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Short-term Forecasting for Empirical Economists: A Survey of the Recently Proposed Algorithms*

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Abstract

Practitioners do not always use research findings, sometimes because the research is not always conducted in a manner relevant to real-world practice. This survey seeks to close the gap between research and practice on short-term forecasting in real time. Towards this end, we review the most relevant recent contributions to the literature, examine their pros and cons, and we take the liberty of proposing some lines of future research. We include bridge equations, MIDAS, VARs, factor models and Markov-switching factor models, all allowing for mixed-frequency and ragged ends. Using the four constituent monthly series of the Stock–Watson coincident index, industrial production, employment, income and sales, we evaluate their empirical performance to

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forecast quarterly US GDP growth rates in real time. Finally, we review the main results regarding the number of predictors in factor based forecasts and how the selection of the more informative or representative variables can be made.

Keywords: Business cycles; Output growth; Time series.

JEL Codes: E32, C22, E27

Contents

1

Introduction

The rapid economic changes during the Great Recession were a big shock to policy makers and the business world. In 2008, the sharp downturn in the economy triggered drastic reactions by policy makers who implemented monetary and fiscal policies to combat the adverse economic situation. In addition, the pervasive effects on retirement plans, stock portfolios and the housing market drastically changed private agents' economic decisions. Since being late in identifying the turning points entailed dramatic economic consequences, the economic agents seemed eager to learn as quickly as possible early detection methods to foresee downturns and recoveries and they acknowledged the need for new tools to monitor economic developments in real time. These forecasts usually include predictions of changes in the gross domestic product (GDP) and its components, both from an expenditure perspective (consumption, gross capital formation, exports and imports) and from a revenue perspective. Sometimes, they also deal with the revenue and expenditure flows among the different institutional sectors, inflation, the labour market, and financial data.

Consequently, business people all over the world seem to have caught gold fever to speedily update the next relevant macroeconomic figures with significant time to onset. Accurate forecasts of these figures allow them to position themselves competitively since advance notice gives the business time to implement new strategies. In this monograph, we focus on several statistical frameworks developed in the literature to perform early assessments of the ongoing economic development, which must unavoidably deal with short-term forecasting. According to this scenario planning, the time period attributed in this monograph to examine the accuracy of short-term forecasts goes from the publication of the latest available figure of one variable of interest to the availability of the next figure. Actually, this time period concentrates the forecasting interest of business people in real time, in what it is called nowcasting, which rarely covers more than a few months.

As a response to this growing interest, this monograph is written as a survey that aims to close the potential gap between research and applied short-term forecasting. We establish some of the key theoretical results and empirical findings in the recent literature on short-term forecasting. Then, we try to translate these theoretical findings into economically meaningful techniques to facilitate their widespread application to compute short-term forecast in economics and to monitor the ongoing business cycle developments in real time. In this sense, the survey does not pretend to be a textbook in forecasting, covering all the aspects of the forecasting exercise, from theoretical definitions of predictability to the definition of loss function for the forecasting exercise. For an excellent survey on the definition of forecasting predictability, Hendry and Mizon (2012) is highly recommended. For a comprehensive guide to forecasting, the books of Clements and Hendry (1998) or Diebold (1998) are excellent references.

It is worth noting that the automatic forecasting frameworks surveyed in this monograph exhibit several advantages with respect to the economic forecasts typically provided by the most relevant economic institutions. Although these institutions usually employ state-of-the-art forecasting methods, they have the possibility of partly basing their forecasts on judgements. Consequently, their forecasts cannot be easily replicated and their forecast failures are difficult to interpret. By contrast, the statistical methods described in this survey seek to avoid this problem by using simple forecasting algorithms which, while doing the job of computing short-term forecasts, have the advantage of forecasting from specific frameworks. Therefore, the methods can be evaluated in terms of transparency and replicability. In addition, the automatic forecasts can be easily updated as new releases for the key economic indicators become available. This considerably reduces the time to process the economic information because it is done as new data arrive and this quick processing facilitates rapid reactions to economic news.

