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

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We are in the early stages of this project. All criticisms and suggestions are welcome. Please do not cite without permission.

This paper was prepared for the International Studies Association annual meeting in San Diego, CA, March 22-25, 2006. The American Political Science Association's Small Research Grant Program and the Chappell Faculty-Student Research Fellowship awarded by the Charles Center at William & Mary facilitated the completion of the study. Grants awarded by the National Science Foundation (SES 0516545 & 0214287) supported generation of the domestic and foreign conflict-cooperation event data used in the study.

The authors would like to thank Will Moore for his useful comments and suggestions in the developmental stages of this paper.

Abstract

While most forced migration studies focus on explanation, this study focuses on prediction. The 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. By accounting for the interaction between civil conflict intensity levels, the ebb and flow of origin and potential host countries' economies, and impinging foreign policy pressures on countries' governments and dissidents, the model can better predict the occurrence and magnitude of forced migration events. Policy makers can use these predictions to aid their planning for humanitarian crises. If we can predict forced migration, we 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. 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.* (Apodaca 1998, 81)

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" (UNHCR 2000, 36). If researchers can identify and predict the risk factors that cause population displacement, they can contingency plan 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 (Dunkley, Kunieda, and Tokura 2004)." 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 (UNHCR 2000, 36).

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. Schmeidl and Jenkins (1998, 472) argue 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." We attempt to incorporate all of theses 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.[1] 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" (Wood 1988, 229). 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 the U.S.

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 U.S., 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

[1] See Schmeidl (1997, 1998, 2000), Davenport, Moore & Poe (2003), Moore & Shellman (2004a), Neumayer (2005a).

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.

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 the model is to explain and predict Haitian migration to the U.S., which appears in the lower right-hand side of Figure 1. The figure shows that Haitian government and rebel behavior towards each other (i.e., levels of violence), Haitian inflation, U.S.-Haiti cross-cultural networks, U.S. foreign policy towards Haiti, U.S. inflation, and U.S. wages affect Haitian migration to the United States. We refer to this set of variables as the risk factors for flight.

The model further conveys how these risk factors are causally related to each other. Haitian government and rebel behavior affect each other, both actors' behavior affect U.S. foreign policy towards Haiti, US foreign policy affects both Haitian government and rebel behavior, and Haitian inflation affects U.S. foreign policy as well as Haiti government and rebel behavior.

To simplify the model, we break it up into five sub-models. We discuss the relevant literatures and studies that inform each of our sub-models. 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 (1997), Davenport, Moore, and Poe (2003), Moore and Shellman (2004), and Neumayer (2005), 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, Stanley (1987) analyzes migration to the U.S. from El Salvador, Morrison (1983) analyzes internal displacement in Guatemala, and Shellman & Stewart (2006) analyze Haitian flight to the U.S. All of the time-series case studies provide more detail to 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 ability 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 (2003) Moore and Shellman (2004), Neumayer (2004), Moore and Shellman (2006a), and Moore and Shellman (2006b) 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 & Stewart (2006) find that as the publicly visible behavior of the dissidents becomes increasingly hostile, larger numbers of individuals flee Haiti to the U.S. 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 (Moore & Shellman 2004).

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 & Zimmermann (1994) suggest that wage differential in the origin and destination countries will be a key factor in international migration decisions. As the economy declines in the origin country, potential foreign destination choices appear more attractive. Borjas (1994) and Massey et al (1993) contend that workers migrate if they feel they can increase their standards of living. Though Schmeidl (1997) finds that economic underdevelopment is not correlated with refugee stocks, others find that GNP/capita levels do affect forced migrant flows (Moore & Shellman 2004; Neumayer 2004). Moreover, Moore and Shellman (2006a) show that asylum GNP/capita levels positively draw forced migrants to their countries. Stanley (1987) shows that economic under-performance does not impact migration from El Salvador to the U.S. 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 & Stewart (2006), consistent with

Neumayer (2004) and Moore & Shellman (2004) find that changes in the monthly Haitian consumer price index (CPI) pushes people out, while U.S. (CPI) deters people from coming. Surprisingly, they found little evidence that changes in U.S. wages attracted Haitian migrants.

