The Economic and Environmental Impact of Modern Piracy on Global Shipping*

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Abstract

Maritime transport has been historically susceptible to piracy. Rough assessments of the impact of modern piracy point to significant losses per year, with most encounters taking place in some of the most important shipping routes globally. In this paper, we unify the sparse theoretical literature with data available for both shipping voyages and pirate encounters to credibly assess the effect of piracy on the shipping industry. We explore theoretical insights to account for strategic behavior based on observed pirate encounters, then compile and analyze a unique geospatial dataset to test those insights. The dataset includes high spatial and temporal resolution information on pirate encounters, individual vessel tracks, and weather at sea. Our results establish the response of the shipping industry to pirate encounters, showing how the reported presence of pirates along a given route increases both the individual and aggregate cost of transportation, as well as its environmental impact, with major implications for the shipping industry at a global scale.

JEL Classification: D20; D80; F14; H41; H87; K33; K42; L20; L90; R40

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1 Introduction

During the late 2000's, and after a sharp increase in the number of encounters and the degree of violence exerted by pirates off the coast of Somalia, piracy became a topic of public concern worldwide. Despite this concern, however, only limited efforts have been devoted to assess the economic angles of this problem. In this paper, we contribute by proposing guidelines of analysis and providing empirical evidence of the connection between pirate encounters, shippers' behavior, and the costd associated with this relationship. We show that pirate encounters cause ships to increase individual distances travelled with an associated increase in fuel consumption and labor requirements, but more importantly, that these marginal adjustments lead to a significant increase in the cost of transportation of globally traded goods along the affected routes. In addition, these adjustments also carry an increased environmental impact in the form of greenhouse emissions and local airborne pollutants.

As pointed out by Adam Smith in his foundational work The Wealth of Nations: "*Coastal areas, and cities on rivers have been the fastest to develop, as their goods can be very cheaply transported across water versus land.*" This statement holds true today. Most metropolitan areas worldwide are located adjacent to rivers or ports, and maritime transportation remains as one of the most efficient methods for international commerce (Fujita, Krugman, and Venables 2001). In fact, more than 80 percent of global trade by volume and more than 70 percent of its value is carried through the oceans (Asariotis et al. 2017). This industry, however, has been and remains susceptible to criminal intervention in the form of piracy.

Historically coinciding with the earliest records of trade, the transportation of goods and the difficulty of enforcement has always offered an opportunity for pirates to predate on commerce routes (Gosse 2012). Maritime commerce routes are particularly susceptible because they offer unique opportunities for ambush and escape. In addition, they often suffer from the lack of clear jurisdictions, which in turn complicates prosecution, or even capture in most cases.[1] But de-

[1] Historians point out that piracy often follows a well defined cycle that usually involves a group of individuals from impoverished coastal areas that would band to perform predation of small-scale poorly enforced shipments.

spite their past reputation and folklore, pirates remain a relevant problem. Official global records point to almost 2,000 pirate encounters between 2012 and 2017, with 351 taking place in 2017 alone. Most of these encounters concentrate in some the busiest trade channels such as the Gulf of Aden, the Gulf of Guinea, and the Malacca Straits, and their usual business model is to hijack vessels for robbery or capture-to-ransom (Hallwood and Miceli 2013). Past efforts to quantify the cost of this problem suggest annual losses in trade volume amount to over $20 billion/year (Burlando, Cristea, and Lee 2015; Bensassi and Martínez-Zarzoso 2012). None of these studies, however, has documented the causal links behind these costs.

In this paper, we merge theoretical insights with data available for both shipping voyages and pirate encounters to credibly assess the causal effect of piracy on the shipping industry. To achieve this goal, we formalize the decision making process of captains based on warning reports, and compile a unique geospatial dataset to test those insights. The dataset includes high spatial and temporal resolution information on pirate encounters from the US National Geospatial Intelligence Agency, as well as individual vessel tracks of all known cargo, tanker, and refrigerated vessels that use the AIS vessel monitoring system. Our empirical results show that a pirate encounter in the past year along a given country-to-country shipping route can result in an average of 19 to 53 additional kilometers traveled by vessels transiting along that route, in attempted avoidance. For areas with high pirate activity, such as the Gulf of Guinea, these estimates point to a lower bound of each vessel having to travel more than 900 km in addition to the regular route distance. When aggregated at the industry level, these adjustments can increase the total cost of transportation by more than nine billion dollars a year as of 2017, due to the increased cost in fuel and labor. Within the shipping industry context, these losses amount to about ten percent of the entire total revenue of Maersk, the biggest company in the industry.[2] Our esti-

These groups would then transition to a state of adjustment, where "competition" dictates their profitability and which of them get to remain in the piracy business (Anderson 1995; Gosse 2012). Most of these observations are based on pirates from previous centuries, but the resemblance with modern pirates is evident. At least for the initial phase of the problem. See Bahadur (2011) and Bueger (2013) for a detailed account of the cycle and organizational mechanisms in the case of the pirates of Somalia, which resembles very closely the documented paths for earlier pirates.

[2]Assuming a revenue level of 30.1 billion, as indicated by the 2018 report to investors of the company. The document is available at: `https://www.maersk.com/press/press-release-archive/`

mates also highlight an undocumented welfare loss in terms of global fuel consumption, as well as the added emissions of both greenhouse gasses and local pollutants.

Our results provide important insights that were previously absent in the literature. First, the piracy problem remains prevalent and of high importance at a global scale. This prevalence not only affects the standard cost-effective composition of regional shipping routes, but it also encourages avoidance behavior by ship captains that translate into an increase in the cost of each individual voyage. Second, because of the volume of voyages associated with the shipping industry, these individual burdens contribute to an overall increase in the cost of transportation, which could have implications for trade flows, and in consequence, welfare effects beyond those directly associated with extra fuel consumption. Third, these results also highlight the value of enforcement and anti-piracy measures for piracy-prone areas. In many cases, a substantial increase in enforcement spending would cost only a fraction of the total value currently lost due to piracy.[3] Consequently, as piracy itself does not capture all of this lost value, our results point to clear win-win scenarios in which the benefits gained from not having to avoid pirates could simultaneously accrue to the shipping industry and help tackle the roots of the piracy problem.

2 Background

2.1 Piracy and trade

Maritime piracy can be defined as the taking of property and persons with violence on or by the sea (Anderson 1995). Unlike its historical predecessors, however, modern piracy is fundamentally a problem of enforcement that could be traced to the poor definition of property rights, and duties, over maritime territory. This type of misalignment is especially acute in international scenarios, where the establishment and enforcement of anti-pirate regulations usually conflicts with sovereign rights (Rubin 1988). These institutional settings reduce the probability of pirates being prosecuted, or even apprehended, which in equilibrium encourages a continued predation of sea

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[3] According to Sonnenberg (2012), a cost-effective deployment of a defense task costs about $241 million/year.

commerce.

From a welfare perspective, Anderson (1995) suggests several types of losses associated with piracy. First, the direct capital losses to violence, which manifest either in the form of damages to the ship or cargo, or as the loss of life. Second, the indirect losses in the form of resources channeled toward evasion and protection that could have been used for other productive activities. For example, the additional bulk of fuel used to maintain evasive maneuvers, or the additional amount of capital required to sustain a steady flow of goods *vis-á-vis* the same exchanges in the absence of piracy. It follows that the magnitude of these responses can lead to both intensive and extensive margin adjustments, which in turn can cause dynamic losses in the form of diminished incentives for producers and merchants to continue with or expand production (Anderson 1995). As pirates rarely capture the entire value of their highjacks (Blanc 2013), any of these effects leads to an effective loss in welfare.

In practice, the realization of these losses has been shown to be harmful for the economy. Historical data suggest that responses to piracy have often been followed by extremely negative impacts to commerce channels and local economies. For example, during the seventeenth century, the "Turkish pirates" completely paralyzed several parts of west England (Gray 1989). During the same period, the predominance of pirate organizations in the Arabian sea also led to severe decreases in trade flow, with devastating consequences for all industries in the region (Scammell 1992). These two cases, however, are not unique. Similar links have been documented for other trade regions in the Caribbean (Andrews 1978), the Philippines (Warren 2007), and Venice (Tenenti 1967). All of these examples illustrate how thriving economies suffer considerable negative effects due to piracy.

Modern piracy has had similar effects. In fact, piracy remains a problem worldwide. According to official reports, between 2011 and 2017, there were an estimated 2,000 pirate and anti-shipping encounters globally, with 351 taking place in 2017 alone.[4] Most encounters, however, take place in a few hotspots; namely: the Gulf of Aden (known for the Somali pirates), the Gulf of Guinea

[4]As reported by the United States National Geospatial Intelligence Agency.

(mostly within the Nigerian EEZ), the Malacca Straits (the shipping channel formed by Sumatra and the Malay peninsula) and the South China sea. For the remainder of the paper we will refer to both the Malacca Straits and the South China sea as one group that we call South East Asia. How the actual number of encounters is distributed over time is shown in Figure 1 (See also Figure 3 for a geographical depiction). From this figure, note that pirate encounters are consistently concentrated in the African region and South East Asia.

