CLIMATE AS A CAUSE OF CONFLICT:

AN ECONOMETRIC ANALYSIS

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Abstract

In recent decades, there has been assertions that climate change triggers conflict via multiple pathways, including food shortages, pest and disease incidence expansion, and water scarcity. However, broad empirical studies on the link are still lacking. This study aims to quantitatively explore that linkage using a global dataset. This involves development of a model that predicts the probability of conflict incidence given climate variations. We apply both parametric and semiparametric techniques in a rolling window scheme, which allows for a system that evolves over time. Two criteria are employed to evaluate out-of-sample predictive capability of the estimated models. Our investigation suggests that precipitation variation has a statistically significant effect on conflict. Generally we find the more that this year's precipitation is smaller than last years the more likely is civil conflict.

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I.1.   Introduction

Both climate change and conflict pose threats to the economy, human welfare, and security. A number of authors have argued that climate is one of the drivers of conflict but there have been counterarguments (e.g., Hsiang et al. 2013; Benjaminsen et al. 2012). Here we investigate the strength of that association using a global dataset. In particular, we econometrically examine if climate directly or indirectly influences the probability of conflict and estimate the effects of projected climate change on conflict incidence.

Numerous countries have suffered or are suffering from conflict in recent history, with devastating and long-lasting effects. Specifically, conflict has eroded physical assets like infrastructure and homes, reduced services from natural assets via destruction or confiscation for military purposes, worsened economic conditions through job losses and high inflation, weakened the labor force via injuries or deaths, and worsened social assets by forced migration or psychological damages (Verner 2010). The literature advances a set of diverse factors that can provoke conflict including social, political, natural resource, economic, foreign aid and climatic ones, but there still remains debate about the linkages and the strength of association among these items (Blattman and Miguel 2010)[1].

The past few decades have witnessed unprecedented climate change with an accelerating rising global average temperature, and observed regional changes in precipitation, extreme event frequency, and increasing sea level among other diverse effects (IPCC 2013, 2014). A continuing degree of future climate change has been projected by many scientific groups. Substantial evidence indicates such climate change influences environmental and social systems (e.g., IPCC 2007 a, b, and c, 2012, 2013, 2014; Carnesale and Chameides 2011; USCCSP 2008). In particular, a series of IPCC reports (2007 a, b, and c, 2012, 2013, 2014) document observed climate change consequences, including melting ice and snow, altered crop and livestock yields, declining populations of certain plants and animals, increased damages from pests, and exacerbated extreme event effects.

It is suggested that climate conditions contribute to conflict (e.g., Burke et al. 2009; Hsiang et al. 2013). While it is unlikely that climate is the unique or dominant cause of conflict, it may act as an accelerant. For instance, climate change might reduce the availability of water and food, which can cause unrest, turning into violent conflict. Military planners term climate change as "a threat multiplier" in certain volatile regions (CNA 2007). Given that climate conditions can cause for example food shortages, pest and disease expansion, and water scarcity, it is reasonable to expect climate change to trigger conflict. Recently, the Intergovernmental Panel on Climate

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[1] Blattman and Miguel (2010) state that the finding that economic conditions are correlated with conflicts is the most significant empirical conclusion in the current literature.

Change (IPCC) examines evidence of the interconnection and calls for more research (IPCC 2014). We therefore examine the climate-conflict nexus as it arises in global data in order to improve understanding of the interactions, and to support policy design and implementation to mitigate conflict and build the conditions for peace. Our parametric and semiparametric analyses render robust evidence showing that the probability of civil conflict is increased by year-over-year declines in precipitation.

I.2.   Literature Review

IPCC (2014) devotes a chapter to "human security" and includes a section on "conflict". The Secretary General of the United Nations (Ki-Moon 2007) states that the conflict occurring in Darfur was being caused by "an ecological crisis, arising at least in part from climate change". Also the "Arab Spring" – wave of protests, uprisings and armed conflict that spread across the Arab world – has been argued to have underlying climatic causes (Werrell and Femia 2013). Admittedly, it is also widely acknowledged that brutal governments or wide gaps in income and many other non-climatic factors may induce conflict (CenSEI 2012).

Over the past decade, a rapidly growing body of literature has explored the connection between climate and conflict. Here we discuss several of the commonly asserted causal chains. We also note that Dell et al. (2014) provides a thorough and exhaustive summary of the current climate-conflict related literature.

Many studies have focused on linkages between temperature, precipitation, and conflict. Burke et al. (2009) conclude that there is a robust linkage between temperature and civil war in Africa with warmer years sparking wars. Gartzke (2012) examines relationships between global average temperatures and interstate conflict, but finds that climate is not necessarily a causal influence. Miguel et al. (2004) investigate the interrelationship between civil war and rainfall variability in Africa and find that a decline in rainfall can fuel conflict. Hendrix and Glaser (2007) arrive at a similar conclusion in sub-Saharan Africa. Ciccone (2011) however argues that a misspecification of rainfall could account for such a conclusion and that inclusion of rainfall levels might be more appropriate. Miguel and Satyanath (2011) illustrate that rainfall variations are treated as instruments in their paper and that Ciccone's (2011) arguments lack theoretical support. Using data from Africa, Hendrix and Salehyan (2012) conclude that extreme rainfall deviations – drought and heavy rainfall – are associated with greater likelihood of conflict. Maystadt and Ecker (2014) find that longer and more severe droughts contribute to conflict outbreak in Somalia. Hsiang et al. (2013) detects a significant correlation between climate and human conflict based on a meta-analysis of 60 previous studies.

