Learning Piracy on the High Seas*

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Abstract

We introduce a novel dataset of 3,362 modern-day piracy incidents that occurred around the world between 1998 and 2007. Our data include detailed information on the location, timing and success of each attack, as well as the material damage and violence inflicted upon the crew and the cargo. We combine these incident-based data with macroeconomic and aggregate measures of per-capita incomes, rates of economic growth and institutional quality of countries whose territorial waters either witnessed these piracy incidents or were in closest proximity. We find that economic factors and the law do matter: higher per-capita incomes as well as more effective legal and political institutions dampen both the physical violence and material damage of modern-day piracy. But we also document significant learning-by-doing and skill accumulation among the pirates: A history of successful attacks improves the odds of future success, making it more likely that pirates launch successful raids aimed at larger vessels closer to land. The learning-by-doing effects are detectable even after controlling for our proxies for capital use and labor input (the number of pirates).

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1. Introduction

It was not long ago that high-seas piracy was mostly the stuff of legends, maritime history, and adventure novels. Starting in the mid-1990s, however, piracy began making a comeback, steadily turning into an epidemic that, today, seriously afflicts sea traffic, trade and commerce.

Consider: The data on international maritime piracy are maintained by the Piracy Reporting Center of the International Maritime Office but, as a sign of the increasing prevalence and relevance of modern maritime piracy in the 1990s, systematic incidents data are available starting only in 1995. These data show that the frequency of reported incidents rose 270 percent within less than a decade, rising from 126 cases of maritime piracy in 1995 to 465 in 2003. In fact, most of that increase was recorded within a shorter span of two years between 1998 and 2000, when the number of piracy incidents went from 191 cases to 483, reflecting an increase of 183 percent. Commensurate with this rise, of course, are the human and material tolls of piracy: In 1998, there were 30 cases in which the crew were physically assaulted; 24 incidents in which hostages were taken; ten cases with crew deaths and 9 ship seizures. Within five years, 40 incidents involved physical assault; 71 cases involved hostage-taking; 9 incidents of crew death; and 33 cases in which the vessels were surrendered to pirates.

The conventional narrative attributes the fall of ancient piracy to a combination of more sophisticated and evasive merchant ships, the naval presence of colonial powers and to international regulations.[1] The reemergence of maritime piracy in the modern era is, then, often explained as a corollary, such as the contemporary prevalence of failed or weak states in East Africa, lax international maritime legislation as well as pirate-friendly technological advances in communications and seafaring technologies. In this, the economic opportunity costs of piracy, by way of economically retarded and weakening states, are also often highlighted as potentially important culprits.

In this paper, we study the determinants of modern-era piracy, in particular, its *success* and *evolution* over time. Our work is based on a new dataset that includes 3,362

[1] Gathmann and Hillmann (2009) study the decline of another form of ancient piracy: They argue that the decline of British privateering in the eighteenth century was based on the expansion of overseas trade and the ensuing decline in the profitability of commerce raiding.

modern-day piracy incidents that occurred around the world between 1998 and 2007. The data encompass detailed information on the location, timing and success of each attack, as well as the material damage and violence inflicted upon the crew and the cargo. We combine these incident-based data with macroeconomic and aggregate measures of per-capita incomes, rates of economic growth and institutional quality of countries whose territorial waters either witnessed these piracy incidents or were in closest proximity.

In the end, we come away with three important empirical findings. First, economic factors do indeed play an important role in the sustenance of modern maritime piracy: higher per-capita incomes dampen both the physical violence and material damage of attacks. For example, higher par-capita incomes and rates of employment are associated with fewer successful attacks that culminated with vessel seizures and ransom demands, while they are related more frequently with cases in which the crews go unharmed. Second, we detect that political institutions and legal enforcement are also important, although not as much nor consistently as economic factors. In particular, we find that incidents that occur in the territorial waters of countries with more effective polities and authoritarian governments tend to involve fewer cases in which pirates launch successful raids, rob the crew or the ship of their cash or seize the vessel. And conversely, such polities and governments are associated with more incidents in which the crews escape safely.

Above all, however, we document significant learning-by-doing and skill accumulation among the pirates that have helped modern piracy evolve into a more potent threat: A history of successful piracy attacks locally improves the odds of success in piracy, making it more likely that pirates target larger vessels in closer proximity to land. To a weaker extent, it even influences the extent to which pirates are able to inflict violence on the crew and seize the ship. Moreover, these learning-by-doing effects are robust to the inclusion of a host of other controls, location, region and year fixed effects as well as some proxies for capital use, such as vessels, equipment and spare parts stolen in previous raids, and labor input, given by the number of pirates involved in attacks.

There aren't many papers in the economics literature that focus on maritime piracy, and empirical work on the topic is scant. But existing studies typically show that institutions and state capacity matter, although there is some debate on whether those determinants exert a non-monotonic influence. According to Piazza (2008), for instance, state failure is more conducive to piracy than higher state capacity. But there are also those, such as Menkhaus (2004), who instead argue that the economic and geographic infrastructure that weak states can sustain — but failed states cannot — complement acts of piracy. Hastings (2009) reconciles these findings by differentiating acts of maritime piracy by the sophistication level required for different kinds of booty: Pirates from failed states commit more time-intensive crimes, such as kidnapping for ransom, because of a lack of legal enforcement and markets in which economically valuable booty can be liquidated. In contrast, pirates who hail from weak states tend to target goods, cargo and vessels that can be seized and sold in markets that are sufficiently deep, liquid and anonymous.[2]

Regarding the role of economic factors in the reemergence of piracy, there is much media coverage but not enough quantitative empirical analyses. Nonetheless, a consensus seems to have converged on the hypothesis that adverse economic conditions help to sustain 21st-century piracy.[3] Any such claims that the economic conditions matter for modern-day piracy are, at least implicitly, based on the political economy literature on production and extralegal appropriation. The hypothesis that extralegal appropriation and violent conflict over the ownership for resources should be modeled as an alternative to economic production was originally articulated by Haavelmo (1954) and further developed by follow-up papers such as Hirshleifer (1991), Grossman (1994), Grossman and Kim (1995), Grossman and Iyigun (1995, 1997), Skaperdas (1992, 2005), Bates et al. (2002), and Hafer (2006). Accordingly, the opportunity cost of modern maritime piracy involves legal and gainful labor employment. On that basis, poor economic opportunities are the prime driver of modern-day piracy, especially as they pertain to the incidents off the eastern coasts of Africa. As our empirical findings indicate, there is some consistent evidence that the level of per-capita incomes and employment are inversely related to the success of piracy attacks and they have explanatory power in the motives for seeking

[2] Two other papers by Leeson (2007) and Ambrus and Chaney (2010) focus on ancient maritime piracy. Leeson's main emphasis is on the informal social and institutional arrangements pirates of the yore mustered in order to operate with some degree of organization and efficiency. Ambrus and Chaney explore the extent to which dynamic bargaining principles applied in Spanish dealings with Barbary Corsairs' ransom demands between the 16th and 18th centuries.

[3] "Modern High Seas Piracy" by Countrman and McDaniels Law Offices (2000, 2005), at http://www.cargolaw.com/presentations_pirates.html#Introduction.

economically-valuable booty.

Beyond that, however, our results have special pertinence, because modern-era piracy is a capital- and skill-intensive endeavour that is subject to potential refinements in technique, a learning curve and job-specific skills acquisition. As Hastings (2009) articulates, modern incidents of piracy require logistical planning and support not only on the *front end*, which defines the point up to the attack and the boarding of vessels. But also the *back end* too, which covers the period from the attack to culmination with a potential liquidation of the booty.

On the front end, skills and capital are required in order to identify, track and close in on targets. On the back end, infrastructure, networks and connections are needed to sell or repurpose the ships and their cargo. Or, in the case of hostages, to set up 'accommodations' during the often lengthy and risky phase of ransom negotiations.[4] Our findings show that modern-era piracy has evolved over time on the basis of accumulated piracy experience locally to yield not only higher success rates, but also more economically-valuable booty and higher risk to the crew. In fact, we find that the learning-by-doing effects in modern maritime piracy are important enough to, at least partially, offset the dampening role of better economic and political conditions.

There is a sizeable literature on the role of learning-by-doing on worker and firm productivity, industrial organization as well as economic growth. Arrow (1962), Lucas (1988), Stokey (1988), Parente (1994), Jovanovic and Nyarko (1996), Iyigun (2006) and Iyigun and Owen (2006) are among those who hypothesize that on-the-job learning and knowledge spillovers are important for endogenous economic growth. More recently, Thompson has taken some empirical exception to the productivity impact of worker learning and experience. Spence (1981), Cabral and Riordan (1994), and Benkard (2004) show the influence of learning by doing on industrial organization by illustrating how firm experience can lead to increases in industry concentration through the emergence of a low-cost dominant firm. There is also a strand which documents the existence of relationship-specific learning. For instance, Kellogg (2009) argues that relation-specificity matters by

[4]Some pirate outfits are organized enough that they have military command-and-control structures and the pirates wear uniforms. Attacks have been recorded as much as 450 km. from the coastlines, made possible in part by the pirates use of mother and satellite ships as well as GPS trackers. There are also cases in which the pirates are known to have inserted moles on board targeted vessels. For more details, see Hastings (2009).

identifying that the joint productivity of an oil production company and its drilling contractor is enhanced significantly as they accumulate experience working together.

