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Forecasting GDP growth: The economic impact of COVID-19 pandemic

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Abstract

The primary goal of this study is to effectively measure the impact of a severe random shock, such as the COVID-19 pandemic on aggregate economic activity in Greece, seven other euro area economies, three Scandinavian countries, and the United States. The class of linear and quantile predictive regression models is proposed for the analysis of real gross domestic product (GDP) growth, and a Bayesian approach for model selection is developed, by using a computationally flexible Markov chain Monte Carlo stochastic search algorithm that explores the posterior distribution of linear and quantile models, and identifies the relevant predictor variables. Penalized likelihood regression models are also implemented to tackle the issue of model selection. The model confidence set approach is applied and verifies that the selected models identified by the stochastic search algorithm belong to the set of superior models. Our analysis confirms that the outbreak of the pandemic had a profound effect on the economies under study, and reveals that different predictor variables are able to explain different quantiles of the underlying real GDP growth distribution for analyzed countries, suggesting that the quantile modeling approach improves the ability to adequately explain real GDP series compared with the standard conditional mean approach that explains only the average of the relationship between real GDP growth and several predictor variables.

KEYWORDS

Bayesian inference, common and specific predictors, linear regression models, model confidence set, model selection, penalized models, quantile regression models

1 | INTRODUCTION

The COVID-19 epidemic originated in the Chinese city of Wuhan in December 2019. Since then, it has spread all over the world, as 230 countries have reported cases. Given the wide spread of the pandemic, it is natural that there are distinct asymmetries in the "life-cycle" of, or, differential trends in evolution of the epidemic across the globe. The severity of the situation is clearly reflected in the underlying numbers; until recently, according to data providers, the total number of worldwide reported cases was around the 550 million level, while more than 6.3 million deaths have been recorded globally. These numbers clearly reveal that the COVID-19 pandemic is not comparable with the SARS (2002–2003) and the Ebola (2013–2016) epidemics but is more related to the 1918 Global Influenza that killed roughly 40 million people worldwide and infected one third of the world population in 1918 and 1919.

In a highly connected and integrated world, the impact of a pandemic goes beyond just health-related issues and mortality. Before the successful release of vaccines, governments were induced to take unprecedented measures, such as severe lockdowns, distancing measures, and even border closures, to control the spread of the pandemic, bringing global economic activity practically close to a halt or shutdown. A significant decline in consumption, production interruptions and, thus, supply chain disruptions, massive layoffs, and shortages of goods were some of the repercussions that have already occurred and been recorded in many economies around the world.

The combined demand and supply-driven shock has had a profound impact on both developed and emerging economies, though not symmetric, as the ultimate effects were largely dependent on the underlying structure of each country's economy. At least theoretically, the main expectation, especially at the outbreak of the pandemic, was that countries with a larger proportion of so-called digital economies, that is, with higher digital or digital-labor intensity, and those that were less reliant on tourism and related sectors would ultimately suffer less. In practice, as a result of the pandemic, the global economy contracted by 3.3% in real terms in 2020. This was the worst rate of contraction in post-war history, far worse than the recent global recession caused by the Global Financial Crisis (GFC). The economic impact was the hardest in the European region, as the European Union and the euro area real economic activity decelerated by 6% and 6.4%, respectively, while the North American economy contracted less, by 3.5%. By contrast, in the Asian Pacific region, real economic activity eked out a small increase, 0.2%.

An aggregate shock of such magnitude has resulted in a surge in unemployment; the International Labor Organization (ILO) initial estimates that 8.8% of working hours were lost during 2020. The COVID-19 crisis has hit labor market harder than initially estimated, especially in the upper-middle and high-income countries. Relative to 2019, total employment fell by 114 million, as a result of workers becoming unemployed or dropping out of the labor force. To put these numbers into perspective, without the specific shock, the global economy would have created an estimated 30 million new jobs in 2020. Taken together, these losses imply that the shortfall in employment increased by 144 million jobs in 2020, drastically absorbing the shortage of employment opportunities that existed prior to the COVID-19 pandemic. Recurrent waves of the pandemic around the globe caused working-hour losses to remain high in 2021, as they led to a shortfall in total working hours of 4.8% in the first quarter and fell slightly to 4.4% in the second quarter of 2021. Europe was once again one of the worst-affected regions, with estimated working-hour losses in each case exceeding 8% in the first quarter and 6 per cent in the second quarter of 2021, according to the ILO. In the United States alone, initial jobless claims surged to unprecedented numbers by the end of April 2020.

One of the most prominent questions regarding the repercussions of the pandemic on the global and also on individual country economies is the direct impact of social distancing policies on the real economy, as well as on agents' expectations. As the pandemic affects almost every aspect of social activity, the underlying spillover effects play a critical role. Tighter lockdown and social distancing measures imply lower economic activity, as activities that require face-to-face interaction and/or some type of mobility are progressively restricted or curtailed. The expectation is that lockdown metrics should be closely related to various measures of underlying economic activity. More specifically, the main expectation is that the stricter the measures, the higher the impact on economic activity, as reflected in leading, coincident, and lagging economic indicators.

The primary goal of this study is to effectively measure the impact of an extreme shock, such as the COVID-19 pandemic, on aggregate economic activity in Greece and seven other euro area countries, namely, Belgium, Finland, France, Germany, Italy, the Netherlands, and Spain. For comparison reasons mainly, three Scandinavian countries, Denmark, Norway, and Sweden, as well as the United States, are included in the underlying analysis. More specifically, the standard linear and quantile regression methodologies are employed to explore the ability of several factors to capture the aggregate shock. The use of the quantile regression framework is rather interesting, in order to identify the type of factors that affect the real GDP (RGDP) growth distribution at different points. In addition, the specific framework enables one to determine whether the estimated parameters of the model change across the different quantiles of the GDP growth distribution. It is anticipated that the use of predictive quantile regression models will allow us to better capture the dynamic nature and nonlinear characteristics of the underlying economic series. This class of models permits the dynamics of the RGDP growth to be asymmetric and different across quantiles of the conditional distribution, especially between the median and the tails of the distribution.

Several model selection methods are used in the analysis. First, a parametric approach to inference based on the likelihood function and certain information criteria is followed. Second, a Markov chain Monte Carlo (MCMC) stochastic search algorithm, within the Bayesian framework/methodology, is developed, which explores the model space in an efficient manner and provides linear and quantile regression models along with their posterior probabilities. As a result, inference can be based on the most probable (MP) model, or a subset of MP models, weighted by their (normalized) posterior model probabilities. The latter approach takes into account model uncertainty, which may be important when different competing models score equally well, or, in cases, where the underlying history of the data is short, as in the case of quarterly RGDP growth series. Another advantage of the proposed algorithm is that it enables the analysis of datasets with high dimensionality regarding the number of factors or predictor variables. In such cases, analytic computation of different information criteria or of the posterior probabilities of each possible model may be computationally prohibitive.

For robustness reasons, the best subset regression approach, an automated procedure used in model building to identify a useful subset of predictors that explores all possible subsets of predictor variables included in the regression models, is also applied in our analysis. In addition, penalized likelihood regression models such as the ridge, the elastic net, and the least absolute shrinkage and selection operator (LASSO) regularization techniques are implemented to tackle the issue of model selection. These techniques are penalized maximum likelihood (ML) or least-squares methods that impose shrinkage to the regression coefficients and allow for automatic variable selection. Last, the model confidence set (MCS) approach of Hansen et al. (2011) that allows the identification of a subset of superior models containing the best model(s) at a given level of confidence confirms that the MP regression models selected by the Bayesian stochastic search algorithm belong to the set of superior models.

The contributions of this work are several. First, we propose modeling the entire distribution of RGDP growth using the quantile regression modeling approach. Second, we propose a Bayesian approach to model selection for conditional quantile regression models based on a stochastic search algorithm that explores the model space and provides posterior model probabilities, and therefore is able to account for model uncertainty. Third, we carry out an extensive empirical analysis to explore several aspects of RGDP growth for a variety of economies/countries by comparing different model selection strategies/techniques and also by investigating the differences between the quantile regression and the conditional mean approach. Finally, we show that the quantile regression approach and the Bayesian methods provide a more powerful framework for modeling GDP growth series.

Several important results emerge from our analysis. First, the primary conclusion of the underlying analysis is that the outbreak of the COVID-19 pandemic has had a profound impact on the real economic activity of Greece and the rest of the countries under study. The factors that proxy the state and spread of the pandemic show up in all critical models and overshadow the explanatory, deterministic, and predictive ability of other economic and/or financial variables to explain and/or predict the variation of RGDP growth. Second, the results indicate that the exposure of the estimated parameters is asymmetric at different states of real economic activity, that is, during periods of economic expansion (periods when RGDP growth is positive) versus periods of economic contraction (periods when RGDP growth is negative). This study, therefore, highlights the asymmetric non-linear features of RGDP growth, as well as the importance of taking them into account when analyzing macroeconomic time series, and may provide useful insights to policy makers. Third, we have found strong evidence for model uncertainty in all regression models considered for GDP growth series, which suggests that model averaging or combination of forecasts may be a more appropriate approach for the prediction of GDP growth series.

The remainder of the paper is organized as follows. A literature review is presented in Section 2. The econometric model specifications are introduced in Section 3, and a Bayesian approach to inference for model selection/comparison is presented in Section 4. Section 5 features the empirical application and illustrates the proposed models using economic data. Finally, Section 6 concludes.

2 | LITERATURE REVIEW

The task at hand is to come up with a framework that can identify changes in the business cycle and capture expansions and contractions in an effective manner and incorporate the devastating impact of the recent pandemic. In the existing literature, there are two broad approaches in nowcasting and forecasting business cycles; the first is through the use of continuous models that forecast aggregate macroeconomic variables, such as economic growth, usually through the application of hidden Markov models, mixed data sampling (MIDAS) models, vector autoregression models (mixed frequency, Bayesian, MIDAS), while the second concentrates on the prediction of different macroeconomic regimes or states typically through the use of binary Probit/Logit models. Early studies using Probit/Logit models include Canova (1994), Dueker (1997), and Estrella and Mishkin (1998), while hidden Markov models have been implemented in Hamilton (1989), Hamilton (1990), Hamilton and Perez-Quiros (1996), Marsh (2000), Banachewicz et al. (2008), Pinson and Madsen (2012), and Nguyen (2018). More recently, there has been quite some interest in applying machine learning algorithms in economic activity and recession forecasting; see, for example, Vrontos et al. (2021) and the references therein.

