

Cluster-Based Early Warning Indicators for Political Change in the Contemporary Levant

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We use cluster analysis to develop a model of political change in the Levant as reflected in the World Event Interaction Survey coded event data generated from Reuters between 1979 and 1998. A new statistical algorithm that uses the correlation between dyadic behaviors at two times identifies clusters of political activity. The transition to a new cluster occurs when a point is closer in distance to subsequent points than to preceding ones. These clusters begin to "stretch" before breaking apart, which serves as an early warning indicator. The clusters correspond well with phases of political behavior identified a priori. A Monte Carlo analysis shows that the clustering and early warning measures are not random; they perform very differently in simulated data sets with similar statistical characteristics. Our study demonstrates that the statistical analysis of newswire reports can yield systematic early warning indicators, and it provides empirical support for the theoretical concept of distinct behavioral phases in political activity.

In recent years, early warning has emerged as a major concern of national and international agencies that respond to political crises (Boutros-Ghali 1994; Davies and Gurr 1998; Dedring 1994; Esty et al. 1995, 1998; Mizuno 1995; Schmeidl and Adelman 1998) and is a topic of renewed interest in the international relations literature (Gurr and Harff 1994, 1996; Rupesinghe and Kuroda 1992; Schmeidl 1996). The policy community has been inspired by the success of famine forecasting models that have enabled international agencies to reduce fatalities by several orders of magnitude over the past twenty years (Rashid 1998; Whelan 1998). Agencies such as the UN High Commissioner for Refugees and the UN Office for the Coordination of Humanitarian Affairs would like to have comparable models for predicting other catastrophic situations—notably, refugee flows—that require emergency humanitarian response. Academics have contributed to these efforts, as evidenced by the collaboration between operational agencies and university-based researchers in the State Failure Project (Esty et al. 1995, 1998) and the Forum for Early Warning and Emergency Response (<http://www.fewer.org>); academic scholarship also has been motivated by sobering assessments of the failure of traditional forecasting methods to anticipate the end of the Cold War (Gaddis 1992).

A central focus of event data research has long been the development of tools for the early warning of political change. Much of the initial impetus and, quite critically, early funding for that research came from the U.S. Defense Advanced Research Projects Agency (DARPA). These efforts, including the Early Warning and Monitoring System (EWAMS), were contempora-

neous with the creation of the World Event Interaction Survey (WEIS) and Conflict and Peace Data Bank (COPDAB) event coding frameworks as well as a variety of systematic forecasting techniques (see Andriole and Hopple 1984; Choucri and Robinson 1979; Daly and Andriole 1980; Hopple 1984; Hopple, Andriole, and Freedy 1984; Laurance 1990; Phillips and Rimkunas 1983; Singer and Wallace 1979).

For both institutional and pragmatic reasons, these initial efforts failed to take hold in the policy community (Laurance 1990). By the mid-1980s, interest in and funding for statistical early warning projects had virtually ceased. The policy community continued to spend billions on analytical forecasts by intelligence agencies, but virtually all *political* prediction—as distinct from projecting economic and demographic trends—used traditional rather than statistical techniques.

Because human-coded event data are expensive to generate, the end of policy-oriented event data research meant that new data collection activity declined dramatically, and the academic community was limited to reanalyzing legacy collections that terminated around 1977. The WEIS data set, which was the centerpiece of the DARPA efforts, was maintained through a variety of public and private efforts through the 1980s and 1990s (Tomlinson 1993), but it was not widely available or used. In addition, several small and geographically specific event data sets were created by scholars (e.g., Ashley 1980; van Wyk and Radloff 1993).

Ironically, the emphasis on event-based early warning research ended at a time when two technological changes rendered the approach more feasible. First, the revolution in electronic communications made available a much greater amount of news about political affairs than was used by previous analyses, which usually relied on a small number of elite Western newspapers. By the early 1990s, much of this information was in machine-readable form, initially through such commercial services as NEXIS and Reuters Business Briefing and now through the World Wide Web. Second, the exponential increase in computational power allowed for statistical and coding techniques that were impossible during the earlier period of DARPA research.

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We received valuable suggestions from Jon Pevehouse, from the "Beer and Politics Seminar" at the University of Kansas, and from the anonymous referees; Rajaa Abu-Jabr provided editorial assistance. This research was funded in part by the National Science Foundation through grant SBR-9410023 and by the University of Kansas General Research Fund grant 3500-X0-0038.

The purpose of this article is to describe several new approaches to early warning that use contemporary technologies and concepts. We begin with a review of the methodological challenges involved in statistical early warning research. We then apply two clustering methods, one based on the distances between points and the other on the changes in the density of the cluster, to an event data set that covers international behavior in the Levant (Egypt, Israel, Jordan, Lebanon, the Palestinians, and Syria) plus the United States and USSR/Russia between April 1979 and December 1998. The Levant has long been regarded as an important example of an international subsystem (Binder 1958; Gause 1999); the relatively large number of actors and varieties of behavior in the region provide for a robust test of any early warning techniques.

Our analyses indicate that events tend to form temporally delineated clusters, and the movement of points in those clusters can be used as an early warning indicator; this finding is consistent with the theories of "crisis phase" that underlie many qualitative approaches to early warning. The clusters we identify generally correspond to demarcations in the time series that we assigned a priori, based on a qualitative assessment of political changes in the region, and differ significantly from clusters found in a set of simulated data with similar statistical characteristics.

STATISTICAL APPROACHES TO EARLY WARNING: A REVIEW

There are some key differences between structural and dynamic models as applied to the early warning problem. We will discuss these and describe the dynamic time-series approach used in our research.

Structural and Dynamic Models

Statistical approaches to early warning can be classified into two broad categories: structural and dynamic.¹ The first category includes studies that use events (or more typically, a specific category of events, such as civil or international war) as dependent variables and explain these using a large number of exogenous independent variables. In the domain of domestic instability, this approach is exemplified by the work of Gurr and his associates, most recently in the State Failure Project (SFP; Esty et al. 1995, 1998). Gurr and Harff (1996) and Gurr and Lichbach (1986) describe a number of such research projects. In the field of international instability, the structural approach is illustrated by the work of Bueno de Mesquita and by the Correlates of War project; Gochman and Sabrosky (1990), Midlarsky (2000), and Wayman and Diehl (1994) provide general surveys. Structural approaches have tended to employ multivariate linear regression

¹ We will not consider the large literature on nonstatistical or qualitative approaches to forecasting, contemporary surveys of which can be found in Davies and Gurr 1998, Rupasinghe and Kuroda 1992, and Schmeidl and Adelman (1998). We also will not deal with long-range forecasting using computer simulation; Ward (1985) and Hughes (1999) summarize that literature.

models but recently have branched out to other techniques; for example, the SFP uses logistic regression, neural networks, and some elementary time-series methods.

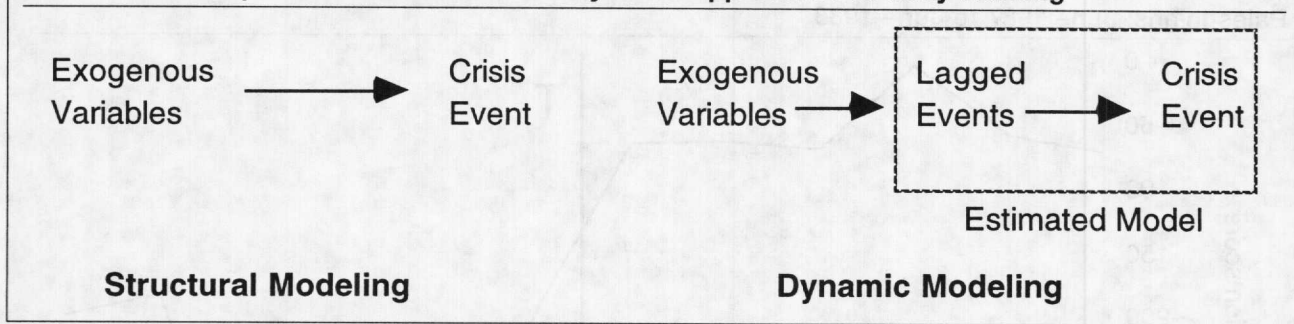
In contrast, dynamic early warning models use event data measures as both the independent and dependent variables. Most projects in the late 1970s employed event-based indicators in dynamic models to predict whether a pair of political actors would become involved in a crisis. For instance, DARPA's EWAMS research evaluated three WEIS-based measures (conflict, tension, and uncertainty) to determine the "alert status" of any dyad. Azar et al. (1977) took a similar approach based on whether behaviors measured with the COPDAB event scale fell outside a range of "normal" interactions for the dyad. More recent efforts have used increasingly advanced econometric time-series methods that model interval-level indicators of events as an autoregressive time series with disturbances. Goldstein and Freeman (1990) provide a book-length example of this approach; Dixon (1986), Goldstein and Pevehouse (1997), Goldstein et al. (2000), Lebovic (1994), Ward (1982), and Ward and Rajmaira (1992) illustrate the continued development of this type of dynamic model.