2. The Empirical Analysis

2.1 Data and Descriptive Statistics

We created our dataset using several specific underlying sources of information. For the full description of each piracy incident between 1998 and 2007, we relied on the annual reports by the International Maritime Bureau (*IMB*) and the annual and monthly reports of the International Maritime Organization (*IMO*). For each attempted incident of piracy and robbery against a seafaring vessel, these publications provided us data on the exact time of the incident (year, month, day and hour); its location by territorial waters (whether or not the attack was attempted in international waters); the identity of the ship including its flag of registry; its gross registered tonnage ($TONNAGE$); the type of violence perpetrated against the crew (ranging from no harm done to deaths); the types of goods stolen or appropriated; and the number of pirates involved.

Based on the location of the attack, we then augmented the above data with country-specific economic and political measures. Data such as real GDP per capita and its growth rate are sourced from the *Penn World Tables*, Mark 6.3. Annual data on unemployment rates are obtained from the *World Databank*. The data on political and institutional measures primarily come from two different sources: *Freedom House* world political and civil freedom measures, and the *Polity IV* project, "Political Regime Characteristics and Transitions." The Freedom House data provide us three measures of political rights and freedoms.[5] Polity IV, on the other hand, supplies the institutionalized democracy score, institutionalized autocracy score and the modified polity score.[6]

[5] Political rights are measured on a one-to-seven scale, with one representing the highest degree of freedom and seven the lowest.

[6] The institutionalized democracy score is conceived as three essential, interdependent elements: The first one is the presence of institutions and procedures through which citizens can express effective preferences about alternative policies and leaders. The second element is the existence of institutionalized constraints on the exercise of power by the executive. The third component then is the guarantee of civil liberties to all citizens in their daily lives and in acts of political participation.

The operational indicators of democracy and autocracy are derived from the competitiveness of political participation, the openness and competitiveness of executive recruitment, and constraints on the

Our data on maritime trade per capita are from the *Shipping Statistics Yearbooks* by the Institute of Shipping and Logistics of Bremen (*ISL*). They are based on the loading and unloading cargo traffic volume by selected ports divided by the total population in the region. There are five geographic regions covered: Asia, Africa, America, Europe and Oceania. We calculate the cargo traffic volume within each region based only on selected ports, although those data represent 71 percent of the actual world seaborne trade over the ten years for which we have data.

Figures 1 and 2 present some of the overall trends in piracy attacks over the period between 1998 and 2007. As shown in Figure 1, 2000 and 2003 were particularly busy years, with the number of incidents declining after Indonesia, Malaysia and Singapore jointly cracked down on maritime piracy in 2005 and 2006, subsequent to the designation of the Malacca Strait as a war zone by Lloyd's of London. Piracy incidents rose subsequently thereafter and the number of incidents in 2007 still remained above the 1998 levels. In Figure 2, we show that the number of incidents involving ship seizures, ransom demands and physical assault on the crew has fluctuated somewhat too, with vessel seizure and physical assaults once again gaining momentum after falling from their peaks in 2003.

[Figures 1 and 2 about here.]

The summary and descriptive statistics of our key variables are listed in the two panels of Table 1. As shown in the top panel, close to 75 percent of all attacks succeeded over the ten years in our sample. And close to 85 percent of all incidents occurred in or off the coasts of Asia and Africa, while the rest took place in or off the coasts of the Americas, Oceania, and Europe. Contrary to widespread public perception, only 20 percent of attacks in our dataset occurred in Africa, whereas close to 65 percent of them took place somewhere in Asia. These incidents occurred in the ports or waters of countries with real per capita incomes of roughly \$ 7,600 based on 2005 constant U. S. dollars, although there is very high variance in the per-capita income levels of countries associated with piracy attacks. The frequency of incidents over time is slightly

chief executive. All of these indexes are based on an additive eleven-point scale (0-10). The Polity score is computed by subtracting the institutionalized autocracy score from the institutionalized democracy score; the resulting unified polity scale ranges from +10 (strongly democratic) to +10 (strongly autocratic).

backloaded although spread fairly evenly, with the average incident occurring between the 5th and 6th years in our decade-long sample (i.e., between 2002 and 2003). Examining the correlation matrix shown in the top panel, we see that the probability of a successful attack, $ATTACK$, is higher in Africa than in Asia; that it is harder to successfully attack larger ships, $TONNAGE$; that the success of attacks declines slightly with increases in per-capita income, $GDPCAP$; and that cumulative histories of successful piracy raids locally and regionally, $CUMATTACK$ and $CUMATTACK\_REGION$ respectively, are slightly positively related to the likelihood of successful future attacks.

Turning to the bottom panel of Table 1, we see that attacks mostly occurred at harbors when the vessels were anchored or in a country's own territorial waters.[7] For every one hundred incidents recorded in our dataset, there were close to two crew deaths, $DEATH$; three in which the pirates sought ransom, $RANSOM$; and 5 cases where the vessels were captured in their entirety, $VESSEL$. All outcomes are more likely in open and international waters, although the probability of success is correlated negatively with $WATER$. Incidents where vessels were stolen or the crew were killed are more likely in areas with higher per-capita incomes, but those in which cash robberies, hostage taking or ransom seeking occurred are less likely in higher-income areas. As shown in the final two rows of our bottom panel, the cumulative number of successful piracy attacks at location i up to and including time $t-1$, $CUMATTACK$, is highly negatively correlated with whether piracy attacks occurred in international waters. A longer and successful local history of piracy attacks also correlates positively, although weakly, with ship seizures and negatively with crew deaths and ransom seeking. The correlation of the regional histories of piracy success, $CUMATTACK\_REGION$, is positive with almost all other variables listed in our bottom panel. And, not surprisingly, $CUMATTACK$ and $CUMATTACK\_REGION$ are very highly and positively correlated.

[Table 1 about here.]

[7]Our variable $WATER$ attains three values: one, if the attack occurred when the vessel was docked or anchored in an harbor; two, if it took place in the territorial waters of a given country; and three, in international waters. Thus, it increases with distance to the shores and state authorities.

2.2 Main Results

2.2.1 Reduced-Form Estimates

We derive our baseline empirical results by estimating the following reduced-form equation:

$$
\begin{aligned}
OUTCOME_{it} \quad = \quad & \alpha_1 \times ATTACK_{it} + \alpha_1 \times CUMATTACK_{it-1} \\
& + \Gamma_{it}\boldsymbol{\beta} + \Omega_{it}\boldsymbol{\gamma} + \sum_{j=1998}^{2007} \psi_j \times I_j + \sum_{k=1}^{29} \lambda_k \times I_k + \varepsilon_{it} \ ,
\end{aligned}
\tag{1}
$$

where $OUTCOME_{it}$ is an outcome of the piracy act that took place in location i at time t; it is based on the type of violence or the nature of the appropriation involved, which we shall explain further below.

$ATTACK_{it}$ is a dummy variable that takes on the value of one if pirates succeeded in boarding the vessel; $CUMATTACK_{it-1}$ is the cumulative count of successful attacks that occurred at location i up to and including year $t-1$; Γ_{it} represents incident-specific explanatory variables related to the vessel or geographic location where the incident occurred; Ω_{it} represents economic or political variables associated location i at time t; I_j and I_k represent controls for time fixed effects and location fixed effects, with the latter being based on the 29 locations in our database where piracy incidents were reported.[8]

The 29 locations covered in our dataset account for 3,039 observations out of the total of 3,362, corresponding roughly to 90 percent of our data points. Since a key variable in our analyses is the cumulative local histories of successful piracy raids, in all of the empirical work below, we are constrained by these 3,039 observations for which we were able to identify the location of attack.

In alternative specifications, our dependent variable $OUTCOME_{it}$ is either one of three main outcomes: whether the crew were subject to some physical harm, $CREW$

[8] On this basis, we end up with ten year fixed effects for 1998 through 2007; five regional fixed effects for Asia, Africa, Oceania, Europe, and the Americas; and 29 location fixed effects that cover Bangladesh, Brazil, Cameroon, Colombia, Dominican Republic, Ecuador, Ghana, Guinea, Guyana, India, Indonesia, Ivory Coast, Jamaica, Kenya, Malaysia, Nigeria, Peru, Philippines, Somalia, Sri Lanka, Tanzania, Thailand, Venezuela, Vietnam, the Malacca Strait, the South China Sea, the Gulf of Aden, the Singapore Strait, the Red Sea.

– $HARM_{it}$; the crew were used for ransom demands, $RANSOM_{it}$; or the attack culminated with the pirates' seizure of the vessel, $VESSEL_{it}$.[9] All of these dependent variables are binary indicator variables, which is why our baseline empirical specifications involve Probit estimates.

In terms of the incident-specific economic or political explanatory variables in the matrix Ω_{it}, we have per-capita GDP, its growth rate between 1998 and 2007, and the unemployment rate at time t in location i, $GDPCAP_{it}$, $GROWTH_{it}$, and $UNEMP_{it}$, respectively. This matrix also includes measures of polity quality, $POLITY_{it}$, and autocracy, $AUTOCRACY_{it}$, respectively.[10] The matrix of vessel-specific and geographic explanatory variables, Γ_{it}, includes the month, year and time of day (am or pm) of the incident, its geographic location, as well as the gross tonnage, flag and the type of vessel.[11]

In Tables 2, 3 and 4, we report our baseline, reduced-form Probit estimates. All regressions in these tables include economic as well as political and institutional measures, in addition to a variety of basic vessel characteristics and geographic variables. There are no fixed effects in the specifications reported in column (1) regressions, but the subsequent three regressions in all three tables respectively add attack location, year and regional fixed effects.

