

Predicting Risk Factors Associated with Forced Migration: An Early Warning Model of Haitian Flight

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This study predicts forced migration events by predicting the civil violence, poor economic conditions, and foreign interventions known to cause individuals to flee their homes in search of refuge. If we can predict forced migration, policy-makers can better plan for humanitarian crises. While the study is limited to predicting Haitian flight to the United States, its strength is its ability to predict weekly flows as opposed to annual flows, providing a greater level of predictive detail than its 'country-year' counterparts. We focus on Haiti given that it exhibits most, if not all, of the independent variables included in theories and models of forced migration. Within our temporal domain (1994–2004), Haiti experienced economic instability, low-intensity civil conflict, state repression, rebel dissent, and foreign intervention and influence. Given the model's performance, the study calls for the collection of disaggregated data in additional countries to provide more precise and useful early-warning models of forced migrant events.

In order to anticipate, assist, or prevent refugee flight, we need to identify and monitor those causes and triggering events of flight.¹

This study seeks to develop a general early-warning model for forced migrant flight. The United Nations High Commission for Refugees (UNHCR) *Handbook for Emergencies* defines early warning as 'the collection, analysis, and use of information in order to better understand the current situation as well as likely future events. The particular focus is on events which might lead to population displacement.'² If researchers can identify and predict the risk factors that cause population displacement, they can create contingency plans for future emergencies. 'Contingency planning is a specific activity whereby a group of relevant agencies get together to plan a potential response for a particular scenario of mass human displacement which is probable but has not yet happened.'³ Knowing reasonably accurate and time-specific answers to questions like when, where, and how many can enable planners to develop a comprehensive response strategy catered to those answers. 'Contingency planning reduces the lead time necessary to mount an effective response' and helps to identify gaps in resources in advance.⁴

While early warning models are successful in forecasting natural disasters like droughts and storms, models employed to forecast humanitarian disasters like refugee movements are not as successful.⁵ Schmeidl and Jenkins contend that that 'improved analysis of temporal processes, automated event data development, the integration of case study, and quantitative methods, and greater clarity about units of analysis should create the capacity to provide timely and policy-relevant information'.⁶ We attempt to incorporate all of these items in our early warning modeling approach by quantitatively analyzing weekly processes using automated event data generated for a particular case.

Previous systematic empirical investigations of asylum and refugee trends analyze annual-level data for many countries, which only reveal the aggregate tendencies of migratory populations over space and time.⁷ We argue that these data mask the details of the migration process and provide a forecast that is ultimately too broad to be useful to policy-makers. Instead, we employ a longitudinal design to capture 'an empirically rich dynamic underlying the process tendencies'.⁸ To address this concern, we divide the temporal units into weeks to provide a closer look at the migration process. In a previous study, we showed that both economic and security variables effect short-run migratory patterns from Haiti to the United States. We build on that study using the data and models to forecast these economic and security variables that affect forced migration. We then use those predicted values to predict Haitian flight to America.

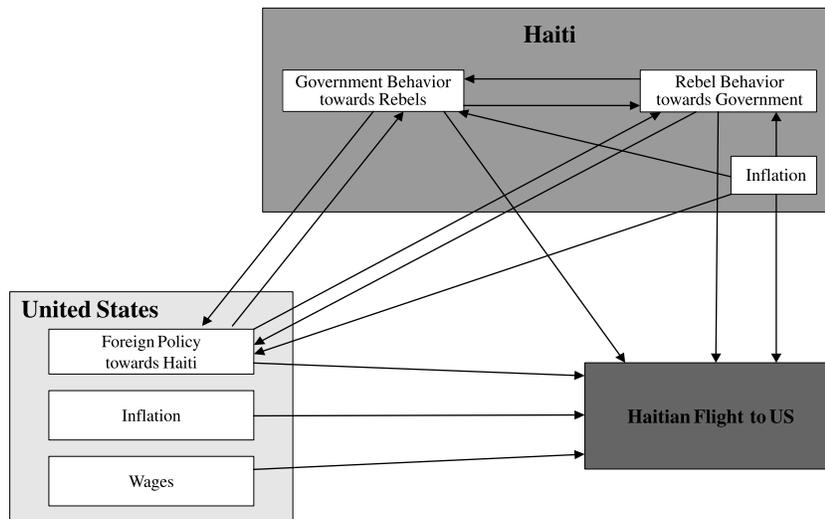
Our study proceeds as follows. First, we begin by introducing the model and discussing the literature which informs each piece of the model. Second, we describe our data used to test and predict the model's values. Third, we present and discuss our results. We conclude by discussing the policy implications of the results and the utility of the model for contingency planners.

THE MODEL

The early warning model we develop grows out of the theoretical and systematic empirical literature on this topic. We argue that in order to predict Haitian migration to the US, we need to predict the variables that affect those flows (e.g., increases in violent behavior). So we need to first develop a model that both predicts migration and predicts the risk factors which predict migration. A model that predicts migration well but fails to be able to predict the variables that cause migration, will be of less use than a model that can predict violence and other risk factors associated with migration.

We along with scholars argue that migration is a function of various domestic and international political, economic, and cultural factors. Of these risk factors the literature points to political violence and culture as being the most important risk factors. We further discuss these studies below, but first, we describe how such variables relate to each other and forced migration in our model. Figure 1 provides an overview of the causal relationships among the variables in our model. The figure does not account for the element of time; its purpose is to identify the key concepts and illustrate the hypothesized relationships among them. The ultimate purpose of

FIGURE 1
THE CAUSAL MODEL



the model is to predict Haitian migration to the US, which appears in the lower right-hand side of Fig. 1.

The figure shows that Haitian government and rebel behavior towards each other (i.e., levels of violence), Haitian inflation, US-Haiti cross-cultural networks, US foreign policy towards Haiti, American inflation and wages affect Haitian migration to the United States. We refer to this set of variables as the risk factors for flight. Our model further conveys how these risk factors are causally related to each other. Haitian government and rebel behavior affect each other and both actors' behavior affect US foreign policy towards Haiti. That policy affects both Haitian government and rebel behavior, and Haitian inflation affects Washington's foreign policy as well as Haiti government and rebel behavior.

To simplify the model, we break it up into five sub-models. Each of the risk factors is identified in the forced migration literature and we draw on other literatures to develop the sub-models (i.e., repression and dissent, foreign policy, domestic economics, etc.). Below, we review these literatures and the various studies in detail that inform our argument and our model. We begin by reviewing the relevant work on forced migration to identify relevant risk factors associated with forced migrant flight, and then move to identifying the variables that predict and explain those risk factors.

Forced Migration Model

The forced migration model we develop grows out of the systematic empirical literature on this topic. Though we focus on a particular case, we draw on the

statistical studies by Schmeidl,⁹ Davenport, Moore and Poe,¹⁰ Moore and Shellman,¹¹ and Neumayer,¹² which develop statistical models to analyze forced migration at the annual-global level. While those studies focus on the global level, a handful of studies focus on particular cases. For example, Stanley¹³ analyzes migration to the US from El Salvador, Morrison¹⁴ analyzes internal displacement in Guatemala, and Shellman and Stewart¹⁵ analyze Haitian flight to the US. All of the time-series case studies give more detail of the process of population displacement in that they focus on smaller units of time for a particular case (months and weeks), but suffer from the inability to generalize to additional cases and other limitations associated with case study research. Nevertheless, similar conceptual variables appear in both the cross-sectional studies and the case studies, and the results are similar across the designs. Though there are some conflicting results across the studies, on the whole, the results suggest that violence, economics, and cultural networks explain variations in forced migration counts.