Though we draw on all of these studies to identify the relevant risk factors correlated with forced migration, we selected the Shellman and Stewart (2006) study and their variables given that this study also focuses on Haiti and weekly migratory flows from Haiti to the U.S. Shellman and Stewart's (2006) model is informed by a stylistic decision framework. 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, U.S. inflation, U.S. wages, and U.S. 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 U.S. from Haiti at time t, $\Delta HGOV_t$ refers to the change in Haiti government behavior on a hostility-cooperation continuum directed towards the Haiti rebels at time t, $\Delta HREB_t$ 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, $\Delta HCPI_t$ refers to the change in the Haiti consumer price index at time t, $HCPI_t$ refers to the level of the Haitian consumer price index at time t, $\Delta USFORPOL_t$ refers to the change in U.S. government behavior on a hostility-cooperation continuum directed towards Haiti at time t, $USFORPOL_t$ refers to the level of U.S. government behavior on a hostility-cooperation continuum directed towards Haiti at time t, $\Delta USCPI_t$ refers to the change in the U.S. consumer price index at time t, $USCPI_t$ refers to the level of the U.S. consumer price index at time t, $\Delta USWAGE_t$ refers to the change in U.S. wages at time t, $USWAGE_t$ refers to the level of U.S. wages at time t, $HAITIUSMIGRANTS_{t-1}$ refers to the number of migrants entering the U.S. 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 & 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 1995; Moore 1998; Moore 2000; Shellman 2004a; Shellman 2006) as well as foreign policy studies (McGinnis and Williams 1989; 2001; Williams & McGinnis 1988) 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 (1993) argue that some pairs of actors will exhibit action-reaction behavior, some will depict rational expectations behavior, and still others will exhibit both. 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:

$$HGOV_t = \alpha_1 + \beta_{11}\, HGOV_{t-1} + \beta_{12}\, HREB_t + \varepsilon \qquad (2)$$
$$HGOV_t = \alpha_2 + \beta_{21}\, HREB_{t-1} + \beta_{22}\, HGOV_t + \varepsilon \qquad (3)$$

where all variables and parameters are defined as above in equation 1. The model can aid in testing multiple hypotheses from the literature.[2] 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 (Keohane 1986, 8). 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 (1990, 23) refer to as "policy inertia."

Gupta, Singh, and Sprague (1993) 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. 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 & Williams (1989; 2001; William and McGinnis 1988) essentially argue that policy-makers anticipate what the enemy is going to do next and act accordingly. Thus, the past

[2] Some argue that (H1) hostility discourages hostility and encourages cooperation (e.g., Snyder and Tilly 1972; Tilly 1978, Moore 2000; 1998; Francisco 1995; 1996; Lichbach 1987) while others posit that (H2) hostility encourages hostility (Gurr 1970; Hibbs 1973; Francisco 1995; 1996). Additional scholars argue that (H3) cooperation encourages hostility (or decreases cooperation) (e.g., Rasler 1996), while still others claim that (4) cooperation encourages cooperation (e.g., Krain 2000; Carey 2004). 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.

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. Moore (1995) 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):[3]

$$\Delta HGOV_t = \alpha_1 + \beta_1 \Delta HREB_t - \beta_2 (HGOV_{t-1} - HREB_{t-1}) + \beta_3 HREB_{t-1} + \varepsilon \quad (4)$$
$$\Delta HREB_t = \alpha_1 + \beta_4 \Delta HGOV_t - \beta_5 (HGOV_{t-1} - HREB_{t-1}) + \beta_6 HGOV_{t-1} + \varepsilon \quad (5)$$

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.

[3] See Banerjee et al. (1993) and De Boef (2001) for details on the GECM.

With respect to foreign policy, we suspect that foreign intervention into the domestic politics of a country will affect relations between governments and dissidents. 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 U.S. government and the Haitian government and rebels. It is possible that U.S. cooperation could increase cooperation between rebels and governments or increase hostility. Much like U.S. hostility could increase hostility between the rebels and the government, or it could quell the dispute. We include both the level and change in U.S. foreign policy in our security models. 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

$$HCPI_t = \alpha_1 + \beta_1 HCPI_{t-1} + \beta_2 HCPI_{t-2} + \ldots + \beta_n HCPI_{t-n} + \varepsilon \qquad (6)$$

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

$$\Delta HCPI_t = \alpha_1 + \beta_1 \Delta HCPI_{t-1} + \beta_2 \Delta HCPI_{t-2} + \ldots + \beta_n \Delta HCPI_{t-n} + \varepsilon \qquad (7)$$

Next, we introduce our U.S. Foreign Policy Models.

U.S. Foreign Policy Models

Our U.S. 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 (1990, 23), argue that countries tend to keep doing the same things they did in the recent past. Consequently, we include lags of the U.S.' recent behavior towards Haiti.

