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Editorial

Editorial for Special Issue "New Frontiers in Forecasting the Business Cycle and Financial Markets"

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The global financial crisis of 2007–2009 and the COVID-19 pandemic have heightened uncertainty in financial markets and the business cycle. The influence of both macroeconomic and financial variables has been scrutinized by economists, who have been asked to investigate the determinants of crises. This empirical evidence is based on advanced econometric models, particularly time series analysis. These studies allow academics and policymakers to contribute technically to forecasting macroeconomic and financial variables' behavior in order to provide accurate new scenarios.

In this Special Issue, the most recent and high-quality research about forecasting the business cycle and financial markets is collected. A total of eight papers have been selected to represent a wide range of applications, from the stock market and yield curve to the business cycle and e-commerce, implementing mainly linear and nonlinear vector autoregressive models, dynamic factors, and machine learning tools.

Bekiros and Avdoulas (2020) [1] investigate the power of the expectation hypothesis considering the cointegration effects in an out-of-sample forecast analysis. They examine the dynamic linkages among money market interest rates in Brazil, Russia, India, China, and South Africa ("BRICS" countries), estimating vector error correction (VECM) and Markov switching VECM (MS-VECM) models on weekly data of the overnight, one-, three-, and six-month, and one-year treasury bill rates from January 2005 to August 2019. They contribute to the literature by exploring the parameter instability in a nonlinear model for the term structures capturing the effects of the global and domestic financial crisis.

Bauer, Fink, and Stoller (2020) [2] study the issuer estimated value (IEV) by investigating the product information sheet of banks and their expected gross margin. They provide an empirical study of the fairness of these disclosed figures with an in-sample forecasting analysis. Relying on a sample of discount and capped bonus certificates, they document how reported issuer margins can be verified using standard option pricing models and they show that hedging costs take on an important role for structured product valuation.

Papana and Spyridou (2020) [3] explore the applicability of the four most implemented approaches to predict financial bankruptcy, focusing on the case of Greece. Two traditional statistical models (discriminant and logit analysis), one non-traditional statistical model (decision trees), and one non-statistical model (neural model) are implemented to infer companies' possible bankruptcy during the ongoing Greek crisis. The results of the forecasting comparison show how the discriminant analysis slightly outperforms the other methods.

Ausloos (2020) [4] investigates optimizing the most suitable valuation methods under a "value-based management" framework through some performance measurement systems. He presents a comprehensive review of three valuations methods, (i) free cash flow valuation model (FCFVM), (ii) residual earning valuation model (REVM), and (iii) abnormal earning growth model (AEGM). Moreover, three study cases related to UK companies with problems (Marks & Spencer, Tesco, and Sainsbury's) are discussed. As the main findings, Ausloos (2020) documents how accounting numbers through models based on mathematical economics truly affect business value.

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Defend, Min, Portelli, Ramsauer, Sandrini, and Zagt (2021) [5] propose the estimation of approximate dynamic factor models with homoscedastic, cross-sectionally correlated errors for incomplete panel data to study the behavior of S&P500. Differently from other approaches, they propose a two-step information-based model selection criterion to determine the unknown factor dimension and autoregressive order, assessed within a Monte Carlo study. In their empirical exercise with weekly S&P500 log-returns, they detect the main drivers of the index development and define two dynamic trading strategies resulting from prediction intervals for the subsequent returns.

Castle, Doornik, and Hendry (2021) [6] study the general principles that seem to be the foundation for successful forecasting and show how these are relevant for methods that did well in the M4 competition. They establish some general properties of the M4 data set, which they use to improve the basic benchmark methods, as well as the Card method that they created for their submission to that competition. They propose a data generation process that captures the salient features of the annual data in M4. As the main results, they document how appropriately handling the seasonality is an important feature of forecasting COVID-19 cases and deaths.

Faehnle and Guidolin (2021) [7] propose a model based on vector autoregressive processes (VAR) and Lasso penalization to detect and study the dynamics that govern real-time price competition in electronic marketplaces. Relying on this model, an empirical study was performed on the price trends of smartphone models on the major electronic sales platforms of the Italian market. As the main finding, they document real-time price variations in single vendors, based on the variations of their direct competitors. This empirical evidence may be useful for e-commerce companies that conduct market analyses of competitors' pricing strategies.

Seip and Zhang (2021) [8] document an accurate forecast of economic growth and upcoming economic recessions, proposing a novel model that improves the treasury yield curve while keeping its parsimony. As the main findings, they show that adding the federal funds rate gives seven months' vs. five months' warning time, and it gives a higher prediction skill for the recessions in the out-of-sample test set. Moreover, they find that including the quadratic term of the yield curve and the federal funds rate improves the prediction of the 1990 recession, but not the other recessions in the period 1977 to 2019. In a forecast "horse race", Seip and Zhang (2021) show how their model outperforms the Michigan consumer sentiment index during the first test year.

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