

# Dynamic Conditional Correlations in Political Science

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*Time-varying relationships and volatility are two methodological challenges that are particular to the field of time series. In the case of the former, more comprehensive understanding can emerge when we ask under what circumstances relationships may change. The impact of context—such as the political environment, the state of the economy, the international situation, etc.—is often missing in dynamic analyses that estimate time-invariant parameters. In addition, time-varying volatility presents a number of challenges including threats to inference if left unchecked. Among time-varying parameter models, the Dynamic Conditional Correlation (DCC) model is a creative and useful approach that deals effectively with over-time variation in both the mean and variance of time series. The DCC model allows us to study the evolution of relationships over time in a multivariate setting by relaxing model assumptions and offers researchers a chance to reinvigorate understandings that are tested using time series data. We demonstrate the method's potential in the first example by showing how the importance of subjective evaluations of the economy are not constant, but vary considerably over time as predictors of presidential approval. A second example using international dyadic time series data shows that the story of movement and comovement is incomplete without an understanding of the dynamics of their variance as well as their means.*

When studying politics over time, it is typically the dynamics of change that are the most interesting. Certainly, political variables change over time, but political relationships may change as well, getting stronger or weaker depending upon the circumstances of a particular period. Additionally, volatility may change over different periods. The circumstances that envelope the political variables and relationships we are interested in matter.

We can work toward a more complete understanding when we pay attention both to the volatility within variables and to the changing nature of the relationship between them. Even in time series analysis, we have often failed to pose our questions such that change over time and volatility are given proper consideration in our models. That is, we study processes over time, but our methods usually impose time-invariant estimators that do not consider volatility.

Time series methods used by political scientists have become increasingly sophisticated over the past 15 years or so; however, researchers still often rely on many methods analogous to describing a single variable using only

its mean. That is, by regressing  $Y$  on  $X$  we are given a single number (the coefficient) that summarizes the relationship between the two for the chosen time period. That single statistic may be only the beginning of how we can describe the association between the variables. There is much more we may wish to know—how does it vary over time, how volatile, and what are the impacts of different circumstances? For example, a regression coefficient can tell us how subjective economic evaluations affect leader or party approval over a long period of data, but it is much less useful in determining how those effects may vary in the months leading up to and following an election (Carey and Lebo 2006).

Time-varying parameter models inform us about how effects are different across time. A Dynamic Conditional Correlation (DCC) increases modeling flexibility by dropping assumptions about constancy in the means and variances of variables and in the relationships among them. The DCC model does so by calculating a current correlation between variables of interest as a function of past realizations of both the volatility within the variables and the correlations between them. The association

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between variables can thus be seen to evolve over time in a manner that not only depends upon whether and to what degree the variables are moving in the same direction, but also takes account of the history of variance that each series has undergone. The DCC method is not the first to allow political scientists to study time-varying relationships, but it does have some important advantages over other methods currently in use.<sup>1</sup> We want to allow for and test whether our series in political science have a constant mean and variance. For example, negative political or economic news, contrasted with positive news, may be expected to result in more volatility due to the psychological way information is processed. It is not just the mean, but also the variance that we are assessing over time.

The remainder of the article proceeds as follows. First, we discuss the motivation for and intuition of the Dynamic Conditional Correlation model. We then present both a test for determining if correlations are constant and the DCC model itself. Following that, we present two illustrations; one is drawn from the field of American politics and the other from International Relations. In the conclusion, we revisit the strengths and limitations of the analyses using the DCC model and the substantive insights offered.

## Intuition of and Motivation for the Dynamic Conditional Correlation Model

An inability to study the importance of circumstances sets traditional time series analysis behind cross-sectional analyses, which can use tools such as interaction terms to study how additional factors affect the connection between independent and dependent variables. There are an increasing number of approaches for studying time-varying parameters which allow us to leverage the temporal information in the data and account for circumstances.

Greene (2008) provides a useful and succinct overview of such methods. Two of the most popular techniques in political science, moving windows and Kalman filters, are discussed below. We agree that these techniques are useful, but think that DCC has unique aspects to add to its value. In particular, rolling regressions and Kalman filters (and their variants)<sup>2</sup> are intended to examine time-varying relationships entered in the mean

<sup>1</sup>We discuss other time-varying parameter models, such as Kalman filters, in the next section.

<sup>2</sup>These variants include Flexible Least Squares (FLS), which according to Montana, Triantafyllopoulos, and Tsagaris (2007) is algebraically equivalent to the more well-known Kalman filter equations. Kladroba (2005) provides a Monte Carlo comparison of FLS

equations whereas DCC allows for the analysis of time variation in variance equations as well.

An initial question we may wish to answer is this: what is the correlation between two series now? (Engle 2004).<sup>3</sup> One way to answer this is to estimate a correlation using all the data we have available to us. One drawback is that this will include old information that may be of far less use to us than recent information. On the other hand, using only a few recent observations—say the last 10—will create more variability because of the small sample size. Further, we will be assigning zero weight to older observations that may be worth including.<sup>4</sup>

Moving-window analyses, also referred to as “rolling correlation estimators,” are a middle ground here, as are smoothing techniques, e.g., exponential smoothing. One specifies some length of time  $s$  where  $s < T$ , the full sample size. The correlation or regression coefficient is then estimated over the period 1 to  $s$ , then 2 to  $s + 1$ , and so on until  $T - s + 1$  to  $T$ . These correlations provide some information on the evolution of the relationship between variables. Martin (1998) points out some disadvantages to this approach: the user must adopt an ad hoc approach to choose window width and moving-window analyses cannot account for abrupt changes in volatility very well. Beck (1983) argues that this approach can give unstable estimates and offers no statistical test. Another drawback is that it equally weights all observations less than  $s$  periods in the past and gives no weight at all to older observations (Engle 2002). Further, suppose we have yearly data from 1901 to 2000 and use a moving-window regression that is 30 years wide. Doing so, the years 1901 and 2000 appear in one regression equation each, the years 1902 and 1999 appear in two, and so on. In all, the years 1930–71 appear in 30 regressions. Again, weighting problems are inherent in this method. The choice of using an Exponentially Weighted Moving Average (EWMA) is not attractive either. Martin (1998) points out that the fixed weight parameter gives inadequate volatility estimates and is a special case of the more general GARCH approach.

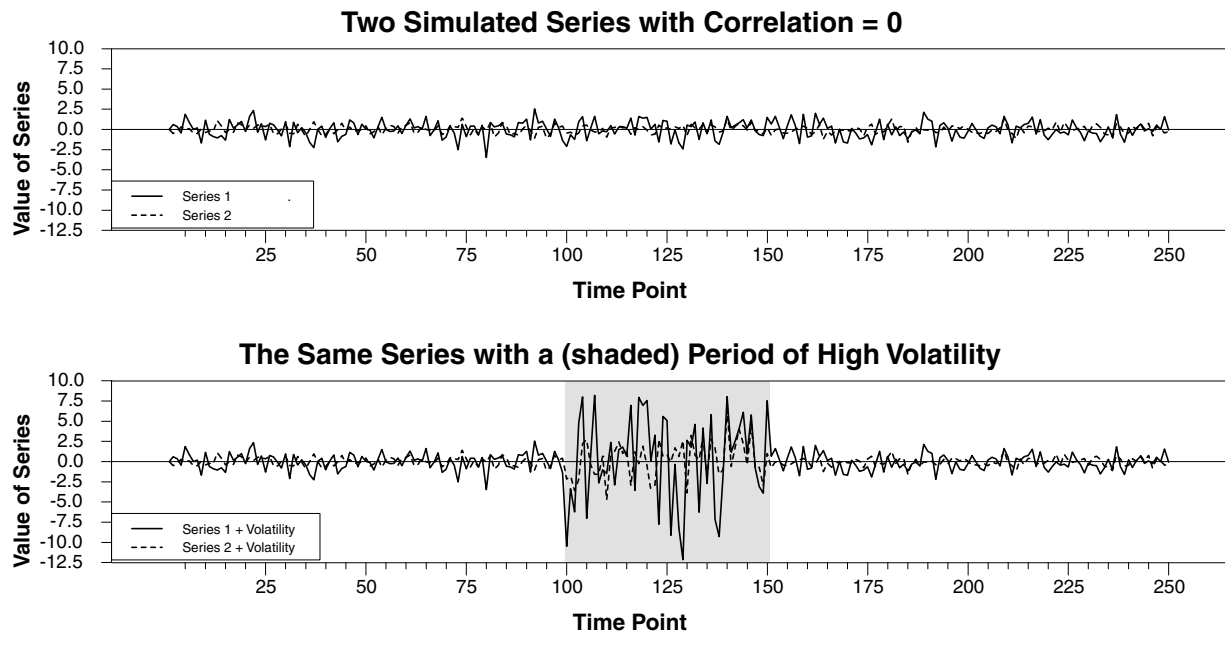
Kalman filtering offers a recursive approach to time-varying estimation that allows us to see the evolution of a

and Kalman filtering as alternative ways to estimate state space models.

