Forecasting maritime piracy using land-based conflict events

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Abstract

This study forecasts maritime piracy using various measures of land-based conflict. In-sample logistic and Poisson regression analysis suggests a positive relationship between conflict on land and piracy in South Asian countries, and indicates that there may exist different relationships between piracy and conflict depending on the latter's location and intensity. Out-of-sample forecasting, however, indicates that conflict event-count and casualty-count variables coded by location do not contribute to a significant improvement in forecasting performance. Reverse causality cannot be ruled out as a possible driver of these mixed results, and issues related to the geographical and temporal scope of the data and variable operationalisation may also play a role.

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Contents

1 Introduction

The rising number of piracy incidents over the past three decades have been a point of concern to the international community, triggering the creation of naval coalitions and patrols in an attempt to protect vital shipping lanes. Maritime piracy represents a major blow to the international economy – Bowden (2010) estimates overall costs which can be attributed to piracy to lie in the range of $7 to $12 billion every year. This rise of criminal activity also damages the economies of pirate-origin countries and their citizens' well-being (Nincic 2009), and so piracy's eradication is of shared international interest. Indeed, the global costs produced by piracy are estimated to be so high that even significantly costly policies such as coordinated naval patrols of key trade routes are deemed worthwhile (Fu, Ng, and Lau 2010). The anti-maritime piracy regime complex has been moderately successful in reducing such criminal activity over the past decade (Struett, Nance, and Armstrong 2013). However, research also indicates that pirates often learn to adapt to counter-piracy operations, avoiding detection through deliberate timing of raids, strategic substitution between locations, and careful management of alliances (Shortland and Vothknecht 2011). There are also limitations to the effectiveness of counterpiracy efforts due to sovereignty concerns as to exclusive economic zones (EEZs) and the territorial water status of key countries (Daxecker and Prins 2015c). The IMB reports that 2020 saw an increase in piracy attacks relative to 2019, with a 40% rise in hijackings in the Gulf of Guinea (a piracy hotspot), indicating that the problem has by no means been solved (ICC 2020).

The piracy literature consistently finds links between piracy and conditions on land, such as GDP, unemployment, and state fragility – it is often conceptualized as a land-based crime that manifests itself at sea (Murphy 2009). Traditional case study approaches examine the political economy of particularly affected states such as Somalia and Nigeria, and regularly point to onshore conditions as a source of offshore crime (Kraska 2010; Perouse de Montclos 2012). More modern, data-driven approaches have begun to use forecasting as a way of testing the strength of these relationships, finding explanatory power in factors such as military capabilities and regime types (Daxecker and Prins 2015b; 2017a). However, there has yet to be significant research conducted on the potential effect of land-based conflict incidents on piracy. While past studies have looked at general relationships between the presence of civil war and piracy (Hastings 2009; Daxecker and Prins 2015b), they have not examined differential effects with respect to the intensity or location of conflict. With increasingly fine-grained datasets being made available for research, growing emphasis is being placed on the importance of predicting crime using *local* variables as opposed to broader, nationally-aggregated ones (Rustad et al 2011). This dissertation aims to take a first step towards filling this gap in the literature by utilizing forecasting to explore the relationship between land-based conflict and maritime piracy.

Forecasting is a suitable method for exploring this relationship as it allows two main goals to be explored. First, evaluation of the predictive power of models including a diverse set of variables can shed light on which factors are associated with piracy. In terms of practical applications, this allows policy makers to target these factors and thus address piracy at its root so as to protect international trade, bolster the economies of pirate-origin countries, and offer safer alternative livelihoods to potential pirates (long-term solutions). Secondly, good forecasting models can predict when and where piracy incidents will happen and thus potentially prevent them, either by increasing the efficiency of piracy-prevention operations such as naval patrols or alerting vulnerable ships so that they might better prepare for possible attack. This may improve the fluidity of international trade and save lives (short-term solutions).

This study attempts to first determine whether there exists a relationship between conflict on land and piracy activity using in-sample analysis, and then employs out-of-sample forecasting to deduce whether land-based conflict has predictive power with regards to piracy. The unit of analysis is the country-month, with the data encompassing conflict events and piracy attacks occurring in African and South Asian coastal states between 1995 and 2017. The main findings of this study are as follows: in-sample analysis points toward a positive relationship between conflict on land and piracy in South Asian countries, suggesting that there may exist differential relationships between piracy and conflict depending on the latter's location and intensity. However, out-of-sample forecasting indicates that conflict event-count and casualty-count variables coded by location do not contribute to a significant improvement in forecasting performance over existing variables in the literature.

The dissertation will proceed as follows. Section 2 presents a literature review of research conducted to date on the topic of maritime piracy and its main drivers. Section 3 outlines the theoretical framework supporting the paper's hypotheses, and Section 4 provides descriptions of the methodology employed and data sources consulted. Section 5 presents the results of in-sample regressions and out-of-sample forecasting models, while Section 6 provides a discussion as to possible drivers of these results and potential limitations of the study performed. Finally, Section 7 concludes and highlights opportunities for further research.

2 Literature Review

The piracy literature has mostly focused on identifying potential predictors of piracy without applying them in a forecasting setting. Case study approaches examine the political economy of individual cases (usually states particularly affected by piracy) and draw conclusions about these cases which could potentially be extrapolated to other contexts if similar conditions apply. Kraska (2010) examines the situation in Somalia, linking piracy to clan structure, government corruption, and unemployment. He argues that the West shouldn't have a general "piracy policy", but rather a "Somalia policy" which aims to bring stability and economic growth to the country in order to eliminate existing incentives for young men to enter the piracy business. Stracke and Bos (2009) also study Somalia, pointing not only to political factors but also to the nation's geographical characteristics which make it especially vulnerable to piracy (e.g. long coastline, high number of chokepoints). Perouse de Montclos (2012), meanwhile, examines Nigeria, the country with the second-highest piracy rate in the world after Somalia. He draws a link between land-based conflicts amongst rival group "godfathers" over oil and maritime piracy, thus suggesting a possible relationship between conflict on land and crime at sea. These case studies are certainly useful for understanding specific situations (usually particularly dire ones) and identifying factors which might contribute to the piracy issue, but it is challenging to generalize their conclusions beyond the cases in question.

Data-driven approaches that examine multiple countries, regions, and even the entire globe address this issue. Spatio-temporal studies are one such type of approach, assessing the role of timing and location of piracy attacks in predicting further hijackings. Moreto and Caplan (2010) use a Risk Terrain Modelling (RTM) approach whereby a set of factors believed to contribute to piracy (chokepoints, shipping lanes, and assessment of states in the Failed States Index) are used to create seven "risk layers" for piracy across the globe. They see moderate success in using logistic regression to predict piracy attack locations based on this risk "map". Marchione, Johnson, and Wilson (2014), meanwhile, use agent-based modelling, which combines data on shipping lanes, volume of vessel flows and piracy attacks in order to predict risk locations and the monthly probability of attack. The relative success of these approaches suggests that these studies can be incredibly useful for predicting timing and/or location of attacks, but they fail to reveal underlying drivers of piracy – they thus offer short-term solutions to the international community in the form of direct prevention of individual attacks, but lack the ability to help actors stop piracy at its root.

Studies focusing on exploring relationships between key land-based variables and maritime piracy using econometric techniques are more relevant for the aim of eliminating the general piracy problem as opposed to preventing individual attacks. In terms of economic factors, Daxecker and Prins (2013) draw a link between depleted fish stocks and the unemployment of fishermen, who turn to piracy as an alternative occupation. Denton and Harris (2019a) support these results by finding a positive relationship between increased illegal, unregulated, and unreported (IUU) fishing and piracy – fishermen face overwhelming competition from foreign firms that fish at a massive scale, and are forced to take up piracy in order to make a living. Jablonski and Oliver (2013) strengthen this theory through their finding that higher unemployment and lower commodity prices are associated with increased pirate activity. More generally, GDP is consistently found to have a negative relationship with maritime piracy (Iyigun and Ratisukpinol 2010; Daxecker and Prins 2013).

As for institutional and political factors, Denton and Harris (2019b) argue that increased military capacity and anocratic governance lead to increases in piracy activity, whereas totally failed states see less piracy. This is supported by De Groot, Rablen, and Shortland (2011), who find that weak governance is associated with more piracy, while very strong governance or a complete absence of it are associated with less piracy. In other words, these findings support a "hump-shaped" relationship between strength of state capacity and piracy – piracy will be highest when a state is fragile, but some semblance of structure remains. Hastings (2009) argues that this relationship holds because only weak states provide the markets and transportation infrastructure required for piracy operations where ships and cargo are hijacked and sold for profit.

In addition, Hastings (2009) finds a negative relationship between ongoing civil war and piracy, theorizing that it might be explained by war's destruction of the aforementioned markets and infrastructure which piracy depends on. Daxecker and Prins (2017b) explore the conflict-piracy relationship in more detail by attempting to predict land-based conflict using piracy activity (essentially the opposite of this study's goal), arguing that resources gained from piracy could potentially be an important source of funding for rebel groups. While they are able to forecast conflict based on piracy fairly well, they admit that they cannot rule out reverse causality due to lack of an instrument which affects conflict only through its effect on piracy. They run a simple piracy incidence model with 12-month lags of conflict incidents as explanatory variables to examine this reverse causality and fail to find a significant relationship. However, this measure ignores potential differential effects with respect to factors such as intensity and location of conflict. In addition, the selection of 12-month lags for operationalising the independent variables appears arbitrary. There thus exists a gap in the literature regarding a more detailed exploration of the potential effects of land-based conflict on maritime piracy.

Further research by Daxecker and Prins suggests that forecasting would be a valuable methodological tool for exploring this conflict-piracy relationship. Daxecker and Prins (2015b) use forecasting in order to predict piracy incidence at the country-year level, aiming to verify the robustness of models which combine many of the predictors discussed above. Including all countries with a coastline in their sample, they find that state fragility has the most predictive power. Daxecker and Prins (2017a) perform similar forecasts but include state reach as a predictor. There thus exists a sufficient body of work on which to base this project's methodological approach.

3 Theory

As suggested by previous research, there appears to exist a possible relationship between conflict based on land and piracy incidents. Case studies point in this direction – Hansen's (2009) in-depth historical account of Somali piracy regularly refers to "offshore security situations" following "onshore situations". He also points to the fact that the most war-torn regions in Somalia have historically seen less piracy, stating that "ironically, some form of local peace is needed for piracy to exist in Somalia" (Hansen 2009, pp.23). One of his explanations, drawn from research on the war economy of Mogadishu, is that conflict creates obstacles to the formation of private business organizations including pirate groups. Another is that due to Somalia's clan-based social structure, paying of dues to factions such as rebel groups is commonplace – thus, in contexts of high conflict, pirates must sacrifice a portion of their earnings to finance such groups. However, in peacetime pirates can reinvest more of their revenue into further piracy activity, thus increasing the volume of attacks while also providing more incentives to pirates in the form of higher compensation. Hastings (2009) also finds a negative relationship between ongoing civil war and maritime piracy, theorizing that complete state failure and anarchy brought about by war can lead to the collapse of the transportation infrastructure required for moving piracy loot and the destruction of markets necessary to find buyers. Other studies, however, contest these explanations and instead defend the existence of a positive relationship between land-based conflict and maritime piracy. Liss (2007) sees the weakening of state structures through war as preventing the enforcement of local laws and thus permitting higher piracy activity. In addition, she argues that conflict's disruption to the economy also increases unemployment and obliges young men to look to criminal activities such as piracy to earn a living. Daxecker and Prins (2015b) concur, arguing that the inability of governments to monitor and police their territories opens up geographic space that enables pirates to act. This space might be at sea (e.g. less naval patrols) but also on land, where pirates organize and plan their raids before selling their stolen goods.

