Lieber, E.M., Power, P., 2019. How the reformulation of oxycontin ignited the heroin epidemic. Review of Economics and Statistics 101, 1–15.

Feigenberg, B., forthcoming. Fenced out: Why rising migration costs matter. Technical Report.

Friebel, G., Guriev, S., et al., 2012. Human smuggling. IZA Discussion Papers 6350. Institute for the Study of Labor (IZA).

Friebel, G., Manchin, M., Mendola, M., Prarolo, G., 2017. Human Smuggling and Intentions to Migrate: Global Evidence from a Supply Shock along Africa-to-Europe Migration Routes.

Frontex, 2009. Frontex Evaluation Report 2009. Technical Report. European Union.

Frontex, 2010. Frontex Evaluation Report 2010. Technical Report. European Union.

Frontex, 2012. Frontex Evaluation Report 2012. Technical Report. European Union.

Frontex, 2014. Frontex General Report 2014. Technical Report. European Union.

Gamalerio, M., 2018. Not Welcome Anymore: The Effect of Electoral Incentives on the Reception of Refugees. CESifo Working Paper Series 7212. CESifo Group Munich.

Gathmann, C., 2008. Effects of enforcement on illegal markets: Evidence from migrant smuggling along the southwestern border. Journal of Public Economics 92, 1926–1941.

Hanson, G., McIntosh, C., 2016. Is the Mediterranean the new Rio Grande? US and EU immigration pressures in the long run. Journal of Economic Perspectives 30, 57–82.

Kniveton, D.R., Smith, C.D., Black, R., 2012. Emerging migration flows in a changing climate in dryland africa. Nature Climate Change 2, 444.

Mannocchi, F., February 12, 2018. Meeting the libyan smugglers getting rich dealing in migrant lives. TheNewArab .

McAuliffe, M., Ruhs, M., 2017. World migration report 2018. Technical Report. Geneva: International Organization for Migration.

Micallef, M., 2017. The Human Conveyor Belt: trends in human trafficking and smuggling in post-revolution Libya. Technical Report. The global initiative against transnational organized crime.

Ministry of Defence, 2013. Mare Nostrum Operation. Technical Report. Italian Government.

MOAS, 2014. Annual Report MOAS 2014. Technical Report. Migrant Offshore Aid Station.

MOAS, 2015. Annual Report MOAS 2015. Technical Report. Migrant Offshore Aid Station.

MOAS, 2016. Annual Report MOAS 2016. Technical Report. Migrant Offshore Aid Station.

MOAS, 2017. Annual Report MOAS 2017. Technical Report. Migrant Offshore Aid Station.

Orrenius, P., Zavodny, M., 2015. Undocumented immigration and human trafficking, in: Handbook of the economics of international migration. Elsevier. volume 1, pp. 659–716.

Peltzman, S., 1975. The effects of automobile safety regulation. Journal of political Economy 83, 677–725.

Porsia, N., 2015. Smuggling networks in libya, in: Heller, C., Pezzani, L. (Eds.), Death by Rescue – the Lethal Effects of the EU's Policies of Non-Assistance. Forensic Oceanography, London.

Tamura, Y., 2010. Migrant smuggling. Journal of Public Economics 94, 540–548.

UNODC, 2018. Global Study on Smuggling of Migrants 2018. Technical Report. United Nations Office on Drug and Crime.

Winston, C., Maheshri, V., Mannering, F., 2006. An exploration of the offset hypothesis using disaggregate data: The case of airbags and antilock brakes. Journal of Risk and Uncertainty 32, 83–99.

Woodland, A.D., Yoshida, C., 2006. Risk preference, immigration policy and illegal immigration. Journal of Development Economics 81, 500–513.

Appendix: Table and Figures

Table A.1: Wave Height in Libya, Tunisia and Algeria: Crossings, Deaths and Crossing Risk

