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Forecasting European Union politics: Real-time forecasts in political time series analysis

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Abstract

Forecasting plays an increasingly important role in the scientific study of European Union politics and in political science in general. This is because forecasts are not only indispensable for (political) actors who need to form expectations about future events, but can also be used to judge the validity of (competing) theoretical models. While the debate about *whether* political science should engage in forecasting is largely over, many questions about *how* this should be done in everyday research are still open. One of these is how forecasts of political time series can be derived from theoretical models. Using a practical example from European Union research, we start to address this question. We first show how forecasts of political time series can be derived from both theoretical and atheoretical models. Subsequently, we use an atheoretical time series (ARMA) imputation approach to demonstrate how they can be fruitfully integrated in order to overcome some of the limitations to making forecasts of political time series which are based on theoretical models.

Keywords

European Union, forecasting, imputation, legislative output, time series

Introduction

A forecast is a conditional statement about how a phenomenon will develop in the future. Forecasts are indispensable for actors in the real world. In order to make

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informed decisions, political actors (legislators, bureaucrats, as well as citizens) need to have an idea of the consequences of their actions. Therefore, forecasting offers crucial information to anticipate, and if necessary counteract, important developments. As a consequence, the demand for providing forecasts of political phenomena has increased. As Schneider et al. (2010) put it: 'Anticipating the future is both a social obligation and intellectual challenge that no scientific discipline can escape'. The need to anticipate and factor in the consequences of actors' choices also underlies rational models of politics, where actors are assumed to form expectations about the payoffs arising from different choices and to subsequently take the action which maximizes their expected utility.

Despite the fact that forecasts play a crucial role in both everyday life as well as rational models of political phenomena, there has been some disagreement in political science about whether the discipline itself can and should make predictions. This debate is a thing of the past. An important argument in favour of forecasting in political science has been forcefully put forward by Ray and Russett (1996). They argue that forecasts should play a larger role in political science, since they can be regarded as a valuable arbiter of competing theories and the (rival) explanations underlying them. Indeed, forecasts constitute honest and strict tests of the validity of theories. Claims about the future, 'cannot be modified, consciously or subconsciously, in order to accommodate the events upon which they focus, since the outcomes to be accounted for by predictions are unknown. This makes the future an important, even irreplaceable, arbiter between contrasting claims based on competing theoretical or epistemological approaches' (Ray and Russett, 1996: 446).

Scholars now largely agree that forecasting can be a valuable task for those engaged in the scientific study of politics. Therefore, while the debate about *whether* political science should engage in forecasting is largely over, many questions concerning *how* this should be done in research on the European Union (EU); and in political science, more generally, are still open. These questions pertain to how forecasts should be made, how they should be assessed and, most importantly, how real-time forecasts of political time series can be derived from theoretical models, i.e. explanatory accounts of the underlying data-generating process. The key problem here is strikingly simple. If we want to predict, for example, how public support for the EU develops in 2012 on the basis of theoretically motivated covariates such as economic development, trust in the EU's political institutions, knowledge about the EU or support for member state governments, we need to know the values of these explanatory variables in 2012. These values, however, are also unknown. Thus, obtaining forecasts from such a theoretical model poses a severe challenge.¹

In this research note we identify one simple approach to forecasting political time series from theoretical models and draw on an example from the latest research on European legislative output to illustrate this approach. We distinguish theoretical and atheoretical forecasting techniques and suggest that researchers try to make use of atheoretical time series models to produce forecasts for those

variables which function as important predictors in their theoretical model. Whenever these processes can be modelled within an ARMA (autoregressive moving average) or another univariate time series framework, we can use this forecast to impute the missing values. Together with the parameter estimates from the theoretical model, these can be used for deriving forecasts of the original variable of interest based on the theoretical model. This combination of atheoretical forecasts and theoretical models allows researchers to actually draw on established theories when providing forecasts of political time series.

Forecasting in European Union research

A cursory look at the most prestigious political science journals suggests that scholars still hesitate to engage in political forecasting. Indeed, articles which explicitly aim to make predictions on how political phenomena will develop in the future are still rare: Krueger and Lewis-Beck (2005) report that out of 1756 articles which have been published in the three leading political science journals (*American Political Science Review*, *American Journal of Political Science*, and *Journal of Politics*) from 1990 to 2005, only 15 (0.9%) engaged in forecasting. This seems to be in line with the opinions of a considerable number of scholars who do not believe that making predictions can and should be a part of political science research. Some of these have argued that political scientists cannot make predictions, because there are no laws to be discovered in the political sphere (Lapid, 1989). Others have pointed out that in the social sciences, predictions are, at least in part, self-fulfilling prophecies, because these will change individuals' behaviour so that it conforms with the predictions made (Berger and Luckman, 1966; Foucault, 1972; Lyotard, 1992).