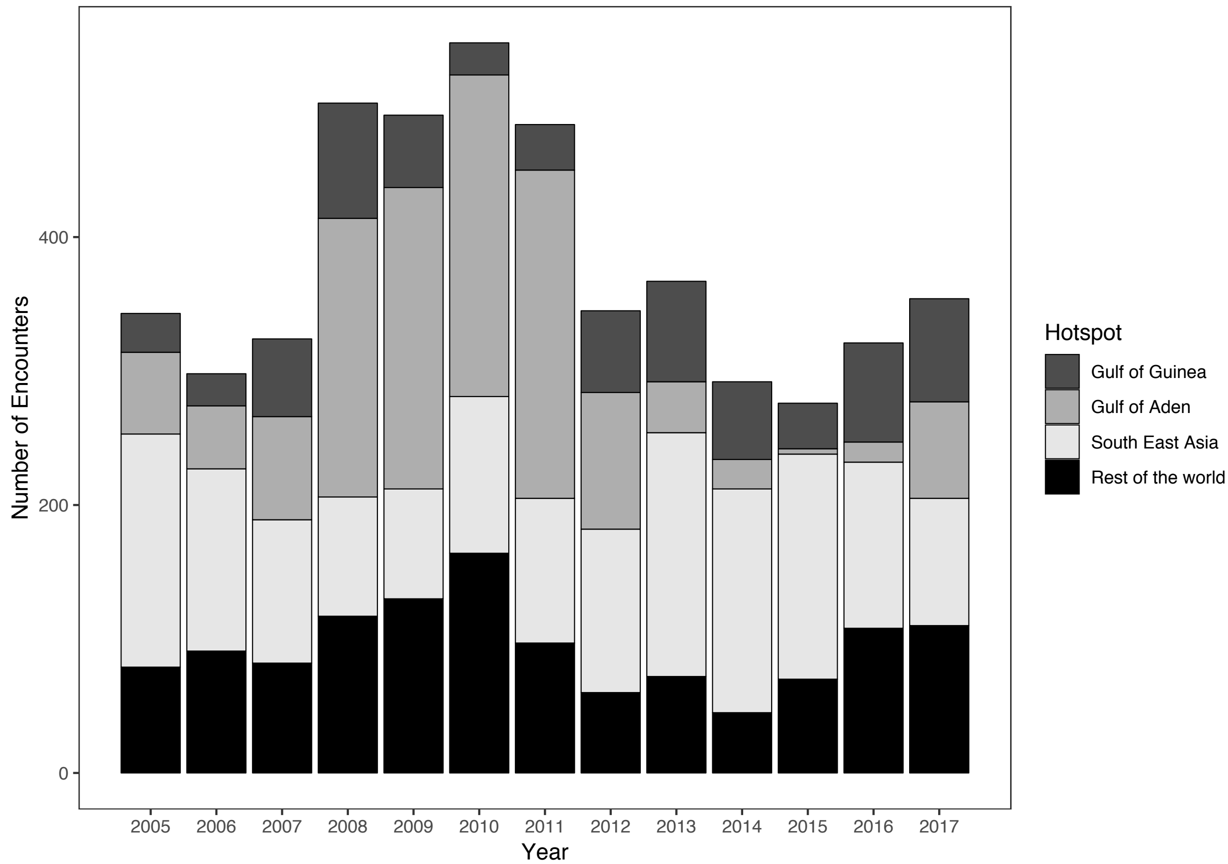

Figure 1: Distribution of encounters across hotspots from 2012 to 2017.

Although sparse, there are several assessments regarding the economic impact of modern piracy. Past estimates suggest that the losses in trade volume due to pirate activities in Somalia accrue to about $24 billion/year (Burlando, Cristea, and Lee 2015). Other estimates are more conservative and suggest that the loss ranged between $1 billion and $16 billion, when accounting for the addition of 20 days per voyage due to re-routing around Africa, and increased insurance, charter rates, and inventory costs (Wright 2008; Bowden et al. 2010; O'Connell and Descovich 2010).[5] In another study, Bensassi and Martínez-Zarzoso (2012) study the aggregated effect of piracy in both the Gulf of Aden and the Strait of Malacca, estimating that 10 additional hijacks in either region reduce the volume of exports between Asia and Europe by about 11% with an estimated cost of about $25 billion per year. These previous studies have estimated losses through the examination of overall trade patterns, but to the best of our knowledge, there is no study focused on the behavior of individual shipping vessels. We believe the latter is a more direct way to disentangle the cost of piracy.[6] It is plausible that the gap in the literature regarding the effect of piracy on shipping patterns is due to the difficulty of obtaining data on individual shipping voyages, but also because of the sparse data on pirate activities. Both of these issues are accounted for in this paper.

On the other hand, theoretical insights regarding the piracy problem can be traced to two papers. Namely, Guha and Guha (2011), who model optimal patrolling and penalties under the option of self insurance, and Hallwood and Miceli (2013), who also explore optimal patrolling and penalties taking into account strategic interactions between pirates and shippers. Although very valuable contributions in terms of formalizing the theory behind pirate behavior, neither paper explored vessel adjustments along shipping routes as they focus on penalties and enforcement.

Other related literature has devoted efforts to several topics on both past and modern piracy. One of those topics relate to anti-piracy efforts. Anderson (1995) documents the historical evolution of state and individual actions to control for piracy along shipping routes. Similarly, Liss (2007) describes how modern piracy incentivizes shippers to employ private military companies or acquire their own defense mechanisms. Other empirical settings, such as the ones presented by Flückiger and Ludwig (2015) and Axbard (2016), study how poor fishing conditions lead to an

[5] These estimates, however, seem to be somewhat contested across different reports. For example, Bahadur (2011) documents that according Lloyd's of London (one of the main insurance companies for maritime transport), most shippers would rather risk hijacking in the Gulf of Aden instead of going around the Cape of Good Hope. This behavior is argued to be a result of the overall low unconditional probability of being a victim of a hijack.

[6] Some comprehensive statistics for the state of global piracy are regularly provided by the non-profit organization Oceans Beyond Piracy. Their work is publicly available at: `http://oceansbeyondpiracy.org/obp-reports`

increase in pirate activity in Africa and Indonesia, respectively.

Finally, another branch of the literature focuses on the institutional settings of pirate organizations. In particular, Leeson (2007) and Psarros et al. (2011) study the factors that contribute to pirates being more or less effective in terms of finding vessels, as well as extracting the most value of these encounters. In addition and specific to the Somali case, O'Connell and Descovich (2010) and Bahadur (2011) document the social and economic institutions associated with pirate activities by identifying ransom procedures, operational supply chains, and community support. In the next section, we provide a summary of how pirate activities -or at least how they have been documented- take place worldwide.

2.2 The business model of modern piracy

Establishing the operational details of pirates is a difficult task. The first and most evident limitation, is that pirates are a criminal organization with little or no incentive to make the details of their operations known to authorities. But despite these uncertainties, there are still a few credible sources that allow us to establish the mechanics behind pirate encounters, and more importantly, use them as a means for identification in the empirical section. In particular, we make use of the work by Bahadur (2011), in which he interviews a number of individuals who claimed to be associated, directly or indirectly, with pirates in Somalia in 2009.[7] Considering the sensitivity of the piracy issue, his accounts provide the best available information on the actual behavior and incentive of pirates.

According to these interviews, pirates in Somalia do not discriminate between vessels, but rather opportunistically hijack vulnerable vessels that cross their path. Once the potential target is identified, pirates pursue the vessel until eventually capturing it, or the vessel is realistically out of reach. Both the search and the pursuit are not constrained by the jurisdictional boundaries of Somalia. The boarding strategy entails the pirate crew splitting into several skiffs, which ap-

[7]A potential concern about this approach is the reliability of these testimonies. Unfortunately, we are not able to formally test for this problem, but all of the interviews and documentation in Bahadur (2011) are consistent with one another.

proach the target vessel from all sides while waving and firing their weapons to scare the ship's crew. If the vessel stops, or the skiffs are able to keep up with it, the pirates would toss rope ladders onto the deck and then proceed to boarding. According to these accounts, crews rarely resist boarding once the pirates successfully get on the deck. The average reported success rate of the pirates was about 20 to 30 percent (Bahadur 2011b).

Once the pirates successfully take control of the ship, they steer the vessel to a friendly port. At this location, an additional set of guards and translators would board the ship, and ransom negotiations will start. Most ransoms would be handled by insurance companies. Upon reaching an agreement, the money is usually delivered via parachute drop-off onto the deck of the ship, and then split amongst the pirates. The amount that each of them would receive is a fixed fraction of the total ransom, and it would vary depending on the task (Bahadur 2011b).[8]

Although 2017 saw a spike in pirate activities in the Gulf of Aden, this region seems to be no longer affected at same scale.[9] According to the latest reports on encounters by the US government (Figure 1) and the International Maritime Bureau of the International Chamber of Commerce (ICC-IMB), most encounters are now reported to take place in the Gulf of Guinea and South East Asia (ICC-IMB 2018). The business model of piracy in these regions, however, can be sometimes different from the hijacking strategy followed by the Somali pirates.

According to the ICC-IMB, pirates in the Gulf of Guinea follow a similar approach when it comes to intercepting a vessel. The difference comes after they have successfully hijacked the ship. Besides hijacking the vessel and its crew, these pirates have also focused on kidnaping only a subset of crew members for ransom (ICC-IMB 2018). Another regular practice in this region, is the robbery of cargo, especially liquid fuel.[10]

[8]According to the interviews in Bahadur (2011), half of the pot would go to the actual men boarding the ship, one third to the investors financing the operation, and a sixth to everyone else assisting with logistics and enforcement.

[9]See *Piracy threat returns to African waters* by CNN, available at: `https://www.cnn.com/2017/05/25/africa/piracy-resurgence-somalia/index.html`

[10]See *Abduction of Crew Off Nigeria Brings Piracy Back to Indian Agenda* by The Wire, available at: `https://thewire.in/diplomacy/abduction-of-indian-merchant-navy-crew-off-nigerias-coast-throws-up-new-challenges-for-india`

Pirate encounters in South East Asia seem to follow a variation of the previous business model. It is important to note that this region is currently one of the most active in terms of encounters, and it is also one that has suffered from this problem since the sixteenth century (Anderson 1995). According to recent reports, and in addition to the practices listed above, encounters include large-scale and sophisticated operations targeted at siphoning fuel from tanker vessels.[11] In this type of attack, vessels are also approached and hijacked, but then they are steered towards a siphoning facility on the shore that retrieves the entire cargo. Under this model, the crew and the ship are usually freed several days after a successful attack (ICC-IMB 2018).

Finally, pirate encounters have also increased in the Caribbean, especially along the coast of Venezuela. Their approach, however, seems to be completely different than the previous regions. Recent reports indicate that due to harsh economic conditions in the Venezuela and northern Colombia, many of the coast inhabitants target private yachts for small robbery.[12] These encounters are suggested to be sporadic, and usually deriving in opportunistic predation of groceries and other valuable items that tourists carry. To our knowledge, no hijacks or ransoms have been reported in this region. The next section generalizes these practices an introduces a simple framework to analyze these interactions.

2.3 A model of pirates and shippers

This section establishes the intuition behind shipping behavior in the face of piracy. In particular, we illustrate the mechanisms behind pirate encounters, and their effect on shipping routes. It follows that all relevant costs associated with piracy can be attributed to deviations from cost-effective behavior in the absence of the threat. The model we propose builds on the previous efforts by Guha and Guha (2011) and Hallwood and Miceli (2013), who championed the theoretical understanding of piracy.