What if both camps are right? One plausible way of reconciling these contrasting arguments could be to make a more nuanced claim regarding the conflict-piracy relationship by accounting for the *intensity* of conflict. Hansen (2009) points in this direction when examining a specific case of conflict in Somalia which produced "unexpected" results within the framework of his wider theory (pp.31). Perhaps a parallel can be drawn with De Groot, Rablen, and Shortland's (2011) argument as to the "hump-shaped" relationship that exists between governance and piracy: while highly competent governance certainly doesn't create conditions favourable for piracy, neither does a total lack of governance. Instead, a fractured but still functioning governance system is most conducive to maritime piracy. The same may hold for land-based conflict – low-intensity conflict might facilitate piracy through the channels alluded to by Liss (2007) and Daxecker and Prins (2015b), but very high-intensity conflict may hinder piracy as theorized by Hastings (2009) and Hansen (2009). This debate in the literature thus gives rise to this project's first research question:

> *RQ1: Do low- and high-intensity conflict have differential effects on maritime piracy activity?*

Another complementary way of reconciling the above positions on the conflict-piracy relationship might involve considering where conflict is *located* on land. Rustad et al (2011) highlights the importance of using local variables as opposed to broad country-level variables when attempting to predict conflict and crime for precisely this reason – he provides the example of a possible civil war which might actually only see fighting in one small part of the country. Thus, if only country-level variables for war such as those used by Hastings (2009) are considered, then possible impacts of the location of conflict are ignored. Indeed, Gates (2002) argues that the location of conflict has a significant impact on recruitment of soldiers. This could plausibly give rise to the argument that if conflict is located near the centres of piracy organisations, then piracy activity might go down as young men become soldiers rather than pirates. However, if conflict is located far away from such centres then this effect may be weaker or even disappear. Daxecker and Prins (2015b) point to another possible channel through which conflict location can impact piracy – they argue that limited government control over a country's coastal area allows pirates access to ports for easy discharge of captured cargo. The intuition here might be that conflict in coastal areas *increases* piracy through weakened governance in those regions, whereas conflict further inland does not have this effect. However, Hastings (2009) would respond by arguing that conflict in coastal areas disrupts infrastructure necessary for the piracy business and thus might *decrease* piracy activity. In order to reconcile these competing hypotheses, one might return to the intensity of conflict and the existence of possible heterogeneous effects with respect to intensity and location – perhaps low- and high-intensity coastal and inland conflict have different impacts on piracy? This gives rise to the second and third research questions considered here:

RQ2: How does the location of conflict influence piracy activity?

RQ3: Do heterogeneous effects exist with regards to the intensity of coastal or inland conflict?

The following expected results stem from the theoretical framework. In answer to *RQ1*, high-intensity conflict is expected to be associated with less piracy due to increased difficulty in the formation of piracy organisations and the dismantling of necessary structures for the piracy trade (Hansen 2009; Hastings 2009). Low-intensity conflict will be associated with more piracy due to distractions of the state away from maritime crime, lower governmental control over territory, and economic damage which incentivizes young men to turn to piracy (Daxecker and Prins 2015b; Liss 2007).

In answer to *RQ2* and *RQ3*, high-intensity coastal conflict might lower piracy activity due to direct disruption of pirates' area of operations and higher recruitment of young men into the military or rebel groups (Daxecker and Prins 2015b; Gates 2002). Meanwhile, low-intensity coastal conflict might boost piracy activity through weakening of government control over these areas (Daxecker and Prins 2015b). A similar dynamic may hold for inland conflict, although effects might be weaker given that there are likely to be less plausible channels through which conflict located miles from the coast impacts piracy out at sea.

4 Methodology and Data

This project aims to forecast piracy activity in a given country-month between 1995 and 2017. Only African and South Asian countries are studied due to the higher urgency of the piracy problem in these regions. Marchione and Johnson (2013) find evidence of differences in macro-level time series with respect to piracy events between major world regions, suggesting that it may be more practical to forecast piracy for specific regions rather than across the entire globe. Therefore, I will forecast both on datasets including all countries (52 in total, with 4 being omitted due to lack of piracy data) and on regional datasets (West Africa, East Africa, and South Asia).

The dependent variable (DV) of interest, piracy activity, is operationalised both as a binary variable (whether or not any piracy incidents occurred) and as an event-count variable (number of piracy incidents) for a given country-month. Hastings (2009) finds suggestive evidence that the causal factors for the onset of piracy may differ from factors explaining actual number of piracy events – therefore, attempting to forecast both will indicate the power of the predictors selected and what function they serve best. Piracy events are "counted if they meet UNCLOS's definition of piracy or the IMO's definition of armed robbery" (Daxecker and Prins 2016, pp.382[1]). All countries experienced at least one piracy incident over the time period studied. Piracy

[1] The question of defining piracy is subject to debate – see Dillon (2005) for a critique of the traditional definition of maritime piracy used by the IMO.

data is drawn from the MPELD dataset (Daxecker and Prins 2015a). A binary response variable is coded as 1 if a piracy incident occurred in a given state's territorial waters in a given month, and 0 otherwise. The count response variable, meanwhile, sums the total number of piracy incidents in a given country-month. It is worth noting that the data almost certainly underestimates the number of piracy events occurring in each country-month – Perouse de Montclos (2012) points to difficulties in measuring piracy attacks on small private fishing boats, which by some estimates may constitute the majority of actual piracy events. Thus, conclusions drawn from this study (and from all previous piracy research) should be understood as applying mostly to larger-scale piracy attacks which are likely to be recorded by international organisations such as the IMO (the principal sources for piracy data).

The main independent variable (IV) of interest concerns land-based conflict events, which are defined as follows: "An incident where armed force was used by an organised actor against another organized actor, or against civilians, resulting in at least 1 direct death at a specific location and a specific date" (Sundberg and Melander, 2013). Several different operationalisations are used to test the hypotheses related to differential effects of intensity and location of conflict: total number of conflict events and casualties, number of conflict events occurring on the coast or inland, and number of casualties resulting from these events in a given country-month. Due to the lack of literature on this particular forecasting topic, there is no established "optimal" lag for the IV – therefore, one-, two-, six-, and twelve-month lags of the IV will be examined. Unfortunately, due to lack of data for key variables from 1994 (sample begins in 1995), n-number of months are lost from the analysis for every n-month lag (e.g. for the six-month lag, January-June 1995 is lost for every country). UCDP-GED data is used for conflict events (Sundberg and Melander 2013), with incidents being aggregated to the monthly level. For the intensity question, a continuous variable measuring total number of casualties is used (where more casualties represent higher intensity conflict). As for the location question, each conflict event is classified as occurring either inland or on the coast based on its PRIO-GRID identification number. A list of coastal PRIO-GRIDs in the states studied is identified on the conditions that they be assigned a GWNO code (meaning they belong to a state and are at least partially on land) and that they have a positive amount of water in them – PRIO-GRIDs that have a GWNO code but contain no water are assumed to be "inland". This filtering process does not exclude PRIO-GRIDs overlapping with inland sources of water such as lakes, however, which is why such grids are manually removed based on the PRIO-GRID map available online. This classification system allows for the counting of both the number of conflict incidents and the number of casualties resulting from these incidents that occur in coastal versus inland locations. While one could possibly extend this approach and take PRIO-GRIDs as the main unit of analysis, Daxecker and Prins (2017b) point out that it is unlikely that the effects of, in this case, conflict on piracy will be localised to just a cell. Indeed, the hypotheses advanced here related to inland conflict are based on the fact that far-away conflict may impact piracy out at sea. It is therefore preferable to adopt a slightly wider focus for the unit of analysis, the country-month.

A series of controls drawn mostly from Daxecker and Prins (2015b), which aggregates existing piracy research into one forecasting model, are also considered. These include economic and demographic variables such as GDP per capita, unemployment, population, fish stocks, military spending, and trade volumes; political and institutional variables such as state fragility, state reach, and ongoing civil war; and geographic variables such as coastline length, chokepoint distance, and number of ports. A major shipping lane control was also included – while it is not present in the literature, it could be a valuable addition given that a quick visual check of the data suggests that most recorded piracy activity clusters along important trade routes. In addition, a new monsoon control was included as a measure of seasonality – Jablonski and Oliver (2013) include an "East Asian Monsoon" control in their forecasting model, but it is applied uniformly across every world country (despite the actual monsoon season varying from region to region). The control used here is instead manually coded based on data regarding the monsoon months in different world regions (e.g. East Asian monsoon vs. West African monsoon/harmattan). Most of the other controls are coded at the year-level (the same value is coded for every month in a given year) due to lack of more fine-grained data. Past research (e.g. Jablonski and Oliver 2013) has also used this method and seen forecasting success. The data for most controls is drawn from the World Bank, Polity IV, and Daxecker and Prins (2015b). A lagged DV predictor is also included – the literature has regularly found a lagged DV to be the most powerful predictor among a model's variables, and its inclusion accounts for temporal dependence in the data.

Due to the wide sample studied (52 countries across 23 years), there are unfortunately a high number of missing values (NAs). NA-value imputation is therefore conducted using the multivariate imputation by chained equations cart (classification and regression trees) and sample (random sample from observed values) methods. Forecasts are conducted for both NA-omitted and NA-imputed datasets to confirm that imputation is not systematically biasing the results.

Logit models are run in order to forecast the piracy binary variable at the country-month level, while Poisson models are used for the event-count variable. Daxecker and Prins, the leading researchers in the piracy forecasting field, have used the logit model consistently to great effect. There is as of yet no evidence that alternative (perhaps more complex) models perform better – Ofosu-Boateng (2017) compared ordinal logistic regression, Bayesian network predictors, and series hazard models for forecasting piracy in the Gulf of Guinea and found that all three models yielded similar results. Models run on in-sample data are examined first, before turning to forecasting on out-of-sample data. A rolling-window approach is used for the test-train split, with predictions occurring on a year-by-year basis from 2010 up to 2017. These models are run on each of the regional datasets described above, and also for each of the lags of the IVs. For the logit models, out-of-sample evaluation metrics such as the receiver operating characteristic (ROC) and precision-recall (PR) curves are examined to compare the predictive power of models that include monthly conflict with baseline models drawn from the literature[2]. For the Poisson models, root-mean-square error (RMSE) is used as the principal evaluation metric.

Before moving to the results, it is worth acknowledging this approach's most significant weakness: it is unfortunately impossible to rule out reverse causality. Daxecker and Prins (2017b) discuss this in the context of their research which finds that piracy has forecasting power as a predictor of conflict. As they point out, without identifying a valid instrument that affects the DV only through its effect on the IV, it is difficult to reject endogeneity entirely. While the same problem applies here, the use of multiple lagged IVs is intended to at least in part address this issue. In addition, this study differentiates itself from Daxecker and Prins (2017b) by examining different measures of conflict related to intensity and location, along with considering a wider range of countries and a broader period of years.

[2]See Ward et al (2010) for discussion of the usefulness of out-of-sample metrics to conflict forecasting research.

5 Results

In-sample regressions

Table 1 presents results from in-sample logistic regressions run on the entire sample (1995-2017) using the binary dependent variable. The dataset used here comprises 14,300 observations, employs the cart method of NA-value imputation, and takes a one-month lag for the conflict predictors. Column 1 and 2 represent the baseline and literature models respectively, and Columns 3 to 6 represent different specifications of models using conflict variables as predictors. Due to multicollinearity issues between variables such as "TotalConflictIncidents" and "Coastal/InlandIncidents", these had to be separated out into different specifications in order to properly assess their individual explanatory power. Column 6 displays results for a model including a lag of the dependent variable as a predictor.

Overall, it appears at first glance that the conflict incident variables are statistically significant predictors of piracy, with a higher number of conflict incidents being associated with a greater chance of piracy attack in a given month. Even when the lagged DV is included as a predictor, "TotalConflictIncidents" remains a statistically significant explanatory variable – the coefficient of 0.006 suggests that a unit increase in TotalConflictIncidents in a given month increases the odds of a piracy attack in the next month by 0.6%, holding other variables at a fixed value.