Scholars defend the dynamic approach, which is at odds with most political science statistical modeling in using only lagged endogenous variables, in three ways. According to the first rationale, many of the structural attributes that are theoretically important for determining the likelihood of conflict do not change quickly enough to be used as early warning indicators; in fact, many are virtually static (e.g., ethnic and linguistic heterogeneity, historical frequency of conflict, natural resource base). Data on variables that do change, such as unemployment rates and economic and population growth rates, are often reported only on an annual basis, and the quality of these reports tends to be low in areas under political stress.

The second argument for the dynamic approach is that it allows for greater parsimony in the specification of the forecasting models than a structural approach. The first phase of SFP, for example, collected data on 75 independent variables (Esty et al. 1995, 9), but the final models found that most of the forecasting power resided in only three variables: infant mortality, trade openness, and democracy (Esty et al. 1998, viii).² In contrast, the event data collections used in dynamic models allow the researcher to monitor political interactions as reported in public media sources. The focus on events leads to models that contain a relatively small number of independent variables, and the reliance on news sources permits the data to be collected systematically in real time.

Finally, a dynamic modeling approach assumes that the exogenous variables incorporated in the structural models do not need to be explicitly included because their effects will be reflected in the pattern of events preceding a major change in the political system. In

² Phase II of the SFP involves some limited analysis of dynamic variables and suggests expanding this approach in future studies.

FIGURE 1. Comparison of Structural and Dynamic Approaches to Early Warning

other words, the dynamic approach uses the lagged values of actual events as a substitute for structural variables, as illustrated in Figure 1.

To take a concrete illustration, Gurr (1995, 7) notes that "ethnic heterogeneity probably is most significant for state failure when it coincides with lack of democracy and low regime durability." Consequently, the SFP includes measures for those three variables: ethnolinguistic diversity, regime democracy, and regime durability. A dynamic approach, in contrast, does not measure these aspects of a political system directly; instead, it assumes that each is reflected in the types of events picked up by the international news media. The presence of democracy, for instance, appears not only in periodic reports of elections but also in a large number of reports discussing disagreements between the government and the elected opposition. A low level of regime durability results in coups and attempted coups. To the extent that ethnicity is an important political factor, there will be ethnically oriented political rallies, outbreaks of violent ethnic conflict, and similar events. A suitably designed event coding scheme should detect the presence or absence of these events and make the appropriate forecast without directly measuring the underlying variables.

At a theoretical level, therefore, dynamic modelers accept the importance of exogenous structural indicators. *Ceteris paribus*, countries with a high level of ethnic heterogeneity will have a greater propensity for conflict than those with a low level, democracies are likely to be different from autocracies, and so forth. The distinction between the two early warning strategies is one of measurement. Structural modeling seeks to identify and measure the indicators directly, whereas the dynamic approach assumes the effects of structural attributes are indirectly incorporated through the patterns of events they generate.

This is an optimistic but not wholly implausible assumption. For instance, in the Reuters-based domestic data with which we have been working, there is a clear contrast between Israel and Syria with respect to the presence of a democratic opposition. Similarly, ethnoreligious conflict in Lebanon is one of the most conspicuous features of the data set and is in sharp contrast to the relative lack of salience of such conflict in Jordan. Our argument is that an increase in democratization in Syria or a decline in ethnoreligious tensions in Lebanon will be reflected in the political events

reported in Reuters, although we have not analyzed this systematically.

An econometric analogy to the distinction between structural and dynamic political early warning is found in the differences between "technical" and "fundamental" approaches to the analysis of stock prices. A fundamental analysis attempts to predict price changes on the basis of underlying factors, such as marketing, management, raw material prices, and macroeconomic trends. A technical approach assumes that these factors will be reflected in changing stock prices; therefore, analysis of patterns in the movement of those prices will provide sufficient information for forecasting. Fundamental analysis corresponds to the structural approach to modeling political events; technical analysis to the dynamic.³

Statistical Characteristics of the Early Warning Problem

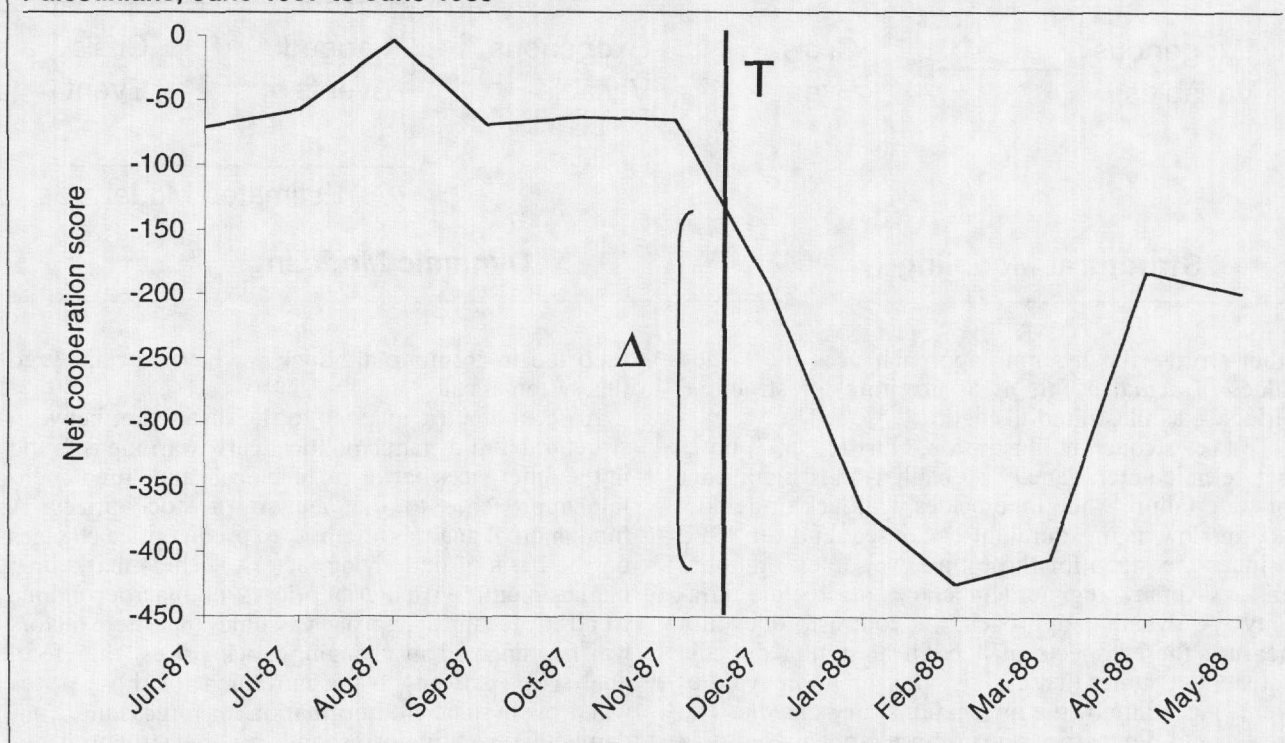
The primary goal of time series is to determine the future values of a variable y , given some present and past values of that variable and possibly the present and past values of a set of exogenous variables X . In other words, time-series analysis seeks to determine a function

$$y_{t+k} = f(y_t, y_{t-1}, \dots, X_t, X_{t-1}, \dots)$$

for some $k > 0$. Due to the importance (and potential financial rewards) of accurate economic forecasts, there is a massive literature on time-series estimation in econometrics (see Hamilton 1994). Standard econometric time-series methods, however, have only limited utility in the problem of early warning, for which the challenge is to identify a time T such that some indicator variable y_t has values consistently different

³ Until relatively recently, technical stock market analysis generally had a bad reputation, due to its use of statistically dubious patterns based on small samples, wishful thinking, and gurus whose fortunes derived more from the sale of books than from trading stock. With the increase in computing power in the 1980s, the situation changed, and "programmed trading systems" can now process sufficiently large amounts of information to generate profits working solely with information endogenous to the market itself. The greater information processing capacity today, in contrast to that available in the 1970s, may have a similar effect on the analysis of political behavior using event data.