Of those variables, violence and cultural networks are the biggest predictors of forced migrant episodes. To begin, Davenport, Moore and Poe,¹⁶ Neumayer,¹⁷ and three separate studies by Moore and Shellman,¹⁸ show that variables representing violations of human rights abuses, guerrilla attacks, and genocide and politicide have a statistically significant, positive impact on numbers of forced migrants. Shellman and Stewart¹⁹ find that as the publicly visible behavior of the dissidents becomes increasingly hostile, larger numbers of individuals flee Haiti to the US. While these are measures of civil conflict, some studies also show that international conflict variables are positively correlated with forced migrant events. For example, Moore and Shellman show that international wars (on the origin country's territory) produce population displacement.

Previous studies also find that networks and cultural communities provide people with information about migration possibilities. Scholars often use lagged values of both the flow and the stock of forced migrants to proxy the cultural network concept and these variables exhibit positive and statistically significant effects on forced migration.²⁰

In addition to violence and culture, the domestic economic situation at home and abroad may affect internal displacement and refugee flows. In particular, the voluntary migration literature argues that economic disparity can cause someone to flee their home as well as potential economic opportunities elsewhere. Bauer and Zimmermann suggest that the wage differential between the origin and destination countries will be a key factor in international migration decisions.²¹ As the economy declines in the origin country, potential foreign-destination choices appear more attractive. Borjas²² and Massey et al.²³ contend that workers migrate if they feel they can increase their standards of living. Though Schmeidl²⁴ finds that economic underdevelopment is not correlated with refugee stocks, others find that GNP/capita levels do affect forced migrant flows.²⁵ Moreover, Moore and Shellman²⁶ show that asylum GNP/capita levels positively draw forced migrants to their countries. Stanley shows that economic under-performance does not impact migration from El Salvador to the US.²⁷ However, his measure is not a direct measure of the economic

situation. Instead he uses a counter variable to proxy the steady decline of the economy which he observes using annual data. Shellman and Stewart,²⁸ consistent with Neumayer,²⁹ and Moore and Shellman³⁰ find that changes in the monthly Haitian consumer price index (CPI) pushes people out, while the US CPI deters people from coming. Surprisingly, they found little evidence that changes in US wages attracted Haitian migrants.

Though we draw on all of these studies to identify the relevant risk factors correlated with forced migration, we selected our study and its variables given that it also focuses on Haiti and weekly migratory flows from Haiti to the US³¹ and is informed by a stylistic decision framework.³² They assume that individuals are purposive and value their liberty, physical person, and life in addition to economic prosperity. Moreover, they monitor their environments and those around them to develop expectations about becoming a victim of persecution as well as potential economic distress or opportunity. When economic distress and/or the probability of being persecuted rises, the expected utility of staying decreases while the utility of leaving increases. Finally, origin domestic policies and asylum foreign policies will also affect an individual's utility calculation.

The core model includes measures of government and rebel behavior, Haitian inflation, US inflation, US wages, and US foreign policy towards Haiti. In this study, we add a few additional related variables and assess their utility in our model. For example, rather than just examining how levels of government and rebel behavior affect population displacement, we also examine how changes in those actors' behavior affect displacement. We include both the change and the level indicators of each concept in our model. Thus, the model is

$$\begin{aligned}
 \text{HAITIUSMIGRANTS}_t = & \alpha + \beta_1 \Delta \text{HGOV}_t + \beta_2 \Delta \text{HREB}_t + \beta_3 \text{HGOV}_t + \beta_4 \text{HREB}_t \\
 & + \beta_5 \Delta \text{HCPI}_t + \beta_6 \text{HCPI}_t + \beta_7 \Delta \text{USFORPOL} \\
 & + \beta_8 \text{USFORPOL}_t + \beta_9 \Delta \text{USCPI}_t + \beta_{10} \text{USCPI}_t \\
 & + \beta_{11} \Delta \text{USWAGE}_t + \beta_{12} \text{USWAGE}_t \\
 & + \beta_{13} \text{HAITIUSMIGRANTS}_{t-1} + \varepsilon
 \end{aligned} \tag{1}$$

where HAITIUSMIGRANTS_t refers to the number of migrants entering the US from Haiti at time t . ΔHGOV_t refers to the change in Haiti government behavior on a hostility-cooperation continuum directed towards the Haiti rebels at time t . ΔHREB_t refers to the change in Haiti rebel behavior on a hostility-cooperation continuum directed towards the Haiti government at time t . HGOV_t refers to the level of Haiti government behavior on a hostility-cooperation continuum directed towards the Haiti rebels at time t . HREB_t refers to the level of Haiti rebel behavior on a hostility-cooperation continuum directed towards the Haiti government at time t . ΔHCPI_t refers to the change in the Haitian consumer price index at time t . HCPI_t refers to the level of the Haitian consumer price index at time t . $\Delta \text{USFORPOL}_t$ refers to the change in US government behavior on a hostility-cooperation continuum directed towards Haiti at time t . USFORPOL_t refers to the level of US government behavior

on a hostility-cooperation continuum directed towards Haiti at time t . $\Delta US CPI_t$ refers to the change in the US consumer price index at time t . $US CPI_t$ refers to the level of the US consumer price index at time t . $\Delta US WAGE_t$ refers to the change in US wages at time t . $US WAGE_t$ refers to the level of US wages at time t . $HAITIUSMIGRANTS_{t-1}$ refers to the number of migrants entering the US from Haiti in week $t-1$. α , β_1 – β_{13} are all parameters to be estimated, and ϵ refers to the error term.

This model reflects the theoretically driven model described in the Shellman and Stewart (2006) study. The exceptions are the ‘change’ or ‘ Δ ’ variables. We add them here because it makes sense that individuals may monitor both the levels of violence, inflation, wages, and foreign policy as well as changes in them. We elaborate below.

Haiti Security Models

We draw on several studies in the repression-dissent literature (e.g., Davenport;³³ Moore;³⁴ Shellman³⁵) as well as foreign policy studies (McGinnis and Williams;³⁶ Williams and McGinnis³⁷) to inform our security models. The focus of these models is on the interactions of rebels and the government inside Haiti. Most of the literature agrees that repression affects dissent and dissent affects repression, they just disagree in what ways. These different studies also invoke different theoretical explanations that give rise to the hypotheses outlined above. Most of these studies fall into two camps: retrospective and prospective. The retrospective studies more or less argue that governments and dissidents react and respond to one another’s behavior, while the prospective studies contend that governments and dissidents generate rational expectations about the opposing actor’s behavior and act based on their expectations. Gates, Quinones, and Ostrom argue that some pairs of actors will exhibit action-reaction behavior, some will depict rational expectations behavior, and still others will exhibit both.³⁸ Thus, we model both processes. Furthermore, our forced migrant equation calls for both level and differenced indicators of government and rebel behavior. One approach informs a model of levels while the other informs a model of differences.