Table 1: In-sample logistic regressions with one-month lagged IVs

	Dependent variable:					
	BinaryPiracyIncident					
	(1)	(2)	(3)	(4)	(5)	(6)
TotalConflictIncidents			0.010***			0.006**
			(0.003)			(0.003)
TotalCasualties			−0.00001			
			(0.0001)			
CoastalIncidents				0.010***		
				(0.004)		
CoastalCasualties				0.0002		
				(0.0002)		
InlandIncidents					0.019***	
					(0.006)	
InlandCasualties					−0.0001	
					(0.0002)	
BinaryPiracyLag						1.796***
						(0.055)
MajorShippingLane			1.219***	1.219***	1.174***	0.946***
			(0.091)	(0.092)	(0.090)	(0.098)
Monsoon			0.199***	0.200***	0.199***	0.150***
			(0.053)	(0.053)	(0.053)	(0.056)
FishStocks		0.00000*	0.00000***	0.00000***	0.00000***	0.00000***
		(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
CoastlineLength		0.00004***	0.00003***	0.00003***	0.00003***	0.00003***
		(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)
Ports		0.009***	0.006**	0.006**	0.006***	0.003
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
ChokepointDistance1		0.0001	0.0004***	0.0004***	0.0004***	0.0003***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ChokepointDistance2		−0.0002***	−0.0004***	−0.0004***	−0.0004***	−0.0003***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)

Chokepoints		−0.058**	−0.061**	−0.056*	−0.066**	−0.077**
		(0.028)	(0.029)	(0.029)	(0.029)	(0.031)
OngoingCivilWar		0.725***	0.654***	0.687***	0.640***	0.445***
		(0.090)	(0.093)	(0.091)	(0.096)	(0.099)
StateFragility		0.019**	0.017**	0.017**	0.018**	0.019**
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
StateReach		−0.272***	−0.256***	−0.247***	−0.269***	−0.206***
		(0.025)	(0.027)	(0.027)	(0.028)	(0.027)
GDPpc	−0.00003***	−0.00002***	−0.00002***	−0.00002***	−0.00002***	−0.00002***
	(0.00000)	(0.00000)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Population	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment	−0.054***	−0.030***	−0.034***	−0.034***	−0.032***	−0.027***
	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Military	0.030***	0.020***	0.022***	0.022***	0.022***	0.019***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Trade	0.004***	0.004***	0.002***	0.002***	0.002***	0.001***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Constant	−1.756***	−1.871***	−2.354***	−2.375***	−2.323***	−2.616***
	(0.049)	(0.133)	(0.143)	(0.143)	(0.143)	(0.150)
Observations	14,300	14,300	14,300	14,300	14,300	14,248
Log Likelihood	−6,352.925	−5,698.043	−5,603.348	−5,602.983	−5,605.995	−5,070.424
Akaike Inf. Crit.	12,717.850	11,426.090	11,244.690	11,243.970	11,249.990	10,178.850

Note: *p<0.1; **p<0.05; ***p<0.01

Casualties, meanwhile, do not appear to have much explanatory power when lagged by one month. This result changes, however, when lagging the conflict IVs by six and twelve months – "CoastalCasualties" becomes significant while "CoastalIncidents" *loses* its significance[3]. The relationship is again positive – higher casualties in coastal areas are associated with greater risk of piracy. These results are consistent for regressions on data using an alternative imputation method based on random sampling. They are also consistent for NA-omitted data, except for the "CoastalIncidents" variable – it loses its significance at all lags. Indeed, returning to Table 1, the coefficient of "InlandIncidents" is 0.019 compared to that of "CoastalIncidents" at 0.010 – together with the losses of significance from lagged IVs and the NA-omitted data, it appears that "InlandIncidents" proves to be a more consistent and powerful predictor of piracy risk than its coastal counterpart. That said, "InlandCasualties" is never significant while "CoastalCasualties" is significant at six- and twelve-month lags. Thus, a preliminary examination of the results reveals that location and intensity of conflict may have differential relationships with piracy risk.

The results from the models run on the regional datasets, meanwhile, suggest that the significance of the coefficients for the conflict IVs may be driven by the South Asian countries. The West Africa and East Africa datasets yield insignificant coefficients, indicating that the nature of the conflict-piracy relationship clearly differs across regions. One possible ex-

[3] See the Appendix for the results from alternative specifications (lags, regions, etc.).

planation for this finding is that land-based conflict is less common in South Asia, and therefore individual conflict events may have a greater effect on piracy activity in Asia than they do in Africa.

The preliminary findings discussed above, however, are called into question when examining results from models which exclude the two "new" controls added to the main models ("MajorShippingLane" and "Monsoon"). Given their strong statistical significance, it is possible that they may be driving some of the results – and indeed, their exclusion (and inclusion of the lagged DV) leads to the loss of significance of the incident variables at all lags. However, when the six-, and twelve-month lags are examined CoastalCasualties remains a statistically significant explanatory variable.

The results reported so far are further supported by the regressions using piracy event count as the DV. Findings from these indicate that the incident variables are significant predictors at the one-month lag and casualties are not, while the inverse is true at greater lags. However, the exclusion of the "new" controls and inclusion of the binary DV produces a similar effect to that discussed above – "CoastalCasualties" becomes a significant predictor at the two-, six-, and twelve-month lags while the incident variables lose their significance. Thus, a tentative conclusion might be that casualties from coastal conflict have a positive relationship with the risk of piracy which only materializes after a period of time longer than one month (perhaps only in South Asian countries, though). In relation to the research questions, these results suggest that both location and intensity (and the location *of* intensity) matter when explaining the conflict-piracy relationship – however, the results do not align with the hypotheses described in Section 3. Higher-intensity conflict appears to be associated with higher rather than lower piracy risk in coastal areas. The relationship between number of conflict incidents and piracy, meanwhile, is less clear-cut as it is not robust to alternative model specifications.

One clear result, though, is that contrary to the arguments of Hansen (2009) and Hastings (2009), it appears that conflict overall has a positive relationship with the risk of piracy (none of the conflict coefficients are negative and statistically significant). This is further confirmed by the strongly significant positive coefficients of the "OngoingCivilWar" variable, which is also consistent across the three world regions examined separately. These results are robust to the inclusion of controls related to state fragility and capacity, which are regularly cited in the literature as the main drivers (excluding economic and geographic factors) of piracy.

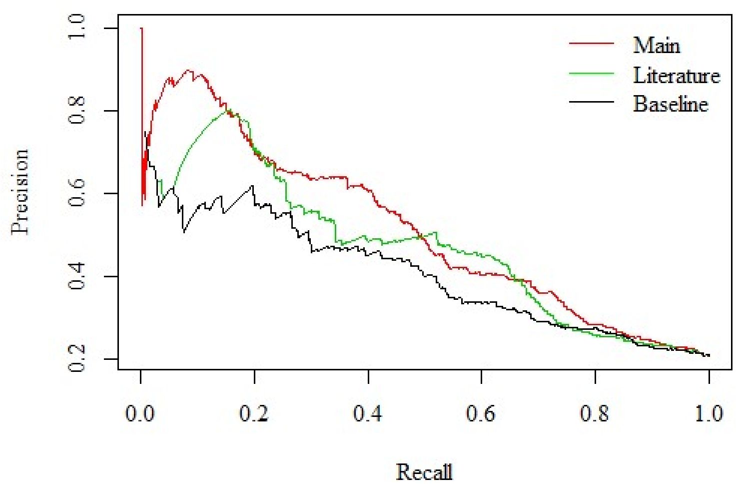
It should also be noted that, despite the issue they posed for the significance of the conflict IVs, the "Monsoon" and "MajorShippingLane" controls are strongly statistically significant and positively related with piracy risk. While their role as predictors may appear "obvious", they have not been used (at least as operationalised here) in the literature thus far and therefore should be noted as possibly valuable variables to include in future models.

Out-of-sample forecasting

Figures 1 and 2 present the precision-recall (PR) and receiver operating characteristic (ROC) curves for the conflict (red), literature (green), and baseline (black) logistic regression models used to forecast the binary piracy DV. These models are trained on a learning set comprised of years 1995 to 2009, and tested on a holdout set made up of data from 2010 to 2017. These particular models are run on the dataset using the cart method of NA-value imputation and a one-month lag for the conflict predictors, with the two "new" controls included and the lagged DV excluded.

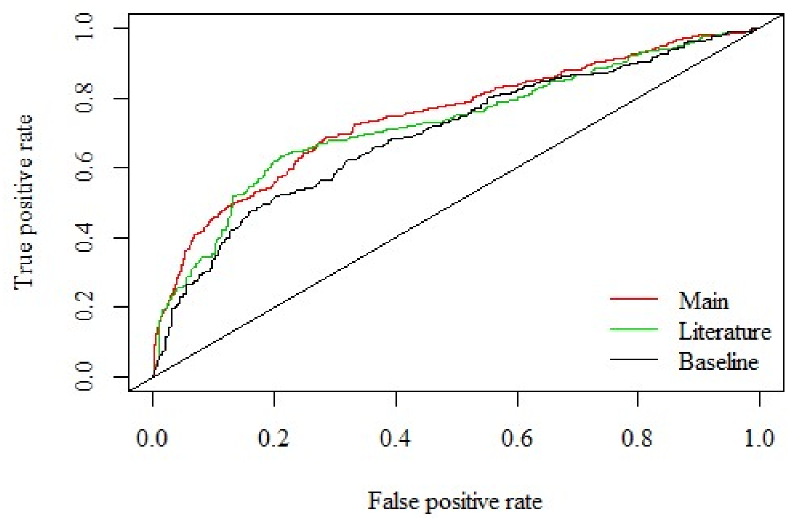
Precision in this case refers to the extent to which the models can be trusted when they predict that a given country-month will experience one or more piracy attacks. This implies that precision can be perfect if the models manage to predict that one single country-month will see piracy and it turns out that piracy does indeed occur in that country-month. Recall, meanwhile, considers "false negatives" and thus penalizes models for not predicting piracy in country-months that actually see piracy (as the aforementioned "perfectly precise" model would do). Figure 1 appears to indicate that the conflict model provides better precision and recall relative to the literature and baseline models.

Figure 1: PR Curves for logistic regression models forecasting binary DV with one-month lagged IVs



The receiver operating characteristic (ROC) curve illustrates the trade-off between true and false positives resulting from the models. It is helpful because a simple examination of the actual number of true and false positives could be misleading due to the arbitrary selection of the prediction threshold – at what point should the models classify a prediction as "piracy occurs" or "piracy does not occur"? The ROC curve overcomes this arbitrary selection issue by examining the performance of the models across the entire range of possible thresholds. Here, the diagonal represents a random classification model – each country-month is assigned a 1 or 0 for piracy at random. The best model will thus maximize the area under the curve (AUC). The AUCs are 0.697, 0.727, and 0.746 for the baseline, literature, and conflict models respectively (Figure 2).

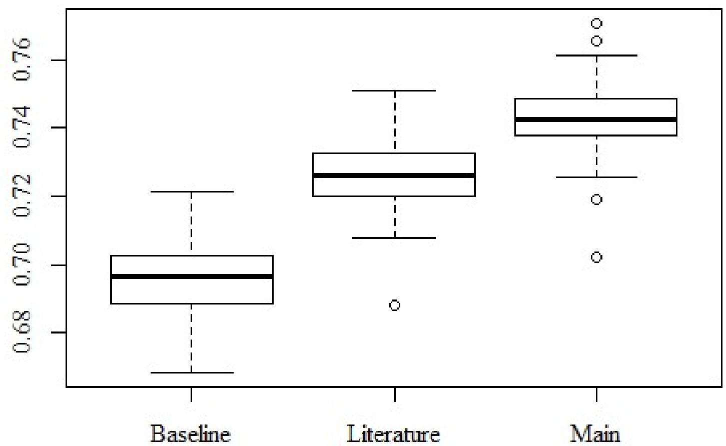
Figure 2: ROC Curves for logistic regression models forecasting binary DV with one-month lagged IVs



In order to examine whether the differences in AUCs between these models are statistically significant, the models are run on random subsets of the data 1000 times and hypothesis testing is then performed. The results of this procedure indicate that the differences between the conflict models and the literature and baseline models is statistically significant at the 1% level (Figure 3).

The PR and ROC/AUC results are consistent across the different lags of the IVs and for the alternative imputation method based on random sampling. For the NA-omitted data, various specifications of the models had to be run in order to avoid rank-deficient fits (similar to the in-sample regressions above when dealing with multicollinearity) – however, the conflict

Figure 3: AUC distributions for repeated simulations of logistic regression models

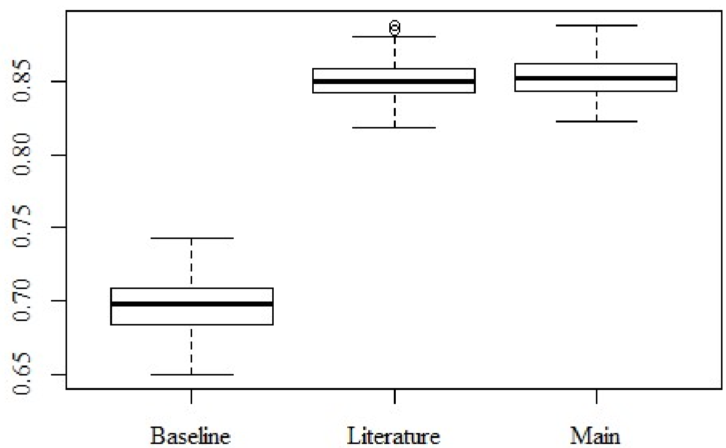


model still outperforms the literature and baseline models. So far, the lagged DV has been excluded – its inclusion in both the literature and conflict models dramatically improves their performance, but shrinks the difference between them as well (AUCs of 0.799 and 0.81). However, the repeated simulation and hypothesis testing procedure still indicates that they are statistically significantly different at the 1% level.

