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The New Barbary Wars: Forecasting Maritime Piracy

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This paper extends systematic analyses of maritime piracy by verifying the robustness of empirical results and examining the forecasting ability of empirical models. Recent research by Ward, Greenhill and Bakke (2010) finds that statistically significant relationships frequently offer poor guidance when it comes to anticipating the inception of civil war. We assess the predictive ability of purported causal factors of piracy using evaluative statistical tools such as receiver-operating characteristic plots, out-of-sample predictions, and outlier analysis. Statistical results for in-sample and out-of-sample tests show that while factors such as military capacity, population size, coastline length, and trade volumes are statistically related to piracy, state fragility has by far the strongest predictive effect despite only being moderately statistically significant in the models. Outlier analysis demonstrates that while several countries experience higher numbers of piracy incidents than predicted, empirical models are generally robust to the presence of outliers. For policymakers, the findings suggest that counter-piracy efforts focused on capacity-building measures have the greatest potential for reducing the piracy threat.

With 80% of global trade carried by cargo ships plying the world's oceans, piracy presents a serious threat to the international economy. So far, in 2012, there have been more than 250 pirate attacks worldwide, many occurring near strategic chokepoints, such as the Gulf of Aden, the Malacca Straits, and the Arabian Sea. As the international community has begun to grapple with this hazard, the magnitude of the problem has become evident. The oceans of the world are large and difficult to police. Further, the tens of thousands of merchant ships now active cannot reasonably be monitored by the limited naval and coastguard forces currently available. While extensive research has been directed at the causes and correlates of terrorist violence, only a handful of studies have been published that assess the drivers of maritime piracy. Not only is there a need to document the conditions under which piracy occurs, but policymakers require assessments that go beyond statistical significance to provide guidance in anticipating and preventing pirate attacks.

Existing research on piracy points to state weakness, economic opportunity, and geography correlating with pirate incidents, but it is unclear whether such empirical findings by themselves provide policymakers with much help in anticipating the extent or location of maritime violence. This is in part a consequence of probabilistic models ignoring "out-of-sample predictive heuristics"

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(Ward et al. 2010:364) to help guide forecasting, as well as neglecting a sophisticated analysis of potentially high-leverage outliers.[1] Admittedly, social scientists have recognized the risk in relying on measures of statistical significance to accurately predict future events. However, few studies actually assess the robustness of models and individual variables using both in-sample and out-of-sample data. Models built using one set of data should be expected to explain variance in those data fairly well since that is typically what researchers are looking for. It is quite a different challenge for the same model and variables to correlate as strongly with the dependent variable using an entirely different set of cases. "Results that are drawn from robust models," as Ward et al. (2010) write, "have a better chance of being correct." And models that correctly capture the data-generating process should offer policymakers a more trustworthy guide in forecasting future events.

This paper is a part of a larger effort to ensure that models of maritime violence are both robust to model specification and generalizable across time and space. Our analyses here assess three types of model sensitivity. First, we examine the robustness of existing results presented in systematic research on piracy. Second, we evaluate the predictive ability of factors currently found to drive piracy. Third, we consider the extent to which individual cases and covariate patterns influence the observed correlational relationships. The paper proceeds as follows. We first provide a brief historical overview of piracy and the subsequent response by powerful states. We then review research on the drivers of piracy to inform our sensitivity analysis evaluating major explanatory concepts proposed in piracy research. Our predictive analyses use receiver operator characteristic (ROC) plots to assess the forecasting ability of a standard model of piracy. We then examine the influence of individual cases and covariate patterns to determine the generalizability of our results. Our analyses show that existing explanations of piracy succeed in generating useful predictions on patterns of piracy. We also find that among these explanatory factors, measures of institutional strength have the strongest predictive power. Finally, our examination of outliers indicates that the coefficient estimates remain largely unaffected by individual observations and covariate patterns. We conclude with some thoughts on the usefulness of such sensitivity analyses for policymakers.

A History of Piracy

Mentions of piracy frequently conjure romanticized notions of swashbuckling, rum-swigging, and skirt-chasing buccaneers hoisting the Jolly Roger. While such images stem from the portrayal of piracy in literature and film, they are of limited use in understanding both ancient and more recent manifestations of maritime banditry. Piracy has a long history in the oceans of the world, and its origins date back to the Phoenicians more than 4,000 years ago. However, as maritime technology increasingly allowed sailing vessels to travel farther away from littoral zones, and without adequate policing of the high seas, piracy not only flourished but was largely sanctioned by the critical powers of the day (Nadelmann 1990). Piracy was not only a means by which individuals accrued wealth, but also a tool of political leaders to increase state power.[2] Further, as trade on the high seas increased with European colonization, cargo ships laden with spices, silks, ivory, and precious metals became lucrative targets for the corsairs of the day.

[1] The aggregated nature of the data on pirate incidents also presents problems for accurate forecasting. Country-level correlates of annual piracy events do not provide the micro-level, real-time information needed by policymakers to respond effectively and rapidly to changes in the location of maritime violence.

[2] In return for a letter of marque, which offered pirates some legitimacy through state sanction, governments received a share of the spoils (Conybeare and Sandler 1993).

The Barbary pirates, for example, were the scourge of American merchant ships immediately following the Revolutionary War.[3] While the British were able to patrol the Mediterranean and protect their trade routes, most states simply paid tribute to the Deys of the Barbary States (Howarth 1991). Ransoming crews (similar to today) as well as tributes were common responses to the North African corsairs. The United States in 1791 offered $49,000 to the Dey of Algeria for ransoming held US sailors and created a tribute account to buy off the North African leaders (Howarth 1991). Other countries, such as Holland, Austria, and Norway, also paid for protection. Despite such efforts, Davis (2003) concludes that upward of a million European sailors were seized and sold into slavery during the height of Barbary power in the eighteenth and nineteenth centuries.

Piracy reached its heyday in the late seventeenth and early eighteenth centuries when it flourished in the seas adjacent to Europe and North America, as well as the Indian Ocean (Dear and Kemp 2005:430). Yet the success of piracy eventually produced a response by the British, whose naval forces had been substantially strengthened toward the end of the seventeenth century (Nadelmann 1990). In part, the naval response to piracy by the British (as well as the Dutch, Spanish, and French) stemmed from the increasingly profitable maritime trade in goods to and from European colonies (Rediker 2004; De Nevers 2007). Consequently, political elites not only attempted to delegitimize criminality on the high seas, but also sought to crush it through the use of naval power (Ritchie 1986).[4] These actions were largely successful as buccaneers around the world were slowly eradicated and their state sponsors persuaded to close down safe havens (Lehr 2007; :vii; Nadelmann 1990).[5]

Piracy all but disappeared from security discussions until the number of pirate attacks started to rise again in the late 1980s. The reemergence of piracy can be attributed to two phenomena. First, the end of the Cold War weakened the political control of states previously supported by the superpowers, which reduced states' ability to provide maritime security. Coinciding with these developments was an increase in international business and trade as a result of globalization (Lehr 2007:viii). Yet despite large increases in piracy incidents, modern manifestations of piracy continue to be largely ignored and thus remain underexplored.