Nel and Righarts (2008) suggest that natural disasters can significantly spur violent conflict particularly in low- and middle- income nations. In contrast, Slettebak (2012) asserts that climatic natural disasters lessen the outbreak of civil war. The studies conducted by Besley and Persson (2011) and Bergholt and Lujala (2012) also obtain opposite conclusions about the relationship between climatic disasters and conflict (Theisen et al. 2013). A number of other studies do not find any significant relationship (e.g., Buhaug 2010; Benjaminsen et al. 2012).

Raleigh and Urdal (2007) state that a higher level of water scarcity increases the risk of conflict. Lecoutere et al. (2010) reach a similar conclusion as do Tir and Stinnett (2012). Dinar et al. (2007) offer a different viewpoint, indicating that nations usually prefer to cooperate with each other instead of fighting when facing water scarcity issues.

To date, it appears that research with a longer time horizon shows effects of climate on conflict as opposed to studies covering a shorter time period. Additionally, climate probably indirectly affects the likelihood of conflict through various channels and manifold factors, such as institutional effectiveness, human migration, crop failures and water shortage (Scheffran et al. 2012). Generally the literature aforementioned does not collectively permit drawing systematic conclusions about the climate-conflict relationship. For example, different specifications and data sources may cause different results across the empirical work. Apart from these, manipulations of fixed effects, potentially endogenous variables, spatial correlation, and heterogeneity can also partially account for the diverse or even contrary findings as well (Dell et al. 2014).

I.3. Data

This study seeks to examine the linkage between climate and conflict using global data. This will be done by econometrically estimating a model that predicts the probabilities of conflict incidence and how they are affected by climate variations. The dataset unifies measures of historical annual climate, conflict incidence and country related characteristics. The final dataset ranges from 1950 to 2006, covering conflict events in 165 countries. The dataset is discussed in the following subsections.

I.3.1. Climate Data

Historical country-year level climate data were drawn from Dell et al. (2012)[2] who sourced data from the Terrestrial Air Temperature and Precipitation: 1900–2006 Gridded Monthly Time Series (0.5 × 0.5), Version 1.01 (Matsuura and Willmott 2007). Additionally Dell et al. (2012) computed country-year level averages using a population-weighting scheme.

Following Miguel et al. (2004), we also include data on "weather variations" from prior years[3]. In particular we construct a "temperature variation" variable as the proportional change from the previous year, $(T_{i,t} - T_{i,t-1})/T_{i,t-1}$, and denote it as ΔT_{it}, where $T_{i,t}$ is the temperature observation for country i in year t. Likewise, we compute a precipitation variation variable as $\Delta P_{it} = (P_{i,t} - P_{i,t-1})/P_{i,t-1}$, where $P_{i,t}$ is the precipitation observation for country i in year t.

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[2] Other global databases could have been used. The major reason we used Dell et al. (2012) is the region to country wide weighting scheme.

[3] NASA indicates that the measure of time determines the difference between weather and climate: "Weather is what conditions of the atmosphere are over a short period of time, and climate is how the atmosphere 'behaves' over relatively long periods of time." Therefore, we hereafter use the "weather" instead of "climate" as Dell et al. (2012) do, given that we study the annual levels of temperature and precipitation in this paper.

I.3.2. Conflict Data

We draw data on conflict incidence from the UCDP/PRIO Armed Conflict Dataset, which defines armed conflict as "a contested incompatibility that concerns government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related deaths" (Gleditsch et al. 2002; Harbom and Wallensteen 2012). Taking into account that conflict is fairly complicated and somewhat difficult to precisely define empirically, we decide to narrow our research scope down to civil war. In this study, we mainly focus on conflict incidence, which is coded as 1 for all country-year observations with at least one conflict and 0 otherwise.

I.3.3. Other Country Characteristics Data

It is well acknowledged that there exist many determinants of conflict. However, it is almost impossible to account for and precisely measure all of them. Consequently, many kinds of control variables have been argued for inclusion along with alternative measurement methods. The control variables included in this study have been identified as significant components in fueling conflict by previous literature and are discussed below.

First, we include population size allowing that larger populations could impose a burden on local development and cause more potential conflict (Cervellati et al. 2011; Fearon and Laitin 2003). Goldstone (1991) and Salehyan and Hendrix (2014) argue that, societies with faster population growth rates, especially agrarian societies, are more likely to exhibit conflict than those with slower rates.

Second, we include economic development in the form of GDP per capita in terms of purchasing power parity (PPP). This allows for the possibility that lower economic levels may stimulate higher probabilities of conflict outbreak as argued by Hegre and Sambani (2006) and Salehyan and Hendrix (2014). Also per capita income reflects financial, military and police strength plus may reflect the ease of recruiting young men to become rebels (Fearon and Laitin 2003).

Third, an indicator of political regime type is incorporated. That indicator ranges from -10 (strongly autocratic) to 10 (strongly democratic) and accounts for the possibility that political status might affect conflict likelihood (Cervellati et al. 2011). These data are obtained from the Polity IV Project (Marshall and Jaggers 2012). Following Hegre (2001), a squared term is also added to allow for a curvilinear effect. That is, we permit countries with the least (-10) and most (10) democratic regime types to be less likely to experience conflict. Both population and GDP per capita data are obtained from the Penn World Table version 7.1 (Heston et al. 2012) and log-transformed to reduce skewness. In addition, all of the control variables are lagged one year, in order to take into account the probability of reversed causality and time lags (Theisen 2008).