[11] See *Pirates in Southeast Asia: The World's Most Dangerous Waters* by Time, available at: `http://time.com/piracy-southeast-asia-malacca-strait/`

[12] See *La piratería regresa al Caribe motivado a la crisis de Venezuela* by El Nacional, available at `http://www.el-nacional.com/noticias/sociedad/pirateria-regresa-caribe-motivado-crisis-venezuela_237067`

For simplicity, assume a situation where there is only one pirate and one shipper. There is a continuum of trajectories, $x \in \mathbb{X} = [0, \bar{x}]$, for a certain route. The cost-effective trajectory is given by $x = 0$, while $x = \bar{x}$ represents the most expensive, but feasible, trajectory. One way to think about this idea would be vessels having to sail farther from the coast than optimal due to the threat of piracy. The cost of deviating from the optimal trajectory, $c(x)$, is strictly convex in x, and $c(0) = 0$. In the presence of piracy, the shipper chooses the route taking into account the possibility of encountering and being attacked by the pirate.

An encounter might occur when the shipper transits through the area monitored by the pirate, which is given by the segment $x : x = [0, \bar{a})$. Because physical limitations prevent pirates from monitoring all possible transportation trajectories, it follows that $\bar{a} < \bar{x}$. The probability of an encounter, however, is strictly positive along the $[0, \bar{a})$ interval, and zero everywhere else. One way to think about this feature is the shipper taking an extremely long trajectory with no risk of piracy, or using other transportation methods such a trains or airplanes. Formally, this relationship can be expressed as:

$$\phi(x;\theta) \begin{cases} > 0 & ; \quad 0 \leq x < \bar{a} \\ = 0 & ; \quad \text{Otherwise} \end{cases} \tag{1}$$

with θ being the vector of parameters that characterize the distribution, including $\bar{a}$ and the search effort with which pirates patrol the susceptible waters. The probability function satisfies $\phi_x(x, \theta) < 0$ and $\phi_{xx}(x, \theta) > 0 \; \forall \; x \in [0, \bar{a})$, and $\phi_x(x, \theta) = \phi_{xx}(x, \theta) = 0 \; \forall \; x \in [\bar{a}, \bar{x}]$.

In this model, the pirate decides to attack only after an encounter takes place, in which the shipper loses h. From the pirate's perspective, however, the assault can be either successful (the pirate gets away) or unsuccessful (the pirate gets caught). An attack implies the pirate obtaining a monetary prize or booty, b, which is not necessarily equal to h, and that he cannot determine until the encounter occurs. This assumption implies that the pirate treats b as a randomly distributed variable with cumulative distribution $F(b)$ over support $[0, \bar{b}]$. One way to think about this realization is the assessment of the ship being "worth" pursuing, as described by Bahadur (2011).

Before attacking, the pirate assesses the monetary value of the booty with the expected costs of being apprehended with probability, p, and fine, f. As the pirate does not serve time incarcerated,[13] it follows that an attack occurs whenever $b \geq pf$. Therefore, conditional on an encounter, the probability of an attack is finally given by:

$$\psi(pf) = [1 - F(pf)] \tag{2}$$

Finally, the model assumes the shipper cannot observe the patrolling effort of the pirate, but a finite number of trajectories previously taken for the origin-destiny combination. Denote this history set as $\mathbf{z} = \{z_1, ..., z_m\}$ for m different voyages. The shipper also knows which trajectories have experienced encounters in the past. This complimentary history set is given by $\mathbf{y} = \{y_1, ..., y_n\}$, for a total of n encounters. With this information, the shipper can estimate the parameters of the encounter probability distribution, including the span of the monitored area, as:

$$\hat{\theta} = \arg\max_{\theta} \{\mathcal{L}(\theta; \mathbf{y}, \mathbf{z})\} \tag{3}$$

with $\mathcal{L}(\theta; \mathbf{y}, \mathbf{z})$ as the likelihood function of $\phi(x, \theta)$. If the market price of the voyage is given by π, it follows that the expected net return for the shipper, R, would be finally given by:

$$R(\pi, x, \hat{\theta}) = \pi - \phi(x, \hat{\theta})\psi(pf)h - c(x) \tag{4}$$

Assuming risk neutrality, the shipper's problem can be solved using standard optimization techniques, and it follows that the optimal trajectory is characterized by the proposition below:

Proposition 1. *The optimal trajectory for a shipper in the face of piracy, x^*, depends on the information of past voyages and pirate encounters, $\{\mathbf{y}, \mathbf{z}\}$, and it satisfies:*

$$-\phi_x(x^*, \hat{\theta})\psi(pf)h = c'(x^*) \tag{5}$$

[13]Guha and Guha (2011) note that a major problem in modern piracy is the lack of credible punishment after aggressors have been apprehended.

with

$$\hat{\theta} = \arg\max_{\theta} \left\{ \mathcal{L}\left(\theta; \mathbf{y}, \mathbf{z}\right) \right\} \tag{6}$$

All proofs are provided in the appendix.

Proposition 1 indicates that the optimal trajectory equalizes marginal expected savings to the marginal cost of deviating from the cost-effective one. The set of feasible optimal trajectories is then given by the Lemma below:

Lemma 1. *The optimal trajectory for a shipper in the face of piracy is contained in the set x : $x \in (0, \bar{a}]$.*

Lemma 1 suggests two points regarding optimal trajectories. First, the shipper will never ignore the threat of piracy. Expected losses from encountering and being attacked by a pirate will always be taken into account and thus avoided following the equimarginal principle. Second and consistent with cost minimizing behavior, if the cost of deviating is low enough, total avoidance will never exceed $\bar{a}$. These ideas are illustrated in figure 2, with panel (a) corresponding to interior solutions and panel (b) corresponding total, or maximum, avoidance.

Now that the shipper's trajectory decision is fully characterized, we turn to establishing the effect of the information set on optimal decisions. In particular, we want to establish how past encounters affect the shippers decision making process. In line with the empirical analysis, we will focus on the frequency of encounters for trajectory x, which is given by the following ratio:

$$k(x) = \frac{|\mathbf{y} : y_i = x|}{|\mathbf{z} : z_j = x|}; \;\; i \in \{1, ..., n\}, j \in \{1, ..., m\} \tag{7}$$

The expected effect of this observable on optimal trajectories is formalized in the proposition below:

Proposition 2. *The effect of the frequency of encounters, $k(x)$, on optimal trajectory, x^*, is*

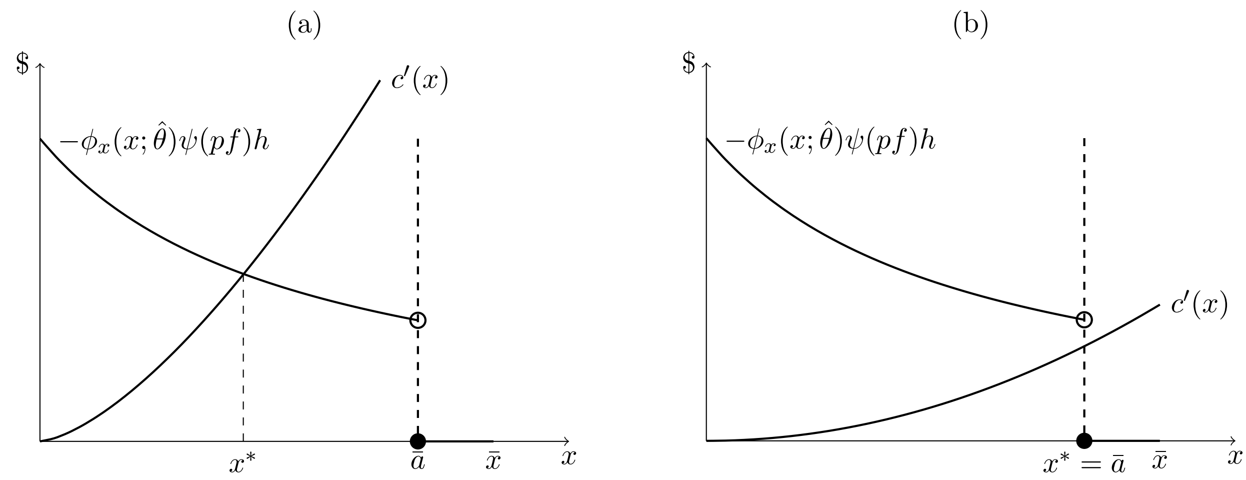

Figure 2: The shipper's trajectory selection problem. Panel (a) shows interior solutions, while panel (b) shows the maximum optimal level of avoidance a shipper will ever take when deviating from the cost-effective trajectory is relatively inexpensive.

given by:

$$\frac{\partial x^*}{\partial k(x)} = -\frac{\psi(pf)h\phi_{x\theta}(x^*,\theta)}{\psi(pf)h\phi_{xx}(x^*,\theta) + c''(x^*)}\frac{\partial\hat{\theta}}{\partial k(x)},\ \forall\, x \in \mathbb{X} \tag{8}$$

Proposition 2 is fairly intuitive: adjustments to optimal trajectories are linked to their effect in the estimated parameters of the probability function, as well as their effect on the probability of an encounter. In other words, marginal optimal adjustments incorporate any information regarding past encounters along the route to inform the expected probability of encounters. This information is then translated into the adjustments prescribed in Proposition 1. As a Corollary, the sign of this relationship is given by:

Corollary 1. *The direction of the effect of the frequency of encounters, $k(x)$, on optimal trajectory, x^*, is given by the sign of the product:*

$$-\phi_{x\theta}(x^*,\hat{\theta})\frac{\partial\hat{\theta}}{\partial k(x)} \tag{9}$$

The sign of the above relationship depends on two components: the cross derivative of the probability function, and the effect of observing more encounters along a given route on the estimate of θ. When this expression is positive, it is optimal to deviate more from the cost-effective trajectory, while the opposite is true if the expression is negative. The reason why the sign switches relates to convexity of the probability of an encounter and the generality assumed for the relationship between the observed encounters and their effect on the probability estimate.

As an illustration, suppose encounters are observed farther from the cost-effective trajectory. Operationally, this means an increase in the estimate for $\bar{a}$ and a change in the slopes of the probability function for any x to the left of $\bar{a}$. The actual change will depend on the searching capability of the pirate. Consider the case in which the pirate can allocate only so much time to search every particular section of the feasible trajectories. The pirate searching farther implies a decrease in the intercept of $-\phi_x(x;\hat{\theta})\psi(pf)h$, or an increase in its slope, or both. Any of these changes effectively reflect a decrease in the probability of encountering the pirate. When this is the case, the intercept with the marginal cost shifts to the left, and thus less avoidance is optimal. Other responses will be then a function of how effective the pirate is when it comes to searching different sections of the trajectory set.

Our main empirical task is to establish the above relationship empiically. With this result, we are then able to estimate the cost of avoidance behavior in the shipping industry due to piracy. We cover our empirical approach in the next section. The characterization of the pirate's behavior is also provided in the Appendix (B).

