

Forecasting in turbulent times

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ABSTRACT

Since the beginning of this century, the global economy has been hit by a series of unforeseen shocks, including the Global Financial Crisis, the euro area's sovereign debt crisis, and most recently, the global inflation surge. To motivate this special issue, we provide a brief overview of recent methods that have been proposed to improve the ability of forecast models to predict shocks and to capture their effects once they have occurred. We also propose a method that may allow central banks to respond more quickly to the kind of inflationary surge that occurred from 2020 to 2022 so that those banks would not have misdiagnosed the surge as a temporary phenomenon.

KEYWORDS: economic shocks, forecasting under uncertainty, model uncertainty, policy decisions

JEL CLASSIFICATION: C52, C53

1 INTRODUCTION

This special issue of the *Journal of Forecasting*, the subject of which is “Forecasting in Turbulent Times,” has been motivated by the series of successive shocks that hit the global economy beginning in early 2020. Both the occurrence of the shocks and their duration caught policymakers by surprise. How can forecasting performance be improved during periods of economic stress? By their nature, shocks are not predictable, but given that a shock has been taken place, what techniques are available to forecast both the magnitude and the duration of the shock? How can the magnitude of a shock be detected once it has taken place? These and other questions are discussed in this issue. The issue consists of 13 papers, apart from this introduction. Six of them are revised versions of papers presented at the 27th International Conference on Macroeconomic Analysis and International Finance held at the Department of Economics at the University of Crete in Rethymno, Crete on May 25–27, 2023, and the remaining seven papers were commissioned; they are authored by experts in the field of forecasting. In what follows, we first provide a brief overview of forecasting in the presence

of extreme events, and we provide a suggestion for detecting the magnitude of shocks once they have occurred so that policymakers can identify that a shock has taken place and, thus, react in a timely manner. We conclude with a brief description of the papers in this issue.

2 FORECASTING UNDER UNCERTAINTY

More than a century ago, Frank Knight published the book, *Risk, Uncertainty and Profit*, in which he distinguished between risk and uncertainty.¹ Risk, he argued, was subject to quantification. For example, the probability of dying at a certain age can be calculated and shifted via insurance to others. Hence, risk is governed by probability distributions and can be treated as an insurable cost, with the cost calculable from stable empirical regularities. There are other, unprecedented, situations, however, in which both the outcome and the probability models that govern them are unknown. In such situations, Knight argued, it is not possible to formulate uncertainty in terms of well-established probabilities. Knight maintained that the latter type of uncertainty gives rise to economic profits.

The century that followed the publication of Knight's book has seen a series of extreme economic events. A partial listing includes the following: the Great Depression, the two oil price shocks of the 1970s, the crisis in Europe's Exchange Rate Mechanism in 1992–1993, the Mexican Peso Crisis of 1994–1995, the Asian Financial Crisis of 1996–1997, the Global Financial Crisis of 2008–2009, the euro-area sovereign debt crisis of 2009–2015, and most recently, the outbreak of global inflation that began with the Covid shock of 2020–2021 and was exacerbated by several subsequent shocks, including supply disruptions, higher energy prices, and Russia's invasion of Ukraine. A common feature of these extreme economic events is that they were not predictable.² As Pisani-Ferry (2013, 6) put it regarding euro-area sovereign debt crisis, “[there] were ... things that we did not know we did not know: genuine surprises that were not, or not fully, foreseen in the academic literature.”

Considering the list of unforecastable events given in the previous paragraph, Knight's distinction between risk and uncertainty can be viewed as being somewhat ambiguous. While each of those individual events might have come as a surprise, the fact that economic surprises keep occurring suggests that, at a higher level, they are forecastable—at least to the extent that we know that large shocks will occur. Economic policies, including bank regulation as well as more conventional fiscal and monetary policies, should be framed in such a way that they are (to the extent possible) robust to these shocks, minimizing their costs. That is, we know that unpredictable events will occur, disrupting the economy. Once they occur, policymakers should be able to respond quickly to lessen their impact. One possible aspect of dealing with these events is to focus our forecasting techniques in such a way that those techniques can quickly detect that something fundamental has affected economic conditions to which policymakers need to respond.

How can forecasters improve their performance in the presence of unforeseen events? The methods that have been proposed include the following.

1. Research by Lars Peter Hansen has explored ways to take Knightian uncertainty into account in econometric estimation by, for example, using a range of models that, in turn, allows for a range of uncertainties, and assigning probabilities to each model.