A typical action-reaction model or retrospective model is captured by a standard set of parameterized action-reaction equations:

$$HGOV_t = \alpha_1 + \beta_{11}HGOV_{t-1} + \beta_{12}HREB_t + \epsilon \quad (2)$$

$$HREB_t = \alpha_2 + \beta_{21}HREB_{t-1} + \beta_{22}HGOV_t + \epsilon \quad (3)$$

All variables and parameters are defined as above in Equation 1. The model can aid in testing multiple hypotheses from the literature. Some argue that (H1) hostility discourages hostility and encourages cooperation³⁹ while others posit that (H2) hostility encourages hostility.⁴⁰ Additional scholars argue that (H3) cooperation encourages hostility (or decreases cooperation)⁴¹ while still others claim that (4) cooperation encourages cooperation.⁴²

Finally, a fifth hypothesis combines a couple hypotheses and contends that actors reciprocate one another’s behavior. As such, support for hypotheses 2 and 4 together

would corroborate the reciprocity hypothesis. The important thing to remember is that for our purposes of early warning, the model should predict risk factors for forced migration – the violent behavior of the government and the rebels – well. Positive and statistically significant coefficients on β_{21} and β_{22} would support the reciprocity hypothesis that actor's return roughly equivalent values of hostility and cooperation contingent on the prior action of the other.⁴³ Negative coefficients would indicate backlash or inverse behavior, such that one actor returns cooperation for hostility and hostility for cooperation. Likewise, if β_{11} and β_{12} are positive and significant, the model would show that the actors continue to do what they themselves have been doing – what Goldstein and Freeman refer to as 'policy inertia'.⁴⁴

Gupta, Singh, and Sprague contend that a curvilinear relationship between repression and dissent such that low level repression and high levels of repression yield little dissent, while moderate levels of dissent yield the highest levels of dissent.⁴⁵ To account for these effects, we add a squared term of each actor's rival's behavior to Equations 2 and 3. If the squared terms are positive and significant, we can deduce a curvilinear relationship between government and dissident behavior.

Of course these action-reaction models are widely criticized. McGinnis and Williams essentially argue that policy-makers anticipate what the enemy is going to do next and act accordingly.⁴⁶ Thus, the past behavior of the other actor should not significantly affect one's current behavior. Instead, actors should seek to limit the other actor's strategic gains. The argument, briefly sketched here, expects actors to choose a hostility level that would roughly match the hostility level anticipated by their opponent. When their expectations are debased, we expect the actors to react to their errors and develop new expectations about their rivals. Moore⁴⁷ extends this argument to rebels and governments. One way to model a rational expectations approach is to use an error correction model. We choose for econometric reasons, which we delve into later, the Generalized Error Correction Model (GECM):⁴⁸

$$\Delta HGOV_t = \alpha_1 + \beta_1 \Delta HREB_t + \beta_2 (HGOV_{t-1} - HREB_{t-1}) + \beta_3 HREB_{t-1} + \varepsilon \quad (4)$$

$$\Delta HREB_t = \alpha_1 + \beta_4 \Delta HGOV_t - \beta_5 (HGOV_{t-1} - HREB_{t-1}) + \beta_6 HGOV_{t-1} + \varepsilon \quad (5)$$

where all variables and parameters are defined as above in Equation 1. If a rational expectations process is at work and both actors are responding to deviations from their expectations of one another's behavior, β_2 will be positively signed and statistically significant and β_5 will be negatively signed and statistically significant. This dynamic implies a long-run equilibrium between the series where both actors, responding to deviations from expected behavior adjust their own behavior to bring it back in line with the other.

To these models we add economic and foreign policy measures. Many scholars argue that poor economic conditions yield higher levels of rebellion. Moreover, a country's economic conditions should also affect how governments behave. As

such, we include measures of Haiti's consumer price index in our security models. We expect that higher levels of inflation will be associated with higher levels of violence.

With respect to foreign policy, we suspect that foreign intervention into the domestic politics of a country will affect relations between governments and dissidents. Gleditsch and Beardsley find that external influence can have powerful effects on domestic actors engaged in civil conflict.⁴⁹ Intervention may range from cooperative initiatives like sending aid and relief packages, to intense hostility like sending troops to quell a violent situation. The same hypotheses apply to relationships between the US government and the Haitian government and rebels. It is possible that US cooperation could increase cooperation between rebels and governments or increase hostility. Much like US hostility could increase hostility between the rebels and the government, or it could quell the dispute. The Gleditsch and Beardsley finding suggests that foreign intervention may have different effects in any given case.⁵⁰ We include both the level and change in US foreign policy in our security models.

Finally, given that there may be a mechanism by which the Haiti government and/or rebels correct for their behavior given prior US behavior, we also include the difference between rebel behavior and US behavior in the prior period as well as the difference between government behavior and US behavior in the prior period. Having described our security equations, we turn attention towards our Haitian economy models.

Haiti Economy Models

Our Haiti economy models are simple autoregressive functions. Specifically, the best predictor of inflation in time t is inflation in time $t-1$. Specifically, we write

$$\text{HCPI}_t = \alpha_1 + \beta_1 \text{HCPI}_{t-1} + \beta_2 \text{HCPI}_{t-2} + \dots + \beta_n \text{HCPI}_{t-n} + \varepsilon \quad (6)$$

where all variables and parameters are defined as above in Equation 1. We estimate similar models for changes in inflation.

$$\Delta \text{HCPI}_t = \alpha_1 + \beta_1 \Delta \text{HCPI}_{t-1} + \beta_2 \Delta \text{HCPI}_{t-2} + \dots + \beta_n \Delta \text{HCPI}_{t-n} + \varepsilon \quad (7)$$

Next, we introduce our US foreign policy models.

US Foreign Policy Models

Our US foreign policy models are informed by both the action-reaction type models described above and the literature on foreign aid and assistance. To begin, Goldstein and Freeman, argue that countries tend to keep doing the same things they did in the recent past.⁵¹ Consequently, we include lags of recent US behavior towards Haiti. We suspect that Washington aims its foreign policy at the political situation in Haiti and especially the interactions between the rebels and the government. For instance on 19 September 1994, President Clinton ordered Operation 'Restore Democracy' in which the leadership of the Cédras coup was forced to surrender and President Jean-

Bertrand Aristide was restored to power.⁵² Thus, the US foreign policy variable should consider the behavior of both the rebels and the government in the recent past. In addition, the US provides aid and assistance to Haiti and so foreign policy should also be driven by the economic conditions in Haiti. Thus, we include the inflation indicator in our models. As such we write

$$\begin{aligned} \Delta\text{USFORPOL}_t = & \alpha_1 + \beta_1\Delta\text{USFORPOL}_{t-1} + \beta_2\text{HGOV}_{t-1} + \beta_3\text{HREB}_{t-1} \\ & + \beta_4\text{HCPI}_{t-1} + \varepsilon \end{aligned} \quad (8)$$

$$\begin{aligned} \text{USFORPOL}_t = & \alpha_1 + \beta_1\text{USFORPOL}_{t-1} + \beta_2\text{HGOV}_{t-1} + \beta_3\text{HREB}_{t-1} \\ & + \beta_4\text{HCPI}_{t-1} + \varepsilon \end{aligned} \quad (9)$$

where all variables and parameters are defined as above in Equation 1. Finally, as in the rebel and government equations, we add to the difference equation, the difference between rebel behavior and US behavior in the prior period as well as the difference between government behavior and US behavior in the prior period. This again, tests for a corrective relationship between US behavior and rebel and government behavior. Now we turn attention towards our last group of sub-models, the US economy models.