FIGURE 2. Example of a Shift in a Time Series at Time T: Israeli Net Cooperation Directed to Palestinians, June 1987 to June 1988



(above a predetermined threshold Δ) after time T than before time T :

$$|y_t - y_{t'}| > \Delta, \text{ for all } t > T > t'.$$

This is what would occur in aggregated event data following a shift in the type of political behavior in which a dyad is engaged. Figure 2 illustrates this situation for the transition in Israeli-Palestinian interactions that occurred with the outbreak of the Palestinian *intifada* in December 1987.

An additional distinction between early warning research and conventional econometric time-series methods relates to the amount of autoregression in the data. Econometric time series tend to be highly autoregressive: The value at time t is usually close to (or a simple function of) the value at time $t - 1$. Examples of autoregressive series include unemployment figures, prices of consumer goods, and inflation rates. Even series that are potentially less stable, such as stock prices, usually have an autoregressive component combined with generally random noise. For instance, the stock market crash of October 1929 was sudden, whereas the high unemployment rates of the Great Depression required two or three years to develop fully.

Dynamic early warning models, in contrast, focus on the shifts in a time series that are not autoregressive, even though the series taken as a whole may be autoregressive. An autoregressive model of war and peace will be very accurate, as illustrated by the presumably apocryphal story about the European political analyst who said: "Every day from 1910 to 1970,

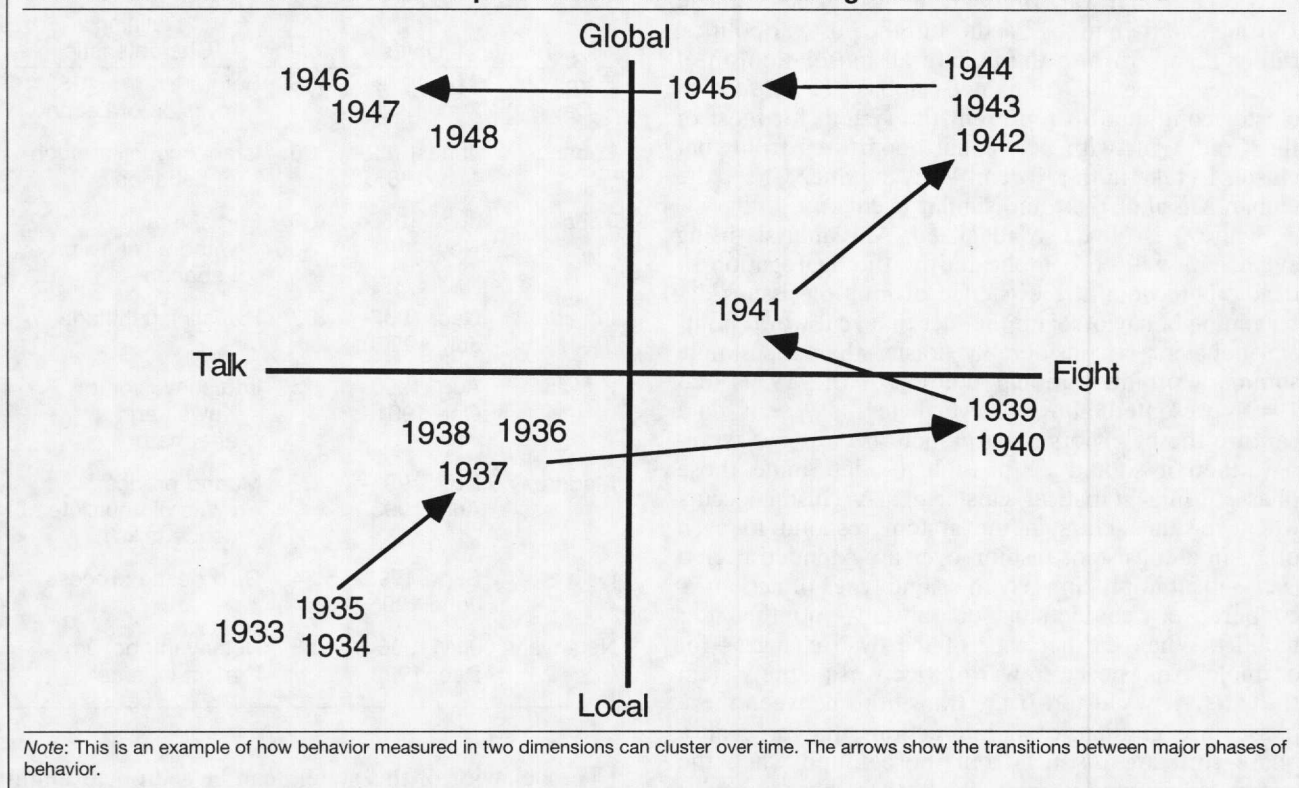
I predicted that Europe would remain at peace when at peace, and remain at war when at war, and I was only wrong four times." This type of model is not, however, very useful. It succeeds according to a frequency-based measure but fails according to an entropy-based measure that places higher weight on the prediction of low-probability events (Pierce 1980).

The econometric question most comparable to political early warning is the forecasting of sudden economic shifts, such as those observed in massive exchange rate fluctuations (e.g., the collapse of the Mexican peso or the European Exchange Rate Mechanism). These problems are similar to political early warning in that they are primarily psychological and do not reflect a major change in the underlying physical reality: The economic fundamentals of the Mexican or European economies did not change dramatically during the days of the exchange rate crises, but the perceptions of the future values of the relevant currencies did shift.

Despite these complications, it should be noted that in two very important respects prediction is an easier problem than the typical econometric estimation problem. First, the accuracy of forecasting models can be evaluated probabilistically. Coefficient estimation problems, in contrast, do not have answers: One can always specify an error structure, prior probability, or alternative model that places the estimated emphasis on different variables, and there is no empirical method of deciding among these specifications.

Second, and closely related to the first issue, forecasting problems are not affected by colinearity, which

FIGURE 3. Informal Schematic Representation of Phases during the World War II Period



is the bane of coefficient estimation in the social sciences because every behavior tends to be linked to every other behavior. Coefficient estimates with low standard errors are clearly useful for obtaining a theoretical understanding of a situation, but they are not essential for the pragmatic purposes of forecasting (Wonnacott and Wonnacott 1979, 81). For this reason, it is not surprising that models with very diffuse coefficient structures that do not clearly identify the importance of specific variables—such as neural networks, hidden Markov models, and vector autoregression (VAR)—are found increasingly in early warning research.

CRISIS PHASE AND PREDICTION

The concept of crisis phase is found frequently in the early warning and preventive diplomacy literatures; recent discussions include Alker, Gurr, and Rupe-singhe (n.d.), Carnegie Commission for Preventing Deadly Conflict (1997), Gurr and Harff (1994), and Lund (1996). In the empirical literature, crisis phase has been coded explicitly in collections such as the Butterworth international dispute resolution data set (Butterworth 1976), Bloomfield and Moulton's (1989, 1997) Computer-Aided System for Analyzing Conflicts (CASCON; <http://web.mit.edu/cascon/>), and SHERFACS (<http://www.usc.edu/dept/ancnr/Paris-in-LA/Database/Sherfacs.html>), developed by Frank Sherman. In a review of these collections, Sherman and Neack (1993, 90) explain:

Conflict is seen "as a sequence of phases." Movement from phase to phase in a conflict occurs as "the factors interact in such a way as to push the conflict ultimately across a series of *thresholds* toward or away from violence" (Bloomfield and Leiss 1969). Characteristics of disputes can be visualized as the timing and sequencing of movement between and among phases. Processes of escalation of violence, resolution or amelioration of the seriousness (threat of violence-hostilities) and settlement are identifiable through the use of phase structures.

CASCON and SHERFACS, for instance, both code six phases: dispute, conflict, hostilities, post-hostilities conflict, post-hostilities dispute, and settlement. A close analog is found in the DARPA-sponsored work of Phillips and Rimkunas (1983, 181–213), which analyzes WEIS data in a two-dimensional space of threat and uncertainty using Thom's (1975) cusp catastrophe model. Their study successfully locates eight of eighteen crises identified in the WEIS data and produces no false positives.

