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One Kind of Lawlessness

Estimating the Welfare Cost of Somali Piracy

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One Kind of Lawlessness: Estimating the Welfare Cost of Somali Piracy*

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Abstract

This paper estimates the effect of piracy attacks on shipping costs using a unique data set on shipping contracts in the dry bulk market. We look at shipping routes whose shortest path exposes them to piracy attacks and find that the increase in attacks in 2008 lead to around a ten percent increase in shipping costs. We use this estimate to get a sense of the welfare loss imposed by piracy. Our intermediate estimate suggests that the creation of \$120 million of revenue for pirates in the Somalia area led to a welfare loss of over \$1.5 billion.

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1 Introduction

For centuries, piracy has posed a threat to ocean-going trade.¹ In essence, it is organized private predation which thrives in locations in which law and order is weak, either because particular states provide safe havens or due to poor international cooperation. And it has repercussions for worldwide trade.

However, despite the long-standing importance of piracy, little is known about its economic costs.² The issue has been brought into sharp relief by the upsurge of piracy in the Gulf of Aden which poses a threat to one of the world's busiest shipping routes. Frequently attributed to the collapse of effective authority in Somalia, it has provoked an international response. However, the threat to shipping remains.

This paper does three things. First, we model the frequency of piracy attacks in two main piracy areas where it is prevalent (Indonesia and Somalia) as a means of generating monthly forecasts of such attacks. Second, we match the piracy forecast to data on around 24,000 shipping contracts by constructing the closest navigable sea distance between each origin and destination port for which a ship has been chartered. This allows us to exploit the monthly time-series variation in the frequency of piracy attacks in our two piracy areas and to estimate how much an upsurge in piracy raises shipping costs. Third, we use these estimates to examine the welfare cost of Somali piracy.

Our core model of piracy attacks posits that an unobserved latent state (law and order) and weather conditions determine the level of piracy attacks. Estimating the parameters of a Markov chain model gives us a measure of underlying persistence in states which is useful for generating piracy forecasts. We show that month-to-month variation in weather conditions also explains the frequency of attacks.

We estimate that shipping costs for dry bulk goods rose by around 10% when pirate activity increased in Somalia. This is partly identified from how such costs react to changes in pirate activity induced by seasonal changes

¹For example, North (1968) argues that a decline in piracy from 1600 to 1850 accounts for a significant proportion of the observed productivity increases in transatlantic shipping in this period.

²Bensassi and Martínez-Zarzoso (2011) study the impact of piracy in the Strait of Malacca on trade costs. Most cited numbers are from One Earth Future Foundation (2010, 2011).

in weather. Our estimates suggest that it is around 14% cheaper to charter ships through the Gulf of Aden during the summer monsoon (June-August) than in spring (March-May). And this seasonal pattern in shipping prices is absent prior to the upsurge in pirate activity in the region during 2008. There is little robust evidence of effects of piracy attacks on shipping that passes through the Indonesia region where piracy attacks are less prevalent and less episodic.

The extra shipping costs that we uncover are mostly due to the increased security measures that are needed to repel pirate attacks and hence constitute a welfare cost as labor and resources are allocated from productive tasks to guard services. We develop a model to compare this extraction of resources through pirate attacks to a tax on shipping which finances an equivalent transfer. This allows us to calculate the welfare loss caused by piracy. Our central estimate suggests that the resource costs incurred in transferring around 120 million USD annually to Somali pirates is well in excess of 1.5 billion USD. This confirms the general point that predation is a lot more costly as a form of extraction than taxation. The former is a form of anarchy while the latter typically requires a state that exercises a monopoly of force.

The paper belongs to a wider literature on the value of establishing the rule of law and its role in securing trade and investment.³ A traditional problem in weakly-institutionalized environments is that bringing goods to market is subject to predation and theft. The consequences of the failure to establish and enforce property rights is a core theme in the development literature, for example, Acemoglu, Johnson and Robinson (2001). The large literature on the economic costs of corruption, another form of widely observed extra-legal transfers is also relevant.⁴

Piracy has always posed a particular issue because of the difficulty of securing international agreement over whose responsibility it is to deal with the problem and how the costs are shared. Private solutions to increase security such as carrying guards aboard ships are inherently less efficient compared to dealing with the public good of security for all.⁵ Our calculation of the welfare cost gives a sense of the magnitude of this benefit and we discuss why this is so high compared to tax-based redistribution.

Insecurity due to piracy causes a rise in shipping costs which are an im-

³See Dixit (2004) and Rose-Ackerman (2010) for excellent overviews and Olken and Barron (2009) for a recent contribution using data from Indonesia.

⁴For a survey and overview, see Olken and Pande (2011).

⁵See Bandiera (2003) for a similar argument.

portant part of total trade costs. In this respect, our paper relates to studies of the consequences of trade costs for trade patterns.⁶ Feyrer (2009) relates in his study of the Suez Canal closure 1967-1975. Our welfare calculations build on his findings.

One of the central difficulties in combatting predation due to piracy is the need for international cooperation. There is a classic public good problem with the usual potential for free-riding. And this appears to have been a major issue historically. For example, the correspondent report on Chinese piracy in *The London and China Telegraph* from 4th February 1867 noted that

"Besides we are not the only Power with large interests at stake. French, Americans, and Germans carry on an extensive trade [...] Why should we then incur singly the expense of suppressing piracy if each provided a couple of gunboats the force would suffice for the safety foreign shipping which is all that devolves upon [..] why should the English tax payer alone bear the expense?"

While the international community has now attempted to introduce naval patrols to combat Somali piracy, this is extremely expensive and requires international diplomacy between a range of states.⁷ In the end, the most promising long-term solution would seem to be to restore a functional Somali state which can deny pirates safe haven, thereby dealing with the problem at source.

The remainder of the paper is organized as follows. In the next section, we discuss the piracy data and develop a statistical model of pirate attacks. In section three, we introduce the time charter data and discuss how piracy affects shipping costs. Section four presents our estimation results and robustness checks. Section five provides a theoretical framework of the welfare loss and combines the framework with our estimates to derive a range for the welfare loss from piracy. Concluding comments are in section six.

⁶For a review see Behar and Venables (2011). See Donaldson (2010) for a recent study of the impact of a change in trade costs due to the advent of railroads in India.

⁷China has recently sent military ships into the Indian Ocean who coordinate with the Indian navy - a sign that piracy now threatens even trade through the Indian Ocean.

2 Forecasting Piracy Attacks

Insurers and shippers need to be able to forecast piracy attacks in order to respond to the risk that it poses. Whether explicit or not, this means having a model of piracy to predict future pirate attacks. In this section, we propose a Markov switching model between two latent states representing weak and strong law and order. We also allow seasonal weather conditions to influence the level of piracy attacks. We use the model to forecast monthly piracy attacks. Below, we will compare this approach to some simpler models to reassure ourselves that the specific structure alone is not driving the results.

2.1 Background and Data

Modern piracy is an organized and sophisticated crime.⁸ Our data on such attacks comes from the ICC International Maritime Bureau (IMB) annual reports which provide the exact position of the attack, details on the ship and its status (anchored or steaming) and the type of attack (attempted, boarded, fired upon, hijacked).⁹

We coded attacks by their geo-code and focus on two main areas where piracy is most prevalent for the period 2003 to 2010. Both of these areas are shown in figure 1. The first is the Somalia area, which we define geographically as the rectangle spanned by the coordinates S11, E38.4 and N18.3, E74.7. The second area is the broader Indonesia area, that includes the Strait of Malacca. We define this area through the coordinates S10, E95.8 and N7.4, E120.7.

The red dots denote the locations of the piracy attacks. We focus on these areas because we believe that there are common factors driving piracy attacks within these zones, i.e. if pirates attack in some part of the area, it is informative about the likelihood of an attack elsewhere within it. For Somali pirates this is well documented. Given that the Indonesia area is smaller, our assumption does not seem unrealistic there either. Figure 1 also depicts two more geographically narrower areas, the Gulf of Aden and the Strait of Malacca, which we use as a robustness check on our results below.

There is considerable variation in the intensity of attacks over time. Figure 2 summarizes the time dimension of attacks in both Somalia (left) and Indonesia (right). Piracy in Indonesia has been the object of a longer-standing

⁸See Leeson (2007) for a discussion of the organization of piracy in history.

⁹We discuss our data in the appendix A. Table A1 provides summary statistics.

international efforts to police the area by the governments of Singapore, Malaysia and Indonesia. Figure 2 shows a distinct shift in the amount of attacks in 2005. Today, the problem is deemed to be largely well-contained.¹⁰

Acts of piracy off the coast of Somalia have intensified more recently; there was an average of 1.7 attacks per month before 2008 and 11 per month from 2008 onwards. Pirates initially masqueraded as coast guards protecting Somali territorial waters from illegal fishing. This cloaked a build up of organized violence. According to Hansen (2009), a key trigger for the upsurge in violence was when the Puntland government in Somalia decided, due to a crisis in the public finances, that it could no longer afford to pay the police. Thus, the primary reason for intensification was the break down in law and order in Somalia which made it increasingly feasible for pirates to operate without sanction.

We attribute the main time series variation in piracy attacks to variation in law and order both on the high seas and surrounding area. In the case of Somalia, the break down of the state of Somalia which made it infeasible for the local government to control attacks in 2008. In the case of Indonesia the main shift seems to be due to the strength of cooperative interventions by Singapore, Malaysia and Indonesia following three-way talks in September 2005.

2.2 A Simple Model

Suppose that in region r, there are M_r active pirate ships and that in each period each pirate receives an opportunity to hijack a ship where V_{irt} is the

¹⁰The Joint War Committe crossed the Strait of Malacca from its list of high risk areas in 2006, http://www.lloyds.com/News-and-Insight/News-and-Features/Archive/2006/08/Market_removes_Malacca_Straits_from_the_List, accessed on 11.04.2012.

benefit and c_{irt} is the cost.¹¹ Pirate *i* in region *r* at date *t* will launch an attack if the expected benefit exceeds the cost:

$$\xi_{rt}V_{irt} \geq c_{irt}$$

where ξ_{rt} is the region specific success probability, V_{irt} is the value of a successful attack and c_{irt} is the cost. We allow the success probability, ξ_{rt} , to depend on climatic conditions and the law and order situation in the region, e.g. whether piracy attacks are policed and there is a safe haven available in which to demand a ransom.

A key parameter is the cost-benefit ratio $\rho_{irt} = c_{irt}/V_{irt}$. We suppose that ρ_{irt} is drawn for each pirate ship *i* in region *r* at date *t* from a uniform distribution on [0, 1]. Given M_r independent draws then the expected number of pirate attacks in region *r* at date *t* is given by:

$$E\left[a_{rt}\right] = \xi_{rt}M_r.\tag{1}$$

According to this mode, forecasting piracy attacks means predicting how ξ_{rt} is likely to vary over time.

2.3 Law and Order

We allow the probability of a successful pirate attack to depend on a latent state, $\ell \in \{S, W\}$ with $\xi(S) < \xi(W)$ where S stands for "strong" and W for "weak". We are assuming that the probability of successfully hijacking a ship and demanding a ransom is higher when law and order is weak. Using this in equation (1), the mean number of pirate attacks in state ℓ is

$$\mu_{r\ell} \equiv \xi(\ell) M_r, \ \ell \in \{S, W\}.$$

$$E\left\{V_{irt} - c_{irt} : \xi_{rt}\right\} > F_{ir}$$

in which case we would also predict that M_r would be a function of ξ_{rt} , i.e.

$$M_{rt} = H(\xi_{rt})$$
.

So we would have

$$E\left[a_{rt}\right] = \xi_{rt}H\left(\xi_{rt}\right)$$

and the expected number of pirate attacks will still depend on ξ_{rt} reflecting underlying law and order.

¹¹To endogenize M_r , suppose that there is a fixed cost becoming an active pirate. Then we would have that a priate will enter if

where $\mu_{rS} < \mu_{rW}$.

Dynamics across law and order states are modeled as a Markov chain governing the process of state transitions. We show in the appendix that this model gives the following formula corresponding to equation (1) for the expected number of attacks at t+1:

$$E\left[a_{rt+1}\right] = \Omega_r + \left(\mu_{rW} - \mu_{rS}\right) \lambda_r P\left(\ell_{rt} = W\right) \tag{2}$$

where Ω_r is a region-specific constant, λ_r is a measure of persistence of the process and $P(\ell_{rt} = W)$ is the probability that region r is in the weak state at time t.¹² The latter is the only time-varying factor in equation (2) and evolves according to the history of piracy attacks. By estimating the parameters of the underlying process, we can construct an empirical counterpart to (1).

The model has some special features. First, the process driving law and order is fixed exogenously. And the assumption of two states is special. What makes these compromises attractive, however, is the fact that it gives us a filter for emerging data on pirate attacks which can be used to construct a forecast for pirate attacks which can capture the sharp non-linear pattern in the data, especially in Somalia, in a way that can be mapped back to an underlying theory. This type of model, first proposed in Hamilton (1989), has been popular among time series economists modeling the non-linear properties of business cycle fluctuations. Below, we will compare it to some less structured approaches.

The model has six parameters for each region. Two state-specific means, two persistence parameters which together determine λ_r and two state-specific variances. The model is estimated by using the data on attacks in a filter provided by Hamilton (1989). One way of estimating the parameters of the piracy process is the Expectation Maximization (EM) Algorithm described in Hamilton (1990) which generates an estimate of the parameters by iteration and is easy to implement.¹³

To use the model to forecast piracy attacks, we use the observed number of attacks in month t to calculate the probability $P(\ell_{rt} = W)$ that a region is in a weak state given a set of known parameters. Equation (2) shows that if $P(\ell_{rt} = W)$ increases then the expected value of attacks next month increases by $(\hat{\mu}_{rW} - \hat{\mu}_{rS}) \hat{\lambda}_r$.

 $^{^{12}}P(\ell_{rt}=W)$, is a function of the particular history of attacks in region r in month t and the set of Markov chain parameters θ_r .

¹³We discuss estimation in appendix B.2.

Estimates for $(\hat{\mu}_{rW} - \hat{\mu}_{rS}) \hat{\lambda}_r$ for Somalia (Panel A) and Indonesia (Panel B) are given in the first row of each panel in Table 1. We estimate the mean number of pirate attacks in Somalia when law and order is weak to be around 15 (column 1) and around 2 when law and order is strong (column 2). The corresponding figures for Indonesia are around 9 and 4. The persistence estimate is given in column (3).¹⁴ The predictions of the fitted model for Somalia (left) and Indonesia (right) are summarized in figure 3. The graphs show the actual number of attacks as a dotted line and the expected number of attacks next month as a solid line. The abrupt swings in the forecast number of attacks are driven by changes in $P(\ell_{rt} = W)$ between values that are close to zero and one while the impact of the estimated probability on expectations is driven by our estimate of $(\hat{\mu}_{rW} - \hat{\mu}_{rS}) \hat{\lambda}_r$.

As a reality check, it is interesting to observe that the predictions made by our model are very much in line with the risk evaluations of the marine hull war insurance business in the London market. Their representative, the Joint War Committee, took the Strait of Malacca off its list of areas under special war risk in August 2006 and added the Gulf of Aden in May 2008. This suggests that we are capturing some common-sense features of the pattern of piracy attacks.