What similarities and differences exist between earlier and more recent forms of piracy? Research argues that differences arise in the geographic reach and the international assessment of piracy (Ong-Webb 2007). Recent piracy events occur primarily in the territorial waters of states, whereas piracy during its heyday was carried out on the high seas (Murphy 2009). In addition, earlier forms of piracy possessed at least conditional legitimacy. Privateering (the procurement of private vessels by states) was given a degree of official government sanction (Abbot and Renwick 1999). In comparison, contemporary piracy is seen as illegitimate and is considered criminal activity under international law.[6] Yet there are also

[3] The Barbary pirates were sponsored, in most instances, by sovereign states, and thus, the term privateer is more accurate. Yet, how much control the Sultans of North Africa had over these ships and crews is not entirely clear. A treaty between Charles V of Spain and the King of Tunis requires the North African leader to offer no shelter to corsairs, pirates, and robbers, which suggests that some pirate vessels were operating independently of state control (Montmorency 1918).

[4] De Nevers (2007) maintains that norm promotion by great powers relies on coercion when directed at weak states and persuasion when directed at strong states.

[5] Interestingly, Nadelmann (1990:491) also maintains that the advent of steam power brought a final end to the incidence of piracy. Pirates could no longer keep up with steam-powered vessels, and the resources needed to build or buy such technologically advanced ships were out of reach of the pirates of the day. Unfortunately, technology now allows even the most resource-limited groups to chase down and threaten large merchant ships.

[6] The criminalization of piracy in international law was completed with the ratification of UNCLOS, which entered into force in 1994 and currently has 161 member states. In addition, many states have domestic legislation against piracy, although substantial variation exists (Murphy 2007:166).

reasons to believe that substantial similarities between ancient and contemporary forms of piracy exist, especially with regard to explanations of piracy. Murphy (2009:21) and Ong-Webb (2007) argue that many of the underlying factors contributing to piracy remain the same. For example, poorly regulated seas, favorable geography, sanctuaries on land, and economic dislocation all provide opportunities and motives for old and new pirates. Such explanations of ancient and contemporary piracy are valuable for the purposes of this paper since we aim to understand the conditions leading to piracy and the extent to which our models of piracy are generalizable across time and space.

Drivers of Maritime Violence

The relationship between weak governing institutions and piracy is stressed in in much of the literature on piracy (Hastings 2009; Murphy 2009; de Groot, Rablen and Shortland 2011).[7] Indeed, the inability of governments to monitor and police their territories opens up the geographic space that enables pirates to act. Space not only refers to territorial waters and the inability of fragile states to provide the naval forces necessary to capture suspected criminals. But it also refers to the space on land where pirates organize and plan their raids. Sometimes, the piracy exists long enough to become accepted and integrated into the local culture and community (Hansen 2009; Murphy 2009:43). Further, limited government control over a country's coastal zone allows pirates access to ports and anchorages for discharging their captured cargo. Such illegal activities might be obvious in strong states with working political institutions (Liss 2007). However, in countries with weak governments, local police forces and bureaucratic officials may be more likely to facilitate piracy rather than hinder it so as to share in the proceeds from the sale of plundered goods or ransom rewards (Hansen 2009; Murphy 2009).[8]

A more conditional argument on state weakness expects that while institutional weakness promotes piracy, complete state failure and anarchy are detrimental to piracy because such states cannot maintain the transportation infrastructure necessary for moving piracy loot and may lack markets necessary to find buyers (Hastings 2009). Consequently, failed states or countries experiencing civil war may be less susceptible to piracy.

The absence of employment opportunities in the legal economy also drives individuals into piracy.[9] This is not to say that poverty or unemployment turns otherwise honest people into pirates. But structural changes in an economy can produce, as Vagg (1995) writes, "the dislocation of segments of the working population." As individuals seek to provide for themselves and their families, the possibility of a large reward in a relatively short amount of time can push some

[7] Research on the onset of civil war expects and finds a similar causal effect from weak political institutions. Hegre, Ellingsen, Gates and Petter Gleditsch (2001), for example, observe anocracy to increase the risk of civil war while both extreme levels of democracy and authoritarianism reduce the risk (also see Ellingsen 2000 and Sambanis 2001). Political grievances may exist in every country, but fragile institutional structures enable groups to challenge state authority. Hegre et al. (2001:44) note that political stability increases as governments move toward the extreme ends of the Polity scale. Stable democratic governments more capably provide the economic and political conditions that alleviate popular grievances, while stable authoritarian states possess the infrastructural capacity to repress incipient insurgencies (Mason, Gurses, Brandt and Quinn 2011).

[8] The underfunding of law enforcement in coastal waters was exacerbated by September 11, 2001. Governments shifted funds to combat terrorism and terrorists on land (Murphy 2008:31; Chalk 2009). Hansen (2009) reports that interviewed pirates from the Puntland region of Somalia indicated that local police helped facilitate piracy by not arresting known pirates in the area. Murphy (2009) insists that corruption within police forces affects not only Somalia, but all piracy-prone areas. In Indonesia, Frécon (2005) found police acting as both partners and security guards.

[9] In their research on civil war, Fearon and Laitin (2003:80) similarly note that "recruiting young men to the life of a guerrilla is easier when the economic alternatives are worse."

fence-sitters into piracy.[10] In countries where *per capita* income can be <$1,000 or $2,000 a year, a single day's payoff of several hundred US dollars is obviously quite valuable and worth sizeable risks (Murphy 2008). Indeed, Eklöf (2005) concludes that individual attacks in Southeast Asia on average result in between $500 and $700 for each pirate.[11]

Some research points out that piracy requires skills that are enjoyed by only a small subset of a country's population (Murphy 2009; Daxecker and Prins 2012;). Raiding a local business on land requires only a weapon and will, but at sea, boat handling and navigational skills are critical to success. This may be why Weir (2009) finds Somali piracy to have been in part driven by the depletion of fish stock after the Barré regime collapses in 1991.[12] Frécon (2005), Burnett (2002), and Murphy (2009) also maintain that unemployed fishermen, sailors, and taxi-boat captains provide a pool of available talent to recruit into piracy. These are individuals that can most easily transition to maritime brigand. Cross-national evidence appears to support the relationship between economic weakness and piracy. Iyigun and Ratisukpimol (2010) find GDP *per capita* to correlate with variation in pirate attacks and Jablonski and Oliver (2013) observe increases in the price of labor-intensive goods to drive pirate attacks higher. Daxecker and Prins (2013) directly address changes in a country's fishing sector and find that decreases in annual fish catches correlate with increasing numbers of pirate incidents.

Another prominent explanation identified in piracy research relates to geography (Hastings 2009; Murphy 2009). Long shorelines and or archipelagic configurations provide both safe havens for pirates and ensure law enforcement is difficult and expensive, suggesting that even moderately strong states may struggle to deter and capture pirates when sanctuaries in concealed bays and coves remain ubiquitous.[13] While Hastings (2009) does not observe a relationship between coast length and type of pirate attack, Daxecker and Prins (2013) find that longer shorelines produce large substantive increases in pirate incidents. Similarly, states located in close proximity to major chokepoints may experience more piracy as a result of their geographic location, but these arguments have not yet been explored systematically (Coggins 2012).[14]

Regime type also may play a role in piracy. The repression so characteristic of autocratic states invites protest, challenges to state authority, and likely corruption and criminal activity. Yet, autocratic leaders respond to factions that keep them in power, which frequently are small subsets of elites or the military. Fewer incentives exist for such leaders to expend scarce resources in combating a criminal activity that is unlikely to threaten the regime's survival. Democrats, in

[10] One of the strongest empirical findings in the research on civil war onset is that economic development decreases the hazard of insurgency (Hauge and Ellingsen 1998; Hegre et al. 2001). Collier, Elliott, Hegre, Hoeffler, Reynal-Querol and Sambanis (2003:53) insist that poverty drives civil conflict or as they write, "they key root cause of conflict is the failure of economic development." Dixon (2009) agrees and observes that nearly all studies that include measures of prosperity (such as GDP or GDP *per capita*) find a negative and statistically significant relationship with civil war onset. Most studies of piracy note a similar relationship with the same measures of wealth (see Iyigun and Ratisukpimol 2010; de Groot et al. 2011). At the individual level, Collier (2000) suggests that political entrepreneurs attract recruits in part through the promise of monetary compensation (also see Gates 2002).