We suspect that U.S. foreign policy will be aimed at the political situation in Haiti and especially the interactions between the rebels and the government. For instance on September 19, 1994, President Clinton ordered “Operation Restore Democracy” in which the leadership of the Cédras coup was forced to surrender and President Aristide was restored to power. Thus, the U.S. foreign policy variable should consider the behavior of both the rebels and the government in the recent past. In addition, the U.S. 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

$$\Delta USFORPOL_t = \alpha_1 + \beta_1\, \Delta USFORPOL_{t-1} + \beta_2\, \Delta HGOV_{t-1} + \beta_3\, \Delta HREB_{t-1} + \beta_4\, \Delta HCPI_{t-1} + \varepsilon \quad (8)$$

$$USFORPOL_t = \alpha_1 + \beta_1\, USFORPOL_{t-1} + \beta_2\, HGOV_{t-1} + \beta_3\, HREB_{t-1} + \beta_4\, HCPI_{t-1} + \varepsilon \quad (9)$$

where all variables and parameters are defined as above in equation 1. Now we turn attention towards our last group of sub-models, the U.S. economy models.

U.S. Economy Models

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

$$USCPI_t = \alpha_1 + \beta_1\, USCPI_{t-1} + \beta_2\, USCPI_{t-2} + \ldots + \beta_n\, USCPI_{t-n} + \varepsilon \quad (10)$$

We estimate similar models for changes in inflation.

$$\Delta USCPI_t = \alpha_1 + \beta_1\, \Delta USCPI_{t-1} + \beta_2\, \Delta USCPI_{t-2} + \ldots + \beta_n\, \Delta USCPI_{t-n} + \varepsilon \quad (11)$$

We write our level and difference wage models as

$$USWAGE_t = \alpha_1 + \beta_1\, USWAGE_{t-1} + \beta_2\, USWAGE_{t-2} + \ldots + \beta_n\, USWAGE_{t-n} + \varepsilon \quad (12)$$

$$\Delta USWAGE_t = \alpha_1 + \beta_1\, \Delta USWAGE_{t-1} + \beta_2\, \Delta USWAGE_{t-2} + \ldots + \beta_n\, \Delta USWAGE_{t-n} + \varepsilon \quad (13)$$

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 a number of 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. 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 the U.S., 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 (Rubin & Moore 2006). 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 (1994) contend that it is important to design studies that analyze as many observations as possible. 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 (Wood 1988, 215). Political science literatures all too often ignore the literature on temporal aggregation.[4] For example the discipline is dominated by large-n pooled cross-sectional time-series studies which analyze county-years, which utilize rather crude measures – often over-aggregated. Empirically, studies reveal that "temporal aggregation usually alters most properties existing at the disaggregated frequency" (Marcellino 1999, 133). Rossana and Seater (1995, 441) 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." Goldstein and Pevehouse report that (1997, 207) "High levels of aggregation (such as quarterly or annual data) tend to swallow up important interaction effects" and Franzosi (1995, 72) shows that "the more aggregated the series, the less likely it is to detect the effects of strikes on production." Using conflict and cooperation event data measures, Shellman (2004a; 2004b) 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 (1988) contention that smaller temporal units allow one to better sense the causal mechanisms at work. In sum, the

[4] See Shellman (2004a) for a review of the economics and political science literatures on temporal aggregation.

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 & Rubin (2006). 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 of 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 (1997), 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 U.S. 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.[5] According to the USCG, the interdiction statistics are updated every morning of each business day.[6] Moreover, the USCG's goal is to capture 87% of the undocumented immigrants trying to enter the U.S.[7] Thus, we contend that our indicator is a reliable measure of U.S. interdictions of Haitians at sea.

With respect to validity, Manheim and Rich (1995, 73-78) 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 & Shellman (2004b) measure of refugee flows (obtained from the UNHCR). We found a .05 statistically significant .67 correlation between the two annually aggregated series.[8] 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

[5] We filed a written request to obtain the US Coast Guard's logs.
[6] See http://www.uscg.mil/hq/g-cp/comrel/factfile/, accessed 9/5/05.
[7] See http://www.uscg.mil/hq/g-cp/comrel/factfile/, accessed 9/5/05.
[8] Weekly-level refugee/migration data is not available.

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 U.S. We know from primary and secondary sources that the most likely choice of transportation by Haitian migrants to the U.S. is by boat. The US Coast Guard patrols the U.S. coastline to impede such migrants from reaching land. In most cases, the U.S. 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 U.S. and ignores those who successfully enter the U.S. illegally. Second, it only captures those individuals traveling to the U.S. by boat (however, boats are the dominant form of transportation) and ignores individuals applying for refugee and asylum status in the U.S. "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 U.S. 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).[9] According to Goldstein (1992, 369) 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. Most event data projects convert events into a measure of conflict-cooperation.[10] 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.[11] 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.[12] 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.[13] Verbs and verb phrases are assigned a category based on the WEIS coding scheme.[14] Then, these categories are scaled on an interval conflict-cooperation continuum using the Goldstein (1992) scale.[15] These data now represent a conflict-cooperation measure of behavior by one actor directed towards another.