2.4 Seasonality

The baseline model identifies law and order as the only underlying cause of fluctuations in piracy attacks over time. However, there is a pronounced seasonal pattern that can also be incorporated into the empirical model. Evidence for the Somali region suggests that pirate vessels there are vulnerable to weather conditions. Most of the attacks are carried out using small vessels, known as "skiffs". These are typically between 7 – 10 meters long and at most two meters wide with a low freeboard. This renders them particularly vulnerable to wind and waves.¹⁵ According to analyses by UN bodies, attacks in the area of Somalia are almost absent during the Monsoon season but resume after winds calm.¹⁶ This reasoning leads us to expect a nega-

¹⁴For an explanation see the appendix. In Somalia persistence is calculated from $\hat{\lambda}_r = 0.92 + 0.95 - 1$ and in Indonesia as $\hat{\lambda}_r = 0.95 + 0.97 - 1$.

¹⁵The Office of Naval Intelligence (ONI), a U.S. navy think tank, publishes the Piracy Analysis and Warning Weekly (PAWW) which uses weather data to predict piracy risks in the Somalia area.

¹⁶See UNOSAT (2010). We confirm this in appendix A4.

tive correlation between the intensity of attacks and seasonal conditions such as wave height or wind speed. We now generalize the model to allow for seasonality.

Suppose that there is now a month specific shock to the success probability, ξ_{rt} . Now the average number of pirate attacks will be month dependent and equation (1) generalizes to

$$\mu_{rm\ell} = \xi_r \left(\ell\right) w_{rm} M_r \tag{3}$$

where w_{rm} is the mean "weather" shock to piracy success in month m in region r. This allows us to rewrite the mean number of attacks as an interaction between an indicator for the weak and strong state $I [\ell = j]$, $j \in \{S, W\}$ and a monthly mean of attacks during times of weak and strong law and order, α_{rmW} and α_{rmS} .

$$\mu_{rm\ell} = I \left[\ell = W \right] \alpha_{rmW} + I \left[\ell = S \right] \alpha_{rmS}.$$

Thus, we have a month-dependent mean in the underlying Markov chain which switches between strong and weak law and order.

The forecast number of attacks at t+1 when that month is m is now a function of the probability of the weak state in t and the mean of attacks during weak and strong law and order states for t+1. Thus (2) generalizes to:

$$E\left[a_{mrt+1}\right] = \Omega_{mr} + \left(\alpha_{rmW} - \alpha_{rmS}\right)\lambda_r P\left(s_{rt} = W\right) \tag{4}$$

where Ω_{mr} is again a constant (now specific to month m and region r).¹⁷

Table 1 summarizes the results from estimating this generalized model. Panel A shows results for the Somalia region. Column (1) contains our estimate of the monthly means: $\hat{\alpha}_{r1W}, \hat{\alpha}_{r2W}, ..., \hat{\alpha}_{r12W}$. The estimates show a clear seasonal pattern of attacks with the month of March and April being particularly active in terms of piracy. Not surprisingly, there is less seasonality in the strong law and order state (column (2)). Column (3) gives our estimate of the persistence of the law and order states. Compared to row (1) persistence has increased slightly. This is mostly because variation in attacks

 $^{^{17} \}rm{We}$ can directly apply the estimation method described above to a richer parametrization with 28 parameters.

¹⁸In appendix A4 we show that monthly average wind speed is highly correlated with the our estimates $\hat{\alpha}_{rmW}$. We can therefore interpret these parameters as being driven by exogenous weather variation.

is attributed to seasonality instead of the underlying state. In column (4) we show the impact of the state of law and order on expected piracy attacks next month.

It is instructive to consider how our monthly forecast responds to observing the upsurge in pirate attacks in May 2008. In our model this corresponds to a switch the state of law and order from 0 to 1. According to the estimates in column (4) in Table 1 induces a change in the forecast number of attacks in June by around 10 whereas for July, weak law and order is associated with fewer than one pirate attack due to seasonality in weather conditions.

Panel B in Table 1 shows the results for Indonesia. Although present in the data, seasonality is generally less important than in Somalia. The change in forecast piracy attacks induced by moving from weak to strong law and order are also generally smaller.

2.5 Comparison to an AR(2) model

As a comparator for the Markov chain model, we also fitted an AR(2) process to the pattern of attacks in each region so that

$$E\left[a_{rt+1}\right] = \hat{b}_{0r} + \hat{b}_{1r}a_{rt} + \hat{b}_{2r}a_{rt-1}.$$

We can compare the results for this case to the more structured approach laid out above.

Figure 4 compares the predictive power of the seasonal Markov Chain model (filled out dots) compared to the AR(2) process (hollow dots). Deviations from the 45 degree line indicate prediction errors. Clearly the seasonal Markov chain model predicts attacks much better than the AR(2) process.¹⁹ This is driven by the seasonal information used in the seasonal Markov chain model. The AR(2) process "interprets" a low level of attacks as a sign of pirate inactivity. The seasonal Markov chain model compares the level of attacks to the level of attacks typical for that month. The absence of attacks during Monsoon is then not interpreted as evidence that piracy has been defeated which seems sensible.

 $^{^{19}\}mathrm{A}$ regression of attacks on the predicted values from the Markov chain model yields a R-sq of 0.8 compared to 0.5 in the AR(2) process. Appendix table A2 reports these regressions.

3 The Cost of Piracy Attacks

We now turn to estimating the impact of forecast piracy attacks on shipping costs using data on chartering contracts in the dry bulk shipping industry. We begin by discussing some of the costs of piracy and how they are shared. We then introduce our data and estimation.

3.1 Cost Factors

There have been a number of costly private responses to the piracy threat. A variety of insurance arrangements have emerged to cover piracy risks with higher premia being paid to travel in areas deemed to be at risk. Ships increasingly carry armed guards and other preventive measures (mostly modifications to ship hulls) have become "best practice" which makes them relevant for insurance purposes.²⁰ In extreme cases, ships can re-route although that would mean foregoing the considerable time and distance saving from using the Suez canal.

The costs to the shipping industry can be decomposed into five main categories: (i) damage to vessels (ii) loss of hire and delay to cargo delivery while a ship is held to ransom (iii) costs of defensive measures (iv) cost of ransoms paid when a crew is kidnapped or a vessel is held (v) re-routing of vessels to avoid areas at risk. We discuss these cost factors in detail in Appendix (C). Ship owners typically buy insurance to cover themselves against a number of these costs with insurance costs being sensitive to developments in the number of piracy attacks.

Our window on measuring costs is through shipping contracts whose prices adjust to reflect the above costs to the extent that they are borne by the ship owner and shifted to the charterer. This is not unrealistic. The association of independent tanker owners, for example, provides model clauses for chartering agreements with regard to piracy risks, stating that:²¹

"Charterers shall indemnify Owners against all liabilities costs and expenses arising out of actual or threatened acts of piracy or

²⁰Best Practice manuals are published and updated regularly by the shipping industry. See http://www.mschoa.org/bmp3/Documents/BMP4\%20low\%20resolution\%20(3).pdf, accessed on 10.04.2012.

 $^{^{21}} Refer$ to http://www.intertanko.com/upload/P'rlse\%20piracy\%20clauses\%202.09.doc, accessed on 10.04.2012.

any preventive or other measures taken by Owners [...], including but not limited to additional insurance premiums, additional crew costs and costs of security personnel or equipment."

Hence, there are good reasons for believing that the lion's share of these costs ultimately falls on charterers who compensate ship owners in the form of higher charter prices.²². Below, we will discuss the sensitivity of our estimates regarding the division of these costs.

3.2 Data on Shipping Contracts

Our shipping price data comes from the web-site of N. Cotzias Shipping Consultants which provides monthly reports on the time charter market for the period November 2002 until December 2010.²³ The data is comprised of 33,529 individual charters in the dry bulk cargo segment of the market. These are ships that transport primary commodities such as iron ore or agricultural products such as grain. This variety of ship constitutes approximately one third of the tonnage of the global shipping fleet. Short term chartering agreements are typical for bulk carrier ships, due to the volatile nature of commodity markets. Since the starting point for these charter agreements are previous agreements ('last done'), shipowners and charterers take an active interest in reports of recent transactions.²⁴ The individual time charter agreements are also used to construct general shipping indices such as the Baltic Exchange Dry Index (BDI). Thus our data-set provides a window onto the wider shipping market.

In a time charter agreement the shipowner places his ship, with crew and equipment, at the disposal of the charterer and bears the costs of keeping the ship operational. The charterer pays a daily charter rate and decides the type and quantity of cargo to be carried and the ports of loading and discharging. The charterer is also responsible for paying bunkers (fuel) and costs like port charges including the payments due, for example, for using the

²²In the container shipping industry, region specific piracy surcharges of 5% of the base rate or \$300 per container are common. See http://www.joc.com/container-lines/freight-rate-surcharge-update-week-april-2-6, accessed on 12.04.2012.

²³In early 2011, Cotzias merged with Intermodial (www.intermodal.gr). As of 25th January 2012, the Cotzias data was available on http://www.cotzias.gr/chart_tc_rep.htm.

²⁴See Stopford (2009) for a detailed discussion of the time charter market.

Suez Canal. The fact that time charter rates are provided on a daily basis makes them comparable across contracts of differing length.

The summaries made available on the web-site provide, among other information, the name of the ship, its deadweight tonnage (DWT), the year it was built, the port of origin and the port or country of destination. From this information we construct our measure of shipping cost - the rate per day per DWT. We also use the origin and destination to assign the ship's voyage to countries (appendix A.3). Most of the charters are from Asia with China making up the bulk of origin and destination locations. Our data set contains information on around 1600 distinct shipping routes.

3.3 Identifying Exposure to Piracy Risks

Our approach requires us to assign a risk of exposure to piracy attacks to each route. We do this by using the information on the origin and destination of the shipping contract. For example, a vessel with a destination in Germany and an origin in China is quite likely to travel through both, the Somalia and Indonesia area. However, there are some cases where it is not entirely clear whether the vessel would travel on a Pacific route or an Indian Ocean and Atlantic route using the Suez canal.

In assigning piracy risk, we therefore employ a path algorithm to obtain an automatic coding of a route.²⁵ We are then able to see whether the shortest sea route passes though the piracy areas that we study. If it does, then we will suppose that the shipping contract is subject to a piracy risk based on the forecast number of attacks in the relevant region

Figure 5 provides a bird's-eye view of the constructed trade-routes for the areas around Somalia. Thicker lines indicate more charter agreements on that trade lane. The bottom right of figure 5 illustrates the bulk trade network allocated to port of Surabaya (Indonesia). Overall, we observe around 7,100 charters for routes going through the Somalia area and 10,600 charters through the Indonesia area.

This approach means that we are only able to assign an intention to treat (ITT) rather than the treatment itself. It is, for example, possible that some ships were re-routing around the Cape of Good Hope to avoid exposure to piracy risks. One way to investigate how important such re-routing is to regress monthly Suez canal traffic (in deadweight tons) on attacks in the

²⁵Details are discussed in the appendix A.3.

Somalia region. This is reported in Table 2. The sign on attacks is negative but the coefficient is insignificant. To control for the effect of world trade caused by the financial crisis, we add a dummy variable for the period after the Lehman Brothers collapse which is strongly negative and significant. The results in Table 2 do not suggest that seasonal patterns in shipments through the Suez Canal are related to pirate attacks. This supports the view of other commentators, such as One Earth Future (2011), that re-routing around the Cape is not important.

3.4 Piracy Costs and Shipping Prices

Our core specification assumes that the dry bulk shipping market is contestable so that pricing is based on the average cost per day for each voyage. We would then expect prices in that market to reflect expected piracy attacks and any other factors that influence costs. We denote the cost per dead weight ton (DWT) per day for a ship of size s on route d in month t as:

$$C\left(s,d,t,A_{dt}\right)$$

where A_{dt} is the forecast number of attacks affecting route d at date t.²⁷ An effect of piracy on costs is not unrealistic as the shipping conditions at so-called "choke points" (the straits of Hormuz and Malacca, the Suez and Panama canals, the Bosporus) are known to affect freight rates.²⁸ Since there are scale economies in shipping, we expect this cost function to be decreasing in s.

For simplicity, we adopt the specification:

$$\log C\left(s, d, t, A_{dt}\right) = c\left(s, d, t\right) + \gamma A_{dt} + \beta x_{dst} + \eta_{dst} \tag{5}$$

where γ is the core parameter of interest, x_{dst} are other time varying controls and η_{dst} captures other idiosyncratic factors which are uncorrelated with A_{dt} .

²⁶See Behar and Venables (2011) for a discussion of the extent of contestability in shipping markets. This is important for our interpretation since otherwise there would be a markup of prices over costs reflecting the extent to which ship owners have market power. In that case, part of the cost of piracy could be absorbed in lower profits.

²⁷Due to the absence of good monthly data on ship traffic for our period 2002-2010 we have to use A_{dt} as a measure of piracy risk. This disregards the fact that dense traffic makes journeys less risky for each ship.

²⁸See, for example, the discussion at the Baltic Exchange under http://www.balticexchange.com/default.asp?action=article\&ID=3.

The cost from piracy depends on the route that the ship takes. As we have already discussed, we construct two treatment indicators for each route depending on whether it passes through the area of Somalia or Indonesia. Denote this as a dummy variable where $\delta_{dr} = 1$ if route d passes through piracy region r. Then:

$$A_{dt} = \delta_{dr} \times E\left[a_{rt+1}\right].$$

is our measure of the cost shock expected on route d where, in the core specification, the forecast is generated by (4). In the basic specification, we do not allow treatment to vary with ship size, s, or route, d. However, we will also allow for a heterogeneous effect in some specifications that we report below.

To reflect this discussion, our core empirical specification is:

$$z_{isdt} = \alpha_s + \alpha_d + \alpha_t + \alpha_w + \gamma A_{dt} + \beta x_{dt} + \varepsilon_{isdt}$$
 (6)

where z_{isdt} is the (log of) daily charter rate per DWT for contract i on a ship of size s, for route d in month t. The parameters $(\alpha_s, \alpha_d, \alpha_t)$ are fixed effects for ship size, route and month. The standard error ε_{isdt} is adjusted for clustering at the route level. Other controls in x_{dt} include the age of the ship and the ballast bonus per DWT (a bonus paid for empty return journeys).

The main parameter of interest is γ which we interpret as the additional shipping cost from anticipated piracy attacks. We are expecting that $\gamma > 0$. The empirical approach can be thought of as a difference-in-difference specification where ships that pass through regions where pirates are expected to attack are compared to ships using different routes over the same time period. This exploits time-series variation in forecast piracy attacks depending on their past history and seasonal weather conditions.

3.5 Core Results

Our core results are reported in Table 3 which uses the specification in (6).

In column (1), forecast piracy attacks are generated using equation (2) for each of our two regions. The only controls are fixed effects for route, time and ship size. For the latter, the omitted ship size category is "small" capesize ships between 80,000 and 150,000 DWTs. There is a strongly significant positive coefficient on the expected number of attacks. The point estimate says that one extra anticipated attack in a month increases the daily

charter rate by a little over 1% in the Somalia region with no significant effect for charters that pass through the Indonesia region. While attacks in the Indonesia continue, it is unlikely that there is much learning going on over this period and most of the effect is probably already absorbed in the route fixed effect.²⁹ Since the mean difference in pirate attacks between high and low law and order states is around 11, this suggests that shipping costs were around 11% higher after the break down in law and order in Somalia which lead to increased piracy attacks.

The ship size dummy variables show evidence of significant scale economies in shipping with the smallest ships being around 63% more expensive per DWT than the excluded category. The point estimates decline across the ship size categories. This is a feature of all the estimates that we show.