Barua (2020) attempts a theoretical mapping of the potential impact of a pandemic in the context of a single country. The mapping assumes different waves of effects over time, either shorter or longer term, and either concurrent or sequential unraveling. In the first wave, the temporary shutdown of production and general businesses, results in a decline in production. As the pandemic spreads, the foreign demand for an economy's goods and services declines substantially, which in turn depresses production further, potentially creating a situation termed supply–demand doom by Fornaro and Wolf (2020). Lower production and supply exhibit knock on effects to the global supply chain that is also affected by the likely suspension of international transport and logistic channels. Moreover, the production and supply chains are disrupted further, if and when there is limited or no human mobility both domestically and internationally, as restrictions and border closures are gradually imposed.

Diebold (2020) shows that the collapse in economic activity during the early phases of the pandemic was reflected in the collapse of the Aruoba–Diebold–Scotti (ADS) index of business conditions (Aruoba et al., 2009). The ADS index of business conditions are designed to track US real economic activity at high frequency. Diebold comments that the specific index recorded a significant drop, more than five times compared with that of any other economic recession since 1960 and concludes that the pandemic led recession is the deepest and likely the shortest on record. Interestingly, he shows that there is a significant negative correlation between the ADS index and a proxy indicator for new COVID-19 cases, namely, the number of deaths led by 20 days.

Konig and Winkler (2020) explore the impact of mandatory and voluntary distancing related to the pandemic on the evolution of GDP in forty six countries. They use the Oxford University Stringency Index to measure the magnitude of mandatory distancing and the fatality rate to measure voluntary distancing. They find that changes in mandatory distancing enforced by governments around the globe, are critical drivers of GDP growth over the first two quarters of 2020. In addition, they show that voluntary distancing measures also impact cross-country differences in GDP evolution, and countries that are more exposed/vulnerable to developments/restrictions abroad, proxied by tourism exposure and trade openness.

Foroni et al. (2022) consider various methods to improve the economic growth nowcasts and forecasts obtained by mixed-frequency MIDAS and Unrestricted MIDAS models with numerous indicators during the COVID-19 crisis and recovery period. Their goal is to consider simple methods that can improve predictability specifically during the COVID-19 crisis and recovery period. The performance of nowcasting models during the GFC could be informative, which is indeed what they detect empirically, at least for the first quarter of 2020. Similar findings emerge when the analysis is conducted for the other G7 countries. Specifically, they find that the drop in GDP growth in the first quarter of 2020 is expected to be particularly severe in France, Italy, and the United Kingdom, limited in Japan, and less so in Germany. Last, they report similar results for US private investment.

A novel approach is that of Makridis and Hartley (2020) that use the digital-labor intensity of each sector/industry to quantify the varying effect of the pandemic across sectors. The intensity is defined as the share of digital workers within each industry. Their core assumption is that each sector will remain "productive" in direct proportion to their degree of digitalization because at least that portion of their workforce can continue working from home and contribute services that do not depend as much on in-person interactions. They estimate a 5% decline in US RGDP growth for every month of partial economic shutdown. Moreover, they show that countries with a larger share of workers in non-tradable sectors are also more heavily affected because those sectors are less diversified and more exposed to local shocks.

Apart from the academic literature, there are numerous original practitioner efforts to quantify the impact of social distancing and restrictive measures on economic activity. A primary example is Goldman Sachs' (GS's) series of global, regional, and country-specific Effective Lockdown Indices (ELI). To create an objective metric, GS's research team combined the government response stringency index created at Oxford University and Google mobility reports into a single index that should reflect policy response and ultimate citizen behavior. The first component proxies a "virus policy" measure, while the Google mobility data proxy a "social distancing" measure. The expectation is that the ELI should be closely related to various measures of underlying economic activity. To be more specific, there should be an inverse relation, with higher ELI readings corresponding to lower activity readings. Indeed, the ELI is inversely related to various composite Purchasing Managers' Indices. The implied sensitivity of economic activity to the ELI is then measured, and the specific parameter is used to convert each economy's ELI value into the impact on GDP growth.

Caperna et al. (2022) propose a data-driven approach based on Google Trends queries to estimate the impact of containment measures on the unemployment rate in the European Union during the first phase of the pandemic. Using machine learning techniques, they choose the search queries that best predict unemployment in each country. In addition, they combine queries and construct search-based unemployment indicators. They find that containment measures are linked to increase searches for unemployment-related queries. Countries that introduced lockdowns exhibit an extreme and time-persistent increase in expectations about the future level of unemployment. The underlying findings are similar to those of Aaronson et al. (2022) for the United States. They show that unemployment-related queries surged before the record increase in unemployment insurance claims that peaked before the lockdown measures were implemented.

Last, but not least, Agoraki et al. (2023) propose a quantile regression modeling approach to study the effects of COVID-19 pandemic on the dynamics of green investment funds. Quantile regression models provide a more comprehensive picture of the effect of COVID-19 on every part of the distribution of returns compared with the standard mean regression approach. They demonstrate the heterogeneous effect of the pandemic and consider explicitly how different measures of COVID-19 affect green assets. They show that the influence of COVID-19 on green assets is considerably more substantial when green asset returns are negative (at the lower quantiles) than when they are positive (at the higher quantiles). Thus, the effect of the pandemic is more pronounced when the green asset market is weak, which is crucial information for both investors and policy makers.

3 | ECONOMETRIC MODELING APPROACHES

In this section, the modeling approaches followed to investigate the forecasting ability of several predictor variables with respect to economic activity in Greece and other advanced economies is presented. First, the predictive standard regression model will be used as a benchmark model to identify important predictor variables for RGDP growth. Next, predictive quantile regression models will be employed to investigate whether different variables are useful in forecasting different quantiles of the RGDP growth distribution. This is crucial in order to identify which predictor variables affect different points of the RGDP distribution and to explore whether exposures (beta parameters) are different/change across different quantiles of the RGDP distribution.

3.1 | Standard predictive regression model specifications

The standard regression model can be used to forecast the dependent variables based on a set of predictor variables through the following equation:

$$y_{t+1} = \alpha + \sum_{k=1}^{K} \beta_k x_{k,t} + \epsilon_{t+1}, \tag{1}$$

where y_{t+1} is the dependent variable, that is, RGDP growth at time $t+1$, $x_{k,t}$ are the predictor variables, $k = 1,\ldots,K$ at time t, and ϵ_{t+1} is the innovation process assumed to be independent and identically distributed with mean zero and variance σ^2. In the analysis, the set of predictor variables include autoregressive terms, different common factors (e.g., West Texas Intermediate [WTI] Oil, the World Uncertainty Index [WUI], and the World Pandemic Uncertainty Index [WPI]), as well as several country-specific economic and financial factors that may have an impact on RGDP growth. This class of predictive regression-type model specifications (1) suggests that the conditional mean of the predictive distribution of RGDP growth y_{t+1} given a set of K predictors $x_{1,t},\ldots,x_{K,t}$ is equal to $E(y_{t+1}|x_{1,t},\ldots,x_{K,t}) = \alpha + \sum_{k=1}^{K} \beta_k x_{k,t}$.

The predictive mean regression models can be estimated using the ordinary least-squares (OLS) method by minimizing the sum of squares $\sum_{t=1}^{T-1}\left(y_{t+1} - \alpha - \sum_{k=1}^{K} \beta_k x_{k,t}\right)^2$, or using the ML approach, after specifying the parametric form of the error distribution. Then, inference on the model parameters can be based on the arising likelihood function using either classical or Bayesian methods. Bayesian techniques offer an advantageous approach to deal with model uncertainty regarding RGDP growth predictability, because inference is drawn based on the posterior probabilities of a set of competing predictive model specifications. The Bayesian approach to inference has been used in the financial literature to address/take into account model uncertainty. For example, Avramov (2002) and Cremers (2002) deal with model uncertainty in the context of stock return predictability, a problem that is similar to the one addressed in this study.

3.2 | Predictive quantile regression model specifications

The previously presented class of linear predictive regression model specifications has been one of the most important statistical tools for empirical economic and financial predictability applications. Regression models can explain/predict the conditional mean, $E(y_{t+1}|x_{1,t},\ldots,x_{K,t})$, of the dependent variable based on a set of predictor variables. However, they quantify and summarize only the average relationship between, in our analysis, RGDP growth and the predictor variables, and, as a result, can only explain the mean and not the whole conditional distribution of RGDP growth. In the underlying analysis it is of great interest to model other characteristics of the unknown predictive distribution, besides its conditional mean, such as the conditional quantiles, and to identify the predictor variables that are most relevant to predict the distribution of RGDP, in particular. Thus, it is rational to use the class of predictive quantile regression models, introduced by Koenker and Bassett (1978) that provide an appropriate way to capture the relation between RGDP growth and a set of predictor variables across different quantiles of the conditional distribution.

The primary motivation for using quantile regression models to predict RGDP growth stems from the dynamic nature of the economic time series that are asymmetrically impacted by different economic, financial, geopolitical, and other random events and shocks, such as market crises and economic downturns, the COVID-19 pandemic, or the recent war in Ukraine. Due to country specific or to worldwide events and episodes, economic series may exhibit non-linearities, fat tails, excess kurtosis, and deviations from normality. In the presence of such characteristics, the conditional mean approach may not capture the effects of different predictors to the entire distribution of the series under consideration and may provide estimates that are not robust. In addition, the quantile regression approach estimates the potential differential effect of a set of predictors on various quantiles in the conditional distribution and provides a natural generalization of the standard conditional mean approach. It allows the detection of multiple forms of shape shifts in the conditional distribution of RGDP growth and produces more robust inferences either in the presence of non-normal, especially skewed, error distributions, or non-linearities and outliers.

In this study, therefore, the predictive quantile regression model for the analysis of RGDP growth is adopted. Consider the following τth quantile regression model of the form:

$$y_{t+1} = \alpha^{(\tau)} + \sum_{k=1}^{K} \beta_k^{(\tau)} x_{k,t} + \epsilon_{t+1}, \tag{2}$$

where $\tau \in (0,1)$; y_{t+1} is RGDP growth at time $t+1$; $x_{k,t}$ is the value of predictor k at time t, $k=1,\ldots,K$; $\alpha^{(\tau)}$ and $\beta_k^{(\tau)}$ are the regression parameters, that is, the intercept and the betas, associated with the τth quantile; and ϵ_{t+1} is an unknown error term. The errors ϵ_{t+1} are assumed independent from an error distribution $g_\tau(\epsilon)$ with τ-quantile equal to 0, that is, $\int_{-\infty}^{0} g_\tau(\epsilon)d\epsilon = \tau$. Model (2) suggests that the τth conditional quantile of y_{t+1} given $x_{1,t},\ldots,x_{K,t}$ is $Q_\tau(y_{t+1}|x_{1,t},\ldots,x_{K,t}) = \alpha^{(\tau)} + \sum_{k=1}^{K}\beta_k^{(\tau)} x_{k,t}$ where the intercept and the regression coefficients depend on τ. Its estimate is given by $\hat{\alpha}^{(\tau)} + \sum_{k=1}^{K}\hat{\beta}_k^{(\tau)} x_{k,t}$. As τ increases continuously, the conditional distribution of y given x is traced out.