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[9] See Shellman, Stewart, and Reeves (2005) for more information on coding rules and procedures.
[10] Such projects include: Cooperation and Peace Data Bank – COPDAB, World Events Interaction Survey – WEIS, Integrated Data for Events Analysis – IDEA, Protocol for the Assessment of Nonviolent Direct Action – PANDA, Intranational Political Interactions Project.
[11] See http://raven.cc.ukans.edu/~keds/index.html for information on the KEDS and TABARI projects.
[12] TABARI recognizes pronouns and dereferences them. It also recognizes conjunctions and converts passive voice to active voice (Schrodt 1998).
[13] These particular data are coded from Associated Press reports available from Lexis-Nexis.
[14] See "World Event/Interaction Survey (WEIS) Project, 1966-1978," ICPSR Study No. 5211.
[15] 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.[15] 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://www.ukans.edu/~keds/data.html for WEIS codes and adaptations PANDA.

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.[16] 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.

Haiti & U.S. Economic Indicators

To measure the economic environment in Haiti, we use the monthly Consumer Price Index from the International Labor Organization (ILO) LABORSTAT database.[17] 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.[18] 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

[16] We also experimented with separating out the military from the government.
[17] See http://laborsta.ilo.org/.
[18] However, the data range from similar starting and ending values and have similar means.

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.[19] 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 ΔHAITICPI associated with it.[20]

To measure the U.S. economic environment, we used monthly U.S. CPI as well as monthly U.S. 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 ΔHAITICPI, we took the first difference in the monthly series and merged them into our weekly master dataset.

U.S. Foreign Policy

Not only will domestic conflict and cooperation affect migration, but foreign pressures should also affect Haitian migration, especially U.S. foreign policy towards Haiti. To measure U.S. foreign policy we use event data summarizing the U.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

[19] 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.
[20] 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.

regenerate data for 1990-1997 and extend the series through 2004 using full-text AP news reports.[21] We then created U.S. to Haiti Government, U.S. to Haiti Military, U.S. to Haiti Rebels and U.S. 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 U.S. 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 models, we chose the GECM as opposed to the Engle-Granger two-step method and the Johansen because our measures of government and rebel behavior are not cointegrated. Most researchers assume that cointegration is necessary to estimate an error correction model, but De Boef and Keele (2005) correctly point out that this is a false assumption. They write "the appropriateness of ECMs need not be linked to cointegration" (De Boef and Keele 2005, 12). 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 the estimate GECMs (See Banerjee 1993; De Boef 2001) using OLS regression. We also performed robustness checks using a seemingly unrelated regression (SUR) estimator, though the results are virtually identical across estimators.

For our "level" Haiti security models, we began by estimating Vector Autoregressions (VARs), but the Akaike Information Criterion and Schwartz Bayesian

[21] The leadership and groups remain consistent from 1997-2004 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.

Criterion suggested that the single lag length models were superior to models including additional lag lengths. Thus we only report the one lag OLS regression 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. The histogram plotted in Figure 2 reveals a Poisson-like distribution which is "derived from a simple stochastic process…where the outcome is the number of times something has happened" (Long 1997, 219). 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 & Stewart (2006) argue that decisions are linked via a common set of information such that they are not independent. 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 (NBRM). This model includes a parameter, α, which enables one to estimate the extent to which the events influence one another within each observation (King 1989, 764-9). Our argument implies that α will be positively signed and statistically significant. We choose the NBREG model because the use of a linear regression model on these data can result in inefficient, inconsistent, and bias estimates (Long 1997, 217).

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.[22]

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.

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% 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 (DGP) 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

[22] These models are widely used for forced migration counts (see Moore & Shellman 2004; Moore & Shellman 2006b; Shellman & Stewart 2006).

government behavior is 5 (e.g., where $REB_{t-1} = 7$ and $GOV_{t-1} = 2$), the government will increase its behavior by 5 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. Other statistically significant variables in these models include the opponent's change in behavior and the opponent's lagged behavior. While change in the opponent's behavior last week increases the change in one's own behavior this week, 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. Finally, U.S. foreign policy has statistically significant effects on changes in rebel and government behavior. The level matters most in the government equation and the change matters most in the rebel equation. Previous coercive U.S. foreign policy towards Haiti increases cooperation levels by the government towards the rebels, while a more coercive change in U.S. foreign policy leads to increases in rebel cooperation towards the Haitian government. 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 R^2's 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 (1993) contention that there is a curvilinear relationship between repression and dissent. When we graph out this relationship (not depicted here) we observe that at high levels of hostility (negative values) and 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 U.S. foreign policy do effect 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 R^2 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.