<sup>3</sup>“Now” depends on the level of temporal aggregation of the series. Freeman’s classic article (1989) discusses the importance of using the appropriate level of temporal aggregation.

<sup>4</sup>Adding dummy variables in time series analysis, i.e., interventions, is usually a theoretically unsatisfying way to account for context. It provides a change in the intercept but cannot measure potential changes in relationships among series. Panel data do allow inferences about slopes and intercepts, but in political science such data sets are usually dominated by cross-sectional units over time periods thus precluding more powerful panel techniques.

**FIGURE 1 Simulated Series Without and With Volatility**



regression coefficient. We start by running a regression using a small number of observations beginning with time-point one. Then an additional data point is added at the end and the regression is run again and so on until all the data are used. We can think of Kalman filtering from a Bayesian perspective in which the posterior distribution changes with each new data point (Meinhold and Singpurwalla 1983). Once all the data are used, the coefficient estimates reach what they would be in a regression with time-invariant parameters.<sup>5</sup> Yet, Kalman filtering shares many of the same flaws as moving-window analyses, such as the weights of older observations being equal to those of the most recent ones. Further, the impact of the most recent observation is inversely proportional to the length of the data that precede it. For example, the impact of a new month of data on a coefficient will be twice as large if the data extend backwards 10 years instead of 20. And, the method is silent to the fact that estimated relationships may change more simply due to higher volatility.

Among these many problems, it is the inattention to volatility that is the most severe limitation of these methods and that can lead to problems of inference. The basic problem stems from the fact that the movement of

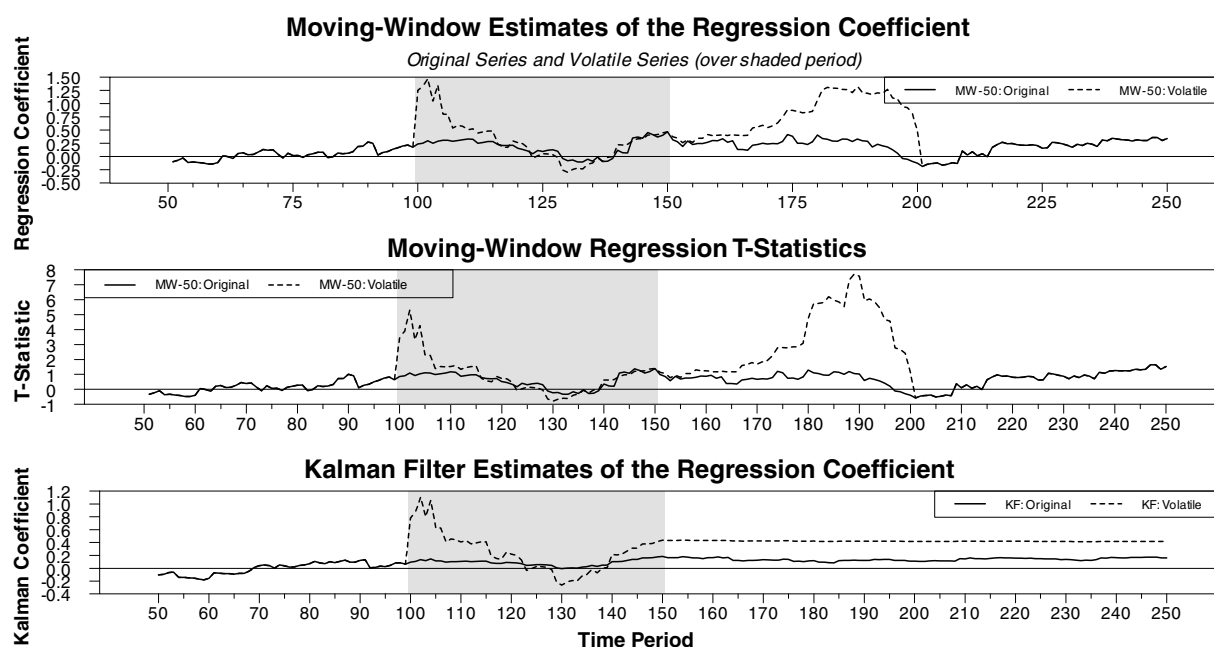
variables has a greater impact on estimated correlations or coefficients during a period of high volatility than one of low volatility; e.g., two variables moving in the same direction when volatility is high will boost a correlation more so than if the movement had been the same in terms of the relative changes in the variables but had occurred during a period of relative tranquility.

For example, the top panel of Figure 1 shows two time series, 250 periods long, randomly generated so that they are both stationary and have a correlation that fluctuates over their shared history but is, on average, zero. The bottom panel shows these series after we multiply the values of each by five for the 100<sup>th</sup> to 150<sup>th</sup> time points (shaded portion). Thus, without changing the relationship between the variables, we have induced a period of increased volatility.

Figure 2 shows the dynamic regression coefficient estimates of moving windows and recursive Kalman filtering. In the top panel, the solid line gives the regression coefficient estimated using a moving window 50 time periods wide. The dotted line does the same for the volatile series. The method is not at all sensitive to volatility—it simply translates the series' larger deviations from their means into wilder predictions of coefficients—movement up or down due to volatility has enormous pull on the regression line. The coefficients tend to be highest when some, but not all, of the volatile period is being used. The bottom panel of Figure 2 shows the Kalman filter's difficulty in accounting for volatility. Again, the coefficient

<sup>5</sup>McAvoy (2006) provides a recent example. He uses this approach to model the time-varying effects of economic and foreign policy approval on overall levels of presidential approval and finds that the effect of the economy is constant while that of foreign policy fluctuates.

FIGURE 2 Moving Window and Kalman Filter Estimates



jumps up wildly as the period of volatility begins. However, unlike the moving-window analysis in which the period of volatility eventually moves out of the window, the estimates of the Kalman filter are thrown off course forever—after by the induced volatility. Also, once the period of volatility is over, the Kalman estimates are not very useful for measuring the time-varying relationship.

One more problem that has not been pointed out previously is that volatility can lead to spurious regression results using these methods. If two series both become more volatile simultaneously, it is easy to make a Type I error and conclude that the series have become significantly related. The middle panel of Figure 2 charts the  $t$ -statistic for the same moving-window regression. When the window does not contain any of the volatile period the  $t$  statistics find, correctly, no significant relationship. Yet, as the period of volatility enters and then leaves the window, the spikes in the  $t$  statistics make it very easy to be fooled that a significant relationship between the series has appeared.

Wood (2000) highlights as a problem for analysts using the Kalman filter that coefficient instability may be sudden or slowly evolving through time. Regime switching models are ideal for series where there are abrupt changes that may be due to events such as political changes or economic crises, e.g., Jackman (1995) and Blomberg (2000), and then the series settle into a period of stability. However, we may wish to allow less abrupt change

and to avoid assumptions about stability in between these changes. Wood and Doan (2003) describe the failure to allow for nonlinear parameter variation within regimes as a major limitation of regime switching models as well. The biggest deficit of these popular methods when compared to DCC is that they estimate time-varying changes in the mean but do not account for time-varying variances. Thus, they are still stuck in the first moment while the second moment is well worth our attention.

Given problems created by changing volatility, scholars turned to extending the well-known Box-Jenkins methodology. Researchers have focused on the facts that most time series in social science do not have a constant mean and most have phases of relative calm followed by periods of high volatility (see Enders 2004). This led to the extensive literature on ARCH (autoregressive conditional heteroskedasticity) processes and all of its related extensions. Specifically, ARCH modeling relaxes the assumption of constant variance (homoskedasticity) and allows time-varying variances.