To consider other country characteristics, such as ethnic polarization and geographical characteristics, we include country fixed effects that are designed to exclude these time invariant influences. Other country level control variables, like income inequality or unemployment rate,

are not incorporated due to missing or dubious values (Miguel et al. 2004). In addition, we investigate models with and without time trend in accordance with the arguments in Nelson and Kang (1984).

I.4.   Methodology

The analysis will be conducted in a rolling window scheme, which allows for a system that is evolving over time (Swanson 1998). That is, the length of the time period for the estimations is fixed but is treated in a way that permits out-of-sample reliability testing. Given that our whole dataset spans 57 years, the last ten years (1997 – 2006) are used for out-of-sample model validation. Particularly, we keep a fixed length of 47 years as the estimation window and then generate one-step-ahead forecasts (i.e., do a prediction for the 48th year). Initially we use the subsample 1950 - 1996 to predict conflict incidence in 1997, and then estimate using the subsample 1951 - 1997 to predict conflict incidence in 1998. We continue this procedure 10 times and at each time the fixed estimation window is rolled ahead one year. In turn, we evaluate predictive capability of the estimated models with two criteria, by comparing the 10-year out-of-sample probability forecasts with the true values. Finally, the best model is selected through a model-validation process. Below we describe the construction and specification of models used in our analysis.

I.4.1.   Parametric Models

Given that our data are collected over multiple time periods for individual countries, panel models are employed to take into account unobserved country level heterogeneity. This helps avoid biased estimations. Another obvious benefit is that panel datasets possess more data points, thus they increase degrees of freedom, flexibility and reduce the possibility of collinearity among covariates (e.g., Hsiao 2003).

The general reduced-form panel model can be characterized by the following function (Dell et al. 2014):

$$y_{i,t}^* = \boldsymbol{\beta} \boldsymbol{f}(\boldsymbol{C}_{i,t}, \boldsymbol{C}_{i,t-1}) + \boldsymbol{\gamma} \boldsymbol{X}_{i,t-1} + \alpha_i + \theta_t + \epsilon_{it} \tag{1}$$

where i and t index country and year. $y_{i,t}^*$ is the outcome of interest – the conflict probability. $\boldsymbol{C}_{i,t}$ represents historical weather variables and a vector of general functional form $\boldsymbol{f}(\cdot)$ is included to permit flexible implications of climatic variables. $\boldsymbol{X}_{i,t-1}$ is a vector of control variables (covariates), containing GDP per capital, political regime types and population. α_i captures the country-specific and time-invariant characteristics, commonly known as "fixed effects". θ_t is a time trend, which enables us to identify the relationships from idiosyncratic disturbances by neutralizing possible common trends (Dell et al. 2014). ϵ_{it} is an idiosyncratic error term with $E(\epsilon_{it}) = 0$, and those disturbances can be correlated across time horizon for each country. $\boldsymbol{\beta}$ is a vector of parameters to be estimated that give weather effects on conflict; $\boldsymbol{\gamma}$ is also a vector of parameters that measures the impacts of the other country-related characteristics on conflict.

Before proceeding, several caveats are worth mentioning. First of all, many studies (e.g., Miguel et al. 2004) utilize climatic variables as instruments to study other non-climatic phenomenon, at the cost of imposing exclusion restrictions to obtain causal inference. Weather instruments, however, may not be strong enough when dealing with the worldwide dataset. Hence the results of subsamples are usually weather dependent (Burke 2012). The reduced-form panel method utilized in this study can achieve more robust results, due to relatively fewer assumptions of identification as argued in Dell et al. (2014). Secondly, we incorporate fixed effects to account for unobserved country level determinants that may influence the likelihood of conflict. Additionally, as Burke (2012) points out, the standard errors need to be robust during estimation to account for heteroscedasticity, and estimation should be performed by clustering across countries to avoid potential serial correlation.

Since the dependent variable $y_{i,t}$ is binary, we use a panel logit approach to estimate the probability of conflict (Greene 2003; Hsiao 2003; Burke and Leiga 2010). The model takes the form

$$Pr\left(y_{i,t} = 1 \middle| \boldsymbol{C_{i,t}}, \boldsymbol{C_{i,t-1}}, \boldsymbol{X_{i,t-1}}, \alpha_i, \theta_t\right) = G(\boldsymbol{\beta} \boldsymbol{f}(\boldsymbol{C_{i,t}}, \boldsymbol{C_{i,t-1}}) + \boldsymbol{\gamma} \boldsymbol{X_{i,t-1}} + \alpha_i + \theta_t) \qquad (2)$$

where $G(\cdot)$ is the logistic distribution. For estimation, a conditional maximum likelihood method is employed.[4]

I.4.2. *Semiparametric Models*

It is well acknowledged that due to the strict assumptions about functional forms, parametric panel models can be misspecified and give rise to inconsistent estimators as a result. To circumvent this problem, we also consider semiparametric single index models. They generally serve as a compromise between confining parametric models and flexible but difficult to estimate fully nonparametric models (Hristache et al. 2001). Additionally, such models are readily interpretable and maintain much of the flexibility of nonparametric models (Härdle et al. 2004). For details about the single index models, please refer to Ichimura (1993) and Li and Racine (2007).