As for vessel characteristics and geographic variables that are controlled for in Tables 2 through 4, we include $ATTACK$ because the extent to which pirates can inflict physical or material harm ought to be highly conditional on pirates successfully boarding the vessel. We include the $TONNAGE$ of the vessels because the damage pirates can inflict could be systematically different for larger vessels due to size-related

[9] Although we chose to focus on three specific outcomes of piracy in particular, we were able to explore other outcomes too. These include, but are not confined to, whether the attack culminated with some or all crew members being taken hostage; it involved at least one crew member being killed; whether or not the pirates stole cash from the crew or the vessel; and a more general measure of economic damage.

[10] Other variables we experimented with but chose not to include in the baseline specifications discussed below include measures of political rights, civil liberties, democracy and political freedoms.

[11] We have dummies for the flags of 20 countries under which the targeted vessels sailed. The incidents involving ships under these country flags account for more than 75 percent of our data. The countries for which we have flag dummies include: Antigua, Bahamas, Cyprus, Denmark, Greece, Hong Kong, Indonesia, India, Liberia, Malaysia, Malta, the Marshall Islands, the Netherlands, Norway, Panama, Saint Vincent, Singapore, Thailand, United Kingdom, and the United States. We also have six carrier-type dummies: liquid containers, tankers, bulk carriers, general cargo ships, fishing boats and chemical tankers.

characteristics that make larger ships more or less vulnerable to piracy acts. Whether or not the incident took place when the ship was anchored at port, or cruising in the open territorial or international seas could also have made it logistically easier or more difficult for pirates to exact some cost. Hence, the inclusion of $WATER$ as a basic right-hand side control. We also include a measure of the volume of maritime trade per capita of the region where the attack occurred, $MTRADECAP$, on the idea that maritime trade volumes could, independently, affect the kinds of damage the pirates inflicted.

The set of our basic economic variables as well as those for political stability and institutional controls are self-explanatory. In any case, the main economic variables are income per capita, $GDPCAP$, economic growth, $GROWTH$, and the unemployment rate, $UNEMP$. And our main controls for political stability and institutional quality are the polity score, $POLITY$, and an index of whether or not the government in power is authoritarian, $AUTOCRACY$.

In Table 2, our dependent variable is whether or not the crew was physically harmed, $CREWHARM$.[12] As shown, the likelihood of the crew being harmed during a piracy incident depends strongly on whether or not the pirates successfully get on board. But controlling for that, the crew can still escape unharmed when larger vessels are involved or the attacks occur closer to shores and harbors. Economic factors do come in with the predicted signs — with GDP per capita and economic growth reducing the likelihood of crew harm and unemployment raising it. Adding fixed effects for the location of attacks, their year and geographic region, respectively in columns (2), (3) and (4), does reveal that GDP per capita is a strongly negative and statistically significant determinant of the extent to which the crew were harmed during a pirate raid. The impact of income on the incidence of piracy attacks that culminate with some physical harm to the crew is quantitatively meaningful: Taking the average of the coefficients on $GDPCAP$ in columns (2) through (4), we get a roughly one percent decline in attacks with crew harm for every \$10,000 increase in per-capita income. It is worthwhile to point out, however, that this impact is not that of incomes on acts of piracy but, rather, that of incomes on undertaking piracy which inflict harm on the crew, conditional on the success of the act.

[12] This is an indicator variable that attains the value of one if the pirates either threatened, physically assaulted, kidnapped or killed someone on the crew, and is zero otherwise.

In our column (2) specification, we see that the volume of maritime trade per capita in the region of the attack negatively and significantly influences the chances of the crew being harmed. But when all fixed effects are controlled for, as we do in columns (3) and (4), this effect switches sign and turns insignificant. As for the impact of state authority on the impact of piracy incidents that are harmful to the crew, we get somewhat mixed results. On the one hand, polity scores come in with positive signs in three regressions although they are never significant. On the other hand, more authoritarian regimes produce fewer piracy incidents as implied by $AUTOCRACY$ yielding negative and significant effects in the first three columns. Once location fixed effects are introduced, as we do in column (4), this latter effect disappears which is indicative of the fact that authoritarian regimes had staying power (at least over the period between 1998 and 2007), thereby the role of $AUTOCRACY$ being absorbed by our location fixed effects.

Most importantly, the cumulative number of successful piracy attacks, $CUMAT-TACK$, comes in with positive and statistically significant effects in three of the four specifications. In essence, we find here that a history of successful piracy attacks at a given location significantly improves the odds of a future attack in which the crew is physically harmed. This effect, too, is independent of any impact local piracy experience has on how successful pirates are in successfully boarding vessels. Thus, an interesting question is the extent to which local piracy experience has an indirect impact on crew safety via pirate attacks that become more *successful* over time due to experience. We shall address this issue further below.

[Table 2 about here.]

In Table 3, we present the impact of our explanatory variables on the extent to which pirates successfully sought ransom. As seen, most of the effects we already unearthed in Table 2 remain in play here, although, most conspicuously, local piracy experience seems to have lead to a shift away from piracy incidents involving ransom demands, with only the final specification yielding statistically significant negative influence.

In Table 4, we explore the determinants of ship seizures by pirates. Our results with vessel capture are mostly in line with those in Table 2, with favorable economic factors being consistently associated with fewer attacks which culminated in the vessel being turned over to the pirates. One exception here appears to be the positive — and, in the first two regressions, significant — role of economic growth in leading to more incidents that culminated with vessel seizures. $AUTOCRACY$ still suppresses acts that culminated in vessel seizures. Most importantly, local piracy experience exerts a positive and statistically significant impact on ship seizures in three of our four regressions. All in all, these findings suggest that pirates were becoming more successful in capturing vessels in their entirety as they accumulated more local experience in launching successful pirate attacks.

[Tables 3 and 4 about here.]

2.2.2 IV Estimates

One problem with the reduced-form estimates we discussed above stems from the fact that three of our explanatory variables are endogenous and outcomes of the piracy acts themselves. In particular, the variables $TONNAGE$ and $WATER$ are choices that the pirates have full control over because they can — and do — decide on which ships to attack and where. $ATTACK$ is not fully in control of the pirates, because whether the latter can be successful in boarding a ship depends on many factors. But, by deciding on the timing and logistics of and the resources devoted to each attack, the pirates do have some influence over this outcome too. This is why we now turn to two-stage least squares estimates (*2SLS*) in which we shall instrument for these endogenous variables.

Our instrument choice is a set of (twelve) dummies for the month of attack. The idea is that weather conditions not only are highly seasonal, but also significantly influence whether or not attacks in the open seas or harbors succeed. The success of piracy attacks plausibly do depend on weather conditions. This in turn might not only shift the location of attacks closer to the shores and away from the open seas, but also make it more or less easy to defend ships based on their size. On this basis, we shall instrument for $ATTACK$, $WATER$ and $TONNAGE$. The working assumption required here is that the incidence of pirate attacks by month is not only orthogonal to the kinds of damage pirates inflict conditional on the success of the attack. But also orthogonal still to any omitted variables we might have in predicting the types of damage inflicted due to piracy.

We derive our baseline *2SLS* results by estimating the following first-stage regressions:

$$\left.\begin{array}{c} ATTACK_{it} \\ WATER_{it} \\ TONNAGE_{it} \end{array}\right\} = \sum_{m=1}^{12} \gamma_m \times I_m + \Gamma_{it}\boldsymbol{\beta} + \Omega_{it}\boldsymbol{\gamma}$$

$$+ \sum_{j=1998}^{2007} \psi_j \times I_j + \sum_{k=1}^{29} \lambda_k \times I_k + \upsilon_{it} \ , \tag{2.a}$$

We then run this second-stage equation:

$$OUTCOME_{it} = \alpha_1 \times \widehat{ATTACK}_{it} + \alpha_2 \times \widehat{WATER}_{it} + \alpha_3 \times \widehat{TONNAGE}_{it}$$

$$+\Gamma_{it}\boldsymbol{\beta} + \Omega_{it}\boldsymbol{\gamma} + \sum_{j=1998}^{2007} \psi_j \times I_j + \sum_{k=1}^{29} \lambda_k \times I_k + \varepsilon_{it} \ , \tag{2.b}$$

where $\widehat{ATTACK}$, $\widehat{WATER}$ and $\widehat{TONNAGE}$ are the predicted values of $ATTACK$, $WATER$ and $TONNAGE$ but all other variables are identical to the ones in the reduced-form specifications we presented above.

Tables 5.a, 5.b and 5.c present our first-stage estimates for $ATTACK$, $WATER$ and $TONNAGE$ respectively. As reported by the F-statistics, our instruments are very strong for $WATER$ and, for the most part, acceptable for $ATTACK$ with two specifications involving $ATTACK$ producing F-statistics above the threshold of 10. With $TONNAGE$ our instruments are clearly weaker with none of our F-statistics registering above five.

In any event, what these first-stage results indicate is that, as the pirates gained experience in launching successful attacks, their success rates rose significantly and they launched fewer attacks in the open seas, targeting larger vessels. All of these effects are statistically significant in ten of the twelve regressions for $ATTACK$, $WATER$ and $TONNAGE$.

[Tables 5.a, 5.b and 5.c about here.]

Our second-stage results are shown in Tables 6 and 7, with harm to the crew and vessel capture as our dependent variables, respectively.[13] As shown in Table 6, the predicted success of attacks and whether or not they occur in the open seas have positive impact on harm to the crew in all four estimates, but none of the estimates enter significantly. The economic and politico-institutional measures enter these estimates in consistence with their roles in our reduced-form specifications, although they show statistical significance in only a few cases. The local histories of successful piracy incidents exert positive effects in all four estimates, and when no fixed effects are controlled for, they enter significantly as well. In Table 7, we see that the results are mostly in line with those in Table 6, although none of the explanatory variables have statistically significant impact on the extent to which piracy incidents culminated with ship seizures.