The probabilities can then be updated—for example, by Bayesian learning—as new information becomes available. See, for example, Hansen (2007, 2014) and Hansen and Sargent (2010).

2. Some central banks provide density forecasts, which, in addition to the mean of the forecast, quantify the variance, or uncertainty, around their forecasts. Presumably, policy could be adjusted in response to both a change in the mean forecast or to a change in the variance. Since 1996, the Bank of England's inflation forecast has been published in the form of a probability distribution—presented in what has become known as “the fan chart.” As stated by Britton et al. (1998, 30): “The aim of the fan chart has been to convey to the reader a more accurate representation of the Bank's subjective assessment of medium-term inflationary pressure, without suggesting a degree of precision that would be spurious.” After the Global Financial Crisis, the ECB and the Federal Reserve Bank of New York began producing density forecasts based on scenario-driven analyses with the aim of taking tail risks into account (Alessi et al., 2014; Binder & Sekkel, 2023).
3. Several studies have found that the use of rolling windows improves forecasting accuracy in the presence of structural breaks: Once a shock has occurred, rolling windows is able to detect its occurrence—see, for example, Pesaran and Timmermann (2007), Medel et al. (2016), and Inoue et al. (2017). The rolling windows technique maintains a fixed estimation period but “rolls” the estimation period through time. For example, if the data sample consists of 30 observations, the first 15 observations (the “holdout sample”) can be used to forecast the 16th observation. Then, the estimation period is updated by one period to comprise the 2nd through the 16th observations, which are used to forecast the 17th observation and so on. The paper by Hall et al. in this issue, however, shows that the rolling windows approach only provides accurate forecasts when the true data generation process changes from stationary to nonstationary.

As mentioned, the upsurge in inflation that began in 2021 was not predicted by forecasters. Both the magnitude and the duration of the rise in inflation came as a surprise. As inflation began to accelerate during the first 9 months of 2021, central bankers—and most other economists—believed that the rise would be “transitory.”³ In what follows, we provide one possible way to quicken policy responses. We argue that, while the initial rise in inflation was a Knightian event—it was not forecastable—a shorter forecasting horizon after the shock occurred may have allowed central banks to respond more quickly to the inflation surge—so that they would not have misdiagnosed the rise as a temporary increase.

3 THE ROLE OF THE INFLATION FORECAST HORIZON

Inflation forecasting and analysis of inflation tend to concentrate on the annual inflation rate, even though higher frequency data are almost always available—certainly quarterly, and for most economies (including advanced economies), monthly inflation data are available with short lags. If we are interested in the annual inflation rate and have quarterly data, then we would be considering the four-quarter percentage change in the price level: define this as $p_{t+4}-p_t$. For example, consider the euro-area headline inflation rate in May 2023. It was 6.1% and was derived as the percentage change in the euro area price level in May 2023 compared

with May 2022. Now consider building a standard AR model of this variable using quarterly data. Because at period t we only observe the annual inflation rate over the previous four quarters, that is $p_{t-1}-p_{t-5}$, by using the annual inflation rate (that is, the rate derived by comparing the price level in the present quarter with the same quarter of the previous year), we would be averaging the latest quarterly rate of inflation with the three previous quarters. Hence, we would be slow to react to a sudden increase in inflation. We suggest that, at times of rapid changes in inflation, it is important to extract as much information as possible from the quarterly data. To do this, we suggest the following simple steps.

1. If the data are seasonal, then seasonally adjust the data using, for example, X13-ARIMA.
2. For ease of interpretation, rescale the data so that the quarterly change is expressed as an annual rate.
3. Build a simple AR model of the rescaled data.⁴ For example, suppose the present quarter is 2020:Q1 we want to forecast inflation one quarter ahead using an AR (3) process. The AR(3) model would include the quarter-over-quarter inflation rates during 2019:Q4 (that is, the annualized inflation rate during 2019:Q4 over 2019:Q3), 2019:Q3, and 2019:Q2.

Tables 1 and 2 report results using this procedure for the euro area and the United Kingdom, respectively. The estimation periods for the AR(3) models were as follows: euro area, 2000:Q1 to 2023:Q3; UK, 2003:Q1 to 2023:Q2. The estimated AR(3) models for the euro area and the UK are the following:

TABLE 1. The AR(3) models for the UK and euro area.