It is important to observe that, by including time dummy variables (for each month), we are controlling for general trends in the global shipping market. These are important over this period given that the economic crisis erupts around 2008 while the capacity of bulk shipping grows considerably. For this to create a problem for us, it would have to be the case that the routes that we have classified as being treated are differentially affected by changes in market conditions in a way that increases shipping costs of bulk shipping. The main trend in this period is, however, a switch of bulk trade in Asia away from Europe and towards other Asian countries, Australia and the Americas.³⁰ This would work against us as it would put a downward pressure on prices for bulk charter agreements between Europe and Asia.

In column (2), we forecast attacks allowing for month specific effects as in equation (4). The effect of forecast attacks in the Somalia region remains positive and significant although the average effect is somewhat lower than in column (1). This suggests an overall effect due to the break down of law and order in Somalia of a little less than 10%. However, the effect across months is heterogeneous. The difference between forecast attacks from the period March-May compared to the summer monsoon season June-August is 19.66. This implies a change in shipping costs of more than 14% between spring and the Monsoon season.

Column (3) adds two additional ship controls: ballast bonus payments and the vessel's age. We find a large variation in rates paid for younger

²⁹An alternative interpretation is that increased military presence by Malaysia, Indonesia and Singapore in this period prevents an impact of piracy. See, for example, http://www.time.com/time/world/article/0,8599,1893032,00.html\#ixzz1kaNw1NTq.

³⁰See the detailed discussion in UNCTAD 2011 and UNCTAD 2010.

compared to older vessels with chartering rates for older vessels being significantly lower. However, the point estimates on forecast piracy attacks do not change much after adding these controls.

In column (4), we use only data after Somali piracy increased in May 2008. The variation in forecast piracy attacks is now identified purely from the seasonal (i.e. monthly) differences due to weather. It is encouraging to observe that the sign and significance of the Piracy effect remains even though the size of the effect is much smaller. However, this is not surprising given that we are, in effect, throwing away the variation due to the main breakdown in law and order in Somalia that precipitated the large increase in piracy attacks.

Column (5) explores whether there is a heterogeneous effect across the different ship sizes travelling through the Somalia area. Due to the precision of the estimates, we can not discern statistically distinct patterns across ship types, except for the very small and very large vessels. The latter observation can be thought of as a robustness check, as the largest Capesize vessels cannot use the Suez Canal.³¹

Overall, these results suggest that piracy in the Somalia area has a positive effect on the cost of shipping through this region. This is true across the specifications that we report in Table 3. It now remains to assess whether the results are sensitive to two main types of robustness check: (i) different ways of forecasting piracy attacks and (ii) different ways of assigning treatment.

3.6 Alternative Forecasts of Pirate Attacks

We first consider how the results vary according to the model that is used to forecast piracy attacks. The results are shown in Table 4.

In column (1) we use the estimated probability of a weak state of law and order as an explanatory variable for shipping cost, i.e. $P(\ell_{rt} = W)$ in equation (2) is used directly as a regressor. The magnitude comes close to the estimate we obtained previously suggesting increases in shipping costs between 10% to 15%.³²

³¹We refrain from coding this category as not treated as some capesize vessels do travel through the Suez Canal (broad vessels and ships in ballast).

³²In the container shipping industry, region specific piracy surcharges of \$300 per container are common already, see for example http://www.joc.com/container-lines/freight-rate-surcharge-update-week-april-2-6. This corresponds to roughly 9.03% of the price of sending a 40 foot container from Shanghai to Europe in March 2010, ac-

Column (2) can be thought of as a robustness check for our EM filter with monthly- and state specific mean levels of attacks. We argued that the significant within-year variation in attacks is due to seasonal wind patterns that affect the success probability, which is itself dependent on the state of law and order. Hence, it makes sense to study whether observed monthly wind speeds, interacted with the probability of the state of law and order being weak, generates similar results to our more sophisticated EM filter. The results suggest that, conditional on the state of law and order being weak, the anticipated drop in wind speeds from its highs in June and July to its lows in February and March give an increase in shipping cost by 11.3%. Taking the seasonal variation and the jump in costs brought about by the change in the state of law and order together, we find that the increase in shipping costs is somewhere between 8.2% and 19.5%. Not surprisingly, wind speed does not predict variation in prices in Indonesia.

In column (3) we use an AR(2) specification to predict attacks. Our regressions indicate that attacks in t can be predicted by attacks in t-1 and t-2 in Somalia but are harder to predict in Indonesia. Accordingly, we find only significant effects for Somalia. The magnitude of the effect is rather similar to using the Markov chain based estimates. Thus, our particular forecasting model does not seem to be driving the results.

In column (4) of Table 4 we simply include the number of attacks as a regressor rather than trying to forecast future attacks based on past data. This would be justified in a world where participants in the shipping market are myopic and simply assume that pirate attacks next month are the same as pirate attacks in the current month. Here too we find a positive and significant coefficient on the charter rate in the Somalia region with no significant effect of attacks in Indonesia. This reinforces the idea that the specific forecast model is not driving everything. However, the size of the effect is somewhat different with something like a 6% effect of pirate attacks on shipping costs after 2008 being predicted. But this naive forecasting model does a poor job at capturing some of the seasonal and persistent factors that charterers ought to consider when trying to forecast attacks.

Column (5) addresses the concern that we have failed to pick up the economic downturn in 2008 properly in our specification to the extent that this differentially impacted some routes. We therefore add GDP growth controls for the origin and destination of each route. Due to the coarseness

cording to the Shanghai Freight Register.

of (especially) the destination data, discussed further in Appendix A, we were forced to aggregate to regional GDP for this exercise. Controlling for either annual regional GDP levels (regressions not shown), interpolated monthly regional GDP levels (regressions not show) or regional GDP growth, as shown in column (5) does not change the pattern of coefficients. In particular, the coefficient on expected piracy attacks in Somalia does not change. However, forecast piracy attacks in Indonesia do now become (marginally) significant in this specification.

In column (6) we add time trends that differ according to the starting location of the vessel. While the point estimate on forecast piracy attacks falls slightly, it remains highly significant.

Taken together these results reinforce confidence in the findings in Table 3. Our finding that pirate attacks in the region of Somalia increase shipping costs is robust to adding further controls and to different ways of forecasting pirate attacks at the time of writing a chartering contract.

3.7 Alternative Treatment Definitions

In order to match the piracy data with the shipping data, it is necessary to impose some structure by defining regions that are susceptible to piracy. We assigned routes to the treatment group if the computed shortest path of the route crossed one of our regions. But evidently, there is some leeway in how this could be done and, in the following specifications, we show that our results are robust to various ways of assigning the treatment and definitions of piracy threat areas. The results are shown in Table 5.

In column (1) we use more narrowly defined piracy regions focusing on two key choke points: the Gulf of Aden and the Strait of Malacca.³³ We use the monthly Markov Chain estimates to forecast attacks in these areas. The results show that piracy in the Gulf of Aden still has a significantly positive impact on shipping prices through that area. The size of the effect is smaller than when we estimate the impact of piracy from the region as a whole.³⁴

Column (2) shows the results when we attempt to disentangle the effect of Somali (Indonesian) piracy on trade through the Gulf of Aden (Strait of

 $^{^{33}}$ For the Malacca strait we use the maritime area bounded by latitude $\in [1, 7.4]$ and longitude $\in [95.8, 104.7]$. For the Gulf of Aden, the bounding box is given by latitude $\in [10.5, 17]$ and longitude $\in [40, 52.2]$.

³⁴This is not surprising. Piracy attacks in the Gulf of Aden feature much weaker seasonal patterns.

Malacca) from the effect on trade in the broader regions. We now use the number of forecast attacks from our main specification and apply it to two subgroups of maritime routes: a) ships that travel through the Gulf of Aden (Strait of Malacca) and b) ships that travel through Somalia (Indonesia), but not through the Gulf of Aden (Strait of Malacca). The key insight from this specification is that we also find a cost of piracy for routes that do not travel through the Gulf of Aden but through the broader Somalia area. The magnitude of this effect is smaller with an increase in prices after 2008 of 4.65% (0.00334*13.92). This suggests that routes between the Middle East and the Far East/Africa are affected by Somali piracy. This observation will be important when we come to calculate the welfare cost below.

Columns (3) and (4) look at robustness regarding the treatment. We need to be wary that ships could be travelling alternative routes in order to avoid the piracy regions. We would expect such re-routing to be more of an issue for maritime routes for which there is a feasible alternative route which does not use the Gulf of Aden and which is not significantly longer than passing through the piracy region. To examine this, we used our algorithm to compute alternative routes while adding the constraint that vessels cannot travel through the Gulf of Aden. We then assign treatment based on these alternative routes if they are at most 10% (column (3)) or 20% (column (4)) longer than the Gulf of Aden route. The point estimate for the Somalia area hardly changes at all for this alternative way of attributing treatment.

However, if we look at Indonesia the point estimate is now positive and significant at 5% when we consider the 20% rerouting exercise. We look into this further by looking into the pattern of routes that are "re-routed" in this case and find that most of the re-routing takes place on routes between Europe and China, Japan and Korea.³⁵ These are now assigned to take the Pacific route, hence avoiding both Somali and Indonesian piracy. The remainder of routes receiving the Indonesian treatment are thus mainly carrying regional trade. This may explain why we observe significant effects in this case, as regional trades are subject to additional risks such as theft while at anchorage, a type of attack which is particularly common in this area.³⁶

³⁵2064 obervations are re-assigned treatment in the Somalia area, 1354 observations have a different treatment in the Indonesia area.

³⁶In a further specification, not shown, we observe similar patterns when interacting piracy treatment with the intensity of treatment as proxied by the share of the overall distance travelled through piracy areas. We observe that the cost effect is highest for

Once again, these robustness checks increase our confidence in the results and the proposition that shipping costs increase due to the risk of maritime piracy attacks.

4 The Welfare Cost of Piracy

We now discuss what our results imply for the welfare cost of piracy. Our welfare criterion takes the transfer from consumers of traded goods (who ultimately bear the cost) to pirates as given. We ask what an efficient transfer of the same magnitude would cost the consumers and compare this to the costs that piracy imposes. To get a more complete measure, we will also add estimates of the costs of policing piracy through military ships using data from other sources.

4.1 Framework

Piracy leads to a transfer of resources to pirates via ransoms. Resources are used by pirates in securing these ransoms and by ship owners and governments in resisting them. The costs of the ransoms and damage to ships are also borne directly by those who pay them. These costs are pooled across the industry through insurance. Resources are also used in writing insurance costs. As with any transfer program, there is a question of who pays in the end. If the market for shipping is competitive then any increased cost must be paid by consumers of the final goods in the form of higher prices.

Suppose that there is a composite traded good, X, for trade between locations which is susceptible to piracy attacks. Suppose that shipping demand has a fixed coefficient technology so that demand for shipping is νX . The number νX is best thought of as ton days, i.e. as the number of shipped tons multiplied by the average maritime journey time.³⁷ We assume that the good X is sold in a competitive market and that the marginal cost per unit is denoted as $\psi + \phi$ where ψ is the production cost and ϕ is the shipping cost per unit. Suppose that there is a representative consumer with utility U(X) and additive quasi-linear utility. This allows us to ignore general equilibrium

dyads for which a significant proportion of the overall journey is through piracy areas.

³⁷This view is very much in line with the usual measure of mile tons. For an interesting discussion regarding this see Stopford (2009). We disregard variable shipping speeds which makes the two measures equivalent.

effects. The representative consumer's optimal consumption is given by:

$$U'\left(\hat{X}\left(\psi+\phi\right)\right) = \psi + \phi$$

and the indirect utility from consuming tradeable goods of the relevant kind is

$$V(\psi + \phi) = U(\hat{X}(\psi + \phi)) - \hat{X}(\psi + \phi)[\psi + \phi].$$

As we have already seen, piracy increases shipping costs. Suppose that part of that cost increase leads to a transfer to pirates denoted by T and that that we attach a "welfare" weight of μ to these transfers, i.e. to pirate welfare. It is somewhat debatable what this weight should be. Ransoms transfer income to a poor country (Somalia) but they go to a particular group, i.e. organized criminals. It is far from clear how these benefits may trickle down to the wider population.³⁸ We feel that it is best to be agnostic about this and base our welfare approach on Coate (2000). Using his reasoning, we should care principally that any transfer made to pirates is accomplished in the most efficient way and hence the welfare loss are the resources spent in the process of delivering the transfer.

For fixed μ , welfare is

$$W(\phi) = V(\psi + \phi) + \mu T.$$

Now suppose that, as above, the cost of shipping final goods is

$$\phi\left(\Delta\right) = \nu\left[c + \Delta\right]$$

where Δ is the increase in transport costs per unit of final of goods expressed in US\$.

The part of the cost (again in US\$) that is a transfer to pirates is denoted by $\tau(\Delta)$. And the total transfer received by pirates is

$$T(\Delta) = \tau(\Delta) \nu \hat{X} (\psi + \nu [c + \Delta]).$$

In order to be agnostic about μ , suppose we were to replace piracy with a tax on shipping, the proceeds of which were transferred to the pirates and which gave the same amount of net revenues as they now receive from engaging in

³⁸Shortland (2011) provides some evidence that piracy revenue trickles into Somali society and has a positive developmental effect.

piracy. Proposing a tax on shipping seems more reasonable than considering lump-sum taxation in this instance and it would clearly fall on the same group as those who currently bear the cost of piracy.

The amount of the required unit tax, t, is defined by

$$t\nu\hat{X}\left(\psi+\nu\left[c+t\right]\right) = \tau\left(\Delta\right)\nu\hat{X}\left(\psi+\nu\left[c+\Delta\right]\right). \tag{7}$$

This equation illustrates the source of the inefficiency of piracy attacks. The increase in charter rates Δ due to piracy is not fully captured by the pirates so that $t < \tau(\Delta) < \Delta$. Were the transfer efficient then $t = \tau(\Delta) = \Delta$. In other words, a tax has only the usual excess burden associated with it while piracy leads to additional costs such as the costs from the guard labor associated with combatting piracy, damage to ships, negotiation costs to release hijacked ships and costs of additional insurance.

Since the tax keeps the transfer to pirates constant, the welfare cost of piracy is measured by:

$$V(\psi + \nu [c+t]) - V(\psi + \nu [c+\Delta])$$
(8)

which, by construction, does not depend on the welfare weight μ .

4.2 Benchmark Estimate

Our benchmark estimate of the welfare cost assumes away any demand response by consumers. Thus $\hat{X}(\psi + \nu [c + \Delta])$ is completely inelastic and $t = \tau(\Delta)$. In this case (8) becomes:

$$L^{1}(\Delta) = [\Delta - \tau(\Delta)] \times \nu \hat{X}. \tag{9}$$

Estimates of this are in column (1) of Table (6). In Panel A we use the detailed data available from the Suez Canal authority on the total amount of tons shipped through the canal.⁴⁰ We translate this number into an amount of DWT×days by using the mean bulk ship speed (from Stopford, 2009) and the average length of the trip in the respective sample.⁴¹ Panel B adds an

³⁹Of course, a tax would be costly to administer and we are not including this in our thought experiment. But evidently that could be part of the calculation too.

 $^{^{40}\}mathrm{See}$ http://www.suezcanal.gov.eg/TRstat.aspx?reportId=7.

⁴¹We make the assumption all of this cargo is comparable to ours in terms of its exposure to higher shipping costs, journey length and travels though the Gulf of Aden.

estimate of the DWT×days that do not travel through the Gulf of Aden but through the broader Somalia area.

To get a feel for the plausible range, we present three sets of estimates.⁴² Our low estimate uses the coefficient from column (2) in Table 3. Our middle estimate is calculated using the same coefficient except that we use monthly data of the traffic through the Gulf of Aden and the monthly piracy projections from Table 1. The high estimate that we use is from column (1) of Table 4.