In the following, we distinguish between out-of-sample predictions and (real-time) forecasts. Out-of-sample predictions are conditional statements about a phenomenon for which the researcher actually has data, i.e. the outcome (or dependent) variable has been observed, but when making the prediction the researcher pretends as if the values of the dependent variable were unknown. Thus, the prediction can instantly be compared with what has been observed. In practice, first the available data is divided into two subsets. Second, the researcher fits a (theoretically motivated or an atheoretical) model to one of these subsets. Third, the estimated parameters are used to predict the phenomenon in the other subset of the data. Finally, the predictions are compared with the observed values and measures of forecasting accuracy are computed and assessed.

A (real-time) forecast is a prediction for a variable whose values are truly unknown, because the outcomes to be accounted for by the prediction have not yet occurred. In this sense, forecasts are real predictions, because we are not yet able to say whether the predictions were correct. In the following we briefly review *some* examples which can be found in the literature on EU politics.

Out-of-sample predictions and forecasting in the study of EU politics

Interestingly, if compared with other subfields in political science, EU research seems to be one of those areas in which scholars already engage in forecasting relatively frequently. Several analysts have, in part explicitly, engaged in producing out-of-sample predictions. In particular, formal theorists and scholars applying spatial models to study European politics have made important contributions in this area. Valuable examples are the decision-making models developed in Bueno de Mesquita and Stokman (1994; note especially Bueno de Mesquita, 1994 in that volume) and, more recently, Thomson et al. (2006). Almost all contributions in Thomson et al. (2006) make predictions about bargaining outcomes in European politics based on different decision-making models. These predictions are then compared with the observed outcomes. This allows researchers to evaluate which bargaining solution concept is the most powerful in the sense that it makes predictions which are more accurate than those from other models. However, such predictions are not necessarily specific to formal or quantitative work. For example, Enderlein and Verdun (2009) review the qualitative predictions scholars have formulated regarding the development of the European Monetary Union (EMU) 20 years ago and compare these with how the EMU has actually developed. This comparison generates insights concerning which empirical developments in the EU are at odds with predictions from different integration theories.

EU research also offers several examples for real-time forecasting. Qualitative research such as that by Zielonka (2006) formulates claims about how institutional change or other internal or external developments will affect the functioning of the EU and the future of European integration.² Such qualitative forecasts usually build on analogies and past experience as does the study by Enderlein and Verdun (2009) which offers statements on how the global financial crisis will affect the EMU. Another example for forecasting in European politics can be found in the literature on *a priori* voting power in the EU (Johnston, 1995; Baldwin et al., 1997; Felsenthal and Machover, 1998; Bilbao et al., 2002; Felsenthal et al., 2003). The aim of these studies is to make forecasts of the effects of institutional change in the EU or enlargement decisions on actors' voting power. There are, however, less studies that make use of econometric techniques for forecasting EU-related events. A notable exception are election studies; compare, for instance, the out-of-sample forecast provided for the latest European Parliament (EP) elections by Simon Hix, Michael Marsh and Nick Vivyan (see <http://www.predict09.eu>).

Unsurprisingly, the possible conclusion of landmark EU treaties and upcoming enlargement rounds have generally increased interest in making forecasts in EU research. Applying a spatial model, König and Bräuninger (2004) provide forecasts of how Eastern enlargement, the institutional changes included in the Nice Treaty, and the constitutional reform of the EU will affect decision-making in the common agricultural policy. In their analysis of the conflict dimensions in the European

Council, Zimmer et al. formulate expectations about ‘how enlargement will affect the emerging political space within the European Union’ (Zimmer et al., 2005: 403) and predict that ‘producers’ and capital interests will be reinforced, with the new members joining the coalition of southern states, who resist further consumer-friendly legislation and trade liberalisation’ (Zimmer et al., 2005: 417). Steunenberg (2002: 112) uses computer simulations to predict that ‘under qualified majority voting, enlargement will not affect the Union’s ability to take new decisions’.

As this brief (and necessarily incomplete) review of the literature demonstrates, scholarship on EU politics already engages in making out-of-sample predictions. We interpret this as a move toward current practice in the natural sciences and economics, where prediction is an established scientific task, which even has its own academic publication outlets.³

Although ‘forecasting is *the* common standard used in time series modeling’ (Brandt and Freeman, 2009: 27) it does not yet play a major role in the scientific study of EU politics and in political science more generally. Obviously, EU research does make use of out-of-sample predictions to evaluate theoretical models. However, it still engages much more actively in making predictions than real-time forecasts. This is unfortunate, because such real-time forecasts may not only help to put theories to a rigorous test, but also provide extremely valuable information to political actors upon which they can form expectations. The reason for why the role of forecasting has thus far been limited is simple: most of the theoretically motivated time series models employed in quantitative research rely on independent variables which are treated as exogenous, but in order to make a forecast, the future values of these variables need to be known.