Following Li and Racine (2007), the single index model is expressed as

$$Y = g(\boldsymbol{X'\beta_0}) + u \qquad (3)$$

where the dependent variable Y is the civil conflict measurement, the vector of independent variables $\boldsymbol{X}$ ($q \times 1$) represents the set of weather and country characteristic variables, $\boldsymbol{\beta_0}$ ($q \times 1$) stands for a vector of parameters to be estimated, and u is the disturbance term with $E(u|\boldsymbol{X}) = 0$. Aside from weather measures, the explanatory variable $\boldsymbol{X}$ includes economic factors, population and democracy degree. $\boldsymbol{X'\beta_0}$ is termed as a "single index" because it is a scalar. Only the linear index ($\boldsymbol{X'\beta_0}$) is specified whereas the functional form $g(\cdot)$ remains unknown. To some extent, a single index model can be treated as a generalized logit model, since it keeps the linear

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[4] Unconditional maximum likelihood (UML) yields biased estimated coefficients for logit models (Hsiao 2003).

index unchanged and relaxes the requirement of function $g(\cdot)$ to be arbitrarily smooth (Härdle et al. 2004).

Many estimation approaches have been proposed for this model. The two most widely used methods are those introduced by Ichimura (1993) and Klein and Spady (1993). The former is appropriate for continuous outcomes while the latter is best suited for binary values (Racine 2009). Given the context of binary variable (conflict incidence), we use the kernel-based estimator by Klein and Spady, with bandwidth determined by the method of cross-validation.

I.4.3. *Model-Selection Criteria*

We utilize two commonly-used criteria to assess the predictive performance of models aforementioned.

The first measure is the Brier score, a quadratic scoring rule with a rich history of applications (Brier 1950; Bessler and Ruffley 2004). It evaluates the prediction ability of models with binary or continuous dependent variables and offers an overall picture of their performance. The lower the Brier score, the better the predictive performance. Yates (1988) further provides a covariance decomposition of the Brier score for more thorough and extensive analyses, which allows accounting for both calibration and resolution by different components.[5] In particular, one term called "calibration-in-the-large" (or Bias) captures the models' general miscalibration over all the probability forecasts. On the other hand, the covariance of predictions and actual outcomes index represents models' resolution or sorting ability. That is, it reflects the ability of a model to distinguish occasions in which event does occur from those where it does not, which is regarded as the core of forecasting strength (Yates 1982). Here higher covariance means better responsiveness of the predictions to the available information. More discussion about each component of Brier score will be presented below, together with the model comparison.

Another way to visualize and evaluate models' performance involves use of the receiver operating characteristic (ROC) curve (Fawcett 2004). The ROC curve characterizes the true positive rate ("sensitivity") versus the false positive rate (1- "specificity") for all possible cutoffs (Fawcett 2004). On the grounds that ROC curves capture models' discrimination performance in a two-dimensional way, it is probably easier to compare different models just based on one dimension – a scalar. Generally, this dimension reduction can be achieved by evaluating the area under the ROC curve (AUC) (Fawcett 2006). An area of 0.5 means a useless model, which is equivalent to random guessing; an area of 1 indicates a perfect model, which can unerringly tell when conflict events do and do not occur. That is, the higher the AUC, the better the discrimination ability of the model (El Khouli et al. 2009).

I.5.   Empirical Results

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[5] Calibration refers to a model's ability to issue a probability that is consistent with its relative frequency, ex post; Resolution refers to a model's ability to partition uncertain outcomes into subgroups that vary from its relative frequency in the long-run (Bessler and Ruffley 2004).

As Friedman (1953) asserts, "The ultimate goal of a positive science is the development of a 'theory' or 'hypothesis' that yields valid and meaningful (i.e., not truistic) predictions about phenomena not yet observed." Accordingly, in this study, we focus on out-of-sample predictive ability to choose the best model.

As aforementioned, a rolling window approach with a fixed time length is implemented to generate dynamic one-step-ahead forecasts of conflict incidence for 1997 – 2006. Additionally, given controversy regarding the inclusion of time trend we consider models with and without the trend variable. We will also look at models with and without adjustments for stationarity. The results in four models are listed as below.

Model 1: Original Series + Quadratic Time Trend
Model 2: Original Series + No Time Trend
Model 3: Stationary Series + Quadratic Time Trend
Model 4: Stationary Series + No Time Trend

In our dataset, GDP is the only nonstationary series (I (1)), thus we take the first difference to render it stationary.

I.5.1. Model Evaluation

In what follows, we will assess models' predictive performance through several widely used criteria.

I.5.1.1. Brier Score and its Yates' Covariance Decompositions

The Brier scores for one-step-ahead forecasts are presented in Table 1. Components from the Yates' covariance decompositions are displayed below them.[6]

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[6] Note that in the case of a binary dependent variable, the Mean Squared Error (MSE) is equivalent to the Brier score. That is, the increase in the Brier scores reflects deterioration in models' forecasting ability.

Table 1: Brier Scores and their Yates' Decompositions

	Panel Logit Model			
	(1)	(2)	(3)	(4)
Brier Score	0.1456	0.1385	0.1452	0.1386
$Bias^2$	0.0138	0.0072	0.0140	0.0081
Scatter	0.0013	0.0017	0.0011	0.0016
MinVar	0.0000	0.0000	0.0000	0.0000
Dvar	0.1298	0.1298	0.1298	0.1298
2Cov	-0.0006	0.0003	-0.0003	0.0010
	Single Index Model			
	(1)	(2)	(3)	(4)
Brier Score	0.1170	0.1131	0.0948	0.0863
$Bias^2$	0.0001	0.0004	0.0000	0.0000
Scatter	0.0213	0.0214	0.0383	0.0338
MinVar	0.0026	0.0034	0.0150	0.0172
Dvar	0.1299	0.1299	0.1298	0.1298
2Cov	0.0369	0.0421	0.0884	0.0946

Notes: Yates' decompositions of Brier Score is given by the numbers below "Brier score" in each column. Brier Score=DVAR+MinVar+Scatter+ $Bias^2$-2Cov.