	Constant	Inflation _{t-1}	Inflation _{t-2}	Inflation _{t-3}
UK	1.2(2.8)	0.26(2.2)	0.55(5.2)	-0.22(1.8)
Euro area	0.66(2.5)	0.55(5.1)	0.35(2.9)	-0.22(1.7)

Note: "t" statistics are in parentheses.

TABLE 2. The AR(3) models based on inflation over four quarters.

	Constant	Inflation _{t-1,t-5}	Inflation _{t-2,t-6}	Inflation _{t-3,t-7}
UK	1.88(3.9)	1.68(3.8)	-0.9(1.17)	-0.55(1.2)
Euro area	1.53(4.7)	1.56(4.6)	-0.76(1.3)	-0.58(1.45)

Note: "t" statistics are in parentheses.

Figures 1 and 2 show (1) the actual (year-on-year) inflation outcomes, (2) forecasts made by the ECB and the Bank of England, both of which make four-quarters ahead forecasts (e.g., 2001:Q1 over 2000:Q1), and (3) forecasts made on the basis of an AR(3) model, estimated using (annualized) quarter-on-quarter data.⁵ As shown in the figures, the use of quarter-on-quarter data based on an AR(3) model is able to track actual inflation much better than the forecasts of the central banks.

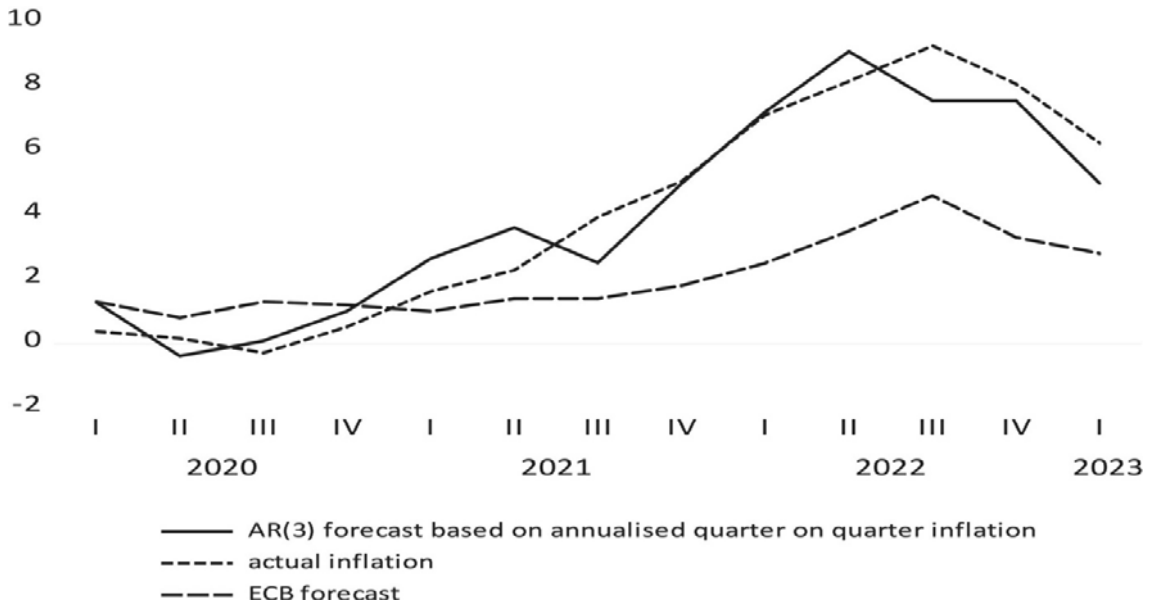


FIGURE 1. The actual inflation rate for the euro area, the ECB forecast, and the forecast based on quarter-on-quarter data.