This missing data problem has plagued forecasting efforts and still limits the extent to which researchers can derive forecasts of political time series from theoretical models. In the following we first illustrate how out-of-sample predictions from theoretical and atheoretical models can be compared. Against this background we outline one simple solution to the apparent inability of current theoretical models to produce forecasts of political time series. We recommend that researchers capitalize on the availability of atheoretical time series (Box–Jenkins [BJ] or ARMA) models in order to obtain forecasts of the variables which function as arguments in the theoretical model. Clearly, ARMA models are not supposed to be explanatory, causal accounts of the underlying data generating process. In this sense, they are atheoretical and descriptive. Nevertheless, whenever exogenous variables in a theoretical model can be modelled within a BJ framework, we can generate real-time forecasts of these variables even if we do not *understand* their (causal) data generating process.⁴ Using these (atheoretical) predictions and the parameters from the theoretical model, forecasts of political time series can be obtained from the theoretical model as well. This procedure may be regarded as a fruitful integration of atheoretical and theoretical models.

Data and models

We now illustrate the approach outlined above with its application to EU legislative output. In EU research, legislative productivity has, for example, been used to study the legislative consequences of European integration (Fligstein and Stone Sweet, 2002; Pollack and Ruhlman, 2009), the effects of European Parliamentary elections (Kovats, 2009), and the impact of enlargement via anticipatory behaviour in EU legislative politics (Hertz and Leuffen, 2009; Leuffen and Hertz, 2010). Thus far, legislative output, i.e. the number of laws produced in a certain period, has widely been used in legislative studies in the US, where it is regarded as a measure of legislative performance (Frendreis et al., 2001) or a political system's capacity to act (Mayhew, 1991; Binder, 1999). Obviously, measuring the quantity of legislation seems to ignore the quality of legislative output. However, as Mayhew (1991: 35) has succinctly argued for the case of the US system, in many respects 'system production should be the final test, not whether presidents happened to get what they wanted'. Accordingly, many important theories of lawmaking, such as veto player theory, encourage scholars to analyse policy stability in terms of legislative output (Tsebelis and Yatağan, 2002).

EU legislative output is an important variable because it measures how intensively this organization makes use of its legislative authority. Thereby, the EU either decreases the set of policy issues which have not been regulated yet or have so far been regulated by national law. While EU lawmaking arguably reduces the influence of national legislatures, it has direct consequences for those national and regional administrations that have to implement its laws. Therefore, these administrations and other actors involved in transposing European law are likely to be interested in knowing how EU legislative output will develop in the future. This makes forecasts of EU legislative activity interesting in its own right.

The time series we use is monthly overall EU legislative output from January 1976 to September 2008 (see Figure 1). The variable was created from information provided by the European Commission (PreLex).⁵

We calibrate two types of model in order to derive out-of-sample predictions and real-time forecasts of EU legislative activity. The first model is theoretically motivated, i.e. explanatory variables are selected for theoretical reasons. In their study of EU enlargement effects, Hertz and Leuffen (2009) derive the corresponding hypotheses in detail. We do not duplicate their theoretical reasoning here and merely introduce the relevant variables. The second model we estimate entirely follows a data-driven approach known as the BJ methodology (Box and Jenkins, 1976). This approach builds on the idea that even if we do not understand the causal data-generating process underlying the phenomenon we are interested in, there may be patterns in the time series we can exploit successfully in order to make forecasts. We first estimate the models using data from January 1976 to September 2007. Subsequently, the estimated parameters are taken to the out-of-sample prediction window to generate predictions of legislative output for the remaining 12 months (i.e. October 2007 to September 2008). Since we have data for this period,

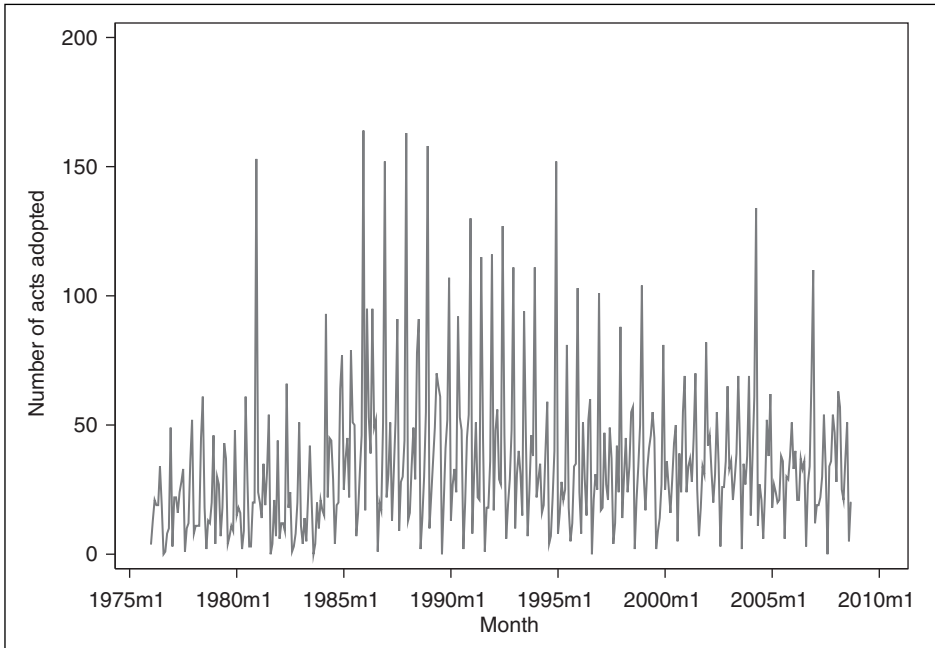


Figure 1. Overall European legislative activity: monthly number of acts adopted, 1976–2008. Data source: Hertz and Leuffen (2009).

we can compare how well the predictions perform against the observed time series. Subsequently, we venture into the forecasting world.