On the basis of Brier score, the semiparametric models exhibit better predictive power than the corresponding parametric models. Generally, within either parametric or semiparametric models, models without time trend perform better than models with time trend (Model 1 vs Model 2; Model 3 vs Model 4). Models with stationary series do a better job than models with original series (Model 1 vs Model 3; Model 2 vs Model 4). The only exception is that Model 2 and Model 4 for parametric models perform about the same. Additionally, one natural question that arises is: in what way do the semiparametric models outperform the parametric ones? This can be answered by examining the results from the Yates' decomposition.

Generally the semiparametric models show a lower "$Bias^2$"[7] (0.000 – 0.004), they therefore do a better job of matching the mean forecasts to the relative frequency of conflict. The semiparametric models also are more sensitive to the information related to the outcomes in the future as measured by the covariance between forecasts and the outcome index (labeled as

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[7] "Dvar" is the variance of the outcome index; "MinVar" is the minimum forecast variance; "Scatter" could be regarded as the excess variability of the forecast (Casillas-Olvera and Bessler 2006); "$Bias^2$" is the squared term of "Bias", where "Bias" is the "calibration-in-the-large"; "Cov" is the covariance between forecast and actual outcomes.

"2Cov"). Moreover, the positive sign of that term indicates the responsiveness is in the right direction. In some cases with negative covariance term (e.g., parametric Model 1 and 3), zero covariance might be chosen instead to minimize the Brier score (Casillas-Olvera and Bessler 2006).

Nevertheless, the semiparametric models do not always outperform the parametric models in every aspect. For instance, compared to the corresponding parametric models, they have larger scatter values (labeled as "Scatter"), which quantify the overall noise in the forecasts. Similarly, semiparametric models portray a larger minimum forecast variance (labeled as "MinVar"), which reflects the minimum amount of forecast variability that must be tolerated (Yates 1988).

To summarize, compared to the semiparametric models, parametric models are superior with respect to the characteristics of "Scatter" and "MinVar", whereas they are inferior with regarding to the metrics of "Bias^2" and "2Cov". Intuitively, covariance reflects the responsiveness of the model to the information pertinent to the conflict incidence, while the scatter indicates the responsiveness of the model to the information not pertinent to the conflict incidence (Casillas-Olvera and Bessler 2006). In this way, we propose that parametric models are better at filtering irrelevant information or excluding noise. However, they screen out some vital information as well, which may play a key role in predicting the probability of conflict incidence. On the other hand, semiparametric models perform comparatively better in capturing useful information. Nevertheless, it is highly likely that they achieve higher covariance values at the cost of incorporating irrelevant knowledge to predict conflict incidence. To some extent, our results appear to be consistent with the results cited in Yates (1982)[8] and Bessler and Ruffley (2004), where an increase in scatter and covariance occurred together. A caveat has to be made here. The component called variance of the outcome index (labeled as "Dvar") has not been discussed in preceding sections. The major reason is that it is entirely out of the models' control, representing the base rate in which conflict does take place (Bessler and Ruffley 2004).

All in all, based on the Brier score and its covariance decomposition, the semiparametric model with stationary series and without time trend (i.e., Model 4) outperforms the other alternative models considered.

Beyond the numeric analyses above, we also present covariance graphs on the model performance (Figure 1). They reflect the resolution ability among models, distinguishing conflicts that take place from those that do not take place. On the x-axis, 0 means conflicts that happen while 1 implies conflicts that do not happen. Accordingly, y-axis represents the probability forecasts for the two kinds of outcomes (i.e., 0 and 1). Therefore, we seek to obtain the desired model that generates low probabilities (at or near 0) for the outcome with 0, and high probabilities (at or near 1) for the outcome with 1 (Casillas-Olvera and Bessler 2006). In other words, models with perfect resolution (or sorting) ability correspond with the 45° line (i.e., the

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[8] Yates (1982) finds that the subject with the best Brier score has both higher scatter and covariance, compared to the subject with the medium Brier score.

solid line in each sub-graph in Figure 1). The dashed-line is the covariance graph for each model by regressing the probability forecasts on the dummy outcome index.