3 Data

To identify and test for the predictions of the theoretical model, we construct a unique data set for global shipping and piracy that provides both temporal and spatial variation that allow us to identify the causal effect of piracy. In particular, we compile a unique global panel dataset from 2012 to 2017 that includes individual shipping voyages and recent anti-shipping encounters along the route of each voyage. The panel includes some of the most important operational components that determine the cost of shipping voyages. This section describes the data sources as well as the additional data construction process.

3.1 Voyages

Individual shipping vessel voyage-tracks come from the Automatic Identification System (AIS) satellite latitude and longitude data provided by ORBCOMM.[14] AIS transponders are required on all vessels greater than 300 gross registered tons while operating on international voyages, and by many countries while operating in certain economic exclusive zones (McCauley et al. 2016). The dataset includes over 150,000 unique known cargo, tanker, and reefer vessels as defined by vessel identification data provided by Global Fishing Watch (Kroodsma et al. 2018),[15] and more than 20 million individual voyages.[16] To establish the start and end location of each voyage, we use port data provided by Global Fishing Watch to group AIS vessel pings (signals to satellite receiver) into discrete voyages between ports. For consistency, we drop voyages that have the same departure and arrival anchorage, voyages registering an average speed higher than their listed design speed, and voyages recording more than three times larger of a distance than the haversine great-circle distance between two ports.

We trace operation cost from two sources: fuel consumption and labor. To establish fuel consumption, however, a number of vessel characteristics are necessary: main engine power, gross tonnage, auxiliary engine power, and design speed. Main engine power and gross tonnage come from the Global Fishing Watch vessel characteristics database (Kroodsma et al. 2018). For each vessel, we determine these characteristics using a hierarchy based on data availability: 1) the offi-

[14] As described by the company itself, ORBCOMM is a global provider of industrial Internet of Things and Machine-to-Machine communication solutions that remotely track, monitor, and control fixed and mobile assets.

[15] Although useful in the context of this analysis, a three category definition might fall short of the actual diversity of the merchant fleet. Stopford (2013) points out that most ships are manufactured to according individual specifications. According to his research, Lloyds Register of Shipping divides shipping vessels into 16 categories of ship as a function of their hull. The four biggest groups, amounting to 76 percent of the total tonnage in the fleet, are oil tankers, bulk carriers, general cargo ships, and container ships. The other groups are more specialized, and include categories such as combined carriers that are able to transport both oil and dry bulk, gas tankers, ro-ro vessels for transport of vehicles, and refrigerated cargo vessels, or reefers.

[16] Global Fishing Watch is a transparency platform that tracks location and behavior of commercial fishing fleets globally. We apply their fishing vessel identification and mapping algorithm to the shipping industry. Further information regarding the organization can be found available at: `http://globalfishingwatch.io`

cial registered information of the vessel; and 2) values inferred by the Global Fishing Watch vessel characteristic neural network when available. Auxiliary power is a function of main engine power, and is calculated using the relationships given by Betz (2011), which links main propulsory requirements with vessel characteristics and auxiliary needs. Design speed is a function of main engine power and gross tonnage, and is also calculated using the relationship given by Betz (2011).[17]

Using these vessel characteristics, we calculate fuel consumption using a standard approach that combines fuel consumed by both the main and auxiliary engines (Corbett, Wang, and Winebrake 2009). Fuel consumption of the main engine is defined by hours of operation, main engine power, main engine specific fuel consumption rates as given by Wang, Corbett, and Firestone (2007), and a cubic law of operational speed relative to design speed. Fuel consumption of the auxiliary engine is defined by operating hours, auxiliary engine power, and auxiliary engine specific fuel consumption rates as given by Wang et al. (Wang, Corbett, and Firestone 2007). Fuel consumption was calculated for each individual AIS ping which were then summed for each voyage.

Daily fuel price data come from Bunker Index.[18] We use the 380 CST Bunker Index, which is the global average price from all ports selling 380 centistoke fuel, the most commonly used fuel in maritime transport. For dates with missing price data, we impute the missing value using the most recent reported price. Most gaps in the data do not exceed more than two days. Total fuel cost for each voyage is then calculated by multiplying the total fuel consumption of the voyage by the fuel price on the date of departure.

On the other hand, we also keep track of labor requirements for individual voyages. Using the

[17] According to Betz (2011), auxiliary engine power can be calculated as:

$$AEP = (0.1913 \times MEP) + 287.2$$

with AEP as the auxiliary engine power and MEP as the main engine power. Design speed on the other hand, can be calculated as:

$$DS = (3.390 \times 10^{-4})MEP + (2.151 \times 106{-}5)GT - (2.742 \times 10^{-9})MEP\ GRT + 12.93$$

with GT as the gross registered tonnage of the vessel.

[18] Available at: `http://www.bunkerindex.com`

relationship suggested by Betz (2011), we estimate the crew needed to operate a vessel as a function of its size and type. The crew wage is calculated using the International Transport Worker's Federation wage scale for the average seafarer.[19]

In addition to operational costs, we also examine the environmental cost of piracy. In particular, we focus on the emissions associated with each voyage. We calculate emissions of CO2, NOx, and SOx for each voyage using the estimated fuel consumption for each voyage. CO2 emissions are calculated using the linear relationship provided by Corbett, Wang, and Winebrake (2009), which uses total fuel consumption of the voyage. SOx emissions are calculated using the linear relationship provided by the same study, and the assumption of 3.3% sulfur content for each kilogram of fuel (Corbett and Fischbeck 1997). Similarly, NOx emissions are calculated using a separate conversion rate for both the main engine fuel consumption (which we assume to be a slow-speed engine) and auxiliary engine (which we assume to be a medium-speed engine) (Corbett and Fischbeck 1997).

Finally, to account for weather conditions that undoubtedly affect shipping routes, we incorporate a proxy in the form of average wind speed and direction along each voyage. We call this proxy the wind-resistance index. Wind data come from the NOAA Global Forecast System Atmospheric Model.[20] Mean daily wind speed and direction information is calculated for 5 x 5 degree grid cells. We take into account wind direction by decomposing the pitch angle relative to the vessel. In other words, the resistance is concave or convex depending on the vessel going against, or with the wind. This measurement is symmetric in absolute terms along each 90°portion of a full circumference and it goes from 0 to 1. Scaling this measurement by the wind speed gives the final wind-resistance index. For each voyage, the time-weighted mean wind-resistance is then calculated based on the voyage's time spent in each 5 x 5 degree cell.

The final panel covers all global valid cargo and tanker voyages between 2012 and 2017, with each entry reporting vessel characteristics (type, size, crew), departure and arrival dates, depar-

[19]Available at: http://www.itfseafarers.org

[20]These data are publicly available at: https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/global-forcast-system-gfs

ture and arrival ports and countries, total distance traveled (km), time traveled (hours), speed (km/hour), fuel consumption (kg), fuel and labor cost (TUSD), and emissions (kg).

3.2 Pirate encounters

We operationalize pirate encounters by using the data provided by the United States National Geospatial Intelligence Agency, which includes dates and locations of hostile acts against ships by pirates, robbers, and other aggressors.[21] We then divide all oceans into a grid of 5 degrees latitude by 5 degrees longitude cells and calculate how many of these cells have experienced an anti-shipping encounter since the start of 2012.[22]

Using this dataset, we also determine hotspots of encounters using density based clustering as described by Ester et al. (1996). Implementing a cluster reachability distance of 500 km, and a minimum number of encounters per cluster of 200, we find three hotspots of intensive pirate activity for the entire panel: the Gulf of Aden, the Gulf of Guinea, and South East Asia. For each voyage, we then determine whether the vessel transited through one or more of these areas.

The final overlap between shipping voyages and pirate encounters, which is the dataset used in the empirical analysis, is shown in Figure 3. Note that pirate encounters concentrate in a few areas in the map. Particularly in the Caribbean, the Gulf of Guinea, the coast of East Africa, the Arabian Sea, and the jurisdictional waters of the Philippines and Malaysia. The aforementioned hotspots are enclosed by the squares.

[21] This dataset is publicly available at: `http://msi.nga.mil/NGAPortal/MSI.portal?_nfpb=true&_pageLabel=msi_portal_page_65`.

[22] At the equator, a cell of 5 by 5 degrees is roughly equivalent 345 by 345 miles, which is a reasonable spatial area over which shipping vessel operators might make route and speed adjustment decisions in relation to recent anti-shipping encounters. Moving at 10 knots, this is an area that potential attackers could cover in just 30 hours.

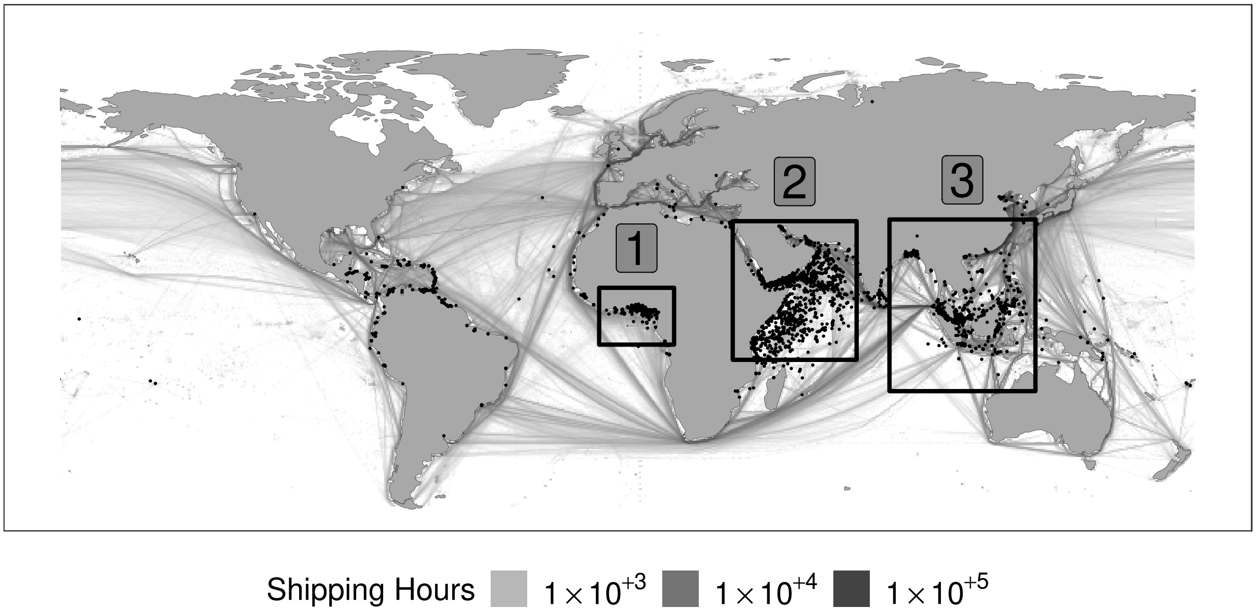

Figure 3: Global overlap of shipping routes and anti-shipping encounters from 2012 to 2017. Shipping routes are shown in blue 0.5 by 0.5 degree cells, and the brightness of each cell corresponds to the volume of shipping traffic (hours). Pirate encounters are overlaid in black. The numbered squares correspond to the main piracy hotspots, namely: 1) Gulf of Guinea, 2) Gulf of Aden, and 3) South East Asia.