[11] Valencia and Johnson (2005) find the payoff to be around $5,000 to $15,000 for each successful attack, which is then split among group members.

[12] Menkhaus (2009) additionally targets illegal foreign fishing as driving individuals to piracy in the greater Gulf of Aden.

[13] Somalia, for example, has over 3,000 km of coastline, the Philippines over 36,000 km, Indonesia nearly 55,000 km, and Malaysia 4,700 km.

[14] The movement of substantial goods through waterways adjacent to a country's shoreline presents lucrative targets for modern-day corsairs. Despite piracy occurring in the waters of many states, certain critical trade routes see extensive pirate activity, such as the greater Gulf of Aden (which includes the coast of Somalia and the Red Sea), the Strait of Malacca and the South China Sea.

contrast, benefit electorally from supplying public goods (see, for example, Bueno de Mesquita, Morrow, Smith and Siverson 2003). Since domestic order and a free and fair market place benefit all, leaders in democratic states will consequently make attacking illegal activity a much higher priority of government compared to their autocratic counterparts. Evidence (albeit limited) does suggest that when one controls for other critical factors, such as state fragility, economic deprivation, and coastline length, democracies do experience fewer hijackings than autocracies, although overall piracy incidents show no such regime distinction (Daxecker and Prins 2013). Drawing on research on civil war, an alternative argument on regime type would be to expect that regimes in the middle of the democracy–autocracy spectrum are most prone to piracy. The literature on civil war suggests that the partly repressive, partly open nature of these regimes creates institutional inconsistencies that promote rebellion. In the context of piracy, one may expect that these contradictions open up space for criminal activity.

Finally, a state's military capabilities logically should correlate with piracy as well. Regimes with strong militaries will be better able to suppress challenges to state authority and thus more likely to deter such challenges from materializing in the first place.[15] But states with strong militaries are also likely to field robust police forces. Increasing the risk of capture and punishment not only reduces piracy through law enforcement but also reduces the expected utility to individuals for such illegal activity. Daxecker and Prins (2013), for example, observe military force size reducing the number of pirate incidents within a country's territorial waters.

Verifying Model Robustness

Social science research seeks to establish "valid inferences about social and political life" (King, Keohane and Verba 1994:3). Frequently, though, empirical models of political processes present widely different results depending on such factors as statistical estimator, unit of analysis, time period, concept operationalization, and included control variables. For example, large-n empirical evaluations of diversionary theory reach very different conclusions about the causal forces driving leader behavior. Many experts posit elections as a critical factor influencing the timing of leader decisions to use military force, but the observed statistical relationship between elections and force varies dramatically across studies. Stoll (1984) observes that uses of military force are less common before national elections while James and Oneal (1991) find that the level of force tends to increase prior to elections. Fordham's (1998) results lead him to conclude the relationship is conditional on war involvement. Still others, such as Meernik and Waterman (1996) and DeRouen (1995), report no relationship between elections and military interventions. Such inconsistent evidence is discouraging for scholars seeking a generalizable model of leader decision making.

Sensitivity analysis consists of efforts to determine the robustness of empirical results (Studenmund 2001:176). One wants to ensure that coefficient estimates

[15] Fearon and Laitin (2003) also find state military and police strength related to civil war onset. They note that the "reach of government institutions into rural areas" remains one of the most critical factors explaining insurgency inception (Fearon and Laitin 2003:80). They proxy the relative weakness of insurgents compared to the state using *per capita* income and find it negatively related to civil war onset (1945–1999). Theoretically, Fearon and Laitin insist that *per capita* income captures a government's "overall financial, administrative, police and military capabilities" as well as a country's level of development, which they maintain associates with roads and the ability of state forces to penetrate rural areas (80). They further note that *per capita* income denotes the economic opportunities, or lack thereof, available to the average young man and thus how easily he can be recruited by rebel leaders. We see similar relationships with piracy using CINC as a measure of state strength and *per capita* fish values as a proxy for economic opportunity.

are not statistical artifacts or mere coincidences, but actually represent a true underlying causal relationship. Typically, sensitivity analysis involves examining results from different model specifications (usually different sets of control variables) and assessing how vulnerable a particular result is to alternative formulations. One hopes that a specific correlation remains unchanged across alternative specifications and different data sets. Leamer's (1983) extreme-bounds analysis generally defines estimates as robust if they remain statistically significant and with the same direction of influence regardless of the model specification.

Sensitivity analysis also involves assessments of model performance out-of-sample as well as an evaluation of covariate pattern influence. Indeed, King and Zeng (2007) maintain that evaluation of a particular result across various model specifications may still be insufficient to avoid incorrect inferences. They insist that standard modeling techniques largely fail to examine the extent to which empirical results are model dependent. "The risk with model-dependent inferences is that substantive conclusions are based more on apparently minor modeling choices than on the empirical evidence" (King and Zeng 2007:184). Out-of-sample forecasting offers a tool more capable of appraising model dependence than statistical significance (Ward et al. 2010:373). Ward et al. (2010) conclude that policy based on "models that are constructed on the basis of pruning that is undertaken with the shears of statistical significance" likely "winnow our models away from predictive accuracy." Consequently, out-of-sample heuristics will likely provide better guidance to policymakers interested in anticipating future events.

Similarly, outlier analyses help ensure inferences are valid and generalizable both in- and out-of-sample. "One of the fundamental goals of inference," King et al. (1994:56) write "is to distinguish the systematic component from the nonsystematic component of the phenomenon we study." Our empirical models should tell us how the world typically works, which again remains a primary aim of social science. Yet, the sample we use to confirm or disconfirm theoretical conjectures may contain small numbers of observations or even a single observation that can disproportionately affect our coefficient estimates. A model where statistical significance changes dramatically with the removal of minor subsets of the sample data clearly does not offer a valid and generalizable description of the underlying data-generating process.

All three evaluative techniques are considered below. We first examine the robustness of existing explanations of piracy by evaluating the statistical significance and predictive ability of various operationalizations of key explanatory concepts. Based on these results, we select the best model for our predictive analyses. We first estimate a model of piracy on country-year data from 1995 to 2006. We then take the same empirical model and assess its performance on piracy data from 2007 to 2010. In this way, the posited causal relationships are examined in two different samples. We draw upon recent research by Ward et al. (2010) that emphasizes the importance of out-of-sample predictive heuristics. Since statistical significance sometimes relates poorly to forecasting accuracy, predictive tools such as ROC plots need to be used to determine the overall predictive power of a model. The ROC plots also provide a comparison at the individual variable level of statistical significance versus predictive power.

The outlier analysis below examines covariate pattern leverage by calculating the decrease in the Pearson chi-squared goodness-of-fit statistic that results from removing single observations that share certain covariate patterns. Not only are we interested in observations that produce large residuals and thus may be poorly predicted by our model. We are also interested in observations with small residuals, but high leverage. These kinds of observations may be disproportionately influencing the coefficient estimates we obtain, and consequently, the model may largely be explaining those few cases rather than the overall sample.