If the concept of crisis phase is valid, then the international behaviors observed should fall into distinct patterns over time. Figure 3 illustrates this informally for the World War II period, using the two dimensions of talking versus fighting and local versus global involvement. Politics in the years immediately before 1936 were predominantly local and involved little violent interstate conflict. The system shifted to a series of militarized crises between 1936 and 1938, then erupted into a full-scale European war in 1939. After a lull in early 1941, the war spread, first to the USSR and

then to the Pacific; the 1942–44 period was differentiated by a global war. In 1945 this war ended, first in Europe and then in the Pacific, but the postwar politics, rather than return to the unilateralism/isolationism of the prewar period, remained global. The 1946–48 cluster continued to represent the system for most of the Cold War, with occasional departures from that cluster to take in the Korean War, the Suez Crisis, the Cuban Missile Crisis, and similar events.

Figure 3 is obviously idealized. Any analysis using event data will be complicated by the aggregation of dyadic behaviors, the existence of multiple issues determining behaviors, and the fact that real-world political behavior is considerably noisier than the simple summary of international politics in the 1930s and 1940s presented above. Nevertheless, if event data capture the behaviors that characterize a phase typology, then it should be possible to determine those phases using statistical clustering. A cluster occurs whenever the actors in the system respond to each other in a consistent fashion over an extended period (i.e., repeat approximately the same types of actions—cooperative, conflictual, or absent—month after month). When the behavior of the dyad changes—for example, from peace to war or vice versa—the system shifts to a new cluster. If the transitions between these phases are gradual, or if interactions that precede a phase shift are distinct from those found when the system is locked in a single phase, then those behavior patterns can be used for early warning of the transition.

A Cluster-Based Approach to Early Warning

To test whether behavioral phase shifts can be used to develop early warning indicators, we analyzed the dyadic behavior of the international actors in the Levant between April 1979 and December 1998. The data were Reuters lead sentences, obtained from the NEXIS and Reuters Business Briefing data services. We coded these leads into WEIS categories using the Kansas Event Data System (KEDS) machine-coding program (Gerner et al. 1994; Schrodt, Davis, and Weddle 1994). We then transformed the individual WEIS-coded events into a monthly net cooperation score for each directed dyad—the actions from a specific source to a specific target—by converting every event to an intensity score, using the numerical scale in Goldstein (1992), and then totaling these numerical values for each of the directed dyads for each month. We examined all the dyads involving interactions among Egypt, Israel, Jordan, Lebanon, the Palestinians, Syria, the United States, and the Soviet Union/Russia; this gives a total of 56 directed dyads, with 237 monthly totals in each dyad.⁴ Appendix A contains additional details on coding and measurement.

⁴ We repeated some of our analyses without the USA→USSR and USSR→USA dyads; this change generated only minor differences in the results. (The events involving these dyads include only the USA-USSR interactions reported in the lead sentences of Reuters stories dealing with the Levant, not USA-USSR interactions in general.)

TABLE 1. A Priori Phase Assignments

Label	Dates	Months	Defining Characteristic
Camp David	Apr. 1979– May 1982	38	Before Israel's 1982 invasion of Lebanon
Lebanon	June 1982– May 1985	36	Israel occupies much of Lebanon
Taba	June 1985– Nov. 1987	30	Partial Israeli withdrawal from Lebanon
Intifada	Dec. 1987– July 1990	32	Palestinian intifada
Kuwait	Aug. 1990– Oct. 1991	15	Iraq's invasion of Kuwait and aftermath
Madrid	Nov. 1991– Aug. 1993	22	Madrid process: bilateral, multilateral peace talks
Oslo	Sept. 1993– June 1996	34	Oslo peace process
Netanyahu	July 1996– Dec. 1998	30	Netanyahu government in Israel

The behavior of this system can be seen by examining the position of the vector

[AB, AC, AD, ..., AH, BA, BC, ..., BH, CA, ..., HF, HG],

where A, B, ..., H are the actors in the system, and each pair of letters represents the total Goldstein-scaled net cooperation for a directed dyad aggregated over one month. The behavior of the system is simply the path that this vector traces over time in a high-dimensional space. In vector terminology, a phase is characterized by a region in the vector space where points cluster over time. If political behavior follows a phase typology, this would be evident by long periods of distinct clusters of behaviors that characterize a phase, with brief transitions between the clusters.

The benchmark for our empirical tests is a set of phases established a priori, based on the dominant political interactions during each period. These phases, shown in Table 1, correspond to the interpretations of "area experts" and are consistent with our own fieldwork in the region. Our discussion will use these a priori clusters as a reference point.

The effectiveness of event-space clustering in early warning depends on whether some measurable characteristic of system behavior changes before the phase transition. In some instances there are few if any precursors to a transition, either because of deliberate concealment by political actors or due to the lack of media interest, as in the examples of Chechnya and Somalia.⁵ Our conjecture is that most political situa-

⁵ On the surface, the Rwanda genocide appears to be an ideal case of absent precursors. Yet, in assessing that situation, Ruso (1996) observes that the appropriate facts were available (but incorrectly interpreted) as early as the UN Rapporteur's Report in 1993

tions, however, go through a gradual deterioration (or improvement) over a period of a few weeks or months before a phase transition, rather than manifest a sharp jump. Furthermore, because news-gathering organizations are usually rewarded for correctly anticipating political events, journalists who are present in the region, understand the local politics, and can get their stories accepted by editors and onto the news wires are likely to report the behaviors they perceive to be precursors to any political phase change.

This approach to early warning is similar to the concept of normal relations range proposed by Azar (1972, 184) nearly 30 years ago:

Over a period of time any two nations establish between them an interaction range which they perceive as "normal." This normal relations range (NRR) is an interaction range . . . which tends to incorporate most of the signals exchanged between that pair and is bound[ed] by two critical thresholds—an upper threshold and a lower threshold. The upper critical threshold is that level of hostility above which signals exhibited by either member of the interacting dyad are regarded as unacceptable to the other. Interaction above the present upper critical threshold . . . for more than a very short time implies that a crisis situation has set in.

The NRR model implies that interactions will cluster, with the diameter of the cluster a function of the upper critical threshold. Consistent with Azar's treatment, we expect that when the system is near the edge of a behavioral cluster, it is in a crisis situation. That crisis will either result in a shift to a new cluster—a phase transition—or be resolved without a transition, in which case the system's interactions will return to the core of the cluster. Unlike Azar, we assume the system is moving away from normal behavior when it consistently nears (or passes) the edge of a behavioral cluster, rather than when it exceeds a single critical threshold. We have generalized Azar's NRR concept by looking at changes in a large number of dyads simultaneously (whereas Azar looked only at one dyad at a time), and we use a standardized metric based on correlation, whereas Azar used a Euclidean metric and established distinct critical ranges for each dyad. Finally, we also look at the density of clusters, defined as the average distance between the points in a cluster, over time. Behavior within the NRR should result in dense clusters, but when a system moves away from one phase/cluster/NRR and into another, there will generally be a period when the points do not cluster densely.

Detection of Phase Using Clustering over Time

Most widely used clustering algorithms are cross-sectional and do not incorporate the time-series element

(Degni-Ségué 1994). Ruso (1996, 8) concludes: "The authors answer Yes to the question, Did those with the capacity to prevent and mitigate the genocide have the information from which such a conclusion might be drawn? In fact, they note that specific information about plans and conspiracies towards this end was picked up by the UN system, most significantly in the notorious Black File of January 1994."

of event data (see Aldenderfer and Blashfield 1984; Bailey 1994; Everitt 1980). A cross-sectional method will not necessarily produce credible time-series clusters. Because the Levantine subsystem as we have defined it does not include all relevant interactions, such as the end of the Cold War, points that are distant in time may still bear a superficial resemblance.

Including time as the dominant dimension simplifies the delineation of clusters. The algorithm we employ in this study is uncomplicated: A new cluster is established at a point x_t when the distance between x_t and the points before it is greater than the distance between x_t and the points after it. This can be expressed in the equation

$$LML_t = \frac{1}{k} \sum_{i=1}^k \|x_t - x_{t-k}\| - \frac{1}{k} \sum_{i=1}^k \|x_t - x_{t+k}\| > \Delta.$$

LML is the lagged distance minus leading distance; x_t is the Goldstein-scaled net cooperation score for month t ;

$$\|x_t - x_{t\pm k}\|$$

is the distance between x_t and $x_{t\pm k}$ according to some metric; and Δ is a threshold parameter that prevents new clusters from being formed because of random fluctuations in the event data that are unrelated to phase transitions.⁶ (A large negative value of LML_t means that the point is still firmly in the current cluster, that is, much closer to points in the past than to points in the future. When the LML_t value is strongly positive, it indicates the point is far away from past points and close to future points.) From the perspective of cluster analysis, this approach is similar to the minimum spanning tree approach (see Backer 1995, chap. 1) in dividing the clusters at places where a large gap is found between adjacent points; it differs in using the dimension of time rather than a graph to determine which points are adjacent.