	(1)	(2)	(3)
	Crossings	Deaths	Crossings Risk
Libya			
Max Wave Tripoli * No Operation	-67.0337**	3.0288	0.1160
	(26.7584)	(2.6249)	(0.0902)
Max Wave Tripoli * Hermes	-51.8115**	-1.2559	0.0021
	(25.2596)	(3.2990)	(0.0445)
Max Wave Tripoli * Hermes Ext	5.3574	0.8191	-0.2543
	(7.6080)	(0.9272)	(0.2629)
Max Wave Tripoli * Mare Nostrum	-116.4626*	1.3282	0.0480
	(61.8803)	(1.1621)	(0.0367)
Max Wave Tripoli * Triton I	-128.9798**	-21.5345	-0.1155
	(54.8963)	(16.5700)	(0.1032)
Max Wave Tripoli * Triton II	-373.1216***	-8.7857	0.0605
	(77.1929)	(6.3895)	(0.0467)
Max Wave Bengazi * No Operation	19.7883	-1.2367	-0.0256
	(23.5885)	(0.7921)	(0.0330)
Max Wave Bengazi * Hermes	73.0291***	0.5464	-0.0452*
	(27.6728)	(3.3992)	(0.0259)
Max Wave Bengazi * Hermes Ext	-6.6175	-0.3451	0.0489
	(4.5539)	(0.4339)	(0.0896)
Max Wave Bengazi * Mare Nostrum	-23.0506	0.3619	-0.0060
	(49.7852)	(0.8808)	(0.0157)
Max Wave Bengazi * Triton I	-94.3467***	2.8536	0.0398
	(32.8576)	(7.1585)	(0.0503)
Max Wave Bengazi * Triton II	41.0232	-1.8818	-0.0149
	(40.3263)	(2.7403)	(0.0296)
Tunisia			
Max Wave Al Huwariyah * No Operation	14.9695	-3.7325	-0.0236
	(19.9139)	(3.5154)	(0.0733)
Max Wave Al Huwariyah * Hermes	-13.8822	-0.3361	0.0332
	(20.8568)	(1.4606)	(0.0337)
Max Wave Al Huwariyah * Hermes Ext	-1.8935	-0.6351	0.1459
	(5.3865)	(0.6028)	(0.1370)
Max Wave Al Huwariyah * Mare Nostrum	4.4023	-4.6305	-0.0626**
	(59.8242)	(2.9744)	(0.0262)
Max Wave Al Huwariyah * Triton I	-31.8680	19.0922	0.0524
	(51.1133)	(13.4917)	(0.0905)
Max Wave Al Huwariyah * Triton II	127.4809***	4.0904	0.0774**
	(42.8920)	(3.0209)	(0.0371)
Algeria			
Max Wave Annaba * No Operation	-40.2799	0.7171	-0.0438
	(25.0427)	(1.0722)	(0.0359)
Max Wave Annaba * Hermes	-31.1082**	-1.4174	-0.0538
	(15.3420)	(1.5742)	(0.0452)
Max Wave Annaba * Hermes Ext	-21.4679**	0.1140	-0.0024
	(8.5363)	(0.2838)	(0.0437)
Max Wave Annaba * Mare Nostrum	-42.1509	2.0454	0.0062
	(48.2929)	(2.1337)	(0.0136)
Max Wave Annaba * Triton I	24.0567	-9.0206	0.0675
	(42.1437)	(8.7411)	(0.0677)
Max Wave Annaba * Triton II	-123.6164***	-3.3210	-0.1072**
	(40.0465)	(2.8207)	(0.0448)
Observations	3,287	3,287	1,521
R-squared	0.0682	0.0121	0.0314
Mean Crossings	170.4411	170.4411	170.4411
Mean Deaths	3.6240	3.6240	3.6240
Mean Crossing Risk	0.0471	0.0471	0.0471
Wave Tripoli	0.8205	0.8205	0.8205
Wave Bengazi	0.9174	0.9174	0.9174
Wave Al Huwariyah	1.0780	1.0780	1.0780
Wave Annaba	1.0373	1.0373	1.0373ì
R-squared	0.0682	0.0121	0.0314
Wee-Year FE	X	X	X

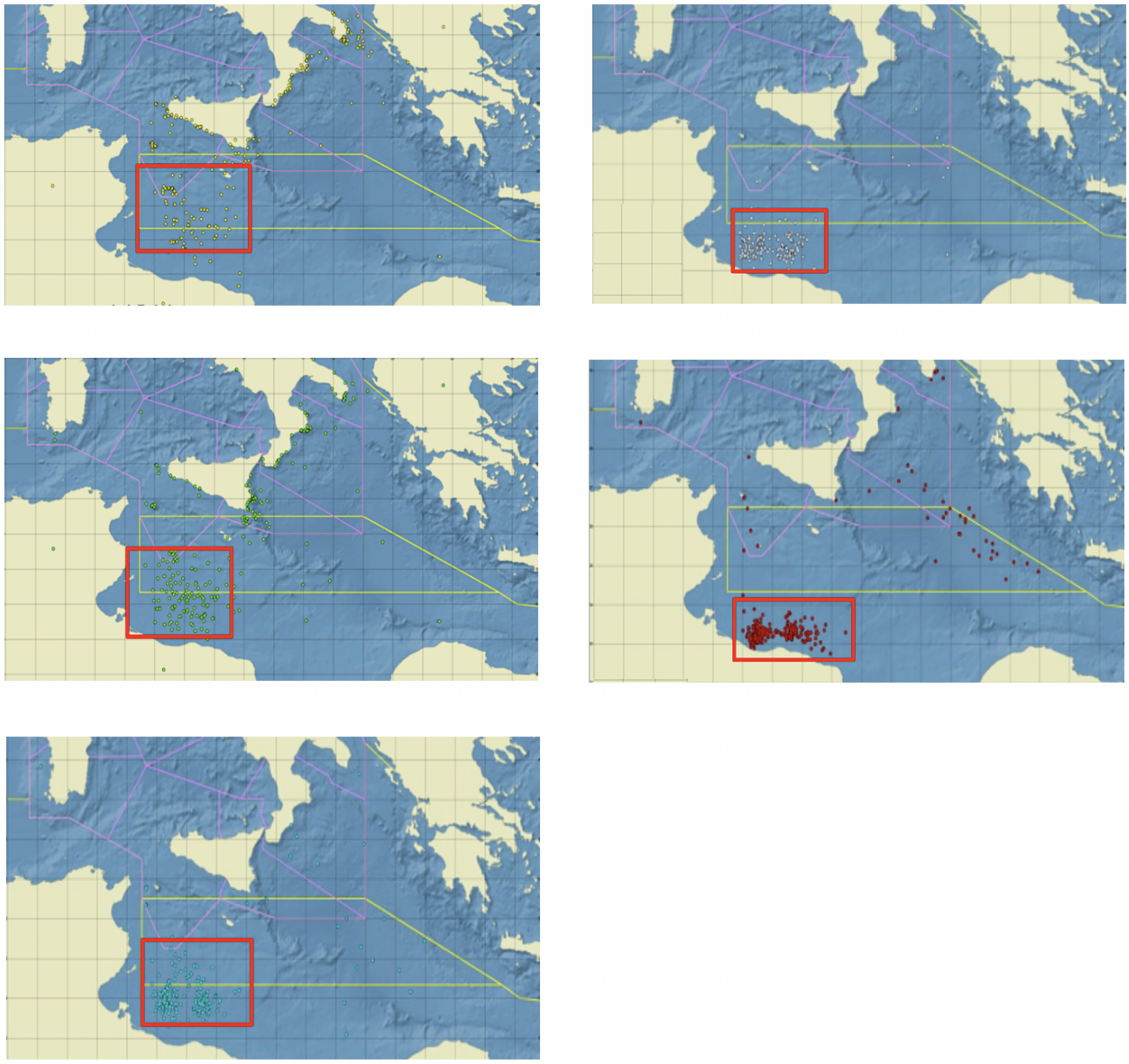
Note: We include dummy for Hermes, Hermes Ext, Mare Nostrum, Triton I and II Operations while the baseline dummy is No Operation period. Max Wave variable takes the maximum between Wave value at time t, t-1 and t-2. Crossing Risk is defined as $R_t^{0,0}$.
* p<.10 ** p<.05 *** p<.01.