The predictive quantile regression model parameters can be obtained by minimizing a sum of asymmetrically weighted absolute residuals, that is, by minimizing $\sum_{t=1}^{T-1}\rho_\tau\left(y_{t+1} - \alpha^{(\tau)} - \sum_{k=1}^{K}\beta_k^{(\tau)}x_{k,t}\right)$, where $\rho_\tau(u)$ is the asymmetric linear loss function or check function $\rho_\tau(u) = u(\tau - I(u<0)) = \frac{1}{2}[|u| + (2\tau-1)u]$. This minimization problem can be solved efficiently by linear programming methods, when conditional quantile regression models are formulated as a linear function of parameters. In the symmetric case of the absolute loss function $(\tau = 1/2)$, estimates of the median regression model are obtained. ML methods can also be used to estimate the predictive quantile regression model parameters, if the parametric form of the error distribution $g_\tau(\epsilon)$ is specified. The error distribution that has been widely used for parametric inference in the quantile regression literature is the asymmetric Laplace distribution (for details, see Galakis et al., 2022; Meligkotsidou et al., 2009; Yu & Moyeed, 2001; Yu & Zhang, 2005).

The advantage of the parametric approach to inference for the proposed predictive linear and quantile regression models is that it enables us to compare different model specifications by using information criteria, such as the Akaike (1973) information criterion (AIC) and the Schwarz (1978) Bayesian information criterion (BIC) based on the likelihood function. This framework enables the establishment of a Bayesian approach to inference based on the estimation of the posterior model probabilities, and to provide, therefore, the best model or a set of the MP models, and in this way to be able to account for model uncertainty. In this sense, Meligkotsidou et al. (2009) introduced the idea of modeling the conditional quantiles of hedge fund returns using a set of risk factors and proposed a Bayesian approach to model selection in order to identify important risk factors in hedge fund pricing and performance evaluation, by considering all 2^K

competing models. In this study, we extend the approach of Meligkotsidou et al. (2009) in quantile regression modeling, by constructing a Bayesian stochastic search algorithm that can be used for the identification of the most important predictors for the GDP growth in the linear and quantile regression models. The proposed Bayesian approach to inference allows for automatic model selection, and enables the analysis of datasets with high dimensionality regarding the number of factors or predictor variables. In such cases, analytic computation of different information criteria or of the posterior probabilities of each possible model may be computationally infeasible.

4 | BAYESIAN APPROACH TO INFERENCE AND MODEL SELECTION

This section describes the Bayesian approach to model comparison that deals with the uncertainty regarding the set of predictors that should enter the linear and quantile regression models. This is a probabilistic approach to inference that is based on the estimation of the posterior probabilities of different predictive regression models. Estimation of these posterior model probabilities is achieved by designing a MCMC algorithm that visits (jumps between) a variety of regression model specifications. It can be seen as a Bayesian-motivated stochastic search algorithm that comes up with linear and quantile regression models together with their posterior probabilities. Then, inference can be based on the MP model or a subset of MP models, weighted by their (normalized) posterior model probabilities. The latter approach takes into account model uncertainty that may be important when different competing models score equally well (Kass & Raftery, 1995) or in cases where the data has relatively short history.

4.1 | Bayesian framework and model comparison using posterior model probabilities

Let us assume that the data $\mathbf{y} = (y_1, \ldots, y_T)'$, and K predictor variables, $\mathbf{x} = (x_{1,t}, \ldots, x_{K,t})'$, $t = 1, \ldots, T$, that are used to predict RGDP growth, y_{t+1}, are observable. A fundamental problem is that of selecting a subset of relevant predictors to enter the linear and quantile regression models (1) and (2). Each possible combination of predictors defines a different regression model, and there are 2^K different model specifications that correspond to different subsets of predictors. It is convenient to indicate each of these 2^K possible choices of subsets by the vector $\boldsymbol{\gamma} = (\gamma_1, \ldots, \gamma_K)'$, where $\gamma_k = 1$ if the kth predictor is included in the model, and $\gamma_k = 0$, otherwise. The vector $\boldsymbol{\gamma}$ is defined as the model identifier. The Bayesian approach to model comparison entails the estimation of the posterior probabilities of all the competing predictive regression models. The posterior probability of model $\boldsymbol{\gamma}$ given the dependent variable $\mathbf{y}$ and the set of predictor variables $\mathbf{x}$ can be computed by

$$p(\boldsymbol{\gamma}|\mathbf{y},\mathbf{x}) = \frac{p(\mathbf{y}|\gamma,\mathbf{x})p(\boldsymbol{\gamma})}{\sum_{\delta} p(\mathbf{y}|\boldsymbol{\delta},\mathbf{x})p(\boldsymbol{\delta})}, \tag{3}$$

where

$$p(\mathbf{y}|\gamma,\mathbf{x}) = \int p(\mathbf{y}|\boldsymbol{\gamma},\mathbf{x},\boldsymbol{\theta}_{\gamma})p(\boldsymbol{\theta}_{\gamma}|\gamma,\mathbf{x})d\boldsymbol{\theta}_{\gamma} \tag{4}$$

is the marginal likelihood of model $\boldsymbol{\gamma}$, $\boldsymbol{\theta}_{\gamma}$ is the parameter vector of the specific predictive linear and quantile regression model identified by the vector $\boldsymbol{\gamma}$, $p(\mathbf{y}|\boldsymbol{\gamma},\mathbf{x},\boldsymbol{\theta}_{\gamma})$ is the likelihood given model $\boldsymbol{\gamma}$, $p(\boldsymbol{\theta}_{\gamma}|\boldsymbol{\gamma},\mathbf{x})$ is the prior density of $\boldsymbol{\theta}_{\gamma}$ under model $\boldsymbol{\gamma}$, and $p(\boldsymbol{\gamma})$ is the prior probability for model $\boldsymbol{\gamma}$.

Given that the estimation of the posterior model probabilities is feasible, inference for a quantity of interest, such as a forecasted value, is straightforward. The specific value can be obtained by using the MP model specification or by using Bayesian model averaging (BMA) that accounts for model uncertainty. A comprehensive discussion of Bayesian model selection and BMA can be found, for instance, in Kass and Raftery (1995), Draper (1995), Hoeting et al. (1999), Raftery et al. (1996), Raftery et al. (1997), Chipman et al. (2001), among several others.

To implement Bayesian model comparison, a prior distribution must be assigned to the model identifier $\boldsymbol{\gamma}$ and to the model parameters. The assignment of a prior distribution assists in addressing some difficulties that may arise in the estimation of the posterior model probabilities; first, the required high-dimensional integrations in Equation (4) may not be estimated analytically and some numerical technique or approximation is needed, therefore. Second, the number of all possible model specifications, 2^K, may be vast and analytic evaluation of (3) might be computationally infeasible, especially in cases where the number of potential predictor variables K is large enough. Below, a brief discussion of ways to address these issues is provided.

4.2 | Prior specification for Bayesian inference

The predictive regression model specifications are tagged by a parameter vector $\boldsymbol{\theta} = (\boldsymbol{\gamma}, \boldsymbol{\theta}_{\gamma})$, where the elements γ_i,

$i = 1,...,K$ of the vector $\boldsymbol{\gamma}$ represent the predictor variables that are included in the model, while $\boldsymbol{\theta}_\gamma$ denotes the parameter vector of the specific predictive regression model identified by the vector $\boldsymbol{\gamma}$. A Bayesian analysis of such class of models is typically done by specifying a prior probability distribution $p(\boldsymbol{\gamma},\boldsymbol{\theta}_\gamma)$ of the form

$$p(\boldsymbol{\gamma},\boldsymbol{\theta}_\gamma) = p(\boldsymbol{\theta}_\gamma|\boldsymbol{\gamma})p(\boldsymbol{\gamma})$$

and specify $p(\boldsymbol{\gamma})$ and $p(\boldsymbol{\theta}_\gamma|\boldsymbol{\gamma})$, separately. The advantage of this specification is that the choice of prior for the model identifier $\boldsymbol{\gamma}$ does not depend on the form of the parametric family indexed by $\boldsymbol{\theta}_\gamma$. The conditional specification of the prior on $\boldsymbol{\theta}_\gamma$ facilitates also the posterior estimation.

A rational prior distribution for $\boldsymbol{\gamma}$, commonly used in variable selection problems,[1] is based on specifying a prior probability π_k, $k = 1,...,K$, for the inclusion of the predictor variable k in a model with K potential variables. Hence, the prior distribution that is adopted for $\boldsymbol{\gamma}$ is of the form

$$p(\boldsymbol{\gamma}) = \prod_{k=1}^{K} \pi_k^{\gamma_k}(1-\pi_k)^{1-\gamma_k},$$

where $\pi_k \in [0,1]$. Under this prior, each predictor x_k, $k = 1,...,K$ enters the predictability model independently with probability $p(\gamma_k = 1) = \pi_k$. Assigning $\pi_k = \pi = 0.5$ for all k yields the uniform prior, $p(\boldsymbol{\gamma}) = 1/2^K$, that is, often used as a representation of ignorance, that is, it implies that the analyst is indifferent/agnostic about the predictor variables that will enter the model.

With regard to the prior distribution for the parameters $\boldsymbol{\theta}_\gamma = (\boldsymbol{\theta}'_R,\sigma^2)'$ of the predictive linear regression model $\boldsymbol{\gamma}$ an independent conjugate prior distribution is assumed, that is, a multivariate normal $N(\boldsymbol{\mu},c\sigma^2\mathbf{V})$ for the vector $\boldsymbol{\theta}_R = (\alpha,\beta_1,...,\beta_k)'$, and an inverted Gamma $IG(d/2,\nu/2)$ prior for σ^2. Choosing $\boldsymbol{\mu} = \mathbf{0}$, which reflects prior ignorance/indifference about the location of the means of the regression coefficients, $c = T$, and $\mathbf{V} = (\mathbf{F}'\mathbf{F})^{-1}$, where $\mathbf{F}$ is the corresponding design matrix that replicates the covariance structure of the data and yields the g-prior of Zellner (1986). The hyperparameters d and ν are chosen in such way that the prior mean $E(\sigma^2) = \frac{\nu}{d-2}$, $d > 2$ equals the ML estimate of σ^2, that is, $\hat{\sigma}^2$, and the prior variance $Var(\sigma^2) = \frac{2}{d-4}\left(\frac{\nu}{d-2}\right)^2$ equals to $100\hat{\sigma}^2$.