We illustrate our calculations of $L^1(\Delta)$ with the low estimate in panel A of Table 1. Column (1) applies our estimate in Table 3, column (2) and the increase in expected attacks in Table 1 to the average rate charter rate of 0.4726. This yields the following estimate of total piracy costs:

$$\Delta \times \nu \hat{X} = 0.00712 * 13.9 * 0.4726 \times 30.3 * 646,064,000$$

= 915.6 million USD

for 2010.⁴³ This is around around 113,000 USD for a Panamax ship.

Our estimate of $\tau(\Delta) \times \nu \hat{X}$ is the gross ransoms paid less the costs incurred by pirates in generating this. A reasonable figure for the gross ransoms is 200 million USD. And netting out the costs of generating these, suggest profits from piracy in the region of 120 million USD.⁴⁴ Together with our estimate of $\Delta \times \nu \hat{X}$ this sums to the number

$$L^{1}(\Delta) = [915.6 - 120]$$
 million USD = 795.6 million USD.

Even from this low estimate it should become clear that the amount spent due to piracy vastly exceeds what it should cost to buy off the pirates, i.e. to offer them a tax-based transfer of comparable magnitude.

Panel B shows, not surprisingly, that the estimated cost is much higher when we calculate the value of shipping for the wider region including all of Somalia. Even our low estimate of the welfare cost increases by around 40%.

⁴²For details see the appendix (E).

⁴³Obviously this number is subject to a large margin of error. For example, container traffic is likely to be less affected. Were we to suppose that there was no effect on container ships then the size of the affected deadweight tonnage would be only 279,063,000 and the cost would be considerably lower. We abstract from this as the value of container goods is likely to be much larger which would incease the cost.

⁴⁴For a careful and transparent calculation see http://www.time.com/time/business/article/0,8599,1891386,00.html. This is in line with estimates in Geopolicity (2011).

Panel C adds in costs incurred by governments in policing piracy. Such costs are typically tax financed and additional to the costs that we have measured in our shipping cost estimates. They should be added to our welfare loss calculation and, in theory, scaled by the marginal cost of public funds to reflect any deadweight loss in raising revenues to fund these operations. Our medium estimate of this cost, for example, is at 640 million USD. The low estimate in panel C is now 84% higher than in panel A. The range for the welfare cost suggested by our benchmark estimates is \$796 million to \$2750 million.

4.3 Developing an Upper Bound

There are further reasons to believe that our estimates in column (1) of Table 6 are a lower bound. We now consider two of these: (i) the possibility of a demand response which reduces trade and (ii) the possibility that only some of the cost of piracy is paid by the charterer.⁴⁵

Allowing for the possibility of a demand response, we show in the appendix that the welfare loss caused by a decrease in trade can be approximated by a simple scaling factor on our estimate above, which depends on the elasticity of trade with respect to transport costs, $\hat{\eta}$, and is given by

$$L^{2}(\Delta) = L^{1}(\Delta) \left[1 + \frac{1}{2} \frac{\Delta - \tau(\Delta)}{c + \Delta} \hat{\eta} \right]. \tag{10}$$

In other words, the loss due to trade reduction can be approximated by the trade elasticity with respect to transport costs times the share of piracy costs in total transport costs.⁴⁶ Obviously, $L^2(\Delta) > L^1(\Delta)$ as long as $\hat{\eta} > 0$. There are several possible numbers we could use for $\hat{\eta}$. Latest results from Feyrer (2009) who uses the Suez Canal closure as a shock to distance and calculates the effects on trade from distance costs suggests that an estimate between 0.2 and 0.5 for $\hat{\eta}$ is realistic. The estimate found in a meta study in Disdier (2008) is 0.9. Given the similarity of the Feyrer (2009) study we use the estimate of 0.5 in column 2 which suggests that $L^2(\Delta) = L^1(\Delta) \times 1.0226$.

⁴⁵Similarly, if we believe that the market for ship capacity is not competitive, we could see that piracy related expenses may be forwarded with a markup. This is a possibility we do not explicitly consider further.

⁴⁶Note that we calculate an upper bound this way as charter costs are just a part of total (maritime) transport costs.

The welfare loss due to changes in quantity are relatively marginal.⁴⁷ This insight is confirmed in Table 6 which provides the estimates corresponding to Table 1 in all three panels.

Column (3) of Table 6 allows for the possibility that the increase in chartering rates fails to capture all of the additional costs imposed by piracy. In particular, we check what would happen if costs were split between ship owner and charterer according to the "general average rule" as it is known in the shipping industry. This rule shares the costs of saving the ship in proportion to the value of the vessel and the cargo. Assume then that a share ζ of the piracy costs are borne by the ship-owner. The charter rate increase Δ is the transfer that compensates the owner for piracy costs over and above what the charterer bears.⁴⁸ Then if charter rates increase by Δ due to shipping costs the overall cost to the industry is now given by $\frac{\Delta}{2\zeta-1}$. This yields our third measure of welfare cost of:

$$L^{3}(\Delta) = \left[\frac{\Delta}{2\zeta - 1} - \tau(\Delta)\right] \times \nu \hat{X}.$$
 (11)

This leads to estimates that are somewhat larger than in column (1) of Table 6. For example, the low estimate allowing for general averaging is 130% higher.

Adding all of our costs together, our largest estimates are in panel C where the range is between 1.5 billion USD and 4.8 billion USD. While the range of estimates is quite large, the comparison between these numbers of the transfer received by pirates of only 120 million USD is telling. Taking our medium estimates in all case, suggests that a reasonable range for the piracy costs is given by the medium estimates in Panel C. This suggests a range for the costs from piracy between 1.86 billion USD and 3.32 billion USD.

⁴⁷This is not unrealistic. The import price of hard coal per metric ton in the first semester 2010 in the EU27 was over 240 \$/ton. From our calculations above we know that the average charter cost on the Aden route was about 14.3 \$/ton so that a 10% increase in this rate would have led to an increase of EU coal import prices of about 0.6 percent. This is much less than the usual price variation from one month to the next.

⁴⁸To get an intuition for the formula assume that the shipping cost is 100. The owner has additional costs due to piracy of 20 and charterer pays 10. The charter rate will go up by 10 due to piracy but overall costs due to piracy is 30. And, indeed, $\frac{1}{2\zeta-1} = \frac{1}{2\frac{2}{3}-1} = 3$ in this case. The details on the calibration of ζ can be found in Appendix F.

4.4 Predation versus Taxation

We can use equation (7) in the previous section to calculate t - the tax rate on shipping through Aden that would yield the same revenue now going to pirates. Disregarding the effect on trade we get this tax rate from the following calculation:

$$t = \frac{\tau(\Delta) \nu \hat{X} (\psi + \nu [c + \Delta])}{\nu \hat{X} (\psi + \nu [c + \Delta])}$$

$$= \frac{120 \text{ million USD}}{0.4726 * 30.3 * 646,064,000 + 0.4648 * 20.67 * 445,000,000}$$

$$= 0.009.$$

This implies that a tax rate of just 0.9 percent on chartering would be needed to generate a transfer of comparable magnitude to that generated by piracy. This contrasts with our estimates of the increase in shipping costs of between 10 and 30 percent. This calculation suggests that predatory activity of the kind undertaken by pirates is between 10 and 30 times more costly as a means of giving a similar level of resources to pirates than taxation would be.⁴⁹

It is worth dwelling on the reason why these costs are so high and how far they provide insight into debates about the costs of failure to establish law and order. There are three key factors: (i) the fact that piracy causes direct damage and loss (ii) the fact that efforts to establish law and order are fragmented.

Direct damage comes partly from the damage to property. However, it also comes in part from the fact that pirates have to hold ships for long enough to establish their credibility. This is like an inefficient war of attrition which increases the cost of doing business and creates delay over and above the cost of the ransom.⁵⁰

When it comes to fragmented law and order, combatting piracy currently has an array of actors all investing in the hope of dealing with the problem. This includes the somewhat uncoordinated efforts of governments. The most efficient outcome would be to establish a monopoly of violence over the seas

⁴⁹Of course, this thought experiment assumes naively that the pirates could be identified and that they could be transfers similar to what they currently earn from piracy.

⁵⁰For an analysis of a strikingly related ransom bargaining process see Ambrus et al. (2011) who analyze ransom negotiations during a period of piracy in the Meditteranean sea from 1575-1739.

as we see in established states.⁵¹ Otherwise, each actor will invest until the marginal benefit equals the marginal cost.⁵² By protecting particular groups this will tend to shift piracy to other vessels rather than reducing attacks. Thus a pirate repelled by one ship is free to go and attack another ship. Thus it is inefficient to leave piracy protection in private hands.

The current reliance of the international community on Naval patrols to combat piracy could succeed in reducing pirate activity further. But compared to re-establishing law and order in Somalia such efforts are likely to be very expensive.

5 Concluding Comments

Piracy is an important source of predation which creates economic disruption. In this paper, we have used estimates of its effect on shipping prices to estimate the welfare cost of Somali piracy.

Somalia is now the focus of international attention although with limited progress. In the context of potential donor interest, it is instructive to consider how many Somali's could be hired for one year using the additional resources that we estimate are expended by the shipping industry in response to the threat of piracy. Using the numbers in panel B of Table 6, a conservative estimate of the costs of piracy to the shipping industry is about \$1.3 billion. We use wage data from the Somali Food Security and Nutrition Analysis Unit (FSNAU) presented in Shortland (2011) to calculate a yearly wage of about \$870.⁵³ This means that the extra spending due to piracy could finance one year of employment for more than 1.5 million laborers at the going market rate in 2010. This does not mean that such a transfer scheme would be realistic or that it would prevent piracy. But it illustrates the scale of losses to the industry relative to the reality of the Somali economy.

While what we have studied here is only one kind of lawlessness, it does provide specific estimates of the costs of predatory activity in this particular

 $^{^{51}}$ See Besley and Ghatak (2010) for development of this argument in relation to property rights enforcement.

⁵²In addition, there is anecdotal evidence for an arms race in which pirates are better and better equipped and ship owners move from minor ship modifications to hiring security crews. For a general discussion of these issues see de Meza and Gould (1992).

⁵³In 2010 the highest daily wage paid in Somalia was about 100,000 Somali Shillings (SSh). Assuming 261 work days and an exchange rate of about 30,000 SSh/\$US this implies a yearly wage of about \$870.

context. We have shown that the cost of piracy is large relative to the size of the transfer to pirates. This is particularly true compared to a tax levied on shipping to pay a transfer to pirates. This further underlines the difference between organized extraction by the state in the form of taxation and disorganized predation. We estimate that the latter is at least ten times more costly. In the language of Olson (2000), pirates are roving bandits while the state is a stationary bandit and hence is in a better place to organize extraction at lower costs. Without a return to strong law and order in Somalia, it seems unlikely that these welfare costs will disappear any time soon.

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A Data

This appendix discusses the data sources and generation of variables. Table A1 provides summary statistics for our data.

A.1 Chartering Contracts

The data on shipping prices comes from the web-site of N. Cotzias Shipping Consultants which provides monthly reports of the time charter market for the period November 2002 until December 2010.⁵⁴ The data is comprised of 33,529 individual fixtures in the dry bulk cargo segment of the market.

It contains details on the vessel that was chartered, the chartering company, the month in which the charter was fixed and the approximate date (day-range / months), when the charter would commence. The details on the vessel give us the current ship name, the year it was built and its deadweight tonnage. The pricing information contains the daily rate in US \$, along with a ballast bonus. From these we construct the daily rate per deadweight ton and the ballast bonus per deadweight ton. On average, about 9% of the charters in our sample include a ballast bonus.

The chartering information provides details about the location of the vessel origin and the vessel destination, i.e. where it will be handed back to the ship owner. Due to the nature of the chartering market, market participants have an active interest in reporting the vessels delivery- and redelivery locations. However, this information comes with varying levels of detail. In particular the redelivery location may either be at (1) port, (2) country, (3) maritime region or it may be missing. Further challenges include that sometimes, the port name is spelled wrongly or abbreviations were used. We harmonize the data to country-level pairs. The raw data contains 2,430 distinct delivery- or redelivery locations. We proceeded in two steps:

1. Try an exact match based on a database of port names.⁵⁵. This will give us, in case of an exact match, a port and the country in which this port

⁵⁴In early 2011, Cotzias merged with Intermodial (www.intermodal.gr). As of 25th January 2012, the Cotzias data was available on http://www.cotzias.gr/chart_tc_rep.htm.

⁵⁵This database contains the details and locations of 27,625 ports all over the world. They include all major ports, but also smaller ports and docks. It can be accessed on http://www.wilhelmsen.com/services/maritime/companies/buss/directory/Operations/Ports/Pages/default.aspx.

is located. In case no exact match was found, we used the Google Search Engine to get a spelling suggestion (in case there was a misspelling in the raw data) and try it again with the corrected spelling. Through this, we are able to filter 570 locations, which account for roughly 2/3 of the observations.

2. For the remainder of the delivery- and redelivery locations, we proceed by performing Google searches in a semi-automated way, double checking and validating the results manually.

A.2 IMB Piracy Data

The IMB runs the piracy reporting centre which can be contacted 24hours by vessels under attack. The information received from the ship Masters is immediately relayed to the local law enforcement agencies requesting assistance. In addition, the information received from the ship Masters is broadcast to all vessels in the Ocean region - thus highlighting the threat to a Master en route into the area of risk. The IMB annual reports reproduce the piracy reports received by the piracy reporting centre. They define a piracy attack as

An act of boarding or attempting to board any ship with the apparent intent to commit theft or any other crime with the apparent intent or capability to use force in the furtherance of that act. (IMB, 2009)

Under this definition, pirate attacks include all actual or attempted attacks on vessels while in port, anchored, berthed or underway. While there is some acknowledged under-reporting, it is the most complete database on maritime piracy that is available. We obtained the annual reports of piracy and robbery incidents from 1999-2010. Each report provides a detailed listing of the piracy incidence, containing the following information:

- Date (usually to day)
- Name of Ship
- Flag of Ship (sometimes)
- Call sign of ship (not always)

- IMO number of ship (not always)
- Information on location of attack, various levels of detail
- A narrative of the attack

In total, data on 5,456 incidents is reported. We were not able to use all observations, as quite often for attacks that take place near some ports or just off some islands, the report does not include a geocoded location. We tried to make use of as many observations as possible by manually geo-coding the missing observations. Furthermore, in early years the data does not give information on whether the vessel was underway- or at anchor when it was attacked. This data was manually extracted by analyzing the narrative of the attack given.

Using the maritime areas we described in the text, we arrive at a monthly number of piracy attacks in that particular maritime area. This time series is then used to forecast the numbers of attacks.

A.3 Algorithm for Maritime Routes and Distances

We first determine start and end points for each journey. We use country start and end points rather than specific ports. This is because there is some ambiguity in the port information. This is more severe for some countries. For example, the United States has access to more than one Ocean so that errors could be quite large.

Each country information is interpreted as a specific position. We assigned the most frequently occurring port as our start and finish point for each country. We are then able automate the way treatment is assigned by computing maritime routes between these points.

The algorithm proceeds as follows. Firstly, we transform a world map into a coarse 1° grid of the world. The coarseness of the grid allows us to compute optimal routes for the 1,600 routes in a reasonable amount of time on a simple Desktop computer.