US Economy Models

Like our Haiti economy models, our US economy models are simple autoregressive functions. We write these equations for both wages and inflation. We write our inflation models as

$$\text{USCPI}_t = \alpha_1 + \beta_1\text{USCPI}_{t-1} + \beta_2\text{USCPI}_{t-2} + \dots + \beta_n\text{USCPI}_{t-n} + \varepsilon \quad (10)$$

We estimate similar models for changes in inflation.

$$\Delta\text{USCPI}_t = \alpha_1 + \beta_1\Delta\text{USCPI}_{t-1} + \beta_2\Delta\text{USCPI}_{t-2} + \dots + \beta_n\Delta\text{USCPI}_{t-n} + \varepsilon \quad (11)$$

We write our level and difference wage models as

$$\begin{aligned} \text{USWAGE}_t = & \alpha_1 + \beta_1\text{USWAGE}_{t-1} + \beta_2\text{USWAGE}_{t-2} + \dots \\ & + \beta_n\text{USWAGE}_{t-n} + \varepsilon \end{aligned} \quad (12)$$

$$\begin{aligned} \Delta\text{USWAGE}_t = & \alpha_1 + \beta_1\Delta\text{USWAGE}_{t-1} + \beta_2\Delta\text{USWAGE}_{t-2} + \dots \\ & + \beta_n\Delta\text{USWAGE}_{t-n} + \varepsilon \end{aligned} \quad (13)$$

Having described all of our sub-models, we discuss our measures for our concepts below.

RESEARCH DESIGN

Case Selection

We could choose to begin developing early warning models for several cases. Haiti is representative of those cases because it exhibits most, if not all, of the independent variables included in theories of forced migration. Within our temporal domain (1994–2004), Haiti experienced economic instability, dissident violence, state violence, and foreign intervention and influence. The Armed Conflict database, which codes the presence and absence of armed conflict as well as the intensity of such conflict, even codes two periods of low-level conflict intensity during the 1990s.⁵³ This range of events in Haiti makes it a representative case for examining how the independent variables contribute to forced migration. Moreover, migrant flows varied over the period allowing us to analyze the different impacts of the independent variables on Haitian–US migration over time. The case study approach allows for more micro-level analysis of key variables on migration rather than the breadth traditionally afforded by macro-level global studies.

Additionally, Haitian migration, in particular, is an important contemporary political issue in America, the study of which can yield powerful policy implications. For example, our analyses can be used by the US government to forecast migrant flows to the US, allowing the government to better prepare for such crises and possibly prevent such crises from happening. The study's policy relevance and weekly temporal unit make it a complement to global-level forecast models.⁵⁴ As a forecasting tool and an example for other cases, we submit that it is a valuable contribution to the policy community and to the extant body of literature.

Unit of Observation

In this study, we analyze migratory flows in smaller temporal units than traditional quantitative studies. We do so for three reasons.

First, King, Keohane, and Verba contend that it is important to design studies that analyze as many observations as possible.⁵⁵ Though we analyze a single case in this study, we analyze many observations within the case and make comparisons among them.

Second, we contend that more fine-grained temporal units provide better resolution for sensing the causal mechanisms at work.⁵⁶ Political science literatures all too often ignore the literature on temporal aggregation.⁵⁷ For example the discipline is dominated by large-*n* pooled cross-sectional time-series studies which analyze country-years. Usually such indicators consist of rather crude measures – often over-aggregated. Empirically, studies reveal that ‘temporal aggregation usually alters most properties existing at the disaggregated frequency’.⁵⁸ Rossana and Seater go as far as to say that it ‘alters the time series properties of the data at *all* frequencies, systematically eliminating some characteristics of the underlying data while introducing others’.⁵⁹ Goldstein and Pevehouse report that ‘High levels of aggregation (such as quarterly or annual data) tend to swallow up important interaction effects’⁶⁰ and Franzosi shows that ‘the more aggregated the series, the

less likely it is to detect the effects of strikes on production'.⁶¹ Using conflict and cooperation event data measures, Shellman⁶² finds that aggregation decisions affect coefficient estimates, block exogeneity tests, and standard errors. Shellman's results are consistent with Goldstein and Pevehouse and Franzosi in that smaller temporally aggregated units tend to reveal stronger statistically significant partial-correlation coefficients than larger units. The results support Wood's contention that smaller temporal units allow one to better sense the causal mechanisms at work.⁶³ In sum, the literature on this topic generally concludes that over-aggregation can mask important causal effects.

Third, we focus on a smaller temporal unit because it provides more useful predictions for policy-makers. With our unit of observation, the model's predictions are more useful than gross annual forecasts such as those provided by Moore and Rubin.⁶⁴ We believe that governmental and nongovernmental agencies are much better off knowing a crisis may occur next week than knowing it will occur next year.

With the literature in mind, daily aggregated data prove to be too small a unit; there is almost certainly a lag effect at the daily level between conflict and migration and it is difficult to model such a lag structure. Following Goldstein and Pevehouse,⁶⁵ we choose to aggregate our conflict-cooperation data and interdiction data by the week, which allows better sensing of causal mechanisms and increases our observations. In addition, weekly observations provide much more information to contingency planners than annual aggregations and predictions.

Data & Measurement

Most of our data are measured at weekly intervals; though, some of our economic indicators only came disaggregated as small as the month. Our measures of the economy, inflation and wages which we discuss in more detail below however, are not likely to vary much by week. We inserted the monthly economic indicators over each month's corresponding weeks. The coefficients (β 's) on such variables indicate that, on average, a one unit change in the monthly economic variable of interest leads to a β -unit change in weekly Haitians interdicted at sea. Below we discuss our measures of the dependent and independent variables.

Dependent Variable

Disaggregated yearly Haitian migrant and refugee data is not currently obtainable. Thus we have to choose a measure that corresponds indirectly to the concept of a migrant. We use weekly Haitian interdictions at sea by the US Coast Guard (USCG) from October 1994 through June 2004 to proxy weekly US-Haiti migration. The data themselves come from the USCG's publicly obtainable interdiction logs.⁶⁶ According to the USCG, the interdiction statistics are updated every morning of each business day.⁶⁷ Moreover, the USCG's goal is to capture 87 per cent of the undocumented immigrants trying to enter the United States.⁶⁸ Thus, we contend that our indicator is a reliable measure of US interdictions of Haitians at sea.