The newest innovations look at how correlations change over time. The DCC approach to the question “what is the correlation now” follows that of ARCH models’ solution to modeling the evolving nature of volatility. Specifically, ARCH models estimate a weighted average of a variable’s entire history of volatility with more weight given to the recent past and less—but not zero—weight given to observations long past. Similarly, the DCC model

estimates a weighted average of correlations that incorporates the entire history of a relationship between variables. Ledoit, Santa-Clara, and Wolf (2003) show in their work that variations of ARCH models almost always perform better than moving-window and smoothing techniques.<sup>6</sup> Tse and Tsui's (2002) MGARCH (multivariate generalized ARCH) model allows for time-varying correlations in multivariate circumstances. Their model and others in this growing field are important because they retain the time history that would be lost in a constant correlation model.

Interestingly, the DCC approach allows series to have periods of positive, negative, or no correlation. Thus, both direction and strength of the correlation can be considered. When two series move in the same direction, the correlation increases and is positive. When they move in opposite directions, the correlation is decreased and may become negative. Such flexibility is intriguing when thinking about political series of interest. For example, perhaps presidential approval is tightly tied to the economy, public opinion about foreign policy, concern about crime, etc., when that issue is salient on the issue agenda and not at other times. The effects of the economy or foreign policy may be stronger during periods of elections and war, respectively.

This information becomes especially important when we are interested in forecasting, a growing area in political science. If the impact of an independent variable changes over time, we want to use only the most relevant correlation when forecasting the dependent variable. Finally, whether or not there is an equilibrium that the series returns to may also lead to new insights.

The DCC approach is well suited for situations where the model structure is well known.<sup>7</sup> We would like to know quite a bit about a relationship before seeing if it varies. The DCC model is not advisable when the series are very short.<sup>8</sup> Also, when time-varying volatility is not an issue,

<sup>6</sup>Of course, there are undoubtedly other data sets that could be tested and other Monte Carlo data sets that could be generated.

<sup>7</sup>How to best determine the model structure remains an area for future research. This question has not been discussed in finance, the origins of the DCC model, because researchers are not interested in building extensive models to explain a single variable. It may be fruitful to look at a DCC of residuals from a multivariate ARFIMA model or VAR instead of an independent variable we think may vary in its effect over time. One way of looking at the current models is that the GARCH in-mean equation has only an intercept. These questions are ripe for further research by social science methodologists.

<sup>8</sup>One concern in small samples is that the distributional assumptions in the error process may not hold. In this case, one can bootstrap the GARCH coefficients and residuals so that exact finite sample statistics via the Empirical Distribution Function can be used, e.g., Dufour et al. (2003).

the relative advantages of DCC are reduced although its elegant approach to weighting still makes it an attractive alternative.

Understanding how correlations change over time and when they will be strong or weak is a persuasive motivation for the models discussed here. A long debate in economic voting has questioned which aggregate measure of subjective economic evaluations—national prospections, national retrospections, personal retrospections, or personal prospections—is most important in determining presidential approval and vote choice. Here, we can hypothesize that the effects of each may vary over time depending on political conditions, including electoral campaign periods and economic conditions. The effects can be asymmetric as well. That is, the weights of positive and negative media coverage on expected vote do not need to be, and indeed are not expected to be, equal. A model that allows for this asymmetry and varying correlation is critical.

Generating time-varying correlations gives political researchers a powerful tool to answer questions glossed over by regressing one time series on another and obtaining a single coefficient. Such questions include the following: Is the relationship between economic performance and governing party support the same during times of war and peace? How do Americans' racial policy preferences vary in relation to macroideology or media coverage over time? Does conflict decrease during periods where trade agreements are in effect? Does the correlation between macropartisanship and macroideology change during periods of economic upturns or downturns, international crises, or election cycles? On the surface, it seems worth using a time-varying estimator to explore whether the circumstances surrounding politics impact the correlations among series. Further, in none of these examples should we assume that the measures of interest have constant levels of volatility. And, discarding that assumption should lead one to choose the DCC method over other available estimators of time-varying parameters.

## Modeling Procedures

With its attention to volatility, the DCC model is based within the family of Generalized ARCH (GARCH; see Bollerslev 1990; Engle 1982) models, which have flourished in recent years in the literatures on finance and econometrics.<sup>9</sup> ARCH models and the generalized

<sup>9</sup>Despite the complexity of these models, advances in software applications including canned programs in RATS, E-Views, Matlab,

extension have been very successful in modeling time-varying variances (e.g., Gronke and Brehm 2002; Tse 2000). Extensions have moved from the univariate to multivariate setting.

A critical first step is for the series to be stationary. If they are not, they first need to be (fractionally) differenced.<sup>10</sup> The next step is to determine which multivariate modeling extensions are appropriate, which involves testing whether the assumption of time-invariant (constant) correlations holds. If correlations are time varying, we then proceed to examine the interaction of multiple series by using Engle's (2002) Dynamic Conditional Correlation multivariate GARCH Model. Engle's (2002) pathbreaking work lays out the DCC model and seems particularly relevant for studies of political phenomena. The method estimates the DCC parameters and the time-varying conditional correlations among the variables of interest. The estimates of correlation can then be used to analyze significant events that occurred as well as the impact of other series.<sup>11</sup>

### Testing for Constant Correlations

Correlations between time series will always vary as the time frame changes, but they may indicate only minor fluctuations rather than noteworthy volatility that can be modeled. Tse (2000) provides a convenient and straightforward Lagrange Multiplier (LM) test for the assumption of constant correlations in a multivariate Generalized-ARCH (GARCH) model. Thus, the Tse test is a useful first step for testing whether varying correlations are statistically significant and whether a DCC estimator is warranted.

Tse (2000) begins by assuming that the variance of time series  $y_1$  to  $y_k$  is conditional (time varying) with

and Stata have made an array of GARCH models, including DCC, accessible to a wide range of researchers. RATS estimates a simple DCC model using their menu-driven GARCH wizard or a single line of code. E-Views programs are available at Engle's website and Sheppard's website. Data and RATS code for our analyses are available at <http://ms.cc.sunysb.edu/~mlebo/details.htm>.

<sup>10</sup>It is certainly reasonable that the level of integration may vary over time as well. For example, the memory of a presidential approval series (the value of  $d$ , the fractional integration parameter) may change the longer the president is in office. Cointegration may ebb and flow and the level of fractional cointegration need not be constant over time. These are issues for future research.

<sup>11</sup>While the first moments of the series, i.e., the mean relationships, can be well understood and modeled via a VAR, or depending on the stationarity of the series, an ECM, further leverage is gained by continuing the investigation into the second moments. Models from the GARCH family are deemed the most useful for such investigations (Enders 2004; Schoftner 2005).

on-diagonal elements of a variance-covariance matrix,  $H_t$ , given by:

$$\sigma_{i,t}^2 = \omega_i + \alpha_i \sigma_{i,t-1}^2 + \beta_i y_{i,t-1}^2, \quad i = 1, \dots, K \quad (1)$$

and off-diagonal elements (time-varying covariances) given by:

$$\sigma_{i,j,t} = \rho_{i,j} \sigma_{i,t} \sigma_{j,t}, \quad 1 \leq i < j \leq K. \quad (2)$$

Although (2) uses elements of the time-varying variance-covariance matrix, its estimate of  $\rho_{i,j}$ , the overall correlation between  $i$  and  $j$  from the correlation matrix,  $R = \{\rho_{ij}\}$ , does not itself vary over time. This follows Bollerslev's (1990) constant correlation model.

To test whether this assumption is appropriate, Tse specifies time-varying correlations as:

$$\rho_{i,j,t} = \rho_{i,j} + \delta_{i,j} y_{i,t-1} y_{j,t-1}. \quad (3)$$

This allows correlations to react to the product of previous observations (Tse 2000, 111). A LM test of the null hypothesis that  $\delta_{i,j} = 0$  establishes whether correlations are time varying. If they are constant, (3) reverts to the constant correlation model. While the equations given pose the test for a GARCH(1,1) test, the Tse test is easily extended to GARCH( $p,q$ ) models.

