Editors' Introduction*

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Forecasters rarely (never?) find themselves in environments characterized by a stable and known data-generating process, making it significantly more challenging to generate reliable forecasts in practice. What can be done to improve the quality of forecasts made in realistic settings with structural breaks in predictive relationships and substantial model uncertainty? The present Elsevier volume represents contributions to this important topic by leading researchers in the field of forecasting.

The chapters in this volume incorporate the latest research on forecasting macroeconomic and financial variables in the presence of structural breaks and/or model uncertainty. The methods analyzed include "robustifying" devices, diffusion indices, combination forecasts, estimation window adjustments, flexible regime-switching models, non-parametric transformations, "bagging," and stochastic unit roots and cointegration. Existing and new methods are surveyed and described in detail, and both classical and Bayesian approaches to forecasting are considered. Many chapters also contain Monte Carlo simulations, and every chapter contains relevant empirical applications in macroeconomic or financial forecasting. Researchers and practitioners alike should find the extensive analysis of existing and new methods especially valuable, as it will help them to understand which particular methods are likely to be the most useful—as well as which methods to avoid—in particular circumstances. Overall, this volume is designed to benefit researchers and practitioners interested in utilizing methods that can help to improve forecast performance in realistic settings.

To facilitate the use of the methods analyzed in this volume, there is a companion web site that contains computer code used to generate the results reported in a number of the chapters. The web site is available at http://pages.slu.edu/faculty/rapachde/. The computer code was generously provided by contributing authors and is written in the GAUSS, MATLAB,

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RATS, Ox, or R programming languages. In addition to computer code, the web site will contain a continuously updated bibliography on papers relating to forecasting in the presence of structural breaks and model uncertainty.[1]

Next, we briefly outline the chapters in the volume, which are organized in two parts. The chapters in Part 1 contain empirical applications based on forecasting macroeconomic variables, while those in Part 2 contain applications relating to forecasting financial variables. The first two chapters in Part 1, by Michael P. Clements and David F. Hendry and Jennifer L. Castle and Hendry, investigate forecasting U.K. inflation using "well-specified" econometric models estimated over an in-sample period. Building on Clements and Hendry (1998, 1999, 2006), the chapters present theoretical results illuminating how a myriad of sources, including structural breaks, can generate forecast errors in an econometric model that appears well-specified when estimated using historical data. In their empirical applications, the authors consider a variety of forecasting methods, including a number of methods designed to "robustify" forecasts to structural breaks. The chapter by Castle and Hendry also examines whether using time-disaggregated data can help to detect structural breaks and improve forecast performance. Together, the theoretical and empirical results reported in the two chapters help to show some of the methods which can be the most useful for forecasting inflation in realistic environments.

In the third chapter of Part 1, Todd E. Clark and Michael W. McCracken analyze the effects of structural instabilities on the forecast performance of small-scale vector autoregression (VAR) models comprised of U.S. output, prices, and interest rates. VAR models are very popular forecasting models in macroeconomics, and as noted by Clark and McCracken, small-scale VARs have also been used recently to model expectation formation in theoretical models. Clark and McCracken provide an extensive analysis of a host of methods designed to accommodate potential structural breaks in VAR models when forming real-time forecasts, and they are able to identify methods that perform consistently well across a variety of horizons.

The next chapter, by Anindya Banerjee, Massimiliano Marcellino, and Igor Masten, studies forecasts of macroeconomic variables generated by diffusion indices based on factor models, recently popularized by Stock and Watson (2002) and others. Importantly, they consider commonly encountered situations where only relatively short samples of data are available (such

[1]Given that the chapters in the present volume provide surveys of many aspects of the recent literature on forecasting in the presence of structural breaks and model uncertainty, we refrain from attempting to provide a comprehensive review of the literature in this introduction. (Such a review is also likely to become outdated relatively quickly, given that this is an active area of current research.) The continuously updated bibliography on the web site will help to keep researchers and practitioners abreast of developments in the literature.

as with data for transition countries) and structural breaks are highly probable. The forecast performance of diffusion indices and more traditional time-series approaches are analyzed using Monte Carlo simulations and empirical applications based on forecasting macroeconomic variables in the Euro area and Slovenia. The results indicate that diffusion indices can improve forecast performance relative to alternative time-series methods when forecasting macroeconomic variables in environments with small samples and structural change.