Returning to the regional examination, the datasets provide strikingly different results. South Asia yields by far the best performance, with the main model achieving an average AUC of 0.852 (lagged DV and controls all included). West Africa is next with an AUC of 0.805, and East Africa is last at 0.762. Aside from the explanation noted above in the discussion of the in-sample analysis results, it is also possible that other controls may fit less well in the African context. The forecasting approach unfortunately does not allow for easy identification of such variables.

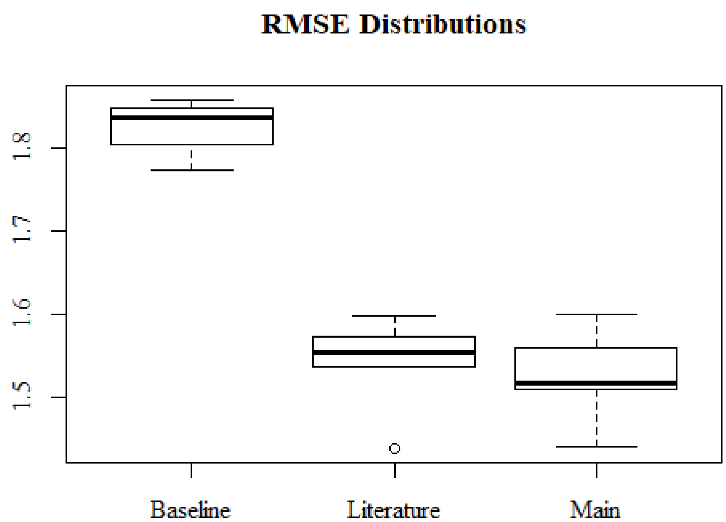
Once again, it is worth excluding the "MajorShippingLane" and "Monsoon" controls from the conflict models to determine whether they are driving the results. Unfortunately, their exclusion reduces the models' forecasting performance considerably. Without the lagged DV predictor, the main model performs slightly better than the literature model in terms of AUC values – however, this difference is not statistically significant at the 10% level. When the lagged DV predictor is included, the difference in performance disappears entirely – this is consistent for alternative conflict IV specifications, lags, and imputation methods. However, it should be noted that the South Asia dataset still provides a higher performance relative to the African data. While the p-values obtained for the difference in AUCs between the main and literature models for West and East Africa are 0.75 and 0.99 respectively, the p-value for South Asia is only 0.21. While still not statistically significant at the 10% level, this value in combination with the actual AUCs still suggests that the conflict IVs may be contributing to slightly improved performance in the South Asian context (Figure 4). However, the only sure conclusion arising from the data is that for the out-of-sample forecasts, the initial significantly superior performance of the main models was in fact mostly driven by the inclusion of the two "new" controls and not by the conflict IVs.

Figure 4: AUC distributions for repeated simulations of logistic regression models; South Asia data, with DV lag included and 2 “new” controls excluded



Even weaker results are found when using Poisson models to forecast the event-count DV. Despite including both “new” controls and excluding the DV lag, the conflict model does not perform significantly better than the literature model in terms of minimizing the RMSE. Figure 5 displays the distributions of RMSEs – while the baseline model is clearly the weakest, the literature and conflict models are relatively equal in performance. These results are once again robust to alternative IV lags and imputation methods. Therefore, the marginal improvements in performance that the conflict IVs *may* have granted the logit models are not observed here. In addition, the two “new” controls do not appear to make significant improvements either, suggesting that they are better suited to forecasting risk of piracy as measured by whether any incidents will occur in a given country-month or not compared to actual incident counts. This supports Hastings' (2009) argument that causal factors for the onset of piracy may not always match factors explaining actual number of piracy events.

Figure 5: RMSE distributions for repeated simulations of Poisson models



6 Discussion

In answer to the three research questions posed for this study, the results are mixed. In-sample logistic and Poisson regression analysis indicates that, in general, land-based conflict is associated with increased risk of piracy attacks at the country-month level. *RQ1* asked whether the *intensity* of conflict mattered for explaining piracy – it appears that the number of casualties resulting from conflict events on the coast is a statistically significant explanatory variable for piracy risk when lagged by more than one month (and, crucially, is robust to alternative model specifications), indicating that more intense coastal conflict has a positive relationship with chances of piracy. This feeds into *RQ2* and *RQ3*, which asked if the *location* of conflict and its level of intensity influenced piracy activity – the results above for intensity only held for coastal areas. Thus, it does seem that where conflict (and its intensity) is located matters for explaining the relationship between piracy and conflict.

The hypotheses outlined in Section 3 which attempted to reconcile the two opposing camps in the conflict-piracy literature are not supported in the data – higher intensity coastal conflict is correlated with greater rather than lesser chances of piracy. Thus, returning to the debate in the literature, the in-sample results from this analysis would suggest that Daxecker and Prins' (2015b) and Liss' (2007) arguments are supported as conflict is positively related to piracy. Their explanations relate to the weakening of state structures intended for law enforcement and economic damage pushing young men towards piracy to earn a living. In addition, the significance of the "CoastalCasualties" variable also lends support to Daxecker and Prins' (2015b) theory that conflict in coastal areas increases piracy through weakened governance in those regions. The results fail to support Hastings' (2009) argument that conflict dismantles the necessary infrastructure for piracy activity to take place, as no negative relationship between any of the conflict variables and piracy is observed.

The results from the out-of-sample analysis paint a different picture, though. While logit models including conflict IVs and the two "new" controls perform significantly better than literature models, this difference disappears when the two controls are removed. It appears that most of the increased forecasting power of these models was being driven by the "MajorShippingLane" and "Monsoon" controls (which in the in-sample analysis were highly statistically significant). Differences between the conflict and literature models predicting an event-count DV are null, even when these two controls are included. In addition, models including the lagged DV as a predictor far outperform other models.

It is worth considering potential explanations for why the conflict IVs lost their predictive power when examined in the context of out-of-sample forecasting. One possible reason is that their effects were simply absorbed by other variables – for example, Daxecker and Prins' (2015b) argument relies on conflict's impact on state structures, implying that perhaps the "StateFragility" or "StateReach" variables captured much of the effects of conflict on piracy.

Another possibility relates to reverse causality. As discussed in Section 4, a valid instrument for conflict in the context of its relationship with piracy has yet to be found. Daxecker and Prins (2017b) found that a six-month moving average lag of piracy had forecasting power with regards to predicting conflict. While they focused on broader conflict event counts as opposed to measures of location and casualties, it is certainly possible that at least part of the in-sample relationships found between conflict and piracy were actually driven by reverse effects (piracy encouraging conflict through e.g. the provision of resources to rebel groups). This could explain why statistically significant results were found for the in-sample analysis, but then disappeared when the models were asked to forecast. If this is the case, though, then at least it has been found that there do appear to exist differential effects with respect to the location of conflict and its intensity – it just may be more valuable for future forecasters to predict the location and intensity of conflict using piracy, rather than the other way around.

There are also issues related to the data. Fortunately, the results were relatively consistent across the different NA-value imputation methods and the NA-omitted dataset, although it should be noted that the difference in forecasting power between the conflict and literature models did decrease when using the NA-omitted data. However, the measures of conflict and piracy used may pose more serious issues. With regards to the conflict IVs, the method for measurement of location was quite crude – events were classified as "inland" or "coastal" based on the PRIO-GRID system described in Section 4 without considering factors such as country size. For example, the "coastal" area of a small West African state such as Equatorial Guinea represents a much larger portion of that country's total territory than for a large country that expands far inland such as Angola. In addition, casualties might not be the optimal measure of conflict intensity – for example, it is possible that in a given country-month there was only one conflict event, but it consisted of a large terrorist attack which killed dozens of people and therefore represented very "intense" conflict. Furthermore, all types of conflict were included in the measures here, meaning that potential differential effects with respect to the nature of conflict have been ignored (e.g. possibly different effects of terrorist attacks on piracy compared to drone strikes). Turning to the piracy measures, a similar issue arises as the DV was not disaggregated into different types of piracy. The relationship between conflict and piracy may differ depending on whether piracy activity is understood to refer to, for example, hijackings as opposed to non-violent robberies. In addition, Hastings (2009) finds evidence that different levels of state failure are associated with varying levels of sophistication of piracy activity. A similar dynamic may apply to the conflict-piracy relationship, but sophistication of piracy incidents was not considered here.

The geographical scope of the study may also represent a limitation. The differences in results obtained from the regional datasets suggest that individual region or country characteristics may contribute to distinct natures of the conflict-piracy relationship. For example, different countries might have entirely different kinds of piracy operations – some may rely on widespread recruitment of young men and domination of coastal villages, while others may be much more clandestine and discreet. Hastings' (2009) argument that conflict decreases piracy activity due to its disruption of infrastructure may hold true in countries where piracy operations do rely on a complex web of transportation and operations networks, but not as much in less sophisticated contexts where loot is sold easily in nearby areas. While the division of the data into regions allowed these potential contextual differences to be controlled for at the *regional* level, there may still exist differences between individual countries which have not been accounted for here. Regardless, the results imply that future research should recognise and account for potential differences in relationships between variables of interest across world regions and countries.

Finally, the temporal scope of the study may have been too wide. The period under examination spans 23 years, and evidence suggests that piracy has evolved over time with regards to its use of technology and ability to adapt to attempted "solutions" such as naval patrols (Shortland and Vothknecht 2011). With increasing sophistication of attacks and the now-widespread availability of technology such as sonar, piracy as an operation is very different now to what it was in the 1990s. The implication is that relationships between the variables under study and piracy risk may too have changed throughout this period, hindering the ability of models to learn from past data in order to forecast the future.

Despite these limitations, the study does appear to suggest that a conflict-piracy relationship exists, and that it may differ depending on measures such as the location and intensity of conflict. However, the usefulness of individual conflict events for forecasting piracy is less clear and may require further research to address the issues raised above. If one point is made here, though, it is that out-of-sample forecasting has great value for the evaluation of potential relationships (Ward et al 2010). If solely in-sample analysis had been conducted, this study would have told a very different, and possibly misleading, story.

7 Conclusion

This study aimed to examine the potential effects of land-based conflict on maritime piracy. While in-sample regression analysis indicates that there is a positive relationship between conflict on land and piracy in South Asian countries (but not in African ones), out-of-sample forecasting suggests that conflict event-count and casualty-count variables coded by location do not contribute to a significant improvement in forecasting performance. However, the results from the in-sample analysis provide evidence that there may exist differential relationships between piracy and conflict depending on the latter's location and intensity. One likely reason for these mixed findings is reverse causality, although alternative explanations related to geographical and temporal scope of the data and IV operationalisation cannot be ruled out. Further research might seek to address these issues via more fine-grained approaches and thus contribute to a greater understanding of the complex relationship between land-based conflict and maritime piracy.