In our analysis, k is measured in months, although in principle it could represent some other interval, such as weeks or even days. The threshold Δ is a free parameter whose value depends on the level of differentiation the analyst wants between the clusters (and the characteristics of the data being used to measure the political activity). For example, if Δ were set to a very high value, such as 0.8, then we would see only two clusters in the data: pre-Oslo and post-Oslo. If it were set to a low value, such as 0.15, then we would find several additional subclusters within the a priori clusters specified in Table 1.

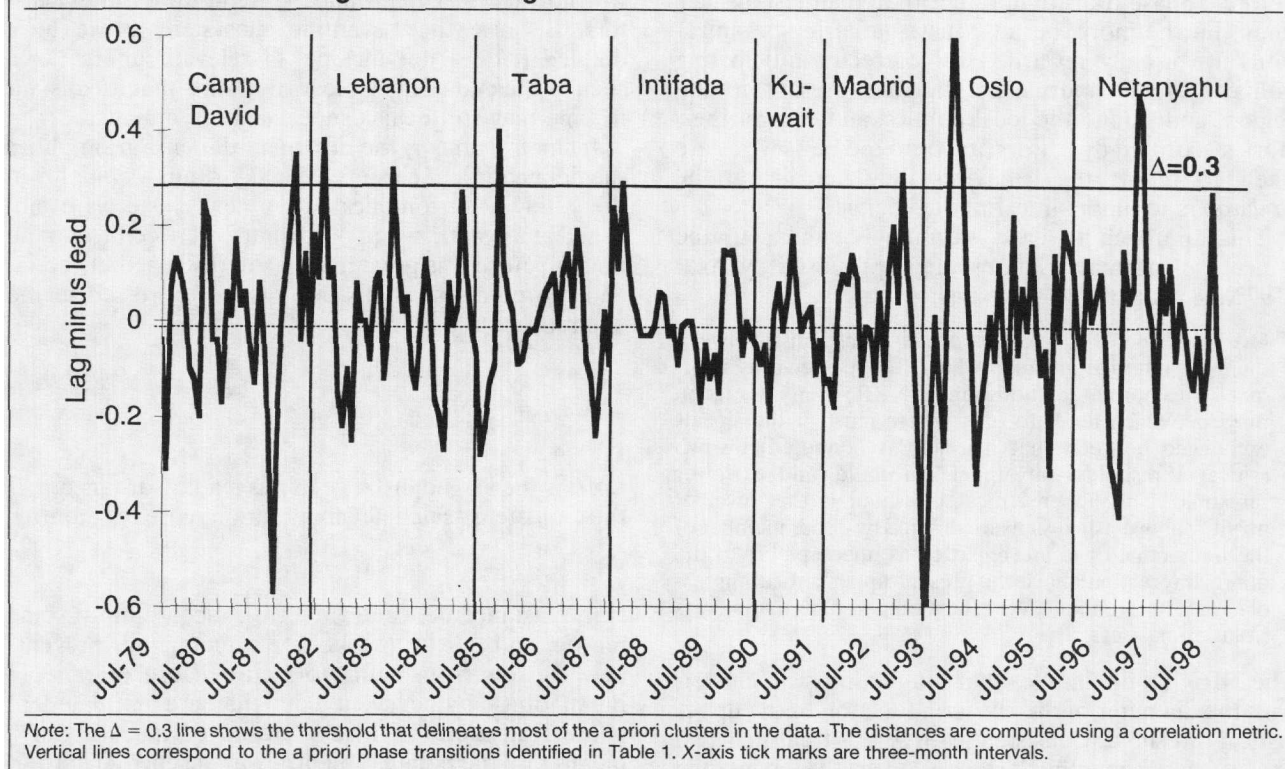
Figure 4 shows the results of analyzing the Levant data set using this algorithm for $k = 4$ and the correlation metric

$$\|x_t - y_t\| = 1 - r_{xy},$$

where r is the Pearson product moment. (In other words, this metric is based on the correlation between

⁶ These calculations were done with a simple (600-line) Pascal program that produced various tab-delimited files that were read into Excel to produce the figures.

FIGURE 4. Four-Month Lag Minus Lead Measure of the Difference in the Distance of a Data Point to Points Preceding and Following It



the Goldstein-scaled scores of the 56 dyads at two times.) The vertical lines on the graph correspond to time points where the a priori cluster divisions from Table 1 are located.

A cluster division occurs when $LML_t > \Delta$. With the threshold level set at $\Delta = 0.30$, the LML measure, by increasing sharply at or very close to the demarcation lines, correctly identifies four of the seven phases determined a priori: Lebanon, Taba, Intifada, and Oslo. Several other plausible transitions are suggested by peaks that do not correspond to the original phases: (1) a pre-Lebanon change, probably reflecting increased tension between Israel and the PLO in 1981; (2) two pre-Taba changes that may correspond to shifts in Israeli, Syrian, and U.S. policy in Lebanon (including extensive diplomatic activity related to the May 17, 1983, agreement and its subsequent abrogation); and (3) a transition in January 1993 that may reflect the change in U.S. policy toward the Middle East that occurred with the shift from the Bush to Clinton administrations. Finally, the analysis identifies March 1997 as the end of the Oslo period. This is reasonable. Although the Netanyahu government came to power in the June–July 1996 period, it was nominally committed to continuing the Oslo peace process initially, and the observed nine-month delay before the end of that process, while unanticipated, is in retrospect unremarkable.

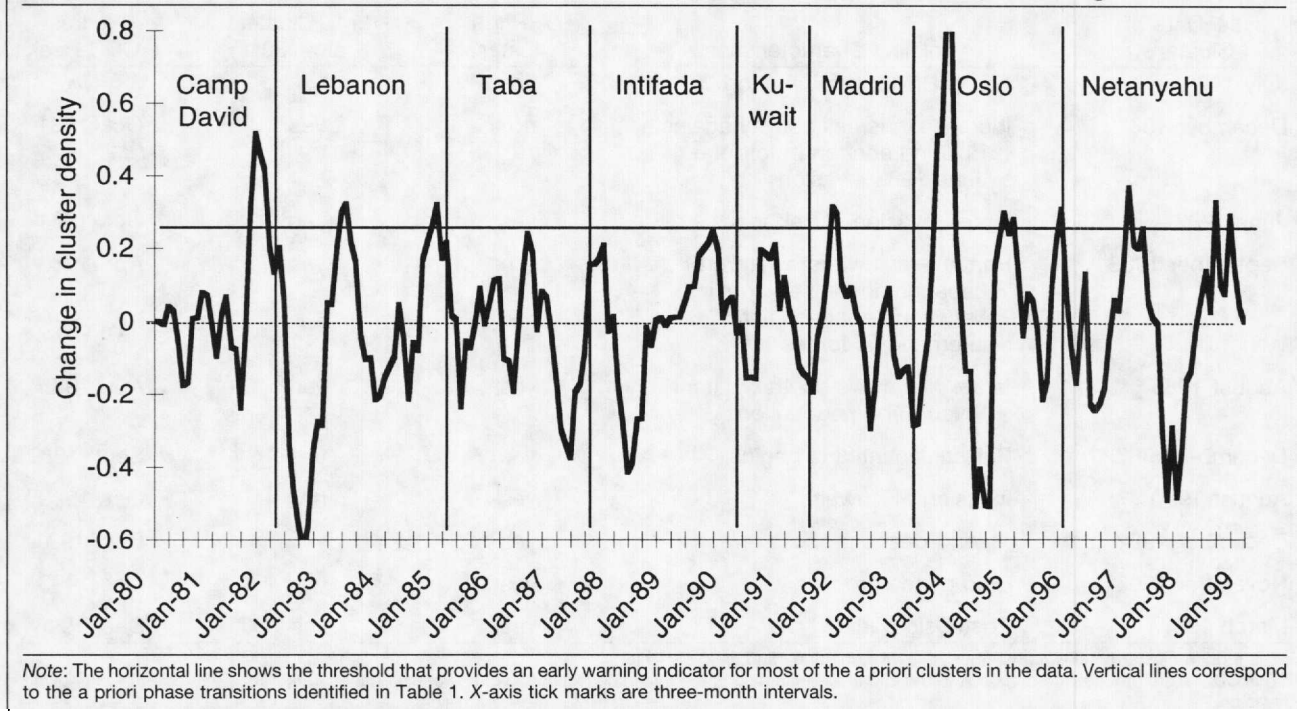
Our LML measure misses two previously chosen transitions: the Kuwait war and the Madrid phase. Including the Kuwait transition as an a priori phase was probably an error. Although Iraq's invasion of the

emirate and the subsequent war had profound implications for the Levant, the initial interactions that characterize this period occurred among actors outside the group we are studying, so it is not surprising that the data do not reflect it. It is less obvious why we fail to identify the Madrid transition. This failure might also be a side-effect of the Kuwait invasion. Much behavior during late 1990 and 1991 was due to circumstances outside the Levant, so the very real shift in politics that accompanied the Madrid process may have been less apparent in the data than were the other transitions.