The chapter by Nii A. Armah and Norman R. Swanson provides an analysis of predictive accuracy tests that account for parameter and model uncertainty when estimating forecasting models using recursive or rolling windows. Armah and Swanson emphasize comparing forecasts from competing models using tests that do not assume correct specification under either the null or alternative hypothesis. This is an especially relevant aspect of model uncertainty, as it is very unlikely that any of the competing models corresponds to the actual underlying data-generating process. Armah and Swanson review recent literature in this area, perform Monte Carlo simulations, and in an empirical application, revisit the question of whether measures of the money stock are useful for forecasting U.S. output growth.

The next chapter, by Walter Enders and Ruxandra Prodan, compares the forecast performance of traditional univariate time-series models that do not attempt to explicitly model structural breaks with that of univariate time-series models that estimate breaks dates using recently developed econometric tests. Their empirical application involves forecasting unemployment rates in ten OECD countries. Enders and Prodan find that traditional time-series models often outperform models that explicitly estimate break dates. Traditional time-series models thus seem to forecast relatively well in the presence of structural breaks, helping to explain their resilience in the forecasting literature. The authors argue that this is likely due to the difficulty in precisely estimating the timing and size of structural breaks. Importantly, Enders and Prodan also find that there are gains to combining the two approaches, so that one should not necessarily forsake either modeling approach.[2]

The final chapter of Part 1 is by Pierre L. Siklos, who contributes to the growing literature on forecasting using real-time data. Interestingly, Siklos finds evidence of structural breaks in cointegrating relationships linking successive benchmark revisions of data, suggesting that these revisions contain information that could be utilized in forecasting. He explores this in

[2]The usefulness of combination forecasts is a result that emerges in many of the chapters of the present volume, indicating that combining methods are particularly useful in environments with structural breaks and model uncertainty.

the context of an empirical application based on forecasting U.S. inflation using a variety of Phillips curve models.

The first three chapters in Part 2 focus on the role of structural breaks when forecasting volatility using models drawn from the very popular generalized ARCH or GARCH class. Eric Hillebrand and Marcelo C. Medeiros first show how the failure to model structural breaks can adversely affect estimates of GARCH model parameters. They then consider a number of approaches for accounting for structural breaks in GARCH models, including a Flexible Coefficient GARCH model that allows for switching between multiple regimes and where the regime switches are governed by an observable variable. They find that this type of regime-switching GARCH model performs well with respect to forecasting volatility for a number of stock market index and exchange rate return series.

In the second chapter of Part 2, Namwon Hyung, Ser-Huang Poon, and Clive W.J. Granger investigate the role of structural breaks in generating evidence in favor of long-memory behavior in volatility. They first show that there is evidence of long-memory in squared and absolute returns for a very large number of asset return series. In their forecasting exercises, they find that short-memory GARCH models that allow for periodic structural breaks deliver the best forecasts only if the structural breaks are treated as known; when the breaks are not treated as known in real time, long-memory fractionally integrated GARCH models often generate the most accurate forecasts at longer horizons. The authors interpret this as evidence that structural breaks are ultimately responsible for the relatively good out-of-sample forecast performance of long-memory GARCH models.

The third chapter of Part 2, by David E. Rapach, Jack K. Strauss, and Mark E. Wohar, analyzes the forecast performance of a class of asymmetric volatility models in the presence of structural breaks. The authors first present evidence that structural breaks in unconditional variance are an empirically relevant feature of a number of U.S. stock index return series. They then investigate whether more accurate volatility forecasts can be generated by adjusting the forecasting model estimation window to accommodate structural breaks. They find that averaging volatility forecasts across asymmetric GARCH models estimated using different window sizes is able to consistently outperform a benchmark model estimated using an expanding window. Uncertainty surrounding the exact timing and size of variance breaks helps to explain the utility of averaging.

The chapter by Dimitris N. Politis and Dimitrios D. Thomakos considers a model-free or non-parametric approach to forecasting volatility based on the "normalizing and variance stabilizing (NoVaS)" transformation. This approach is likely to be especially useful in unstable environments, as it does not require the estimation of model parameters that may have experienced structural breaks. Politis and Thomakos find that the NoVaS approach often outperforms parametric GARCH models estimated using an expanding window for simulated data and a pair of stock return series. The chapter by Politis and Thomakos provides a useful non-parametric complement to the first three chapters of Part 2.