The grid is thus a 360×180 matrix, which we can think of as a graph. Each cell in the matrix represents a node of the graph. We assume that vessels can travel into any of the 8 neighboring cells. The transformation into a grid takes into account that moving along a diagonal corresponds to a larger distance (i.e. higher costs) than moving along straight line vertices. We then assigned each cell a cost of crossing using the map on which the grid

was defined. We normalize this cost of crossing to be 1 for sea- or oceans and passing a very large number for landmass. We had to manually close the North-West passage and, due to the coarseness of the grid, we had to open up the Suez canal, the Malacca Straits and the Panama canal.

The start- and end-locations, given as GPS coordinates, are then mapped into a particular cell in this graph. We can use simple shortest-path algorithms to compute an optimal path from any two points on the grid. The shortest-path implementation we used is a Dijkstra algorithm implemented in the R package Gdistance.⁵⁶

The algorithm delivers three things: a shortest path as a sequence of GPS coordinates, its distance and a cost measure. We use the actual path for the intention to treat assignment and the distance for some robustness checks.

A.4 Wind and Seasonality of Attacks

We obtained wind data from the National Oceanic and Atmospheric Administration (NOAA), which, among others, provides detailed satellite and observational weather data for the world's oceans. For our purposes we accessed the NOAA Multiple-Satellite Blended Sea Winds database. This particular database has the advantage that it is compiled from several satellites, which limits the number of coverage gaps. Another advantage is, that it provides the data on a fine spatial grid of 0.5° and is available, without gaps from 1987 onwards.

From this database we extracted the monthly mean wind speed pertaining to the geographical grid of our piracy regions. For each month, we have around 8,800 observations of the monthly mean wind speed per 0.5° cell corresponding to our grid. We use this to compute the average wind speed in any month for both the Somalia and Indonesia area.

Figure A1 shows the average monthly wind speed for the Somalia area (dotted line) and the predicted wind speed (solid line). The predicted wind speed is calculated from a regression of wind speed on month dummies

$$E\left[wind_{t}\right] = \sum_{m=1}^{12} month_{m}\left(t\right) + \epsilon_{t}.$$

This regression has a R^2 of 0.997. The strong seasonal pattern is also apparent in figure A1 which clearly shows the summer monsoon seasons with

 $^{^{56}{}m The~R}$ package is available from http://cran.r-project.org/web/packages/gdistance.

increased wind speeds and January and February with very calm winds.

Figure A2 shows the connection of the average wind speed prediction (lagged) and our estimates of piracy attacks, α_{r1W} , α_{r2W} , ..., α_{r12W} , from table 1. Clearly attacks and lagged wind speed are highly correlated. According to UNOSAT (2010) to the lag reflects the latency period for the pirate militias to redeploy their vessels from the main militia bases along the Puntland coast.

B Markov Chain Forecasts

B.1 Set up

Assume that attacks in region r at time t are given by the following "switching" model:

$$a_{rt} = \mu_{r\ell} \left(1 - \delta \left(\ell_{rt} \right) \right) + \mu_{rW} \delta \left(\ell_{rt} \right) + \varepsilon_{rt} \quad \text{with } \varepsilon_{rt} \sim N(0, \sigma_{r\ell_{rt}}^2)$$
 (12)

where $\delta\left(S\right)=0$ and $\delta\left(W\right)=1$. Thus, μ_{rS} is the mean number of attacks in the inactive state and μ_{rW} is the number of attacks when pirates are active. This allows for the possibility that $\mu_{rS}>0$. The transition matrix between states is given by:

$$\begin{array}{ccc} & \ell_{rt-1} = W & \ell_{rt-1} = S \\ \ell_{rt} = W & p_r & 1 - q_r \\ \ell_{rt} = S & 1 - p_r & q_r \end{array}$$

and state in region r at date t, follows the process:

$$\ell_{rt} = 1 - q_r + \lambda \ell_{rt-1} + v_{rt}$$
 where $\lambda_r = q_r + p_r - 1$

where v_{rt} is an error term with a state-contingent distribution of

$$v_{rt} \mid (\ell_{rt-1} = W) = \begin{cases} 1 - p_r & \text{with probability} \quad p_r \\ -p_r & \text{with probability} \quad 1 - p_r \end{cases}$$

and

$$v_{rt} \mid (\ell_{rt-1} = S) = \begin{cases} -(1 - q_r) & \text{with probability} \quad q_r \\ q_r & \text{with probability} \quad 1 - q_r. \end{cases}$$

Assuming a Markov Chain implies that we have a vector of six regionspecific parameters

$$\theta_r \equiv \left\{ \mu_{rW}, \mu_{rS}, \sigma_{rW}^2, \sigma_{rS}^2, p_r, q_r \right\}$$

which is a complete description of the parameters governing the process of piracy in region r. Most of our use of the model will turn around just three parameters from this vector: μ_{rW} , p_r and q_r

The history of attacks is used to estimate the probability $P(\ell_{rt} = W \mid H_{rt}, \theta_r)$ given the attack history H_{rt} and the parameter vector θ_r . (details are below) This probability can then be used to form expectations about the level of future attacks in region r, i.e. a_{rt+1} . It is easy to show that given equation (12) the estimate of attacks in the next month is

$$E(a_{rt+1}: H_{rt}) = \mu_{rW} (1 - q_r) + \mu_{rS} q_r + (\mu_{rW} - \mu_{rS}) \lambda_r P(s_{rt} = W \mid H_{rt}, \theta_r)$$
(13)

where $\lambda_r \equiv p_r + q_r - 1$. The first two terms in equation (13) are time-invariant functions of the regional parameters θ_r . One can interpret them as the expected level of attacks in times of inactivity, i.e. at $P(s_{rt} = W \mid H_{rt}, \theta_r) = 0$. The second term shows that the expected violence in the next period only depends on the estimated probability of conflict in t, the differences in attacks between active and inactive months and the persistence, λ_r .

B.2 Estimation

A good starting point for the calculation of the probability of being in conflict, $P(\ell_{rt} = W \mid H_{rt}, \theta_r)$, is Bayesian updating in period t. In period t, the extrapolation of last period $P(\ell_{rt} = W \mid H_{rt-1}, \theta_r)$ is updated with attacks in t according to the standard formula:

$$P(\ell_{rt} = W \mid H_{rt}, \theta_r) = \frac{f(a_{rt} \mid \ell_{rt} = W, H_{rt-1}, \theta) P(\ell_{rt} = W \mid H_{rt-1}, \theta_r)}{\sum_{j=S}^{W} f(a_{rt} \mid \ell_{rt} = j, H_{rt-1}, \theta_r) P(\ell_{rt} = W \mid H_{rt-1}, \theta_r)}.$$

The immediate insight from this formula is that the probability can only be calculated with an estimate of θ_r because the conditional densities are given by

$$f(a_{rt} \mid \ell_{rt} = j, H_{rt-1}, \theta_r) = \frac{1}{\sqrt{2\pi\sigma_{rj}^2}} \exp\left(-\frac{(a_{rt} - \mu_{rj})^2}{2\sigma_{rj}^2}\right)$$

and therefore depend on parameters in θ_r .

The probability $P(\ell_{rt} = W \mid H_{rt}, \theta_r)$ can be calculated if the past estimate $P(\ell_{rt-1} = W \mid H_{rt-1}, \theta_r)$ is known. To see that this dependency of $P(\ell_{rt} = W \mid H_{rt}, \theta_r)$ on $P(\ell_{rt-1} = W \mid H_{rt-1}, \theta_r)$ note that

$$P(\ell_{rt} = W \mid H_{rt}, \theta_r) = \sum_{i=0}^{1} P(\ell_{rt} = W, \ell_{rt-1} = j \mid H_{t-1}, \theta_r).$$

and

$$P(\ell_{rt} = W, \ell_{rt-1} = j \mid H_{t-1}, \theta_r) = P(\ell_{rt} = 1 \mid \ell_{rt-1} = j) P(\ell_{rt-1} = W \mid H_{rt-1}, \theta_r)$$

where $P(\ell_{rt} = W \mid \ell_{rt-1} = j)$ is nothing else than the estimated p and 1 - q contained in θ . Hence, one needs $P(\ell_{rt-1} = W \mid H_{rt-1}, \theta_r)$ to calculate $P(\ell_{rt} = W \mid H_{rt}, \theta_r)$.

This reliance of $P(\ell_{rt} = W \mid H_{rt}, \theta_r)$ on $P(\ell_{rt-1} = W \mid H_{rt-1}, \theta_r)$ implies that previous probabilities of conflict have to be calculated first. The filter therefore takes a starting value $P(\ell_{r0} = 1 \mid H_{r0}, \theta_r)$ and calculates

$$P(\ell_{r1} = 1 \mid H_{r1}, \theta_r), P(\ell_{r2} = 1 \mid H_{r2}, \theta_r) ... P(\ell_{rT} = 1 \mid H_{rT}, \theta_r)$$

by iteratively updating the probability of conflict with the monthly attacks data a_{rt} . To some degree this is what the charter parties of a shipment through region r would have done, too.

However, this simple filter relies on the availability of the vector θ_r . The problem is that θ_r cannot be calculated without knowing the states $\ell_{r1}, \ell_{r2}...\ell_{rT}$ which are unobserved. Hence, the estimation method needs to determine when regime shifts occurred and at the same time estimate the parameters of the model. One way of estimating the parameters of the violence process is the Expectation Maximization (EM) Algorithm described in Hamilton (1990) which generates an estimate of θ_r by iteration.

In each iteration the algorithm makes use of the "smoothed" probability of conflict which is based on the entire violence data for a region

$$P(\ell_{rt} = 1 \mid a_{rT}, a_{rT-1}, ..., a_{r1}, \theta_r).$$

C Cost Factors

C.1 Damage to Vessels

Direct damage is typically due to attempts attempting to board a vessel. This could be damage due to small arms fire or rocket propelled grenades.

Damages to the cargo are typically small, at least in bulk shipping which we focus on, while damage to the hull is more common.⁵⁷ As a consequence, the risk to hulls has now been unbundled from the Hull and Machinery (H&M) insurance and put into special War Risk Insurance. The latter now depends on the area of sea that a ship crosses. In May 2008 the Joint War Committee in London declared the Gulf of Aden as an area of high risk. This high risk area has since then expanded considerably and now covers the whole area called "Somalia" in figure 2.⁵⁸ Cargo insurances do not typically charge additional premiums for specific sea areas.⁵⁹ Since hull damage is covered by insurance we expect such costs to be passed on to ship charterers.

C.2 Loss of Hire and Delay

The distribution of costs coming from loss of hire depends on the individual chartering agreements. These determine to what extent a charterer has to pay the daily chartering rate for the time that a ship is being held by pirates. According to an industry norm the charterer is responsible for the first 90 days following seizure. With an estimated rolling average of 205 days under seizure at the end of 2010 this implies a relatively even share of costs. The risk of not being operational after release (due to damage to ship during captivity) is with the ship owner. This risk is substantial as immobility of several months without maintenance is bound to incapacitate a ship.

C.3 Ransom Payments

Ransom payments typically reach several million dollars and are, in principle, shared between the owner of the vessel, a chartering party and the owner of the cargo or special insurances that these parties purchased.⁶² However, this

 $^{^{57}}$ Hastings (2009) stresses that cargo is not stolen during captivity in the case of Somalia because the infrastructure for transporting it off is lacking.

⁵⁸For details see http://www.lmalloyds.com/Web/market_places/marine/JWC/Joint_War.aspx.

⁵⁹See Marsh's Global Marine Practice available at http://usa.marsh.com/LinkClick.aspx?fileticket=jLOZA8S3gds\%3D\&tabid=1985\&mid=10432.

⁶⁰This norm is the "BIMCO Piracy Clause 2009". BIMCO is the largest international shipping associations representing ship-owners.

⁶¹For a summary see MARSH (2011).

applies only on journeys with cargo on board. In addition, the crew falls into the ship owners obligations if brought off the ship.⁶³ Both the ship owner's H&M insurance and the war risk insurance will cover part of this ransom. Kidnap and Ransom (K&R) insurance policies, introduced in 2008, provide additional cover for the payment of ransoms. It is unclear what proportion of ships are insured by these policies.⁶⁴ However, the fact that these are designed for shipowners is indicative that these bear the main burden of ransom payments. Even if ransoms are not paid ship owners need to pay a significant wage risk bonus to crew when travelling through pirate territory.

C.4 Security

The maritime industry's Best Practices manual lists a long list of changes to ship and crew stretching from barbed wire, high pressure fire hoses and citadels to additional security teams, that can help prevent a successful pirate attack/hijack.⁶⁵ All these expenses will be borne by the ship owner. The notion of an "arms race" between better equipped pirates and ever more sophisticated defence mechanisms by ship owners suggests that there might be costs on the side of ship owners that exceed the expected sum of ransom payments. According to The Economist 40 % of ships carried security crews by 2012.⁶⁶ We expect these costs to be passed on to charterers.

C.5 Re-routing

The cost of re-routing around the Cape of Good Hope, especially among very large vessels, has been highlighted as a major element of the costs of piracy in early publications on the issue.⁶⁷ In the public debate this notion was often supported by a drastic decrease in Suez canal traffic in 2008. However, Suez canal traffic data can be misleading in this regard as world bulk trade collapsed only a few months before the increase in pirate activity. In addition,

⁶³For a discussion see MARSH (2011) and http://usa.marsh.com/LinkClick.aspx? fileticket=jL0ZA8S3gds\%3D\&tabid=1985\&mid=10432, accessed on 10.04.2012.

 $^{^{64}}$ Though some industry experts claim that as of 2009, the proportion of ships covered by such policies was less than 10 %, see http://www.time.com/time/world/article/0, 8599,1892366,00.html.

 $^{^{65}}$ These are updated regularly. The version referred to here is BMP4 (2011) "Best Management Practices for Protection against Somalia Based Piracy".

⁶⁶ Laws and guns. The Economist. April 14th 2012.

⁶⁷See, for example, One Earth Future (2010) and Bendall (2011).

it should be kept in mind that large Capesize Bulk Carriers were never able to cross the Suez canal and would go around the Cape regardless of pirate activity. Indeed, more recent evidence using satellite imaging suggests that re-routing around the Cape is likely to be a minor issue.⁶⁸ Rerouting costs are in principle fully recoverable from the charterer since contracts are written for daily ship hire and any increase in fuel costs can be passed on.

The bottom line from this discussion is that looking at contract prices in shipping should pick up a good deal of the increased costs imposed by piracy. However, we would expect this to be a lower bound on the overall cost to the shipping industry since some of the direct costs paid by charterers may not be captured. This issue taken into account in our welfare calculations.

D Calculating the Quantity Reaction

The general formula for the welfare loss can be written

$$V(\psi + \nu [c+t]) - V(\psi + \nu [c+\Delta]) = Q(t)$$

$$\simeq Q(\Delta) + Q'(\Delta) [t-\Delta] + \frac{1}{2}Q''(\Delta) [t-\Delta]^{2}.$$

Note that

$$V\left(\psi+\nu\left[c+t\right]\right)=U\left(\hat{X}\left(\psi+\nu\left[c+t\right]\right)\right)-\hat{X}\left(\psi+\nu\left[c+t\right]\right)\left[\psi+\nu\left[c+t\right]\right].$$

When we derive the partial derivative using

$$\frac{\partial U\left(\hat{X}\left(\psi+\nu\left[c+t\right]\right)\right)}{\partial \hat{X}\left(\psi+\nu\left[c+t\right]\right)} = \psi+\nu\left[c+t\right]$$

we find that

$$Q'(t) = -v\hat{X}(\psi + \nu [c+t]).$$

Now observe that:

$$Q(\Delta) = 0$$

$$Q'(\Delta) = -\nu \hat{X} (\psi + \nu [c + \Delta])$$

$$Q''(\Delta) = -\nu^2 \hat{X}' (\psi + \nu [c + \Delta])$$

⁶⁸See One Earth Future (2011).