Comparison of graphs in panel (A) and panel (B) indicates the superiority of semiparametric models relative to parametric models in sorting. Parametric models assign low forecast probabilities to both outcome index 0 and 1, so the dashed lines in panel (A) are much flatter than those of semiparametric models in panel (B). Admittedly, semiparametric models' covariance graphs show a larger dispersion in their forecasts for outcome index 0 and 1 than parametric ones. Still, their larger slopes (0.142 – 0.364) compared to the parametric ones' (-0.002 – 0.004) strongly indicate their better goodness of sorting conflict incidence cases, under the context of conflict. Particularly, the semiparametric model 4, again, dominates, owning to its largest slope (0.364) among all the models investigated here.
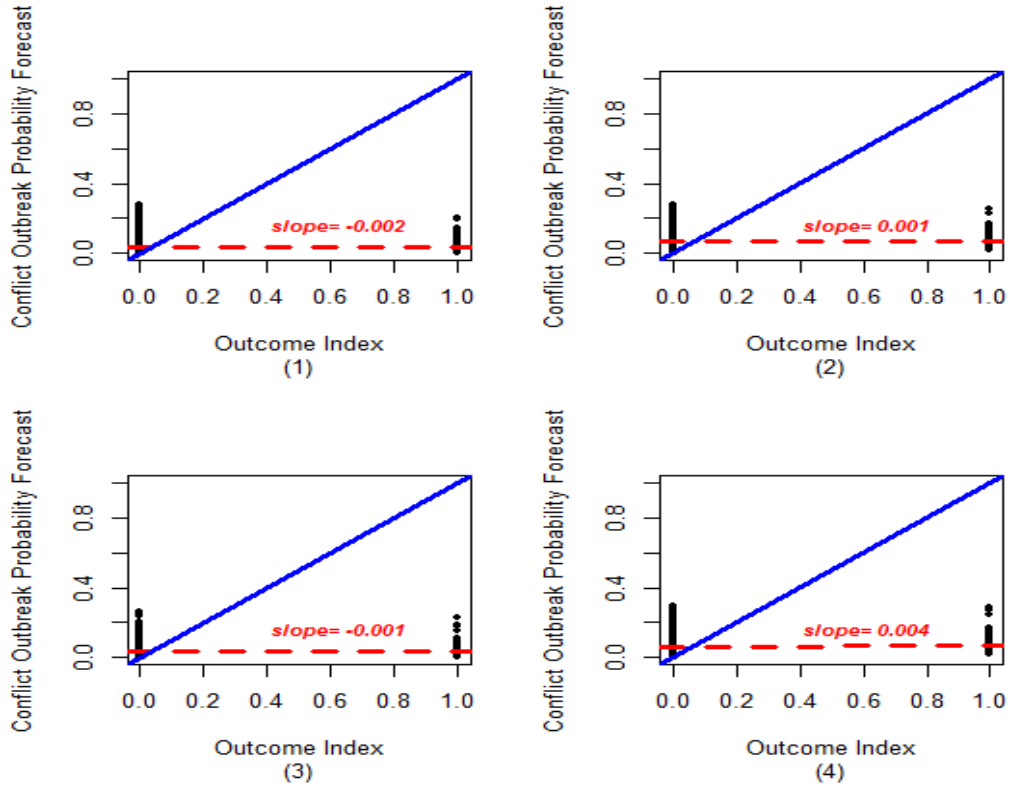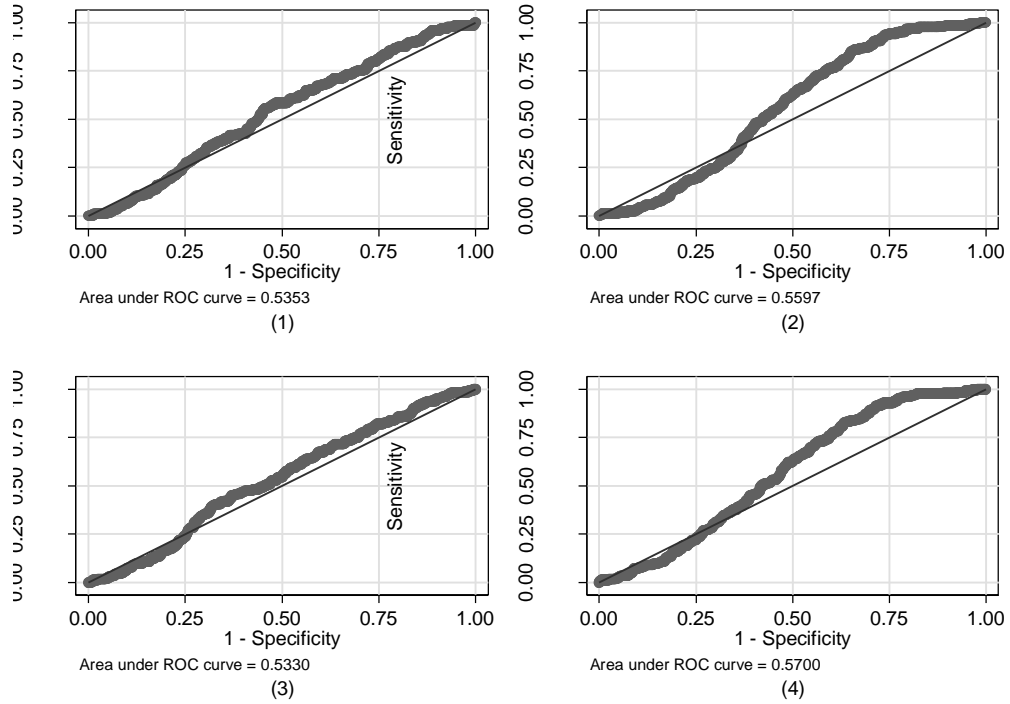
(A) Panel Logit Model
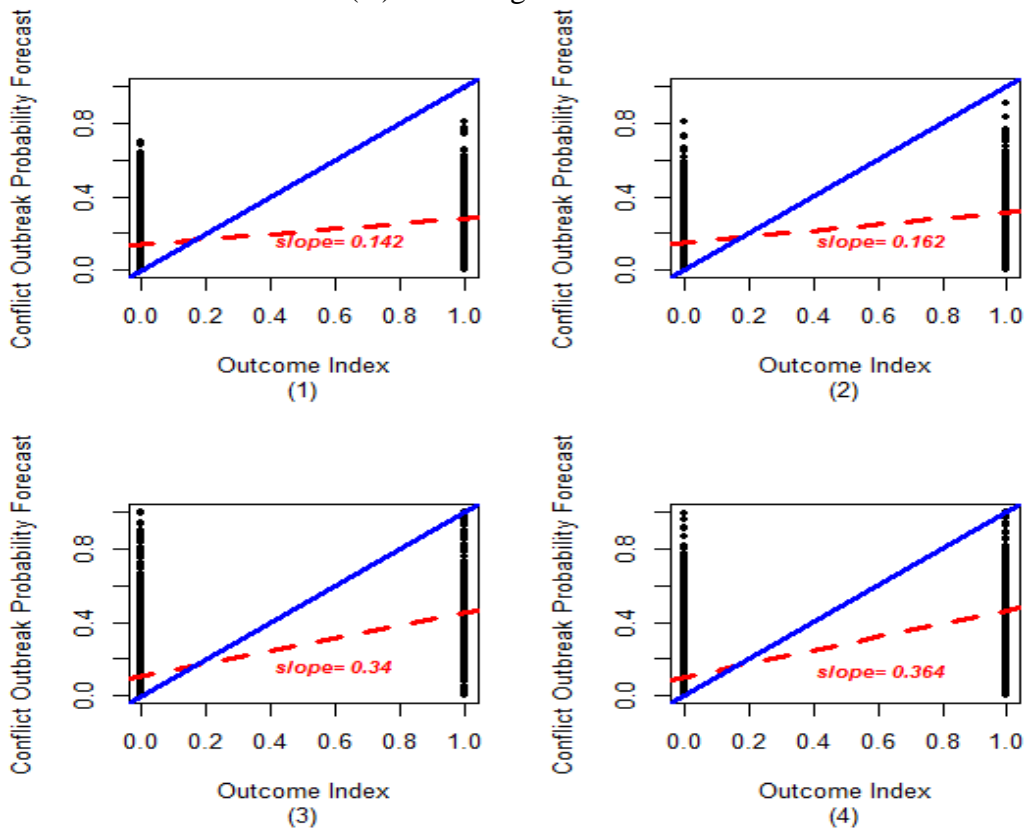
(B) Single Index Model