Table A.2: Robustness: Different Types of Crossing Risk

	(1) CR Type 3A	(2) CR Type 4A	(3) CR Type 3B	(4) CR Type 4B
Max Wave Tripoli * No Operation	0.0998**	0.1170**	0.0157	0.0325
	(0.0410)	(0.0572)	(0.0143)	(0.0438)
Max Wave Tripoli * Hermes	-0.0332	0.0006	-0.0147	-0.0001
	(0.0236)	(0.0238)	(0.0136)	(0.0148)
Max Wave Tripoli * Hermes Ext	0.0123	0.0833	-0.0528	-0.0101
	(0.0962)	(0.1155)	(0.0625)	(0.0741)
Max Wave Tripoli * Mare Nostrum	0.0573	0.0461	0.0398	0.0284
	(0.0537)	(0.0395)	(0.0357)	(0.0246)
Max Wave Tripoli * Triton I	-0.0334	0.0210	-0.0182	0.0036
	(0.0449)	(0.0691)	(0.0327)	(0.0374)
Max Wave Tripoli * Triton II	0.1220***	0.1546***	0.0617**	0.0929***
	(0.0367)	(0.0380)	(0.0265)	(0.0313)
Observations	2,065	2,099	2,325	2,347
R-squared	0.0266	0.0341	0.0175	0.0246
Week-Year FE	X	X	X	

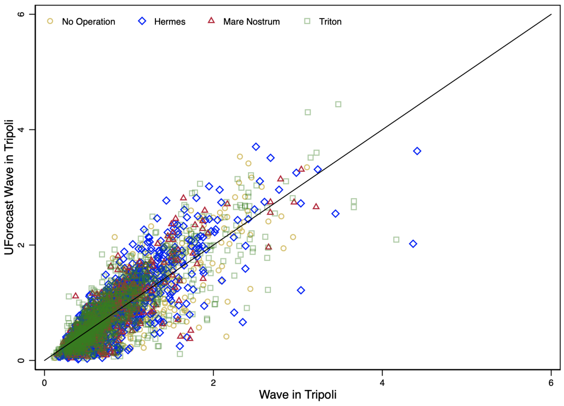
Note: We include dummy for Hermes, Hermes Ext, Mare Nostrum, Triton I and II Operations while the baseline dummy is No Operation period. Max Wave variable takes the maximum between Wave value at time t, t-1 and t-2. Crossing Risk 3A is defined as $R_t^{1,3}$, Crossing Risk 4A is defined as $R_t^{1,4}$, Crossing Risk 3B is defined as $R_t^{2,3}$ and Crossing Risk 4B is defined as $R_t^{2,4}$.
* p<.10 ** p<.05 *** p<.01.

Figure A.1: SAR Operations 2012-2016



Note: Area of higher concentration of SAR in red square. Purple and Yellow lines are the Italian and Maltese SAR areas, respectively.
2012 (Upper-Left Panel): outside Italian territorial waters (south of Lampedusa island);
2013 (Medium-Left Panel): between Maltese and Libyan territorial waters;
2014 (Bottom-Left Panel): outside Libyan territorial waters;
2015 (Upper-Right Panel): few miles outside Libyan territorial waters;
2016 (Medium-Left Panel): near the outer limits of Libyan territorial waters.
Source: Italian maritime rescue coordination centre, 2016.