With respect to validity, Manheim and Rich⁶⁹ contend that researchers should demonstrate an indicator's internal and external construct validity to show that the proposed measure corresponds to the concept it is intended to represent. To demonstrate such validity requires that we have an alternative indicator that we can check our indicator against. To demonstrate the indicator's internal construct validity, we correlated the annual sums of interdictions with the available Moore and Shellman⁷⁰ measure of refugee flows (obtained from the UNHCR). We found a .05 statistically significant .67 correlation between the two annually aggregated series.⁷¹ This tells us that our measure reflects other similar aggregate measures and that our indicator is internally valid. Our results below demonstrate external validation. That is to say that we show statistically significant partial-correlations between our interdiction measure and our independent variables in the anticipated directions. Such results show that our measure is related to other variables in the ways in which our theory predicts.

Finally, we contend that our measure has face validity. We are trying to capture migration from Haiti to the US. We know from primary and secondary sources that the most likely choice of transportation by Haitian migrants to the US is by boat. The US Coast Guard patrols the American coastline to impede such migrants from reaching land. In most cases, the US Coast Guard is the first agency to have contact with such migrants and such contacts are logged daily by the agency. All of these migrants are interviewed and then either returned to Haiti or forwarded to another agency such as Immigration and Naturalization Services (INS) for further processing. Thus, on the face, our measure is a valid indicator of US-Haitian migration.

Of course, the measure is not without its limitations. To begin, the measure only captures those individuals who are caught trying to enter the US and ignores those who successfully enter illegally. Second, it only captures those individuals traveling to the US by boat (however, boats are the dominant form of transportation) and ignores individuals applying for refugee and asylum status at the US 'in-country' office located in Port-au-Prince. However, the interdiction data provide a unique view of migration patterns, allowing us to track responses to individual events in a way that data aggregated at higher levels would not allow. We contend that our measure serves as a good indicator of weekly migratory flows from the US to Haiti because of its demonstrated internal, external, and face validity. Moreover, the data allow for a new disaggregated level of temporal aggregation.

Haiti Domestic Security Indicators

To measure the threat to one's physical person, we used event data from Project Civil Strife (PCS).⁷² According to Goldstein event data are 'day-by-day coded accounts of who did what to whom as reported in the open press', and offer the most detailed record of interactions between and among actors.⁷³ Most event data projects convert events into a measure of conflict-cooperation.⁷⁴ The conflict-cooperation variable is said to measure the intensity of one actor's behavior directed towards another actor.

We use the automated coding program Text Analysis By Augmented Replacement Instructions (TABARI), developed by Phil Schrodt, to generate domestic political event data.⁷⁵ TABARI uses a ‘sparse-parsing’ technique to extract the subject, verb, and object from a sentence and performs pattern matching using actor and verb dictionaries.⁷⁶ In short, TABARI matches words from an electronic text file (news story) to words contained in the actor and verb dictionaries and assigns a corresponding code to each actor and verb, and finally, spits out the date.⁷⁷ Verbs and verb phrases are assigned a category based on the WEIS coding scheme.⁷⁸ Then, these categories are scaled on an interval conflict-cooperation continuum using the Goldstein scale.⁷⁹

These data now represent a conflict-cooperation measure of behavior by one actor directed towards another. The coding scheme captures events ranging from highly cooperative events such as a rebel group becoming a political party and joining the government to positive statements made by public officials to negative comments, to episodes of violent armed conflict.

To demonstrate how events are coded from natural language contained in news reports, we provide some examples below. The phrases contained in quotes below are assigned corresponding numerical codes which are then weighted on the Goldstein (1992) scale. In terms of hostility, several armed conflict events (on different days) occurring during the ‘armed rebellion’ by the Revolutionary Artibonite Resistance Front against President Aristide and his supporters in 2004 are coded as -9.00 on the -10 (hostility) to $+10$ (cooperation) scale.⁸⁰ Similarly, the government’s ‘torturous activities’ reported by the press are also coded as -9.00 .⁸¹ With regard to cooperation, Aristide’s ‘optimist comments’ about the future of Haiti are coded as $+0.40$, and his ‘promise’ of elections is coded as $+4.00$ on that same continuum.

The literature contends that individuals monitor the behavior of government forces and guerrillas and flee when the perceived threat is heightened. Thus, we aggregated rebel actors together, government actors together, rebel targets together, and government targets together.⁸² Finally, we averaged the conflict-cooperation values associated with each directed dyad (rebels to government and government to rebels) by week. In the end, we created directed dyadic event scores on a -10 (hostility) to $+10$ (cooperation) continuum that summarize the weekly level of behavior directed by the rebels towards the government and the government towards the rebels. Weeks in which no events were recorded were scored a zero; however, very few weeks in the data set contain no events.

Haiti and US Economic Indicators

To measure the economic environment in Haiti, we use the monthly Consumer Price Index (CPI) from the International Labor Organization (ILO) LABORSTAT database.⁸³ The CPI measures changes in the prices of goods and services that are directly purchased in the marketplace. Most think of the CPI as measuring the inflation rate, while others refer to it as a cost of living index. While many point out the distinctions between CPI and a complete cost of living index, the CPI can convey

the changes in the prices of goods and services, such as food and clothing. Therefore, it serves as a good indicator of the monthly economic environment in Haiti over time.

Unfortunately, the data came in two series, each having a different base year, which do not overlap.⁸⁴ Furthermore, there were eight months of missing data in 1996. The first series runs from October 1994 to December 1995 (1990 = 100). The second series runs from September 1996 to June 2004 (2000 = 100). To begin, we linearly extrapolated the first series through August 1996. Then, we merged the two together and created a dummy variable set equal to 1 from September 1996 through the end of the time-series. The dummy variable will tell us if the level of the time-series changes as a result of the second series.⁸⁵ We also interact Haitian CPI with the dummy variable to see if the estimated effect of CPI changes as a result of the 'new' series. We also took the first difference (Δ HAITICPI). We chose to do this in the original monthly dataset such that when we merged the monthly change series with our weekly dependent variable, each week in each month would have the same value of Δ HAITICPI associated with it.⁸⁶ To measure the US economic environment, we used monthly US CPI as well as monthly US wages. These measures capture the economic pull of the United States. We expect inflation to be negatively signed and wages to be positively signed. We downloaded both series from the ILO LABORSAT website. Like Δ HAITICPI, we took the first difference in the monthly series and merged them into our weekly master dataset.

US FOREIGN POLICY

Not only will domestic conflict and cooperation affect migration, but foreign pressures should also affect Haitian migration, especially US foreign policy towards Haiti. To measure Washington's foreign policy we use event data summarizing America's net conflict-cooperation directed towards Haiti. These data were also generated using TABARI but instead of coding domestic conflict and cooperation, they represent international conflict-cooperation levels and events. We originally sought to use Goldstein and Pevehouse's dataset available on the KEDS website. However, the temporal span of the data ends in mid-1997. We chose to use the existing dictionaries to regenerate data for 1990–97 and extend the series through 2004 using full-text AP news reports.⁸⁷ We then created US to Haiti government, US to Haiti military, US to Haiti rebels and US to Haiti (all) directed dyads. Finally, we averaged the Goldstein weighted event scores for each directed dyad by the week. In the end, the only series having an effect in our model is the US to Haiti (all) directed dyad. All of our measures' descriptive statistics appear in Table 1. We now turn to our results.