[Tables 6 and 7 about here.]

All in all, these results are indicative of the fact that piracy experience has altered the outcome of attacks mainly by raising the likelihood of pirates getting on board, successfully targeting larger vessels and launching attacks closer to land. Beyond that, however, it seems to have not impacted the extent to which attacks led to more physical harm to the crew or the vessels' seizure.

2.2.3 Alternative Specifications & Robustness

While our results suggest that a history of successful piracy aided pirates in becoming more successful or, perhaps to some extent, altering their objectives too, they do not fully corroborate the idea that this history is a pure manifestation of learning by doing. The reason for this is that resources devoted to piracy might have evolved over time as well.

The descriptions of modern-era piracy leave little doubt that it is a labor- and capital-intensive activity. With our broad sample of 3,362 observations we do not have data to control for such inputs. But for roughly 70 percent of all incidents in our

[13] We have chosen not to report the second-stage findings for $RANSOM$ here as they were very much line with those for $VESSEL$. Of course, all results discussed but not shown are available upon request.

dataset, we have a record of the number of pirates involved in the attack. Hence, for a restricted subsample of our observations, we can control for piracy labor input. For the 2,300 observations for which we have data on the number of pirates, we see that each attack involved roughly six pirates, although with high variance. Most attacks took one audacious pirate, but close to ten percent of these attacks involved more than ten pirates, and 43 were reported to take more than twenty. We have five incidents in which there were more than 80 pirates involved with a maximum of 200 pirates in one case.

Controlling for changes in the pirates' physical capital stock is also a daunting challenge. Nevertheless, recall that our dataset includes information on the extent to which the piracy acts culminated with the appropriation of spare parts and equipment from the vessels or the latter's' seizure. Thus, ignoring depreciation, one could take the cumulative sum of the incidents in which the pirates stole spare parts and equipment or seized ships at a given location up to the time of the incident as a crude proxy of the amount of physical capital available to the pirates.

This is exactly what we have done in producing the results we report in our next table, where $PIRATES$ denotes the number of pirates involved in the attack and $KAPITAL$ represents our proxy for the physical capital pirates employed in carrying out their raids. As shown in Table 8, the number of pirates typically exerts a positive impact on the likelihood that the crew is harmed during the attack as well as the odds that the vessel is taken full control of by the pirates. However, in only one specification — that in column (2) where $CREWHARM$ is the dependent variable — does this effect enter statistically significantly. More interestingly, we see that, when we control for the labor and capital inputs, the local history of successful piracy acts once again starts to positively and significantly influence harm inflicted upon the crew. And although we have chosen not to report our first-stage estimates that correspond to the second-stage outcomes reported in Table 8, the history of local piracy experience still mainly manifests itself through three channels: Even after one controls for the number of pirates and proxies for piracy physical capital, local piracy experience produces higher odds of attack success in general, and more success against larger vessels and in attacks closer to land. These result suggest to us that the impact of learning-by-doing on the part of the pirates is generally robust to the inclusion of controls for labor input and proxies for the stock of physical capital at the disposal of pirates.

[Table 8 about here.]

Note that our dependent variables predominantly include binary outcomes data. As such, the distribution of these variables could lend themselves most appropriately to Probit or Poisson (negative binominal) estimation techniques. With this in mind we ran our baseline regressions with Probit regressions. In any event, we also ran the Probit specifications in Tables 2, 3 and 4 using linear probability models as well. We have elected not to report on those findings, but our qualitative results were very similar to — in fact, in many cases stronger than — those we show in Tables 2 through 4.

Next, we investigated the extent to which the cumulative history of piracy experience influenced future acts of piracy at a higher level of aggregation regionally. To this end, we used our alternative series of cumulative piracy experience that tracks the total number of successful piracy attacks at the regional level. This variable, denoted $CUMATTACK\_REGION_{i(I)t-1}$, is the sum of attacks (in which perpetrators came on-board) up to time $t-1$ in geographic region I (where i is located).[14] We replicated the regressions in the second and fourth columns of Tables 5, 6 and 7, this time also including $CUMATTACK\_REGION$ as an additional control. Our first-stage results with $ATTACK$, $WATER$ and $TONNAGE$ are not shown. But they are similar to those we report in Tables 5.a through 5.c in that successful local piracy experience, $CUMATTACK$, helps to influence the odds of success, $ATTACK$, and leads to more incidents closer to the shores, $WATER$, and aimed at larger vessels, $TONNAGE$, while experience at the regional level, $CUMATTACK\_REGION$, is not as important. Our second-stage regressions are listed on Table 9. As shown, the inclusion of regional piracy history does not alter our findings for ship seizures, with the main influence of piracy experience stemming from its first-stage role in $ATTACK$, $WATER$ and $TONNAGE$. But, as columns (1) and (2) attest, local piracy experience matters positively in the extent to which the crew is physically harmed whereas regional experience does not, even after controlling for the first-stage roles of local and regional piracy experience.

[Table 9 about here.]

[14] Rceall that we have five regions in our sample: Asia, Africa, Oceania, Europe, and the Americas.

In our next set of tables, 10.a through 10.e, we carry out our IV investigations at the regional subsample level for Asia and Africa.[15] As these findings indicate, the role of learning-by-doing in the odds of success, place and target of attacks as well as outcomes, such as physical harm on the crew and vessel seizures, is primarily an Asian phenomenon.

[Tables 10.a through 10.e about here.]

Although we have chosen to report a subset of the analyses we conducted, we also experimented with a variety of alternative specifications to test the robustness of our qualitative results. For example, besides the three institutional and polity measures we have included in the tables above, we have other related measures such as democracy, civil liberties political freedoms and property rights indexes. We have utilized these variables in conjunction with or in lieu of $POLITY$ and $AUTOCRACY$ in a variety of alternative regressions. Our key results did not alter in any meaningful way. Although the measures we reported on above generally produced the most significant effects on outcomes, the signs of their coefficients were not always consistent with predictions.

While we primarily focused on and reported results for a subset of our dependent variables (that is, $CREWHARM$, $RANSOM$, $VESSEL$, $ATTACK\ WATER$ and $TONNAGE$), we also examined the role of our standard explanatory variables in explaining variations in other dependent variables as well. These included specific outcomes such as incidents that resulted in crew deaths or cargo stolen from the vessels. But we also had at our disposal broader measures of violence or material damage, which aggregate various outcomes we discussed above into instances of violence or material damage.[16] With our broad violence or material damage measures, we got results that were fairly in line with what we have already reported, with learning by doing effects typically producing more violent outcomes and more material damage in reduced-form

[15] Recall that 85 percent of our data cover these two continents. The remainder of our observations were scant enough for each of the other three regions of Europe, Oceania and the Americas that we were only able to carry out region-level analyses only for Africa and Asia.

[16] For example, our general $VIOLENCE$ measure attains values of zero when the crew escaped unharmed; one if the crew were threatened with physical violence; two if they were physically assaulted; three if they were kidnapped and four if at least one crew member was killed. The variable $GOODS$, in similar fashion, rank orders material damage inflicted, ranging from none to the vessel being commandeered away.

estimates and working through first-stage effects in our IV specifications. With other specific outcomes, the results regarding the impact of learning by doing were sometimes mixed and sometimes weaker. With respect to other explanatory variables, we did find, however, that both higher incomes per capita and polity scores produced fewer cases of cash robberies. And higher incomes per capita also accounted for fewer threats to the crew.

Finally, we also explored if there were non-linear time trends, but did not detect any when our year fixed effects were included. However, when the latter were removed most, if not all, of our specifications showed statistically significant negative but declining time trends. That is, until around 2005, we found declining incidents, but roughly sometime around then the net effect of the time trends usually turned positive.

3. Conclusion

Modern pirates are learning. As a result, the nature of contemporary piracy attacks is evolving.

We reach this conclusion on the basis of empirical work using a dataset which includes 3,362 modern-day piracy incidents that occurred around the world between 1998 and 2007. It records detailed information on the location, timing and success of each attack, as well as the material damage and violence inflicted upon the crew and the cargo. There are also peripheral data on macroeconomic and aggregate measures of per-capita incomes, rates of economic growth and institutional quality.

On this basis, we highlighted three main findings: First, economic factors play a role in the sustenance of modern maritime piracy: higher per-capita incomes and employment dampen both the physical violence and material damage of modern-day piracy. For example, higher par-capita incomes are associated with fewer successful attacks that culminated with cash robberies and ransom demands, while they are related more frequently with cases in which the crew escaped unharmed. Second, political institutions and legal enforcement are also important, although not as much nor consistently as economic factors. For instance, incidents that occur in the harbors of territorial waters of countries with more effective polities tend to involve fewer cases in which pirates captured the vessel, robbed the crew and the ship of their cash and more incidents in which the crew escaped safely.

Most importantly, however, we document significant learning-by-doing and skill accumulation among the pirates that have helped modern piracy evolve over time into a more potent ordeal. In particular, we find that, over the period between 1998 and 2007, a history of successful piracy attacks locally improved the odds of future success, making it more likely that pirates launched successful raids aimed at larger vessels closer to land. The learning-by-doing effects are detectable even after controlling for our proxies for capital use and labor input (the number of pirates).