### The DCC Model

If the correlations are dynamic and not constant, the next step is to model the series in a multivariate setup. The dynamic conditional correlation model (DCC) allows analysts to do so while summarizing the dynamic properties of two or more series.<sup>12</sup> With the DCC model one can "pinpoint precisely the timing and nature of plausible changes in the time series' comovement" (Lee 2004, 1). That is, in addition to measuring and accounting for the volatility of the series, the correlations can be measured and predicted. For each timepoint, the DCC method gives a value that serves as the forecasted correlation between series for the next period. Given these capabilities, the DCC method moves beyond the Tse test and well beyond the tests of structural stability that break the series into subperiods and compare parameters in each section, such as the popular Chow (1960) test or the Bai and Perron (1998) test.

The estimation of DCC is broken into two stages, which simplifies the estimation of a time-varying correlation matrix.<sup>13</sup> In the first stage, univariate volatility parameters are estimated using GARCH models for

<sup>12</sup>DCC also allows volatility forecasting and thus holds particular promise for conflict scholars.

<sup>13</sup>One-step estimation is also possible. However, as Pelagatti and Rondena (2004) point out, the asymptotic distribution of the

each of the variables. In the second stage, the standardized residuals from the first stage are used as inputs to estimate a time-varying correlation matrix. Two-step estimation of the likelihood function is consistent, albeit inefficient (Engle and Sheppard 2001). The DCC allows asymmetries, meaning that the weights are different for positive and negative changes to a series, which is an insightful advantage of this model.<sup>14</sup>

Engle (2002) and Kearney and Poti (2003) provide guidance on how the model is implemented. We begin with:

$$r_t | I_{t-1} \sim N(0, H_t). \quad (4)$$

Where  $r_t$  is the  $k \times 1$  vector of demeaned variable values conditional on information available at  $t - 1$ , which is denoted as  $I_{t-1}$ ;  $r_t$  is assumed to be conditionally multivariate normal;  $H_t$  is the conditional covariance matrix and is:

$$H_t = D_t R_t D_t. \quad (5)$$

Where  $R_t$  is the  $k \times k$  time-varying correlation matrix and  $D_t$  is a  $k \times k$  diagonal matrix of conditional, i.e., time varying, standardized residuals,  $\varepsilon_t$ , that are obtained from the univariate GARCH models. The key point to note is that  $R_t$  is a correlation matrix that varies over time, distinguishing the model from the constant conditional correlation model, which uses  $D_t R_t D_t$ .

Engle (2002) shows that the likelihood of the DCC estimator may be written as:

$$L = -0.5 \sum_{t=1}^T (k \log(2\pi) + 2 \log(|D_t|) + \log(|R_t|) + \varepsilon_t' R_t^{-1} \varepsilon_t). \quad (6)$$

Importantly, there are two components in the likelihood function that can vary. The first is the volatility component and contains only terms in  $D_t$ . The second is the correlation component and contains only terms in  $R_t$ . This is why the estimation can occur in two steps.

In the first step, only the volatility component,  $D_t$ , is maximized. This is done by replacing  $R_t$  with a  $k \times k$  identity matrix, giving the first-stage likelihood. Doing this means that the log likelihood is reduced to the sum of the log likelihoods of univariate GARCH equations.<sup>15</sup>

two-stage estimates has been derived by Engle and Sheppard (2001), and this makes testing possible. Pelagatti and Rondena further propose a three-step estimation and in doing so allow for more than four series to be estimated together.

<sup>14</sup>The asymmetries are in the variances, not in the correlations (Cappiello, Engle, and Sheppard 2003).

<sup>15</sup>See Kearney and Poti (2003) for further details on using GARCH equations as the first step. Engle (2002) explains the weighting of more recent observations.

The second step maximizes the correlation component,  $R_t$ , conditional on the estimated  $D_t$  (with elements  $\varepsilon_t$ ) from the first step. The second step gives the DCC parameters,  $\alpha$  and  $\beta$ :

$$R_t = (1 - \alpha - \beta) \bar{R} + \alpha \varepsilon_{t-1} \varepsilon_{t-1}' + \beta R_{t-1}. \quad (7)$$

If  $\alpha = \beta = 0$ , then  $R_t$  is simply  $\bar{R}$ , and the constant conditional correlation model is sufficient. Engle and Sheppard's (2001) original article provides extensive discussion of the estimation procedure and the theoretical and empirical properties of the estimator.

The advantage of the model is summed up by Kearney and Poti: "the model preserves the simple interpretation of the univariate GARCH models, while providing a consistent estimate of the correlation matrix" (2003, 5). The models have GARCH-type dynamics for both the conditional correlations and the conditional variances. Time-varying conditional variances can be interpreted as a measure of uncertainty and thus gain insight into what causes movement in the variance. In short, we gain modeling flexibility and lose assumptions about constant relationships.

## Applications

### Is It Always the Economy?

While political scientists have agreed upon the basic fact that the economy matters to perceptions of government performance, the literature on economic voting continues its long evolution. An early line of research focused on *what* aspects of the economy matter to voters (e.g., Alesina, Londregan, and Rosenthal 1993; Arcelus and Meltzer 1975; Mueller 1970). Looking at measures of economic performance such as unemployment, inflation, and growth rates, researchers attempted to discern what affected evaluations and vote choice the most. Another area of research focused on "how does the economy matter?" That is, how are objective economic factors translated into subjective judgments, which in turn affect political opinions (e.g., Clarke and Stewart 1994; Haller and Norpoth 1997; Key 1968; Kinder and Kiewiet 1981; Kramer 1983; MacKuen, Erikson, and Stimson 1992)? Other research has asked: "For whom does the economy matter?" (Duch 2001; Gomez and Wilson 2001, 2006; Lebo and Cassino 2007). Certainly, all three of these questions have been revisited in different settings, as still more scholars have asked, "where does the economy matter?" and extended models of American voting behavior to other countries (e.g., Lewis-Beck 1988; Monroe and Erickson 1986; Stevenson 2001).

One area that has been neglected throughout, and one that DCC is particularly suited to address, is the question of “when does the economy matter?” We know that not all elections focus on the economy and that factors such as honeymoons and rally effects can move approval levels every bit as much as the economy. However, we know comparatively little about either the impact of political circumstances on how important the economy is or the systematic regularities that affect the level of importance of the economy.<sup>16</sup>

We examine the dynamics of the relationship between monthly measures of the Index of Consumer Sentiments (ICS) and presidential approval to begin to answer these questions.<sup>17</sup> As the standard aggregate measure of voters’ subjective evaluation of the economy, the ICS has been used in numerous studies as a predictor of presidential approval (e.g., Clarke and Stewart 1994; DeBoef and Kellstedt 2004; Holbrook 1994; MacKuen, Erikson, and Stimson 1992). While these articles have disagreed over the appropriate method and/or control variables to use when measuring this relationship, they have each begun with the assumption that a single parameter could capture the *constant* relationship between the variables.

To test the credibility of this assumption, we begin our analyses by using Tse’s (2000) test of the null hypothesis of constant correlations. The Tse test examines the residuals of a broad GARCH model, thus allowing maximum flexibility by not imposing zero restrictions on models’ components. In Table 1, we find that a GARCH (2,1) model with asymmetric effects fits best for the presidential approval series.<sup>18</sup> Glosten, Jagannathan, and Runkle (1993) estimate the following model:

<sup>16</sup>Debate among researchers in British politics regarding the impact of the Falklands War on the approval ratings of Margaret Thatcher and her Conservative government focused attention on the importance of political events, but modeled events as variables to be controlled for, rather than as different periods during which the effects of economic variables might vary. See, for example, Clarke, Stewart, and Zuk (1986) and Sanders et al. (1987). Lin (1999) studies the historical variation in economic voting in presidential elections from 1872 to 1996 using primarily moving-window techniques and Chow tests.

<sup>17</sup>These data are collected from <http://www.sca.isr.umich.edu/> for the ICS and its components, and from <http://www.pollingreport.com/> for Gallup’s monthly approval rating. Our sample period is January 1978 to July 2004.