Estimation Methods

We use OLS regression to estimate all of our sub-models. Each of the dependent variables for our sub-models is continuous. With regard to our error correction

TABLE 1
DESCRIPTIVE STATISTICS

Variable	Mean	Standard Deviation	Minimum	Maximum
HAITIINTERDICT _{t-1}	31.9	93.1	0	918
USFP _{t-1}	0.115	1.91	-10	10
ΔUSFP _{t-1}	1.02e-09	2.64	-10	10
USWAGE _{t-1}	14.0	1.20	2.09	16.4
ΔUSWAGE _{t-1}	0.034	0.063	-0.110	0.200
USCPI _{t-1}	97.9	6.54	86.8	110
ΔUSCPI _{t-1}	.198	.241	-0.407	0.813
HREB _{t-1}	-0.709	2.59	-10	10
ΔHREB _{t-1}	-0.004	3.44	-14.7	12.3
HGOV _{t-1}	-0.447	2.39	-10	10
ΔHGOV _{t-1}	-0.011	3.38	-16	14.1
HCPI _{t-1}	138	61.9	65.5	258
ΔHCPI _{t-1}	1.21	3.79	-20.1	17.6
haiti_usin ~ 1	-0.019	130	-918	909
HCPI Dummy _{t-1}	.785	.411	0	1

models, we chose to estimate a slightly modified version of the GECM.⁸⁸ Most researchers assume that cointegration is necessary to estimate an error correction model, but De Boef and Keele correctly point out that this is a false assumption. They write ‘the appropriateness of ECMs need not be linked to cointegration’.⁸⁹ Though we found no evidence of cointegration in our series, we are attracted to the link between theory and method and as such chose to estimate the modified GECMs (See Banerjee et al.⁹⁰; De Boef⁹¹) using OLS regression.

For our ‘level’ Haiti security models, we estimate Vector Autoregression (VAR) models. The Akaike Information Criterion and Schwartz Bayesian Criterion suggested that the single-lag length models were superior to models including additional lag lengths. Thus, we report the one-lag VAR models.

With regard to our forced migration model, we estimate a Zero-Inflated Negative Binomial (ZINB) regression model because the dependent variable is a count and is not normally distributed. A histogram (not reported here for reasons of space) reveals a Poisson-like distribution which is ‘derived from a simple stochastic process...where the outcome is the number of times something has happened’.⁹² However, most situations in the social sciences rule out the Poisson statistical model because it assumes that each event is independent of one another; each event has no effect on the probability of the event occurring in the future. Moreover, the model assumes that the conditional mean of the outcome is equal to the conditional variance. Shellman and Stewart argue that decisions are linked via a common set of information such that they are not independent.⁹³ As such the theory excludes the use of a Poisson model to estimate our dependent variable. The appropriate statistical technique used to analyze such a distribution is the negative binomial-regression model. This model includes a parameter, α , which enables one to estimate the extent to which the events influence one another within each observation.⁹⁴ Our argument implies that α will be positively signed and statistically significant. We choose the

negative binomial regression-model because the use of a linear regression model on these data can result in inefficient, inconsistent, and bias estimates.⁹⁵

Two-thirds of our dependent variable's observations are zero. To model this characteristic in our data, we use a zero modified estimation strategy. Given our argument, our negative binomial distribution, and our zero-inflated counts, the most appropriate model is the Zero-Inflated Negative Binomial (ZINB) regression model.⁹⁶

Finally, because we are modeling time processes, there may be problems with serial correlation. Thus, we report robust standard errors for all of our models.

RESULTS

We report our results for our sub-models in Tables 2–5. While we would like to touch on each and every finding in the study, space limits our ability to do so. Thus we discuss the key findings and summarize others. We pay closer attention to the ZINB results in Table 6 than our sub-model results. While we do not go into great depth interpreting all the coefficients in our sub-models, the predictions from those equations are used to generate the forced migrant predictions. Given that our goal is prediction, we concentrate on how well our model as a whole predicts forced migration given the model's predictions for civil conflict, US foreign policy, and the US and Haitian economies.

Haiti Security Results

We begin by analyzing the results for our Haiti security models in Table 2. The first two columns of Table 2 report the coefficient estimates for our GECMs. Both GECMs produce fairly high R^2 s for these types of models. Both models explain about 50 per cent of the variance in the dependent variables. Moreover, when we use the model to predict values for our dependent variable and correlate them with the actual values of the dependent variables, they correlate around .70 for both models. Thus, the model predicts the dependent variable fairly accurately.

The main independent variable we want to consider is the EC term. We observe that both terms are statistically significant and one term is positive while the other is negative. This is exactly how they should behave if a rational expectations date generating process is at work. Furthermore, both terms are about equal to the absolute value of 1. For example, in the first equation, if the difference between rebel and government behavior is five (e.g., where $REB_{t-1} = 7$ and $GOV_{t-1} = 2$), the government will increase its behavior by about five points on that same scale holding all other independent variables constant. This brings their behavior back in line with the rebels. The same relationship holds true for the rebels. Given the same values as described above, the rebels will decrease their behavior by about 4.5, holding all other variables constant. This demonstrates a long-run equilibrium relationship between the rebels and the government as the rational expectations approach predicts. It is important to remember how these variables are measured and that negative values are more hostile than positive values.

TABLE 2
HAITI SECURITY MODELS

Variable	Changes (GECM)		Levels	
	Δ HGOV _t Coef. (SE)	Δ HREB _t Coef. (SE)	HGOV _t Coef. (SE)	HREB _t Coef. (SE)
Δ HGOV _{t-1}	-	0.001 (.039)	-	-
HGOV _{t-1}	-	-.821*** (.124)	-0.041 (.054)	0.056 (.058)
HGOV ² _{t-1}	-	-	-.007 (.008)	0.021*** (.009)
Δ HREB _{t-1}	0.002 (.034)	-	-	-
HREB _{t-1}	-1.11*** (.131)	-	0.042 (.049)	0.095** (.053)
HREB ² _{t-1} (.007)	-	-	0.007 (.007)	-.010 (.008)
HREB _{t-1} - HGOV _{t-1} (EC Term)	1.12*** (.118)	-0.815*** (.112)	-	-
Δ HCPI _{t-1}	-0.040* (.032)	-.050** (.029)	-	-
HCPI _{t-1}	-	-	-0.006** (.003)	-0.003 (.003)
HCPI Dummy _{t-1}	0.251 (.290)	0.070 (.295)	-0.500 (.443)	-0.300 (.477)
Δ USFP _{t-1}	-0.012 (.070)	-0.111** (.063)	-	-
USFP _{t-1}	-	-	-0.117** (.058)	-0.031 (.062)
HGOV _{t-1} - Δ USFP _{t-1}	.114* (.091)	-	-	-
HREB _{t-1} - Δ USFP _{t-1}	-	-.069 (.091)	-	-
Constant	-0.575*** (.261)	-0.632*** (.257)	0.723 (.725)	-0.067 (.781)
R ²	0.51	0.45	.02	.03
Correlation between Predicted & Actual values	0.71***	0.67***	.14***	.18***
N	463	463	464	464