Sensitivity Analysis

Data and Variables

We create a data set that includes all countries with coastlines for the 1995–2010 period.[16] We first assess whether key theoretical concepts proposed in the piracy literature affect piracy as expected. Using Hegre and Sambanis' (2006) sensitivity analysis of civil war onset as a model, we evaluate how sensitive our inferences are to changes in the operationalization of explanatory variables. After selecting the variables producing the most consistent results for each theoretical concept, we examine models' predictive power with in-sample tests on the years 1995–2006 but reserve the years 2007–2010 for out-of-sample predictions. The final section proceeds to evaluate whether influential observations drive empirical findings on piracy.

Data on piracy incidents come from the International Maritime Bureau (IMB).[17] In assigning piracy incidents to countries, we follow the IMB's procedures, which use information on the location of incidents and the pirates' country of origin to assign events to states.[18] We collect data for two dependent variables, namely piracy incidents and hijackings (the most serious and empirically rare type of piracy incident). While the IMB reports information on the actual number of piracy incidents for each state per year, we transform these event counts into dummy variables for three reasons. First, this paper aims to evaluate which factors are most influential in producing the presence or absence of piracy rather than the specific number of incidents that occur in each country per year, thus making a focus on comparing cases without piracy to cases with some piracy most meaningful. Second, a wide variety of tools for examining models' predictive power exist for models with dichotomous dependent variables but are not available for event-count models. Finally, some research on piracy suggests that the causal processes contributing to the onset of piracy are different from processes that explain the actual number or types of piracy incidents that occur once countries first experience piracy, which is why it can be useful to limit the focus to piracy onset (Hastings 2009). We create two separate dummy variables for incidents and hijackings. The variable for incidents is coded 1 for countries that experience at least three piracy incidents in a given country-year, 0 otherwise. The dependent variable for hijackings is coded 1 if a country experiences at least one hijacking, 0 otherwise.[19]

The independent variables included operationalize major explanations of piracy put forward in the literature.[20] Based on the theoretical discussion

[16] Landlocked countries are excluded from the analysis since they cannot experience piracy.

[17] The IMB is widely considered the best available source for piracy incidents, which is why we do not evaluate explanations of piracy using alternative operationalizations of the dependent variable (Murphy 2008:60).

[18] With regard to location, the IMB uses two criteria. First, incidents in states' territorial waters are assigned to the respective country. Second, incidents in international waters are assigned to the country in closest proximity to the event.

[19] We use a cutoff of three incidents because we are interested in exploring the determinants of piracy in states that have a significant piracy problem rather than those that experience isolated incidents. Since hijackings are much rarer and require a substantial level of sophistication, we use a threshold of one for hijackings. Based on these cutoffs, 15.5% of cases experienced three or more incidents, and 5% of cases experienced one or more hijackings. We also experimented with lower and higher cutoffs for incidents but results were similar. See Appendix 1 for a description of the original event count frequencies and how the new dichotomous dependent variables used in the empirical analyses below have been truncated. To be sure the truncation of the dependent variable did not affect our results, we ran negative binomial models of piracy incidents and hijackings. Results for the independent variables are nearly identical to the logit model results presented below both in terms of direction of influence and statistical significance. In fact, no substantive changes emerge when going from an event count to a logit specification. Further, we examined variation in piracy incidents across countries to assess whether Somalia or a small subset of states account for large counts. In fact, 21 separate countries experienced nine or more incidents during the 1995–2010 time period, including Colombia, Peru, Nigeria, China, Bangladesh, Sri Lanka, Vietnam, and Indonesia.

[20] Because of endogeneity concerns, all independent variables with the exception of time-invariant measures are lagged by 1 year.

above, we identify five concept categories and include several operationalizations for each of the theoretically relevant concepts. Concept categories, a description of variables in each category, and data sources are listed in Table 1. The first concept relates to permissive institutional environments. Our first measure of state weakness uses data on state fragility from the Center for Systemic Peace. The data score countries on both the effectiveness and legitimacy of economic, security, political, and social conditions in the state. The resulting index ranges from 0 to 25, with higher scores indicating greater state weakness. Data for two additional measures of state weakness come from the World Bank Governance Indicators (Kaufmann et al. 2009). Control of corruption measures the extent to which public power is exercised for private gain. The data score countries in percentile rank terms and range from 0 to 100, with higher values corresponding to better outcomes. Government effectiveness is an indicator of the quality of government services, the degree of independence from political pressures, and the quality of policy formulation and implementation. The data again score countries in percentile rank terms and range from 0 to 100, with higher values corresponding to better outcomes.

We create two variables to evaluate whether state collapse and civil war are a detriment to piracy (concept 2). First, we create a dummy variable coded 1 for states in the bottom fifth percentile of the state fragility index available from the Center for Systematic Peace. Second, we use data from the UCDP Armed Conflict database to create dummy variable coded 1 for years in which countries experienced intrastate armed conflict (Gleditsch et al. 2002).

The third concept accounts for explanations centered on economic opportunity.[21] The first operationalization of economic opportunity is a measure of GDP *per capita*. Data for GDP come from the Penn World Tables. The variable is log-transformed to reduce skewness in the data. The second independent variable focuses on opportunities for piracy in states' fishing sectors. We use data on fisheries production values (in US dollars) collected by the FAO Fisheries and Aquaculture Statistics to create a variable that indicates the *per capita* value of fisheries production.[22] These data are based on officially reported values of fisheries production from FAO member countries, and we divide yearly values by each country's population size.

We measure favorable geography (concept 4) by including variables for states' coastline length in kilometers, distance (in nautical miles) from major chokepoints, and two regional dummies for Africa and Asia, the two regions with the highest numbers of piracy incidents.[23]

Regime type is the fifth concept we evaluate. Democratic leaders should be more concerned with public goods provision than their authoritarian counterparts and thus have greater incentives to combat criminal activities. We include a continuous measure of democracy (ranging from -10, most authoritarian, to $+10$, most democratic) using data from the Polity IV project.[24] We use the same data source to account for a possible inverted *U*–shaped relationship between regime type and piracy (Hegre et al. 2001). We include the continuous term

[21] While we explore two operationalizations of economic opportunity, we do not examine the robustness of Jablonski and Oliver's (2013) findings on price changes and piracy. Their research design uses country-months as the unit of analysis and it is quite different from other research that focuses primarily on yearly changes in piracy across countries.

[22] http://www.fao.org/fishery/statistics/global-capture-production/en.

[23] Regional classifications come from the Correlates of War project. The CIA World Factbook provides data on coastline length. Finally, data on distance from chokepoints come from Coggins (2012) and measure the distance (in nautical miles) from the country's capital city to the nearest chokepoint.

[24] We use the Polity2 measure.

TABLE 1. Concept Categories and Variables

Concept Label	*Variable Name*	*Description*	*Data Source*
State Weakness	Fragility	State fragility index	Center for Systemic Peace
	Corruption	Control of corruption, percentile rank	World Bank Governance Indicators
	Government Effectiveness	Government effectiveness, percentile rank	World Bank Governance Indicators
State Failure	Failed	Bottom 5% of states in state fragility index	Center for Systemic Peace
	Civil War	Presence of intrastate armed conflict	Uppsala Conflict Data Program
Economic Opportunity	GDP *per capita*	GDP *per capita*, logged values	Penn World Tables
	Fish values *per capita*	Fisheries production values *per capita*	FAO Fisheries and Aquaculture Statistics
Geography	Coastline	Coastline length in kilometers	CIA Factbook
	Chokepoint distance	Distance between capital and closest maritime chokepoint	Coggins (2012)
	Africa	Regional dummy for African states	Correlates of War Project
	Asia	Regional dummy for Asian states	Correlates of War Project
Regime Type	Polity	Polity score	Polity IV
	Polity squared	Square of polity score	Polity IV
Other Controls	Regional trade	Trade volumes by region	World Trade Organization
	CINC score	Composite index of national capabilities	Correlates of War Project
	Population size	Population size in thousands, logged	Penn World Tables
	Peace Years	Years since last year with >3 piracy incidents, polynomial	Authors' coding

and the squared term to examine whether regimes in the middle of the autocracy–democracy spectrum are more prone to experience piracy.