Figure A.2: Unbiased (left) and Biased (right) Forecasts of Waves



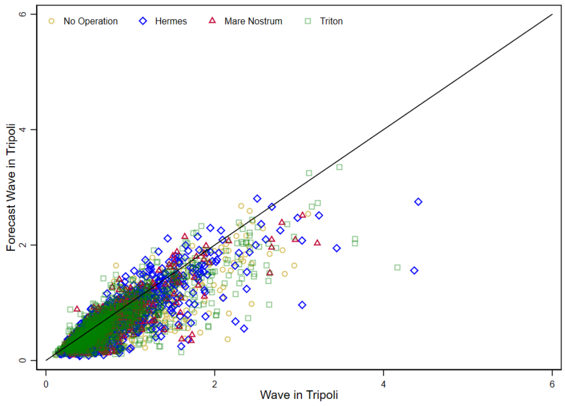


Figure A.3: Crossings, Waves and EU Operations

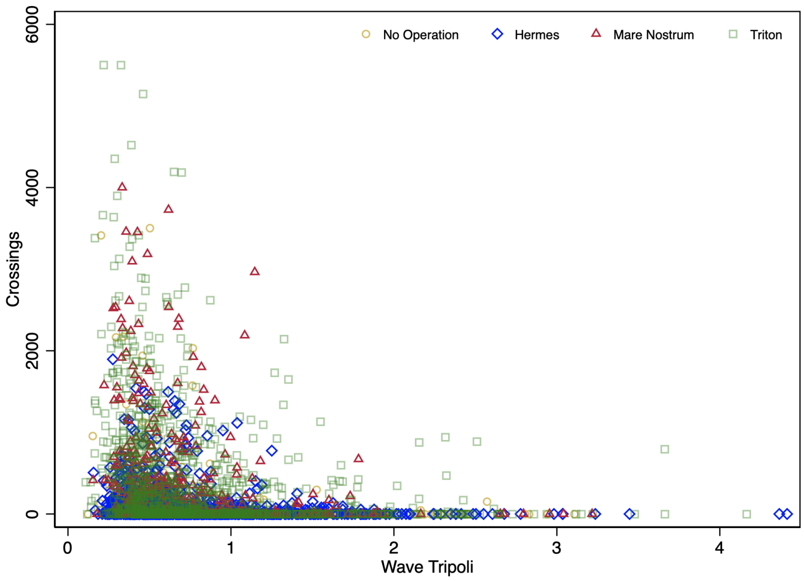
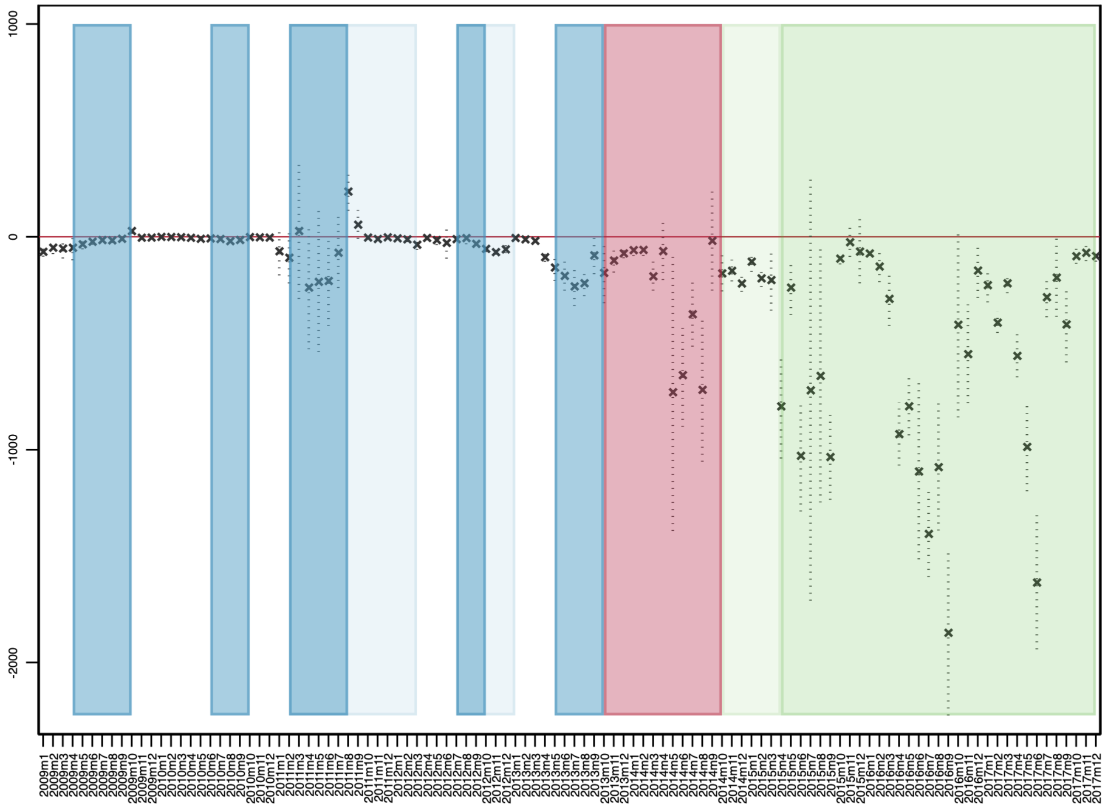
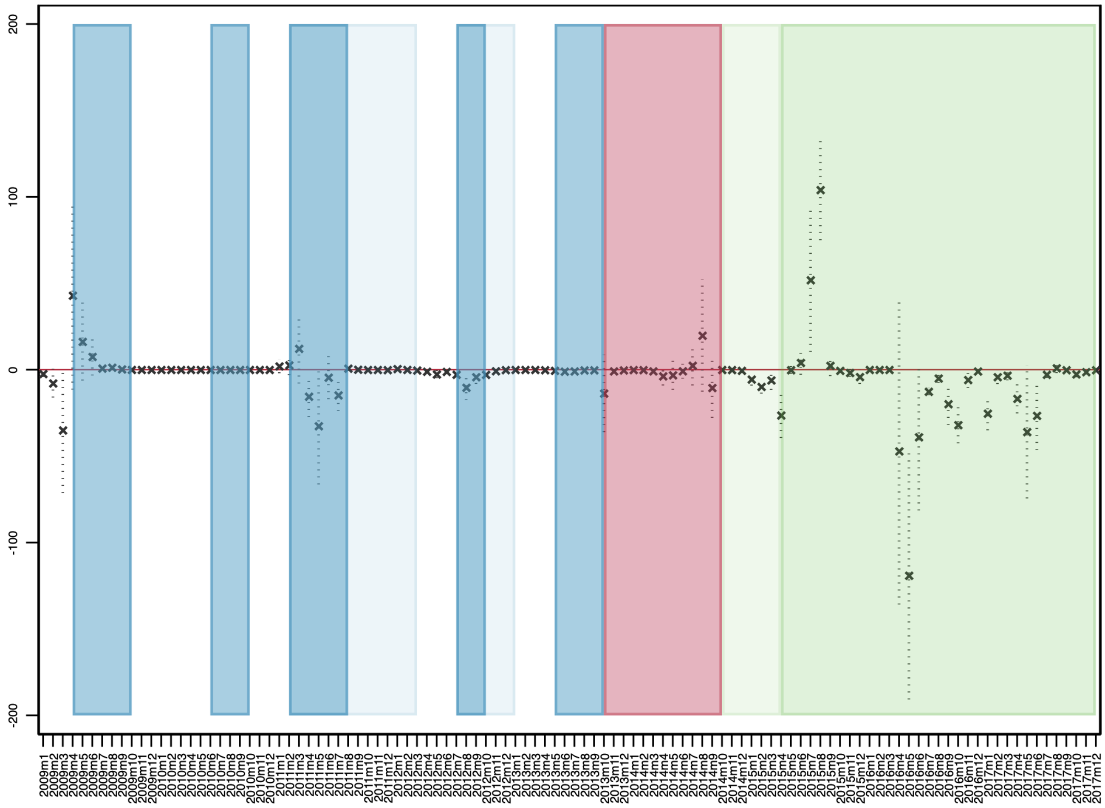