One tail tests * = p < .10; ** = p < .05; *** = p < .01

Other statistically significant variables in these models include the opponent's lagged behavior. The opponent's level last week decreases change in one's own behavior this week. In terms of the economy, change in inflation causes rebels to become more violent (the coefficient is negative and statistically significant) as expected. However, changes in inflation have no effect on government behavior. With respect to US foreign policy, US behavior last week has a statistically significant effect on the change in rebel behavior, but not government behavior. However, the difference between government behavior and US behavior in the previous time period has a negative and statistically significant effect on the change in Haiti

TABLE 3
HAITI ECONOMY MODELS

Variable	Changes $\Delta HCPI_t$ Coef. (SE)	Levels $HCPI_t$ Coef. (SE)
$\Delta HCPI_{t-1}$	0.882*** (.065)	–
$\Delta HCPI_{t-2}$	0.000 (.058)	–
$\Delta HCPI_{t-3}$	–0.083* (.052)	–
CPI_{t-1}	–	0.989*** (.010)
CPI_{t-2}	–	–0.000 (.002)
CPI_{t-3}	–	0.010*** (.004)
CPI Dummy $_{t-1}$	0.205 (.289)	2.18** (1.17)
Constant	0.128 (.329)	–1.59*** (.700)
R ²	.72	.98
Correlation between Predicted & Actual values	.85***	.99***
N	463	463

One tail tests * = $p < .10$; ** = $p < .05$; *** = $p < .01$

government behavior. Overall, these models accurately reflect the relationships between changes in rebel and government behavior.

This, unfortunately, is not the case when it comes to explaining levels of government and dissident behavior. The R²s are very low and the actual and predicted values correlate for both models at .14 and .17, respectively. That said, the model does support Gupta, Singh and Sprague's contention that there is a curvilinear relationship between repression and dissent.⁹⁷ When we graph out this relationship (not depicted here) we observe that at high levels of hostility (negative values) and

TABLE 4
US FOREIGN POLICY MODELS

Variable	Changes $\Delta USFP_t$ Coef. (SE)	Levels $USFP_t$ Coef. (SE)
$\Delta USFP_{t-1}$	–0.199*** (.053)	–
$USFP_{t-1}$	–	0.050 (.047)
$\Delta HGOV_{t-1}$	–0.172*** (.049)	–
$HGOV_{t-1}$	–	0.060* (.040)
$\Delta HREB_{t-1}$	–0.067* (.043)	–
$HREB_{t-1}$	–	–0.018 (.037)
$HGOV_{t-1} - \Delta USFP_{t-1}$.393*** (.059)	–
$HREB_{t-1} - \Delta USFP_{t-1}$.147*** (.050)	–
$\Delta HCPI_{t-1}$	–0.03 (.033)	–
CPI_{t-1}	–	–0.001 (.002)
CPI Dummy $_{t-1}$	0.103 (.288)	0.083 (.337)
Constant	0.304 (.250)	0.141 (.544)
R ²	.37	.01
Correlation between Predicted & Actual values	.61***	.10**
N	463	464

One tail tests * = $p < .10$; ** = $p < .05$; *** = $p < .01$

TABLE 5
US ECONOMY MODELS

Variable	Changes		Levels	
	Δ USWAGE _t Coef.	Δ USCPI _t Coef.	USWAGE _t Coef.	USCPI _t Coef.
	(SE)	(SE)	(SE)	(SE)
Δ USWAGE _{t-1}	0.696*** (.050)	–	–	–
Δ USCPI _{t-1}	–	0.819*** (.037)	–	–
USWAGE _{t-1}	–	–	1.00*** (.002)	–
USCPI _{t-1}	–	–	–	1.00***
Constant (.002)	0.011** (.002)	0.036*** (.009)	0.010 (0.35)	–0.015 (.172)
R ²	0.48	0.67	1.00	1.00
Correlation between Predicted & Actual values	0.69***	0.82***	1.00***	1.00***
N	467	467	468	468

One tail tests * = $p < .10$; ** = $p < .05$; *** = $p < .01$

high levels of cooperation (positive values), there is less rebel hostility. The highest levels of hostility (negative values) result when government hostility-cooperation is moderate (low positive and negative values). This curvilinear relationship is not supported for the government model. However, we see that levels of inflation and US foreign policy do affect government levels of behavior directed towards the rebels. Increases in both variables increase hostility levels (negative values) by the government towards the rebels. Overall, these models do not perform as well as the GECMs. This implies that an error correction dynamic generated by a rational expectations theoretical framework is superior to an action-reaction framework for studying rebel–government interactions in Haiti.

Haiti Economy Results

Table 3 reports our results for the Haiti CPI models. Both models reveal high R² values and the actual and predicted values correlate at .85 for the change model and .99 for the level model. Overall these models perform well in terms of explaining current levels and changes in CPI using lagged dependent variables.

US Foreign Policy Results

Table 4 reports the results for our US foreign policy models. As with the security models, the change model performs better than the level model. The R² values are .37 and .01 respectively. Previous changes in foreign policy best explain current changes in foreign policy, while previous Haiti government behavior towards the rebels best explains the current level of US foreign policy. The correlation between the actual and predicted values of change in government behavior is .61, while the same correlation for the level variables is only .10.

TABLE 6
ZERO INFLATED NEGATIVE BINOMIAL ESTIMATES OF WEEKLY HAITIAN INTERDICTIONS
BY US COAST GUARD (1994–2004)

Category	Count	Inflate
Variable	Coefficient (SE)	Coefficient (SE)
<i>Haiti Security</i>		
Predicted Δ HGOV _t	-0.494** (.254)	-0.691** (.407)
Predicted HGOV _t	-1.98** (.914)	-3.73** (2.22)
Predicted Δ HREB _t	-0.013 (.061)	0.067 (.105)
Predicted HREB _t	-0.914** (.427)	-1.52* (1.04)
<i>Haiti Economy</i>		
Predicted Δ HCPI _t	-0.024 (.061)	-0.035 (.053)
Predicted HCPI _t	-0.017** (.010)	-0.036** (.020)
Predicted HCPI Dummy 1996–2004	-1.07 (1.49)	-0.923 (1.45)
<i>US Foreign Policy</i>		
Predicted Δ USFP _t	-.149 (.197)	-0.017 (.215)
Predicted USFP _t	-9.38*** (4.00)	-11.57** (7.19)
<i>United States Economy</i>		
Predicted Δ US CPI	-.934*** (.362)	1.29** (.664)
Predicted Δ US WAGE	1.25 (1.89)	4.15* (2.94)
Predicted US CPI	0.052 (.141)	0.440** (.216)
Predicted US WAGE	-0.924 (1.04)	1.56 (1.44)
<i>Network</i>		
HAITIINTERDICT _{t-1}	0.005*** (.001)	-0.017*** (.006)
Count	0.007 (.013)	-0.040*** (.016)
Constant	11.04 (15.72)	-41.8** (20.83)
N (zeros)	461 (311)	461 (311)
<i>Model Fit</i>		
Alpha (Poisson v. Negative Binomial)	.93***	
Wald Chi-Square	149.70***	
Correlation between Predicted & Actual values	.74***	

Significance Levels: *** < .01 level; ** < .05 level; * < .10 level (one tail tests)

US Economy Results

Table 5 reports the results for our US economy models. Both the change and the level models for both wages and CPI perform well, though the level models outperform the change models. The R^2 values for the change variables are .48 for our wage model and .67 for our CPI model. Both our R^2 values for the level wage and CPI models are .99. Furthermore, the correlations between the actual and predicted values for all the models are above .69 and for the change models are 1.0. Overall, these simple lagged dependent variable models perform well at modeling the economic series.