4.3 | Calculation of the marginal likelihood

Details regarding the calculation of the marginal likelihood for the predictive linear and quantile regression models are presented below. For the standard linear regression models (1), with parameter vector $\boldsymbol{\theta}_\gamma = (\boldsymbol{\theta}'_R, \sigma^2)' = (\alpha,\beta_1,...,\beta_k,\sigma^2)'$, and assuming a normal - inverse gamma prior, the marginal likelihood $p(\mathbf{y}|\gamma,\mathbf{x})$ can be evaluated analytically, because the model parameters are integrated out. The marginal likelihood takes the form:

$$\begin{aligned} p(\mathbf{y}|\gamma,\mathbf{x}) &= \frac{|\mathbf{V}^*|^{1/2}}{c^{p/2}|\mathbf{V}|^{1/2}} \frac{\nu^{d/2}}{(\nu^*)^{(d+(T-1))/2}\pi^{(T-1)/2}} \\ &\quad \frac{\Gamma((d+(T-1))/2)}{\Gamma(d/2)}, \end{aligned}$$

where

$$\begin{aligned} \mathbf{V}^* &= \left(\frac{\mathbf{V}^{-1}}{c}+\mathbf{F}'\mathbf{F}\right)^{-1}, \nu^* = \mathbf{y}'\mathbf{y}+\boldsymbol{\mu}'\frac{\mathbf{V}^{-1}}{c}\boldsymbol{\mu} \\ &+\nu-(\boldsymbol{\mu}^*)'(\mathbf{V}^*)^{-1}\boldsymbol{\mu}^*, \boldsymbol{\mu}^* = \mathbf{V}^*\left(\mathbf{F}'\mathbf{y}+\frac{\mathbf{V}^{-1}}{c}\boldsymbol{\mu}\right). \end{aligned}$$

See, for example, Zellner (1971) and O'Hagan and Forster (2004).

For the proposed predictive quantile regression models (2), analytic evaluation of the marginal likelihood is not possible. Kass and Raftery (1995) provide an extensive description of available numerical strategies that can be used to deal with the specific problem. Some well-known asymptotic approximations are the Laplace or Gaussian approximation (De Bruijn, 1970; Tierney & Kadane, 1986), variants of Laplace's method based on the ML estimator, and an approximation of the Hessian matrix (Kass & Vaidyanathan, 1992; Tierney et al., 1989). In our analysis, the marginal likelihood is estimated using the BIC approximation that is given by

$$\ln\hat{p}(\mathbf{y}|\gamma,\mathbf{x}) = \ln p\left(\mathbf{y}|\boldsymbol{\gamma},\mathbf{x},\widehat{\boldsymbol{\theta}}_\gamma\right) - \frac{dim(\boldsymbol{\theta}_\gamma)}{2}\ln(T-1),$$

where $\widehat{\boldsymbol{\theta}}_\gamma$ denotes the ML estimate of $\boldsymbol{\theta}_\gamma$, $dim(\boldsymbol{\theta}_\gamma)$ is the dimension of $\boldsymbol{\theta}_\gamma$, and $T-1$ is the sample size used to estimate the model parameters. The BIC approximation is efficient, quite intuitive, but less accurate, and can be used without introducing a prior density for the regression parameters $\boldsymbol{\theta}_\gamma$ in the underlying quantile regression model.

4.4 | MCMC stochastic search algorithm

Identification of the most important predictive variables for inclusion in a model is difficult, especially in problems where the number of potential variables is large, and as a consequence, the number of possible models can be vast. In such cases, it is computationally prohibitive to compute the posterior probability of each possible model. To address the problem, a MCMC algorithm, which efficiently searches over such high-dimensional model spaces to detect the models with the highest posterior model probabilities, is described in this section. This algorithm enables the analysis of high dimensionality datasets with respect to the number of predictor variables. Under the specific conditions, the algorithm will still detect the region of highest posterior probability models but will require a larger amount of time to reach it, as it needs to scan a vast model space.

The proposed algorithm enables us to implement BMA and to account, therefore, for model uncertainty. The Metropolis–Hastings-type algorithm simulates a Markov chain sequence of models $\boldsymbol{\gamma}^{(1)}$, $\boldsymbol{\gamma}^{(2)}, \boldsymbol{\gamma}^{(3)}, \ldots$, that under certain regularity conditions (see, e.g., Smith & Roberts, 1993; Tierney, 1994) converges to the equilibrium distribution $p(\boldsymbol{\gamma}|\mathbf{y})$. The Metropolis–Hastings algorithm is constructed as follows: Starting with an initial model $\boldsymbol{\gamma}^{(0)}$, iteratively simulate the transitions from the current model $\boldsymbol{\gamma}^{(i)}$, at the ith iteration, to model $\boldsymbol{\gamma}^{(i+1)}$ at the next iteration by using the two steps:

- simulate a candidate model $\boldsymbol{\gamma}'$ from a proposal distribution $q\left(\boldsymbol{\gamma}^{(i)}, \boldsymbol{\gamma}'\right)$
- set $\boldsymbol{\gamma}^{(i+1)} = \boldsymbol{\gamma}'$ with probability

$$a\left(\boldsymbol{\gamma}^{(i)}, \boldsymbol{\gamma}'\right) = \min\left\{\frac{q\left(\boldsymbol{\gamma}', \boldsymbol{\gamma}^{(i)}\right)}{q\left(\boldsymbol{\gamma}^{(i)}, \boldsymbol{\gamma}'\right)} \frac{p\left(\mathbf{y}|\boldsymbol{\gamma}'\right)}{p\left(\mathbf{y}|\boldsymbol{\gamma}^{(i)}\right)} \frac{p\left(\boldsymbol{\gamma}'\right)}{p\left(\boldsymbol{\gamma}^{(i)}\right)}, 1\right\}, \quad (5)$$

otherwise, set $\boldsymbol{\gamma}^{(i+1)} = \boldsymbol{\gamma}^{(i)}$.

Transition kernels $q\left(\boldsymbol{\gamma}^{(i)}, \boldsymbol{\gamma}'\right)$ are taken into consideration that generate candidate models $\boldsymbol{\gamma}'$ from $\boldsymbol{\gamma}^{(i)}$ by randomly choosing among the following steps:

- *Birth*: Randomly select a predictor variable from those possible (i.e., those not present in the current model) and add it in the subset to create a new proposed model with one additional variable
- *Death*: Randomly select a predictor from those present in the current model and delete it from the subset to create a new proposed model with one less variable
- *Change*: Randomly select a predictor variable from those present in the current model and change it with a new one from the remaining variables

These steps permit the algorithm to move efficiently through models of the same (through *Change*step) or different (through *Birth* and *Death* steps) dimensionality, that is, number of predictors, in order to generate a sample from the posterior distribution of $\boldsymbol{\gamma}$.

The proposed Bayesian stochastic search algorithm can be used for the identification of the most important predictors for RGDP growth in the linear and quantile regression models. This approach is based on, and extends, the algorithms of Vrontos et al. (2008), Giannikis and Vrontos (2011), and Vrontos (2012), who used Bayesian model selection techniques to identify important risk factors and predictor variables in univariate and multivariate regression models with GARCH-type conditional variances (and covariances) in the context of asset pricing and performance evaluation and that of hedge fund predictability, respectively. In these studies, model parameters were integrated out by using variants of the Laplace approximation method. The proposed method is also based on, and extends, the approach of Dellaportas and Vrontos (2007) and Galakis et al. (2022), who used Bayesian model selection techniques to identify the MP tree topologies (non-linear thresholds) for tree-structured multivariate GARCH models and tree-structured quantile regression models, respectively, assuming a fixed (known) number of regressors in the respective model specifications. As a result, the proposed predictive quantile regression model and Bayesian approach to inference allows for automatic model selection and identification of the most important predictors, and in this sense, it extends the aforementioned approaches.

5 | DATA AND EMPIRICAL ANALYSIS

In the following section, the analyzed data is outlined and the empirical study is presented. As previously mentioned, the aim is to develop a predictive linear and quantile regression model framework to identify the predictor variables that determine RGDP growth during the turbulent outbreak and spread of the COVID-19 pandemic across different countries. Furthermore, a robustness analysis of selected predictor models based on penalized likelihood techniques, such as ridge, elastic net, and LASSO, is carried out, while the output of the MCS approach, that allows the identification of a subset of superior models containing the best model(s) at a given level of confidence, is also presented.

5.1 | The data

One of the primary conclusions of the existing business cycle-related research is the considerable variation embedded in the both macroeconomic and financial variables that contain critical information in identifying, determining and predicting economic activity at different stages of the cycle and, especially, in turning points. In addition, as their effectiveness is to a large extent time dependent, it is only rational to include a relatively large set of explanatory variables with leading, coincident, and lagging properties in the analysis. Given that the primary task of the underlying research is to estimate the impact of the COVID-19 pandemic on a country's economic activity, a group of pandemic-related variables is used in the analysis.

The research focuses on measuring the impact of the COVID-19 pandemic primarily on the economic activity of Greece, as well as seven Eurozone countries for comparison reasons. The seven Eurozone countries are Belgium, Finland, France, Germany, Italy, the Netherlands, and Spain. The choice of the specific set was not arbitrary, as it was deemed necessary to include economies of different size and level of significance, but with a number of common characteristics in the analysis. The expectation is that the specific set of countries will exhibit a certain degree of homogeneity given their advanced level of economic integration and interdependence, as they are all part an economic and monetary union. As a consequence, both Germany, Eurozone's largest economy, and Belgium, an economy that is smaller yet closer to that of Greece, are part of the specific set. Apart from economic diversity and significance, two additional dimensions are taken into account for the final formulation of the sample, namely, population density and the severity and impact of the pandemic. Regarding population density, the Nordic countries (Denmark, Norway, and Sweden) are a rational option, as they are not so densely populated. Finally, the United States is included in the sample, as a proxy of a non-European country that the impact of the pandemic was less severe.

A country's economic activity is represented by the quarterly change of its underlying RGDP growth. RGDP growth is measured by the difference of the natural logarithm of each country's chain linked index, seasonally and calendar adjusted, for the period between the first quarter of 2001 and the third quarter of 2021. The difference of the natural logarithm is modeled in order to avoid high persistence in the dependent variable. Thus, the analysis includes seven datapoints that range between the outbreak of the COVID-19 pandemic in Europe and its continuation, that is, the period between the first quarter of 2020 and the third quarter of 2021.

As it is well documented in the literature that there is sizeable autocorrelation in the underlying RGDP growth series, lagged values of the individual RGDP series are employed in the models. More specifically, for each country/economy four autoregressive terms ($RGDP_{t-1}$, $RGDP_{t-2}$, $RGDP_{t-3}$, and $RGDP_{t-4}$), are included in the models to address the high autocorrelation issue, as well as to extract their information content for projected estimates.