Figure A.4: Crossings and Max Wave Conditions



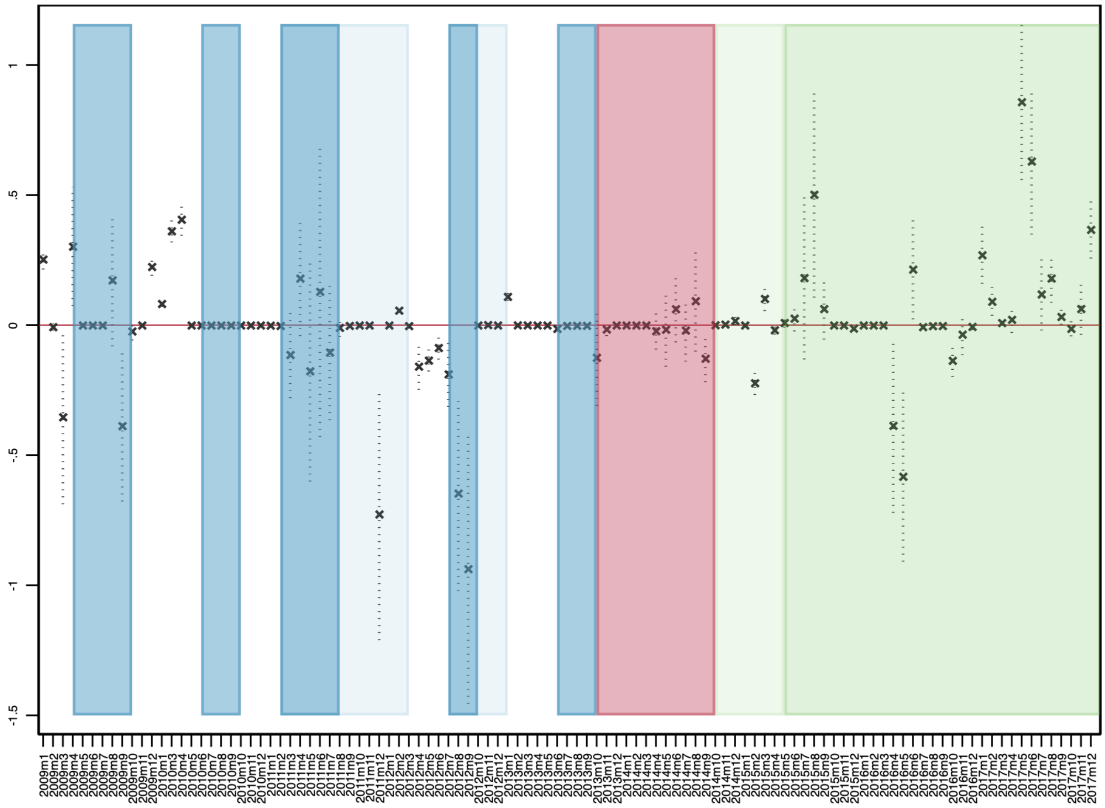
Note: Each "X" corresponds to an estimate of β_m, along with 95% confidence intervals (i.e., the responsiveness of crossings to weather conditions). The dark and light blues, the red and the green shaded backgrounds indicate when Hermes and its Extension, Mare Nostrum and Triton were operating, respectively. Year×Week fixed effects included.