Change in Cluster Density as an Early Warning Indicator

The LML measure cannot be used for early warning. It requires information from both before and after a phase transition, so it can only be used to delineate clusters of behavior retrospectively. Consequently, in order to develop an early warning indicator, some alternative measure is required. An examination of Figure 4 shows that the LML measure often begins a rapid increase several months before a phase transition. This is consistent with the underlying theory: The changing interactions in the system cause the points to pull away from the cluster center before a final break, rather like what happens when pulling on a piece of taffy. This pattern suggests that a decrease in cluster density—the extent to which the points within the cluster are close—may serve as an early warning. Since a change in cluster density can be determined solely on

FIGURE 5. Eight-Month Change in Four-Month Cluster Density as an Early Warning Indicator



the basis of information available up to and including time t , it can be identified prospectively.

Figure 5 shows the behavior of the cluster density change (CDC) measure. The measure is calculated by first computing the average total distance between the points in a cluster of four consecutive months,

$$CD_t = \frac{1}{6} \sum_{i=0}^3 \sum_{j=i+1}^3 \|x_{t-i} - x_{t-j}\|,$$

and then calculating the difference between CD_t at points that are eight months apart:⁷

$$CDC_t = CD_t - CD_{t-8}.$$

The CDC measure generally corresponds well with both the a priori phases and LML-identified transitions, despite the fact that the LML clusters were based on post-hoc information. At each point where the CDC exceeds a threshold set at one standard deviation (0.23), there is a corresponding LML cluster transition within 1–10 months of the point, as seen in Table 2. Unlike the LML measure, the CDC analysis does identify the Madrid transition—it exceeds the 0.23 level in November 1991 ($x_t = 0.24$) and December

1991 ($x_t = 0.27$)—but still fails to show the Kuwait transition. A peak in the CDC measure in October 1989 ($x_t = 0.24$) probably corresponds to the decline of reports of activity in the Palestinian intifada (Gerner and Schrodt 1998); the peaks in early 1995 and 1996 may reflect changes associated with the problems encountered in the Oslo peace process before the cluster break identified in March 1997.

The CDC measure is continuous and can be interpreted as proportional to the probability that a major change will occur; most of the event data models developed in the 1970s provided only a yes/no prediction of change. From the perspective of early warning analysis, the disadvantage of CDC is that it indicates only that some sort of systemic shift is pending; it tells nothing about what form that change will take. Furthermore, the phases determined by CDC do not necessarily correspond to the overt military-political changes that one might wish to forecast with an early warning system.

This is most conspicuously the case for Lebanon in 1981–82. According to the CDC measure, the system shifted into the Lebanon phase about a year before the Israeli invasion in June 1982. At the time of the actual invasion, the CDC measure is at one of the lowest points seen in the entire time series. On the one hand, the Israeli policies that culminated in the invasion were put into effect long before, so placing the true phase shift in mid-1981 is politically plausible. It is widely accepted that Israel planned the invasion of Lebanon as much as a year in advance, and then engaged in provocative military maneuvers throughout the first half of 1982 in an effort to goad the Palestinians into a

⁷ There are six possible comparisons within a cluster of four months: x_t to x_{t-1} , x_t to x_{t-2} , through x_{t-2} to x_{t-3} . Therefore, the divisor six is used to compute the average. The lag of eight months was established empirically. In other regions of the world it may be shorter or longer, depending on the time required for political decisions to be made. The choice of eight months is not critical. Because the CDC calculation involves data from two periods of four consecutive months, values of CDC_t at lags one or two months shorter or longer than the eight-month lag employed here will be strongly correlated with the eight-month value.

TABLE 2. Clusters Determined by the Analysis

Initial Date of Cluster	Political Characteristics	A Priori Cluster?	LML Cluster $\Delta > .30$	Nearest CDC Peak
July 1979	Camp David; pre-Lebanon	yes	NA	NA
December 1981	Increase in Israeli activity against PLO in Lebanon before the June 1982 invasion	no	yes	Oct. 1981
June 1982	Israeli invasion of Lebanon	yes	yes	Oct. 1981
September 1983	Partial Israeli withdrawal from Lebanon; increased conflict between Lebanese and international forces	no	yes	Apr. 1983
August 1985	Israel withdraws south of Litani River; Taba negotiations	yes ^a	yes	Apr. 1985
December 1987	Palestinian intifada begins	yes	yes	Sept. 1987
August 1990	Invasion of Kuwait	yes	no	Oct. 1989 ^b
December 1992	Madrid peace process	yes ^c	yes	Dec. 1991
November 1993	Oslo peace process	yes	yes	Oct. 1993
March 1997	Post-Oslo period	yes ^d	yes	Dec. 1996

^aThe a priori cluster break was two months earlier, in June 1985.

^bThis CDC score probably corresponds to the end of the intifada and the Syrian consolidation of power in Lebanon, rather than a forecast of the Kuwait invasion.

^cThe a priori cluster break was almost a year earlier, in November 1991.

^dA break at some point during the Netanyahu government period was anticipated; the exact timing was not.

response that would justify armed intervention (Gerner 1994; Hiro 1992; Jansen 1982; Morris 1999, chap. 11; Petran 1987; Randel 1983; Reilly 1983). On the other hand, the situation on the ground looked very different in July 1982 than in April 1982, a period during which the CDC measure plummeted. This is clearly not a "barometric" early warning that allows a political analyst to say: "The CDC indicators are real low this month, nothing to worry about." This may be because CDC is based on a correlation distance and is sensitive to changes in policy configurations—who is coordinating policy with whom—rather than to the direction of change. Using CDC as an early warning in combination with a Euclidean measure sensitive to the direction of change might provide both types of information.

Our research generally supports the crisis phase model, but the measures are somewhat ad hoc. How do we know our findings are not simply a statistical artifact, reflecting a combination of chance and self-deception? In Appendix B we compare our results to those obtained with a randomly generated simulated data set that has the same mean, variance, and autocorrelation as the observed data. The Monte Carlo analysis of the LML and CDC measures found that these two indicators behave quite differently in the randomly generated simulated data sets and in the observed data. This suggests our results are due to actual political characteristics in the region and are not simply an artifact of the clustering methods.

SUMMARY OF FINDINGS

Table 2 summarizes the empirically determined clusters in Levantine political behavior for the period studied. For the most part, these divisions correspond to the a priori clusters; when they do not, the differences are plausible. The LML cluster analysis identifies two phases that were not part of the a priori set. The first is an increase in tension between Israel and the Palestinians before the Lebanon invasion; the second is a postinvasion, pre-Taba period that corresponds to continuing instability and the Israeli withdrawal from the area around Beirut. The end of the Oslo phase occurs about nine months into the Netanyahu administration; we did not anticipate this particular date, but it is quite plausible.⁸ The CDC measure—although not the LML cluster analysis—indicates significant changes following the Oslo phase. Based on CDC, we might also have designated a postintifada, pre-Madrid cluster beginning in late 1989. All our analyses missed the Kuwait transition.

⁸ This cluster break occurs near the splice between the NEXIS and Reuters Business Briefing (RBB) sources: The "leading" cluster for March 1997 contains about ten weeks of NEXIS data and about six weeks of RBB. It is possible that the change in data source affects the delineation of the cluster, but this seems unlikely for three reasons. First, this cluster shift is consistent with the changing policies of the Netanyahu administration. Second, the cluster break is anticipated by four months in the CDC measurements that contain no RBB data. Finally, most of the LML scores across the splice are quite low: Many are close to zero, and only the March and April 1997 calculations show evidence of a shift in behavior.

The CDC measure usually provides two to six months of warning, but it gave no signal of the Oslo transition and no distinct alert before the June 1982 invasion of Lebanon. The CDC measure also has some false positives where it peaks just below the critical level. This is to be expected: Any measure that does not contain false positives is probably insufficiently sensitive to political events. For example, the several CDC peaks associated with the Oslo and Netanyahu periods are consistent with the fits and starts of that negotiation. More generally, we have not included in this model interactions among domestic actors—such as the various political parties and factions within Israel and Lebanon, and sometimes those interactions can be important. We are not dealing with a deterministic system, and at times a false positive may reflect precursors to transitions that failed to occur because of a reaction in the international system or in domestic subsystems that prevented the phase change.