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Table 1: Descriptive Statistics and the Correlation Matrix

1998 – 2007			*The Correlation Matrix*								
$n = 3362$	*Mean*	*St. Dev.*	*ATK.*	*AFRICA*	*ASIA*	*YEAR*	*TONN.*	*GDPC.*	*POL.*	*MTCAP.*	*CATT.*
ATTACK	.744	.436	1	...	...	...	...	...	...	...	...
AFRICA	.204	.403	.023	1	...	...	...	...	...	...	...
ASIA	.645	.479	−.005	−.681	1	...	...	...	...	...	...
YEAR	5.44	2.62	−.021	.113	−.106	1	...	...	...	...	...
TONNAGE	16.8	21.6	−.127	−.072	.083	−.002	1	...	...	...	...
GDPCAP	7595	39803	−.062	−.072	.068	−.040	−.023	1	...	...	...
POLITY	4.26	4.35	.069	−.343	.195	.024	.057	−.113	1	...	...
MTRADECAP	1.15	1.12	.030	−.339	.028	.079	−.017	.013	.155	1	...
CUMATTACK	122	170	.073	−.256	.418	.314	.137	−.053	.345	.053	1
CUM_REGION	591	475	.015	−.344	.596	.634	.047	.009	.157	.059	.588

1998 – 2007			*The Correlation Matrix*								
$n = 3362$	*Mean*	*St. Dev.*	*ATK.*	*WTR.*	*GDPC*	*POL.*	*HARM.*	*DEATH*	*RNSOM.*	*VESL*	*CREG.*
ATTACK	.744	.436	1	...	...	...	...	...	...	...	...
WATER	1.80	.780	−.358	1	...	...	...	...	...	...	...
GDPCAP	7595	39804	−.062	.116	1	...	...	...	...	...	...
POLITY	4.26	4.35	.069	−.128	−.113	1	...	...	...	...	...
CREWHARM	.528	.499	.399	−.051	.038	−.016	1	...	...	...	...
DEATH	.019	.135	.051	.061	.030	.013	.130	1	...	...	...
RANSOM	.028	.165	.100	.148	−.012	−.062	.160	.003	1	...	...
VESSEL	.045	.208	.127	.088	.018	.002	.202	.128	−.036	1	...
CUMATTACK	122	170	.073	−.190	−.053	.345	.071	−.050	−.054	.053	1
CUM_REGION	591	475	.015	.029	.009	.157	.052	−.001	.003	.079	.588

Table 2: Probit Estimates with Location-Specific LBD & Crew Assaults Outcomes

VARIABLES	(1)	(2)	(3)	(4)
CUMATTACK	0.000827***	0.000397	0.000647*	0.000945*
	(0.000182)	(0.000243)	(0.000338)	(0.000523)
GDPCAP	-7.15e-07*	-4.10e-07	-8.31e-07***	-1.60e-06***
	(3.89e-07)	(4.10e-07)	(2.98e-07)	(3.06e-07)
GROWTH	0.000357	-0.00190	0.000845	0.000973
	(0.00395)	(0.00293)	(0.00291)	(0.00285)
UNEMP	0.0410**	0.0321**	0.0337**	0.0132
	(0.0167)	(0.0164)	(0.0158)	(0.0279)
AUTOCRACY	-0.0115***	-0.00804*	-0.00886**	0.00447
	(0.00388)	(0.00422)	(0.00404)	(0.00288)
POLITY	-0.00184	0.00871	0.000965	0.00699
	(0.0157)	(0.0170)	(0.0159)	(0.0158)
ATTACK	1.510***	1.558***	1.489***	1.597***
	(0.105)	(0.112)	(0.122)	(0.110)
WATER	0.173***	0.208***	0.270***	0.180***
	(0.0648)	(0.0617)	(0.0538)	(0.0581)
TONNAGE	-1.14e-05***	-1.06e-05***	-1.06e-05***	-1.06e-05***
	(1.71e-06)	(1.67e-06)	(1.69e-06)	(1.78e-06)
MTRADECAP	-0.198	-0.378*	0.408	0.267
	(0.181)	(0.197)	(0.511)	(0.562)
YEAR FE	N	Y	Y	Y
REGION FE	N	N	Y	Y
LOCATION FE	N	N	N	Y
Observations	3039	3039	3039	3039

Standard errors by location in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Probit Estimates with Location-Specific LBD & Ransom Demands

VARIABLES	(1)	(2)	(3)	(4)
$CUMATTACK$	-1.81e-05	-0.000859	-0.000792	-0.00380**
	(0.000827)	(0.000945)	(0.00111)	(0.00188)
$GDPCAP$	-2.18e-06**	-9.02e-07	-1.36e-06	0.000125**
	(9.48e-07)	(1.02e-06)	(9.21e-07)	(5.48e-05)
$GROWTH$	0.00443*	0.00174	0.00403	-0.00531
	(0.00246)	(0.00553)	(0.00608)	(0.00944)
$UNEMP$	-0.000402	-0.00675	0.00108	0.304*
	(0.0376)	(0.0410)	(0.0463)	(0.157)
$AUTOCRACY$	-0.0189***	-0.0156***	-0.0166***	-0.0147
	(0.00368)	(0.00518)	(0.00455)	(0.0108)
$POLITY$	0.0128	0.00885	-0.00656	-0.0626
	(0.0293)	(0.0312)	(0.0313)	(0.0457)
$WATER$	0.664***	0.678***	0.728***	0.763***
	(0.117)	(0.119)	(0.101)	(0.147)
$TONNAGE$	-9.62e-05***	-0.000102***	-0.000104***	-0.000106***
	(2.63e-05)	(2.71e-05)	(2.79e-05)	(3.54e-05)
$MTRADECAP$	-0.458	-0.688**	0.0681	-0.267
	(0.397)	(0.309)	(1.191)	(1.732)
YEAR FE	N	Y	Y	Y
REGION FE	N	N	Y	Y
LOCATION FE	N	N	N	Y
Observations	2270	2270	2270	1608

Standard errors clustered by location in parentheses;
$ATTACK$ dropped; predicts outcomes perfectly.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Probit Estimates with Location-Specific LBD & Ship Seizures

VARIABLES	(1)	(2)	(3)	(4)
CUMATTACK	0.00178***	0.00183***	0.000411	0.00162**
	(0.000399)	(0.000445)	(0.000507)	(0.000792)
GDPCAP	-2.19e-06*	-2.29e-06**	-2.74e-06**	-8.54e-06
	(1.24e-06)	(1.07e-06)	(1.17e-06)	(4.15e-05)
GROWTH	0.00537**	0.00780**	0.00895	0.00904
	(0.00267)	(0.00394)	(0.00568)	(0.00890)
UNEMP	0.00306	-0.0107	0.0700*	0.0443
	(0.0288)	(0.0303)	(0.0425)	(0.0863)
AUTOCRACY	-0.00519*	-0.00739**	-0.0130**	0.274
	(0.00299)	(0.00364)	(0.00569)	(0.419)
POLITY	-0.00568	0.00292	0.00306	0.0596
	(0.0174)	(0.0174)	(0.0163)	(0.193)
WATER	0.396***	0.458***	0.333***	0.291***
	(0.0922)	(0.0914)	(0.0823)	(0.0716)
TONNAGE	-5.26e-05	-4.92e-05	-4.85e-05	-4.81e-05
	(3.34e-05)	(3.15e-05)	(3.17e-05)	(3.22e-05)
MTRADECAP	-0.0974	-0.0839	-0.399	-0.483
	(0.202)	(0.190)	(0.775)	(1.118)
YEAR FE	N	Y	Y	Y
REGION FE	N	N	Y	Y
LOCATION FE	N	N	N	Y
Observations	2270	2270	1974	1820

Standard errors clustered by location in parentheses;
ATTACK dropped; predicts outcomes perfectly.
*** p<0.01, ** p<0.05, * p<0.1

Table 5.a: 2SLS IV Estimates — First Stage Results with *ATTACK*

VARIABLES	(1)	(2)	(3)	(4)
CUMATTACK	0.000171***	0.000197***	0.000513***	0.000132
	(0.00005)	(0.000053)	(0.000066)	(0.000122)
GDPCAP	-8.01e-07***	-7.99e-07***	-9.08e-07***	-5.45e-07***
	(2.17e-07)	(2.18e-07)	(2.11e-07)	(2.29e-07)
GROWTH	0.000254	0.000563	0.00197***	0.00124
	(0.00047)	(0.00052)	(0.00055)	(0.00085)
UNEMP	-0.0123***	-0.0130***	-0.0184***	-0.00548
	(0.0023)	(0.0023)	(0.0028)	(0.0050)
AUTOCRACY	0.00343***	0.00318**	0.00300***	-0.000140
	(0.0005)	(0.00059)	(0.00059)	(0.0012)
POLITY	0.00272	0.00427*	-0.00279	0.000669
	(0.0024)	(0.00025)	(0.00252)	(0.00465)
MTRADECAP	0.0324	0.0364	0.217**	0.229*
	(0.022)	(0.0239)	(0.103)	(0.121)
JANUARY	0.0349	0.0362	0.0393	0.0520
	(0.0382)	(0.0381)	(0.0367)	(0.0362)
MAY	-0.0599*	-0.0597*	-0.0360	-0.0374
	(0.0374)	(0.0374)	(0.0361)	(0.0354)
AUGUST	-0.0628**	-0.0576	-0.0549	-0.0389
	(0.0384)	(0.0383)	(0.0370)	(0.0363)
DECEMBER	-0.0527	-0.0593*	-0.0517*	-0.0413
	(0.0386)	(0.0384)	(0.0371)	(0.0365)
YEAR FE	N	Y	Y	Y
REGION FE	N	N	Y	Y
LOCATION FE	N	N	N	Y
Observations	3039	3039	3039	3039
R-squared	0.053	0.065	0.130	0.179
F-statistic	9.31	7.70	14.95	11.40