Figure A.5: Deaths and Max Wave Conditions



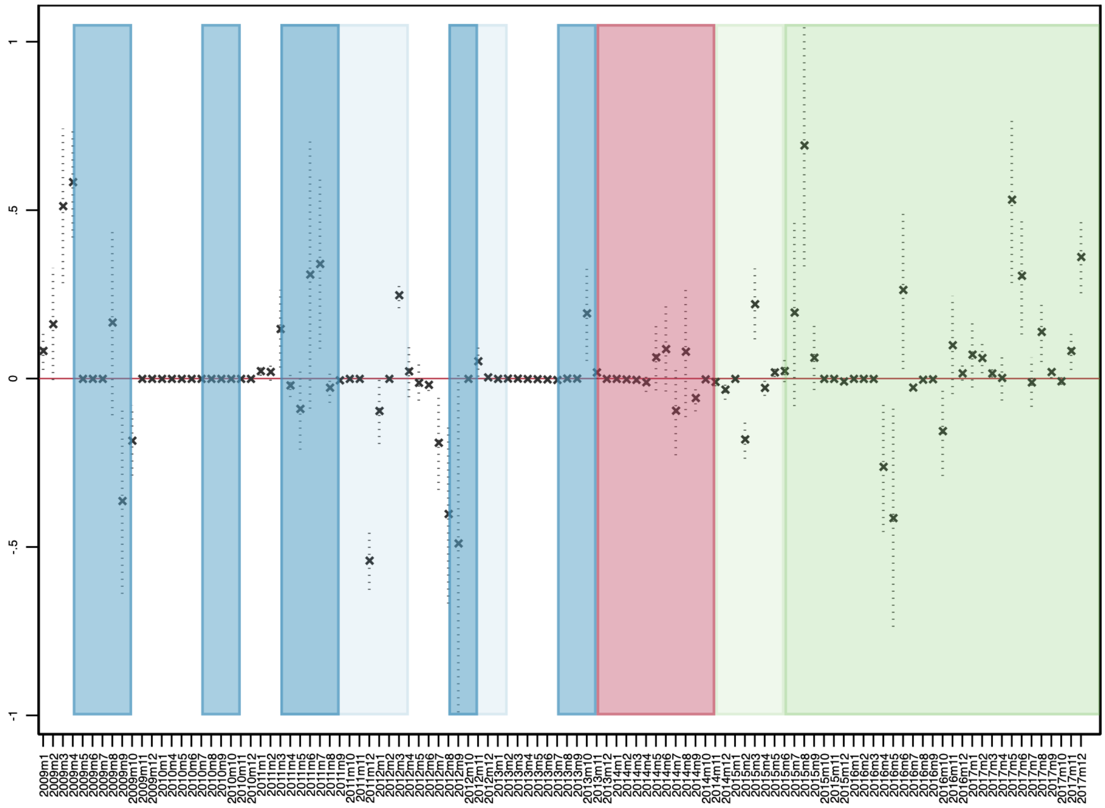
Note: Each "X" corresponds to an estimate of β_m, along with 95% confidence intervals (i.e., the responsiveness of crossings to weather conditions). The dark and light blues, the red and the green shaded backgrounds indicate when Hermes and its Extension, Mare Nostrum and Triton were operating, respectively. Year$\times$Week fixed effects included.

Figure A.6: Crossing Risk and Max Wave Conditions



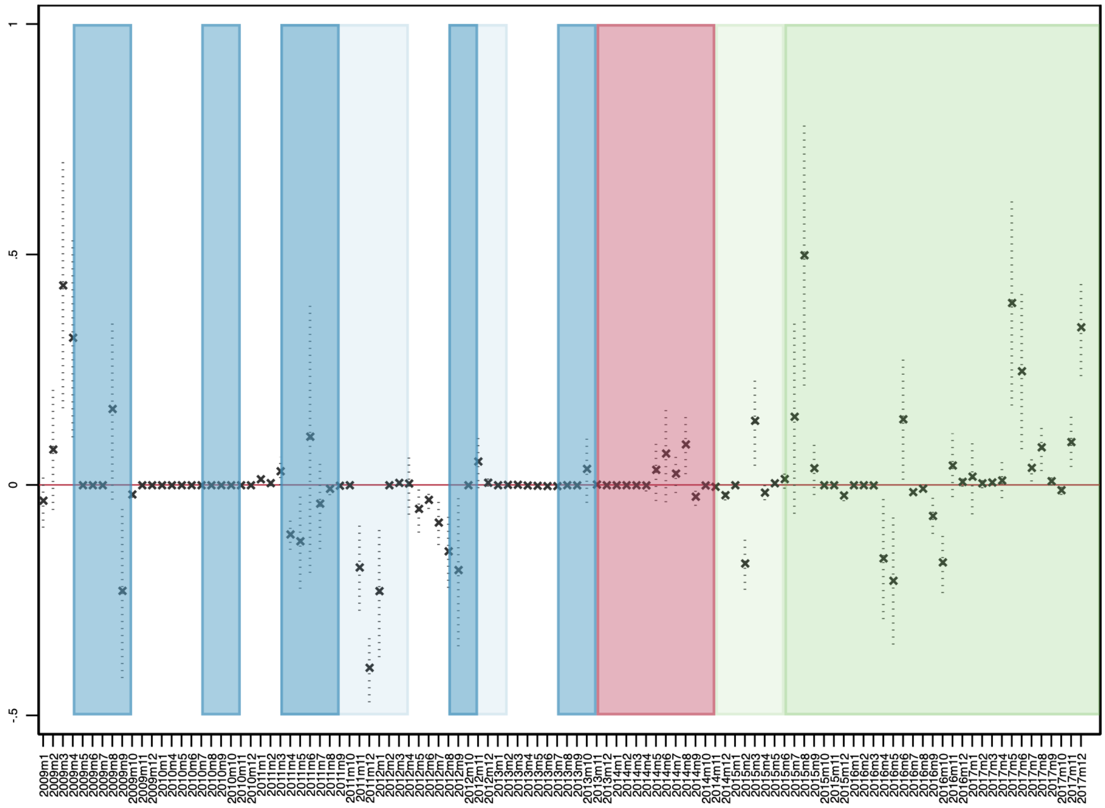
Note: Each "X" corresponds to an estimate of β_m, along with 95% confidence intervals (i.e., the responsiveness of crossings to weather conditions). The dark and light blues, the red and the green shaded backgrounds indicate when Hermes and its Extension, Mare Nostrum and Triton were operating, respectively. Year×Week fixed effects included.