Three additional variables control for regional trade volumes, military capabilities, and population size. While we are not aware of additional operationalizations of these explanatory variables, existing systematic research on piracy shows that these variables are significantly related to piracy (Hastings 2009; Daxecker and Prins 2013; Jablonski and Oliver 2013). To account for large increases in the volume of international trade that may contribute to the rise of piracy (Lehr 2007),[25] we include a measure of regional trade from the World Trade Organization. Trade volumes are measured as the value of a region's imports and exports in millions of current US dollars.[26] States with greater military capacity should be better equipped to fight maritime piracy, and we use data from the Correlates of War data set on national capabilities (CINC) to operationalize military strength. Third, we add a measure of population size, which is standard in models of civil war and has been shown to correlate with piracy in existing empirical research (Hastings 2009; Daxecker and Prins 2013; Jablonski and Oliver 2013). A final variable included in all models counts the number of years without piracy to control for temporal correlation.[27]

[25] More accurately, maritime piracy has never disappeared completely, but was limited to small areas and occurred less frequently. In line with our argument, the persistence of piracy was most prominent in areas close to important trading routes, such as the Southeast Asian archipelago (Murphy 2008:162).

[26] The measure is log-transformed because of high skewness.

[27] Following Carter and Signorino (2010), we model time dependence using a cubic polynomial approximation (peace years, peace years squared, and peace years cubed).

Model Robustness

Results presented in Table 2 show support for many arguments put forward in the piracy literature.[28] With regard to state weakness (concept 1), all three operationalizations of the concept perform well with regard to predictive power, but only the state fragility measure is statistically significant for both incidents and hijackings in the expected direction, which is why we select this measure for the "best" models presented in Table 3. The coefficients for corruption and government effectiveness have the correct sign for piracy incidents, but miss conventional levels of statistical significance for both incidents and hijackings. For state failure (concept 2), we find that the presence of civil war significantly lowers the risk of piracy incidents as argued in Hastings (2009), but has no effect on hijackings. While the state failure measure is highly significant for hijackings (but not incidents), it appears to increase the likelihood of hijackings, contradicting the expectation in Hastings (2009). Neither measure is consistently related to both types of piracy events, but because the civil war variable is significant for incidents and supports the theoretical argument, we select it for the models in Table 3. Both *per capita* fish values and *per capita* GDP (concept 3) are negatively related to piracy, but only the coefficient for the GDP variable is statistically significant (albeit only for piracy incidents). Lacking significant results for fisheries values, we select GDP for models in Table 3. With regard to geography (concept 4), we find significant results for coastline length, chokepoint distance, and the regional dummies, but only coastline length is significantly related to incidents and hijackings. In addition, the variable performs better in terms of predictive power as indicated in the slightly larger areas under the curve, which is why we select it for the best models presented in Table 3. For regime type (concept 5), we do not find a significant relationship for either one of the model operationalizations. Coefficients for the linear and squared terms of the democracy variable do not reach statistical significance. We retain the linear specification for the empirical models because regime type has been emphasized in the literature, but it does not appear to have a direct effect on piracy.

Predictive Analysis

In-Sample Analysis, 1995–2006

Table 3 shows in-sample results for the most robust operationalizations of key explanatory concepts together with additional control variables. In the incidents models, coefficients for the variables measuring state weakness, civil war, GDP, coastline length, military capacity, regional trade, population size, and peace years are statistically significant and in the expected direction. For the hijackings model, coefficients for state fragility, coastline length, CINC, regional trade, population, and peace year are statistically significant and confirm theoretical expectations for these variables. In both models, variables for CINC, population size, peace years, and coastline length (albeit limited to hijackings) are the most highly significant at the 99% confidence level. Based on statistical significance, one might thus conclude that military power, population size, a history of piracy, and geographic factors are among the most successful and consistent predictors of maritime piracy, yet as our predictive analyses show, focusing primarily on statistical significance can be misleading.

We start our in-sample predictive analyses by examining the number and percentage of cases correctly and incorrectly classified by the models. Using a

[28] Different operationalizations of the same concept are included in separate models. Because of space constraints, we only present the coefficient for the respective concept operationalization rather than all variables in each model.

TABLE 2. Results for Concept Variables

Variables	*Coefficient*	*Standard Error*	*Area Under the Curve*
Fragility			
Incidents	0.076*	0.035	0.926
Hijackings	0.106*	0.046	0.878
Corruption			
Incidents	−0.009	0.006	0.934
Hijackings	0.002	0.010	0.892
Government Effectiveness			
Incidents	−0.006	0.008	0.933
Hijackings	0.004	0.015	0.891
Failed			
Incidents	0.292	0.335	0.923
Hijackings	1.454**	0.541	0.883
Civil War			
Incidents	−0.496†	0.254	0.926
Hijackings	0.173	0.378	0.878
GDP *per capita*			
Incidents	−0.393†	0.184	0.926
Hijackings	−0.042	0.252	0.878
Fish values *per capita*			
Incidents	−0.004	0.003	0.925
Hijackings	−0.001	0.002	0.879
Coastline			
Incidents	0.221*	0.100	0.926
Hijackings	0.416**	0.123	0.878
Chokepoint distance			
Incidents	0.032	0.118	0.925
Hijackings	−0.227**	0.080	0.878
Africa			
Incidents	0.944*	0.375	0.925
Hijackings	0.59	0.776	0.875
Asia			
Incidents	0.514	0.394	0.925
Hijackings	1.414**	0.444	0.875
Polity			
Incidents	0.008	0.022	0.926
Hijackings	−0.007	0.024	0.878
Polity squared			
Incidents	−0.009	0.007	0.928
Hijackings	−0.012	0.011	0.874

(*Notes*. Most robust concept variables in bold.
$^{**}p < .01$, $^{*}p < .05$, $^{\dagger}p < .1$ (two-tailed tests).)

threshold of 0.5, Table 4 shows that the incidents model correctly predicts 143 actual piracy cases, with 79 missed incidents and 57 false positives.[29] The hijackings model correctly predicts 13 hijackings, with 59 missed hijackings and eight false positives. Across these models, the number of false positives is small compared with the correctly predicted cases of piracy, which suggests that the models' predictive power does not come at the cost of large numbers of falsely predicted instances of piracy. Since these classification tables require choosing an arbitrary threshold (from 0 to 1), we next present receiver-operating characteristic (ROC) plots. The ROC curve depicted in these plots allows for a compar-

[29] While of course arbitrary, $p = .5$ is a natural starting point for a dichotomous dependent variable. We present contingency tables in addition to ROC plots to convey information on false negatives.