<sup>18</sup>As noted above, Tse’s test and the DCC analyses that follow rely on the stationarity of series. In addition to extensive arguments made elsewhere (e.g., Box-Steffensmeier and Smith 1996; Lebo, Walker, and Clarke 2000), further tests find these variables to be fractionally integrated. Thus, we use RATS’ FIF.SRC to fractionally difference our series. Using Robinson’s (1995; RGSER.SRC in RATS) estimator, the values for differencing are ICS ( $d = 0.89$ ), five-year National Projections ( $d = 0.75$ ), National Retrospections ( $d = 1.10$ ), Personal Projections ( $d = 0.67$ ), Personal Retrospections ( $d = 0.76$ ),

**TABLE 1 Tse (2000) Tests for Constant Correlations with Presidential Approval**

Economic Variable	Average Correlation	$p$ Significance Level*
ICS	0.107	0.018
5-Year Nat. Projections	0.143	0.004
National Retrospections	0.097	0.059
Personal Projections	0.132	0.008
Personal Retrospections	0.019	0.478

\*One-tailed tests with a null of constant correlations.

$$h_t = c_0 + a_1 \varepsilon_{t-1}^2 + b_1 h_{t-1} + b_2 h_{t-2} + m_1 \varepsilon_{t-1}^2 I_{\varepsilon > 0} \quad (8)$$

where  $I$  is an indicator function such that it equals 1 when standardized residuals of the series ( $\varepsilon_t$ ) are positive and equals 0 otherwise. A negative value of  $m$  means that periods with negative residuals will be immediately followed by periods of higher variance than will be periods of positive residuals. This is exactly what one would expect for the approval series where unanticipated drops signal periods of greater volatility.

We use this GARCH specification for the approval series as well as the monthly ICS and subjective measures of the economy<sup>19</sup> and display the results of Tse’s test in Table 1. The first column lists the average correlations between the approval variable and each of the economic series. While none of these correlations are particularly high, the second column shows that the first four series are not constant in their correlations either. Also important to note is the fact that the volatility within the series is not constant. For example, the variance in the approval series is quite different across presidencies (roughly 65 for Carter, 55 for Reagan, 207 for Bush I, 48 for Clinton, and 130 for Bush II). For both of these reasons, a DCC model is warranted.

Table 2a displays estimation results of the DCC(1,1) model for the ICS and presidential approval. The

and Presidential Approval ( $d = 0.95$ ). Both procedures are available for RATS from the Estima website ([www.estima.com](http://www.estima.com)).

<sup>19</sup>These come from the University of Michigan’s Survey of Consumers, which creates indices based on the following questions: Five-year national projections: “Looking ahead, which would you say is more likely—that in the country as a whole we’ll have continuous good times during the next five years or so, or that we’ll have periods of widespread unemployment or depression, or what?”; national retrospections: “Would you say that at the present time business conditions are better or worse off than they were a year ago?”; personal projections: “Now looking ahead, do you think you (and your family living there) will be better off financially, or worse off, or just about the same as now?”; personal retrospections: “Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?”

**TABLE 2a GARCH-DCC(1-1) Estimates for ICS and Approval, 1978–2004**

Parameter	Estimate	Standard Error	t-value
$c_{ICS}$	15.767	11.958	1.319
$a_{ICS}$	0.094	0.085	1.098
$b_{1,ICS}$	0.037	0.766	0.049
$b_{2,ICS}$	-0.236	0.315	-0.748
$m_{ICS}$	0.038	0.116	0.323
$c_{Approval}$	1.507	0.621	2.425**
$a_{Approval}$	0.118	0.057	2.080*
$b_{1,Approval}$	0.278	0.135	2.059*
$b_{2,Approval}$	0.417	0.119	3.516**
$m_{Approval}$	-0.302	0.132	-2.286*
$\alpha$	0.058	0.043	1.353
$\beta$	0.839	0.104	8.091***
$\bar{R}$		0.107	

\* $p < .05$ , \*\* $p < .01$ , \*\*\* $p < .001$ . Estimation is based on the DCC-GARCH model:

$$h_t = c_i + a_i u_{t-1}^2 + b_1 h_{t-1} + b_2 h_{t-2} + m_i u_{t-1}^2 I_{u>0} \text{ for all } i = 1, 2 \text{ and } R_t = (1 - \alpha - \beta)\bar{R} + \alpha \varepsilon_{t-1} \varepsilon'_{t-1} + \beta R_{t-1}.$$

univariate GARCH parameters ( $a$ ,  $b_1$ ,  $b_2$ , and  $m$ ) are far more appropriate for the approval series than for the ICS series.<sup>20</sup> This is especially true for the asymmetric parameter  $m$ , which shows for the approval series that drops in approval are followed by periods of increased volatility. The significant GARCH parameters demonstrate time variation and dependence in the variance, further indicating we should prefer DCC models here to other time-varying estimators. As for the DCC estimates, the  $\beta$  parameter easily achieves statistical significance while  $\alpha$  does not. In tandem, these again point to the unsuitability of assuming constant correlations. Further, having a value of  $\beta$  close to 1 indicates the strong degree of persistence in the series of correlations,  $R_t$ , while a sum of  $\alpha$  and  $\beta$  close to 1 indicates high persistence in the conditional variance.<sup>21</sup>

From the DCC model we extract the conditional correlations between the ICS and presidential approval and

display them in Figure 3.<sup>22</sup> Most obviously, the figure shows a great deal of variation in the correlations. Indeed, the correlation between the two is not even reliably positive as it slips below 0 on several occasions and is negative for 39 of the 318 months in the sample period. So, when does the economy matter? An early peak in the series is the spring of 1980 where the convergence of the increased importance of economic opinions and the poor state of the economy doomed President Carter in the fall election to come. In the Reagan years, we can see a decline in the importance of the economy so that, by the summer of 1986, with the press beginning to uncover the Iran-Contra scandal and shifting the economy to the back burner, the series is clearly in negative territory. As George H. W. Bush takes office, the correlations reach a low point, but steadily increase over the course of his term. Indeed, presidential candidate Bill Clinton seemed to realize this more than the president did when his team stressed, “it’s the economy, stupid.” Sure enough, the correlation peaks right at the time of the 1993 election.

Then, as was the case with the Reagan years, the importance of the economy decreases over the first six years of Clinton’s presidency, only to see a resurgence in the two years leading up to an election with no incumbent. Lastly, the series dives deeply into negative territory following the terrorist attacks of September 2001. Here, subjective beliefs about the state and hopes for the economy were justifiably gloomy at the same time as presidential approval ratings hit all-time highs. With so much volatility in the importance of economic judgments, theories that make conclusions without reference to circumstances are worthy of reconsideration.

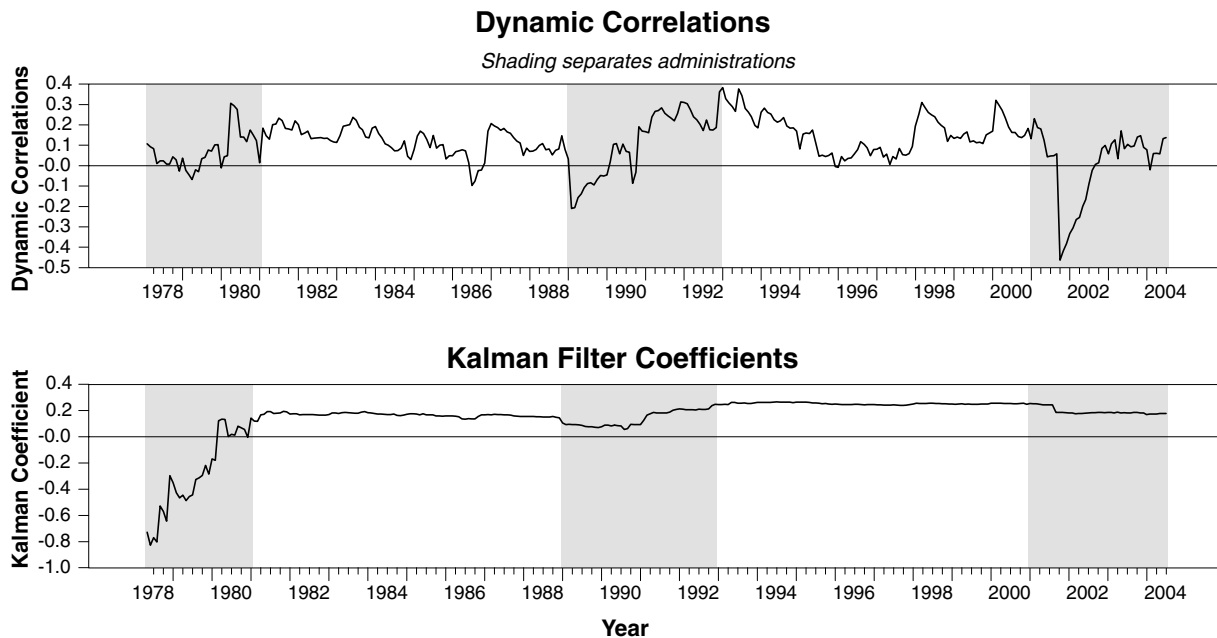
With that in mind, we take the additional step of modeling the correlations themselves. Table 2b displays a transfer function model of the dynamic correlations

<sup>20</sup>Recall that the estimation of the  $\alpha$  and  $\beta$  parameters in the DCC model relies on the standardized residuals of these univariate GARCH models. Thus, having additional, though insignificant, parameters estimated for the ICS series is both harmless and preferable to having missing parameters for the approval series.