Figure A.7: Crossing Risk Type 2A and Wave Conditions



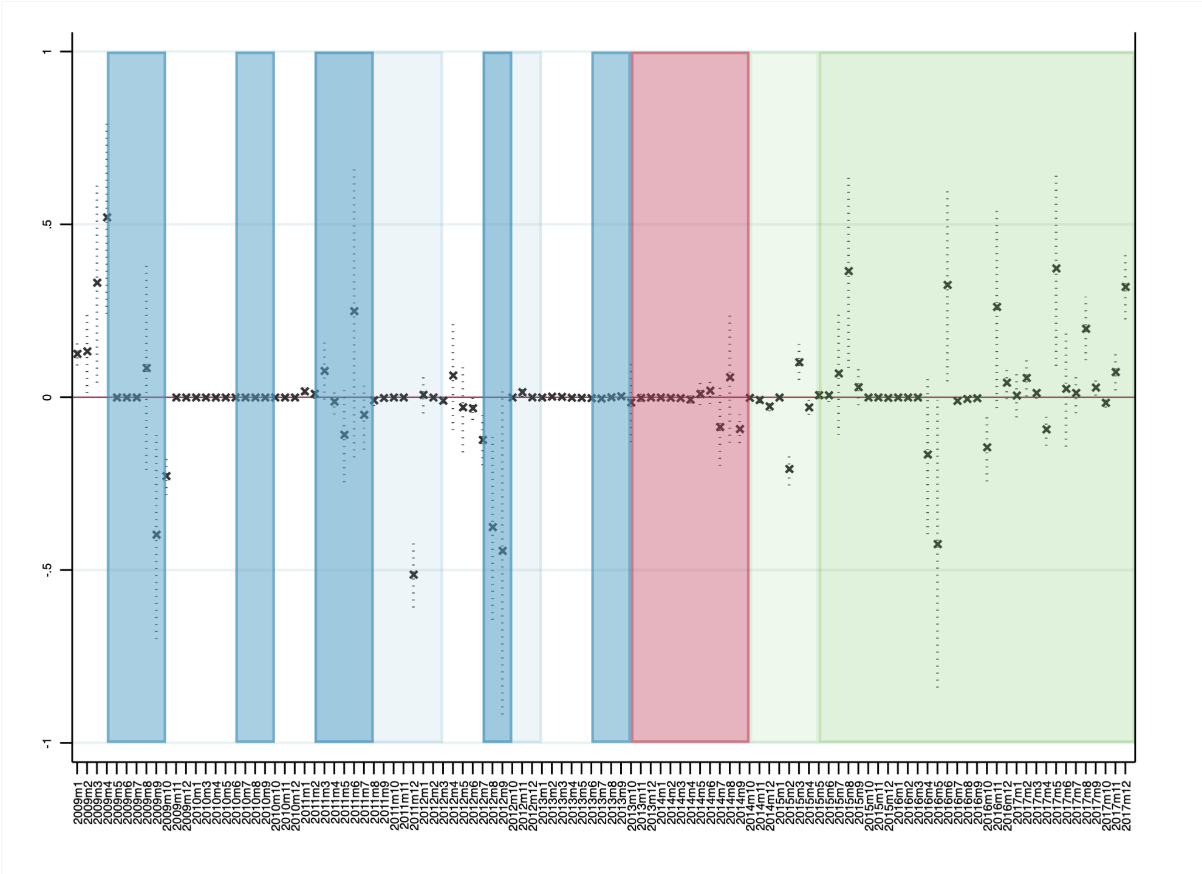
Note: Each "X" corresponds to an estimate of β_m, along with 95% confidence intervals (i.e., the responsiveness of crossings to weather conditions). The dark and light blues, the red and the green shaded backgrounds indicate when Hermes and its Extension, Mare Nostrum and Triton were operating, respectively. Year×Week fixed effects included.

Figure A.8: Crossing Risk Type 2B and Wave Conditions



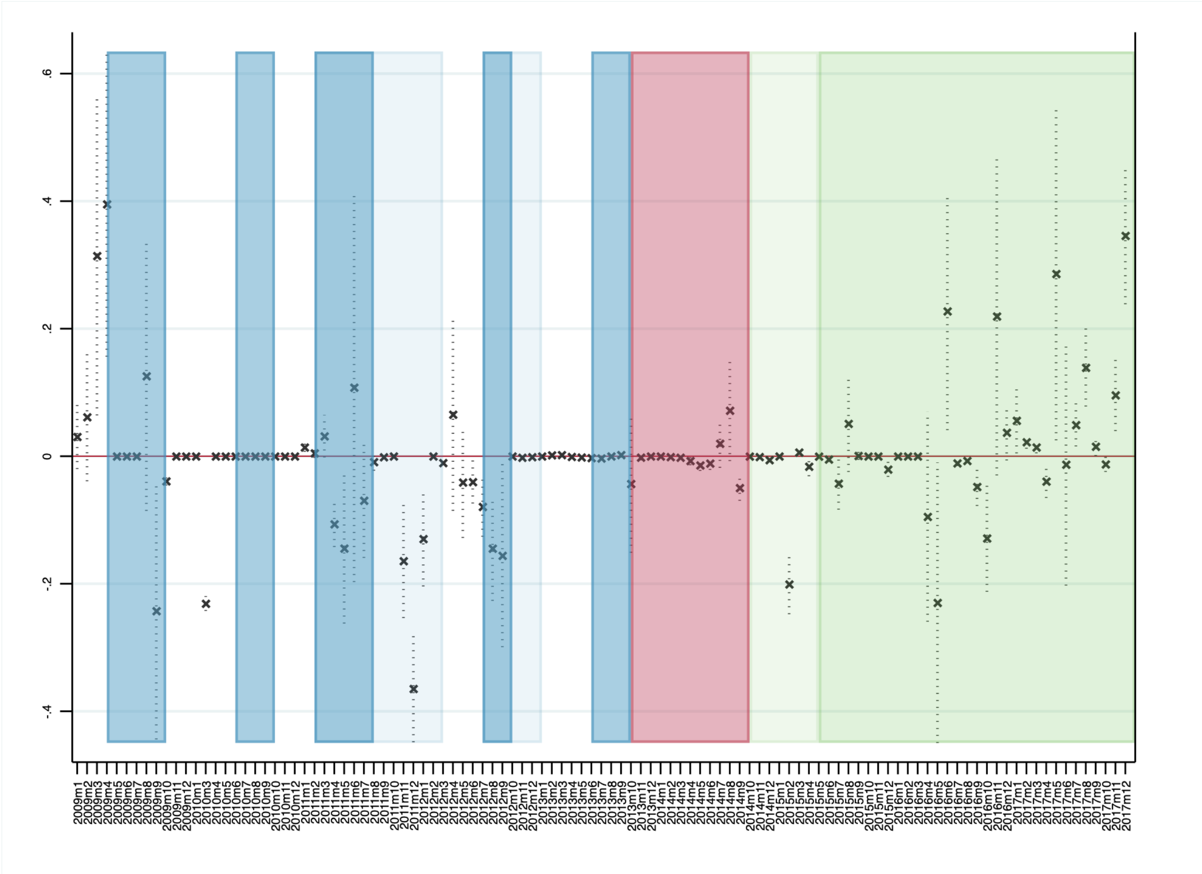
Note: Each “X” corresponds to an estimate of β_m, along with 95% confidence intervals (i.e., the responsiveness of crossings to weather conditions). The dark and light blues, the red and the green shaded backgrounds indicate when Hermes and its Extension, Mare Nostrum and Triton were operating, respectively. Year×Week fixed effects included.