Theoretically motivated model

Let us briefly introduce the variables used in the theoretical model, in which the covariates are supposed to represent explanatory factors. For reasons of clarity we employ a more parsimonious variant of the model of Hertz and Leuffen (2009). Since our dependent variable is a count of the number of legislative acts that exhibits overdispersion, i.e. its variance is greater than the mean, we estimate a negative binomial regression model (see King, 1988: 230–238, and Long, 1997):

$$y_t = \exp(\beta_0 + \beta_1 x_t) \exp(\epsilon_t) \quad (1)$$

where y_t is legislative output in period t , X_t is an explanatory variable, and ϵ_t an error term. We add the following explanatory variables to Equation (1). The first variable *Commission Submission (lag 4)* simply counts the number of legislative proposals submitted by the Commission 4 months ago. Arguably, the higher the number of proposals, the higher the legislative output. Group size is often claimed to

affect decision-making. Therefore, we add several dummy variables to account for the different EU enlargement rounds (*EU 10*, *EU 12*, *EU 15*, *EU 25*). Several variables are included to model anticipative dynamics preceding enlargement rounds (*Anticipation 1981*, *Anticipation 1986*, *Anticipation 1995*, *Anticipation 2004*). Four variables account for institutional changes following the Single European Act (*Post Single European Act*), the Maastricht treaty (*post Maastricht*), the Amsterdam treaty (*post Amsterdam*) and the Nice treaty (*post Nice*). To pick up the effects of the single market program we include a dummy variable for Jacques Delors' term as Commission president (*Delors*). Two dummy variables account for the fact that most acts are passed at the end of a presidency in *June* and *December*.

Table 1 shows the results. As our objective is to illustrate how these results can be used in forecasting, we refrain from substantively interpreting and discussing the estimation results at this point.

Table 1. Negative binomial regression model of European legislative activity

Commission Submission (lag 4)	0.006***	(0.002)
EU 10	0.255*	(0.148)
EU 12	0.556**	(0.236)
EU 15	0.542***	(0.163)
EU 25	0.302*	(0.177)
Anticipation 1981	1.053***	(0.099)
Anticipation 1986	0.788***	(0.183)
Anticipation 1995	0.583***	(0.145)
Anticipation 2004	1.179***	(0.125)
Post Single European Act	-0.012	(0.156)
Post Maastricht	-0.153	(0.163)
Post Amsterdam	-0.049	(0.176)
Post Nice	0.135	(0.158)
Delors	0.067	(0.174)
June	0.765***	(0.081)
December	1.374***	(0.099)
Constant	2.577***	(0.104)
N	377	
LL	-1606.16	
AIC	3240.32	
BIC	3295.37	

Coefficients shown with robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

LL, log-likelihood; AIC, Akaike information criterion; BIC, Bayesian information criterion.

ARMA model

The second model we estimate follows a data-driven strategy known to time series analysts as the BJ methodology (Box and Jenkins, 1976). We opt for ARMA models, because they are relatively simple to apply, and the resulting forecasts may already be of sufficient quality for our purposes (Harris and Sollis, 2003: 10). Thus, although there are other, much more complex forecasting techniques, we follow Granger and Newbold (1986: 151) who point out that: ‘the cost of making particular forecasting errors should always be balanced against the cost of producing forecasts, for it is hardly worth expanding large resources to obtain a relatively small increase in forecast accuracy if the payoff, in terms of improved decision making is likely to be only marginally beneficial’.

The idea which underlies BJ or ARMA models is that even if we do not understand the data-generating process of a political phenomenon, we may still be able to exploit patterns in the time series to make forecasts. This means that we can build a univariate ‘model’ and subsequently forecast a political time series, for example, EU legislative productivity, as a function of past observed values (autoregressive [AR] terms), shocks (moving average [MA] terms) and seasonal components (seasonal AR and/or MA terms). Such ARMA modelling has been applied in an impressive number of diverse scientific disciplines, ranging from meteorology to leisure research, from astrophysics to empirical finance. Already in their authoritative treatment of ARMA modelling and forecasting, Box and Jenkins (1976) use time series data of 12 diverse phenomena.⁶ Among these are chemical process concentration, temperature and viscosity readings, IBM stock prices, sunspot numbers and international airline passenger numbers (Box and Jenkins, 1976: 524). Formally, an ARMA(1, 1) model is given by

$$y_t = \phi y_{t-1} + \psi \epsilon_{t-1} + \epsilon_t \quad (2)$$

where y_t is a process at time t and ϵ_t denotes an independent and identically distributed disturbance term with $E(\epsilon_t) = 0$ and $\sigma^2(\epsilon_t) < \infty$. Thus, y_{t-1} is the autoregressive (or AR(1)) component and ϵ_t is the moving average (or MA(1)) component. Clearly, this approach aims to make forecasts and not to evaluate empirical implications of theoretical models or estimate causal effects. Although the ARMA terms are not causal in the common sense⁷, i.e. not assumed to represent a causal model of the data-generating process, this approach may in some cases provide relatively useful forecasts.