The first set of explanatory and/or predictor variables used in the regression framework are perceived to be common for all countries, as they are supposed to capture global effects, given the universal nature of the COVID-19 pandemic. The original set of common factors included three variables, the oil price, an implied equity volatility index, and an uncertainty index. The rationale is to employ factors that reflect the economic effects of a significant random impact, such as the outbreak of the COVID-19 pandemic. Similar variables have been previously used in the literature; see, for example, Chudik et al. (2021). The three common variables are the change in WTI oil price index (WTI), the CBOE S&P500 equity implied volatility index (VIX), and the WUI, as compiled by Ahir, Bloom, and Furceri.[2] Given the high correlation between the VIX and the WUI factor, the VIX Index was eventually excluded from the model.

Apart from the economic-financial common factors, an additional COVID-19-related factor is included in the model. Even though, the pandemic had asymmetric effects on different continents–regions of the world, a global measure could provide significant insights regarding the scale and spread of the pandemic and its likely impact on the world economy. An example of such measure is the WPI.[3]

Moving on to the country-specific factors, the initial set of explanatory/predictive variables contains 32 macroeconomic and financial market-related indicators, the majority of which are widely followed by both policy makers and practitioners and have been used in the existing literature for nowcasting and/or business cycle predictability. In general, the forecasting variables are representative of categories related to output and productivity, the labor market, the housing market, orders and inventories, money and credit, interest rates, prices, the financial markets, and business and consumer confidence surveys. Apart from the "usual suspects," that is, predictive variables such as the yield curve, long-term interest rates, leading indicators, and other financial market and economic activity related indicators, a number of less studied factors, such as the change in passenger car registrations and real productivity growth are included in the analysis. The data are obtained from several economic and financial databases and cover the period between the first quarter of 2001 and the third quarter of 2021 (83 quarterly observations). More specifically, the Federal Reserve Bank of St. Louis' FRED database, the Eurostat database, the OECD Statistics database, and the European Central Bank's database were the primary data sources.

Given that there is sizable correlation between several macroeconomic and financial variables in the initial set, and in order to avoid the presence of multicollinearity in the regression models, the set of factors employed in the analysis is reduced to nine factors. More specifically, we consider the real productivity growth (RPOD), the growth in car registrations (CREG), the rate of unemployment (UNEM), the consumer inflation rate (Consumer Price Index [CPI]), the producer inflation rate (Producer Price Index [PPI]), the growth in construction production (Construction Volume Index of Production [CONPROD]), long-term interest rates (LONGR), equity market returns (STOCK), and the change in the OECD Leading Indicator (LEAD). Similar factors have been employed in various business cycle-related studies: Baumeister and Guérin (2021), Berger et al. (2023), Cimadomo et al. (2022), and Morley and Wong (2020). Table A1 reports the ultimate set of factors, as well as their corresponding transformations, that is, the underlying series are transformed by either taking differences in the natural logarithms (Δln) or the first difference (Δlv) to achieve stationarity. One needs to bear in mind that the aim is to create a uniform set of explanatory/predictive factors across the countries of interest for comparability reasons.

Moving on to COVID-19 country-specific factors, numerous pandemic indicators were considered. First, Ravenpack's Coronavirus Media Monitor database was considered. Apart from the reported cases, deaths and recoveries on a global and per country basis, the specific database includes indicators that aim to measure and evaluate the impact of the pandemic on the macroeconomic backdrop and financial markets. The specific database includes the Coronavirus Panic, the Coronavirus Media Hype, the Coronavirus Fake News, the Coronavirus World Sentiment, the Coronavirus Infodemic, and the Coronavirus Media Coverage Indices. For instance, the Coronavirus Panic Index measures the level of news chatter that makes reference to panic or hysteria in relation to the COVID-19 pandemic.[4] Second, the University of Oxford-Blavatnik School of Government COVID-19 Response Tracker database was employed. As expected, there is an overlap in part of the data (cases, deaths, and recoveries); however, the Response Tracker collects systematic information on policy measures that governments have taken to tackle the COVID-19 pandemic. In practice, the country-specific pandemic indicators were not included in the final model, as the pandemic effect is largely reflected and "absorbed" by the WPI.

Table A2 reports summary statistics for both the dependent and explanatory/predictor variables employed in the linear and quantile regression models. More specifically, numerous descriptive statistics, such as the mean, the median, the standard deviation, the 0.25 and 0.75 quantiles, and the skewness and kurtosis are presented for the dependent, common and country-specific factors. In general, the descriptive statistics confirm that there is considerable variability in the RGDP growth series and that they exhibit skewness and excess kurtosis (fat tails). It is for this reason that the proposed framework and the application of predictive quantile regression models is crucial and appropriate to account for the presence of potential outlier effects and could lead to better inference. The presence of positive excess kurtosis is also detected in numerous common and country-specific factor series.

5.2 | Empirical findings

The empirical results are presented in this section. As previously mentioned, the model employs a set of common and country-specific macroeconomic, financial, and world pandemic-related variables to investigate how a severe shock, such as the COVID-19 pandemic, impacts economic activity, as proxied by RGDP growth. In addition, it is of interest to explore the factors that drive economic activity during periods of turbulence based on the proposed linear and quantile regression modeling approaches, as well as based on techniques such as the best subset regression approach, and penalized likelihood regression models. As a consequence, the modeling framework is implemented on Greek real economic activity, on that of several Eurozone and Nordic countries, as well as on the US economy.

In the analysis, we first develop explanatory and predictive linear regression models with the aim to identify the most critical factors that influence real economic activity and to investigate certain aspects of model uncertainty that affect RGDP growth. Different model selection strategies are used to identify variables with explanatory and predictive ability. More specifically, the proposed Bayesian approach to model selection–comparison was implemented that accounts for model uncertainty, and produces the MP model specifications. For comparative reasons, the stepwise regression approach (STEP), the AIC, and the Schwarz (1978) BIC were applied. Moreover, given the nature of the underlying data, quantile regression models are used, as well as the corresponding model selection methodologies and techniques to identify which variables are important for predicting different (conditional) quantiles of the RGDP growth distribution. Hence, on the one hand, we attempt to model and explain the distributional dependence of RGDP growth to different factors–predictors, as it is reasonable to expect that different factors influence economic activity at different stages of the business cycle, and its fluctuations and, on the other, the factors that impact the growth of the economy, especially during periods of high uncertainty that is caused by tail events, like geopolitical events and/or random shocks, such as the COVID-19 pandemic. During the latter cases, we expect that quantile regression models will be particularly useful and might be even more appropriate than the conditional mean regression models, in order to capture more effectively the underlying distributional characteristics of RGDP growth.

5.2.1 | Predictive linear regression models

The class of linear regression models provides a standard approach to modeling and predicting RGDP growth, and is, typically, used as a benchmark model in comparative studies. As a result, this is the starting point of our analysis. First, the Bayesian methodology to model selection is followed, and two approaches are adopted: the "Exact" approach that calculates the posterior probabilities for the collection of all 2^K regression models and the "Stochastic Search" approach that refers to the Bayesian stochastic search algorithm implemented over 200,000 iterations, which returns the MP model specifications. Table 1 reports the five MP predictive regression model specifications that poses predictive ability over RGDP growth and their associated posterior model probabilities for each of the 12 analyzed countries and reveals that there is strong evidence for the presence of model uncertainty. Focusing on the Stochastic Search approach, the MP model ranges from 1.3% for Finland to 12.5% for France, while the probabilities of the five MP model specifications sum up to just around 5.4% for Finland and 27.7% for France, suggesting that a single model cannot predict RGDP growth. In addition, Table 1 points out that the performance of the Bayesian stochastic search algorithm, that explores the posterior distribution of the regression model space and provides posterior model probabilities, is efficient, as each of the five MP models identified by the stochastic search algorithm is identical or very close to its counterpart taken from the "Exact" algorithm. Moreover, the posterior model probabilities estimated by the stochastic search algorithm are almost equal across different number of iterations, as well as very close with those obtained from the "Exact" approach. In general, the algorithm converged to the posterior distribution swiftly, that is, in a smaller fraction of iterations, indicating flexibility and efficiency, a very important attribute, especially in cases where the number of predictors K is large enough, and the total number of models is vast.

Next, the focus is targeted on the predictor variables that impact each country's RGDP growth. Once again, the results are presented in Table 1 and reveal that the predictors included in the MP linear model specifications appear to have some common characteristics, that is, some degree of homogeneity, but at the same time, exhibit some differences across different countries. That is, predictor variables that are crucial across all countries can be identified. As expected, the WPI appears in all models indicating that the COVID-19 pandemic has had a profound impact on real economic activity across all the 12 analyzed countries. Moreover, changes in the OECD Leading Indicator seem to be important for most countries. By contrast, movements in the equity market are critical for Denmark and the Netherlands, while car registrations play an important role in Norway and the United States.

Given the significant autocorrelation present in the quarterly RGDP growth series, it is not accidental that the lagged values of each country's RGDP growth series contains crucial information for the projected path of RGDP. In most cases, that is, in seven out of the 12 countries, the autoregressive terms at Lags 1 and 2, that is, RGDP_{t-1} and RGDP_{t-2} are important predictors that account for potential influence/impact of lagged GDP values to future values, while for other four countries, the autoregressive terms at Lag 1, 2, or 3 appear as valuable predictors. Interestingly, the only exception is Greece, where the autoregressive terms are not part of the MP models. That could be the result of the significant disruption caused by the Greek debt crisis, especially on domestic activity.

A core expectation, especially for the Eurozone countries, is that the influential factors should exhibit a high degree of homogeneity, given the anticipated advanced level of economic integration within the Eurozone economy. It is true, that a certain degree of homogeneity appears to exist for some countries, such as Denmark and the Netherlands (where the variables that appeared in the two MP models are identical), as well as Sweden, Belgium, Norway, and Germany that share many common predictors such as the autoregressive terms at Lags 1 and 2, the WPI, and the OECD Leading Indicator. Having said that there is also some diversity. For instance, the rate of unemployment plays an important role in predicting RGDP growth mainly for Spain, Greece, Germany, and, to a lesser extent, Belgium and the Netherlands. In addition, real productivity growth seems to be critical for France, Belgium, and the United States but less so for Finland and Sweden.

These findings are also confirmed by estimating the posterior probability of inclusion of each predictor variable in the linear regression models. This quantity forms a statistic that can be used to investigate the robustness of predictors in regression models (see Avramov, 2002;

TABLE 1 Posterior model probabilities for the five most probable predictive linear regression model specifications regarding the real GDP growth for the analyzed countries.