U.S. Foreign Policy Results

Table 4 reports the results for our U.S. foreign policy models. As with the security models, the change model performs better than the level model. The R^2 values are .21 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 U.S. foreign policy. The correlation between the actual and predicted values of change in government behavior is .45, while the same correlation for the level variables is only .10.

U.S. Economy Results

Table 5 reports the results for our U.S. 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 .99. Overall, these simple lagged dependent variable models perform well.

Haiti-U.S. Forced Migration Results

Now we turn attention towards our model of Haiti-U.S. migration. 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 .73. The plotted actual v. predicted values in Figure 3 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 change in foreign policy, the predicted level of foreign policy, the predicted change in U.S. CPI, and the lag of the interdiction count.

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 & Stewart (2006), but the government findings are inconsistent with the results of that study. They found no statistically significant relationship between government and rebel behavior.

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.

Both predicted U.S. foreign policy variables are statistically significant. The level is negative, while the change is positive. This implies that predicted weekly cooperative policy changes lead to more people fleeing to the U.S. 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 U.S. Hostile relations towards Haiti cause individuals to seek asylum in the U.S., while cooperative policies yield fewer asylum seekers. This finding is consistent with Shellman & Stewart (2006).

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.

To summarize the results, many of our predicted risk factors prove to predict U.S. Coast Guard interdiction counts. Many of the results are consistent with the large-n and small n systematic studies. Given the .73 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 flight. It models the causes and triggering events of flight and is able to anticipate weekly numbers of Haitians attempting to enter the U.S.

Conclusion

Our model performs well with respect to explaining and predicting U.S. Coast Guard interdictions at sea. We feel that this translates well to explaining and predicting migratory patterns from Haiti to the U.S. 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 such large-N models.

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. We urge interested parties, like the UNHCR, to publicly provide such data from camp registration records 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 us to model such processes in various cases.

As we have alluded, there is room for improvement in our model and we welcome any criticisms and comments that would improve its utility. We think the next step is to perform one step ahead out of sample forecasting, but before we undertake that effort, we would appreciate useful comments and criticisms on our baseline model.

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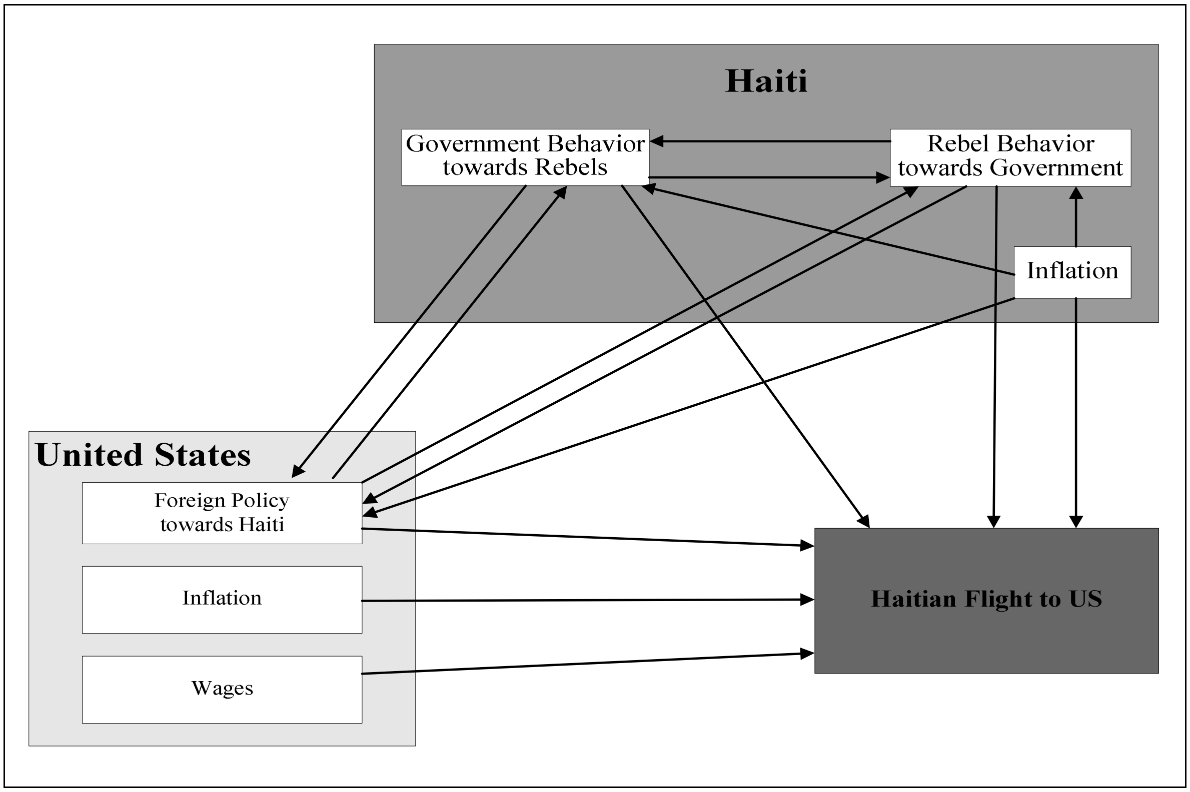