The pre-Lebanon peak in LML may be an example. In 1981, allies of Israel may have persuaded Prime Minister Menachem Begin that an invasion of Lebanon would result in eventual Syrian hegemony there, the development of a militant Islamic fundamentalist movement on Israel's northern border, and the end of Begin's political career. Only after another year had passed did the contrary and disastrous design of Defense Minister Ariel Sharon prevail.

CONCLUSION

With the end of the DARPA-sponsored research, the development of quantitative early warning models went into eclipse. When evaluated against what is possible today, the DARPA efforts were necessarily primitive in their dependence on human coding and mainframe computers with only a tiny fraction of the speed and memory now available. The event-based quantitative forecasting efforts of the late 1970s were unsuccessful, but the contemporary situation is quite different. The quantity, consistency, and timeliness of event data have improved substantially due to the advent of machine-coded data sets based on news wire sources. With increased computer power and greater sophistication of statistical research in international relations, a variety of new early warning techniques can now be applied to that data.

We draw two general conclusions from our analysis of time-delimited clusters. First, the empirical results support both the theoretical concept of crisis phases and the strategy of analyzing the movement of a point defined by the vector of dyadic interactions in an international system. The pattern of variation in LML_t , seen in Figure 4 is exactly what we expected the model to generate: brief periods of large movement followed by long periods of little movement.

These time-delineated clusters are much cleaner and more consistent than clusters determined by cross-sectional techniques, such as the K-Means analysis found in Schrodtt and Gerner (1997). The $LML_t > \Delta$ method we used to delineate the clusters is conceptually straightforward and computationally efficient; in

fact, the algorithm is sufficiently simple that it may be possible to determine analytically some of its statistical properties. Nonetheless, it locates most of the clusters we expected to find.

The CDC measure also appears promising as the basis of an early-warning indicator. It provides a two- to six-month warning for most of the changes in the data set, and its behavior is consistent with the theoretical predictions of the crisis phase approach. Both the LML and the CDC measures act quite differently in real-world and simulated data, which suggests that they reflect underlying political behavior rather than statistical artifacts.

Time-delimited clusters are a dynamic rather than a structural early warning approach, but their effectiveness should not be regarded as evidence against the structural approach; we regard these two research strategies as complementary rather than competitive. Structural methods are particularly good at telling analysts where to look for potential trouble, and they are apt to provide theoretical guidance about why a specific system is likely to experience problems. This, in turn, may provide insights into the types of action to take to resolve an impending crisis. Structural models are unlikely to excel at predicting the exact timing of breakdowns, however, because the variables they identify as theoretically important change much too slowly. This is where dynamic models come into play.

Our analysis does not consider an alternative class of dynamic models, those based on event sequences, rules, patterns, and precedents (see Cimbalá 1987; Hudson 1991). These models generally provide more contextual information than is supplied by numerical time-series methods. As a consequence, they, too, may be useful in identifying the immediate events leading to a crisis. For instance, although the Kuwait transition is invisible in our cluster analysis, the events preceding the Iraqi invasion follow very closely Lebow's (1981) "justification of hostility" crisis type. Recognizing such patterns could be useful for very short-term forecasting. Also, an assortment of computationally intensive nonlinear forecasting techniques have been developed in recent years (e.g., Casdagli and Eubank 1992; Richards 2000), although relatively little attention has been paid to these in the quantitative international political literature. In short, a variety of unexplored methods may be applicable to the early warning problem.

We believe the ideal early warning model should combine elements of both the structural and dynamic approaches. The optimal model might vary depending on the structural precursors in a specific case. Presumably, an internal breakdown in Lebanon, which is relatively wealthy and highly differentiated by religion, does not occur in the same fashion as a breakdown in Rwanda, which is relatively poor and not differentiated by religion. The literature on domestic conflict and state breakdowns (e.g., Esty et al. 1995, 1998; Gurr and Lichbach 1986) could provide theoretical guidance on this issue.

The reason integrated models have not emerged is due largely to resources: The political science discipline is still developing accurate structural and dynamic

models, and no researcher has been able to assemble data sets sufficiently large to study structural and dynamic dimensions simultaneously. As the investigation of both types of models identifies more focused sets of variables and techniques, it should be practical to combine the approaches.

APPENDIX A: DATA SOURCES AND MEASUREMENT

Our source for April 15, 1979, to June 10, 1997, was the NEXIS "REUNA" file; Reuters Business Briefing (RBB) was used for June 11, 1997, to December 31, 1998. The change of sources was required because Reuters stopped supplying data to NEXIS on June 10, 1997. The two data services provide a somewhat different mix of stories, but we see no evidence of a significant discontinuity when the stories are coded and aggregated at a monthly level.

The following search command was used to identify relevant stories in NEXIS:

(ISRAEL! OR PLO OR PALEST! OR LEBAN! OR JORDAN! OR SYRIA! OR EGYPT!) AND NOT (SOCCER! OR SPORT! OR OLYMPIC! OR TENNIS OR BASKETBALL)

To locate stories in RBB, we used the RBB search software (version 2.0 for Macintosh) to select "Political" and "General" news stories that dealt with Egypt, Israel, Jordan, Lebanon, and Syria; the "Reuters Sports" source was explicitly excluded. (The "Israel" category includes stories on the Palestine National Authority as well as Israel.) Some additional filtering was done on both the NEXIS and RBB downloads to eliminate Reuters "Highlights," historical calendars, and other irrelevant material.

The KEDS machine coding program does some simple linguistic parsing of the news reports—for instance, it identifies the political actors, recognizes compound nouns and compound verb phrases, and determines the references of pronouns—and then employs a large set of verb patterns to determine the appropriate event code. Details on the mechanics of the KEDS system are found in Gerner et al. (1994) and Schrod, Davis, and Weddle (1994). For example, consider the following lead sentence: "Palestinian President Yasser Arafat accused Israeli Prime Minister Benjamin Netanyahu on Tuesday of intentionally prolonging their peacemaking crisis."

The key components of the sentence are

Subject: Palestinian President Yasser Arafat

Verb: accused

Object: Israeli Prime Minister Benjamin Netanyahu

Based on the dictionaries used by the KEDS program, the proper noun in the subject—"Arafat" (or the adjective "Palestinian")—is assigned the actor code PAL and becomes the source of the event. The proper noun in the direct object—"Netanyahu" (or the adjective "Israeli")—is assigned the actor code ISR and becomes the target. The event is determined by the verb ("accused") and is assigned a value (121 in this case) corresponding to the appropriate code in the WEIS event coding system. Bond et al. (1997), Huxtable and Pevehouse (1996), and Schrod and Gerner (1994) discuss extensively the reliability and validity of event data generated using Reuters and KEDS.

We coded only the lead sentences of the stories, which produced a total of 92,687 events. The search command, however, generated a number of events outside the 56 directed dyads considered in this study. Those 56 dyads produced 43,328 events.

The data and the source code for the computer programs used in the analysis, as well as the KEDS program (version 0.9B6.2) and the dictionaries used for this coding session, are available from the web site <http://www.ukans.edu/~keds> (accessed August 15, 2000).

APPENDIX B: COMPARISON WITH A NULL MODEL

Here we develop a null model and look at the distribution of various indicators in simulated data generated by that model. We wish to determine whether a Monte Carlo analysis using randomly generated data with the same means, variances, and autocorrelations as our Levant dyads will show the same patterns of change in distance that we found in the actual data. If this occurs, it means our results are simply an artifact of the analytical method, rather than a reflection of the underlying politics.

Our null model duplicates the sample size (192) and number of dyads (54) found in an earlier version of the data set, as well as the mean, variance, and first-order autocorrelation of the data within each dyad.⁹ Specifically, we generated simulated data using a first-order autoregressive (AR[1]) process,

$$y_t = c + \phi y_{t-1} + \varepsilon_t$$

where $c = \mu(1 - \rho)$; $\phi = \rho$; $E(\varepsilon) = 0$; $\text{Var}(\varepsilon) = s^2(1 - \rho^2)$. As Hamilton (1994, 53–4) notes, this will produce a time series with mean μ , variance s^2 , and first-order autocorrelation ρ . In order to avoid initial value effects, the simulated data were taken from the interval $[y_{51}, y_{242}]$, with $y_0 = \mu$. To save computation time, ε were generated by random selection from a table of 5,000 normally distributed random variables produced by Excel 4.0. We created a sample of 1,000 such data sets.