A visual inspection of the monthly EU legislative activity data (Figure 1) suggests that a high degree of seasonality is present in this time series. Autocorrelation and partial autocorrelation plots underscore this impression. We identify three promising seasonal ARMA models. According to the information criteria, a seasonal ARMA model which consists of seasonal AR(12) and seasonal MA(4 5 6 7 9 10 12) terms fits the data best. Table 2 presents the estimation results.

Table 2. Seasonal autoregressive moving average (ARMA) model of European legislative activity

AR(12)	0.962***	(0.017)
MA(4)	0.075*	(0.045)
MA(5)	0.083**	(0.042)
MA(6)	0.118***	(0.039)
MA(7)	0.186***	(0.037)
MA(9)	0.060*	(0.0353)
MA(10)	0.105**	(0.044)
MA(12)	-0.680***	(0.044)
Constant	29.46	
N	381	
LL	-1645.57	
AIC	3311.15	
BIC	3350.58	

Coefficients shown with robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

LL, log-likelihood; AIC, Akaike information criterion; BIC, Bayesian information criterion.

For obvious reasons, there is not much use in interpreting the estimated coefficients. However, it is interesting to note that according to the goodness-of-fit measures (log-likelihood, Akaike information criterion [AIC], Bayesian information criterion [BIC]), the theoretical model performs slightly better than the ARMA model. In the next section we provide within-sample forecasts based on both the theoretical and the atheoretical model and briefly demonstrate how these predictions can be compared.

Out-of-sample predictions of EU legislative activity

We take the estimated parameters from both models to the October 2007 to August 2008 period, which is our out-of-sample predictions window. Based on the coefficients estimated above and the exogenous covariates used in the theoretical model, we obtain predictions of monthly legislative activity.⁸ For the ARMA prediction we only need the time series itself and the estimated ARMA parameters. The predictions from both models and the observed EU legislative productivity series are shown in Figure 2.

Looking at Figure 2, it seems that neither of the two models predicts EU legislative productivity considerably better than the other. Both models predict too strong a peak in Winter 2007, fail to predict a maximum in Spring 2008 and reasonably well predict the peak in July 2008.

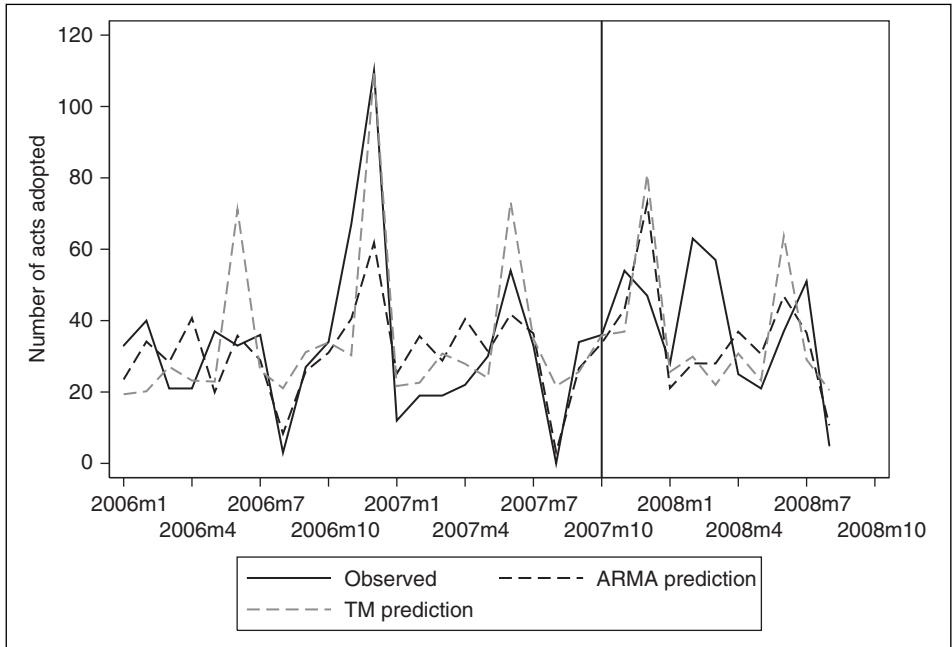


Figure 2. Out-of-sample predictions of legislative activity (2007–8). The vertical line indicates where the out-of-sample prediction starts.