4 Methods

4.1 Empirical challenges

Establishing the causal effect of crime on production behavior posses several challenges. One possibility is a self-selection process that arises when pirates target specific ships, or it may be also plausible that some vessels are actively looking to be hijacked. In the presence of any of these possibilities, any estimate will be polluted with omitted variable bias.

For example, recall that according to the documented testimonies, most of the initial encounters occur at random. In other words, pirates decide to attack after observing the vessel that they happen to run into. The randomness behind these encounters would normally be sufficient for identification, but the presence of sophisticated pirates challenges this claim. It is plausible that the encounters could actually be planned by pirates or the crew, which implies that they do not occur at random. This is particularly likely to be the case in South East Asia.

The nature of the shipping industry, however, allows us to propose a solution for this problem. By most accounts, the shipping industry operates on a set schedule regardless of the type of cargo or location. That is, the date at which vessels depart is pre-determined and plausibly exogenous to pirate encounters in the past (Jansson 2012; Stopford 2013). As these schedules are contracted years in advance (Stopford 2013), the timing at which pirates encounters occur in the past is likely exogenous for any given voyage. We construct the empirical model around this unique characteristic of both the criminal activity, as well as the shipping industry.

Finally, maritime transportation is highly susceptible to weather conditions. It could be possible that route adjustments after pirate encounters are merely a result of spurious correlation between weather patterns and the timing of any given encounter. To account for this possibility, we control for wind patterns along each individual voyage. Wind speed and direction are valid controls for sailing weather conditions as, along with fetch (area of water over which the wind blows), it determines the size of waves in the ocean (Massel 2013).

With these limitations and assumptions in mind, we then are able to estimate the effect of piracy on shipping routes. Below are the details for how we operationalize this approach in the data.

4.2 Estimation approach

To measure the effect of pirate encounters on shipping behavior we rely on a quadratic regression model. In particular, we are interested in the trajectory (distance, duration, and speed) of voyage i, along route r, at time t, and their associated consequences in terms of operational costs and emissions. The model is as follows:

$$y_{irt} = \alpha + \beta TNE_{rt-1} + \gamma TNE_{rt-1}^2 + \delta_i VC_i + \lambda_i W_i + \eta_r R_i + \theta' X_t + \epsilon_{irt} \tag{10}$$

y is the dependent variable, TNE is the total number of encounters during the last year, with β as the mean effect on trajectory and γ as the mean cumulative effect of additional encounters along the route. This approach gives us a clear notion of how past encounters influence routes, as well as potential non-linearities.

VC is a vector of fixed effects according to vessel characteristics (type of vessel and size) conducting voyage i, while W is the time-weighted mean wind-resistance for a given voyage. Finally, R is a vector of fixed effects by route, while X_t is a battery of month by year fixed effects.

With these empirical models, we set out to test the responses by the shipping industry to pirate encounters, namely:

(I) The occurrence of piracy in the past along any given port-to-port route affects current shipping behavior along that route.

(II) The response to these recent past encounters is to avoid pirates by deviating from the cost-effective route

The results of implementing this methodology are illustrated in the next section.

5 Results

This section reports the results of the empirical analysis establishing the causal effect of piracy on avoidance behavior by shipping vessels. In particular, we focus on the margins of adjustment that ships make in the face of maritime piracy, and their effects in terms of operational cost.

Table 1 shows the summary statistics for the main set of covariates grouped by hotspot. The mean distance traveled varies across the sample, but it is bounded between 3,200 and and 800 kilometers per voyage. The data, however, also show a somewhat high level of dispersion, with some voyages clocking more than 46,000 kilometers.

Table 1: Summary statistics for all shipping routes included in the data

	Distance (km)	Time (hr)	Speed (km/hr)	Encounters (#/year)
Gulf of Aden				
Mean	1,456.23	77.07	18.03	5.12
Std.Dev.	2,650.18	156.86	7.31	11.79
Median	584.39	33.77	19.15	1
Max	34,622.62	16,902.13	41.42	185
Gulf of Guinea				
Mean	3,140.24	157.38	18.71	22.68
Std.Dev.	3,909.02	225.38	7.41	17.64
Median	1,101.08	65.72	19.91	18
Max	35,135.41	26,766.99	39.01	115
South East Asia				
Mean	809.42	45.64	15.81	7.42
Std.Dev.	1,972.72	108.63	6.78	20.11
Median	190.49	15.60	15.85	0
Max	46,300.27	34,799.25	44.42	147
Rest of the world				
Mean	899.55	46.26	18.42	1.75
Std.Dev.	1,977.79	104.03	6.54	10.43
Median	258.04	15.70	18.88	0
Max	41,781.18	34,013.48	43.57	257

Not surprisingly, the average voyage time follows a similar pattern as the distance traveled. The voyages crossing the three hotspots vary between 77 and 157 hours per voyage, while the average time for the rest of the world is is about 46 hours. On the other hand, the average cruising speed for all vessels ranges between 16 and 18 kilometers per hour, which approaches the documented average cruising speed in the industry for regular size ships (Stopford 2013). The speed measurement remains consistent in and out of hotspots.

Regarding the number of past pirate encounters along a given route, the data are also consistent with simple intuition. Tightly concentrated hotspots, such as the Gulf Guinea, will expose vessels to a higher level of past encounters. For example, the Gulf of Guinea experiences an average of 23 piracy encounters per year that may affect the behavior of all vessels transiting along that route. This hotspot is followed by South East Asia with 7, and the Gulf of Aden with 5. In contrast, the rest of of the world has in average about 2 encounters per year for a given route. Note, however, that some routes (unique origin-destiny combination) experience orders of magnitude larger pirate activity, as reflected in the summary of maxima.

5.1 Average piracy effect on trajectories

Table 2 shows the results of the analysis for the total distance traveled for all recorded voyages in the dataset, as well as for the voyages exclusively going through one of the hotspots. Each column of the table presents a different regression model under the full set of controls.[23] The results show that each additional past encounter leads vessels to travel longer distances, but at a decreasing rate. This result is consistent for both the global sample and voyages passing through just one of the hotspots. The point estimates show that at the global level, the first encounter in the past year increases the average distance traveled by 19 km per voyage. Both linear and quadratic terms are statistically significant.

The effect in hotspots, however, varies geographically (Table 2). In the Gulf of Aden, the first encounter increases travel distance in about 53 km, while in the Gulf of Guinea the response

[23]See the Appendix for the progression of estimates as different controls are included in the analysis (Ap. D).

Table 2: Linear regression estimates for the average piracy effect on voyage distance

	Total Distance (km)			
	Global	G. of Aden	G. of Guinea	South East Asia
One year ago	18.71***	53.42***	18.67***	21.56*
	(3.82)	(11.30)	(4.50)	(8.48)
(One year ago)^2	-0.07*	-0.28***	-0.10	-0.16*
	(0.03)	(0.08)	(0.05)	(0.08)
Time FE	Y	Y	Y	Y
Size FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Observations	18353036	664716	186366	6683025

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column is a different regression analysis for different samples. The first column refers to the global sample, while the rest only takes into account voyages goin through a specific hotspot.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

is about 18 km. For both of these hotspots the linear point estimate is statistically significant, while the quadratic term is only statistically significant for the Gulf of Aden. For the case of South East Asia, the point estimate indicates an increase in 21 km after the first attack in the past year, albeit lower precision, relative to the previous estimates. Both the linear and the quadratic term are only statistically significant to the 95 percent confidence level.

If shippers travel longer after finding out about pirate encounters, then it is possible for them to also adjust along other margins. Tables 3 shows how piracy affects the duration of the voyages. The results indicate that past pirate encounters also lead to an increase at a decreasing rate in the average time at sea. The estimates are consistent across the samples, and range between 0.9 and 2.2 additional hours after the first attack. For the global sample, the first encounter one year ago increases the average time of a voyage by one hour, with both linear and quadratic estimates being statistically significant at the 1 percent confidence level. For hotspots, the response is estimated to be two, 0.9, and one hour for the Gulf of Aden, the Gulf of Guinea, and South East Asia, respectively. All of the linear coefficients are statistically significant, while only the quadratic term for the Gulf of Guinea fails to pass a significance test.

Table 3: Linear regression estimates for the average piracy effect on voyage time

	Total Time (hours)			
	Global	G. of Aden	G. of Guinea	South East Asia
One year ago	1.04***	2.19***	0.90***	1.20**
	(0.18)	(0.48)	(0.22)	(0.46)
(One year ago)^2	-0.01***	-0.01***	-0.00	-0.01*
	(0.00)	(0.00)	(0.00)	(0.00)
Time FE	Y	Y	Y	Y
Size FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Observations	18,353,631	664,763	186,367	6,683,367

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column is a different regression analysis for different samples. The first column refers to the global sample, while the rest only takes into account voyages goin through a specific hotspot.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The plausible reason for why the Gulf of Aden presents such a different pattern could be attributed to the prominence that Somali piracy has had in public perception, but also to the geographical characteristics of the region. From these results, however, the measurable response of shippers to attacks in the Gulf of Aden seems to be double the avoidance response everywhere else on the planet.

Finally, we find only a minimal relevant effect of pirate encounters on speed (See Ap. C). Although some of the precision observed in the previous two analyses remain, the changes detected are economically meaningless. We interpret these results as an indication that adjustments to speed are a less cost-effective avoidance measure. This behavior is consistent with optimal avoidance since the cost of each additional unit of distance traveled grows linearly, while the cost per each additional unit of cruising speed grows exponentially (Wang and Meng 2012). In addition, we evaluate an alternative specification of the model where past pirate encounters are treated as a binary variable. In other words, the average effect of a route having experienced pirate encounters in the past. This set of additional results are consistent consistent with the ones discussed above and provided in the Appendix (Ap. E).