Standard errors clustered by location in parentheses;
FEBRUARY, *MARCH*, *APRIL*, *JUNE*, *JULY*, *SEPTEMBER*, *OCTOBER*, *NOVEMBER* included but not shown.
*** p<0.01, ** p<0.05, * p<0.1

Table 5.b: 2SLS IV Estimates — First Stage Results with $WATER$

VARIABLES	(1)	(2)	(3)	(4)
$CUMATTACK$	-0.0008***	-0.0008***	-0.0020***	-0.00016
	(0.000085)	(0.00009)	(0.00011)	(0.00016)
$GDPCAP$	1.9e-06***	2.0e-06***	2.11e-06***	-3.22e-08
	(3.75e-07)	(3.7e-07)	(3.41e-07)	(3.0e-07)
$GROWTH$	0.0048***	0.0026***	-0.000159	-0.00107
	(0.00081)	(0.0009)	(0.0009)	(0.0011)
$UNEMP$	0.0175***	0.0203	0.0541***	0.00887
	(0.004)	(0.004)	(0.0046)	(0.00657)
$AUTOCRACY$	-0.0109***	-0.0089***	-0.010***	-0.000653
	(0.0009)	(0.001)	(0.001)	(0.00156)
$POLITY$	-0.0108***	-0.013***	0.00291	-0.00414
	(0.0042)	(0.004)	(0.0041)	(0.0061)
$MTRADECAP$	0.0552	0.0106	0.202	-0.411***
	(0.0380)	(0.041)	(0.166)	(0.159)
$APRIL$	0.197***	0.191***	0.149***	0.0637
	(0.064)	(0.062)	(0.057)	(0.046)
MAY	0.0953*	0.0838	0.0257	0.0141
	(0.0650)	(0.063)	(0.0582)	(0.0463)
$AUGUST$	0.178***	0.158**	0.156***	0.0860**
	(0.0662)	(0.065)	(0.060)	(0.0475)
$NOVEMBER$	0.150**	0.139**	0.148**	0.0585
	(0.066)	(0.065)	(0.059)	(0.0473)
YEAR FE	N	Y	Y	Y
REGION FE	N	N	Y	Y
LOCATION FE	N	N	N	Y
Observations	3039	3039	3039	3039
R-squared	0.119	0.162	0.292	0.559
F-statistic	22.71	21.63	41.30	66.37

Standard errors clustered by location in parentheses;
$FEBRUARY$, $MARCH$, $APRIL$, $JUNE$, $JULY$, $SEPTEMBER$, $OCTOBER$, $NOVEMBER$ included but not shown.
*** p<0.01, ** p<0.05, * p<0.1

Table 5.c: 2SLS IV Estimates — First Stage Results with *TONNAGE*

VARIABLES	(1)	(2)	(3)	(4)
CUMATTACK	14.43***	17.90***	20.10***	18.70***
	(2.464)	(2.65)	(3.43)	(6.43)
GDPCAP	-0.00913**	-0.0112	-0.00902	-0.0103*
	(0.0109)	(0.011)	(0.011)	(0.0120)
GROWTH	64.49***	85.15***	65.84**	20.40
	(23.52)	(26.17)	(28.34)	(44.50)
UNEMP	340.1***	416.6***	259.2*	167.9
	(115.7)	(117.8)	(148.0)	(263.6)
AUTOCRACY	-17.59	-43.44	-24.20	-94.74
	(26.65)	(29.66)	(30.65)	(62.56)
POLITY	208.5*	162.6	205.1	-156.4
	(120.6)	(125.2)	(131.4)	(244.5)
MTRADECAP	-585.8	647.9	-8,613	-11,428*
	(1,099)	(1,200)	(5,349)	(6,374)
JANUARY	-2,902*	-2,439	-2,452	-3,694**
	(1,915)	(1,916)	(1,915)	(1,902)
JUNE	-4,179**	-3,578*	-3,534*	-2,911
	(1,941)	(1,944)	(1,942)	(1,922)
OCTOBER	-3,268**	-3,197*	-3,391*	-3,447*
	(1,864)	(1,866)	(1,865)	(1,848)
NOVEMBER	-2,378	-2,287	-2,279	-2,132
	(1,918)	(1,918)	(1,916)	(1,898)
YEAR FE	N	Y	Y	Y
REGION FE	N	N	Y	Y
LOCATION FE	N	N	N	Y
Observations	3039	3039	3039	3039
R-squared	0.028	0.034	0.037	0.074
F-statistic	4.77	3.98	3.89	4.16

Standard errors clustered by location in parentheses; *FEBRUARY*, *MARCH*, *APRIL*, *JUNE*, *JULY*, *SEPTEMBER*, *OCTOBER*, *NOVEMBER* included but not shown.
*** p<0.01, ** p<0.05, * p<0.1

Table 6: 2SLS IV Second-Stage Estimates with Crew Assaults as Dependent Variable

VARIABLES	(1)	(2)	(3)	(4)
$\widehat{ATTACK}$	0.141	0.335	0.243	0.265
	(0.539)	(0.560)	(0.635)	(0.545)
$\widehat{WATER}$	0.0439	0.0861	0.0587	0.00968
	(0.204)	(0.212)	(0.198)	(0.242)
$\widehat{TONNAGE}$	-2.45e-05	-2.11e-05	-2.02e-05	-1.31e-05
	(1.61e-05)	(1.76e-05)	(1.80e-05)	(1.58e-05)
$CUMATTACK$	0.000618**	0.000499	0.000627	0.000529
	(0.000231)	(0.000326)	(0.000455)	(0.000403)
$GDPCAP$	-6.05e-07*	-4.39e-07	-5.13e-07	-6.12e-07
	(3.38e-07)	(4.10e-07)	(4.69e-07)	(4.88e-07)
$GROWTH$	0.00174	0.00114	0.00211	0.000895
	(0.00273)	(0.00267)	(0.00289)	(0.00134)
$UNEMP$	0.0169*	0.0156*	0.0127	0.00332
	(0.00916)	(0.00858)	(0.00990)	(0.00667)
$AUTOCRACY$	-0.00259	-0.00225	-0.00242*	0.000204
	(0.00153)	(0.00137)	(0.00138)	(0.00202)
$POLITY$	0.00506	0.00712	0.00344	0.00107
	(0.00847)	(0.00751)	(0.00628)	(0.00614)
$MTRADECAP$	-0.0664	-0.105	0.0856	0.0277
	(0.0681)	(0.0784)	(0.181)	(0.200)
YEAR FE	N	Y	Y	Y
REGION FE	N	N	Y	Y
LOCATION FE	N	N	N	Y
Observations	3039	3039	3039	3039
R-squared	0.056	0.061	0.065	0.084

Standard errors clustered by location in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: 2SLS IV Second-Stage Estimates with Ship Seizures as Dependent Variable

VARIABLES	(1)	(2)	(3)	(4)
$\widehat{ATTACK}$	0.219	0.227	0.229	0.150
	(0.159)	(0.170)	(0.190)	(0.190)
$\widehat{WATER}$	0.00920	0.00173	0.0127	0.00744
	(0.115)	(0.125)	(0.105)	(0.108)
$\widehat{TONNAGE}$	5.13e-06	5.78e-06	4.67e-06	1.33e-06
	(6.05e-06)	(7.33e-06)	(5.81e-06)	(8.73e-06)
$CUMATTACK$	-1.11e-05	-6.16e-05	-0.000207	5.19e-05
	(0.000165)	(0.000223)	(0.000318)	(0.000172)
$GDPCAP$	1.64e-07	2.15e-07	1.72e-07	-2.32e-07
	(3.38e-07)	(3.99e-07)	(3.56e-07)	(1.82e-07)
$GROWTH$	-0.000179	-0.000290	-0.000583	-0.000195
	(0.000511)	(0.000816)	(0.000820)	(0.000744)
$UNEMP$	-7.33e-05	-0.00119	0.00488	0.00115
	(0.00254)	(0.00253)	(0.00532)	(0.00248)
$AUTOCRACY$	-0.00110	-0.00106	-0.00126	0.000429
	(0.00144)	(0.00128)	(0.00123)	(0.000968)
$POLITY$	-0.00214	-0.00200	-0.000623	-0.00343
	(0.00333)	(0.00394)	(0.00274)	(0.00264)
$MTRADECAP$	0.000169	-0.0116	0.0103	-0.0377
	(0.0215)	(0.0280)	(0.0938)	(0.102)
YEAR FE	N	Y	Y	Y
REGION FE	N	N	Y	Y
LOCATION FE	N	N	N	Y
Observations	3039	3039	3039	3039
R-squared	0.002	0.003	0.003	0.009

Standard errors clustered by location in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: 2SLS IV Estimates with Number of Pirates & Proxies for Capital Stock