<sup>21</sup>The former point is a common characteristic of GARCH conditional variance estimates (see Engle 2002 and Engle and Sheppard 2001) and can be seen in the term  $\beta R_{t-1}$  in equation (7). The latter point is evident in the term  $(1 - \alpha - \beta)\bar{R}$  in the same equation.

<sup>22</sup>Shading demarcates presidential administrations. There are no standard error bands on the correlations because, technically, the conditional correlation is a forecast of the correlation that would be appropriate next period conditional on this period’s data, and therefore the uncertainty in this forecast (assuming the correctly specified model) is simply due to parameter uncertainty. One could conceivably take the joint confidence interval of the DCC parameters, possibly corrected for the two-step estimation problem and possibly also corrected for the GARCH parameters, and form prediction intervals, though this has not yet been done in the literature. The parameters are typically estimated with a high degree of accuracy so these intervals are likely to be quite small, particularly as the number of observations grows. Similarly, one could ask: what is the interval that would include the actual correlation with some confidence level? In fact, we never observe or estimate the actual correlation so this is difficult to formulate precisely. As for the joint interval for the next observation, this is given by standard probability ellipses, at least assuming normality with the given variances and covariances (personal correspondence with Robert Engle, June 19, 2006).

**FIGURE 3 Presidential Approval and the ICS, 1978–2004**



between the ICS and presidential approval. We follow the bulk of the literature and include as predictor variables major events that can be expected to alter the relationship between the economy and approval—the Iranian Hostage Crisis, Operations Desert Shield and Desert Storm, the September 2001 terrorist attacks, and the election victories of new presidents-elect—as well as a series of miscellaneous events that should have smaller effects.<sup>23</sup> In addition, we include a honeymoon variable following the inauguration of a new president and a monthly measure of GDP growth.

Most of these effects are easy to predict. For example, the dynamic correlations drop drastically (0.531) in the month of the 2001 terrorist attacks as approval skyrocketed while economic evaluations plummeted. Honeymoon effects drop the correlation by .05 but this is only short-lived as .614 of the drop rebounds in the following month, as measured by the  $\delta$  parameter. Miscellaneous events also lower correlations both contemporaneously and with a two-month lag, though again correlations bounce back quickly. The changes in correlations in the months surrounding Operations Desert Shield and

Desert Storm and during the months following presidential elections are more idiosyncratic. Lastly, the effects of GDP growth are interesting as higher levels of growth are associated with a weakening in the following month of the link between economic judgments and presidential approval. These effects appear short-lived as well with a rebound in the next month nearly equal to the initial drop. Interestingly, improvements in the economy—while rewarding presidents in their raw effect on approval—have diminishing marginal returns as they reduce the impact of the electorate’s evaluation of the economy.

For comparison, the bottom panel of Figure 3 analyzes the same data using a Kalman filter. As the estimates progress there is less and less movement in the coefficient. New observations are simply swamped by the mass of data points that precede them. In particular, the vast change in the correlation between approval and the ICS that is seen in late 2001 in the DCC model is barely noticeable in the Kalman estimates.

What is different between this model and a model of approval that includes the ICS?<sup>24</sup> In this model we are able to make conclusions about interaction effects—rather than seeing the effects of the economy on approval alongside other effects, we can see how the size and direction

<sup>23</sup>The dependent variable is the series displayed in Figure 3, the dynamic correlations between the series:  $\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{ii,t}q_{jj,t}}}$ , where  $q$  represents elements of the conditional variance-covariance matrix of the standardized errors ( $\epsilon_t$ ) of the separate GARCH models, computed as:  $q_{i,j,t} = \rho_{i,j} + \alpha(\epsilon_{i,t-1}\epsilon_{j,t-1} - \rho_{i,j}) + \beta(q_{i,j,t-1} - \rho_{i,j})$  with  $\rho_{i,j}$  being the overall correlation.

<sup>24</sup>Future research should investigate the degree of observational equivalence between models such as this one, DCC models that begin with the residuals of a well-specified model, and DCC models with more comprehensive mean equations in the GARCH portion.

**TABLE 2b Box-Jenkins Model of Correlations between ICS and Presidential Approval**

Independent Variable	Coefficient	Standard Error	<i>P</i> Significance Level
Constant	0.010	0.005	.034
Honeymoon	-0.050	0.019	.012
Honeymoon $\delta$	0.614	0.214	.004
Misc. Events	-0.011	0.006	.092
Misc. Events <sub><i>t</i>-2</sub>	-0.011	0.005	.027
Misc. Events $\delta$	0.734	0.148	.000
Iran Hostages	0.284	0.040	.000
Desert Shield Begins	-0.163	0.040	.000
Desert Shield Begins <sub><i>t</i>-2</sub>	0.217	0.040	.000
Desert Storm Ends	0.106	0.039	.006
Desert Storm $\delta$	0.595	0.211	.005
September 11	-0.531	0.040	.000
Reagan Wins	0.198	0.041	.000
Bush I Wins	-0.222	0.041	.000
Clinton Wins	0.196	0.040	.000
Bush II Wins	0.121	0.041	.003
GDP Growth <sub><i>t</i>-1</sub>	-0.0021	0.001	.048
GDP Growth <sub><i>t</i>-2</sub>	0.0017	0.001	.104
<i>R</i> <sup>2</sup>		0.56	
Durbin-Watson		2.03	
N		312	

of the economic effects are themselves affected by other phenomena. This highlights the ability of time series analysis to study relationships among variables across circumstances. It is also worth noting the profound differences between forecasts we might get by using updated correlations. During some periods, we would forecast a positive change in the ICS to move presidential approval substantially while at other times, we would expect a very muted relationship. Using the correlation that exists at the time of the forecast, rather than the average correlation over the entire series, holds particular promise for improved political modeling.

### Retrospective, Prospective, National, or Personal, Why Choose?

DCC methods also shed new light on another long-standing debate over the specifics of economic voting. While the importance of the economy to voting has long

been established, disagreement still exists over which aspect of economic performance matters most to voters. When assessing leaders, do voters look to the national economy (sociotropic) or to their pocketbooks (egocentric)? Do they look at the past (retrospective) or the future (prospective)? As different shades of Key's (1968) original pocketbook voting argument, each of these four dimensions has its own supporters. Particularly prominent among this body of research are Norpoth (1996), who maintains the importance of national retrospections, and MacKuen, Erikson, and Stimson (1992), who argue instead for the prominence of national prospections.

These empirical studies share an "all or nothing" perspective on the question and the use of methodology that allows, at best, a ranking of alternatives. With few exceptions,<sup>25</sup> researchers do not allow for the possibility that the relative efficacy of these dimensions may not be constant. Indeed, it is quite possible that during some periods—for example, those immediately following elections—voters make closer ties between national prospections and leadership approval. Thus, political conditions may play a vital role in understanding how voters use economic information to evaluate presidents, prime ministers, and governing parties over time.

With these queries in mind, as well as the clear results of Tse's test rejecting the null of constant correlations, we estimate a DCC(1,1) model for the relationship between presidential approval and the five-year national prospections variable.<sup>26</sup> Looking at Table 3, the univariate portion used is again the GARCH (2,1) models with asymmetric effects, but here we find much stronger effects for the economic series than for the ICS. The positive asymmetric coefficient, however, tells us that—contrary to the approval series—increases in economic prospections are followed by increased volatility. So while expectations increase, so does the variability. The significance of the GARCH parameters again points to the desirability of DCC.