In the next chapter, John M. Maheu and Thomas H. McCurdy propose a new model for returns in which "jumps" capture the persistence in conditional volatility. These jumps can be viewed as a type of structural instability that affects the variance of asset returns. Maheu and McCurdy employ a Bayesian estimation strategy that can be used to make inferences concerning all of the model parameters as well as the probability of a jump occurring in a given period. Maheu and McCurdy find that their jump model compares favorably to more conventional stochastic volatility and GARCH models with respect to forecasting the volatility of Japanese yen-U.S. dollar exchange rate returns.

Tae-Hwy Lee and Yang Yang analyze bootstrap aggregating ("bagging") in the sixth chapter of Part 2. Intuitively, instead of estimating the parameters of a forecasting model by relying on a single realization of a time series (the available historical sample), bootstrapping methods can be used to generate additional samples capable of producing more reliable estimates of model parameters and thus more reliable forecasts. Building on Lee and Yang (2006), the authors investigate the performance of bagging in a variety of settings for forecasting asset returns. They find that bagging typically improves upon "unbagged" forecasts, especially when trying to forecast extreme values for which there are relatively few observations available in the historical sample.

The chapter by Robert Sollis discusses stochastic unit roots and cointegration. These frameworks naturally accommodate structural breaks, as they have time-varying parameter representations, and they also allow for conditional heteroskedasticity. Sollis uses these methods to forecast U.S. Treasury bond yields and Eurocurrency rates with a variety of maturities. These interest rate series appear to be characterized by structural breaks and conditional heteroskedasticity and hence provide an interesting application. Sollis finds that these approaches deliver significant out-of-sample forecasting gains relative to more conventional approaches, suggesting that the stochastic unit root and stochastic cointegration frameworks provide additional tools that can help to improve forecasts in the presence of structural breaks.

The final two chapters of Part 2 develop frameworks that allow for structural instability and model uncertainty in the processes governing expected stock and bond returns. Importantly, these two chapters analyze the economic gains from a portfolio management perspective associated with explicitly accounting for structural breaks and/or model uncertainty when forecasting asset returns. The chapter by Francesco Ravazzolo, Richard Paap, Dick van Dijk, and Philip Hans Franses develops a Bayesian framework that simultaneously accounts for parameter uncertainty, model uncertainty, and structural instability in the data-generating process for stock returns. Indeed, in their empirical application involving U.S. stock returns, the authors find that the economic gains associated with forecasting stock returns are typically the largest when all three features are taken into account.

The chapter by Massimo Guidolin and Carrie F. Na models instabilities in the return-generating process using a flexible regime-switching VAR framework. They find that allowing for multiple regimes in a VAR model—including bear, bull, stable, and expansionary regimes—helps to significantly improve forecasts of U.S. stock and bond returns. They also find that combining forecasts generated by various return forecasting models, including regime-switching VAR models, typically produces the largest economic gains from a portfolio management perspective. Combining forecasts across models accommodates the consequences of model uncertainty, while the inclusion of forecasts generated by regime-switching models when combining forecasts helps to deal with structural instability. Overall, the final two chapters of Part 2 should prove quite useful to researchers and practitioners in finance, especially with respect to portfolio management, as they develop methods for forecasting returns in realistic settings with substantial model instability and uncertainty.

Finally, we note that the present volume should serve as a useful complement to Elsevier's recently published *Handbook of Economic Forecasting.* The *Handbook of Economic Forecasting* is very broad and contains chapters by distinguished scholars, with useful surveys of all important areas of economic forecasting. In contrast, the present volume focuses on forecasting in environments characterized by structural instability and model uncertainty. In line with this difference, the present volume contains numerous empirical applications on this topic, while space constraints clearly preclude the inclusion of a large number of empirical applications for each of the topics covered in the individual chapters of the *Handbook of Economic Forecasting.* Chapters in the *Handbook of Economic Forecasting* most closely related to the present volume include Clements and Hendry (2006), Corradi and Swanson (2006), and Timmermann (2006).

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[3]During the conference, St. Louis appeared to provide special inspiration to researchers interested in forecasting volatility using ARCH models.

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