However, computing the short-term forecasts in real time is not straightforward. To start with, the analysts performing multiperiod forecasting must choose between either using a one-period model that is iterated forward, or instead a multi-period model estimated with a loss function tailored to the forecast horizon. Although the iterated method produces more efficient parameter estimates than the direct method and does not require different models for different forecasting horizons, it is prone to bias if the one-step-ahead model is misspecified and usually requires separate forecasting models for the explanatory variables. Which approach is better will depend on the characteristics of the forecasting model and, ultimately, will be an empirical matter.

In addition, performing short-term forecasts in real time faces specific problems of the day-to-day monitoring of economic developments. The first problem is that the real-time data flow of all the variables involved in the forecasting analysis does not occur at the same time. Although the national statistical agencies release economic data in blocks and the releases follow a relatively stable calendar, most of the releases are asynchronous. Moreover, the economic indicators of the current state of the economy are available with different delays. Typically, hard indicators, which refer to economic activity data, exhibit relatively long reporting lags, which usually extend to two months. Soft indicators, which are based on opinion surveys, are released on a more timely basis since they are usually available at the end of the reference month. Financial data are available on a daily basis and are also available at the end of the month. According to this particular release process, the automatic forecasting models should support reading linked data in an asynchronous manner.

Not accounting for this publication pattern would imply that the users of traditional forecasting models, which develop the forecasts from balanced panels of data, will unavoidably incur one of the two following substantial costs. The first appears when forecasts are made from the latest available balanced panel. In this case, the forecasts lose the latest and most valuable information contained in the promptly issued indicators at the time of the assessments. The second cost is that of being late. If the analysts decide to wait until all the business cycle indicators become available, their inference will refer to the past.

The second problem of real-time short-term forecasting is that it usually involves time series data sampled at different frequencies. Many important macroeconomic indicators, which are the key time series to be predicted, are sampled at low frequency and are published with a significant delay. One noticeable example is GDP, whose data are sampled quarterly and are released with a delay of about one and a half months with respect to the end of the reference quarter. With the aim of obtaining early estimates of these low-frequency variables, the analysts frequently focus on higher-frequency economic indicators. These indicators typically show high correlation with the low-frequency variables but exhibit much more timely information at monthly, weekly, daily, or even higher frequencies.

The earliest attempts to assess the peculiarities of real-time forecasting were based on bridge equation models. Essentially, these are single-equation autoregressive models that focus on the lower-frequency variable of interest which is modeled as a function of aggregations of the higher-frequency economic indicators. To compute the forecasts, the higher-frequency indicators are usually predicted in separate autoregressive models. Although bridge equations usually incur parameter proliferation problems, they are very popular in Central Banks and research institutions because of their simplicity and modest technical requirements.

With parsimony in mind, MIDAS models are general frameworks that require a small number of hyperparameters relative to the sampling rate of the higher-frequency. Typically, they employ distributed lag polynomials as weighting functions of lagged values of the higher-frequency indicators, which require nonlinear estimation techniques. Since they are relatively new on the forecasting arena, they are a fruitful place to consider further developments. In this monograph, we review the latest research and take the liberty of suggesting future lines on this topic.

Some other proposals assume that the models operate at the highest frequency in the data, which implies that some values of the lower-frequency data and the latest data of the indicators with longer publication delays are unobserved. The models are conveniently cast in state-space representations and are estimated by using the Kalman filter since it has the ability to account for missing observations in a data set in a relatively straightforward manner. In short, the strategy consists of skipping some calculations while others do not need to be changed, so the basic Kalman filter remains valid and the parameters of the model can be estimated by maximum likelihood. This feature is of practical relevance when computing the forecasts since one can regard the future values of the time series as a set of missing observations. As a consequence, the Kalman also delivers the necessary computations for forecasting. Given the population parameters, the Kalman filter also provides the mean square forecast error (MSFE). In addition, these models have been extended to account for regime-switching nonlinearities. They are used to infer the probabilities of recession that serve as a barometer for the state of the business cycle.