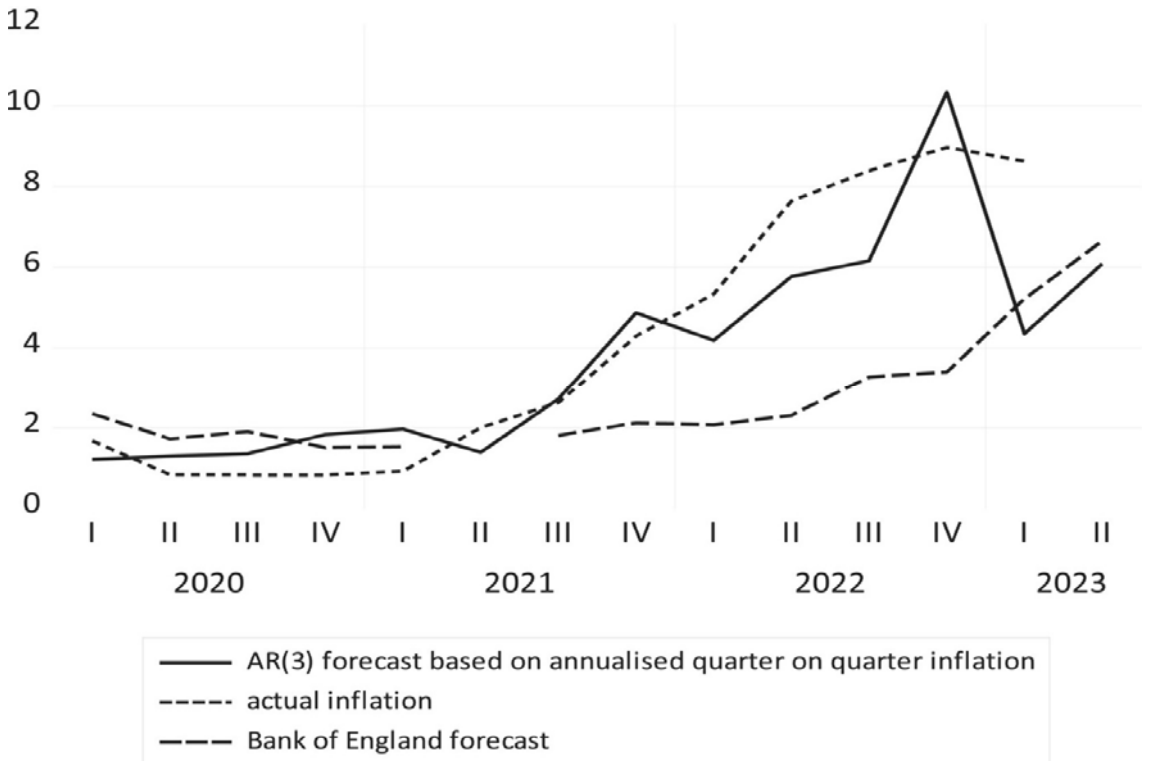


FIGURE 2. The actual inflation rate for the UK, the Bank of England forecast, and the forecast based on quarter-on-quarter data.

A question that arises is whether the improved forecasts using the AR(3) model were due to the particular model or to the use of quarter-on-quarter data. To address this issue, we estimated an AR(3) model of inflation using year-on-year inflation rates—for example, the rate of inflation during 2020:Q1 compared with 2019:Q1.

Figures 3 and 4 present the forecasts based on that year-on-year data with the actual inflation rates and the forecasts based on the AR(3) model using the quarter-on-quarter rates of inflation as in the previous figures. These figures show that the AR(3) model estimated on the basis of quarter-on-quarter inflation rates capture the upturn in inflation in 2021 much more closely and more quickly than does the AR(3) model estimated on the basis of year-on-year inflation rates.