Table 3. Best Models of Piracy Events 1995–2006, In-Sample

Variables	*Incidents Model*	*Hijackings model*
Fragility	0.076* (0.035)	0.106* (0.046)
Civil War	−0.496† (0.254)	0.173 (0.378)
GDP *per capita* (ln)	−0.393† (0.184)	−0.042 (0.252)
Coastline (ln)	0.221* (0.100)	0.416** (0.123)
Polity	0.008 (.022)	−0.007 (0.024)
CINC Score	−20.558** (5.116)	−17.891* (8.186)
Regional Trade (ln)	0.273* (0.131)	0.346* (0.153)
Population size	0.546** (0.128)	0.289* (0.144)
Peace Years	−1.506** (0.279)	−1.545** (0.442)
Constant	−11.861** (4.321)	−17.454** (5.788)
LR χ^2	185.21 (p < .0000)	119.13 (p < .0000)
Pseudo-R^2	0.474	0.312
N	1,433	1,433

(*Notes.* Estimates are coefficients with robust standard errors in parentheses. Results for Peace Years squared and cubed not shown.
**p < .01, *p < .05, †p < .1 (two-tailed tests).)

Table 4. Actual Predictions of Piracy Events 1995–2006, In-Sample

	Incidents Model		*Hijackings model*	
	$p < .5$	$p > .5$	$p < .5$	$p > .5$
No piracy	1,154 (80.5%)	57 (3.9%)	1,353 (94.4%)	8 (0.5%)
Piracy	79 (5.5%)	143 (9.9%)	59 (4.1%)	13 (0.9%)
	N = 1,433		N = 1,433	

(*Note.* Percent Reduction in Error: incidents—39%; hijackings—6.5%.)

ison of the share of correctly predicted events to the share of false positives across the entire range of thresholds. The overall predictive power of the model can be evaluated by examining the area under the ROC curve, which will cover a larger area for models with better predictive power. As Figure 1 depicts, the areas under the curve for the three piracy models are 0.926 for incidents and 0.878 for hijackings. Evaluations of the models' overall predictive power thus show that existing explanations of piracy do a good job in identifying actual incidents of piracy.

We now proceed to evaluating the predictive power of individual variables in these models. As Ward et al. (2010) point out, assessing the practical importance of a variable based on statistical significance alone is limited and possibly even misleading. We follow Ward et al.'s (2010) approach and examine the predictive power of all significant variables in Table 3 by removing each variable and comparing the area under the ROC curve with and without each variable. We then compare individual variables' contribution on predictive power to the statistical significance of these variables using *z*-scores. Figure 2 plots the change in predictive power for each variable on the *y*-axis and *z*-scores for each variable in the incidents and hijackings models on the *x*-axis. The figure also includes a solid line depicting the overall relationship between significance and predictive power and a dotted line indicating the threshold for statistical significance at $z = 1.96$. Figure 2 shows that with the exception of the CINC score measure in the hijacking model, all variables make a positive contribution to the models' predictive power (meaning that they do not reduce models' ability to predict).

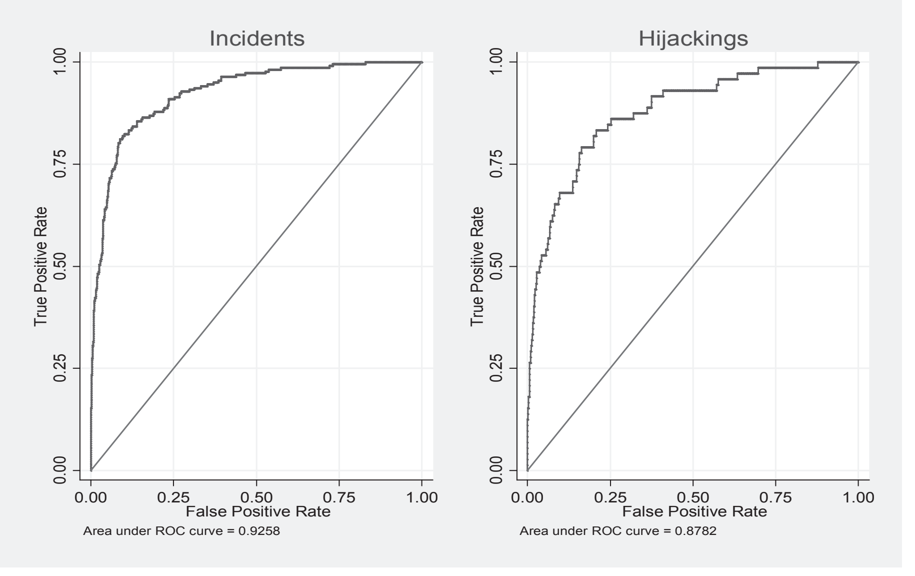

Fig. 1. Receiver Operator Characteristic Plots for In-Sample Models, 1995–2006

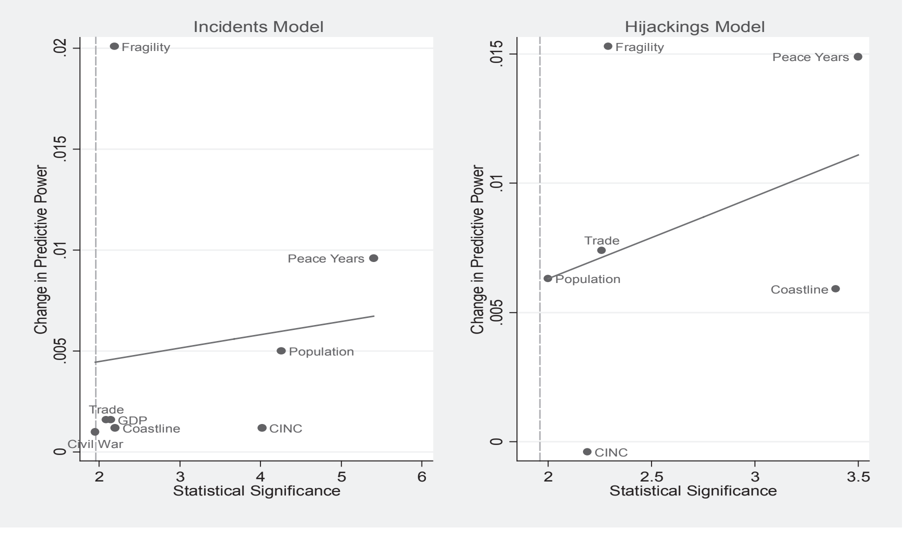

Fig. 2. Predictive Power and Statistical Significance, 1995–2006

Yet, the figure also shows that the predictive power of the state fragility variable exceeds the contribution by any other variable in all of the models, increasing models' predictive power by 0.02 for incidents and 0.015 for hijackings even though the *z*-scores for this variable (2.19 and 2.29 for incidents and hijackings) were smaller than many other variables in the models. Conversely, the predictive power of several variables with high statistical significance levels is marginal. For example, the population variable has a *z*-score of 4.0 in the incidents model, but increases the model's predictive power by only 0.005 units. Similarly, the *z*-score for the peace years variable ($z = 4.26$), the highest in the incidents model, does not match the state fragility measures' improvement in the model's predictive power, increasing it by 0.012. The problem of relying on statistical significance alone is also demonstrated in the hijackings model. The fragility measure was less significant than indicators for peace years or coastline length, but makes the largest contribution to the model's predictive power. Moreover, measures at similar levels of statistical significance, such as CINC ($z = 2.19$), actually slightly reduce the model's predictive power.

Out-of-Sample Analysis, 2007–2010

We now examine the predictive power of our models by conducting out-of-sample tests on the years 2007–2010. While a true out-of-sample test would require predictions that actually reach into the future and thus forecast piracy in years that have not yet occurred, we believe that evaluating the predictive power of covariates on data that were not used in any previous analyses is helpful in that we can immediately assess the accuracy of our predictions (Gleditsch and Ward 2010). We use covariate values for the year 2006 to predict piracy for the years 2007–2010.[30] Data on piracy incidents for these years were not used in any of the previous analyses, and we do not use information on covariates beyond the year 2006 for the out-of-sample tests. Of the 479 country-years, the data include 66 cases with three or more incidents and 16 instances of hijackings.