Figure 1 The Causal Model

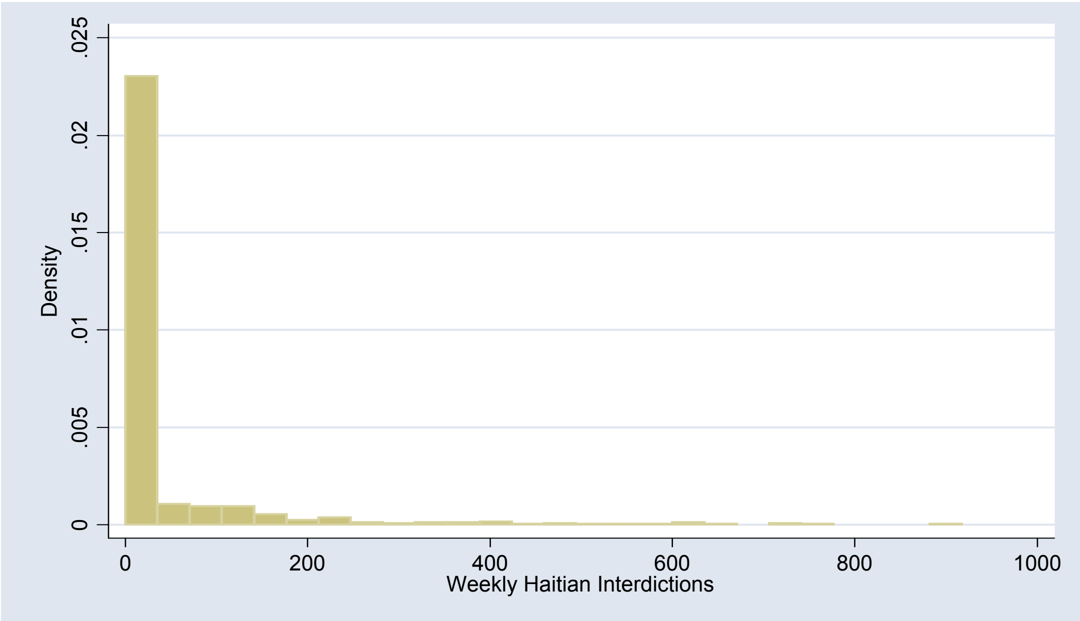

Figure 2 Histogram of Total Weekly Haitian Interdictions by US Coast Guard, 1990-2004

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
$\Delta USFP_{t-1}$	1.02e-09	2.64	-10	10
$USWAGE_{t-1}$	14.0	1.20	2.09	16.4
$\Delta USWAGE_{t-1}$	0.034	0.063	-0.110	0.200
$USCPI_{t-1}$	97.9	6.54	86.8	110
$\Delta USCPI_{t-1}$	.198	.241	-0.407	0.813
$HREB_{t-1}$	-0.709	2.59	-10	10
$\Delta HREB_{t-1}$	-0.004	3.44	-14.7	12.3
$HGOV_{t-1}$	-0.447	2.39	-10	10
$HGOV_{t-1}$	-0.011	3.38	-16	14.1
$HCPI_{t-1}$	138	61.9	65.5	258
$\Delta HCPI_{t-1}$	1.21	3.79	-20.1	17.6
haiti_usin~1	-0.019	130	-918	909
HCPI $Dummy_{t-1}$	.785	.411	0	1