Table 3. Out-of-sample predictions of European legislative activity: goodness-of-fit measures

	Theoretical model	ARMA model
MSPE	352.40	323.62
U_n	1.032	0.801
U_a	1.288	

MSPE, mean squared prediction error.

Visual inspection has its limits though. What we need is a measure of prediction accuracy, which allows us to compare how the two models perform in terms of predicting the monthly number of EU legislative acts. A first approach would be to compare the mean squared prediction errors (MSPEs) from both forecasts.⁹ As can be seen from Table 3, the MSPE of the atheoretical model is smaller than that of the theoretical model. A drawback of the mean squared prediction error (and other measures such as the mean absolute error) is that its size depends on the scale of the data. The literature has developed a useful measure of prediction accuracy,

which is invariant to the scale of the data (Kirchgässner and Wolters, 2007: 86). This measure, called Theil's U (Theil, 1966), is defined as

$$U_n = \sqrt{\frac{\sum_{t=1}^T (y_t - f_{t,h})^2}{\sum_{t=1}^T (y_t - y_{t-1})^2}} \quad (3)$$

The numerator is the sum of squared prediction errors for the model's forecast $f_{t,h}$ and the denominator is the sum of the squared deviations of the observed values y_t from a naive prediction. In most applications, the naive prediction is the 'no change' prediction y_{t-1} , i.e. we expect that legislative output in month t will be what it was in $t-1$. The subscript n indicates that this measure is derived by comparing the forecast with the prediction of a naive prediction. If U_n is greater than one, the prediction does not outperform the naive forecast. We compute Theil's U to assess the out-of-sample performance of the theoretically motivated and the BJ models. Table 3 presents the results along with the MSPE. The theoretical model performs slightly worse than the naive prediction, since Theil's U is slightly larger than 1. The atheoretical ARMA model outperforms the naive prediction as Theil's U suggests.

We can also use Theil's U to summarize how well the predictions from the theoretical model perform against those from the atheoretical model. To that end we slightly modify Equation (3) as follows:

$$U_a = \sqrt{\frac{\sum_{t=1}^T (y_t - f_{t,h})^2}{\sum_{t=1}^T (y_t - y_{t,a})^2}} \quad (4)$$

where $y_{t,a}$ is the prediction at time t from the atheoretical model. Again, if U_a is greater than 1, the theoretical model's prediction performance is worse than that of the atheoretical model. If U_a is smaller than 1, this indicates that the theoretical prediction is more accurate than the atheoretical prediction. Unsurprisingly, the prediction derived from the atheoretical model outperforms the theoretical model's prediction.

In the following section we first present real-time forecasts derived from the atheoretical ARMA model. Second, we explain why in almost all cases theoretical models are in need of some sort of atheoretical out-of-sample predictions in order to be useful for out-of-sample forecasts of political time series. Finally, we show how predictions from atheoretical models can be fruitfully integrated into theoretical models in order to make theoretically grounded real-time forecasts.

Real-time forecasts: Using ARMA imputation to solve the missing data problem

Our aim is to obtain two real-time forecasts, one based on the theoretical and the other based on the atheoretical model. Generating a dynamic forecast on the basis of the atheoretical ARMA model is relatively simple. We have data for the

estimation window (monthly EU legislative activity data from January 1976 to September 2008) and we have already calibrated an ARMA model which relates the present realization of our outcome variable (EU legislative activity) to its past realizations (AR terms) and past innovations (MA terms). If we want to forecast EU legislative activity in October 2008, i.e. the first period for which we do not have an observation, we simply predict the number of acts adopted in this period based on the data at hand and the estimated model parameters. Iteratively, we can predict future realizations as well. Once we have extended far enough in the future, predicted values from previous periods will enter the forecasting model. For example, we have estimated an ARMA model which includes a seasonal AR(12) term. In order to make a forecast for May 2010, we therefore need to know European legislative activity in January 2010. Although we only have observations until September 2008, we can use the forecast we generated for December 2008 to compute our prediction for December 2009. By this logic, it is possible to iteratively make a forecast which does not rely on any additional exogenous information. The only crucial assumption is that the patterns we have identified in the data will also hold in the future.

The situation becomes more challenging once we intend to use our theoretical model for making a real-time forecast, as this poses a missing data problem. In our application the number of Commission submissions 4 months ago is assumed to affect this month's legislative productivity. The forecasting problem is now obvious: how should one forecast legislative output in December 2010 on the basis of the theoretical model if the number of Commission submissions in August 2010 is unknown?

Of course, one might argue that for some variables which are assumed to affect legislative activity (or any other dependent variable a researcher focuses on) we can make a plausible, theoretically informed guess. First note that these guesses (or assumptions) are of course themselves some sort of qualitative real-time forecasts. For example, we can assume that there is no increase in the size of the EU, which implies that there are also no anticipation effects which precede enlargement rounds (Leuffen and Hertz, 2010). The Delors variable is constant and for the Lisbon treaty, we assume (at the time of writing of this research note) that it will be ratified by Ireland and thus enacted in early 2010.¹⁰

While for some variables researchers may make such informed guesses, especially if they pertain to single events such as the ratification of a treaty or the number of EU member states, these variables are often dummy variables which seldom vary across time. Therefore, their contribution to forecasting variance will be limited to shifts in the level of the outcome variable. While the seasonal June and December dummies can be included without having to make additional assumptions, thereby inducing variance in the forecast, theoretically informed guesses seem to be very difficult for variables such as the Commission submission variable, which varies considerably in our sample. How do we expect the number of legislative proposals submitted by the Commission to develop in 2010? We need to answer this question to provide a real-time forecast of EU legislative activity.