We assume that the demand function has a constant price elasticity η so that we can write

$$\hat{X}(\psi + \nu [c+t]) = (\psi + \nu [c+t])^{-\eta}.$$

and inserting all this we get an approximation of the welfare loss

$$Q(\Delta) + Q'(\Delta) [t - \Delta] + \frac{1}{2} Q''(\Delta) [t - \Delta]^{2}$$

$$= \nu \hat{X} (\psi + \nu [c + \Delta]) [\Delta - t] - \frac{1}{2} \nu^{2} \hat{X}' (\psi + \nu [c + \Delta]) [t - \Delta]^{2}$$

$$= \nu \hat{X} (\psi + \nu [c + \Delta]) [\Delta - t] \left[1 + \frac{1}{2} \eta \frac{\nu (\Delta - t)}{\psi + \nu [c + t]} \right]$$

$$= \nu \hat{X} (\psi + \nu [c + \Delta]) [\Delta - t] \left[1 + \frac{1}{2} \hat{\eta} \frac{\Delta - t}{c + \Delta} \right]$$

$$\geq \nu \hat{X} (\psi + \nu [c + \Delta]) [\Delta - \tau (\Delta)] \left[1 + \frac{1}{2} \frac{\Delta - \tau (\Delta)}{c + \Delta} \hat{\eta} \right].$$

Where we replaced the trade elasticity with regard to price η (which we do not have) with the trade elasticity with regard to transport costs, $\hat{\eta}$ (available from the trade literature). Observe that the trade elasticity with respect to transport costs, $\hat{\eta}$, in terms of our model is

$$\hat{\eta} = \frac{\partial \log X}{\partial \log \phi} = \eta \frac{\phi}{\psi + \phi}$$

so that, using the definition of ϕ above, we get

$$\eta = \hat{\eta} \frac{\psi + \nu \left[c + \Delta \right]}{\nu \left[c + \Delta \right]}.$$

The last inequality uses the fact that $\tau(\Delta) \leq t$. So this gives a lower bound on the welfare loss and depends on observables. Comparing this to equation (9) we can rewrite the welfare loss

$$L^{2}(\Delta) \simeq L^{1}(\Delta) \left[1 + \frac{1}{2} \frac{\Delta - \tau(\Delta)}{c + \Delta} \hat{\eta} \right].$$

E Calculations of Welfare Costs

The first column in table 6 reports:

$$L^{1}(\Delta) = [\Delta - \tau(\Delta)] \nu \hat{X} (\psi + \nu [c + \Delta])$$

in this appendix we first present the calculations for column (1) in Panel (A) and (B). We then discuss the calculations of column (2) and (3). Military costs in Panel (C) are discussed last.

Total Cargo shipped through the Suez Canal is around 646,064,000 tons per year.⁶⁹ According to data from Stopford (2009) bulk ships travel at around 26km per hour (14 knots) and the average distance that charters travel which pass through the Gulf of Aden is 16,400 km with a typical charter length of 26.3 days. To this we add 4 days on charter for loading and unloading. This does not include waiting time in Suez and neglects the possibility of re-routing.

Our estimates in Panel B in Table 6 add the costs imposed by piracy on maritime traffic through the broader Somali area to this cost. In order to calculate this we use the estimates in column (2) of Table 5. In order to give a number to the tonnage travelling through this area (but not the Gulf of Aden) we use UNCTAD data on maritime transport between the Middle East and Africa/Asia. The data suggests that about 445,000,000 tons were shipped through the area in 2010. Most of this are oil exports from the Middle East. As before we use our data to calculate the average charter length (20.67 days) and the average charter rate (0.4646 USD/DWT days).

Low estimate:

Gulf of Aden

```
0.00712 * 13.9 * 0.4726 * 30.3 * 646064000 = $915.6  million -$120  million = $795.6  million
```

Somalia

```
0.00807 * 13.9 * 0.4726 * 30.3 * 646064000 = $1,037.8 \text{ million}

0.00334 * 13.9 * 0.4648 * 20.67 * 445000000 = $198.5 \text{ million}

-$120 \text{ million}

= $1,116.3 \text{ million}.
```

Our medium estimate for the welfare loss is calculated exactly as the lower bound except that we use monthly data of the traffic through the Gulf of Aden available from the Suez Canal authority and the monthly piracy

⁶⁹See http://www.suezcanal.gov.eg/TRstat.aspx?reportId=7.

projections from Table 1. Details of these calculations (for Somalia) are in appendix Table A3.

Medium estimate:

Gulf of Aden

\$995.4 million -\$120 million = \$875.4 million

Somalia (see calculations in appendix table A4):

\$1,112.8 million +\$183.8 million -\$120 million = \$1,176.6 million.

Our high estimate uses the estimate on the law of order state in column (1) of Table 4 to derive the costs of piracy. That estimate suggests that piracy leads to an increase of charter rates by 14.6 percent.

High estimate:

Gulf of Aden

$$0.146 * 0.4726 * 30.3 * 646064000 = $1,350.7 \text{ million}$$
 $-$120 \text{ million}$
 $= $1,230.7 \text{ million}$

Somalia: we use estimates from a regression which we have not reported. It gives estimates of 0.163 for the Gulf of Aden and 0.08 for non-Gulf of Aden trade lanes. Thus:

$$0.163 * 0.4726 * 30.3 * 646064000 = $1,508$$
 million $0.08 * 0.4648 * 20.67 * 445000000 = 342 million $-$120$ million $= $1,730$ million.

Column (2) in Table 6 applies the additional factor derived in equation (10). We estimate of the relative increase in transport costs due to piracy as

$$\frac{\Delta}{c+\Delta} = 0.00712 * 13.9 = 0.1$$

and get an estimate of

$$1 - \frac{\tau(\Delta)}{\Delta} = 1 - \frac{\$120 \text{ million}}{\$915.6 \text{ million} + \$198.5 \text{ million}} = 0.903.$$

There are several possible numbers we could use for $\hat{\eta}$. Latest results from Feyrer (2009) who uses the Suez Canal closure as a shock to distance and calculates the effects on trade from distance costs suggests that an estimate between 0.2 and 0.5 for $\hat{\eta}$ is realistic. The estimate found in a meta study in Disdier (2008) is 0.9. Given the similarity of the Feyrer study we use the estimate of 0.5 in column 2. This leads to an adjustment of

$$L^{2}(\Delta) = L^{1}(\Delta) \times \left[1 + \frac{1}{2}\left(1 - \frac{\tau(\Delta)}{\Delta}\right) \frac{\Delta}{c + \Delta}\hat{\eta}\right]$$
$$= L^{1}(\Delta) \times 1.0226$$

which is applied to the whole welfare loss caused by price increases. The low estimate for Aden is, for example,

$$(\$915.6 \text{ million} - \$120 \text{ million}) \times 1.0226 = \$813.6 \text{ million}.$$

In order to calculate the values in column (3) of Table 6 we need an estimate of ζ (equation (11)). We use commodity price data ship price data and match the latter with ship characteristics in our sample. In addition, we calculate the share of transits in ballast through the Suez canal to adjust our estimate of the general average accordingly. The details for these calculations are in the appendix F. We find a median value for the share borne by the shipowner of around $0.7346.^{70}$ so that if the general average was applied our estimates would underestimate the true cost by a factor of up to 2.13. Combined with our high estimate this would imply an increase in chartering cost by 30 percent. However, for reasons laid out in section 3.1 this is likely to be an upper bound. The low estimate for Aden, for example, can then be calculated as

$$$915.6 \text{ million } \times 2.13$$

$$-$120 \text{ million}$$

$$= $1,830.2 \text{ billion}$$

⁷⁰Of course, for other kinds of cargo such as oil, this could be a significantly lower factor. This highlights the fact that backing out the costs of piracy from changes in the charter rate is particularly realistic in the bulk shipping sector in which most goods are relatively cheap.

Panel C in Table 6 adds the costs of naval operations which try to limit pirate activities. The costs of Atalanta for the European Union in 2009 was \$ 11 million⁷¹ To this we need to add the costs of the EU member countries. The only available estimates indicate that additional operational costs for the German military involvement (1 vessel, 300 personal) in 2010 was around \$ 60 million.⁷² Since the overall size of the Atalanta mission is between 4 and 7 vessels this indicates total costs of about \$ 340 million for the Atalanta mission. In addition to Atalanta there are two more operations which are, at least partially, occupied with preventing piracy attacks: NATO's Ocean Shield and the Combined Force 151. Causality from piracy to the presence of some of the military forces in the Arabian sea is harder to establish.⁷³ Panel (C) simply adds military costs of \$340, \$680 and \$1,020 million to the low, medium and high estimates respectively.

F General Average Computation

The general average insurance rules imply that the cost of piracy is borne by both cargo owners as well as by the ship owners. It is the ship owners, who in turn pass on this cost to the chartering parties in form of higher chartering rates. This is what we estimate in our main specification. However due to the general average principle, this effect is underestimated, since the ship owner's insurer pays only a share of the piracy cost in cases in which the ship is laden. In this appendix we describe at how we arrive at the scaling factor $\zeta > 1$ used in the welfare calculations paper.

The first step is to estimate the market value of the vessels in our dataset. Second, we estimate the values of the cargo that these ships transport. The ratio of the values is indicative for general average rules. In a third step, we estimate the share of ballast journeys, in order to correct for the fact that, during these journeys, the ship owner bears the entire cost of piracy.

From weekly market reports of the ship brokerage firm Intermodial⁷⁴, we obtained recorded sales of dry bulk vessels on the second hand market for

⁷¹See http://www.eunavfor.eu/about-us/mission/, accessed on 10.04.2012.

⁷²Deutscher Bundestag Drucksache 17/179. Fortsetzung der Beteiligung bewaffneter deutscher Streitkräfte an der EU-geführten Operation Atalanta zur Bekämpfung der Piraterie vor der Küste Somalias.

⁷³For example, the Combined Froce 151 includes two US aircraft carriers stationed there.

⁷⁴These reports can be accessed on http://www.intermodal.gr/site/market/market.php

2010. In total, there were 402 recorded transaction. For a subset of 379 of these transactions, we know the age of the ship, the vessel's deadweight tonnage and the value of the transaction.

Using these data on transactions, we can estimate the value of the ships 2010 in our dataset for the year. These estimates use two common controls in both data-sets: the age of ship and its tonnage to carry out this matching. Clearly, there are many more controls that correlate with the price that a vessel achieves on the market. However, we abstract from these due to data limitations. Either way, our estimated values are likely constitute a lower bound on a ship's value due to the standard adverse selection problem.

Using the 379 recorded sales, we estimate a regression of the form:

Ship
$$Price_l = \beta_0 + \beta_1 Age_l + \beta_2 DWT_l + \epsilon_l$$

Using the estimated coefficients, we generate fitted values for our main sample for the ships in 2010. The estimated values for vessels travelling through the Suez Canal in our sample are as follows:

Quartile	Value (\$)
Lower Quartile	26,791,260
Median	32,637,280
Upper Quartile	37,281,280

This compares well with industry-wide figures published by ship brokerage firms. For 2010, Intermodal for example reports that a five year old Panamax vessel with 75,000 tons deadweight was estimated to be worth \$ 39 Million. In our dataset, the median ship on the Aden route is 7 years old, i.e. slightly older and with 73,726 tons deadweight slightly smaller. This makes us confident that the fitted ship values are indeed quite realistic for 2010.

We estimate the value of the cargo carried by the dry bulk ships in our sample using Suez Canal Traffic statistics. These provide a very crude disaggregation into the different types and quantities of goods carried through the Suez canal. We try to link this disaggregation with average commodity price data for the year 2010 obtained from the IMF and the World Bank. Any matching to these average commodity values is quite crude since the Suez authorities, for example, do not decompose such broad categories as cereals, ores and metals, coal and coke or oil seeds.⁷⁵ With this caveat, we

 $^{^{75}}$ These four commodities make up at least 48.3% of all commodities in the Suez traffic that can broadly be classified as (dry) bulk cargo.

match to our data using four main commodity prices: coal, iron ore, soybean and wheat. Using the traffic statistics on these four broad commodities, we compute the value of the average ton of these commodities passing through the Suez canal.

Using this, we estimate the value of the average ton of dry bulk carried through Suez Canal. Using the median ship in our dataset, this allows us to estimate the value of cargo. We compute lower- and upper-bound values for these estimates using plain commodity prices for coal and wheat. This yields the following range of estimates:

Cargo type	Price (\$) per Ton	Cargo Value (\$)
(Low value) Coal cargo	106.03	7,451,675.41
Average Suez dry bulk cargo	165.97	11,663,908.20
(High value) Wheat	223.67	15,719,087.90

Using the previously estimates, we can compute the ratio of the cargo to ship value. However, using this share as a scaling factor ζ , we are likely to underestimate the general average share paid by the ship owner. This is due to a significant proportion of voyages being ballast journeys (i.e. without cargo). Using Suez canal traffic data, we find that in 2010, 25.7% of the dry bulk carrier transits were ballast journeys. Hence, the general average share of the ship owner should be:

$$\zeta = (1 - b) * (1 - \operatorname{cargo/ship}) + b$$

where b is the share of the ballast journey.

Using this, we arrive at the following general average shares for our median ship value:

Cargo type	Cargo-to-ship value	ζ
Average Suez dry bulk cargo	0.35738	0.7346

The value of ζ from this table is used in the Table 6 to estimate the welfare loss.