Table 2 Haiti Security Models

	Changes (GECM)		Levels	
	$\Delta HGOV_t$	$\Delta HREB_t$	$HGOV_t$	$HREB_t$
Variable	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
$\Delta HGOV_t$	-	0.111*** (.048)	-	-
$HGOV_{t-1}$	-	-.779*** (.077)	-0.018 (.067)	0.056 (.050)
$HGOV^2_{t-1}$	-	-	-	0.022*** (.007)
$\Delta HREB_t$	0.096*** (.041)	-	-	--
$HREB_{t-1}$	-0.906*** (.080)	-	0.044 (.039)	0.126*** (.053)
$HREB^2_{t-1}$	-	-	0.007 (.005)	-
$HREB_{t-1} – HGOV_{t-1}$ (EC Term)	1.01*** (.069)	-0.885*** (.052)	-	-
$\Delta HCPI_{t-1}$	-0.036 (.028)	-.046* (.029)	-	-
$HCPI_{t-1}$	-	-	-0.006** (.003)	-0.002 (.002)
HCPI $Dummy_{t-1}$	0.249 (.287)	0.058 (.290)	-0.489 (.420)	-0.313 (.422)
$\Delta USFP_{t-1}$	-0.001 (.070)	-0.109** (.060)	-	-
$USFP_{t-1}$	-.121* (.089)	.080 (.088)	-0.119** (.069)	-0.033 (.067)
Constant	-0.517** (.256)	-0.579*** (.250)	0.679 (.672)	-0.096 (.694)
R^2	0.51	0.45	.02	.03
Correlation between Predicted & Actual values	0.72***	0.67***	.14***	.17***
N	463	463	464	464

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

Table 3 Haiti Economy Models

	Changes	Levels
	$\Delta HCPI_t$	$HCPI_t$
Variable	Coef. (SE)	Coef. (SE)
$\Delta HCPI_{t-1}$	0.882*** (.065)	-
$\Delta HCPI_{t-2}$	0.000 (1.0)	-
$\Delta HCPI_{t-3}$	-0.084** (.052)	-
CPI_{t-1}	-	0.989*** (.011)
CPI_{t-2}	-	-0.000 (1.0)
CPI_{t-3}	-	0.010*** (.004)
CPI $Dummy_{t-1}$	0.212 (.292)	2.284*** (1.18)
Constant	0.122 (.331)	-1.75*** (.734)
R^2	.72	.98
Correlation between Predicted & Actual values	.85***	.99***
N	462	462

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

Table 4 U.S. Foreign Policy Models

	Changes	Levels
	$\Delta USFP_t$	$USFP_t$
Variable	Coef. (SE)	Coef. (SE)
$\Delta USFP_{t-1}$	-0.451*** (.066)	-
$USFP_{t-1}$	-	0.050 (.046)
$\Delta HGOV_{t-1}$	0.042 (.041)	-
$HGOV_{t-1}$	-	0.059* (.039)
$\Delta HREB_{t-1}$	0.001 (.033)	-
$HREB_{t-1}$	-	-0.018 (.036)
$\Delta HCPI_{t-1}$	-0.019 (.036)	-
CPI_{t-1}	-	-0.000 (.002)
CPI $Dummy_{t-1}$	0.046 (.325)	0.080 (.352)
Constant	-0.006 (.275)	0.144 (.537)
R^2	.21	.01
Correlation between Predicted & Actual values	.45***	.10**
N	463	464

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

Table 5 U.S. Economy Models

	Changes		Levels	
	$\Delta USWAGE_t$	$\Delta USCPI_t$	$USWAGE_t$	$USCPI_t$
Variable	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
$\Delta USWAGE_{t-1}$	0.696*** (.050)	-	-	-
$\Delta USCPI_{t-1}$	-	0.819*** (.037)	-	-
$USWAGE_{t-1}$	-	-	1.00*** (.002)	-
$USCPI_{t-1}$	-	-	-	1.00*** (.001)
Constant	0.011** (.002)	0.036*** (.009)	0.009 (.035)	-0.015 (.171)
R^2	0.48	0.67	.99	.99
Correlation between Predicted & Actual values	0.69***	0.82***	.99***	.99***
N	467	467	468	468

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

Table 6 Zero Inflated Negative Binomial Estimates of Weekly Haitian Interdictions by US Coast Guard (1994-2004)