The DCC parameters,  $\alpha$  and  $\beta$ , are also both clearly statistically significant in this case and demonstrate a good deal of persistence in the correlation process. The correlations between the two series are definitely not constant and depend a great deal on circumstances. Logically, we should expect to see a stronger pattern here than we did with the ICS series. As a combination of several series looking both backwards and forwards in time, the importance of temporal context is dampened quite a bit in

<sup>25</sup>Sanders and Carey (2002) use rolling recursive estimates; Carey and Lebo (2006) use a repeated cross-sectional design. Both use British data.

<sup>26</sup>The significance of this variable was the key to MacKuen, Erikson, and Stimson's (1992) contention that the American electorate was composed of "bankers" rather than "peasants."

**TABLE 3 GARCH-DCC(1-1) Estimates for National Prospections and Approval, 1978–2004**

Parameter	Estimate	Standard Error	t-value
$c_{NPros}$	63.110	10.333	6.107***
$a_{NPros}$	0.320	0.139	2.299*
$b_{1,NPros}$	-0.089	0.056	-1.604
$b_{2,NPros}$	-0.175	0.090	-1.945*
$m_{NPros}$	0.380	0.141	2.693**
$c_{Approval}$	1.507	0.621	2.425**
$a_{Approval}$	0.118	0.057	2.080*
$b_{1,Approval}$	0.278	0.135	2.059*
$b_{2,Approval}$	0.417	0.119	3.516**
$m_{Approval}$	-0.302	0.132	-2.286*
$\alpha$	0.075	0.031	2.428*
$\beta$	0.852	0.071	12.056***
$\bar{R}$		0.143	

\* $p < .05$ , \*\* $p < .01$ , \*\*\* $p < .001$ . Estimation is based on the DCC-GARCH model:

$$h_t = c_i + a_i u_{t-1}^2 + b_i h_{t-1} + b_i h_{t-2} + m_i u_{t-1}^2 I_{u>0} \text{ for all } i = 1, 2 \text{ and } R_t = (1 - \alpha - \beta) \bar{R} + \alpha \varepsilon_{t-1} \varepsilon'_{t-1} + \beta R_{t-1}.$$

the ICS series. National prospctions are based on a single time horizon and, while MacKuen, Erikson, and Stimson (1992) found it to be a fine determinant of approval, we should expect the time frame of the question to increase the variability of its value.

Figure 4 displays both the series themselves and the dynamic correlations between them (lower panel). The top panel clearly shows that the two series are sometimes moving together but frequently not. The correlations (lower) show even wilder fluctuations than between the ICS and approval (the left-hand axis has changed). Here the dynamic correlations reach a peak of .58 in June of 1993 and fall as low as -.50 in October of 2001. Just within a single term of Bill Clinton’s presidency the correlations fluctuate between 0.58 and -0.11 (January 1996).<sup>27</sup> We can speculate that the time horizon of the question plays an important role here as, through the course of his first term, the electorate’s evaluation of Clinton came to be more closely tied with his (past) strong economic record. As a president spends more time in office and his record becomes more substantial, voters’ evaluations of him will become based less on prospects of the future and more on evaluations of the past. Further, in the known last years of

<sup>27</sup>We see a similar pattern during the Reagan presidency with correlations reaching an early peak followed by a long decline. Thus, reversals and negative correlations are not particular to post-September 2001 effects.

a presidency a question asking to look ahead five years—well into the term of the president’s successor—should have a somewhat muddled relationship with the approval level of the current president. For example, worry by some of poor economic times to come once a president they like leaves office would push the correlations toward negative territory. The DCC model clearly reveals this pattern.

This example shows we can move away from debates such as that between Norpoth (1996) and MacKuen, Erikson, and Stimson. Figure 4 shows that neither is always right. Political circumstances play a vital role in understanding how voters use economic information to evaluate presidents, prime ministers, and governing parties over time. Intuitively, this makes sense, and the DCC model’s relaxation of assumptions provides the flexibility to examine these questions.

### International Cooperation and Conflict

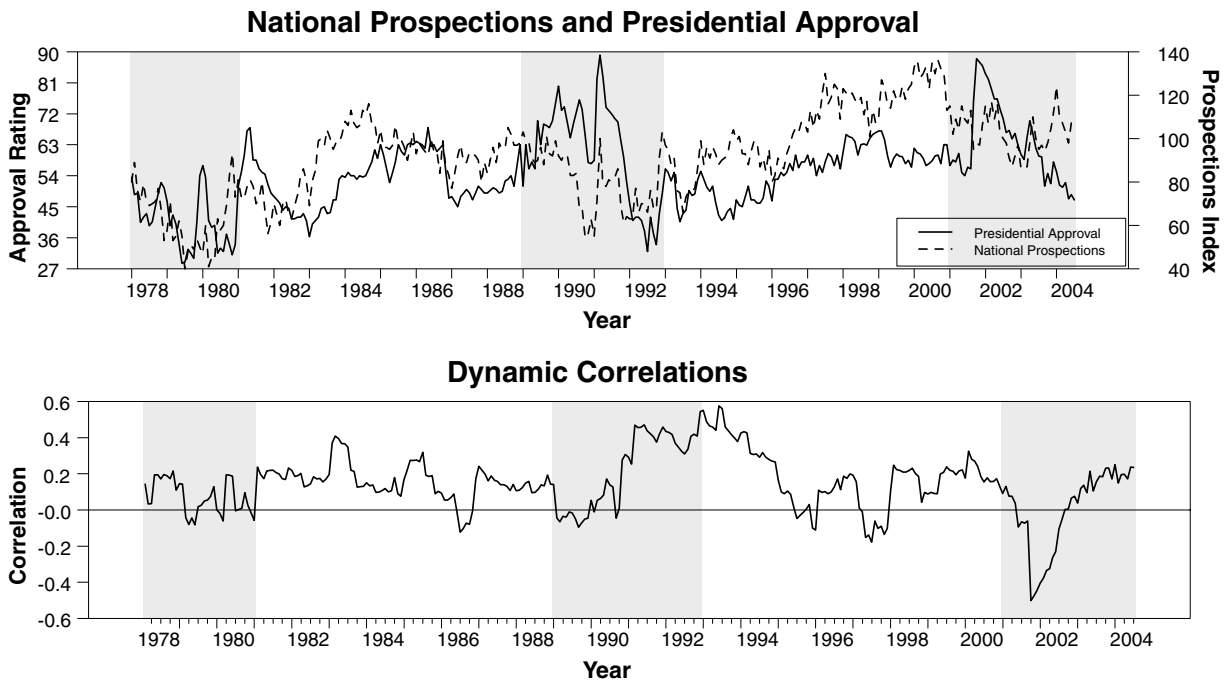
The area of international cooperation and conflict in foreign policy is another area that is theoretically and empirically concerned with questions that DCC models are ideally suited to answer. Studies of conflict, cooperation, and conflict resolution have been at the heart of international relations scholarship for over 50 years. In particular, this literature has been interested in the complex patterns of reaction and memory of the cooperation and conflict series. Ward (1982) introduces an action-reaction framework to examine the hypothesis that cooperation and conflict interact with one another as they evolve over time. He concludes that there is a high degree of reactivity among contemporary nation-states. This framework was subsequently used by many others (e.g., Dixon 1983, 1985; Goldstein 1991, 1995; Goldstein and Freeman 1990, 1991; Goldstein and Pevehouse 1997; Lebo and Moore 2003; Pevehouse and Goldstein 1999; Rajmaira and Ward 1990).

DCC models help us to better understand the interrelationship between cooperation and conflict by being less restrictive in our assumptions. Essentially, we have a much more flexible model that provides an evolutionary look at the interrelationship between the series.

We use Goldstein (1992) scores of monthly directed dyad data from the Kansas Event Data System (KEDS) for Palestine and Jordan for the period 1979–2004.<sup>28</sup> The average correlation for the two series is 0.434. The Tse

<sup>28</sup>Following Lebo and Moore’s (2003) use of fractional integration in directed dyads, we find that  $d = 0.21$  for the Jordan to Palestine series and  $d = 0.39$  for the Palestine to Jordan series. We again use fractional differencing to make each stationary prior to estimating the DCC model.

FIGURE 4 The Varying Efficacy of National Prospections, 1978–2004



test shows that we can reject constant correlations with a statistically significant p value < 0.0001. The *t*-statistic is -4.47.