Models	"Exact"	"Stochastic Search"	Models	"Exact"	"Stochastic Search"
Germany			France		
1 2 7 10 16	0.072	0.072	2 7 8	0.124	0.125
1 2 7 10 15 16	0.049	0.048	2 3 7 8	0.062	0.060
1 2 7 10 11 15 16	0.029	0.027	2 4 7 8	0.051	0.050
1 2 7 10 11 16	0.026	0.025	2 7 8 12	0.021	0.023
1 2 7 15 16	0.024	0.023	2 6 7 8	0.019	0.019
Italy			Spain		
1 2 3 7 16	0.074	0.073	1 2 4 7 10	0.122	0.120
1 2 3 7 11 16	0.049	0.051	1 2 4 7 9 10	0.068	0.070
1 2 3 7 8 16	0.032	0.031	1 2 4 7 10 12	0.027	0.029
1 2 3 6 7 16	0.026	0.028	1 2 4 7 9 10 12	0.025	0.028
1 2 3 7 15 16	0.022	0.022	1 2 4 5 7 10	0.024	0.023
Greece			Belgium		
7 10	0.023	0.022	1 2 7 8 16	0.060	0.057
7 10 11	0.018	0.019	1 2 7 8 10 16	0.044	0.044
7 10 11 12	0.018	0.018	1 2 7 8 9 16	0.028	0.031
7 10 12	0.015	0.015	1 2 7 8 10	0.021	0.020
4 7 12	0.013	0.012	1 2 7 8 15 16	0.020	0.020
Finland			Sweden		
3 7 16	0.014	0.013	1 2 7 16	0.070	0.071
3 7 12 16	0.012	0.013	1 2 7 8 16	0.042	0.044
1 3 7 8 12 13 15	0.009	0.010	1 2 7 8 9 16	0.033	0.034
1 3 7 8 12 15	0.009	0.009	1 2 7 15 16	0.032	0.031
3 7 15 16	0.008	0.009	1 2 7 9 16	0.024	0.025
Norway			Denmark		
1 2 7 9 16	0.074	0.072	1 2 7 15 16	0.032	0.035
1 2 7 11 16	0.045	0.043	1 2 7 16	0.028	0.030
1 2 7 16	0.042	0.042	1 3 7 9 15	0.018	0.017
1 2 7 9 11 16	0.040	0.041	1 3 7 15	0.014	0.014
1 2 7 9 12 16	0.028	0.029	7 15	0.014	0.013
The Netherlands			USA		
1 2 7 15 16	0.090	0.092	3 7 8 9 10 12	0.032	0.032
1 2 7 16	0.042	0.042	7 8 12 16	0.031	0.032
1 2 7 10 15 16	0.039	0.038	3 7 8 12	0.027	0.026
1 2 3 7 15 16	0.038	0.040	3 7 8 9 10 11 12	0.024	0.027
1 2 7 11 15 16	0.023	0.024	3 7 8 12 16	0.017	0.015

Note: The table reports the five most probable predictive linear regression model specifications that predict real GDP growth and their associated posterior model probabilities for the analyzed period, from 2001:Q2 to 2021:Q3. "Exact" refers to the method that calculates the posterior probabilities for the collection of all 2^K models and returns the most probable models. "Stochastic Search" refers to the Bayesian stochastic search algorithm implemented for 200,000 iterations, in order to return the most probable models. Model specifications are identified by the numbers associated with the corresponding predictor variables. Thus, 1 is the real GDP growth lagged once ($RGDP_{t-1}$), 2 is the real GDP growth lagged twice ($RGDP_{t-2}$), 3 is the real GDP growth lagged thrice ($RGDP_{t-3}$), 4 is the real GDP growth lagged four times ($RGDP_{t-4}$), 5 is the WTI oil price (OIL), 6 is the World Uncertainty Index (WUI), 7 is the World Pandemic Uncertainty Index (WPI), 8 is real productivity growth (RPROD), 9 is the change in car registrations (CREG), 10 is the rate of unemployment (UNEM), 11 is the growth in the Consumer Price Index (CPI), 12 is the growth in the Producer Price Index (PPI), 13 is the change Construction Volume Index of Production (CONPROD), 14 is the long-run interest rates (LONGR), 15 is the stock index return (STOCK), and 16 is the change in the OECD Leading Indicator (LEAD).

Meligkotsidou et al., 2009) and is reported in Table A3. As anticipated, the WPI is important for economic growth in all countries, with probabilities of inclusion above 62%. The lowest probability of inclusion is that of Finland (62%), the United States (82%), and Norway (86%), while the corresponding rate for the other countries is above 91%.

A core conclusion is that the outbreak of the COVID-19 pandemic has had a profound impact on real economic activity across regions and countries, as a shock of such magnitude caused an immediate rise in overall uncertainty, as reflected by the WPI, that spread rapidly across all sectors of the global economy. One needs to bear in mind that the specific shock had an initial impact that was more sizeable compared with that of the 2008 GFC.

Last, but not least, the predictor variable exposures identified in the underlying analysis are presented. More specifically, Table 2 shows the parameter estimates and their corresponding standard errors (for the intercept and the beta coefficients) of the predictor variables included in the MP linear regression model specifications per country. The findings reveal that the all estimated intercepts are positive ranging from 0.02 for the United States to 1.15 for Sweden; however, only the population alpha parameters of Germany (estimated at 0.62); Spain (estimated at 0.89); Belgium (estimated at 0.80); and the Nordic countries, that is, Sweden (estimated at 1.15), Norway (estimated at 0.82), Denmark (estimated at 0.53), and the Netherlands (estimated at 0.79) are statistically significant. Regarding the critical predictors of RGDP growth, it is evident that the WPI appears in all model specifications with a statistically significant negative beta exposure, ranging from −0.21 for Finland to −1.34 for Spain, indicating that the outbreak of the COVID-19 pandemic has had, as was expected, a negative impact on every country's real economic activity. There is, however, considerable variability in the beta estimates of the analyzed countries. The estimated parameters reveal that the pandemic is expected to have a larger effect on Spain (−1.34), Italy (−1.08), and Belgium (−0.92) relative to the rest of the countries. Interestingly, the countries with smaller exposure on the pandemic index were Finland (−0.21), Norway (−0.22), the United States (−0.24), and Denmark (−0.29), followed by Sweden (−0.41), the Netherlands (−0.51), Greece (−0.53), and Germany (−0.56). The initial expectation that the pandemic's impact might be lower in less densely populated countries seems to be confirmed. The second most important predictor appears to be the OECD Leading Indicator (LEAD), which has a positive and significant effect on RGDP growth of most of the analyzed countries, such as Germany (0.42), Italy (0.70), Belgium (0.18), Finland (0.35), Sweden (0.57), Norway (0.23), Denmark (0.33), and the Netherlands (0.29). In addition, real productivity growth (RPROD) has a positive and significant effect on French (1.92), Belgian (0.90), and the United States (0.54) RGDP growth. As already mentioned, the autocorrelation structure of the individual RGDP growth series points to the fact that autoregressive parameters are important predictors. This is the case for all countries, apart from Greece. The autoregressive terms are significant at different lags, typically at Lags 1 and 2, but in some cases at Lag 3 (Italy, Finland, and the United States), and/or Lag 4 (Spain). The estimated coefficients at Lags 1 and 2 exhibit a negative impact for projected RGDP values, while the opposite is true at Lag 4, which seems reasonable because the underlying RGDP data are quarterly. The estimated autoregresive coefficients capture the autocorrelation patterns, as reflected by the underlying series' partial autocorrelation plots.[5]

5.2.2 | Predictive quantile regression models

In this section, the results obtained by applying Bayesian approach to model selection based on the quantile regression methodology are presented. The rationale behind the predictive linear regression models is that the explanatory/predictor variables attempt to explain/predict the data series of interest, that act as dependent variables, on average. As there is considerable empirical evidence that RGDP growth is expected to respond differently and asymmetrically to changes in economic and financial market conditions, especially during periods of high uncertainty caused by random shocks, that is, tail events, such as geopolitical events (wars), or global pandemics, such as the recent COVID-19 pandemic, it would be interesting to explore how RGDP growth conditional quantiles are exposed to different predictors, that is, to further explore the distributional characteristics of the individual RGDP growth series.

As in the linear regression model-based analysis, the Bayesian methodology to model selection based on the "Exact" and the "Stochastic Search" approach is implemented.[6] Table 3 reports the three MP predictive quantile regression models and their associated posterior model probabilities of the RGDP growth series of each of the 12 analyzed countries, for different quantiles, that is, the 10th, the 25th, the 50th, the 75th, and the 90th. The results reveal that there is strong evidence indicating the presence of model uncertainty, as the posterior probabilities of the MP quantile models are relatively small, ranging from 1.4% for the 75th quantile of the Danish RGDP growth distribution to 16.4% for the 90th quantile of the Dutch RGDP growth distribution. The Bayesian

TABLE 2 Parameter estimates and standard errors of the predictor variables included in the most probable predictive linear regression model specifications for the real GDP growth series of different countries.

Predictor variables	Germany	France	Italy	Spain	Greece	Belgium	Finland	Sweden	Norway	Denmark	The Netherlands	USA
α	0.62	0.15	0.14	0.89	0.04	0.80	0.28	1.15	0.82	0.53	0.79	0.02
	(0.15)	(0.16)	(0.18)	(0.19)	(0.24)	(0.13)	(0.15)	(0.17)	(0.13)	(0.14)	(0.13)	(0.17)
$RGDP_{t-1}$ (1)	−0.62		−0.64	−0.55		−0.34		−0.53	−0.54	−0.39	−0.53	
	(0.09)		(0.09)	(0.07)		(0.08)		(0.11)	(0.10)	(0.12)	(0.10)	
$RGDP_{t-2}$ (2)	−0.81	−0.67	−1.04	−0.90		−1.02		−0.52	−0.52	−0.36	−0.71	
	(0.11)	(0.07)	(0.12)	(0.08)		(0.08)		(0.122)	(0.10)	(0.12)	(0.11)	
$RGDP_{t-3}$ (3)			−0.26				0.27					0.31
			(0.08)				(0.10)					(0.09)
$RGDP_{t-4}$ (4)				0.18								
				(0.06)								
OIL (5)												
WUI (6)												
WPI (7)	−0.56	−0.72	−1.08	−1.34	−0.53	−0.92	−0.21	−0.41	−0.22	−0.29	−0.51	−0.24
	(0.08)	(0.09)	(0.11)	(0.11)	(0.11)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.06)
RPROD (8)		1.92				0.90						0.54
		(0.17)				(0.18)						(0.21)
CREG (9)									0.03			0.06
									(0.01)			(0.02)
UNEM (10)	−1.92			−1.45	−0.72							0.53
	(0.71)			(0.29)	(0.30)							(0.19)
CPI (11)												
PPI (12)												0.12
												(0.04)
CONPROD (13)												
LONGR (14)												
STOCK (15)										0.03	0.04	
										(0.02)	(0.02)	
LEAD (16)	0.42		0.70			0.18	0.35	0.57	0.23	0.33	0.29	
	(0.08)		(0.15)			(0.06)	(0.11)	(0.11)	(0.07)	(0.13)	(0.08)	

Note: The table reports the parameter estimates and standard errors of the predictor variables included in the most probable predictive linear regression model specifications based on the sample period (from 2001:Q2 to 2021:Q3). The predictor variables are the real GDP growth lagged once ($RGDP_{t-1}$), the real GDP growth lagged twice ($RGDP_{t-2}$), the real GDP growth lagged thrice ($RGDP_{t-3}$), the real GDP growth lagged four times ($RGDP_{t-4}$), the WTI oil price (OIL), the World Uncertainty Index (WUI), the World Pandemic Uncertainty Index (WPI), the real productivity growth (RPROD), the change in car registrations (CREG), the rate of unemployment (UNEM), the growth in the Consumer Price Index (CPI), the growth in the Producer Price Index (PPI), the Construction Volume Index of Production (CONPROD), the long-run interest rate (LONGR), the stock index return (STOCK), and the change in the OECD Leading Indicator (LEAD). MP1, MP2, and MP3 denote the three most probable predictive regression model specifications, respectively.