This specification represents a compromise between a null model that is excessively random and one that duplicates all the features of the original data set. On the one hand, in a null model using white noise (no autocorrelation), points generated by the dyads will jump around in the vector space far more than one would ever expect to see in event data based on actual political behavior and presumably will show only very small clusters. On the other hand, if we also duplicate the cross-correlation between dyads, the simulated data set will have most of the statistical characteristics of the actual data, and it would not be surprising to find similar results. Our choice is an intermediate model in which the simulated time series have the same general characteristics within each dyad but have no relationship between dyads. (Autocorrelation above the first order is significant in only a small number of the dyads in the original data.)

In comparing the simulated data with the actual data, we looked at the following measures:

- the total number of points at which $LML_t > \Delta$, with $\Delta = 0.2$, the threshold that best delineated clusters in this 1979–96 data set;
- the number of $LML_t > \Delta$ points that signal a new cluster. This is defined (somewhat arbitrarily) as an $LML_t > \Delta$ point that had no $LML_t > \Delta$ points in the previous two periods.¹⁰ These times are called "cluster-defining points";

⁹ This analysis was done in April and May 1996. Because the simulations are quite time consuming, we have not rerun them with the data set that goes through December 1998. There is no reason to believe that the results would be any different using the newer data.

¹⁰ In other words, this definition ignores the strings of consecutive $LML_t > \Delta$ points that are generated by rapid movements away from

TABLE B-1. Statistics Computed from 1,000 Simulated Data Sets, $\Delta = 0.2$

Statistics for $\Delta = 0.2$ (N = 1,000)	Simulated Mean	Simulated Standard Dev.	Observed Value	One-Tailed Proportion
Total $LML_t > \Delta$	31.55	5.67	15	0.003 (<)
Cluster-defining $LML_t > \Delta$	15.63	2.61	9	0.006 (<)
St. dev. of CDC	0.30	0.04	0.23	0.026 (<)
St. dev. of LML	0.25	0.03	0.15	0.001 (<)
Cluster break at t and $CDC_{t-k} > \text{St. dev.}$				
$k = 0$	0.41	0.11	0.56	0.090 (>)
$k = 1$	0.22	0.10	0.22	0.461 (>)
$k = 2$	0.21	0.09	0.11	0.893 (>)
$k = 3$	0.20	0.09	0.11	0.869 (>)
$LML_t > \Delta$ within $t \pm k$ of a priori break				
$k = 0$	0.03	0.03	0.07	0.136 (>)
$k = 1$	0.10	0.06	0.27	0.011 (>)
$k = 2$	0.17	0.08	0.40	0.006 (>)
$k = 3$	0.23	0.09	0.47	0.008 (>)

TABLE B-2. Statistics Computed from 1,000 Simulated Data Sets, $\Delta = 0.35$

Statistics for $\Delta = 0.35$ (N = 1,000)	Simulated Mean	Simulated Standard Dev.	Observed Value	One-Tailed Proportion
Total $LML_t > \Delta$	13.56	4.34	15	0.680 (>)
Cluster-defining $LML_t > \Delta$	8.48	2.49	9	0.660 (<)
St. dev. of CDC	0.30	0.04	0.23	0.026 (<)
St. dev. of LML	0.25	0.03	0.15	0.001 (<)
Cluster break at t and $CDC_{t-k} > \text{St. dev.}$				
$k = 0$	0.54	0.17	0.56	0.462 (>)
$k = 1$	0.31	0.16	0.22	0.731 (>)
$k = 2$	0.30	0.16	0.11	0.915 (>)
$k = 3$	0.28	0.15	0.11	0.903 (>)
$LML_t > \Delta$ within $t \pm k$ of a priori break				
$k = 0$	0.03	0.06	0.07	0.247 (>)
$k = 1$	0.10	0.10	0.27	0.074 (>)
$k = 2$	0.16	0.13	0.40	0.054 (>)
$k = 3$	0.23	0.14	0.47	0.060 (>)

- the standard deviation of LML_t and the early warning measure, CDC; the means of both measures are zero;
- the number of CDC measures greater than one standard deviation above zero at 0, 1, 2, and 3 months prior to a cluster-defining point; and
- the number of $LML_t > \Delta$ points within 0, 1, 2, and 3 months of the six a priori cluster transitions we identified in our data set, as a proportion of the total number of $LML_t > \Delta$ points.¹¹

Because the CDC measure can only be computed after twelve months of data are available, and computing the LML_t requires three additional months, the interval on which these measures were computed contains $192 - 11 - 3 = 178$ time points. (The total number of months in a sixteen-year period is 192. We eliminate the first eleven months where the CDC measure cannot be computed and the final three months where the LML measure cannot be computed, leaving 178 months.)

The results of the Monte Carlo analysis are presented in Table B-1, where the “one-tailed proportion” indicates the proportion of the values in the simulated data that are less than (<) or greater than (>) the observed value. The distribution of the values of the statistics are generally smooth, symmetrical, and more or less normally distributed;

an existing cluster; these are quite common in the simulated data and are seen in the actual data in the Lebanon transition. This measure should also be less sensitive to the level of Δ .

¹¹ In the simulated data, these a priori transitions are arbitrary because they were determined by changes in the actual, rather than the simulated, data. Nonetheless, these indicators measure the likelihood of finding $LML_t > \Delta$ points in the vicinity of a set of six transition points spaced at the intervals in the a priori set. We look at the proportion because the number of $LML_t > \Delta$ points in the simulated data is substantially higher than in the actual data.

the probabilities are based on the actual distributions of the statistics in the simulated data rather than on a normal approximation.

With the exception of one set of statistics—the relationship between CDC and the cluster-defining points—the values observed in the actual data are substantially different from those found in the simulated data and vary in the expected direction. The number of $LML_t > \Delta$ points found in the actual data, whether total or cluster defining, is about half that found in the simulated data. The standard deviations of the LML and CDC measures are substantially less in the observed data than in the simulated data. Generally, an $LML_t > \Delta$ point is about twice as likely to occur near one of the a priori cluster breaks in the actual data than in the simulated data.

The relationship between CDC and the cluster-defining points is somewhat puzzling. The observed $k = 0$ point is significantly greater (at the 0.1 level) than the simulated values, as we expected. The $k = 1$ value, however, is simply equal to the mean, and the $k = 2$ and $k = 3$ values are significantly less than the simulated data at the 0.15 level. This suggests that, on average, CDC_{t-k} may be a better early warning indicator than demonstrated in this data set, although its performance is due to autocorrelation in the data rather than to any more complex political characteristics that involve dyadic interactions.

The large number of $LML_t > \Delta$ points combined with standard deviations of LML and CDC that are higher in the simulated data than in the observed data suggests that the value of Δ —a free parameter that was established arbitrarily—may have been set too low for the simulated data. We reran the simulated data sets with $\Delta = 0.35$, a level of Δ that gives roughly the same number of cluster-defining points in the simulated data as were found in the observed data with

$\Delta = 0.2$. This adjustment of Δ effectively eliminated one additional degree of freedom in the simulated data; the results of this analysis are reported in Table B-2.

This modification changes the one-tailed probabilities somewhat but in general does not alter the conclusions of the analysis. The curious pattern of CDC and the cluster-defining points is retained—and actually strengthened at $k = 2$ and $k = 3$ —except that the $k = 0$ point is no longer significant. The relationship between the $LML_i > \Delta$ measures and the a priori breaks is slightly less strong, but the $k > 0$ probabilities are still quite low. We conclude that the behavior of the predictive measures is not solely due to the difference in the number of $LML_i > \Delta$ points.

The results of the Monte Carlo analysis are affected by the existence of the free parameter Δ , but in no circumstances do the results from the analysis of random data closely resemble those found in the real data. If we assume the $\Delta = 0.2$ separation threshold, then the observed data have far fewer clusters than we would expect the null model to generate. By raising the level of Δ , we can match the number of empirically determined clusters, but the behavior of the CDC statistic and the coincidence of $LML_i > \Delta$ points and the a priori points are still quite different in the simulated data. Furthermore, the necessity of raising the value of Δ to match the expected number of clusters means that the number of points at which a large change occurs in LML_i is greater in the simulated data than in the observed data because the variance of LML_i is higher in the simulated data. This in turn would be expected if the observed data actually settle into clusters and remain there for a time—as predicted by crisis phase theories—rather than jump around. We suspect that the standard deviation of LML_i is lower in the observed data because of cross-correlation (and in a few dyads, higher-order autocorrelation) of the dyads.

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