Practitioners usually compute the MSFEs as if their estimated parameters were the "true" ones. Therefore, they do not take into account the uncertainty associated to the estimation of the parameters, and their prediction intervals are usually narrower than they should be. To overcome this problem, Wall and Stoffer (2002), Pfeffermann and Tiller (2005) and Rodriguez and Ruiz (2009) propose using bootstrap techniques to compute mean square errors (MSEs) in state-space models.

Within this setup, one of the most compelling approaches is the mixed-frequency VAR framework. However, computing the forecasts from this approach usually relies on serious dimensionality problems, especially when the number of time series or their frequency increases. Fortunately, the mixed-frequency VAR stated in state-space form can, alternatively, be estimated using Bayesian methods.

The parameter proliferation problem can also be addressed by means of the well known reduction dimensionality allowed by factor models. Since macroeconomic data are usually very collinear, it is reasonable to conjecture that they are multiple, indirect measurements of some low-dimensional underlying sources, which can be used to reproduce most of the variability of a data set, although typically they cannot be directly measured. Therefore, factor models have the additional appeal of computing indexes of the overall economic activity, which are very useful for tracking the economic developments.

Although much professional attention has recently been devoted to examining the pros and cons of these alternative forecasting approaches, it is difficult to rank them based purely on theoretical considerations. The matter is ultimately empirical, requiring detailed comparative assessment. However, while numerous empirical applications have been proposed in the literature, there is lack of comparative evaluation of the empirical performance of the different models. In this monograph, we comprehensively examine the performance of the most significant models that have been suggested in the academic literature to compute short-term forecasts in economics for the same economy and time period.

The case we analyze is one of the most relevant for policy making, namely forecasting quarterly US GDP growth. The set of monthly indicators used to compute the forecasts comprises the monthly growth rates of industrial production, employment, income and sales, which become available in different time periods and with different publication delays.[1] At any point t in real time, we simply use the time-t data vintage to extract the short-term forecast of the next unobserved US GDP figure. As time progresses, we re-estimate all the models for each period, always using the latest data vintage to compute the forecast. Therefore, the experiment mimics the day-to-day monitoring of the economic activity as it would have been developed in real time. Our results suggest that all the models that use indicators represent a massive improvement in forecasting over the pure autoregressive ones, with marginal differences across the different specifications. However,

[1] Although the NBER Business Cycle Dating Committee does not have a fixed definition of economic activity, it acknowledges on its home page that these are the five indicators that examine to analyze the US business cycle conditions.

the nonlinear specification has the advantage of computing timely and accurate real-time inferences about the US business cycles.

Banbura et al. (2011, 2013) provide complementary surveys of the short-term forecasting literature. The econometric framework used by Banbura et al. (2011) is a large scale linear dynamic factor model, which is also one of the models used in the empirical application of Banbura et al. (2013). Although we consider linear factor models in this survey, they are treated as one alternative among a list of competing forecasting models. In addition, the models surveyed in this monograph are applied to a small group of indicators for forecasting. The forecasting role of the number of time series in dynamic factor models has already been treated in Alvarez et al. (2012). Readers interested in forecasting with larger data sets are referred to the above mentioned surveys and the reviews of factor models developed in Bai and Ng (2008b), Stock and Watson (2011) and Breitung and Choi (2013).[2]

The monograph proceeds as follows. In Section 2, we introduce the notation and main characteristics of the data for short term forecasting. In Section 3, we review the main models used for this purpose address the role of the number of series in factor models. In Section 4, we illustrate the forecasting performance of the different models reviewed in Section 3 through an empirical application. Finally, in Section 5, we conclude and propose some lines of further research.

[2] After the monograph was reviewed by the editor, we became aware of the working paper by Foroni and Marcellino (2013). In an independent research, they also survey some of the models that we consider. We differ from their work by focusing on different data features and by including an empirical application with a real time comparison of the reviewed models.

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