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Nowcasting French GDP in real-time with surveys and "blocked" regressions: Combining forecasts or pooling information?

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ABSTRACT

This paper empirically investigates two alternative combination strategies, namely forecast combination and information pooling, in the context of nowcasting French GDP in real time with monthly survey opinions. According to the encompassing paradigm, we claim that the outperformance of the forecast combination strategy reported by recent works may be related to the issues of model selection and misspecification. To address these issues, we promote the *blocking* modeling approach to allow us to handle mixed frequencies in a linear framework that is compatible with an automatic model selection algorithm. Selected restricted- and pooled-information models are specified and tested for forecast encompassing in order to determine the best combination strategy. The results suggest that the forecast combination strategy dominates as long as no individual (restricted) model encompasses the rivals. However, when a predictive encompassing model is obtained by pooling the information sets, this model outperforms the most accurate forecast combination scheme.

1. Introduction

Since the influential work by Bates and Granger (1969), forecasters have been aware that combining the forecasts obtained from two or more models can yield more accurate forecasts, in the sense that the forecast error variance of the combined forecasts is not larger than the smallest forecast error variance of the individual forecasts.[1] However, Diebold (1989) claimed that there is no role for forecast combination in a world where information sets can be combined instantaneously and without cost. Indeed, "when the user of the forecasts is in fact the model builder, the possibilities for combination of information sets – as opposed to forecasts – are greatly enhanced" (Diebold, 1989, p. 591). Sitting between these two combination strategies, the encompassing paradigm described by Hendry and Richard (1989), Mizon (1984) and Mizon and Richard (1986), among others, states that the forecasting model that provides the best explanation

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[1] This result is derived by Bates and Granger (1969) under the assumptions that the individual forecast errors are stationary and that the forecasts are unbiased, and provided that they are not too strongly correlated. Moreover, the weights used in the combination are chosen so as to minimize the overall error variance of the combined forecasts. For comprehensive surveys of forecast combination, the reader is referred to Clemen (1989) and Timmermann (2006).

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(prediction) of the data is a model that is capable of explaining the results obtained from rival models. As was summarized by Chong and Hendry (1986, p. 677), "… the composite artificial model which might be considered for forecast encompassing essentially coincides with the 'pooling of forecasts' formula… Note that the *need* to pool forecasts is *prima facie* evidence of a failure to encompass, and if H_1 is an econometric model and H_2 a univariate time series model (say) then if H_1 does not encompass H_2 it seems highly suggestive of the possibility that H_1 is dynamically misspecified…". Hence, Bates and Granger (1969) assume in their theoretical framework that such a H_1 encompassing econometric model is not available to the forecaster, while Diebold (1989) implicitly supposes that it is always possible to specify an econometric model beyond H_2. Actual forecasting situations can usually be ranged between these two antithetical positions. However, Diebold and Pauly (1990) pragmatically observe that an information pooling strategy is very often either impossible or prohibitively costly, such as in real-time forecasting. For this reason, as well as for the sake of econometric convenience, the forecast combination strategy has gained substantial credit over the last two decades.

The debate on pooling information vs. combining forecasts has been revived recently in an empirical area that is of great relevance for most national and international economic institutions: short-term GDP forecasting. Recent empirical contributions to this body of literature have provided strong support for the forecast combination strategy. For instance, Clements and Galvão (2006, 2008) point out that combining forecasts from single-indicator Autoregressive Distributed Lag (ADL) or MIxed DAta Sampling (MIDAS) regressions of US GDP is better than combining indicators within a single model. Kuzin, Marcellino, and Schumacher (2013) find similar results when the forecast combination strategy is compared to a model selection alternative: combined forecasts from single-indicator models provide robust predictive performances overall across several countries and econometric specifications (MIDAS, factor-MIDAS). These findings might be viewed as illustrating the encompassing paradigm: they suggest that the individual model to which combined forecasts are compared is not an encompassing model.

Nevertheless, the encompassing paradigm has been challenged recently in a simulation analysis reported by Huang and Lee (2010): they show that the forecast combination strategy provides a predictive accuracy that is superior to that of the information combination strategy whether the model pooling the information is specified correctly or not. Huang and Lee (2010) suggest that an explanation for such results can be found in the bias–variance trade-off between parsimonious and heavily parameterized models in finite samples. In the absence of the bias–variance trade-off, the pooling information strategy is expected to dominate the forecast combination strategy. According to Huang and Lee (2010), this result is not ensured in finite samples, but it follows from the encompassing paradigm that it has better chances of holding if careful attention is paid to the specification of the pooled information models. However, the main concern of both the empirical contributions and the simulation experiments mentioned above is neither the issue of model misspecification nor its link with the model selection problem. The main contribution of our paper is to address precisely these issues. For this purpose, we compare the two combination strategies, namely forecast combination and information pooling, by illustrating the particular case of nowcasting the *first-release* French GDP in a real-time framework.

We depart from the empirical approach described in the literature mentioned above along three dimensions. First, given an exhaustive information set, we aim to detect the encompassing model in a way that is akin to the "GEneral-To-Specific" (GETS) selection approach described by Krolzig and Hendry (2001): if a first-guess model (a General Unrestricted Model, GUM, for instance) turns out to be misspecified, a selection process is iterated following a reduction algorithm until a satisfactory in-sample alternative is found and encompassing is achieved, from which optimal forecasts follow directly. Hence, particular care is taken over the selection of the forecasting models, whether full or restricted information sets are being used. Second, due to the potentially large number of competing models involved in the GETS selection approach, purely computational matters suggest the adoption of a linear framework, at least as a first instance. Within this linear framework, we promote the *blocking* modeling approach, combined with a GETS selection algorithm (*Autometrics*), in order to provide *first-release* GDP nowcasts while dealing with the mixed-frequency issue raised by the use of monthly information as predictors. This method consists of splitting the high frequency information into multiple low frequency series. In our case, this means splitting the monthly survey data into three quarterly series to match the GDP frequency, thus providing a linear framework for dealing with mixed-frequency regressions. In a recent paper, written independently of our paper but concurrently, Foroni, Marcellino, and Schumacher (2015) studied in detail a MIDAS regression based on unrestricted linear lag polynomials, namely the Unrestricted MIDAS (U-MIDAS), which is closely related to our *blocking* approach. Specifically, our approach involves allowing for restrictions on the linear lag polynomials (the temporal aggregation scheme) through a model selection procedure. To the best of our knowledge, this approach has seldom been used in the literature for nowcasting purposes, and therefore it will be discussed in greater detail here. In this work, nowcasts are obtained using exclusively soft data (surveys). Indeed, the peculiarity of the French case is that, in addition to Markit (provider of the well-known Purchasing Managers Index survey), the National Statistical Institute and the Banque de France also collect their own survey data on business conditions in the manufacturing sector (monthly business surveys). Since surveys are usually the earliest monthly-released data that convey information on economic activity in the current quarter, they have often proven to be particularly useful for nowcasting GDP (Banbura, Giannone, Modugno, & Reichlin, 2013). Full advantage of this early monthly information can be taken by adopting the simple linear framework allowed by the *blocking* approach. Moreover, unlike recent alternative mixed-frequency approaches, such as MIDAS regressions (Foroni et al., 2015;