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9 Appendix

9.1. *In-sample Analysis - Alternative Specifications*

Table 2: 2-month lag; Cart imputation

	Dependent variable:					
	BinaryPiracyIncident					
	(1)	(2)	(3)	(4)	(5)	(6)
TotalConflictIncidents			0.010***			0.007***
			(0.003)			(0.003)
TotalCasualties			−0.00002			
			(0.0001)			
CoastalIncidents				0.010***		
				(0.004)		
CoastalCasualties				0.0002		
				(0.0002)		
InlandIncidents					0.020***	
					(0.006)	
InlandCasualties					−0.0001	
					(0.0002)	
BinaryPiracyLag						1.796***
						(0.055)
MajorShippingLane			1.230***	1.219***	1.182***	0.960***
			(0.090)	(0.091)	(0.089)	(0.097)
Monsoon			0.194***	0.195***	0.195***	0.147***
			(0.053)	(0.053)	(0.053)	(0.056)
FishStocks		0.00000*	0.00000***	0.00000***	0.00000***	0.00000***
		(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
CoastlineLength		0.00004***	0.00003***	0.00003***	0.00003***	0.00003***
		(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)
Ports		0.009***	0.006***	0.006***	0.007***	0.002
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
ChokepointDistance1		0.0001	0.0004***	0.0004***	0.0004***	0.0003***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ChokepointDistance2		−0.0002**	−0.0004***	−0.0004***	−0.0004***	−0.0002**
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Chokepoints		−0.055*	−0.062**	−0.057**	−0.067**	−0.075**
		(0.028)	(0.029)	(0.029)	(0.029)	(0.031)
OngoingCivilWar		0.683***	0.617***	0.655***	0.596***	0.422***
		(0.090)	(0.092)	(0.091)	(0.095)	(0.099)
StateFragility		0.020***	0.019**	0.019**	0.020**	0.020**
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)

StateReach		-0.268^{***}	-0.256^{***}	-0.248^{***}	-0.271^{***}	-0.206^{***}
		(0.025)	(0.027)	(0.027)	(0.028)	(0.027)
GDPpc	-0.00003^{***}	-0.00002^{***}	-0.00002^{***}	-0.00002^{***}	-0.00002^{***}	-0.00002^{***}
	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00001)	(0.00001)
Population	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment	-0.053^{***}	-0.029^{***}	-0.033^{***}	-0.033^{***}	-0.032^{***}	-0.029^{***}
	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Military	0.016^{***}	0.007	0.012^{*}	0.012^{*}	0.012^{*}	0.010
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Trade	0.005^{***}	0.004^{***}	0.002^{***}	0.002^{***}	0.002^{***}	0.002^{***}
	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Constant	-1.740^{***}	-1.883^{***}	-2.381^{***}	-2.399^{***}	-2.348^{***}	-2.624^{***}
	(0.050)	(0.133)	(0.143)	(0.143)	(0.143)	(0.150)
Observations	14,248	14,248	14,248	14,248	14,248	14,196
Log Likelihood	−6,336.745	−5,692.048	−5,592.889	−5,594.276	−5,595.958	−5,057.965
Akaike Inf. Crit.	12,685.490	11,414.100	11,223.780	11,226.550	11,229.920	10,153.930
Note:				*p<0.1; **p<0.05; ***p<0.01		

Table 3: 6-month lag; Cart imputation

	Dependent variable:					
	BinaryPiracyIncident					
	(1)	(2)	(3)	(4)	(5)	(6)
TotalConflictIncidents			0.008^{***}			0.006^{**}
			(0.003)			(0.003)
TotalCasualties			0.00002			
			(0.0001)			
CoastalIncidents				0.006		
				(0.004)		
CoastalCasualties				0.0004^{**}		
				(0.0002)		
InlandIncidents					0.018^{***}	
					(0.006)	
InlandCasualties					−0.0001	
					(0.0002)	
BinaryPiracyLag						1.799^{***}
						(0.055)
MajorShippingLane			1.217^{***}	1.200^{***}	1.180^{***}	0.944^{***}
			(0.092)	(0.092)	(0.090)	(0.099)
Monsoon			0.193^{***}	0.193^{***}	0.195^{***}	0.147^{***}
			(0.053)	(0.054)	(0.053)	(0.057)
FishStocks		0.00000	0.00000^{***}	0.00000^{***}	0.00000^{***}	0.00000^{***}

		(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
CoastlineLength		0.00004***	0.00003***	0.00003***	0.00003***	0.00003***
		(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)
Ports		0.008***	0.006**	0.006**	0.006***	0.003
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
ChokepointDistance1		0.00001	0.0003***	0.0003***	0.0003***	0.0002**
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ChokepointDistance2		−0.0001	−0.0003***	−0.0003***	−0.0003***	−0.0002*
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Chokepoints		−0.056*	−0.056*	−0.051*	−0.060**	−0.071**
		(0.029)	(0.029)	(0.029)	(0.029)	(0.031)
OngoingCivilWar		0.735***	0.683***	0.716***	0.661***	0.470***
		(0.090)	(0.093)	(0.091)	(0.096)	(0.099)
StateFragility		0.019**	0.016**	0.016**	0.017**	0.019**
		(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
StateReach		−0.273***	−0.253***	−0.248***	−0.266***	−0.203***
		(0.025)	(0.027)	(0.027)	(0.028)	(0.027)
GDPpc	−0.00003***	−0.00003***	−0.00002***	−0.00003***	−0.00002***	−0.00002***
	(0.00000)	(0.00000)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Population	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment	−0.054***	−0.031***	−0.035***	−0.035***	−0.034***	−0.028***
	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Military	0.028***	0.016**	0.018***	0.018***	0.018***	0.015**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Trade	0.005***	0.004***	0.002***	0.002***	0.002***	0.002***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Constant	−1.747***	−1.811***	−2.312***	−2.319***	−2.284***	−2.583***
	(0.050)	(0.136)	(0.146)	(0.146)	(0.146)	(0.153)
Observations	14,040	14,040	14,040	14,040	14,040	13,988
Log Likelihood	−6,260.313	−5,633.384	−5,540.779	−5,540.556	−5,542.482	−5,012.422
Akaike Inf. Crit.	12,532.620	11,296.770	11,119.560	11,119.110	11,122.960	10,062.840

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4: 12-month lag; Cart imputation

	Dependent variable:					
	BinaryPiracyIncident					
	(1)	(2)	(3)	(4)	(5)	(6)
TotalConflictIncidents			0.006**			0.005*
			(0.003)			(0.003)
TotalCasualties			0.0001			
			(0.0001)			

CoastalIncidents				0.001		
				(0.004)		
CoastalCasualties				0.0004***		
				(0.0002)		
InlandIncidents					0.019***	
					(0.006)	
InlandCasualties					−0.0001	
					(0.0001)	
BinaryPiracyLag						1.801***
						(0.056)
MajorShippingLane			1.208***	1.181***	1.189***	0.954***
			(0.091)	(0.092)	(0.090)	(0.098)
Monsoon			0.182***	0.184***	0.182***	0.135**
			(0.054)	(0.054)	(0.054)	(0.057)
FishStocks		0.00000**	0.00000***	0.00000***	0.00000***	0.00000***
		(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
CoastlineLength		0.00004***	0.00003***	0.00003***	0.00003***	0.00003***
		(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)
Ports		0.009***	0.006**	0.006***	0.007***	0.003
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
ChokepointDistance1		0.0001	0.0004***	0.0004***	0.0004***	0.0003***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ChokepointDistance2		−0.0002*	−0.0003***	−0.0003***	−0.0003***	−0.0002**
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Chokepoints		−0.072**	−0.071**	−0.067**	−0.076**	−0.080**
		(0.029)	(0.030)	(0.030)	(0.030)	(0.032)
OngoingCivilWar		0.620***	0.641***	0.670***	0.596***	0.439***
		(0.092)	(0.094)	(0.093)	(0.097)	(0.101)
StateFragility		0.026***	0.020**	0.020**	0.021***	0.020**
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
StateReach		−0.271***	−0.251***	−0.249***	−0.267***	−0.198***
		(0.026)	(0.027)	(0.028)	(0.028)	(0.027)
GDPpc	−0.00003***	−0.00002***	−0.00003***	−0.00003***	−0.00003***	−0.00002***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)
Population	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment	−0.057***	−0.032***	−0.038***	−0.038***	−0.037***	−0.032***
	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Military	0.028***	0.022***	0.027***	0.027***	0.027***	0.020***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Trade	0.005***	0.004***	0.002***	0.002***	0.002***	0.002***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Constant	−1.763***	−1.945***	−2.386***	−2.383***	−2.362***	−2.637***
	(0.050)	(0.130)	(0.140)	(0.140)	(0.140)	(0.147)
Observations	13,728	13,728	13,728	13,728	13,728	13,676
Log Likelihood	−6,129.886	−5,522.616	−5,430.624	−5,429.987	−5,429.518	−4,901.954

Akaike Inf. Crit.	12,271.770	11,075.230	10,899.250	10,897.970	10,897.040	9,841.909

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5: 1-month lag; NA-omitted

	Dependent variable:					
	BinaryPiracyIncident					
	(1)	(2)	(3)	(4)	(5)	(6)
TotalConflictIncidents			0.008**			0.006**
			(0.003)			(0.003)
TotalCasualties			−0.0001			
			(0.0001)			
CoastalIncidents				0.006		
				(0.004)		
CoastalCasualties				0.0001		
				(0.0002)		
InlandIncidents					0.023***	
					(0.008)	
InlandCasualties					−0.0004	
					(0.0004)	
BinaryPiracyLag						1.796***
						(0.055)
MajorShippingLane			1.195***	1.182***	1.155***	0.946***
			(0.127)	(0.128)	(0.125)	(0.098)
Monsoon			0.214***	0.216***	0.212***	0.150***
			(0.070)	(0.070)	(0.070)	(0.056)
FishStocks		0.00000***	0.00000***	0.00000***	0.00000***	0.00000***
		(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
CoastlineLength		0.00004***	0.00003***	0.00003***	0.00003***	0.00003***
		(0.00000)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Ports		−0.011***	−0.010***	−0.009***	−0.009***	0.003
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ChokepointDistance1		−0.002***	−0.002***	−0.002***	−0.002***	0.0003***
		(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
ChokepointDistance2		0.002***	0.002***	0.002***	0.002***	−0.0003***
		(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Chokepoints		−0.278***	−0.292***	−0.290***	−0.303***	−0.077**
		(0.039)	(0.040)	(0.040)	(0.040)	(0.031)
OngoingCivilWar		1.418***	1.185***	1.198***	1.158***	0.445***
		(0.136)	(0.144)	(0.143)	(0.145)	(0.099)
StateFragility		0.049***	0.048***	0.048***	0.049***	0.019**
		(0.011)	(0.011)	(0.011)	(0.011)	(0.008)
StateReach		−0.420***	−0.380***	−0.374***	−0.402***	−0.206***

		(0.029)	(0.030)	(0.031)	(0.032)	(0.027)
GDPpc	−0.00001	−0.00000	−0.00001	−0.00001	−0.00001	−0.00002***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Population	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment	−0.108***	−0.094***	−0.108***	−0.108***	−0.107***	−0.027***
	(0.009)	(0.012)	(0.012)	(0.012)	(0.012)	(0.007)
Military	0.025***	0.025***	0.025***	0.025***	0.025***	0.019***
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.007)
Trade	0.003***	0.0004	−0.001*	−0.001*	−0.001*	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0004)
Constant	−1.347***	−0.495***	−1.027***	−1.027***	−0.975***	−2.616***
	(0.074)	(0.176)	(0.192)	(0.193)	(0.191)	(0.150)
Observations	8,326	8,326	8,326	8,326	8,326	14,248
Log Likelihood	−3,705.020	−3,158.060	−3,109.785	−3,110.994	−3,109.007	−5,070.424
Akaike Inf. Crit.	7,422.040	6,346.120	6,257.571	6,259.988	6,256.013	10,178.850
Note:				*p<0.1; **p<0.05; ***p<0.01		

Table 6: 1-month lag; Cart imputation; South Asia

	Dependent variable:					
	BinaryPiracyIncident					
	(1)	(2)	(3)	(4)	(5)	(6)
TotalConflictIncidents			0.009**			0.004
			(0.004)			(0.003)
TotalCasualties			−0.001			
			(0.0004)			
CoastalIncidents				0.011**		
				(0.005)		
CoastalCasualties				−0.001		
				(0.0005)		
InlandIncidents					0.037***	
					(0.013)	
InlandCasualties					−0.002	
					(0.002)	
BinaryPiracyLag						1.046***
						(0.097)
MajorShippingLane			5.075***	5.072***	5.053***	4.086***
			(0.584)	(0.584)	(0.580)	(0.604)
Monsoon			0.033	0.035	0.027	0.035
			(0.090)	(0.090)	(0.090)	(0.093)
FishStocks		0.00000***	0.00000***	0.00000***	0.00000***	0.00000***
		(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)