With this set of results, we show that the hypotheses regarding avoidance behavior hold in the data. In other words, that an increase in reported encounters results in shippers implementing avoidance measures. This avoidance behavior manifests as an increase in the distance and time traveled. To establish the economic importance of these adjustments, we now examine the monetary cost of the measured responses. We cover these topics in the next section.

5.2 Average piracy effect on operational costs

The results for a simple linear average effect of piracy are stacked in Table 4 for fuel, labor, and total operational costs, respectively. The results show that trajectory adjustments increase the fuel cost the most. According to the estimates, the marginal effect of an additional encounter increases the average operational cost of the vessel by hundreds of dollars in fuel consumption alone. The point estimates are consistent with trajectory adjustments and suggest that vessels passing through the Gulf of Aden face the biggest burden of all samples, while those in South East Asia face the least.

On the other hand, the estimated effect in terms of labor costs represent at most half of the adjustment cost when compared to additional fuel consumption. Finally, we get at an estimate of the effect of piracy on operational costs by aggregating both fuel and labor costs, and performing the regression analysis again. These results are reported in the last row of Table 4, and suggest that the marginal increase in operational costs due to avoidance measures ranges from over 300 dollars to over a thousand dollars per each additional past encounter. All estimates for fuel, labor and total operational cost are statistically significant at the 0.1 percent confidence level.

Taking advantage of the granularity of the voyage data, we can project these estimates and approximate the total cost that the shipping industry incurs due to piracy. These results are shown in Tables (5) and 6), in which we decompose the different sources of cost by year. These results

Table 4: Linear regression estimates for the average piracy effect on operational costs

	Global	G. of Aden	G. of Guinea	South East Asia
	Total Cost of Fuel (TUSD)			
One year ago	0.29***	0.76***	0.20***	0.08***
	(0.05)	(0.17)	(0.04)	(0.02)
	Total Cost of Labor (TUSD)			
One year ago	0.08***	0.18***	0.11***	0.05***
	(0.01)	(0.03)	(0.02)	(0.01)
	Total Operational Cost (TUSD)			
One year ago	0.55***	1.17***	0.77***	0.34***
	(0.07)	(0.22)	(0.09)	(0.06)
Time FE	Y	Y	Y	Y
Size FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Observations	18,353,631	664,763	186,367	6,683,367

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column and row is a different regression analysis for different samples. The first column refers to the global sample, while the rest only takes into account voyages goin through a specific hotspot. The first row refers to the effect of past piracy encounters on the cost of fuel per voyage, while the second refers to the cost of labor per voyage. The third row refers to the effect of past pirate encounters on the total operational cost estimated per voyage.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

are further categorized by source of cost by sample and year. Table (5) shows the cost associated with fuel consumption and labor, while Table (6) shows the calculated total cost based on regression estimates for the total operational cost per voyage.

	Year					
Fuel (Millions of USD)	2012	2013	2014	2015	2016	2017
Global	2,601	3,488	4,319	4,796	3,703	3,082
Gulf of Aden	6,901	9,255	11,461	12,727	9,826	8,179
Gulf of Guinea	1,828	2,452	3,036	3,372	2,603	2,167
South East Asia	724	971	1,203	1,336	1,031	858
Labor (Millions of USD)	2012	2013	2014	2015	2016	2017
Global	715	959	1,187	1,318	1,018	847
Gulf of Aden	1,598	2,144	2,654	2,948	2,276	1,894
Gulf of Guinea	1,035	1,388	1,719	1,908	1,473	1,226
South East Asia	411	552	683	758	586	487

Table 5: The total cost of piracy in terms of fuel and labor

	Year					
Total (Millions of USD)	2012	2013	2014	2015	2016	2017
Global	4,929	6,610	8,186	9,090	7,018	5,842
Gulf of Aden	10,593	14,208	17,594	19,537	15,085	12,556
Gulf of Guinea	6,975	9,354	11,584	12,863	9,932	8,267
South East Asia	3,056	4,098	5,075	5,636	4,351	3,622

Table 6: The total cost of piracy as a function of added fuel consumption and labor

These results are intuitive. As expected, even if the individual vessel adjustments are relatively minor (about one percent of the total voyage distance), when taking into account the shipping traffic in places where pirate encounters occur the most, the total economic impact becomes highly relevant. To put these numbers in perspective, Maersk reported a total revenue level of about \$30 billion USD in 2017.[24] The total estimated losses due to piracy, and the respective individual response of each shipper, stack up to 30 percent of the revenue generated by one of the biggest

[24] As indicated by the 2018 report to investors of the company. The document is available at: `https://www.maersk.com/press/press-release-archive/a-p-moller-maersk-annual-report-2017`

company in the sector. In the next section, we explore further how these costly adjustments also translate into additional emissions and their associated environmental impact.

5.3 Average piracy effect on shipping emissions

In addition to quantifying the operational cost of avoidance measures, we also utilize the highly granular data to establish the emission profile of each voyage. In particular, we explore the link between pirate encounters and additional CO2, NOx and SOx emissions by shipping vessels. The results of the simple linear regression for each of these emissions are stacked in Table 8.

Table 7: Linear regression estimates for the average piracy effect on emissions

	Global	G. of Aden	G. of Guinea	South East Asia
	CO2 (ton)			
One year ago	2.03***	5.38***	1.43***	0.56***
	(0.36)	(1.17)	(0.25)	(0.16)
	NOx (kg)			
One year ago	52.18***	139.20***	35.35***	13.96***
	(9.26)	(30.39)	(6.59)	(4.15)
	SOx (kg)			
One year ago	42.24***	112.08***	29.69***	11.76***
	(7.41)	(24.40)	(5.31)	(3.35)
Time FE	Y	Y	Y	Y
Size FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Observations	18,353,631	664,763	186,367	6,683,367

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column and row is a different regression analysis for different samples. The first column refers to the global sample, while the rest only takes into account voyages goin through a specific hotspot. The first row refers to the effect of past piracy encounters on CO2 emissions, the second refers NOx emissions, and the third row refers to SOx emissions, respectively.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As expected from the analysis on fuel consumption, the regression measures a statistically significant increase in emissions due to past pirate encounters. In particular, increases in CO2 range from half a ton from more than five tons per voyage per past pirate encounter. NOx and SOx emissions due to piracy are less than the increase in CO2, due to their significantly smaller concentrations in bunker fuel relative to carbon. Regression estimates point to increases between ten and more than a hundred kilograms of these type of emissions due to pirate encounters. All of the point estimates are statistically significant at the 0.1 confidence level.

To illustrate the practical significance of these estimates, we project total emissions due to piracy for our entire dataset. These results are reported in Table 8. According to these calculations, the average increase in CO2 emissions ranges between 18 and 34 million metric tons a year. Relative to the total level of emissions of the industry, which is estimated at over 900 million tons per year, this accounts for less than a 3 percent increase. As with the previous results, the Gulf of Aden remains as the region that concentrates most of the impacts, while South East Asia only reflects increases below 10 million additional metric tons of CO2 per year due to piracy.

	Year					
CO2 (Metric tons $\times 10^3$)	2012	2013	2014	2015	2016	2017
Global	18,320	24,570	30,427	33,787	26,087	21,713
Gulf of Aden	48,611	65,197	80,737	89,653	69,222	57,616
Gulf of Guinea	12,878	17,272	21,389	23,751	18,338	15,264
South East Asia	5,102	6,842	8,473	9,409	7,265	6,047
NOx (Metric tons)	2012	2013	2014	2015	2016	2017
Global	471,186	631,949	782,579	869,002	670,964	558,473
Gulf of Aden	1,256,905	1,685,745	2,087,557	2,318,091	1,789,819	1,489,745
Gulf of Guinea	319,186	428,088	530,126	588,670	454,517	378,315
South East Asia	126,023	169,020	209,308	232,422	179,455	149,368
SOx (Metric tons)	2012	2013	2014	2015	2016	2017
Global	381,418	511,553	633,487	703,444	543,135	452,076
Gulf of Aden	1,012,093	1,357,406	1,680,956	1,866,588	1,441,209	1,199,582
Gulf of Guinea	268,127	359,608	445,324	494,503	381,810	317,797
South East Asia	106,219	142,460	176,417	195,899	151,255	125,896

Table 8: The environmental impact of piracy in terms of added emissions

From Table 8, we can also examine the projected effects in terms of NOx and SOx emissions.

The total calculated effect of piracy, both globally and in hotspots increases total NOx and SOx emissions by more than half a million metric tons globally. In the Gulf of Aden, the additional emissions burden is more than a million metric tons per year. Relative to the global levels of emissions, which puts total NOx and SOx emissions at an average of 25 and 15 million tons globally, these results also suggest an increase of no more than 3 percent in emissions due to piracy. The potential implications for these, and the previous set of results are discussed in the next section.

6 Discussion

In this paper, we examine the effect of piracy on the shipping industry. We document the mechanisms through which shippers adjust their trajectories in response to reported pirate encounters, and their implications in terms of the cost of shipping. We find that piracy induces captains to avoid risk by traveling longer distances for an extended amount of time. These adjustments are relatively small at the individual level, but when taking into account the total flow of ships across routes, and the prevalence of pirate attacks in some of the busiest shipping channels, the effect grows to become a major source of cost for the overall industry.

We frame the problem in terms of adjustment as a function of reported encounters, derive theoretical intuition for the avoidance behavior, and then test these notions with a highly granular geospatial dataset for the global shipping industry from 2012 to 2017. The theory suggest that ships will optimally adjust to reduce the probability of encounters, but those adjustments do not necessarily mean a complete change of routes. This intuition holds in the data, with ships going longer trajectories, which in turn imply a higher level of consumption of fuel and labor time. Each additional encounter increases this response, and the effects have long-term implications after a single encounter is reported. The resolution of the data allows us to precisely estimate these responses for both the global shipping industry, as well as for the vessels that go through particular piracy hotspots.

The overall analysis provides evidence for how the provision of a public good in the form of safe passage for shipping vessels can have large consequences in the aggregate. In particular, piracy is a perfect example for how the poor definition of property rights, or duties in terms of safety of passage, has considerable detrimental effects for a large set of individuals. In addition, this study illustrates how individually minimal incentives could have relevant and large effects in the aggregate. These estimates are economically significant, and have remained largely ignored, or underestimated, by prior literature. More importantly, our estimates likely represent a lower bound on the overall operational losses associated with pirates globally. For example, we have not included any sources of costs associated with vessel defense, supplies or insurance. Other vessels may also adjust their trajectories outside the 5x5 degree grid, which also reduces the magnitude of our estimate. Further refinements that take these items into account could only increase the estimated cost of piracy for the industry.