TABLE 3 Posterior model probabilities for the three most probable predictive quantile regression model specifications for the real GDP growth of the analyzed countries.

Countries	Quantiles	MP1	PP	MP2	PP	MP3	PP
Germany	$Q_{0.10}$	3 5 6 7 8 9 13 16	0.019	2 3 4 5 6 7 9 14 16	0.016	3 5 6 7 8 9 10 13 16	0.012
	$Q_{0.25}$	2 3 7 16	0.061	2 3 6 7 11 16	0.036	2 3 7 11 16	0.032
	$Q_{0.50}$	1 2 15 16	0.022	1 2 6 15 16	0.019	1 2 10 16	0.018
	$Q_{0.75}$	1 2 10 16	0.053	1 2 16	0.043	1 2 6 10 16	0.026
	$Q_{0.90}$	1 2 4 8 10 11 13 14 16	0.023	1 2 3 16	0.021	1 2 3 14 16	0.020
France	$Q_{0.10}$	2 4 7 16	0.049	1 2 4 7 16	0.033	2 4 7 8 16	0.033
	$Q_{0.25}$	2 4 7 16	0.115	2 4 7 8 16	0.061	1 2 4 7 16	0.035
	$Q_{0.50}$	2 4 7 8 16	0.041	2 4 7 16	0.038	2 7 8 16	0.020
	$Q_{0.75}$	2 8	0.047	8 15	0.017	8	0.016
	$Q_{0.90}$	1 2 3 7 8 15	0.040	1 2 3 7 8 10 15	0.021	1 2 3 8 15	0.021
Italy	$Q_{0.10}$	2 7 10 15 16	0.021	2 7 10 13 15 16	0.020	2 7 10 12 13 16	0.015
	$Q_{0.25}$	2 7 12 16	0.090	2 4 7 12 16	0.035	2 7 8 12 16	0.027
	$Q_{0.50}$	2 7 16	0.065	2 7 10 16	0.034	2 3 7 16	0.022
	$Q_{0.75}$	3 7	0.032	1 2 7 16	0.026	2 7 16	0.017
	$Q_{0.90}$	1 2 3 4 7 9 11 16	0.067	1 2 3 4 7 8 11 15 16	0.035	1 2 3 4 7 9 11 15 16	0.034
Spain	$Q_{0.10}$	1 3 4 7 8 9 11 16	0.071	1 2 3 4 7 8 9 11 16	0.055	1 2 3 4 7 8 9 11 13 16	0.022
	$Q_{0.25}$	1 2 3 4 7 8 9 10	0.140	1 2 3 4 7 8 9 10 16	0.050	1 2 3 4 7 10 16	0.026
	$Q_{0.50}$	4 10	0.044	1 3 4 7 10	0.043	10	0.021
	$Q_{0.75}$	10	0.032	3 4 10	0.031	3 10	0.025
	$Q_{0.90}$	1 2 3 6 8 10	0.105	1 2 3 6 8 10 16	0.041	1 2 3 6 8 10 14	0.038
Greece	$Q_{0.10}$	1 3 4 7 15	0.045	3 4 7 15	0.022	1 4 7 8 15	0.021
	$Q_{0.25}$	2 3 7 9	0.033	3 7 9	0.024	2 3 7 9 15	0.019
	$Q_{0.50}$	2 10	0.025	3 7 9	0.022	2 7 10	0.019
	$Q_{0.75}$	10 12	0.058	5 10 12	0.021	10 12 15	0.016
	$Q_{0.90}$	1 4 5 8 10 11 14 15	0.032	1 4 5 8 9 10 11 14 15	0.028	1 5 8 10 11 14 15 16	0.021
Belgium	$Q_{0.10}$	2 4 7 10 11 15 16	0.037	2 4 7 10 15 16	0.033	2 7 8 10 15 16	0.026
	$Q_{0.25}$	2 7 8 10 15 16	0.080	2 7 8 10 12 15 16	0.027	2 7 8 16	0.025
	$Q_{0.50}$	2 7 8 10 16	0.065	2 7 8 16	0.042	2 7 8 10 12 16	0.032
	$Q_{0.75}$	2 7 8 16	0.052	1 2 7 8 15 16	0.032	1 2 7 8 16	0.026
	$Q_{0.90}$	1 2 3 4 7 8 15 16	0.148	1 2 3 4 5 7 8 15 16	0.130	1 2 3 4 5 7 8 13 15 16	0.032
Finland	$Q_{0.10}$	3 5 7 9 13 15 16	0.096	3 5 7 9 13 15	0.044	3 5 7 9 11 13 15 16	0.033
	$Q_{0.25}$	3 7 16	0.051	2 3 7 16	0.042	3 7 11 16	0.022
	$Q_{0.50}$	3 16	0.079	3 8 16	0.027	3 6 16	0.025
	$Q_{0.75}$	3 16	0.041	1 7 8 11 15 16	0.013	3 10 16	0.011
	$Q_{0.90}$	1 6 7 8 9 11 13 15 16	0.026	1 5 6 7 8 9 11 13 15 16	0.026	1 2 6 7 9 13 16	0.025
Sweden	$Q_{0.10}$	2 4 6 7 10 11 12 16	0.134	2 6 7 10 11 12 16	0.082	2 6 7 10 12 16	0.050
	$Q_{0.25}$	7 15 16	0.036	15 16	0.026	5 15 16	0.025
	$Q_{0.50}$	16	0.086	5 16	0.032	7 16	0.027
	$Q_{0.75}$	1 15 16	0.015	1 16	0.014	1 8 16	0.013
	$Q_{0.90}$	1 2 3 5 6 8 16	0.028	1 2 3 5 8 13 14 16	0.016	1 2 3 5 14 16	0.015

TABLE 3 (Continued)

Countries	Quantiles	MP1	PP	MP2	PP	MP3	PP
Norway	$Q_{0.10}$	1 2 7 10 16	0.093	1 2 7 16	0.075	1 2 7 9 16	0.031
	$Q_{0.25}$	1 2 7 12 16	0.056	1 2 7 16	0.042	1 2 7 11 16	0.040
	$Q_{0.50}$	1 2 6 9 11 16	0.033	1 2 4 9 12 16	0.029	1 2 9 12 16	0.027
	$Q_{0.75}$	1 2 6 9 11 16	0.132	1 2 6 11 16	0.023	1 2 6 9 10 11 16	0.021
	$Q_{0.90}$	1 2 3 6 7 8 9 11 16	0.046	1 2 4 6 9 11 16	0.035	1 2 4 6 9 10 11 16	0.026
Denmark	$Q_{0.10}$	2 3 6 7 8 11 14 16	0.060	1 3 5 7 9 11 16	0.029	1 2 3 6 7 11 14 16	0.025
	$Q_{0.25}$	3 7 15	0.017	3 7 11 15 16	0.012	7 15 16	0.011
	$Q_{0.50}$	16	0.030	–	0.028	11 16	0.021
	$Q_{0.75}$	3	0.014	3 8 15	0.010	3 11 12 16	0.010
	$Q_{0.90}$	1 6 7 15	0.039	1 3 6 7 15	0.028	1 6 7 10 15	0.017
The Netherlands	$Q_{0.10}$	2 3 5 7 16	0.026	1 2 3 5 6 7 13 16	0.025	1 2 3 5 6 7 16	0.023
	$Q_{0.25}$	1 2 3 7 15	0.048	1 2 3 4 7 15	0.029	1 2 3 7 15 16	0.024
	$Q_{0.50}$	3 7 15	0.057	3 15	0.033	2 3 15	0.015
	$Q_{0.75}$	3 6 7 13 15	0.039	3 6 15	0.010	2 3 7 16	0.010
	$Q_{0.90}$	1 2 5 7 8 16	0.164	1 2 4 5 7 8 16	0.052	1 2 5 7 8 15 16	0.049
USA	$Q_{0.10}$	5 6 7 8 16	0.026	2 5 7 8 12 16	0.025	2 5 7 8 12 13 16	0.014
	$Q_{0.25}$	3 7 8 12	0.026	3 7 8 9	0.025	3 5 7 8	0.018
	$Q_{0.50}$	8 11 12 16	0.028	3 6 8 12	0.019	3 8 11 12 16	0.016
	$Q_{0.75}$	8 10 11 12 16	0.028	8 11 12 16	0.024	1 8 10 11 12	0.020
	$Q_{0.90}$	5 9 10 11 12	0.125	3 5 9 10 11 12	0.040	5 6 9 10 11 12	0.038

Note: This table reports the three most probable quantile regression model specifications that predict the real GDP growth and their associated posterior model probabilities for the analyzed period from 2001:Q2 to 2021:Q3. Model specifications are identified by the numbers associated with the corresponding predictor variables. Thus, 1 is the real GDP growth lagged once ($RGDP_{t-1}$), 2 is the real GDP growth lagged twice ($RGDP_{t-2}$), 3 is the real GDP growth lagged thrice ($RGDP_{t-3}$), 4 is the real GDP growth lagged four times ($RGDP_{t-4}$), 5 is the WTI oil price (OIL), 6 is the World Uncertainty Index (WUI), 7 is the World Pandemic Uncertainty Index (WPI), 8 is real productivity growth (RPROD), 9 is the change in car registrations (CREG), 10 is the rate of unemployment (UNEM), 11 is the growth in the Consumer Price Index (CPI), 12 is the growth in the Producer Price Index (PPI), 13 is the change Construction Volume Index of Production (CONPROD), 14 is the long-run interest rates (LONGR), 15 is the stock index return (STOCK), and 16 is the change in the OECD Leading Indicator (LEAD).

approach to inference can be used to take into account model uncertainty by estimating, for example, forecasts based on BMA over a set of MP models, or it can be used to make inference regarding the predictors that have a material impact on RGDP growth by estimating the posterior probability of inclusion of each predictor variable in the quantile regression models. The latter is reported per country in Table A4.