Table 1: EM estimates of Markov chain parameters

Panel A: Markov chain estimates for Somalia		(1) number of attacks per month with weak law and order	(2) number of attacks per month with strong law and order	(3) persistence factor (lambda)	(4) change in forecast attacks from strong to weak state: ((1) - (2)) x (3)
no monthly means		15.25	2.09	0.87	11.45
monthly means	January	11.88	2.24	0.98	9.43
	February	7.14	2.40	0.98	4.64
	March	29.99	2.82	0.98	26.58
	April	31.83	4.36	0.98	26.87
	May	23.18	3.79	0.98	18.96
	June	12.57	1.96	0.98	10.37
	July	4.09	3.26	0.98	0.81
	August	9.35	1.81	0.98	7.38
	September	15.16	1.15	0.98	13.71
	October	18.39	3.11	0.98	14.94
	November	26.13	1.97	0.98	23.63
	December	11.93	1.97	0.98	9.75
	average	16.80	2.57		13.92
	SD	9.09	0.92		8.53
Panel B: Markov chain		(1) number of attacks per month with weak law	(2) number of attacks per month with strong law	(3) persistence factor	(4) change in forecast attacks from strong to weak state:
Panel B: Markov chain estimates for Indonesia		number of attacks per	number of attacks per		change in forecast attacks
		number of attacks per month with weak law	number of attacks per month with strong law	persistence factor	change in forecast attacks from strong to weak state: ((1) - (2)) x (3) 4.52
estimates for Indonesia	January	number of attacks per month with weak law and order	number of attacks per month with strong law and order	persistence factor (lambda)	change in forecast attacks from strong to weak state: ((1) - (2)) x (3) 4.52 0.58
estimates for Indonesia no monthly means	January February	number of attacks per month with weak law and order 8.86	number of attacks per month with strong law and order 3.95	persistence factor (lambda) 0.92	change in forecast attacks from strong to weak state: ((1) - (2)) x (3) 4.52 0.58 2.20
estimates for Indonesia no monthly means	,	number of attacks per month with weak law and order 8.86 3.68	number of attacks per month with strong law and order 3.95 3.05	persistence factor (lambda) 0.92 0.92	change in forecast attacks from strong to weak state: ((1) - (2)) x (3) 4.52 0.58
estimates for Indonesia no monthly means	February	number of attacks per month with weak law and order 8.86 3.68 5.03	number of attacks per month with strong law and order 3.95 3.05 2.65	persistence factor (lambda) 0.92 0.92 0.92	change in forecast attacks from strong to weak state: ((1) - (2)) x (3) 4.52 0.58 2.20
estimates for Indonesia no monthly means	February March	number of attacks per month with weak law and order 8.86 3.68 5.03 9.69	number of attacks per month with strong law and order 3.95 3.05 2.65 3.82	persistence factor (lambda) 0.92 0.92 0.92 0.92 0.92	change in forecast attacks from strong to weak state: ((1) - (2)) × (3) 4.52 0.58 2.20 5.40
estimates for Indonesia no monthly means	February March April	number of attacks per month with weak law and order 8.86 3.68 5.03 9.69 15.14	number of attacks per month with strong law and order 3.95 3.05 2.65 3.82 5.85	persistence factor (lambda) 0.92 0.92 0.92 0.92 0.92 0.92	change in forecast attacks from strong to weak state: ((1) - (2)) × (3) 4.52 0.58 2.20 5.40 8.55 4.66 5.45
estimates for Indonesia no monthly means	February March April May	number of attacks per month with weak law and order 8.86 3.68 5.03 9.69 15.14 9.48	number of attacks per month with strong law and order 3.95 3.05 2.65 3.82 5.85 4.41	persistence factor (lambda) 0.92 0.92 0.92 0.92 0.92 0.92 0.92	change in forecast attacks from strong to weak state: ((1) - (2)) × (3) 4.52 0.58 2.20 5.40 8.55 4.66
estimates for Indonesia no monthly means	February March April May June	number of attacks per month with weak law and order 8.86 3.68 5.03 9.69 15.14 9.48 11.10	number of attacks per month with strong law and order 3.95 3.05 2.65 3.82 5.85 4.41 5.17	persistence factor (lambda) 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92	change in forecast attacks from strong to weak state: ((1) - (2)) × (3) 4.52 0.58 2.20 5.40 8.55 4.66 5.45
estimates for Indonesia no monthly means	February March April May June July	number of attacks per month with weak law and order 8.86 3.68 5.03 9.69 15.14 9.48 11.10 7.59	number of attacks per month with strong law and order 3.95 3.05 2.65 3.82 5.85 4.41 5.17 3.46	persistence factor (lambda) 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92	change in forecast attacks from strong to weak state: ((1) - (2)) x (3) 4.52 0.58 2.20 5.40 8.55 4.66 5.45 3.80
estimates for Indonesia no monthly means	February March April May June July August	number of attacks per month with weak law and order 8.86 3.68 5.03 9.69 15.14 9.48 11.10 7.59 9.99	number of attacks per month with strong law and order 3.95 3.05 2.65 3.82 5.85 4.41 5.17 3.46 3.82	persistence factor (lambda) 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92	change in forecast attacks from strong to weak state: ((1) - (2)) × (3) 4.52 0.58 2.20 5.40 8.55 4.66 5.45 3.80 5.68
estimates for Indonesia no monthly means	February March April May June July August September	number of attacks per month with weak law and order 8.86 3.68 5.03 9.69 15.14 9.48 11.10 7.59 9.99 5.58	number of attacks per month with strong law and order 3.95 3.05 2.65 3.82 5.85 4.41 5.17 3.46 3.82 3.64 4.51 3.94	persistence factor (lambda) 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92	change in forecast attacks from strong to weak state: ((1) - (2)) x (3) 4.52 0.58 2.20 5.40 8.55 4.66 5.45 3.80 5.68 1.78
estimates for Indonesia no monthly means	February March April May June July August September October	number of attacks per month with weak law and order 8.86 3.68 5.03 9.69 15.14 9.48 11.10 7.59 9.99 5.58 9.78 9.50 5.83	number of attacks per month with strong law and order 3.95 3.05 2.65 3.82 5.85 4.41 5.17 3.46 3.82 3.64 4.51 3.94 3.96	persistence factor (lambda) 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92	change in forecast attacks from strong to weak state: ((1) - (2)) x (3) 4.52 0.58 2.20 5.40 8.55 4.66 5.45 3.80 5.68 1.78 4.86 5.11 1.72
estimates for Indonesia no monthly means	February March April May June July August September October November	number of attacks per month with weak law and order 8.86 3.68 5.03 9.69 15.14 9.48 11.10 7.59 9.99 5.58 9.78 9.50	number of attacks per month with strong law and order 3.95 3.05 2.65 3.82 5.85 4.41 5.17 3.46 3.82 3.64 4.51 3.94	persistence factor (lambda) 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92 0.92	change in forecast attacks from strong to weak state: ((1) - (2)) x (3) 4.52 0.58 2.20 5.40 8.55 4.66 5.45 3.80 5.68 1.78 4.86 5.11

Notes: The parameters under "no monthly means" are estimated with the EM Algorithm under the assumption that there is a single mean level of attacks in the weak and strong state of law and order. The numbers under "monthly means" are estimated under the assumption of a seasonal pattern in piracy attacks which leads to a month-specific mean under weak and strong law and order. The persistence factor is explained in the appendix. The time series of attacks from January 2002 till December 2010 were used to estimate the parameters.

Table 2: Suez canal traffic and pirate attacks

	(1)	(2)
VARIABLES	Suez canal traffic	Suez canal traffic
piracy attacks	-145.5	26.51
	(96.03)	(104.4)
post Lehmann Brothers		
bankruptcy		-6,712***
		(2,180)
R-squared	0.048	0.213

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. "Suez canal traffic" is the montly number of tons shipped through the canal. "Piracy attacks" is the number of piracy attacks in the same month. "Post Lehmann Brothers bankruptcy" is a dummy that takes the value of 1 after September 2008.

Table 3: Main Results

	(1)	(2)	(3)	(4)	(5)
VARIABLES	daily charter rate per dwt	daily charter rate per dwt			
forecast number of attacks					
(Somalia)	0.0103*** (0.00273)	0.00712*** (0.00177)	0.00726*** (0.00182)	0.00300** (0.00141)	
forecast number of attacks (Indonesia)	0.00437 (0.00285)	0.00177 (0.00152)	0.00197 (0.00146)	0.0139*** (0.00525)	0.00208 (0.00161)
forecast attacks * handysize (Somalia)					-0.000235 (0.00298)
forecast attacks * handymax (Somalia)					0.00800*** (0.00274)
forecast attacks * panamax (Somalia)					0.00828***
forecast attacks * small					(0.00183)
capesize (Somalia)					0.00798*** (0.00249)
forecast attacks * capesize (Somalia)					-0.000883 (0.00313)
ballast bonus per dwt			-9.408* (5.264)		(0.00313)
ship age			-0.00613*** (0.000789)		
handysize	0.625*** (0.0225)	0.624*** (0.0224)	0.638***	0.609*** (0.0370)	0.621*** (0.0255)
handymax	0.401*** (0.0217)	0.401*** (0.0219)	0.403*** (0.0205)	0.354*** (0.0312)	0.393*** (0.0257)
panamax	0.150*** (0.0141)	0.150*** (0.0140)	0.151*** (0.00890)	0.151*** (0.0219)	0.153*** (0.0152)
capesize	-0.0380 (0.0396)	-0.0380 (0.0390)	-0.0508* (0.0298)	-0.0898 (0.0870)	-0.0252 (0.0478)
dyad fixed effect	yes	yes	yes	yes	yes
month fixed effect	yes	yes	yes	yes	yes
Observations	24363	24363	24332	10058	24363
R-squared	0.873	0.873	0.877	0.862	0.874

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. "Dwt" is deadweight tonnage. "Daily charter rate per dwt" is the log of the time charter rate per day per deadweight tonnage. All attack variables are interactions between a dummy that indicates whether a ship will cross a pirate territory and the number of attacks in that territory. The "forecast number of attacks" is calculated as in equation (2) in column (1) and as in equation (4) in columns (2) to (5). "Handysize" is a dummy that indicates ships with dwt< 35000. "Handymax" are ships with 35000<dwt<55000. "Panamax" are ships with 55000<dwt<80000. "Small capesize" are ships with 80000<dwt<150000 (omitted). "Capesize" are ships with dwt>150000. "Ballast bonus" is a payment that compensates the ship owner for travelling without cargo on return. Column (4) only uses data after the surge in piracy in the Somalia region May 2008. Column (5) controls for interactions between ship categories and the respective region dummy.

Table 4: Robustness to Alternative Measures of Pirate Attacks and Controls

VARIABLES	(1) daily charter rate per dwt	(2) daily charter rate per dwt	(3) daily charter rate per dwt	(4) daily charter rate per dwt	(5) daily charter rate per dwt	(6) daily charter rate per dwt
VARIABLES .	rate per awt					
weak law and order state						
(Somalia)	0.146*** (0.0341)	0.305*** (0.0818)				
weak law and order state						
(Indonesia)	0.0153 (0.0124)	-0.0721 (0.111)				
weak law and order *						
windspeed (Somalia)		-0.0253*** (0.00960)				
windspeed (Somalia)		0.00533 (0.00389)				
weak law and order *		,				
windspeed (Indonesia)		0.0153				
windspeed (Indonesia)		(0.0198) -0.0200				
windspeed (indonesia)		(0.0141)				
forecast number of attacks						
(Somalia)			0.00786*** (0.00175)		0.00869*** (0.00281)	0.00494*** (0.00132)
forecast number of attacks			(0.00170)		(0.00201)	(0.00102)
(Indonesia)			0.000595		0.00454*	-0.000704
number of attacks (Semalia)			(0.00296)	0.00572***	(0.00264)	(0.00247)
number of attacks (Somalia)				(0.00572		
number of attacks (Indonesia)				0.000178		
, , , , , , , , , , , , , , , , , , , ,				(0.00120)		
annual GDP growth start region					-0.360***	
g g					(0.0733)	
annual GDP growth destination					0.407*	
region					0.127* (0.0660)	
					(0.0000)	
ship size controls	yes	yes	yes	yes	yes	yes
dyad fixed effect	yes	yes	yes	yes	yes	yes
month fixed effect	yes	yes	yes	yes	yes	yes
dely country time trends	no	no	no	no	no	yes
Observations	24363	24363	24363	24363	24,332	24363
R-squared Notes: Robust standard errors in parentle	0.874	0.874	0.873	0.873	0.878	0.878

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. "Dwt" is deadweight tonnage. "Daily charter rate (per dwt)" is the log of the time charter rate per day (per deadweight tonnage). All piracy variables are interactions between a dummy that indicates whether a ship will cross a pirate territory and the number of (expected) attacks in that territory. "Weak law and order state" measures the probability that an area features weak law and order in that month. "Windspeed" is the (predicted) seasonal windspeed in the piracy area in the same month. "Forecast number of attacks" is the forecasted number of attacks next month calculated using an AR(2) model for column (3) and equation (4) for columns (5) and (6)

Table 5: Robustness to Alternative Treatment Definitions

	(1) daily charter	(2) daily charter	(3) daily charter	(4) daily charter
VARIABLES	rate per dwt	rate per dwt	rate per dwt	rate per dwt
forecast number of attacks				
(Gulf of Aden)	0.00998**			
	(0.00472)			
forecast number of attacks				
(Malacca)	-0.00839			
	(0.00882)			
Somalia forecast number of				
attacks (Gulf of Aden)		0.00807***		
Somalia forecast number of		(0.00205)		
attacks (not Gulf of Aden)		0.00334***		
attacks (not Guil of Aden)		(0.00128)		
Indonesia forecast number of		(0.00120)		
attacks (Strait of Malacca)		0.00133		
, , , , , , , , , , , , , , , , , , , ,		(0.00150)		
Indonesia forecast number of		,		
attacks (not Strait of Malacca)		0.00272		
		(0.00292)		
forecast number of attacks			0.00=00+++	0.00000
(Somalia)			0.00580***	0.00692***
forecast number of attacks			(0.00170)	(0.00169)
(Indonesia)			0.00203	0.00333**
(macricola)			(0.00154)	(0.00159)
ship size controls	yes	yes	yes	yes
dyad fixed effect	yes	yes	yes	yes
month fixed effect	yes	yes	yes	yes
Observations	24,084	24,363	24,363	24,363
R-squared	0.874	0.873	0.873	0.873

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. "Dwt" is deadweight tonnage. "Daily charter rate (per dwt)" is the log of the time charter rate per day (per deadweight tonnage). All piracy variables are interactions between a dummy that indicates whether a ship will cross a pirate territory and the number of expected attacks from application of the EM algorithm for that territory. Column (1) takes a smaller treatment area and uses piracy estimates from attacks in this area. Column(2) uses the piracy estimates from our main specification and applies them to different treatment areas. Columns (3) and (4) have an alternative treatment assignment. Alternative routes not using the Suez canal were used if the alternative route was at most 10% and 20% longer than the Suez route, respectively.

Table 6: The Welfare Cost of Piracy in 2010

Panel A: Gulf of Aden	(1)	(2)	(3)
	L1 (in million USD)	L2 (in million USD)	L3 (in million USD)
low estimate	795.6	813.6	1830.2
medium estimate	875.4	895.2	2000.2
high estimate	1230.7	1258.5	2757.0
Panel B: Somalia	(1)	(2)	(3)
	L1 (in million USD)	L2 (in million USD)	L3 (in million USD)
low estimate	1116.3	1141.5	2513.3
medium estimate	1176.6	1203.1	2641.8
high estimate	1730.0	1769.1	3820.5
Panal C: Somalia Including			
Costs of Military Intervention	(1)	(2)	(3)
	L1 (in million USD)	L2 (in million USD)	L3 (in million USD)
low estimate	1456.3	1481.5	2853.3
medium estimate	1856.6	1883.1	3321.8
high estimate	2750.0	2789.1	4840.5

Calulcalations are discussed in section 4 and the apprendix E. Column (2) adjusts the welfare loss by taking into account the change in trade. Column (3) adjusts the cost to take into account the share of costs borne by charterers. Panel B uses data on trade from the Middle East to calculate the costs for the area including the Indian Ocean. Panel C adds cost estimates of the military intervention of 340, 680 and 1,020 for the low, medium and high estimate respectively.