Despite these results, several potential caveats remain. The first and most important to our identification, is the fact that pirate encounters arguably occur at random. This assumption seems to hold in many instances, but some of the documented cases put the randomness assumption into question. In particular, hijacks that are specifically targeted to certain types of ships, or the possibility of encounters targeting one particular vessel. We control for all available observables, and use the nature of shipping contracts to minimize the risk of presenting biased results. Given the robustness of our results, we believe that we have effectively controlled for these issues. The second potential source of bias is the possibility of comparing routes under different weather conditions. Weather patterns are one key factor in the ease of transportation across water bodies, and ignoring them can lead to misleading results. We address this issue by adding a high resolution proxy for weather conditions, that in addition to all of the other controls, is likely to alleviate this concern.

Bearing these difficulties in mind, the effect of piracy is clear and consistent in the analysis. These results highlight how problematic piracy is, not only for the shipping industry, but for the entire economy as well. The effects associated to this problem manifest through three channels.

The first channel is through the waste of capital. Because each individual shipper implements avoidance measures to reduce the probability of an encounter, they must allocate capital to cover these actions. Such capital could have been used somewhere else, either in the form additional voyages, or as an input to other productive activities. The second channel is through environmental impact. The adjustments to piracy are not emission-neutral. In the aggregate, maritime commerce remains as one of the most emission-intense methods of transportation, with direct contributions to global greenhouse emissions, as well as local air pollutants (Corbett and Fischbeck 1997). Our calculation of additional emission burdens shed some light on these potential effects, and highlight how piracy may indirectly result in significant and harmful increases in emissions.

The third and final channel is through potential indirect effects in the cost of trade. Depending on the level of competitiveness of the industry, and the routes in particular, the associated costs in transportation could simultaneously affect producers and consumers. This consequence would have, undoubtedly, a major impact in terms of welfare. Previous studies have tried to implement this problem in a trade context before, but we believe that our approach of examining individual vessel patterns could clearly help identify such effects, both at a local and a global scale. That line of research could unveil important implications for the policy making process that ensures maritime security and fluid trade across nations globally.

Finally, the insights of this study go well beyond just the shipping industry. The level of losses that we estimate using the best available information also highlight a clear win-win scenario situation. As the losses are spread across the industry, the benefits gained from not having to avoid pirates could simultaneously accrue to the shipping industry and help tackle some of the roots of the piracy problem. Partnerships involving both public and private participation could prove highly cost-effective and generate benefits at a large scale. Studying the design and implementation of such policies is a promising area for future research.

We have formal evidence that piracy is an economically important problem. We show that the documented presence of pirates encourages avoidance strategies by the shipping industry, which in turn translate into a waste of resources. These insights apply to both the global shipping industry, as well as for those directly affected in the main hotspots of piracy. In a world where international trade is fundamental for the welfare of its inhabitants, finding mechanisms to control, or completely eradicate the piracy problem, becomes a priority if commerce is to be conducted efficiently.

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A Proofs

A.1 Proposition 1

Proof. The shipper's problem is given by:

$$\max_x \{\pi - \phi(x, \hat{\theta})\psi(pf)h - c(x)\} \tag{11}$$

Taking partials with respect to x and equalizing to zero:

$$-\phi_x(x, \hat{\theta})\psi(pf)h - c'(x) = 0 \tag{12}$$

Rearranging and multiplying by minus one:

$$-\phi_x(x^*, \hat{\theta})\psi(pf)h = c'(x^*) \tag{13}$$

Finally, $\hat{\theta}$ is estimated by examining the sequence of where past encounters took place, $\mathbf{y} = \{y_1, ..., y_n\}$, as:

$$\hat{\theta} = \arg\max_\theta \{\mathcal{L}(\theta; \mathbf{y}, \mathbf{z})\} \tag{14}$$

These two equations define the optimal trajectory for the shipper based on past encounters, and complete the proof. □

A.2 Lemma 1

Proof. First, consider the case of zero avoidance, or $x^* = 0$. From the shipper's problem we know that optimal deviation must satisfy:

$$\phi_x(x, \hat{\theta})\psi(pf)h = -c'(x) \tag{15}$$

Because $c(x)$ is convex and $c(0) = 0$, it follows that $c'(0) = 0$. Substituting into the optimality condition then gives:

$$\phi_x(0, \hat{\theta}) = 0 \tag{16}$$

which is equivalent to say that the only possibility for x to be equal to zero is if $\phi_x(0, \theta) = 0$, which is never true by design.

Second, consider the case of total avoidance, or $x^* \geq \bar{a}$. Recall that

$$\phi_x(x, \theta) = 0 \; ; \; \forall \; x \geq \bar{a} \tag{17}$$

This condition implies that any deviation beyond $\bar{a}$ renders no further reduction in the probability of an encounter. Because of the convexity of $c(x)$, it follows that any $x > \bar{a}$ is strictly inferior to $x = \bar{a}$. Therefore, if $\nexists \; x \in [0, \bar{a}) \; : \; \phi_x(x, \hat{\theta})\psi(pf)h = -c'(x)$, optimal decision making dictates $x^* = \bar{a}$. All other scenarios are described the optimality condition, which completes the proof. □

A.3 Proposition 2

Proof. Consider the optimality condition:

$$-\phi_x(x^*, \hat{\theta})\psi(pf)h = c'(x^*) \tag{18}$$

Totally differentiating with respect to $k(x)$ gives:

$$-\psi(pf)h\left(\phi_{xx}(x^*, \hat{\theta})\frac{\partial x^*}{\partial k(x)} + \phi_{x\theta}(x^*, \hat{\theta})\frac{\partial \hat{\theta}}{\partial k(x)}\right) = c''(x^*)\frac{\partial x^*}{\partial k(x)} \tag{19}$$

Rearranging with the respect to the partial effect on optimal routing x^*:

$$\frac{\partial x^*}{\partial k(x)} = -\frac{\psi(pf)h\phi_{x\theta}(x^*, \hat{\theta})}{\psi(pf)h\phi_{xx}(x^*, \hat{\theta}) + c''(x^*)}\frac{\partial \hat{\theta}}{\partial k(x)} \tag{20}$$

This equation characterizes the total effect of $k(x)$ on x^*, and completes the proof. $\square$

A.4 Corollary 1

Proof. The total effect of $k(x)$ on x^* is given by:

$$\frac{\partial x^*}{\partial k(x)} = -\frac{\psi(pf)h\phi_{x\theta}(x^*,\hat{\theta})}{\psi(pf)h\phi_{xx}(x^*,\hat{\theta}) + c''(x^*)}\frac{\partial\hat{\theta}}{\partial k(x)} \tag{21}$$

By design, $\phi_{xx}(x^*,\hat{\theta}) > 0$ and $c''(x^*) > 0$, which implies that the sign of the relationship between $k(x)$ and x^* is completely characterized by the inverse of the product between $\phi_{x\theta}(x^*,\hat{\theta})$ and $\partial\hat{\theta}/\partial k(x)$. This statement completes the proof. $\square$

B Optimal pirate behavior

In this section, we expand the theoretical insights of the paper to include the behavior of the pirate when deciding on how intense to search for the target vessels. The working assumption of the model was that the pirate encounters whenever $b \geq pf$. The expected value of a successful encounter is then given by:

$$G(pf) = \int_{pf}^{\bar{b}} (b - pf)dF(b) \tag{22}$$

In this model, the pirate cannot directly observe the routing of the shipper, but he can still create have an estimate. This estimate follows from observing past encounters, $\mathbf{y} = \{y_{(1)}, ..., y_{(n)}\}$, and its own search effort, θ. Further, the pirate knows the probability of an encounter is given by $\phi(x,\theta)$. He is then able to estimate the trajectory of the shipper and the associated probability of an encounter as:

$$\hat{x} = \arg\max_x \{\mathcal{L}(x;\theta,\mathbf{y})\} \tag{23}$$

with $\mathcal{L}(x;\theta,\mathbf{y})$ as the likelihood function of $\phi(x;\theta)$. If the pirate has a search cost $s(\theta)$, which is increasing in $\bar{a}$, the expected return to piracy is then given by:

$$R^p(\theta) = G(pf)\phi(\hat{x}, \theta) - s(\theta) \tag{24}$$

In addition, the pirate has a total time constraint, $h = b + t(\theta)$, with b denoting the time working in non-pirate activities for wage w. $t(\theta)$ is a function that denotes the total time devoted to searching for vessels. The pirate's concave utility of income is then given by:

$$u(m, \theta) = wb + R^p(\theta) \tag{25}$$

The time constraint can be rearranged as:

$$b = h - t(\theta) \tag{26}$$

and the utility function can be solely expressed as a function of θ as:

$$u(m, \theta) = w(h - t(\theta)) + R^p(\theta) \tag{27}$$

Taking partials with respect to θ and equalizing to zero gives:

$$-u'(\bullet)(bt'(\theta) + G(pf)\phi_\theta(\hat{x}, \theta) = 0 \tag{28}$$

This expression defines optimal set adjustments for the pirate, which are captured by θ^*, and implicitly defined by:

$$\phi_{\theta^*}(\hat{x}, \theta^*) = \frac{bt'(\theta^*)}{G(pf)} \tag{29}$$

This expression suggests that optimal pirate effort equates the marginal expected gain of increasing the probability of an encounter with the marginal opportunity cost of working in non-pirate activities. Following the same approach as with the shipper, it is straight forward to show that the optimal pirate response to changes in the estimated trajectory are given by:

$$\frac{\partial \theta^*}{\partial \hat{x}} = -\frac{\phi_{x\theta}(\hat{x}, \theta^*)}{\phi_{\theta\theta}(\hat{x}, \theta^*) - \frac{b}{G(pf)} t''(\theta)} \tag{30}$$

Our setting does not allow to sign the above expression. Nonetheless, with a few assumptions regarding both the probability and the time requirement function, clear predictions associated with the pirate behavior in the face of different observables are possible.

C Results for the average effect of piracy on voyage speed

Table 9: Linear regression estimates for the average piracy effect on voyage speed

	Average Speed (km/hr)			
	Global	G. of Aden	G. of Guinea	South East Asia
One year ago	0.02***	0.08***	0.02	0.02*
	(0.01)	(0.01)	(0.02)	(0.01)
(One year ago)^2	-0.00	-0.00***	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Time FE	Y	Y	Y	Y
Size FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Observations	18,353,631	664,763	186,367	6,683,367

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column is a different regression analysis for different samples. The first column refers to the global sample, while the rest only takes into account voyages goin through a specific hotspot.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D Specifications

D.1 Specifications for the effect of piracy on voyage distance

The tables below show the results for voyage distance distance under different specifications. Each table represents a different sample. Namely, the global sample, the Gulf of Aden, the Gulf of Guinea, and South East Asia, respectively. Only fixed effects are manipulated, while all other assumptions in the model remain the same.