Haiti-US Forced Migration Results

Now we turn attention towards our model of Haiti-US migration in Table 6. The first quantities of interest to point out appear at the bottom of the table. The alpha parameter is positive and statistically significant indicating that the negative binomial is appropriate. The correlation between the actual and predicted values

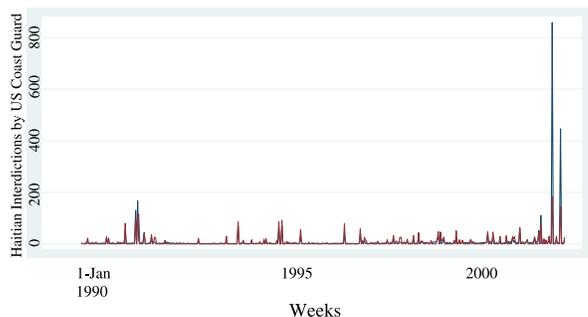
is .74. The plotted actual versus predicted values in Fig. 2 illustrate the great similarity between these the two series. The high correlation and plot indicates that the model predicts well the actual number of interdictions at sea each week.

The results demonstrate that the key variables in the model are the predicted change in government behavior, the predicted level of government behavior, the predicted level of rebel behavior, the predicted Haiti CPI level, the predicted level of foreign policy, the predicted change in US CPI, and the lag of the interdiction count. When comparing the standardized coefficients (not shown here) on each of the risk factors predicted by the sub-models, our networks variable yields the strongest effects. This is followed by changes in US CPI, US foreign policy and government violence. The effects are consistent with results reported at the global level in that our violence and cultural variables yield strong effects. However, our model also shows that the host country's foreign policy towards the origin country and the host's economic situation yield strong effects on forced migration.

Of the security indicators, both the predicted level and change in government behavior had an inverse effect on interdiction counts, such that the greater the change and level of violence, the greater the number of interdictions. The predicted level of rebel behavior had the same anticipated effect. Though the coefficient on predicted ΔREB_t is negative, it does not achieve statistical significance. The rebel level finding is consistent with Shellman and Stewart, but the government findings are inconsistent with the results of that study.⁹⁸ The previous study found no statistically significant relationship between government behavior and interdictions at sea.

Of the Haiti economy variables, only predicted $HCPI_t$ is statistically significant and surprisingly negative. As consumer prices rise, less people leave the country. Though, one should remember that consumer prices are already so high that small fluctuations in them may not encourage people to flee.

FIGURE 2
THE MODEL-PREDICTED VALUES VERSUS THE ACTUAL VALUES



The level predicted US foreign policy variable is statistically significant, while the predicted change variable is not. The level is negative, which implies that predicted weekly cooperative policy changes lead to more people fleeing to the US and weekly predicted hostile policy changes lead to less people fleeing. On the contrary, hostile policies (i.e., levels) yield more Haitian flight to the US. Therefore, hostile relations towards Haiti cause individuals to seek asylum in the US, while cooperative policies yield fewer asylum-seekers. This finding is consistent with Shellman and Stewart.⁹⁹

Of course, the lag of Haitian interdictions is also positive and statistically significant indicating that the number of last week's interdictions does a good job at predicting this week's interdictions. It also provides support for the cultural networks hypothesis advanced in the literature. However, even in the presence of a lagged dependent variable, many of our other indicators contribute to explaining variance in our dependent variable and achieve statistical significance indicating that the other variables do matter.

Figure 2 depicts the actual and predicted values plotted against time. Both lines tell similar stories, revealing that the predicted values closely resemble the true number of weekly interdictions. Thus, we feel that the model is useful for US policy-makers planning for Haitian flight to the United States.

To summarize the results, many of our predicted risk factors prove to predict US Coast Guard interdiction counts. Many of the results are consistent with the large-n (global pooled cross-sectional statistical) and small-n (case) studies. Given the .74 level of correlation between the actual and predicted values the model produces, we feel the model is useful for detecting-early warning risk factors of Haitian flight. In other words, it models the causes and triggering events of flight and is able to anticipate weekly numbers of Haitians attempting to enter the US.

CONCLUSION

Our model performs well with respect to predicting US Coast Guard interdictions at sea. We feel that this translates well to predicting migratory patterns from Haiti to the US. The model is able to predict rather well the changes in violence, US foreign policy, and the US and Haitian economies which trigger such migration. While this study only applies to Haiti, we contend that time-series case studies, like ours, will bear more fruit in terms of building and developing contingency planning models. Policy-makers are more apt to pay attention to case specific forecasts than forecasts derived from pooled models and average effects. That is, time-series case specific forecasts will prove more valuable to a policymaker dealing with contingency planning for a specific case than large-N models, which look at forced migration at the country-year level throughout the world.

Our study contends that more attention needs to be paid to daily, weekly, and quarterly patterns if we are to provide useful models to contingency planners. The study reveals the importance of specific causal mechanisms which are only revealed when studying migration on a low level of temporal aggregation and

focusing on a specific case. Thus, we urge others studying forced migration to move towards collecting such data in smaller temporal units so that we can continue to make strides at producing useful early warning models. As more data become available, it will only strengthen our efforts, allowing even more effective forced migration early warning models to emerge.

NOTES

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75. See <<http://web.ku.edu/keds/index.html>> for information on the KEDS and TABARI projects.
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79. KEDS has introduced new codes in addition to those used by McClelland and the WEIS project. Most of these are borrowed from the Protocol for the Assessment of Nonviolent Direct Action (PANDA) project. The KEDS project investigators assigned weights to the new codes that are comparable to the Goldstein weights, and we used those weights in tandem with the Goldstein weights to create the scaled event data series analyzed in this study. See <<http://web.ku.edu/keds/data.html>> for WEIS codes and adaptations PANDA.
80. The verbs rebel and force are coded as -9.0.
81. The verb torture and its variations are coded by TABARI.
82. We also experimented with separating out the military from the government.
83. See <<http://laborsta.ilo.org/>> .
84. However, the data range from similar starting and ending values and have similar means.
85. It would not be surprising to find that there is a level shift, since it is clear from looking at the series that there is a clear downward shift in the series though the means are similar and share a similar range.
86. If we had merged the level in first and then taken the first difference, this would not be the case as several observations would be zero since the monthly value did not change from week 3 to week 4.
87. The leadership and groups remain consistent from 1997 to 2004 so we feel that using the existing dictionaries rather than creating new ones does not pose great threat to the data's reliability and validity.
88. Given that the GECM assumes contemporaneous correlation and we are predicting using past values, we lag the contemporaneous 'change' term.
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