Table A1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
deadweight tonnage (dwt)	80092.19	39495.48	5169	300000
rate per day per dwt (in US\$)	0.45	0.30	0.01	4.04
number of attacks in Somalia	7.03	9.06	0	42
number of attacks in Indonesia	6.08	3.93	1	23
ballast bonus per dwt (in US\$)	1.03	70.26	0	1.10E+04
distance (in km)	8014	6846	0	2.41E+04
shipage (in years)	9.45	7.31	0	39
average predicted wind speed in m/s (Somalia)	6.34	1.38	4.36	8.81
average predicted wind speed in m/s (Indonesia)	5.80	0.57	4.69	6.58
forecast number of attacks Somalia (Markov Chain)	7.73	5.22	2.79	14.20
forecast number of attacks Indonesia (Markov Chain)	5.74	1.94	4.13	8.62
forecast number of attacks Somalia (AR(2))	14.59	13.75	1.98	57.26
forecast number of attacks Indonesia (AR(2))	7.20	2.36	3.64	17.18

Table A2: Prediction of pirate attacks through different models

	(1)	(2)	(3)	(4)	(5)	(6)
	attacks in					
VARIABLES	Somalia	Somalia	Somalia	Indonesia	Indonesia	Indonesia
AR(2) prediction	1.000***			1.000***		
7 ii ((2) prodiction	(0.0999)			(0.191)		
lagged probability of						
weak state		13.44***			4.775***	
		(1.591)			(0.773)	
prediction using seasonal						
Markov chain			1.081***			1.132***
			(0.0540)			(0.110)
Observations	98	98	98	98	98	98
R-squared	0.511	0.426	0.807	0.222	0.285	0.522

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Calculating the cost of piracy with monthly weights Gulf of Aden

		change in forecast			
	Suez canal traffic	attacks from weak	coefficient *	rate per dwt per	monthly piracy
2010	(1000 tons)	to strong state	voyage time	day	cost
1	66440	9.43	0.244521	0.4292725	65764352.33
2	58736	4.64	0.244521	0.3824704	25488034.19
3	67528	26.58	0.244521	0.4723519	207310211
4	65744	26.87	0.244521	0.4532415	195780584.9
5	71089	18.97	0.244521	0.4991807	164605250.8
6	70233	10.38	0.244521	0.3851997	68665830.42
7	71868	0.81	0.244521	0.2889743	4113352.812
8	78314	7.38	0.244521	0.335882	47467751.74
9	72810	13.71	0.244521	0.3581775	87426471.33
10	74601	14.94	0.244521	0.3184269	86780302.29
11	72464	23.63	0.244521	0.2934963	122886682.2
12	76563	9.75	0.244521	0.2844657	51924177.89
				TOTAL	1,128,213,002

Not-Gulf of Aden

2010	traffic (1000 tons)	change in forecast attacks from weak to strong state	coefficient * voyage time	rate per dwt per dav	monthly piracy cost
1	37083	9.43	0.0690378	0.5173657	12490249.97
2	37083	4.64	0.0690378	0.4017614	4772522.603
3	37083	26.58	0.0690378	0.6091805	41453649.8
4	37083	26.87	0.0690378	0.4869402	33496937.34
5	37083	18.97	0.0690378	0.4428866	21509072.13
6	37083	10.38	0.0690378	0.4039374	10734287.52
7	37083	0.81	0.0690378	0.3062704	635114.2385
8	37083	7.38	0.0690378	0.3215037	6074410.558
g	37083	13.71	0.0690378	0.3774568	13248493.99
10	37083	14.94	0.0690378	0.3100852	11860238.99
11	37083	23.63	0.0690378	0.3333106	20163905.42
12	37083	9.75	0.0690378	0.2962804	7395530.672
-			TOTAL		183,834,413

Figure 1: Attacks and Treatment Areas

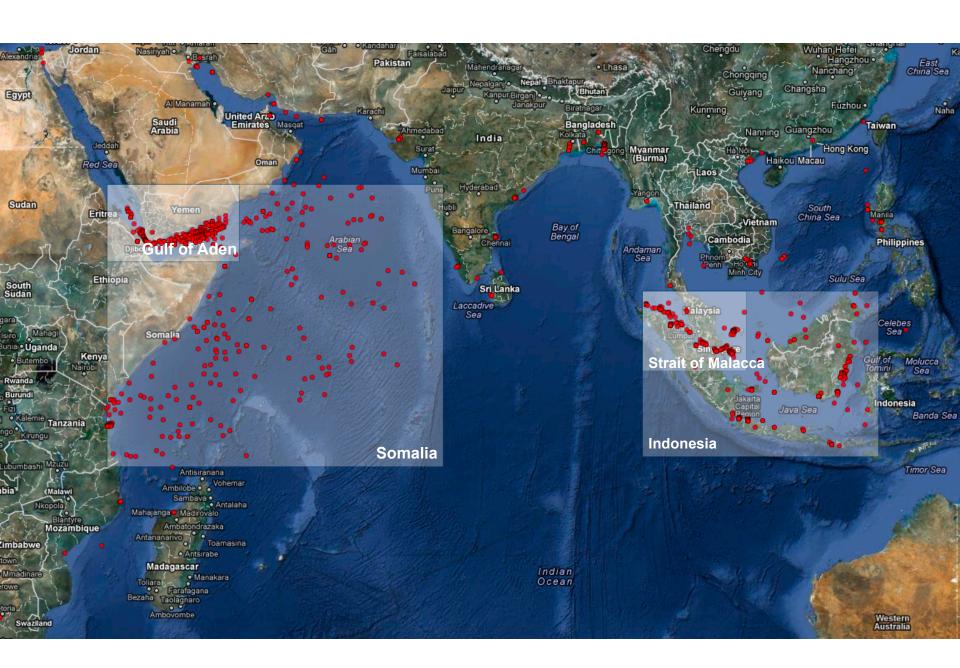


Figure 2: Time Series of Attacks in Somalia (left) and Indonesia (right)

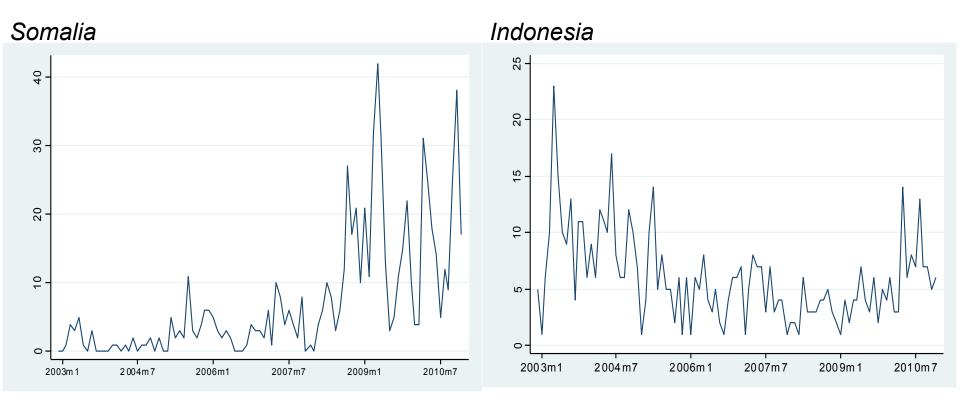
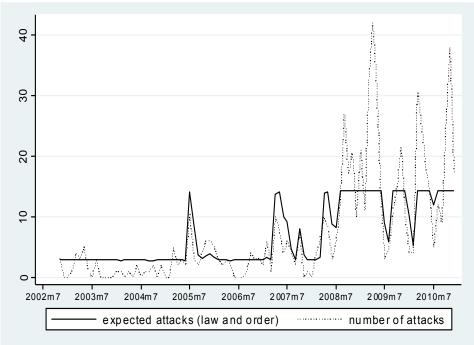


Figure 3: Expected attacks - Markov Chain Without Seasons





Indonesia

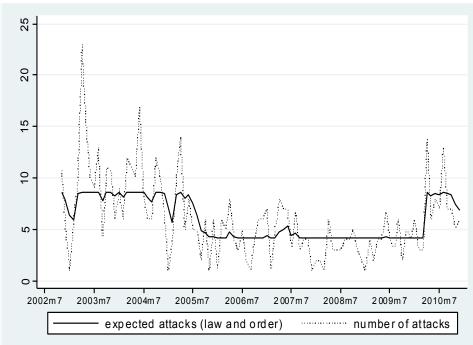


Figure 4: Prediction of Pirate Attacks

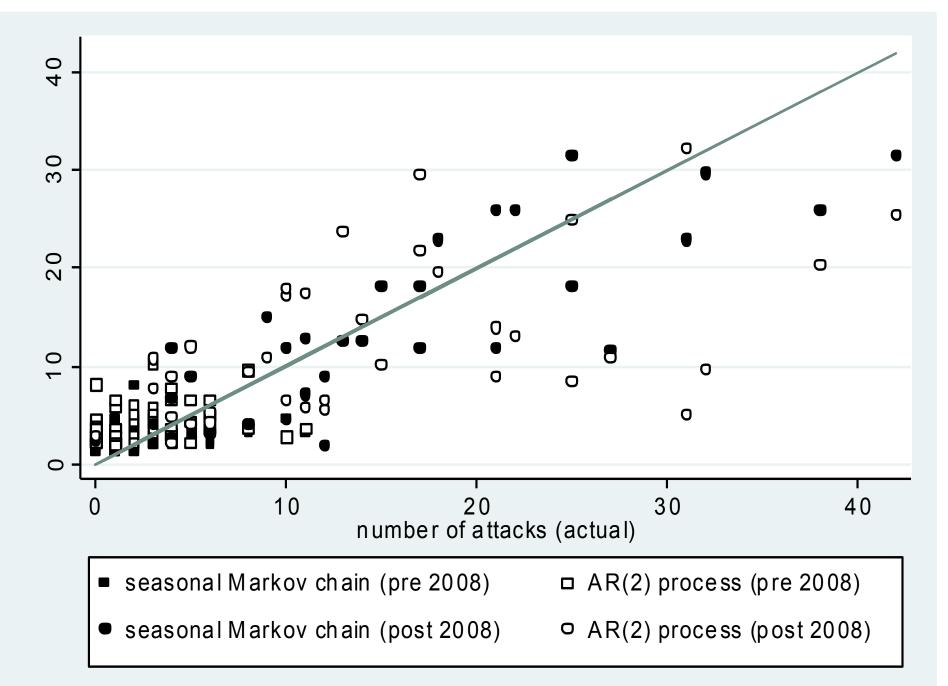


Figure 5: Calculated Shipping Lanes

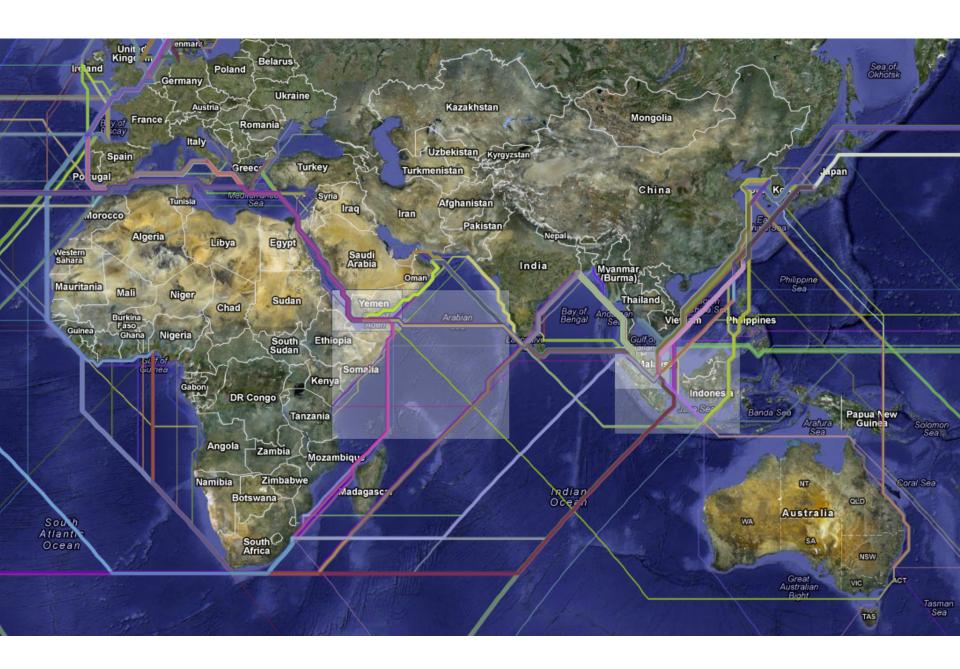


Figure A1: Wind Speed in the Somalia Area

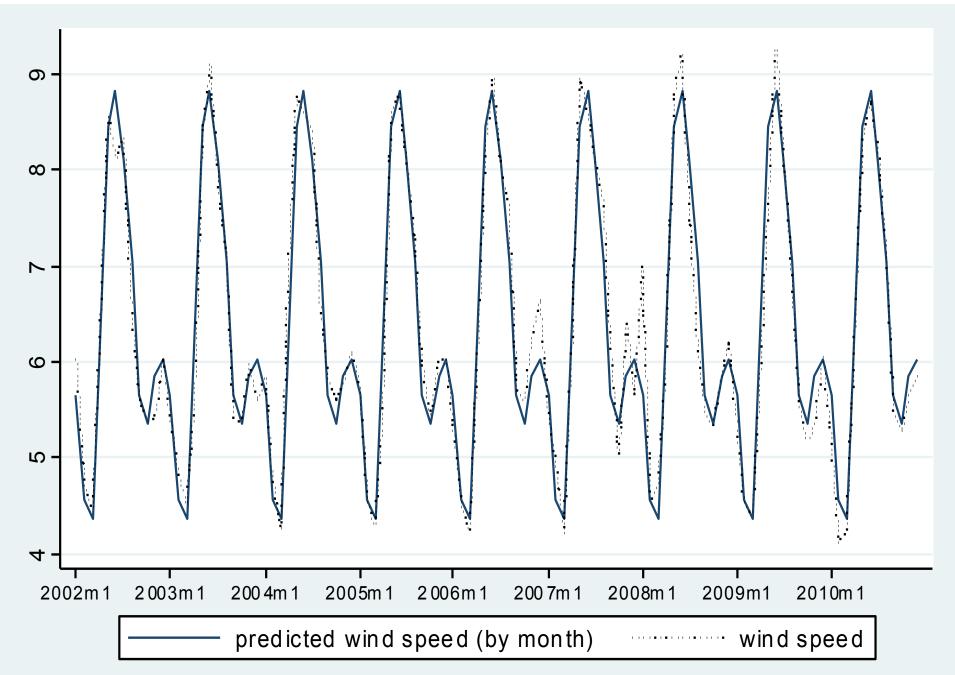
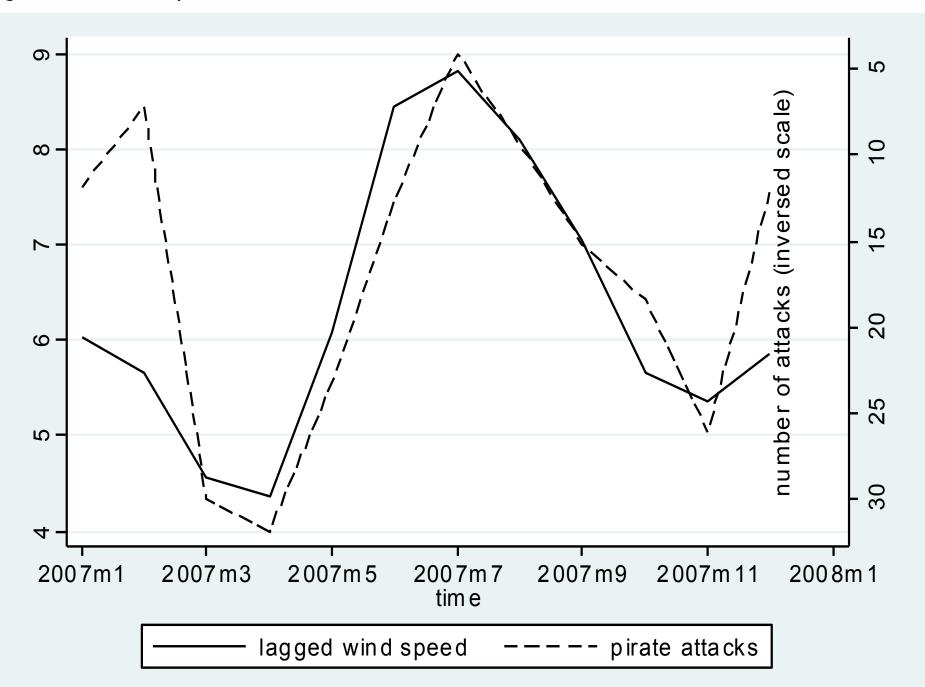


Figure A2: Wind Speed and Attacks in the Somalia Area



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