Category Variable	Count Coefficient (SE)	Inflate Coefficient (SE)
Haiti Security		
Predicted $\Delta HGOV_t$	-0.114* (.091)	-0.453*** (.184)
Predicted $HGOV_t$	-1.19** (.438)	-1.91** (.982)
Predicted $\Delta HREB_t$	-0.040 (.045)	0.186** (.091)
Predicted $HREB_t$	-0.355** (.194)	-0.243 (.474)
Haiti Economy		
Predicted $\Delta HCPI_t$	-0.005 (.057)	-0.020 (.049)
Predicted $HCPI_t$	-0.009* (.006)	-0.020** (.009)
Predicted HCPI Dummy 1996-2004	-1.30 (1.17)	-0.257 (1.10)
US Foreign Policy		
Predicted $\Delta USFP_t$	0.157** (.093)	-0.100 (.142)
Predicted $USFP_t$	-2.94** (1.56)	-6.60** (3.21)
United States Economy		
Predicted Δ USCPI	-1.01*** (.332)	1.32** (.663)
Predicted Δ USWAGE	0.871 (1.83)	4.37* (2.92)
Predicted USCPI	0.053 (.097)	0.457** (.218)
Predicted USWAGE	-0.067 (.618)	1.60 (1.44)
Network		
$HAITIINTERDICT_{t-1}$	0.005*** (.001)	-0.017*** (.006)
Constant	1.43 (2.62)	-45.1 (20.59)
N (zeros)	461 (311)	461 (311)
Model Fit		
Alpha (Poisson v. Negative Binomial)	.90***	
Wald Chi-Square	163.17	
Correlation between Predicted & Actual values	.73***	

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

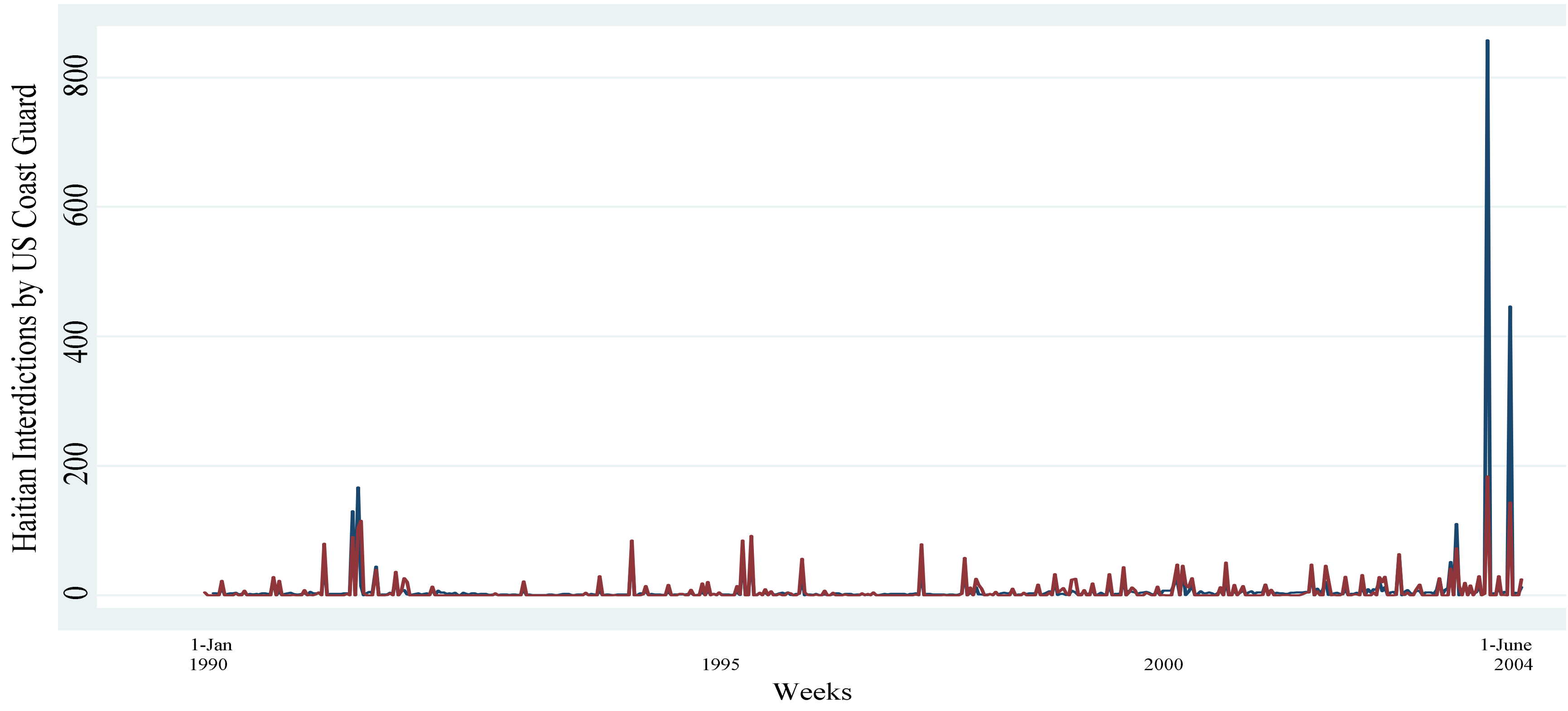

Figure 3 The Model-Predicted Values Versus the Actual Values