Figure A.9: Crossing Risk Type 1A and Wave Conditions



Note: Each "X" corresponds to an estimate of ω_m, along with 95% confidence intervals (i.e., the responsiveness of crossings to weather conditions). The dark and light blues, the red and the green shaded backgrounds indicate when Hermes and its Extension, Mare Nostrum and Triton were operating, respectively. Year×Week fixed effects included.

Figure A.10: Crossing Risk Type 1B and Wave Conditions



Note: Each "X" corresponds to an estimate of ω_m, along with 95% confidence intervals (i.e., the responsiveness of crossings to weather conditions). The dark and light blues, the red and the green shaded backgrounds indicate when Hermes and its Extension, Mare Nostrum and Triton were operating, respectively. Year$\times$Week fixed effects included.

Appendix: Additional Tables and Figures

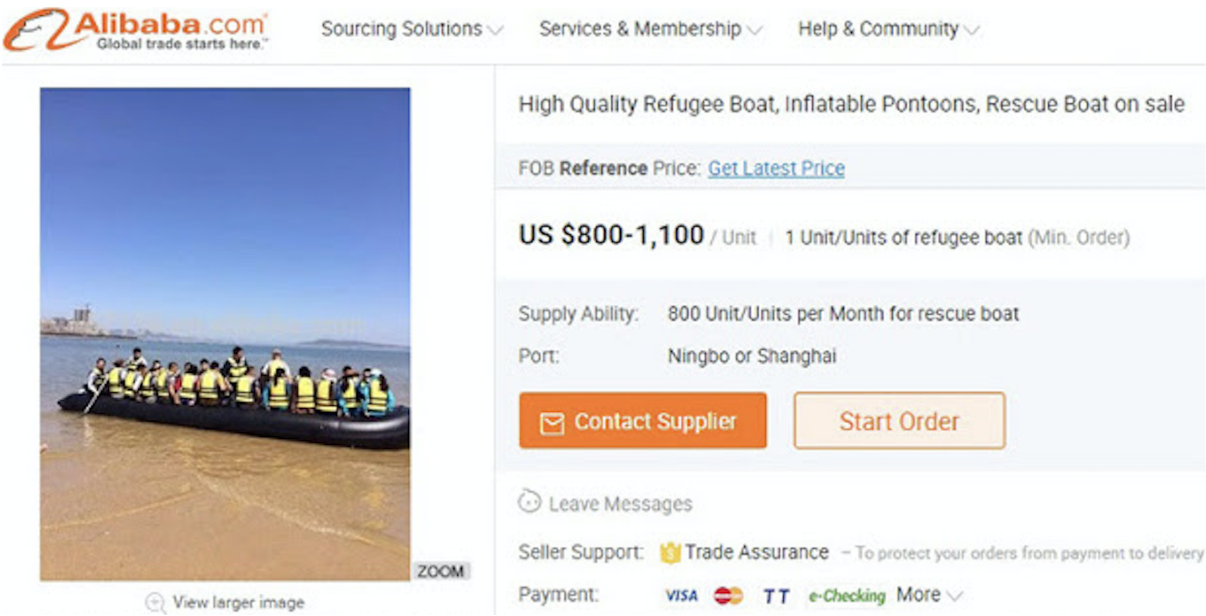
Table B.1: Wave and Swell Explanations

Wave: Description	Height (metres)	Effect
Calm (rippled)	0.00 - 0.10	No waves breaking
Smooth	0.10 - 0.50	Slight waves breaking
Slight	0.50 - 1.25	Waves rock buoys and small craft
Moderate	1.25 - 2.50	Sea becoming furrowed
Rough	2.50 - 4.00	Sea deeply furrowed
Very rough	4.00 - 6.00	Sea much disturbed with rollers
High	6.00 - 9.00	Sea disturbed with damage to foreshore
Very high	9.00 - 14.00	Towering seas
Phenomenal	>14	Precipitous seas (only in cyclones)

Swell: Description	Wave Length (metres)	Wave Height (metres)
Low swell of short or average length	0 - 200	0 - 2
Long, low swell	over 200	0 - 2
Short swell of moderate height	0 - 100	2 - 4
Average swell of moderate height	100 - 200	2 - 4
Long swell of moderate height	over 200	2 - 4
Short heavy swell	0 - 100	over 4
Average length heavy swell	100 - 200	over 4
Long heavy swell	over 200	over 4

Note: The Bureau of Meteorology. See `http://www.bom.gov.au/marine/knowledge-centre/reference/waves.shtml`

Figure B.1: Alibaba Web Site



Note: Source: `https://www.alibaba.com`.