Assume for a moment that we live in a world of perfectly bivariate causal relationships (i.e. one exogenous variable x_t perfectly explains the outcome variable y_t) and suppose we found the theoretical model which could perfectly explain and forecast y_t as a function of the exogenous variable x_t . As long as we do not yet have an equally powerful theory for explaining x_t in terms of another variable z_t , we still need (more or less atheoretical) predictions about how x_t will evolve in the future in order to make a real-time forecast of y_t . One might try to argue that maybe there is a theory and a strong theoretically justified predictor, say a_t , for z_t as well. However, the same reasoning applies to a_t . Since we are not (and maybe never will be) able to explain everything, at some point the researcher needs an atheoretical prediction for his exogenous variable in order to make a forecast for the outcome variable based on his theoretical model. This is the point where atheoretical BJ models may fruitfully be integrated into theoretical models.

The extent to which we can compare forecasts with realizations of the outcome variable in the future obviously is also a function of how well the exogenous variables were predicted. Consequently, instead of making a crude and most likely inconsequential (in case a predictor is assumed to be constant within the forecasting window) assumption about their exogenous variables, we recommend that researchers try to obtain real-time forecasts from atheoretical (ARMA) models for those time-varying variables which function as explanatory factors in their theoretically motivated model. These forecasts can then be used as predictors together with the parameter estimates from the theoretical model so that real-time forecasts of political time series can be made on the basis of the theory. Thus, while the choice of the variables used to forecast the outcome variable is driven by theory, in the real-time forecast the actual values of these variables are generated on the basis of atheoretical forecasting models. We illustrate this procedure with our Commission submission variable in order to generate real-time forecasts of EU legislative productivity based on the theoretical model.

To obtain a real-time forecast based on our theoretical model of EU legislative productivity, we predict the values of the Commission submission variable employing an atheoretical ARMA model. First, we estimate an atheoretical ARMA model of the number of legislative proposals submitted by the European Commission. Second, we use the ARMA model to generate forecasts of the number of Commission submissions for the September 2008 to September 2010 period, i.e. we ARMA-impute the missing values. Finally, this prediction is used to generate a real-time forecast of EU legislative activity based on the theoretical model. The results are displayed in Figure 3.

Both models predict a roughly comparable pattern with maxima of 60 to 80 legislative acts in December and June. This is a consequence of the strong seasonality in EU legislative output which has been accounted for by both the theoretical and the atheoretical model. The ARMA forecast in addition predicts minima in August.

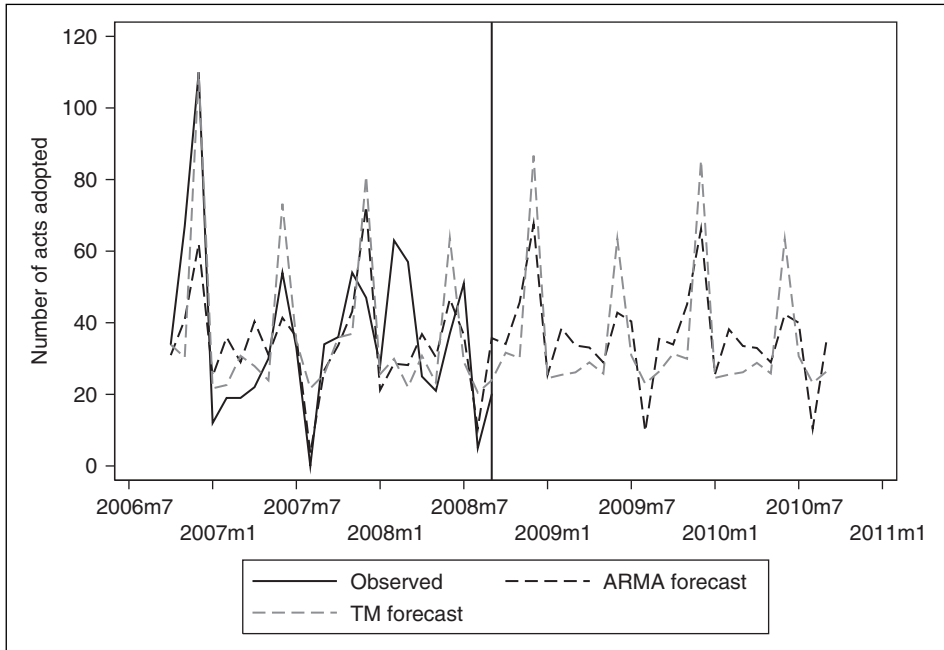


Figure 3. Real-time forecasts of legislative activity (2009–10). The vertical line indicates where the real-time forecast starts.