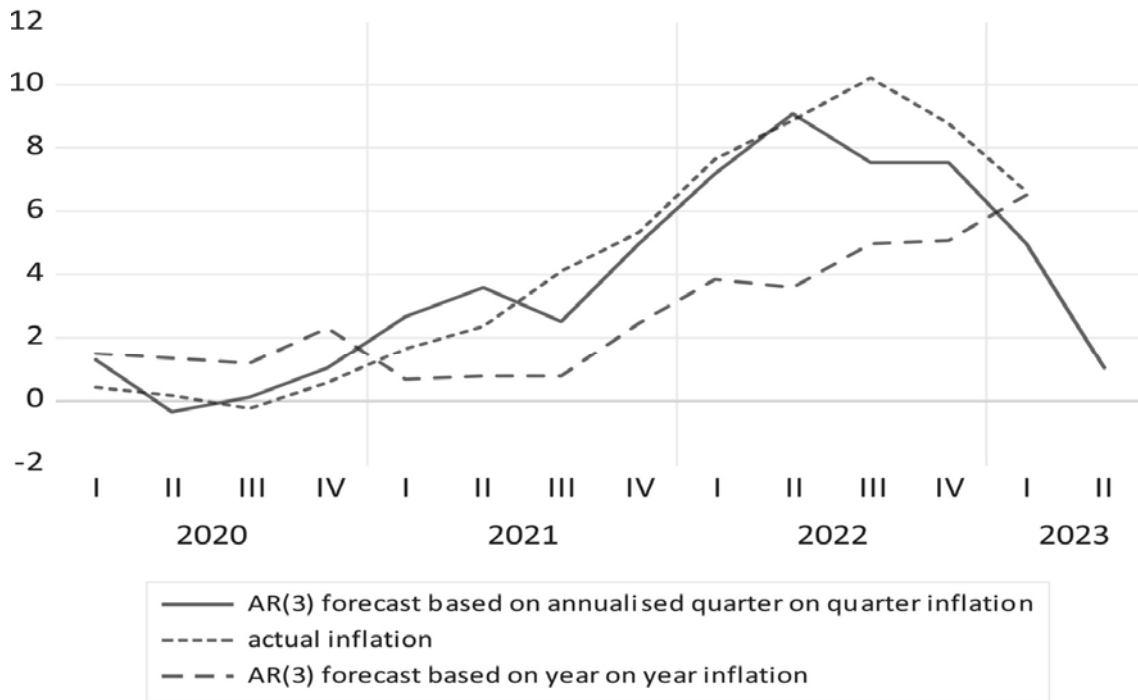


FIGURE 3. The actual inflation rate for the euro area, the forecast based on year-on-year data, and the forecast based on quarter-on-quarter data.

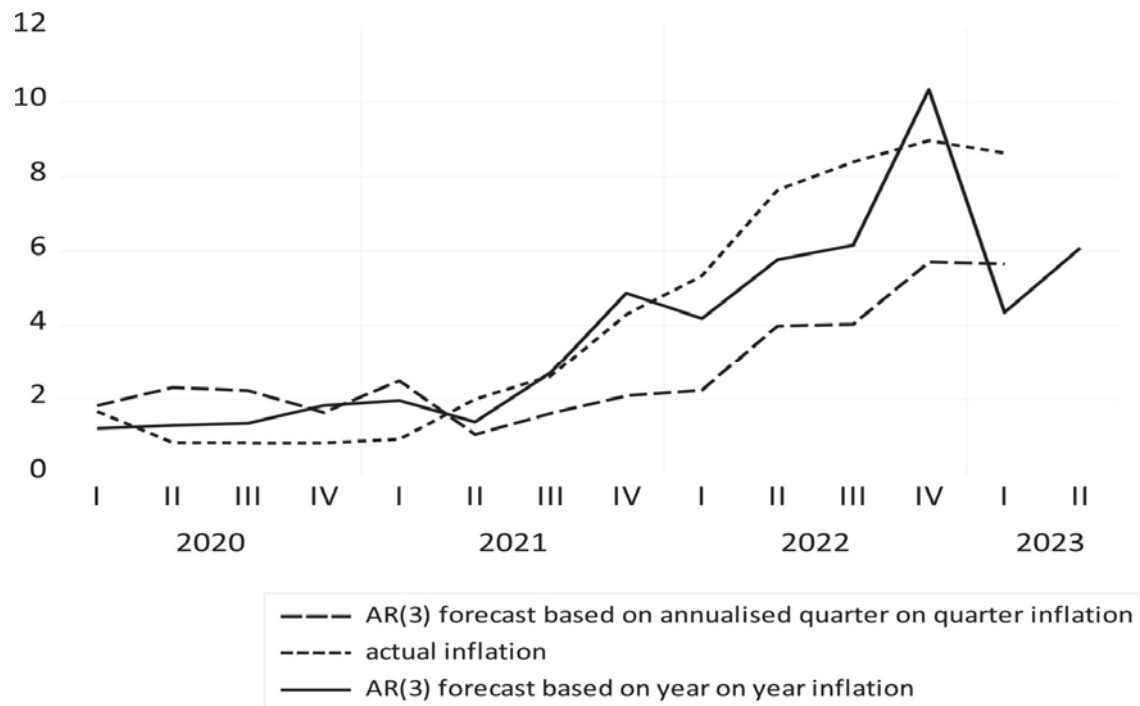


FIGURE 4. The actual inflation rate for the UK, the forecast based on year-on-year data, and the forecast based on quarter-on-quarter data.