Figure 1. Covariance Graph for Probability Forecasts on Conflict Incidence

I.5.1.2. Receiver Operating Characteristic (ROC) Curve

ROC curves for all models studied are displayed in Figure 2. The diagonal straight line $y = x$ stands for models containing no useful information, while the point (0, 1) reflects perfect classification. In other words, the better models lie in the upper triangular region and are further away from the diagonal.

It can be seen that all parametric models have smaller AUC values than semiparametric models. Moreover, all of these values are statistically significant greater than 0.5 using the Wilcoxon nonparametric tests. That is, all models do better in prediction, compared to random guessing. Interestingly, the results agree with those suggested by the Brier score: namely models without time trend outperform models with time trend; semiparametric models outperform parametric ones. Consequently, depending on the values of AUC, the semiparametric model with stationary series and without time trend (Model 4) is the best candidate model (AUC = 0.8878).

(A) Panel Logit Model
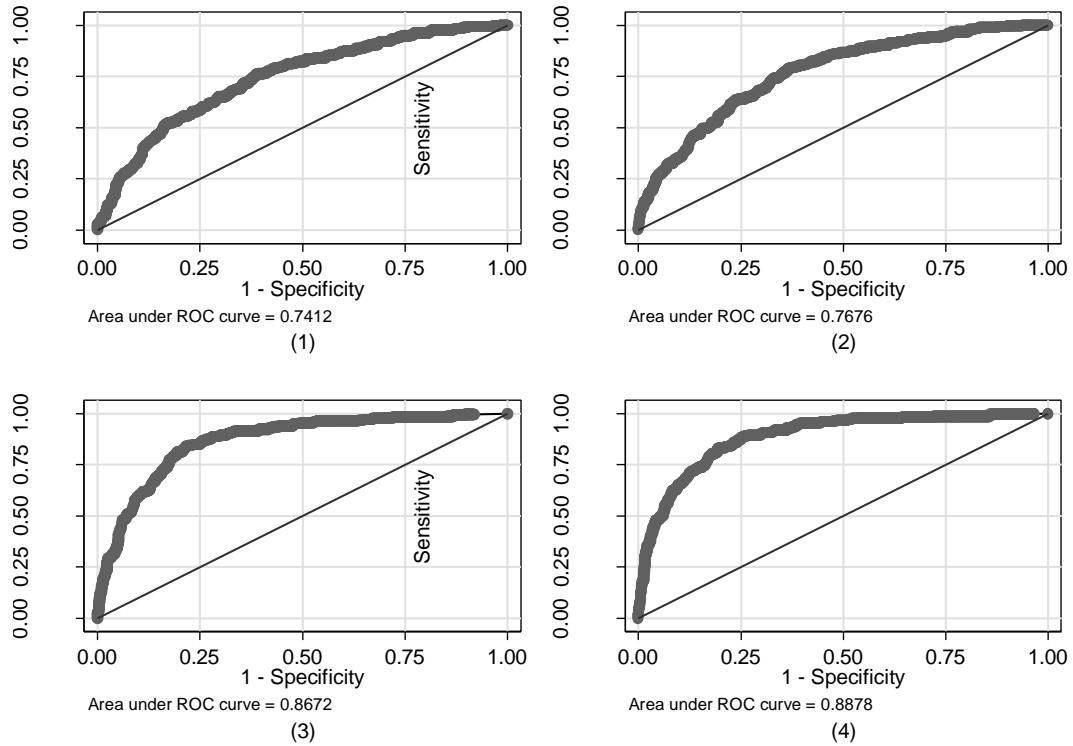
(B) Single Index Model

Figure 2. Receiver Operating Characteristic (ROC) Curve

I.5.2.   Weather Effects Results

Now we use the best performing single index model (stationary series, without time trend – Model 4) to analyze the climate conflict nexus with the whole dataset.