Next, we estimate the GARCH-DCC(1,1) model for Palestinian-Jordanian interaction from 1979 to 2004 and present the results in Table 4. The significance of the GARCH parameters is a clear sign that the story of the movement—and comovement—of these series is incomplete without an understanding of the ups and downs in their variance, as well as their means. Both of the DCC parameters,  $\alpha$  and  $\beta$ , are statistically significant. This confirms that we should not assume constant correlations. Looking at the estimate of  $\beta$ , we see strong persistence in the series.

Figure 5 presents the dynamic correlations for Palestinian and Jordanian interaction. We see substantial variation over time. The peak is approximately 0.8 in 1985. It was around this time that the “Amman Agreement,” calling for a Palestinian state in the West Bank, was signed between Jordan and the PLO. We see a precipitous drop begin about a year later, coinciding with the nullification of the Amman Agreement after Arafat refused to endorse United Nations resolutions. It was then that President Reagan refused to acknowledge Palestinian rights as well. The low point in the figure is approximately 0.14 in the mid-1980s. This was around the 20-year anniversary of occupation for the Palestinian territories and many associated

TABLE 4 GARCH-DCC(1-1) Estimates for Palestinian-Jordanian Interaction, 1979–2004

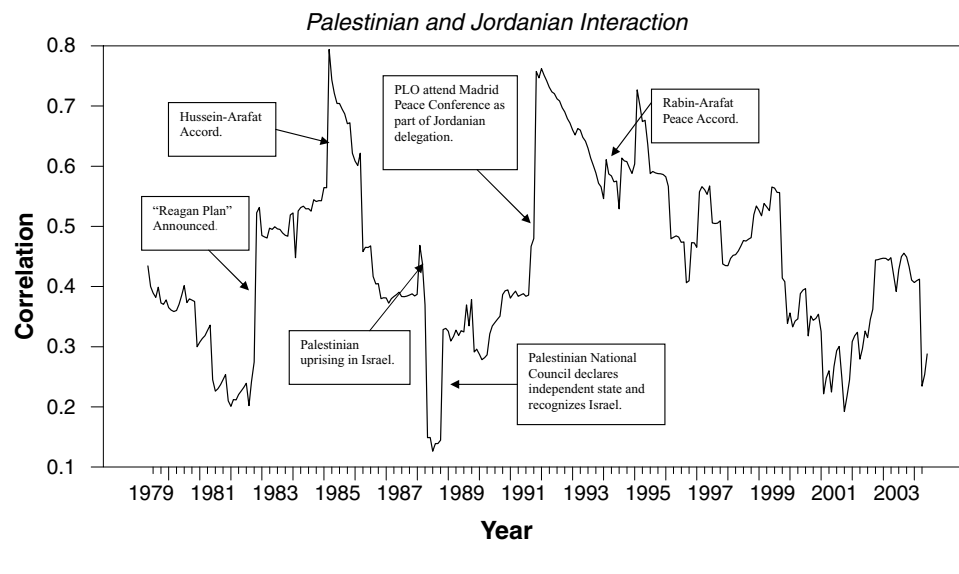
Parameter	Estimate	Standard Error	<i>t</i> -value
$c_{Pal-Jor}$	16.629	0.700	23.752***
$a_{Pal-Jor}$	0.096	0.034	2.837**
$b_{Pal-Jor}$	0.391	0.022	17.479***
$c_{Jor-Pal}$	12.594	0.956	13.169***
$a_{Jor-Pal}$	0.240	0.033	7.289***
$b_{Jor-Pal}$	0.502	0.021	23.877***
$\alpha$	0.057	0.018	3.121***
$\beta$	0.902	0.030	30.137***
$\bar{R}$		0.434	

\**p* < .05, \*\**p* < .01, \*\*\**p* < .001. Estimation is based on the DCC-GARCH model:

$$h_t = c_i + a_i u_{t-1}^2 + b_i h_{t-1} \text{ for all } i = 1, 2 \text{ and } R_t = (1 - \alpha - \beta) \bar{R} + \alpha \epsilon_{t-1} \epsilon'_{t-1} + \beta R_{t-1}.$$

uprisings. The volatilities reflect major shocks to the system being studied. The higher correlations show greater stability in the relationship for Palestine and Jordan. It is not surprising in the study of politics that we do not see sustained and high correlations, particularly in this region of the world.

FIGURE 5 Dynamics Correlations



The DCC approach may be especially informative in the search for dynamic early warnings of international conflict. As Schrodtt and Gerner discuss, the search for a “crisis phase” between countries is best aided by tools more sensitive than regression models. They point out that “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” (2000, 807). Using dynamic correlations can help researchers and policymakers identify the key thresholds that may push a relationship “toward or away from violence” (Bloomfield and Leiss 1969). Again looking at Figure 5, we can see that the peak correlation of 0.8 achieved in early 1985 indicates the height of give-and-take relations between the Palestinians and Jordan, their most natural ally in the region. The steep decline in the reciprocity between the two nations may well cross precisely the type of threshold for which Schrodtt and Gerner (2000) have correctly sought more sensitive dynamic analyses capable of detecting crisis phases before they occur. Indeed, as relations with Jordan, their sponsor in the peace process, fell into chaos, the Palestinians turned fully to violence against Israel and launched the first *Intifada*.

## Conclusion

Using the Dynamic Conditional Correlation model, we found substantial variation in important political relationships over time. The effect of the ICS on presidential approval varies a great deal over the last 30 years.

Indeed, the effect is frequently negative. Likewise, the effects of the components of the ICS are time varying. Voters are not unconditionally more retrospective than prospective and the reverse is not true either. Rather, the importance of these measures vary over time and in predictable patterns over the course of an election cycle. If we want to make predictions about how the economy will affect approval or an election, we are better off paying attention to the most relevant correlations rather than those based on equally weighting all the available data. In our last example, we saw tremendous variation in the dynamic interactions of Jordan and Palestine. At times the two are well synchronized in their interactions, allowing some stability in their relationship, yet instability can come about quite suddenly. In all three examples, the first step of the DCC process, the estimation of univariate GARCH models, showed the strong presence of time-varying variance. Thus, among the many time-varying estimation strategies, the DCC approach is the most appropriate.

And, of course, all of this variation is lost in studies that estimate single time-invariant parameters. The DCC modeling innovation is important because it allows us to pinpoint changes (both when they occur and how) in the interdependence between series. The key advantages of the DCC model are that it accounts for volatility and allows correlations to vary over time, have asymmetric effects, and be either positive or negative. It also provides insight into the memory of the correlations so we can judge whether correlations naturally revert to an equilibrium level. As analysts, we are no longer constrained to imposing one correlation value for the entire series.

On the other hand, it is important to remind users that the DCC approach is best suited for situations where the model structure is well known. We would like to know quite a bit about a relationship before seeing if the relationship varies. Further, the DCC model is not advisable when the series are very short and it loses value when volatility is not an issue.

In the examples, the evolution of the conditional variance in the context of economic voting and international conflict and cooperation, as well as the conditional correlation for the series, was explored. Procedurally, fractional differencing was first used to create stationary series that were not dependent on their own past histories. Second, we used the DCC method to estimate and account for the volatility of our series. Finally, their time-varying correlations with each other were estimated. The more nuanced DCC model is recommended as analysts are cautioned against making generalized statements about the effect of series using traditional methods that are not contextually based. For example, the DCC model shows that the comovement between prospections and presidential approval reaches a high of .58 in June of 1993, while the low is of almost the opposite magnitude,  $-.50$  in October of 2001. The dynamic correlations for Palestinian and Jordanian interaction also reveal substantial variation over time. The peak is approximately 0.8 in 1985, followed by a precipitous drop that began about a year later, and the low point is approximately 0.14 in the mid-1980s.

Allowing for contextual variation over time is an important step to more fully understanding the dynamic processes at work in a variety of important substantive areas. The DCC modeling approach is an important innovation in time series analysis, one that fits well with the understanding of political scientists, and one that should be embraced by the discipline as another useful technique at our disposal as we have more and more time series data, particularly high frequency data, at our fingertips across substantive fields. The relaxation of assumptions about constant relationships in a multivariate time series setting as well as the incorporation of variance components provide a more flexible approach for analysts and allow new substantive insights to emerge.

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