CoastlineLength		0.00004^{***}	-0.00001	-0.00001	-0.00001	-0.00001
		(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Ports		-0.007	-0.003	-0.003	-0.003	-0.003
		(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
ChokepointDistance1		-0.0005^{*}	0.002^{***}	0.002^{***}	0.001^{***}	0.001^{***}
		(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
ChokepointDistance2		-0.002^{***}	-0.0004	-0.0004	-0.0004	-0.001
		(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Chokepoints		8.147^{***}	0.004	0.167	-0.409	-0.008
		(1.256)	(1.531)	(1.536)	(1.529)	(1.582)
OngoingCivilWar		-4.148^{***}	-3.854^{***}	-3.813^{***}	-3.998^{***}	-3.356^{***}
		(0.398)	(0.408)	(0.405)	(0.416)	(0.422)
StateFragility		0.084^{***}	0.077^{**}	0.075^{**}	0.081^{**}	0.078^{**}
		(0.032)	(0.033)	(0.033)	(0.033)	(0.034)
StateReach		0.413^{***}	-0.302^{*}	-0.274	-0.384^{**}	-0.284
		(0.153)	(0.171)	(0.172)	(0.174)	(0.177)
GDPpc	-0.00003^{***}	0.00005^{***}	0.00003^{***}	0.00003^{***}	0.00003^{***}	0.00003^{***}
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Population	0.000^{***}	-0.000^{***}	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment	0.300^{***}	0.245^{***}	0.040	0.041	0.032	0.028
	(0.020)	(0.032)	(0.042)	(0.042)	(0.041)	(0.043)
Military	0.086^{***}	0.062^{***}	0.052^{***}	0.052^{***}	0.052^{***}	0.048^{***}
	(0.014)	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)
Trade	0.001^{*}	-0.017^{***}	-0.016^{***}	-0.016^{***}	-0.016^{***}	-0.014^{***}
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	-1.756^{***}	-15.204^{***}	-2.918	-3.232	-2.093	-2.904
	(0.099)	(2.391)	(2.719)	(2.731)	(2.712)	(2.808)
Observations	3,300	3,300	3,300	3,300	3,300	3,288
Log Likelihood	−1,970.631	−1,539.892	−1,498.555	−1,498.292	−1,497.175	−1,435.978
Akaike Inf. Crit.	3,953.262	3,109.785	3,035.109	3,034.584	3,032.350	2,909.955

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7: 1-month lag; Cart imputation; Poisson model for event-count DV

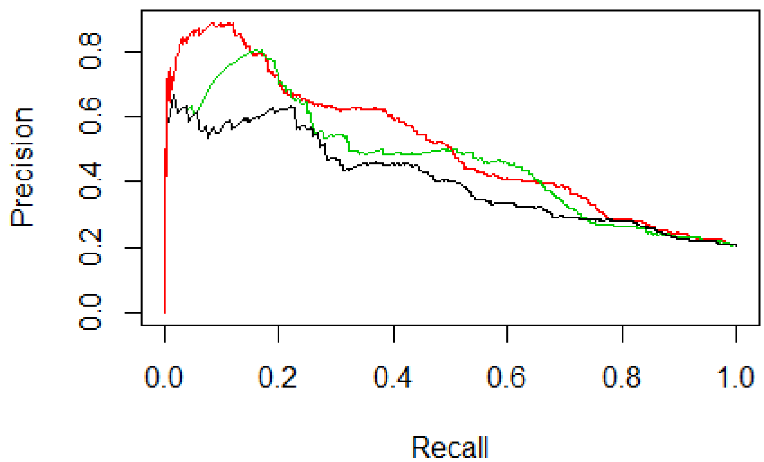
	Dependent variable:					
	CountPiracyIncidents					
	(1)	(2)	(3)	(4)	(5)	(6)
TotalConflictIncidents			0.007^{***}			
			(0.002)			
TotalCasualties			-0.0001			
			(0.0001)			

CoastalIncidents			0.006**		
			(0.003)		
CoastalCasualties			−0.00002		
			(0.0002)		
InlandIncidents				0.022***	0.006
				(0.006)	(0.005)
InlandCasualties				−0.0003	
				(0.0003)	
CountPiracyLag					0.355***
					(0.009)
MajorShippingLane		1.311***	1.301***	1.283***	0.607***
		(0.102)	(0.103)	(0.101)	(0.076)
Monsoon		0.167***	0.168***	0.164***	0.182***
		(0.055)	(0.055)	(0.055)	(0.045)
FishStocks	0.00000***	0.00000***	0.00000***	0.00000***	0.00000**
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
CoastlineLength	0.00004***	0.00002***	0.00002***	0.00002***	−0.00001***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Ports	−0.016***	−0.015***	−0.015***	−0.015***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ChokepointDistance1	−0.002***	−0.002***	−0.002***	−0.002***	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
ChokepointDistance2	0.002***	0.002***	0.002***	0.002***	−0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Chokepoints	−0.322***	−0.384***	−0.381***	−0.396***	−0.157***
	(0.033)	(0.033)	(0.033)	(0.033)	(0.026)
OngoingCivilWar	1.900***	1.605***	1.622***	1.563***	0.520***
	(0.112)	(0.117)	(0.116)	(0.118)	(0.083)
StateFragility	0.030***	0.037***	0.037***	0.039***	0.033***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.007)
StateReach	−0.447***	−0.405***	−0.399***	−0.426***	−0.271***

	(0.025)	(0.026)	(0.026)	(0.027)	(0.023)	
GDPpc	0.00001	−0.00001	−0.00001	−0.00001	−0.00001*	−0.00002***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00000)
Population	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment	−0.113***	−0.102***	−0.112***	−0.111***	−0.110***	−0.023***
	(0.009)	(0.010)	(0.011)	(0.011)	(0.011)	(0.006)
Military	0.046***	0.044***	0.037***	0.037***	0.038***	0.016***
	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)
Trade	0.002***	−0.0002	−0.003***	−0.003***	−0.003***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0003)
Constant	−1.190***	0.449***	−0.095	−0.098	−0.068	−1.784***
	(0.082)	(0.147)	(0.159)	(0.160)	(0.159)	(0.123)
Observations	8,326	8,326	8,326	8,326	8,326	14,248
Log Likelihood	−6,609.615	−5,848.930	−5,766.981	−5,768.947	−5,765.880	−9,537.906
Akaike Inf. Crit.	13,231.230	11,727.860	11,571.960	11,575.890	11,569.760	19,113.810

Note: *p<0.1; **p<0.05; ***p<0.01

Figure 6: Conflict IVs + 2 "new" controls; 2-month lag; Cart imputation



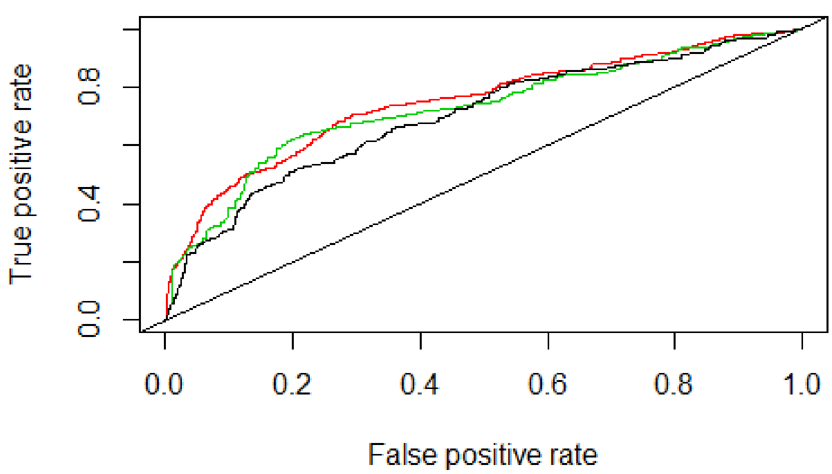
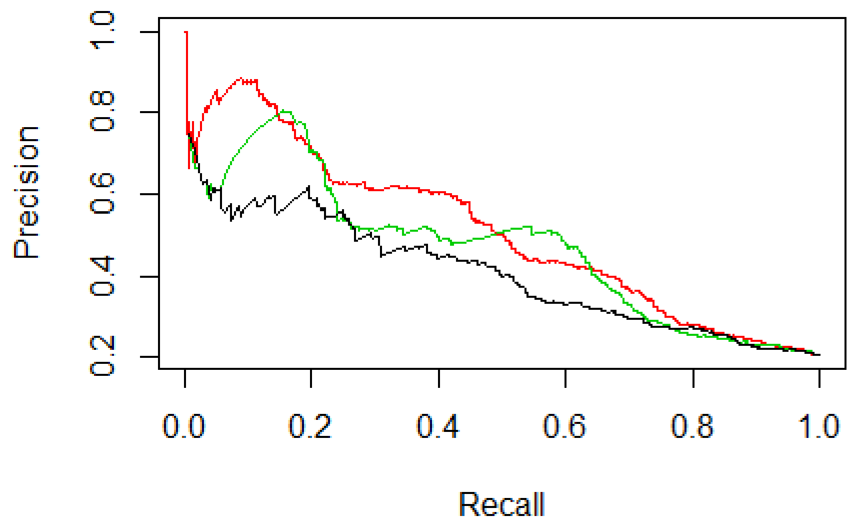


Figure 7: Conflict IVs + 2 “new” controls; 6-month lag; Cart imputation



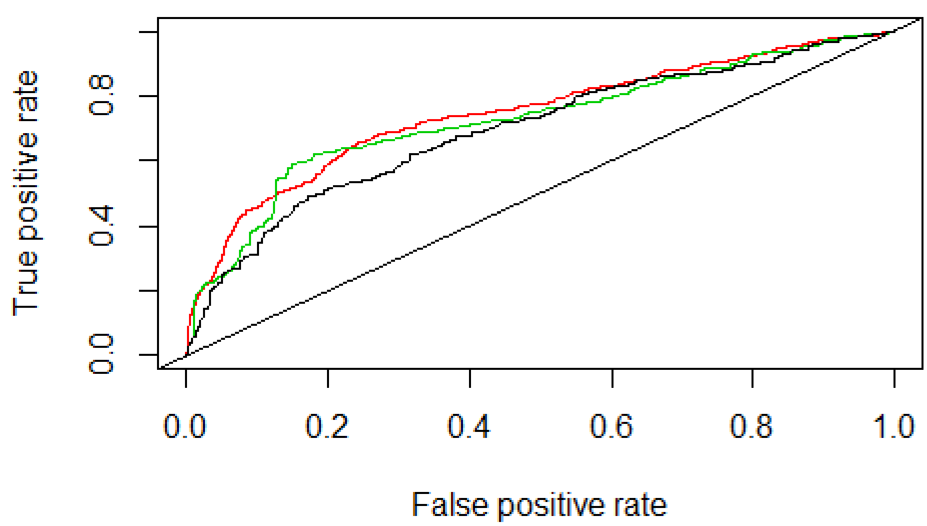
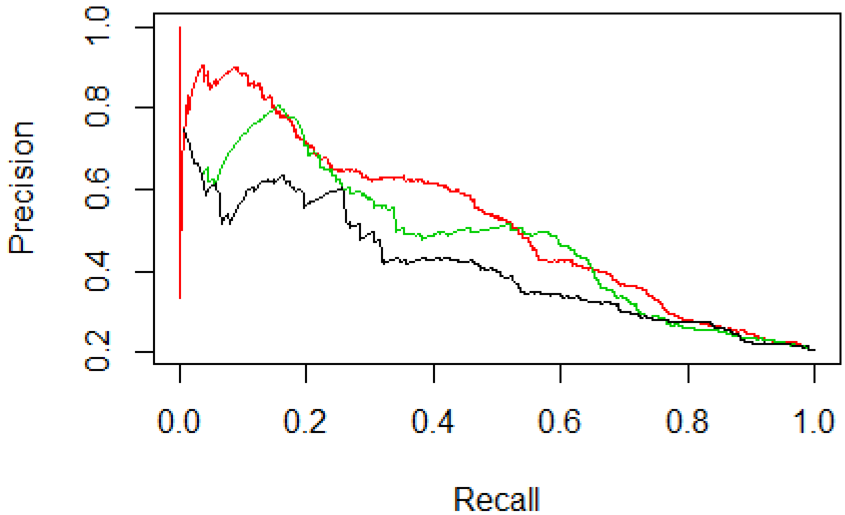