4 THIS ISSUE

The above discussion was motivated by the upsurge in inflation which began in 2021 and caught most forecasters by surprise. Similarly, that inflation upsurge and the series of shocks that underpinned it have motivated the papers that appear in this issue.

Many of the papers address the issue of forecasting inflation. A brief description of the papers is as follows.

- Can rolling window techniques be used to forecast inflation more accurately? In the paper “Inflation Forecasting with Rolling Windows: A Reappraisal”, Stephen Hall, George Tavlas, Yongli Wang, and Deborah Gefang find that rolling window techniques are superior to simple AR models only when the nature of inflation changes from a stationary to a nonstationary process.
- In the paper “How We Missed the Inflation Surge: An Anatomy of Post-2020 Inflation Forecast Errors”, Christoffer Koch and Diia Noureldin find evidence of forecast bias and rigidity in forecast revision when new information is available.
- In the paper “Post-COVID Inflation Dynamics: Higher for Longer”, Randal Verbrugge and Saeed Zaman focus on the dynamics of US inflation. The authors construct a nonlinear structural auto regression to explore counterfactual conditional inflation

forecasts in order to provide policymakers with a reliable sense of the tradeoffs they face going forward.

- In the paper “Using Deep (Machine) Learning to Forecast U.S. Inflation in the COVID-Era”, David Stoneman and John Duca develop a recurrent neural network (RNN) to forecast US long-term inflation and report accurate inflation forecasts over the period 2021–2022.
- A crucial factor that affects the impact of shocks on inflation and economic activity is the trust in the central bank's inflation target and trust in its capacity to stabilize the banking cycle. In the paper “Trust and Monetary Policy”, Paul De Grauwe and Yuemei Ji find that negative and large supply shocks cause good and bad trajectories to the output gap and inflation. In all the bad trajectories, trust on central banks decreases dramatically, but it is not affected in the good trajectories.
- How do central banks formulate their inflation forecasts and how have those forecasts performed during the inflation surge that began in 2021? How do central banks formulate their forecasts and how have those forecasts performed during the inflation surge that began in 2021? In the paper “An Evaluation of the Forecasting Performances of the Bank of England, the European Central Bank, and the Federal Reserve”, Eleni Argiri, Stephen Hall, Angeliki Momtsia, Daphne Marina Papadopoulou, Ifigeneia Skotida, George Tavlas, and Yongli Wang, the authors, describe the forecasting methodologies of the Bank of England, the ECB, and the Fed and evaluate their forecasting performances. They report evidence that inflation forecasts made by the three central banks have been unbiased and efficient at the one-quarter-ahead forecasting horizon, but the accuracy diminishes as the forecasting horizon increases.

The remaining papers in this issue focus on other areas of recent forecasting performance.

- In the paper “Combine to compete: Improving fiscal forecasts accuracy over time”, Laura Carabotta and Peter Clayes suggest that, although information rigidity and forecast bias cannot be eliminated, combining budget forecasts that focus on recent performance can improve forecasting results.
- In the paper “Forecasting Exchange Rates: An Iterated Combination Constrained Predictor Approach”, Antonios Alexandridis, Ekaterini Panopoulou, and Ioannis Souropanis propose a hybrid Iterated Combination with Constrained Predictor approach in forecasting exchange rate returns.
- In the paper “The term structure of interest rates and economic activity: Evidence from the COVID-19 pandemic”, Evangelos Salachas, Georgios Kouretas, and Nikiforos T. Laopodis show that term structure models can predict the nominal yield curves for up to 18 months ahead, while models with an enhanced information set have better forecasting ability than baseline models.
- In the paper “Forecasting GDP growth: the economic impact of COVID-19 Pandemic”, Ioannis Vrontos, John Galakis, Ekaterini Panopoulou, and Spyridon Vrontos report an interesting interplay between real GDP growth and predictor variables as different predictor variables explain different quantiles of the real GDP growth distribution.
- Another interesting research question is how inflation dynamics and forecasts behave during crises, such as the global financial crisis, the COVID-19 pandemic, and other turbulent events. In the paper “Forecasting food price inflation during global crises”,

Roberto Duncan and Patricia Toledo argue that the best predictor of the domestic food price inflation during such periods is the international food price inflation.