Conclusion and outlook

In this research note we have elucidated two possibilities for generating real-time forecasts of political time series data with an application to EU research. We distinguish theoretical and atheoretical forecasting techniques and suggest that researchers try to make use of atheoretical time series models to produce real-time forecasts for those variables which function as important predictors in their theoretical models (ARMA imputation). Whenever these processes can be modelled within an ARMA or another univariate time series framework, an ARMA forecast can be made to impute the missing values. Together with the parameter estimates from the theoretical model, these can be used for deriving forecasts of the original variable of interest based on the theoretical model. Thereby, researchers can combine atheoretical real-time forecasts and theoretical models to actually draw on established theories when providing real-time forecasts of political time series.

Our aim was to exemplify how atheoretical models may aid in making forecasts and how they can be used to derive forecasts from theoretical models via ARMA imputation, not to prove the superiority of one approach over the other. Also, our choice of using EU legislative output as an illustration should not be taken to imply that the approach laid out here only works for legislative output data. Quite the

contrary, we believe that this approach has the potential to be helpful for a variety of other political time series, e.g., support for European integration or EU spending patterns.

Forecasts which are based on a theoretical model enjoy the advantage that they imply claims about causal relations. Thus, these forecasts can be used to evaluate the (competing) claims of our theoretical models. To capitalize on this strength, we recommend that researchers more frequently generate real-time forecasts, which can later be compared against what could be observed. Yet, forecasts may sometimes be valuable in their own right, regardless of whether they are derived from a theoretical or an atheoretical model. A fisherman may not be interested in the reasons for why storms occur, but he certainly is interested in knowing in advance when they do. In our example, the ARMA model predicted legislative output slightly better in the out-of-sample prediction than the theoretical model. This might often be the case in areas where our theories are still relatively weak or where the patterns in the time series are strong enough that they allow for good atheoretical predictions which merely exploit the structure in the process. At least for the public, these forecasts may still be useful.

We have used a very simple, linear ARMA approach to impute values we need in order to derive a forecast from a theoretical model. However, it is important to note that there are many other more advanced and non-linear techniques which may prove useful for forecasting political time series. Even though their main purpose is in making forecasts, such data-driven models may assist research in theory development, because they help to reveal patterns in political processes which call for theoretical explanations. Thus, the seemingly less noble task of studying patterns in political time series can help to think more seriously about the *dynamics* which underlie political phenomena more generally.

Notes

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1. In the analysis of survey (King, 2001) and time series cross-section data (Honaker and King, 2009), a related problem is addressed by multiple imputation. Unfortunately, this approach can obviously not be used in our case, because the covariates which are needed to impute the data are also unknown.
2. See Tetlock (2005) for a treatment of expert forecasts.
3. Examples are the *Journal of Forecasting* and the *International Journal of Forecasting*, which explicitly invite submissions of applications in such diverse fields as ‘business, government, technology and the environment’ (see <http://www.wiley.com/WileyCDA/WileyTitle/productCd-FOR.html>, 4 May 2009). Economic forecasting is also a well-established sub-field in economics with publications present in all leading empirical economics journals (e.g. *Review of Economics and Statistics*, *Journal of Econometrics* and *Journal of Empirical Finance*) and even has its own outlet (*Journal for Economic Forecasting*).

4. These forecasts can of course be of interest to political actors, e.g. politicians, bureaucrats and citizens. At this point, we should mention other time series techniques which can be useful for forecasting purposes, e.g., smooth transition autoregressive models, which allow for regime switches, spectral analyses, exponential smoothing techniques or state space models, although one should note that there is a state space representation of ARMA models and that exponential smoothing models can be written using analogous state space equations.
5. Our dataset is similar in structure to that provided by König et al. (2006) but has the advantage of covering a longer time period. Results from ADF and PP unit root tests are included in the online replication archive.
6. Brandt and Williams (2001) combine AR time series and count models for cyclical and short-memory processes.
7. In the terminology of time series analysis the term 'causal' has a different meaning. A linear time series process x_t is called causal if it can be reconstructed as the sum of weighted past innovations ϵ_t .
8. Obviously, this approach is not prototypical of a within-sample forecast. This is because when producing a within-sample forecast, we normally pretend that the data was unknown, which of course implies that the covariates are also missing. Consequently, we would not be able to generate a forecast derived from the theoretical model. Since we allow the theoretical model to use the covariates at this point, we also generate the ARMA forecast using the actual y_t values to keep things 'fair'.
9. Another goodness-of-fit measure used in the literature is the mean absolute error. In this application we prefer the MSPE, as it gives larger forecasting errors a higher weight. This reflects our wish to avoid large mistakes when making forecasts. Another tool for assessing the predictive power would be the receiver operator characteristics.
10. One could also build different 'scenarios' for how these variables develop and subsequently compute and compare forecasts for each of these scenarios.

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