Figure 8: Conflict IVs + 2 “new” controls; 12-month lag; Cart imputation



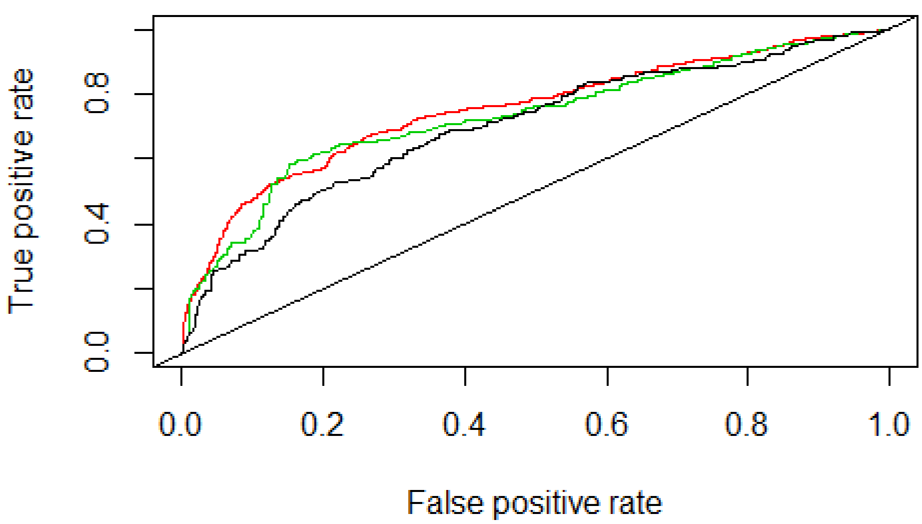
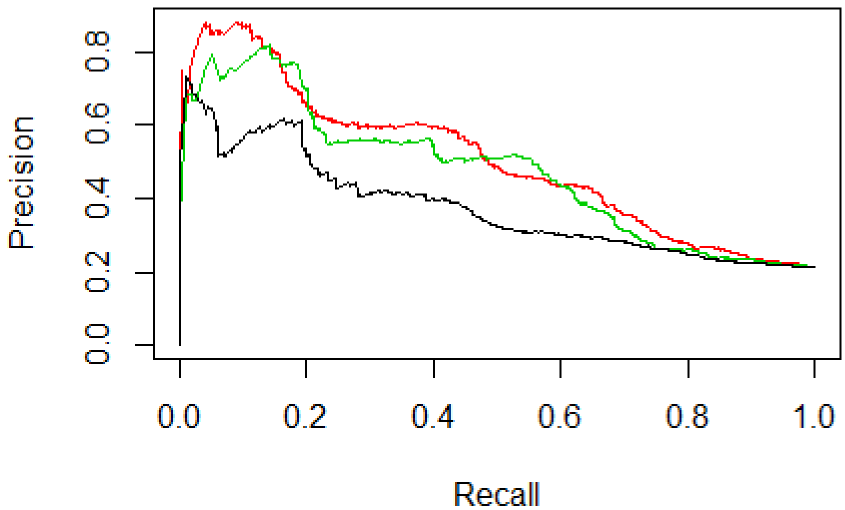


Figure 9: Conflict IVs + 2 "new" controls; 1-month lag; Random sample imputation



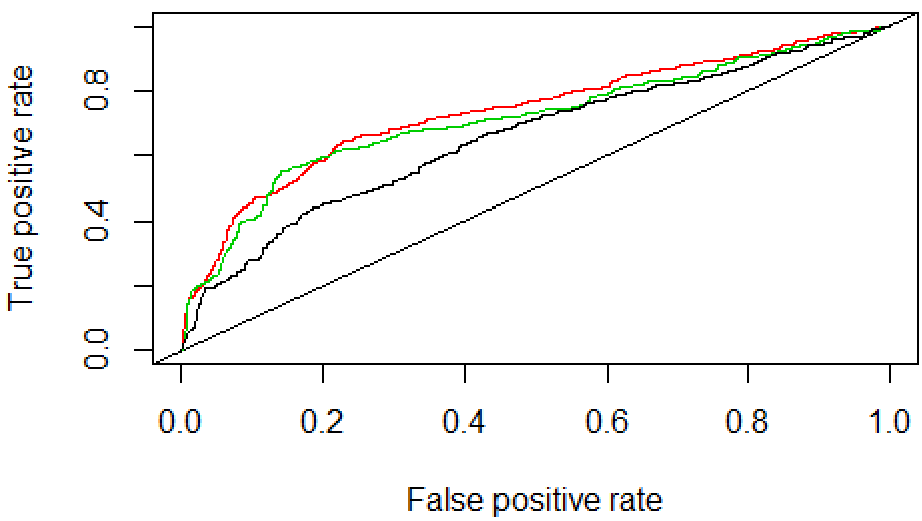
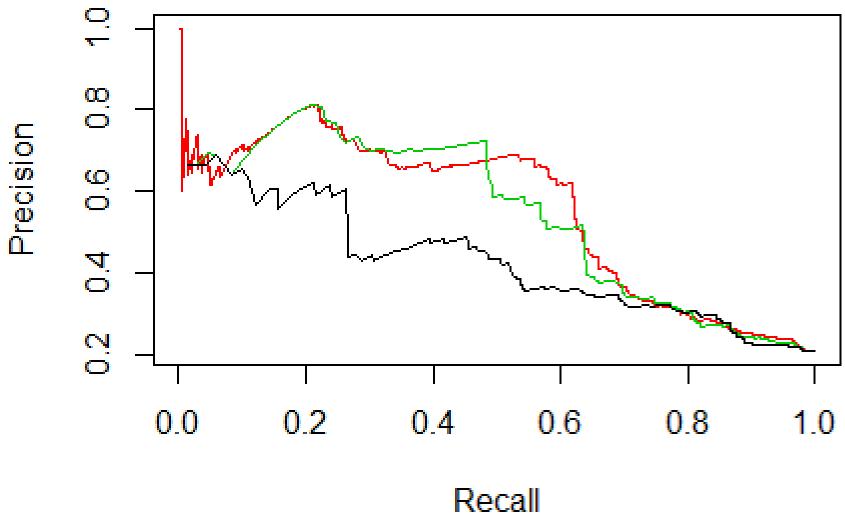


Figure 10: "Total" Conflict IVs (inclusion of all implied rank-deficient fits) + 2 "new" controls; 1-month lag; NA values omitted



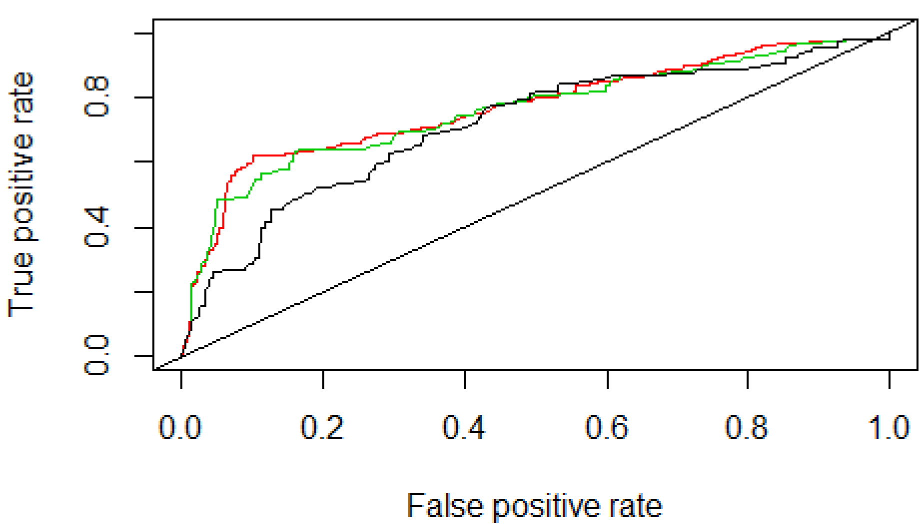
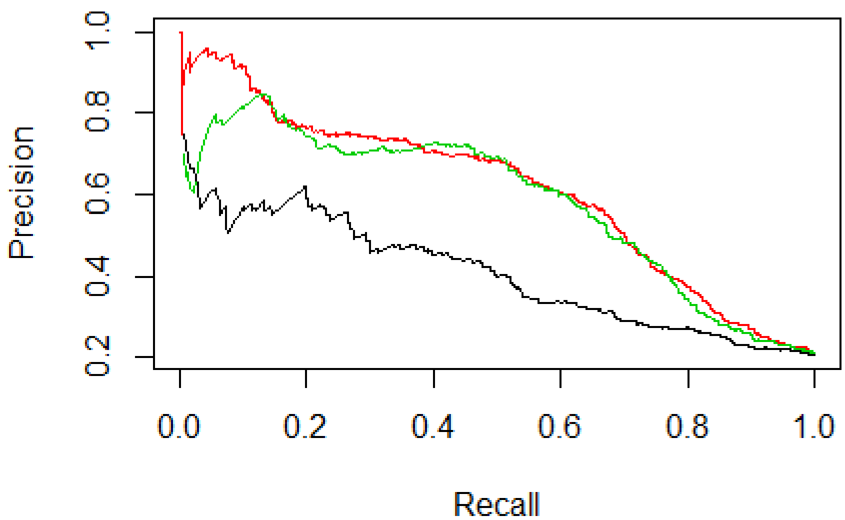


Figure 11: Conflict IVs + 2 “new” controls + DV lag; 1-month lag; Cart imputation



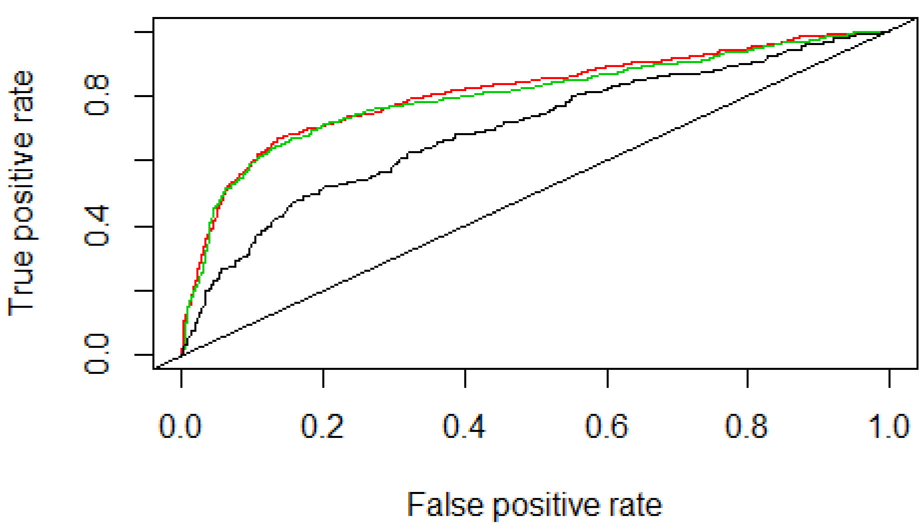
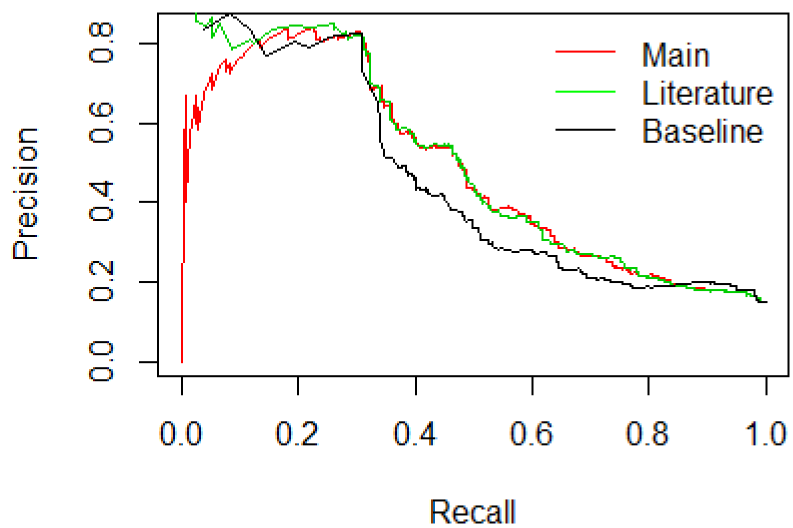


Figure 12: Conflict IVs + 2 “new” controls + DV lag; 1-month lag; Cart imputation; West Africa; warnings for rank-deficient fits