We begin by evaluating overall predictions generated from the models using a threshold of 0.5. Table 5 summarizes that the incidents model correctly predicts 48 incidents, misses 18, and incorrectly predicts piracy in 12 cases. As in the in-sample tests, the model performs well in producing correct predictions without simultaneously generating large numbers of false positives or negatives. Our predictions for hijackings are substantially improved compared to in-sample tests. The model correctly predicts 10 hijackings, misses 6, and produces only two false positives. Table 6 presents a list of actual countries and years for predictions from the incidents and hijackings model. We first discuss findings with regard to cases of piracy incorrectly predicted (that is, false positives) by these models. As findings for the incidents model show, all of the false positives (shown in the upper-right cell) except incidents in Kenya actually experienced piracy in other years, meaning that our predictions are only slightly off and would not have created policy concerns for countries that do not experience any piracy with the exception of Kenya. Moving on to cases of piracy incidents that our models do not predict correctly (that is, false negatives shown in the bottom-left cell), findings show that the incidents model misses actual incidents in several West African and Latin American countries. Since the model does not generate correct predictions for any of these countries in other years, future research should consider what factors might help explain the occurrence of piracy in these regions.

With regard to hijackings, both of the false positives in the upper-right cell, Nigeria and Indonesia, actually experienced hijackings in several other years, which increases our confidence in the model's forecasting abilities. As the bottom-right cell with false negatives shows, the model fails to predict hijackings in several country-years for which we generate correct predictions or false positives in other years. For example, we miss a hijacking in Indonesia in 2010, but the model generated several correct predictions for other country-years. In addition, the missed hijacking in 2009 in Oman's territorial waters was in all likelihood carried out by Somali pirates, and the model performs well in correctly predicting hijackings by Somali pirates in all years. Missed hijackings in Liberia, Malaysia, and Thailand remain as cases not well anticipated by the models. Yet the accuracy of the out-of-sample predictions, in particular the hijackings model, is notable in light of substantial changes in piracy patterns in the 2007–2010

[30] Changing the out-of-sample period to 2008–2010, or 2006–2010, respectively, did not significantly change the results.

Table 5. Actual Predictions of Piracy Events 2007–2010, Out-of-Sample

	Incidents Model		Hijackings Model	
	$p < .5$	$p > .5$	$p < .5$	$p > .5$
No piracy	401 (83.7%)	12 (2.5%)	461 (96.2%)	2 (0.4%)
Piracy	18 (3.7%)	48 (10.0%)	6 (1.2%)	10 (2.1%)
N	479		479	

(*Note*. Percent Reduction in Error: incidents—54.6%; hijackings—50.00%.)

period. For example, areas off the coast of Somalia experienced an explosion of piracy incidents starting in 2007, all of which were correctly predicted by our models.

We also present ROC plots that examine the predictive power of out-of-sample models across the entire range of thresholds. Figure 3 shows the areas under the ROC curve at 0.935 for incidents and 0.938 for hijackings, respectively. The out-of-sample predictive performance of the models is impressive in that it exceeds the in-sample predictions. Given that regional patterns of piracy shifted fairly substantially over these years, we are confident that empirical models of piracy can be a useful guide for policymakers interested in improving the international community's policy response.

Outlier Analysis

We now examine whether the results are driven by outliers and influential observations. Outliers represent cases in the data set that are poorly predicted by the model. Consequently, deviance measures generally rely on sums of squared residuals to assess model fit. We first examine whether removing single observations results in a decrease in the Pearson chi-squared goodness-of-fit statistic.[31] According to Hamilton (1992:237), "large values indicate that the model would fit the data much better" if a specific covariate pattern or single observation were deleted. Values above four on this measure arguably point to a statistically significant change in model fit (Hamilton 1992).

Second, we evaluate leverage by calculating Pregibon's beta, which calculates how much coefficients change as a result of removing single observations from the data set.[32] Pregibon's beta is similar to Cook's D in that rather than measure the influence a single case has on a specific coefficient value, it measures the influence a single case has on the model as a whole (Hamilton 1992:132).[33] Figure 4 combines both statistics in a single plot. The *Y*-axis measures fit (Δ in Pearson χ^2) while the size of the circle measures influence (Δ in Pregibon's beta). The *X*-axis measures the predicted probability of a piracy event (incidents or hijackings). Cases high up on the *Y*-axis with larger circles are poorly fit by the model and influential when it comes to the estimated coefficient values. For piracy incidents, Gabon, Jamaica, Guyana, Cuba, Guinea-Bissau, and the Democratic Republic of Congo have higher numbers of piracy incidents in some years than expected based on coefficient values in our models. Yet piracy incidents in Guinea-Bissau in 2001 were in all likelihood carried out by pirates based in the

[31] Pearson χ^2 is the sum of squared Pearson residuals (Hamilton 1992:236).

[32] Actually, Pregibon's beta measures influence by removing all observations that share a covariate pattern (cases where values on each *X* variable are identical). Each observation in our sample data has a unique *X* pattern.

[33] A DFBeta statistical similarly measures influence in ordinary least squares regression by calculating the change in a single coefficient value when the *i*th case is removed from the dataset. DFBetas > 0 indicate the *i*th case increases the value of the estimated coefficient while DFBetas < 0 signify that the *i*th case decreases the value of the estimated coefficient.

TABLE 6. Actual Versus Predicted Piracy Events 2007–2010, Out-of-Sample

	Incidents Model		*Hijackings Model*	
	$p < .5$	$p > .5$	$p < .5$	$p > .5$
No piracy	401 country-years	Brazil 2008 Ghana 2007, 2010 Haiti 2007–2008 Ivory Coast 2007, 2009 Kenya 2008–2010 Philippines 2009 Tanzania 2010	461 country-years	Indonesia 2009 Nigeria 2010
Piracy	Cameroon 2009, 2010 Colombia 2009, 2010 Costa Rica 2009 DRC 2007, 2010 Ecuador 2010 Guinea 2009–2010 Guyana 2007 Mozambique 2007 Oman 2007, 2009 Sri Lanka 2007 Venezuela 2008–2010	Brazil 2007, 2009–2010 Bangladesh 2007–2010 Ghana 2008, 2010 Haiti 2009–2010 India 2007–2010 Indonesia 2007–2010 Ivory Coast 2008, 2010 Malaysia 2007–2010 Nigeria 2007–2010 Peru 2007–2010 Philippines 2007–2008, 2010 Somalia 2007–2010 Tanzania 2007–2009 Venezuela 2008–2010 Vietnam 2007–2010	Eritrea 2007 Liberia 2007 Malaysia 2008, 2010 Oman 2009 Thailand 2007	Indonesia 2007–2008, 2010 Nigeria 2007–2009 Somalia 2007–2010