VARIABLES	(1) $CREWHARM$	(2) $CREWHARM$	(3) $VESSEL$	(4) $VESSEL$
$\widehat{ATTACK}$	0.471	0.450	-0.00749	-0.0893
	(0.585)	(0.478)	(0.118)	(0.0884)
$\widehat{WATER}$	0.172	0.0175	-0.0874	-0.0687
	(0.175)	(0.180)	(0.0966)	(0.0809)
$\widehat{TONNAGE}$	-2.09e-05	-1.66e-05	-1.22e-06	-5.64e-06
	(1.37e-05)	(1.09e-05)	(4.76e-06)	(5.35e-06)
$CUMATTACK$	0.00132*	0.00152**	-0.000711	0.000561
	(0.000766)	(0.000570)	(0.000533)	(0.000460)
$PIRATES$	-6.28e-05	0.00346**	0.00317	0.00205
	(0.00242)	(0.00156)	(0.00258)	(0.00227)
$KAPITAL$	-0.00466	-0.00532**	0.00409	-0.00263
	(0.00426)	(0.00244)	(0.00243)	(0.00194)
$GDPCAP$	-5.64e-07	-6.96e-07**	4.76e-08	-2.35e-07**
	(3.50e-07)	(3.05e-07)	(1.85e-07)	(9.53e-08)
$GROWTH$	0.000642	0.00146	0.00125**	0.000113
	(0.00255)	(0.00148)	(0.000548)	(0.000522)
$UNEMP$	0.0154*	0.000297	-0.000761	0.000979
	(0.00860)	(0.00581)	(0.00300)	(0.00220)
$AUTOCRACY$	-0.00221	3.83e-05	-0.00146**	-0.000670
	(0.00142)	(0.00206)	(0.000688)	(0.000945)
$POLITY$	0.00542	8.28e-05	-0.000253	0.000776
	(0.00952)	(0.00628)	(0.00284)	(0.00173)
$MTRADECAP$	-0.0420	0.0699	0.0112	-0.0481
	(0.0751)	(0.200)	(0.0231)	(0.0882)
YEAR FE	Y	Y	Y	Y
REGION FE	N	Y	N	Y
LOCATION FE	N	Y	N	Y
Observations	2083	2083	2083	2083

Standard errors clustered by location in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Estimates with Location- and Region-Specific LBD & Outcomes

VARIABLES	(1) $CREWHARM$	(2) $CREWHARM$	(3) $VESSEL$	(4) $VESSEL$
$\widehat{ATTACK}$	0.405	0.527	0.0111	-0.0881
	(0.629)	(0.480)	(0.105)	(0.0883)
$\widehat{WATER}$	0.201	0.0738	-0.0743	-0.0692
	(0.195)	(0.188)	(0.0980)	(0.0860)
$\widehat{TONNAGE}$	-2.22e-05	-1.56e-05	-1.79e-06	-5.65e-06
	(1.37e-05)	(1.05e-05)	(4.79e-06)	(5.23e-06)
$CUMATTACK$	0.00187**	0.00168***	-0.000780	0.000521
	(0.000895)	(0.000554)	(0.000648)	(0.000521)
$CUMATT\_REGION$	-0.000236*	-0.000115	0.000115	2.70e-05
	(0.000131)	(0.000197)	(8.79e-05)	(6.29e-05)
$PIRATES$	-0.000174	0.00310*	0.00268	0.00204
	(0.00226)	(0.00152)	(0.00246)	(0.00228)
$KAPITAL$	-0.00576	-0.00598**	0.00372	-0.00248
	(0.00412)	(0.00261)	(0.00244)	(0.00215)
$GDPCAP$	-6.22e-07	-6.86e-07**	1.63e-08	-2.31e-07**
	(3.71e-07)	(2.79e-07)	(1.79e-07)	(9.97e-08)
$GROWTH$	0.000794	0.00150	0.00111**	9.63e-05
	(0.00248)	(0.00138)	(0.000508)	(0.000503)
$UNEMP$	0.00480	0.00105	0.00456	0.000804
	(0.0105)	(0.00670)	(0.00294)	(0.00227)
$AUTOCRACY$	-0.00112	0.000173	-0.00175**	-0.000667
	(0.00177)	(0.00197)	(0.000846)	(0.000928)
$POLITY$	0.00560	-6.78e-06	0.000231	0.000661
	(0.00990)	(0.00610)	(0.00284)	(0.00168)
$MTRADECAP$	0.0158	0.234	-0.0161	-0.0847
	(0.0836)	(0.316)	(0.0287)	(0.101)
YEAR FE	Y	Y	Y	Y
REGION FE	N	Y	N	Y
LOCATION FE	N	Y	N	Y
Observations	2083	2083	2083	2083
R-squared	.003	0.028	.005	.005

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10.a: Estimates with LBD & Outcomes by Region — First-Stage with *ATTACK*

VARS.	(1) *ASIA*	(2) *ASIA*	(3) *ASIA*	(4) *AFRICA*	(5) *AFRICA*	(6) *AFRICA*
CUMATT.	0.001***	0.001***	0.0003*	0.0004	0.0005	0.00022
	(0.00008)	(0.00008)	(0.00015)	(0.0006)	(0.0006)	(0.0000)
GDPCAP	-8e-08***	-8e-08***	-6e-08***	3e-05**	4e-05***	3.0e-05**
	(2.0e-08)	(1.9e-08)	(2.1e-08)	(1.3e-05)	(1.3e-05)	(1.6e-05)
GROWTH	0.00082	0.0008	0.0018	0.00025	0.0001	-0.0003
	(0.0009)	(0.0009)	(0.0011)	(0.0009)	(0.0009)	(0.0011)
UNEMP	-0.044***	-0.046***	-0.0173**	-0.008**	-0.01**	-0.011**
	(0.0043)	(0.0043)	(0.008)	(0.0040)	(0.0041)	(0.0051)
AUTOCR.	-0.007***	-0.007***	-0.007***	0.004***	0.004***	0.001
	(0.0016)	(0.0017)	(0.0018)	(0.0006)	(0.0007)	(0.0011)
POLITY	-0.009***	-0.008***	-0.005	-0.006*	-0.005	-0.01
	(0.003)	(0.003)	(0.0045)	(0.005)	(0.005)	(0.0067)
JANUARY	0.095**	0.094**	0.099**	-0.0295	-0.0230	-0.0286
	(0.046)	(0.046)	(0.0455)	(0.0755)	(0.076)	(0.0758)
APRIL	.0193	0.0162	0.0675	-0.133*	-0.140*	-0.144*
	(0.0435)	(0.0434)	(0.0432)	(0.078)	(0.079)	(0.078)
JULY	0.0540	0.0525	0.0485	-0.116	-0.113	-0.0950
	(0.0453)	(0.0451)	(0.0448)	(0.080)	(0.080)	(0.079)
NOVEMBER	.0178	0.0148	0.0346	-0.098	-0.096	-0.071
	(0.0447)	(0.0446)	(0.0444)	(0.078)	(0.078)	(0.079)
YEAR FE	N	Y	Y	N	Y	Y
LOCAT. FE	N	N	Y	N	N	Y
Observations	2165	2165	2165	686	686	686
R-squared	0.082	0.093	0.117	0.144	0.157	0.198
F-statistic	10.6	8.39	7.42	6.25	4.72	4.44

Standard errors clustered by location in parentheses;
MTRADECAP, *FEBRUARY*, *MARCH*, *MAY*, *JUNE*, *AUGUST*, *SEPTEMBER*, *OCTOBER*, *DECEMBER* included but not shown.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10.b: Estimates with LBD & Outcomes by Region — First-Stage with $WATER$

VARS.	(1) $ASIA$	(2) $ASIA$	(3) $ASIA$	(4) $AFRICA$	(5) $AFRICA$	(6) $AFRICA$
$CUMATT.$	-0.003***	-0.003***	-0.0004**	0.003***	0.0023**	0.0029**
	(0.00012)	(0.0001)	(0.0002)	(0.001)	(0.001)	(0.0014)
$GDPCAP$	2e-06***	2e-06***	8e-06***	-6e-05**	-7e-05**	-6e-05***
	(3.1e-07)	(3.0e-07)	(2.6e-06)	(3.0e-05)	(3.0e-05)	(3.1e-05)
$GROWTH$	0.004***	0.0033**	-0.006***	-0.004**	-0.0028*	-0.0011
	(0.0014)	(0.0013)	(0.0015)	(0.002)	(0.0015)	(0.0016)
$UNEMP$	0.115***	0.122***	-0.019*	0.0035	0.0097	0.012
	(0.069)	(0.007)	(0.010)	(0.0065)	(0.0063)	(0.0075)
$AUTOCR.$	0.012***	0.012***	0.010***	-0.01***	-0.01***	0.0002
	(0.0027)	(0.0026)	(0.0022)	(0.001)	(0.001)	(0.002)
$POLITY$	0.030***	0.029***	0.019***	-0.0122	0.000878	0.0157
	(0.004)	(0.0042)	(0.0057)	(0.0081)	(0.008)	(0.010)
$APRIL$	0.033	0.033	0.050	0.237*	0.238*	0.239**
	(0.070)	(0.068)	(0.055)	(0.127)	(0.122)	(0.115)
$JULY$	-0.171**	-0.158**	-0.151***	0.0676	0.0832	0.0215
	(0.073)	(0.071)	(0.057)	(0.130)	(0.124)	(0.116)
$AUGUST$	0.191**	0.165**	0.097	0.145	0.201	0.133
	(0.073)	(0.072)	(0.057)	(0.130)	(0.124)	(0.118)
$NOVEMBER$	0.169**	0.160**	0.048	0.212*	0.216*	0.130
	(0.072)	(0.070)	(0.056)	(0.127)	(0.122)	(0.114)
YEAR FE	N	Y	Y	N	Y	Y
LOCAT. FE	N	N	Y	N	N	Y
Observations	2165	2165	2165	686	686	686
R-squared	0.255	0.301	0.557	0.262	0.338	0.436
F-statistic	40.81	35.34	70.34	13.13	12.96	13.92

Standard errors clustered by location in parentheses;
$MTRADECAP$, $JANUARY$, $FEBRUARY$, $MARCH$, MAY, $JUNE$, $SEPTEMBER$, $OCTOBER$, $DECEMBER$ included but not shown.
*** p<0.01, ** p<0.05, * p<0.1