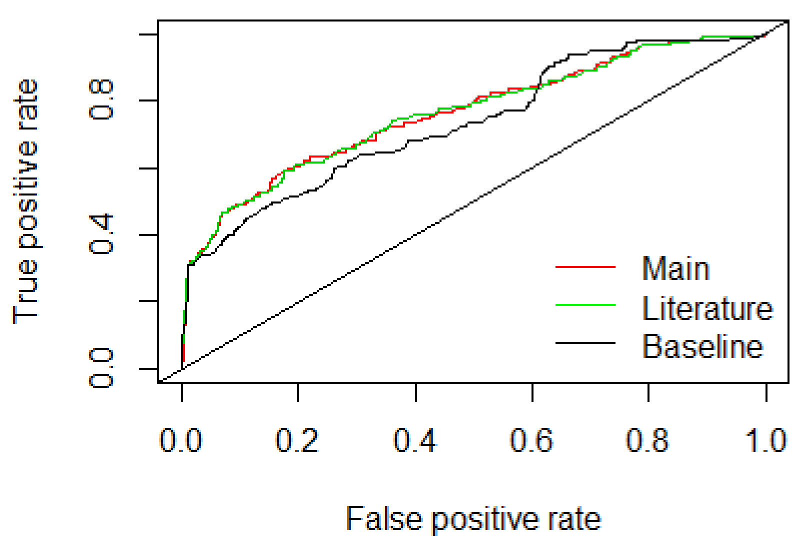
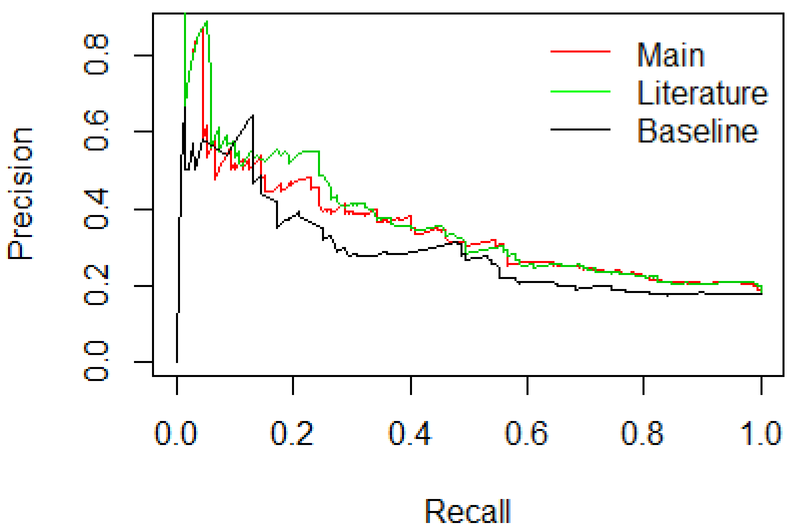


Figure 13: Conflict IVs + 2 “new” controls + DV lag; 1-month lag; Cart imputation; East Africa



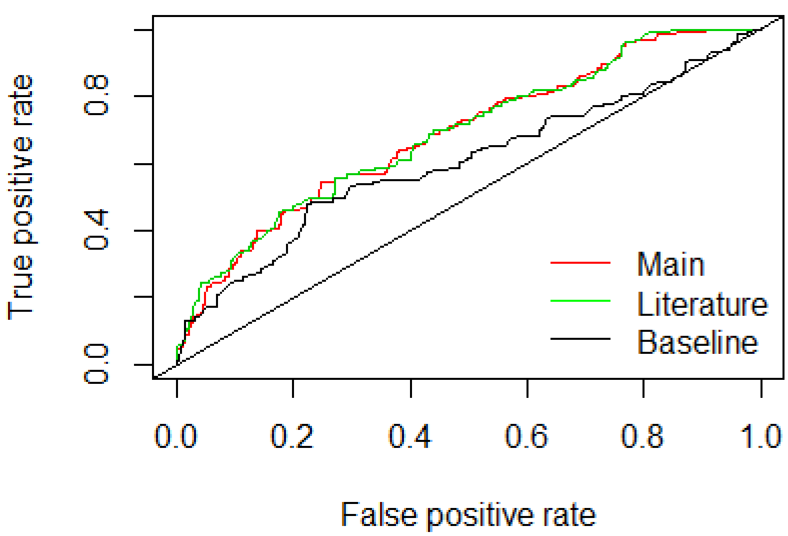
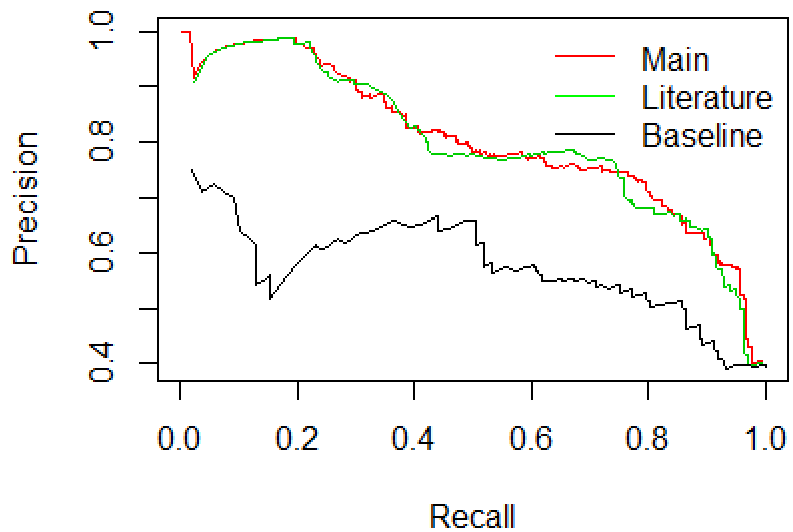


Figure 14: Conflict IVs + 2 “new” controls + DV lag; 1-month lag; Cart imputation; South Asia



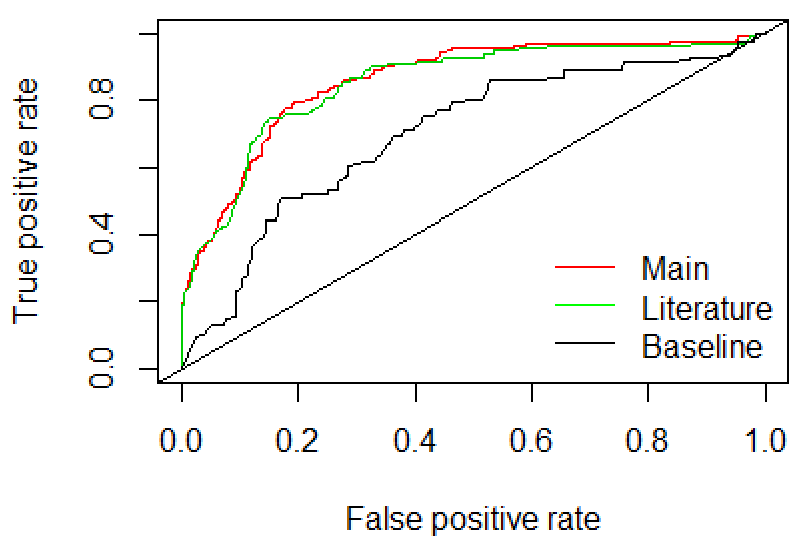
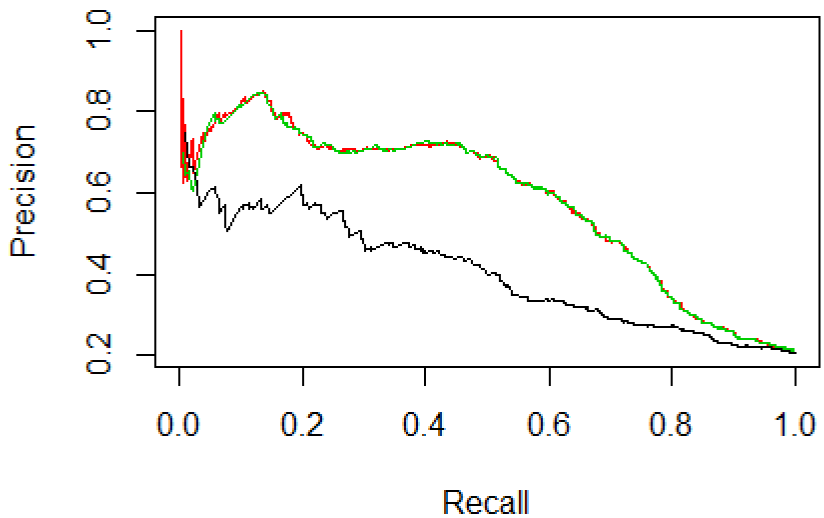
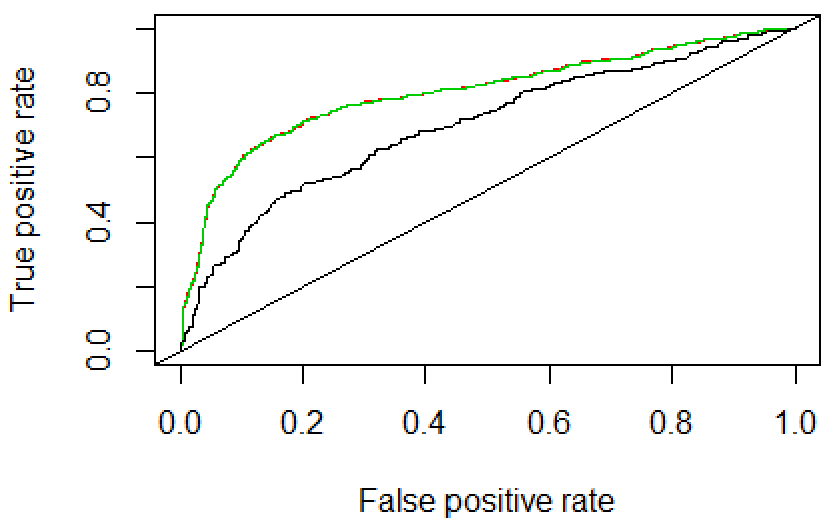


Figure 15: Conflict IVs + DV lag (2 “new” controls excluded); 1-month lag; Cart imputation





9.3. Out-of-sample Analysis - Poisson Model Alternative Specifications

Figure 16: Conflict IVs + 2 "new" controls + DV lag; 1-month lag; Cart imputation

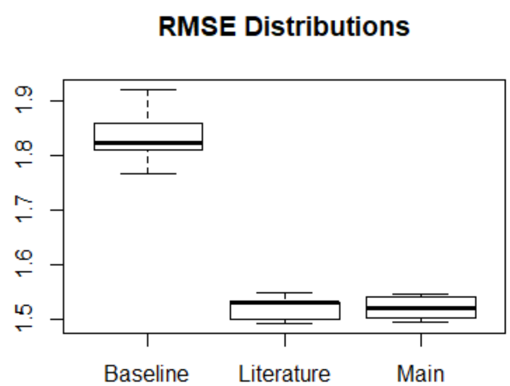


Figure 17: Conflict IVs, 2 "new" controls and DV lag excluded; 1-month lag; Cart imputation

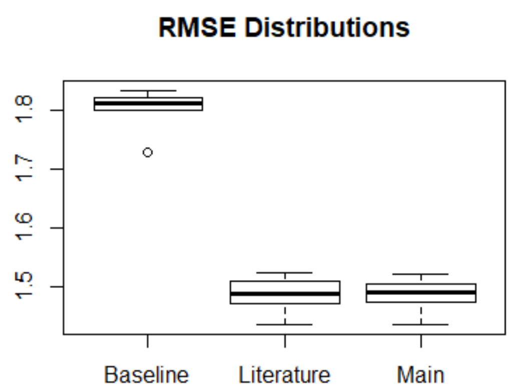


Figure 18: Conflict IVs, 2 "new" controls and DV lag excluded; 2-month lag; Cart imputation

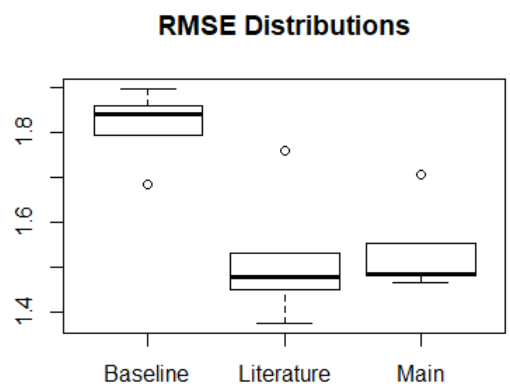


Figure 19: Conflict IVs, 2 "new" controls and DV lag excluded; 6-month lag; Cart imputation

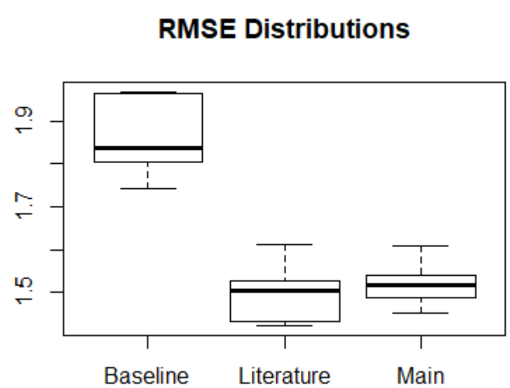


Figure 20: Conflict IVs, 2 “new” controls and DV lag excluded; 12-month lag; Cart imputation