To quantify the effects of the weather variation on conflict incidence, we compute the Average Marginal Effects (AME). These measure the change in probability of conflict outbreak when an independent variable (i.e., weather variation) increases by one unit while keeping all the other independent variables unchanged. To make the results comparable across different studies, the effects are standardized by transforming the original AME to a relative change in the dependent variable – conflict incidence (Hsiang et al. 2013). Given that only the coefficient of precipitation variation (not temperature variation) is statistically significant during the estimation, we focus on the standardized AME of precipitation variation in this discussion

The panel logit model suggests that a 1% increase in the difference in precipitation from this year to last lowers the probability of civil conflict outbreak by 5.68% at the 0.01 level of significance. Likewise, the single index model also implies a 3.37% in conflict probability decrease with a 1% higher amount that this year's precipitation than last year's, with a 0.01 significance level. As a consequence, the optimal out-of-sample forecasting model, selected through a rolling window scheme, suggests that a higher level of precipitation this year relative to last will statistically significantly lower the risk of civil conflict.

Additionally, we find some interesting results when estimating the panel logit model, which is displayed in Table 2.[9]

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[9] In semiparametric estimation, we set the first component of the coefficient vector equal to one to obtain scale normalization. The coefficients therefore are not interpretable, but we calculate the average marginal effects (AME) instead, to quantify the impacts of weather variation on conflict incidence.

Table 2: Dependent Variable: Conflict Incidence, 1950 – 2006.

Independent Variable	Panel Logit Model
Variation in Temperature at t	-0.003
	(0.847)
Variation in Precipitation at t	-0.225**
	(0.101)
First Differenced Log(GDP) at t	-3.819***
	(0.935)
Regime Type at t-1	-0.010
	(0.033)
Regime Type Square at t-1	-0.011*
	(0.006)
Log(Population) at t-1	1.640***
	(0.483)
Observations	3826
Pseudo_R^2	0.071
BIC	2565.4

standard error in parentheses

* $p<0.1$, ** $p<0.05$, *** $p<0.001$

Table 2 shows that the effect of precipitation variation on conflict incidence is significantly negative at the level of 0.05. Intuitively, the lower the precipitation this year relative to the last the higher the probability the country may suffer from civil conflict. Such a robust result offers strong evidence of a negative relationship between precipitation abundance and civil war incidence, which is in line with the findings of several other studies (Miguel et al. 2004; Hendrix and Glaser 2007).

We do not find significant direct correlations between temperature variation and civil conflict, albeit the fact that many researchers advocate higher temperature increases the risk of conflict (Hsiang et al. 2013; Burke et al. 2009). Additionally, interesting findings emerge by looking at other country characteristics. For example, GDP growth has statistically significant negative impacts on conflict incidence while population shows significant positive effects. That is to say, a country with higher GDP growth and lower population is less likely to experience civil

conflict. In addition, the significant coefficient of the squared term of regime type indicates its curvilinear effects on conflict incidence, consistent with regimens at either end of the spectrum having less conflict.

I.6.   Discussion

Our estimation yields strong evidence that a lower level of precipitation this year relative to last increases the risk of civil conflict. Climate change can contribute to this. IPCC (2007a, 2013) predicts that total global precipitation will increase as a whole, whereas the patterns differ significantly across regions. In addition, variability of rainfall is projected to increase with 90% certainty, which may give rise to or intensify extreme events such as droughts or flooding. As a consequence, the predictions of increased variability and extreme event incidence portend greater conflict incidence. Analytically, suppose precipitation follows the normal distribution, with mean μ and standard distribution σ. An increase in variability means that the standard distribution σ becomes larger. In other words, precipitation data spreads out covering a wider range of values. The probability of extreme values (i.e., extreme low precipitation/drought or high precipitation/flood) therefore grows. This has implications for policy design regarding climate change and conflict.

   First of all, our analysis suggests that conflict prevention can be enhanced by several means. Certainly there is the obvious need to pursue climate change mitigation or adaptation. Additionally, actions such as provision of irrigation or other water supply enhancements would lessen the impact of precipitation fluctuations. Furthermore, forecasts of places where climate change would increase the probability of adverse precipitation events can help target efforts on pre-conflict peacebuilding interventions. This might involve enhancement of adverse event early warning systems, enhanced water supply reliability, and drought resistance increases through agricultural research (e.g., drought resistant varieties and crops). Moreover, the quantitative analysis may well benefit policy-makers and other stakeholders by predicting conflict hot spots in advance allowing potential preemptive actions. Second, methodologically we find semiparametric methods – single index models – are superior forecasters, which can be applied in other conflict and climate related analyses. They increase flexibility compared with parametric models and avoid the "curse of dimensionality" commonly existing among fully nonparametric models (Hristache et al. 2001; Härdle et al. 2004). Furthermore, the rolling window approach, which requires repeated regressions over a sequence of rolling window with a fixed length, provides higher flexibility of potential structural changes (O'Reilly and Whelan 2005).

   There are some limitations of our research worth noting. First, there exist numerous other determinants that make countries (or areas) more susceptible to conflict. For instance, economic elements that reflect the development level of a nation are closely linked to the risk of conflict. Poverty, economic inequality, economic structures such as the primary commodities countries rely on, policies, and the like are all examples. Given myriads of potential conflict-inducing factors, we cannot conclude that precipitation variation contributes the most to the conflict outbreak. Second, because we use reduced-form methods, our research cannot fully reveal or

distinguish the climate-conflict mechanisms underlying the relationship. Consequently, extensions are essential to further illuminate the precise causal pathway, allowing one to tailor more efficient and effective localized policies as discussed in Miguel et al. (2004) and Burke et al. (2014). Third, our estimation results reveal short-run linkages and additional work might be done on long-run impacts considering possible adaptation (Dell et al. 2014).

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