- Will Brexit have long-lasting effects on the UK economy? In the paper “Modelling the effects of Brexit on the British economy”, Patrick Minford and Zheyi Zhu examine the effects of Brexit on the UK economy and find that any disruption on the UK economy is only temporary. Short-run negative effects are found on GDP and trade, and positive short-run effects are found on inflation and interest rates.

In summary, the papers collected in this issue address a range of methodological and empirical issues related to forecasting and highlight the dilemmas faced by agents within the economy and policy makers. Best-practice methods are proposed as means of improving forecasting performance and thereby delivering better policy decisions [Correction added on 26 March 2024, after first online publication: The brief description regarding Charles Goodhart and Manoj Pradhan paper has been removed from this section in this version.].

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ENDNOTES

¹ See Knight (1921). The discussion in this paragraph is based on Blaug (1985) and Stigler (1987).

² On November 4, 2008, Queen Elizabeth visited the London School of Economics, where she was given a briefing of the origins and effects of the Global Financial Crisis. At the end of the briefing, she asked: “Why did no one see it coming?” (Turner, 2017).

³ Federal Reserve Chairman, Jerome Powell, characterized the rise in inflation during the first part of 2021 as “transitory” in two speeches made in both July 2021 and August 2021, respectively. See Schneider (2023).

⁴ The use of AR(3) was arrived at using standard lagged selection techniques.

⁵ The ECB forecasts are available on the following data portal: <https://data.ecb.europa.eu/data/datasets/MPD/data-information>. The Bank of England forecasts are available from the Bank of England Monetary Policy report 2023 (<https://www.bankofengland.co.uk/-/media/boe/files/monetary-policy-report/2023/august/monetary-policy-report-august-2023.pdf>).

Biographies

Nikolaos Giannellis is an Associate Professor at the Department of Economics at the University of Crete. He has previously taught at the University of Peloponnese and the University of Ioannina. He received his PhD in Economics from the University of Crete and his M.Sc. in Economics from the University of York. His research interests lie in the area of macroeconomics and international finance, including monetary policy, European economics, exchange rate economics, and financial stability. He has numerous academic publications.

Stephen G. Hall is a Professor of Economics at Leicester University. He was Professor at Imperial College and a professorial research fellow at the London Business School. Before that, he was an Economic advisor at the Bank of England and a senior research fellow at the National Institute of Economic and Social Research in London. His interest lies in the broad area of applied macro-econometrics and economic modelling. He has been a consultant to The United Nations, the IMF, the European Central Bank, The European Commission as well as many other Central Banks. He has published widely.

Georgios P. Kouretas is a Professor of Banking and Finance at the Department of Business Administration at the Athens University of Economics and Business and holder of the Jean Monnet Chair on European Economic Policy. He is a Director of the Master of Business Administration-MBA programme of AUEB. He obtained his BA in Economics from the University of Piraeus (1981), MA in Economics from the University of Notre Dame (1983), MA in Economics from Wayne State University (1985), and a PhD in Economics from the University of Birmingham (1988). His research interests lie in banking, international finance, European financial markets and monetary issues, international money and capital markets, and open economy macroeconomics. He is an Associate Editor of the *Journal of Forecasting* and of the *Journal of Economic Asymmetries*.

George S. Tavlas is the Alternate to the Governor of the Bank of Greece at the Governing Council of the European Central Bank and Distinguished Visiting Fellow at the Hoover Institution at Stanford University. He was a member of the Monetary Policy Council of the Bank of Greece from 2013 to 2020. Before joining the Bank of Greece, Tavlas was a Division Chief at the International Monetary Fund. He also worked as a senior economist at the U.S. Department of State, and as an advisor for the World Bank and the Organization of Economic Cooperation and Development. He is the Editor-in-Chief of *Open Economies Review* and a Visiting Professor at Leicester University. He has been a visiting scholar at the Brookings Institution, the Reserve Bank of South Africa, the LeBow School of Business at Drexel University, the Becker Friedman Institute at the University of Chicago, and Duke University's Center for the History of Political Economy. He earned his PhD at New York University. He is an active researcher in the areas of monetary policy, monetary doctrine, and time-series econometrics, with numerous academic publications. His book, *The Monetarists: The Making of the Chicago Monetary Tradition, 1927-1960*, was published by the University of Chicago Press in 2023.

DATA AVAILABILITY STATEMENT

All data are taken from publicly available data sources as defined in the data appendix. The vintage of data used in this study is available upon request from the authors.

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