Table 10.c: Estimates with LBD & Outcomes by Region — First-Stage with *TONNAGE*

VARS.	(1) *ASIA*	(2) *ASIA*	(3) *ASIA*	(4) *AFRICA*	(5) *AFRICA*	(6) *AFRICA*
CUMATT.	10.64***	10.87***	15.38**	41.6*	46.3*	85.6**
	(4.07)	(4.11)	(8.00)	(25.0)	(25.7)	(38.3)
GDPCAP	-0.015	-0.013	-0.0095	0.202	0.116	-0.282
	(0.010)	(0.011)	(0.012)	(0.516)	(0.524)	(0.693)
GROWTH	96.4**	84.80*	25.39	58.65	52.50	5.278
	(46.0)	(46.4)	(62.4)	(37.8)	(38.6)	(43.0)
UNEMP	1,042***	1,082***	576.4	184.0	212.3	253.8
	(232.3)	(235.3)	(436.0)	(164.0)	(166.7)	(211.6)
AUTOCRACY	-246.1***	-218.0**	-176.2*	-29.3	-27.70	-93.7**
	(89.10)	(90.3)	(98.0)	(26.4)	(26.9)	(46.9)
POLITY	-30.09	-6.367	-56.16	317.6	212.3	99.40
	(137.5)	(143.1)	(243.7)	(205.4)	(166.7)	(278.4)
JANUARY	-3,243	-2,897	-4,087*	-3,730	-4,072	-4,156
	(2,485)	(2,486)	(2,479)	(3,088)	(3,129)	(3,143)
MARCH	-1,601	-1,104	-1,059	-549.2	-762.5	-1,128
	(2,447)	(2,454)	(2,443)	(3,305)	(3,359)	(3,404)
APRIL	-1,348	-1,167	-1,316	-2,074	-2,542	-2,919
	(2,359)	(2,361)	(2,355)	(3,192)	(3,241)	(3,252)
OCTOBER	-5,276**	-5,372**	-5,479	2,280	1,800	-2,231
	(2,337)	(2,339)	(2,449)	(3,216)	(3,248)	(3,229)
YEAR FE	N	Y	Y	N	Y	Y
LOCAT. FE	N	N	Y	N	N	Y
Observations	2165	2165	2165	686	686	686
R-squared	0.040	0.046	0.066	0.061	0.066	0.095
F-statistic	4.98	3.98	3.98	2.41	1.80	1.90

Standard errors clustered by location in parentheses;
MTRADECAP, *FEBRUARY*, *MAY*, *JUNE*, *JULY*, *AUGUST*
SEPTEMBER, *NOVEMBER*, *DECEMBER* included but not shown.
*** p<0.01, ** p<0.05, * p<0.1

Table 10.d: Estimates with LBD & $CREWHARM$ by Region — Second-Stage

VARIABLES	(1) $ASIA$	(2) $ASIA$	(3) $ASIA$	(4) $AFRICA$	(5) $AFRICA$	(6) $AFRICA$
$\widehat{ATTACK}$	1.103**	1.278**	1.338**	0.304	0.377	0.224
	(0.498)	(0.524)	(0.508)	(0.677)	(0.479)	(0.578)
$\widehat{WATER}$	0.172	0.251	0.264	0.397	0.297*	0.288
	(0.149)	(0.173)	(0.178)	(0.268)	(0.158)	(0.211)
$\widehat{TONNAGE}$	-3.9e-06	-1.7e-06	1.65e-06	1.2e-05**	7.7e-06	8.5e-06
	(7.8e-06)	(7.3e-06)	(6.8e-06)	(5.2e-06)	(5.5e-06)	(7.93e-06)
$CUMATT.$	-0.00022	-0.00018	3.1e-05	0.0027	0.0027*	-0.00081
	(0.00038)	(0.00039)	(0.00021)	(0.0015)	(0.0013)	(0.0013)
$GDPCAP$	2.66e-07	2.58e-07	-2.21e-07	7.32e-05	6.28e-05	-8.61e-06
	(4.3e-07)	(4.1e-07)	(1.9e-07)	(4.2e-05)	(4.3e-05)	(0.00021)
$GROWTH$	-0.00290	-0.00269	0.000561	-0.00365	-0.00246	0.00364
	(0.00314)	(0.00254)	(0.00129)	(0.00274)	(0.00309)	(0.00504)
$UNEMP$	0.0439*	0.0358	0.00945	-0.0106	-0.0133*	-0.00443
	(0.0218)	(0.0205)	(0.0173)	(0.00989)	(0.00707)	(0.0141)
$AUTOCRACY$	-0.0457	-0.0296	0.258***	0.00199	0.000320	0.00484
	(0.0445)	(0.0522)	(0.0674)	(0.00198)	(0.00315)	(0.00383)
$POLITY$	-0.0221	-0.0120	0.120***	0.00553	0.00279	-0.0108
	(0.0151)	(0.0226)	(0.0280)	(0.0143)	(0.00957)	(0.0207)
$MTRADECAP$	0.215	0	0	-3.654*	0	0
	(0.133)	(0)	(0)	(1.641)	(0)	(0)
YEAR FE	N	Y	Y	N	Y	Y
LOCAT. FE	N	N	Y	N	N	Y
Observations	2063	2063	2063	551	551	551

Standard errors clustered by location in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10.e: Estimates with LBD & $VESSEL$ by Region — Second-Stage

VARIABLES	(1) $ASIA$	(2) $ASIA$	(3) $ASIA$	(4) $AFRICA$	(5) $AFRICA$	(6) $AFRICA$
$\widehat{ATTACK}$	0.0180	-0.0501	0.0136	0.190	0.243	0.334
	(0.378)	(0.377)	(0.282)	(0.179)	(0.166)	(0.187)
$\widehat{WATER}$	-0.0182	-0.00738	-0.0342	0.0906	0.111	0.0952
	(0.0900)	(0.108)	(0.120)	(0.0709)	(0.0917)	(0.145)
$\widehat{TONNAGE}$	2.9e-06	2.3e-06	1.4e-06	6.7e-07	7.1e-07	4.5e-07
	(3.0e-06)	(2.7e-06)	(3.3e-06)	(1.4e-06)	(1.3e-06)	(2.2e-06)
$CUMATT.$	-0.00018	-0.00010	7.2e-05	-0.00055	-0.00056	-0.0011
	(0.00015)	(0.00015)	(0.00011)	(0.00052)	(0.00052)	(0.00081)
$GDPCAP$	4.6e-09	-7.6e-08	-3.3e-07**	-7.6e-06	-7.1e-06	-4.2e-05
	(2.0e-07)	(1.7e-07)	(1.3e-07)	(1.5e-05)	(1.5e-05)	(0.00013)
$GROWTH$	0.00054	0.00083	-0.00040	0.00075	0.00068	0.0022
	(0.0013)	(0.0013)	(0.0013)	(0.00084)	(0.00073)	(0.0020)
$UNEMP$	0.0120	0.0068	-0.0035	-0.0018	-0.0014	-0.0012
	(0.007)	(0.0064)	(0.017)	(0.0015)	(0.0016)	(0.0061)
$AUTOCRACY$	-0.022	-0.019	0.015	-0.0008	-0.00081	-0.00055*
	(0.020)	(0.027)	(0.050)	(0.00098)	(0.00095)	(0.00029)
$POLITY$	-0.0088	-0.0075	0.0013	0.0034	0.004	0.0116
	(0.0089)	(0.011)	(0.024)	(0.0023)	(0.0026)	(0.00642)
$MTRADECAP$	0.0820	0	0	-0.104	0	0
	(0.0660)	(0)	(0)	(0.874)	(0)	(0)
YEAR FE	N	Y	Y	N	Y	Y
LOCAT. FE	N	N	Y	N	N	Y
Observations	2063	2063	2063	551	551	551

Standard errors clsutered by location in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 1: Attempted and Successful Attacks by Year

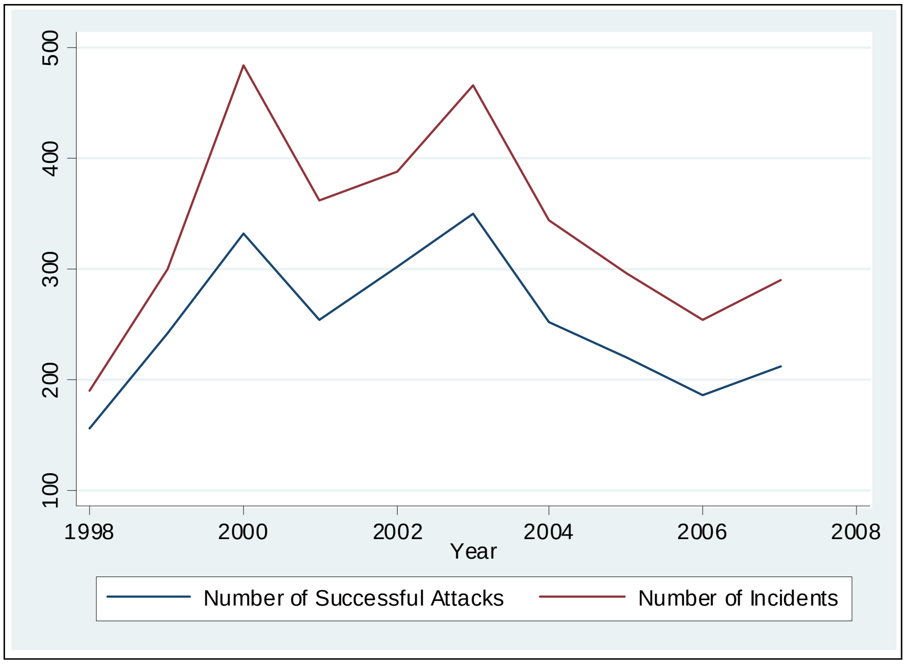

Figure 2: Incident Rates by Year