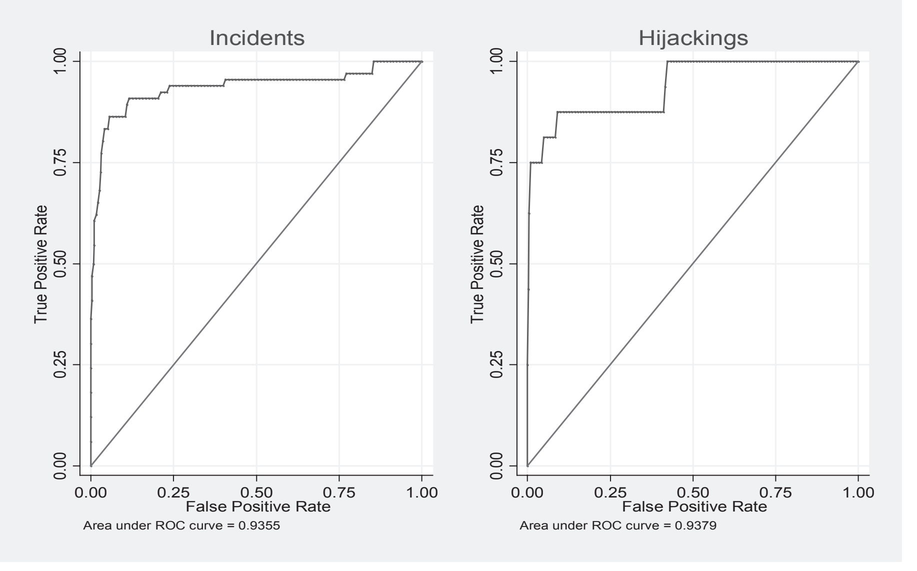

Fig. 3. Receiver Operator Characteristic Plots for Out-of-Sample Models, 2007–2010

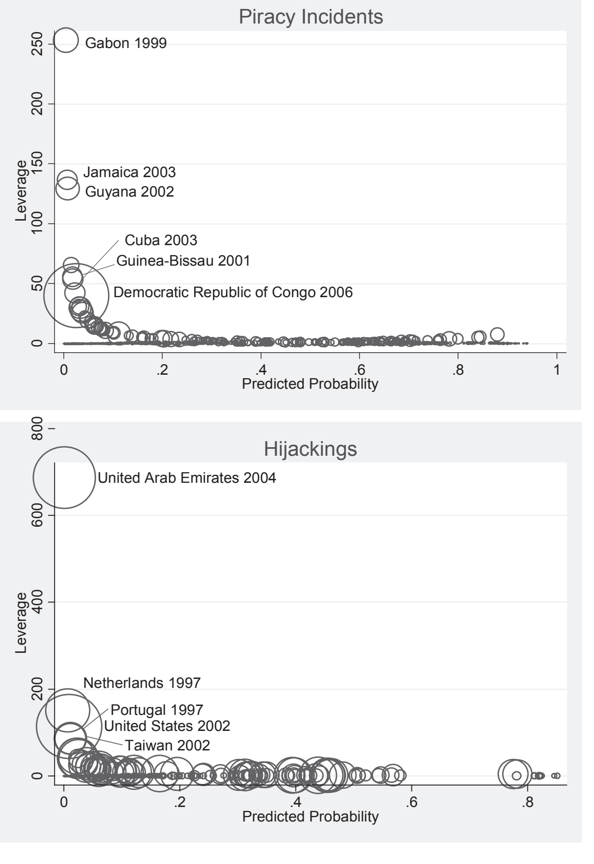

Fig. 4. Outlier Analysis of High Influence Observations, 1995–2006

Sierra Leone or Guinea and should thus probably be excluded from the model. Both Sierra Leone and Guinea score high on the fragility index and low on the corruption index (meaning more corrupt) and both experienced steady numbers of pirate incidents over the 1993–2010 period. Gabon experiences seven incidents in 2002, which is over twice as many incidents as had been occurring annually in Gabon's waters. Again, it is likely that piracy in Gabon's waters was driven by pirates working out of Nigeria or Cameroon. Both countries see large increases in pirate events beginning in the late 1990s. The three remaining outliers seem poorly explained by our models. For example, the DRC, while struggling with high levels of state fragility because of ongoing civil war, has a coastline of 37 km and low values of fish catch. Several of the outliers (for example, Guyana and the DRC) were also poorly predicted by our models in the out-of-sample tests presented above. Nevertheless, to ensure that that these observations do not influence the findings, we re-specified the incidents model and found that results remained unchanged when excluding them.[34] The consistency of results without these observations suggests that outliers are poorly explained by our models rather than that these observations drive empirical findings.

Outlier analysis for hijackings shows that the United Arab Emirates, the Netherlands, the United States, Portugal, and Taiwan experienced more hijackings than expected. All five cases experienced a single hijacking during the period under analysis, yet our model would expect a low risk of piracy based on low state fragility and high-income levels in these countries. We again re-run the model without the most influential cases and find that results for coefficients remain similar. Importantly, the outlier analysis shows that outliers in our models are observations for which we would not expect piracy given their values on key independent variables. We also do not identify outliers for which the model predicts high probabilities of piracy events, yet no incidents occurred. Overall, the consistency of results when excluding these observations confirms that outlying observations are cases poorly explained by our models rather than observations that have strong leverage on the findings.

Conclusion

Since the IMB first started recording information on piracy incidents in 1991, the number of incidents has increased dramatically. The international community has recently taken notice of this increasingly pressing problem, but counterpiracy efforts have thus far not succeeded in abating piracy.[35] This difficulty in identifying the best policy solutions to piracy suggests that empirical research on piracy could be a useful guide for policymakers. In this paper, we attempt to evaluate the empirical promise of several existing explanations of maritime piracy. Yet, different from other systematic research on piracy, we not only evaluate the statistical significance of existing explanations, but also examine the sensitivity of these findings with regard to predictive power and the presence of influential observations. As our results show, existing explanations of piracy perform well in identifying the countries most prone to piracy in both in and out-of-sample analyses. Yet our findings also indicate that some factors are more

[34] In the re-specified models (both incidents and hijackings), we exclude observations with dbeta values >0.25 and dx2 values >50, which removes approximately five observations. If we lower the thresholds to dbeta values of 0.10 and dx2 values of 25, the results still remain substantively unchanged.

[35] Naval cooperation between the European Union, the United States, and the United Nations was established to create a safe shipping corridor in the Gulf of Aden off the coast of Somalia. Created in 2008, these efforts appear to have succeeded in reducing Somali piracy for the first time in 2012, but it is not yet clear whether deterrent measures can abate piracy in the long term. In addition, IMB statistics show that piracy is increasing in other areas, such as in the Gulf of Guinea.

relevant in predicting piracy than others, indicating that institutional weakness has the largest effect on models' predictive power for all types of piracy incidents. It thus appears that improving governance mechanisms would carry the most promise in reducing the incidence of piracy and should be more effective than focusing on economic opportunities, improvements in military capacity, or the policing of coastlines. Finally, the predictive analyses and examination of outliers in the paper also suggest room for improvement in empirical work on piracy. For example, piracy in some countries in West African, Latin America, and the Caribbean remains poorly explained by the models and future research should try to identify potentially omitted factors for piracy in these states.

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Appendix 1
Frequencies of Original Counts of Country-Years with Piracy Incidents and Hijackings

	Incidents		Hijackings	
# of Piracy Events	Frequencies	%	Frequencies	%
0	996	69.42	1357	94.98
1	142	9.91	45	3.14
2	73	5.09	13	0.91
3	42	2.93	5	0.35
4	27	1.88	3	0.21
5	26	1.81	2	0.14
6	17	1.19	1	0.07
7	13	0.91	1	0.07
8	13	0.91	0	0.00
9	12	0.84	1	0.07
≥ 10	72	5.04	1	0.07
N	1,433	100%	1,433	100%

(*Note*. Frequencies are based on sample data used in the empirical models presented in Table 3.)