Table 10: Linear regression specifications for the effect of piracy on distance for the global sample

	Total Distance (km)				
One year ago	76.88***	21.23***	20.86***	19.16***	18.71***
	(14.98)	(4.25)	(4.34)	(3.78)	(3.82)
(One year ago)^2	-0.39***	-0.09**	-0.09*	-0.08*	-0.07*
	(0.11)	(0.03)	(0.03)	(0.03)	(0.03)
Time FE	N	N	Y	N	Y
Size FE	N	N	N	Y	Y
Country FE	N	Y	Y	Y	Y
Observations	18354384	18353036	18353036	18353036	18353036

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column is a different regression analysis for the same sample controlling for different observables

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Linear regression specifications for the effect of piracy on distance for the Gulf of Aden

	Total Distance (km)				
One year ago	135.37***	43.74***	54.07***	43.22***	53.42***
	(13.35)	(9.46)	(11.35)	(9.43)	(11.30)
(One year ago)^2	-0.82***	-0.22**	-0.29***	-0.21**	-0.28***
	(0.12)	(0.07)	(0.08)	(0.07)	(0.08)
Time FE	N	N	Y	N	Y
Size FE	N	N	N	Y	Y
Country FE	N	Y	Y	Y	Y
Observations	665764	664716	664716	664716	664716

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column is a different regression analysis for the same sample controlling for different observables

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Linear regression specifications for the effect of piracy on distance for the Gulf of Guinea

	Total Distance (km)				
One year ago	-52.84	19.86***	19.39***	19.30***	18.67***
	(35.05)	(4.66)	(4.77)	(4.44)	(4.50)
(One year ago)^2	0.60	-0.12*	-0.09	-0.13**	-0.10
	(0.44)	(0.05)	(0.05)	(0.05)	(0.05)
Time FE	N	N	Y	N	Y
Size FE	N	N	N	Y	Y
Country FE	N	Y	Y	Y	Y
Observations	187306	186366	186366	186366	186366

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column is a different regression analysis for the same sample controlling for different observables

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Linear regression specifications for the effect of piracy on distance for South East Asia

	Total Distance (km)				
One year ago	78.92***	25.71**	25.50**	22.03**	21.56*
	(19.41)	(9.34)	(9.84)	(8.06)	(8.48)
(One year ago)^2	-0.60***	-0.19*	-0.19*	-0.16*	-0.16*
	(0.16)	(0.08)	(0.09)	(0.07)	(0.08)
Time FE	N	N	Y	N	Y
Size FE	N	N	N	Y	Y
Country FE	N	Y	Y	Y	Y
Observations	6684348	6683025	6683025	6683025	6683025

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column is a different regression analysis for the same sample controlling for different observables

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D.2 Specifications for the effect of piracy on voyage time

The tables below show the results for voyage time under different specifications. Each table represents a different sample. Namely, the global sample, the Gulf of Aden, the Gulf of Guinea, and South East Asia, respectively. Only fixed effects are manipulated, while all other assumptions in the model remain the same.

Table 14: Linear regression specifications for the effect of piracy on time for the global sample

	Total Time (hours)				
One year ago	3.68***	1.11***	1.09***	1.06***	1.04***
	(0.70)	(0.20)	(0.20)	(0.18)	(0.18)
(One year ago)^2	-0.02***	-0.01***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time FE	N	N	Y	N	Y
Size FE	N	N	N	Y	Y
Country FE	N	Y	Y	Y	Y
Observations	18354384	18353036	18353036	18353036	18353036

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column is a different regression analysis for the same sample controlling for different observables

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Linear regression specifications for the effect of piracy on time for the Gulf of Aden

	Total Time (hours)				
One year ago	5.87***	1.73***	2.20***	1.72***	2.19***
	(0.62)	(0.40)	(0.48)	(0.40)	(0.48)
(One year ago)^2	-0.04***	-0.01**	-0.01***	-0.01**	-0.01***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Time FE	N	N	Y	N	Y
Size FE	N	N	N	Y	Y
Country FE	N	Y	Y	Y	Y
Observations	665764	664716	664716	664716	664716

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column is a different regression analysis for the same sample controlling for different observables

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Linear regression specifications for the effect of piracy on time for the Gulf of Guinea

	Total Time (hours)				
One year ago	-2.67	0.94***	0.92***	0.93***	0.90***
	(1.52)	(0.22)	(0.22)	(0.22)	(0.22)
(One year ago)^2	0.03	-0.00	-0.00	-0.00	-0.00
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)
Time FE	N	N	Y	N	Y
Size FE	N	N	N	Y	Y
Country FE	N	Y	Y	Y	Y
Observations	187306	186366	186366	186366	186366

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column is a different regression analysis for the same sample controlling for different observables

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: Linear regression specifications for the effect of piracy on time for South East Asia

	Total Time (hours)				
One year ago	3.64***	1.35**	1.33**	1.24**	1.20**
	(0.92)	(0.49)	(0.51)	(0.45)	(0.46)
(One year ago)^2	-0.03***	-0.01*	-0.01*	-0.01*	-0.01*
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Time FE	N	N	Y	N	Y
Size FE	N	N	N	Y	Y
Country FE	N	Y	Y	Y	Y
Observations	6684348	6683025	6683025	6683025	6683025

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column is a different regression analysis for the same sample controlling for different observables

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D.3 Specifications for the effect of piracy on voyage speed

The tables below show the results for voyage average speed under different specifications. Each table represents a different sample. Namely, the global sample, the Gulf of Aden, the Gulf of Guinea, and South East Asia, respectively. Only fixed effects are manipulated, while all other assumptions in the model remain the same.

Table 18: Linear regression specifications for the effect of piracy on speed for the global sample

	Average Speed (km/hr)				
One year ago	0.12*	0.06*	0.06*	0.02***	0.02***
	(0.05)	(0.03)	(0.03)	(0.01)	(0.01)
(One year ago)^2	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time FE	N	N	Y	N	Y
Size FE	N	N	N	Y	Y
Country FE	N	Y	Y	Y	Y
Observations	18354384	18353036	18353036	18353036	18353036

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column is a different regression analysis for the same sample controlling for different observables

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 19: Linear regression specifications for the effect of piracy on speed for the Gulf of Aden

	Average Speed (km/hr)				
One year ago	0.22***	0.06***	0.09***	0.05***	0.08***
	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
(One year ago)^2	-0.00***	-0.00**	-0.00***	-0.00*	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time FE	N	N	Y	N	Y
Size FE	N	N	N	Y	Y
Country FE	N	Y	Y	Y	Y
Observations	665764	664716	664716	664716	664716

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column is a different regression analysis for the same sample controlling for different observables

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 20: Linear regression specifications for the effect of piracy on speedfor the Gulf of Guinea

	Average Speed (km/hr)				
One year ago	0.06	0.03	0.03	0.02	0.02
	(0.06)	(0.02)	(0.02)	(0.02)	(0.02)
(One year ago)^2	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time FE	N	N	Y	N	Y
Size FE	N	N	N	Y	Y
Country FE	N	Y	Y	Y	Y
Observations	187306	186366	186366	186366	186366

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column is a different regression analysis for the same sample controlling for different observables

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 21: Linear regression specifications for the effect of piracy on speed for South East Asia

	Average Speed (km/hr)				
One year ago	0.23***	0.09*	0.09*	0.02*	0.02*
	(0.05)	(0.04)	(0.04)	(0.01)	(0.01)
(One year ago)^2	-0.00***	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time FE	N	N	Y	N	Y
Size FE	N	N	N	Y	Y
Country FE	N	Y	Y	Y	Y
Observations	6684348	6683025	6683025	6683025	6683025

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column is a different regression analysis for the same sample controlling for different observables

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

E Pirate encounters as a binary indicator

In addition to the model in the main body of the paper, we also explore the effect of any pirate encounters on shipping behavior. In particular, we are interested in how the occurrence of any pirate encounter affects shipping trajectories (distance, duration, and speed) of voyage i, along route r, at time t. The model is as follows:

$$y_{irt} = \alpha + \beta \mathbb{1}_{\{TNE_{rt-1}>0\}} + \delta_i VC_i + \lambda_i W_i + \eta_r R_i + \theta' X_t + \epsilon_{irt} \tag{31}$$

y is the dependent variable, TNE is the total number of encounters during the last year, with β as the mean effect at least one past encounter on trajectory. In addition, VC is a vector of fixed effects according to vessel characteristics (type of vessel and size) conducting voyage i, while W is the time-weighted mean wind-resistance for a given voyage. Finally, R is a vector of fixed effects by route, while X_t is a battery of month by year fixed effects.

Table 22: Linear regression estimates for the average effect at least one pirate encounter on voyage distance

	Total Distance (km)			
	Global	G. of Aden	G. of Guinea	South East Asia
Experienced encounters	255.45***	346.16***	94.97	310.44***
	(21.12)	(99.84)	(63.10)	(32.82)
Size FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Observations	18353631	664763	186367	6683367

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column is a different regression analysis for different samples. The first column refers to the global sample, while the rest only takes into account voyages goin through a specific hotspot.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 23: Linear regression estimates for the average effect at least one pirate encounter on voyage time

	Total Distance (km)			
	Global	G. of Aden	G. of Guinea	South East Asia
Experienced encounters	15.30***	15.53***	2.01	21.04***
	(0.91)	(4.13)	(5.53)	(2.29)
Size FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Observations	18353631	664763	186367	6683367

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column is a different regression analysis for different samples. The first column refers to the global sample, while the rest only takes into account voyages goin through a specific hotspot.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 24: Linear regression estimates for the average effect at least one pirate encounter on voyage speed

	Total Distance (km)			
	Global	G. of Aden	G. of Guinea	South East Asia
Experienced encounters	0.32***	0.55***	0.91	0.22***
	(0.05)	(0.13)	(0.72)	(0.05)
Size FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Observations	18353631	664763	186367	6683367

Note: Standard errors in parentheses and clustered by country pair. The unit of of observation is a voyage. Every column is a different regression analysis for different samples. The first column refers to the global sample, while the rest only takes into account voyages goin through a specific hotspot.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$