A good starting point is to compare the median and linear regression model specifications. From the results in Table 3, that present the MP quantile model specifications, it is evident that a different set of predictor variables influence the 50th quantile compared with those that impact the mean of the RGDP growth for the analyzed countries. Moreover, in the case of Germany, Italy, Spain, Finland, Sweden, Denmark, the Netherlands, and the United States, a larger number of predictors is used to explain the conditional mean versus those needed in the conditional median regression model. For instance, for Italy, there are some common predictors included in both models, such as the autoregressive term at Lag 2, $RGDP_{t-2}$, the World Pandemic Index, and the OECD Leading Indicator, but the conditional mean regression model additionally includes the autoregressive terms at Lags 1 and 3. For Spain, the autoregressive term at Lag 4, $RGDP_{t-4}$, and the rate of unemployment are common predictor variables, but the conditional mean model also includes the autoregressive terms at Lags 1 and 2 and the WPI. By contrast, in the cases of France and Norway, a larger number of variables are part of the median regression model. For example, regarding France, the common predictors in both models are the autoregressive term at Lag 2, $RGDP_{t-2}$, the WPI, and real productivity growth, while the median model contains also the equity market returns and the OECD Leading Indicator.

Next, the focus is shifted to the comparison of the estimated quantile regression models. Important findings emerge from the results in Table 3, regarding the predictor variables that impact each country's RGDP growth quantiles. The main observation is that different predictor variables are included in different quantile model specifications. More specifically, a larger number of predictors impacts the tails of the RGDP growth distribution, especially in the 10th and/or the 90th quantile. Focusing on Germany, Belgium, Finland, and Sweden, a larger number of predictors is identified both in the 10th and 90th "extreme" quantiles compared with the other conditional quantiles and the conditional mean. Regarding France, Italy, Greece, and Norway, a large number of predictors is present in the 90th conditional quantile, while in the case of Spain and Denmark, the lower quantiles require a larger number of variables relative to the 90th and mainly versus the central quantiles.

In addition, interesting conclusions are derived from the underlying analysis. The results reveal that the predictors included in the MP quantile model specifications and/or have inclusion model probabilities above 50% are different for different quantiles across the set of countries. The WPI appears to be an important predictor variable only regarding the lower quantiles and not the upper quantiles of the RGDP growth distribution of Germany, Spain, Greece, the United States, Sweden, Norway, and the Netherlands. By contrast, it impacts both the lower and the upper quantiles of the RGDP growth distribution of Finland and Denmark and all the quantiles of the Belgian and Italian real growth distribution. The change in the OECD Leading Indicator is critical for all quantiles of German, Norwegian, Swedish, and Finnish growth, for most of the Italian and Belgian quantiles, and mainly for the lower and central quantiles of French, and only for the lower quantile of Spanish and Danish economic growth. Similar findings can be observed with respect to the autoregressive terms (lagged RGDP growth); for example, for Greece, the lowest quantile can be explained by the autoregressive terms at Lags 1, 3, and 4, the 25th quantile is explained by the autoregressive terms at Lags 2 and 3, while other autoregressive terms are included in the median and the upper 90th quantile model. Bear in mind that for Greece, the autoregressive terms were not included in the MP linear regression model specifications. The quantile regression analysis, therefore, reveals that in many cases, different predictor variables impact certain quantiles in the tails but not in the center of the distribution. This clearly highlights the advantages of the quantile regression approach relative to the standard linear regression approach.

In Table 4 (panels A and B), the parameter estimates and the corresponding standard errors (for the intercept and beta coefficients) of the predictor variables included in the MP quantile regression model specifications are presented. It is noteworthy that (i) different predictor variables are included in different quantile model specifications and (ii) that the parameter estimates of the corresponding predictors vary across different quantile models. Another interesting finding is that the tails of the RGDP growth distribution, especially in the 10th and/or the 90th quantile is affected by a larger number of predictors. Below, the results for each analyzed country are discussed.

We saw that German RGDP growth is explained, on average, by the autoregressive terms at Lags 1 and 2, the WPI, the rate of unemployment, and the change in the OECD Leading Indicator. Table 4 (panel A) reveals that the autoregressive terms impact mainly the upper quantiles (the 75th and the 90th) of RGDP growth, while the autoregressive term at lag three, the WTI oil price index, the World Pandemic Index, real productivity growth, and the change in car registrations are important predictors for the 10th quantile. In addition, the autoregressive term at Lag 4, the rate of unemployment, and CPI inflation can explain the 90th quantile. The change in the OECD Leading Indicator seems to be a significant predictor across all quantiles.

The RGDP growth of France can be explained, on average, by the autoregressive term at Lag 2, the WPI, and real productivity growth. Based on the quantile regression analysis (Table 4, panel A), it is easily observed that the autoregressive term at Lag 2 can be used to explain all the analyzed quantiles; in addition, the autoregressive term at Lag 4, the WPI, and the OECD Leading Indicator seem to be significant predictors regarding the lower quantiles of French RGDP growth. The autoregressive terms at Lags 1 and 3, real productivity growth, and the equity market index return can be used to explain the 90th quantile.

Analyzing Italian RGDP growth, reveals that the autoregressive terms at Lags 1–3, the WPI, and the change in the OECD Leading Indicator are significant predictors, on average. However, the quantile regression analysis (Table 4, panel A) shows that some of these predictors may affect most of the analyzed quantiles; for example, the autoregressive term at Lag 2 is an important predictor for the 10th, 25th, and 90th quantiles, the WPI affects the 10th, 25th, and 75th quantiles, while the change in the OECD Leading Indicator explains the 10th, 25th, 50th, and 90th quantiles. Other predictor variables have an impact only on the upper or the lower quantiles of the RGDP growth distribution. For example, the autoregressive terms at Lags 1 and 4 and the growth in the CPI affect only the 90th quantile, while the rate of unemployment and the equity market return influence only the 10th quantile.

Spanish RGDP growth was forecasted by autoregressive parameters at Lags 1, 2, and 4; the WPI; and the rate

TABLE 4 Parameter estimates and standard errors of the predictor variables included in the predictive quantile regression model specifications for the analyzed real GDP growth series for different countries.

Panel A															
	Germany					France					Italy				
Predictor variables	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
α	−1.08	−0.08	0.52	0.93	1.60	−0.32	0.11	0.37	0.56	1.45	−0.90	−0.46	0.10	0.43	1.60
	(0.16)	(0.15)	(0.13)	(0.14)	(0.16)	(0.13)	(0.08)	(0.13)	(0.09)	(0.33)	(0.15)	(0.13)	(0.11)	(0.07)	(0.18)
$RGDP_{t-1}$ (1)			−0.18	−0.36	−0.80					−0.29					−0.72
			(0.15)	(0.13)	(0.13)					(0.11)					(0.19)
$RGDP_{t-2}$ (2)		−0.36	−0.14	−0.30	−0.52	−0.45	−0.50	−0.49	−0.11	−0.53	−0.35	−0.49	−0.32		−0.94
		(0.20)	(0.11)	(0.06)	(0.09)	(0.03)	(0.03)	(0.47)	(0.08)	(0.17)	(0.06)	(0.04)	(0.26)		(0.18)
$RGDP_{t-3}$ (3)	0.36	0.15								−0.21				0.11	−0.47
	(0.10)	(0.04)								(0.09)				(0.02)	(0.07)
$RGDP_{t-4}$ (4)					−0.28	0.09	0.11	0.11							−0.23
					(0.15)	(0.02)	(0.02)	(0.08)							(0.10)
OIL (5)	0.03														
	(0.01)														
WUI (6)	−0.01														
	(0.01)														
WPI (7)	−0.40	−0.35				−1.05	−1.01	−0.95		−0.16	−0.76	−0.95	−0.70	−0.16	−0.41
	(0.05)	(0.26)				(0.03)	(0.03)	(0.91)		(0.36)	(0.07)	(0.04)	(0.47)	(0.03)	(0.40)
RPROD (8)	−0.65				0.34			0.43	0.88	1.61					
	(0.26)				(0.32)			(0.67)	(0.46)	(0.27)					
CREG (9)	0.10														−0.04
	(0.01)														(0.0
UNEM (10)				−0.99	−2.07						0.86				
				(0.57)	(0.59)						(0.42)				
CPI (11)					−0.72										1.64
					(0.38)										(1.01)
PPI (12)												0.15			
												(0.14)			
CONPROD (13)	0.01				0.01										
	(0.01)				(0.01)										

(Continues)

TABLE 4 (Continued)

Panel A	**Germany**					**France**					**Italy**				
Predictor variables	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
LONGR (14)					1.40										
					(0.50)										
STOCK (15)			0.03							0.08	0.03				
			(0.01)							(0.03)	(0.01)				
LEAD (16)	0.34	0.21	0.20	0.28	0.38	0.33	0.20	0.15			0.55	0.38	0.32		0.70
	(0.10)	(0.07)	(0.08)	(0.06)	(0.08)	(0.06)	(0.05)	(0.06)			(0.08)	(0.06)	(0.08)		(0.27)
	Spain					**Greece**					**Belgium**				
Predictor variables	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
α	−0.85	−0.20	0.40	0.82	2.06	−2.04	−0.82	0.18	1.02	2.21	−0.03	0.25	0.59	0.83	2.15
	(0.11)	(0.22)	(0.07)	(0.08)	(0.14)	(0.27)	(0.23)	(0.20)	(0.21)	(0.34)	(0.09)	(0.09)	(0.14)	(0.17)	(0.30)
$RGDP_{t-1}$ (1)	0.52	0.34			−0.76	0.18				−0.23					−0.73
	(0.15)	(0.24)			(0.07)	(0.21)				(0.11)					(0.19)
$RGDP_{t-2}$ (2)		−0.33			−0.37		0.17	0.19			−0.56	−0.73	−0.61	−0.44	−0.78
		(0.16)			(0.04)		(0.13)	(0.15)			(0.02)	(0.08)	(0.55)	(0.45)	(0.26)
$RGDP_{t-3}$ (3)	0.28	0.18			−0.15	0.16	0.24								−0.26
	(0.02)	(0.09)			(0.03)	(0.07)	(0.08)								(0.09)
$RGDP_{t-4}$ (4)	0.19	0.23	0.14			0.15				−0.09	0.05				−0.18
	(0.02)	(0.06)	(0.03)			(0.08)				(0.09)	(0.03)				(0.10)
OIL (5)										0.06					
										(0.03)					
WUI (6)					−0.01										
					(0.01)										
WPI (7)	−0.92	−1.16				−0.88	−0.83				−0.86	−0.92	−0.75	−0.49	−0.32
	(0.03)	(0.09)				(0.08)	(0.15)				(0.02)	(0.03)	(0.66)	(0.61)	(0.43)
RPROD (8)	0.19	0.36			−0.37					0.11		0.44	0.44	0.53	0.43
	(0.10)	(0.23)			(0.20)					(0.07)		(0.21)	(0.34)	(0.21)	(0.34)
CREG (9)	0.07	0.03					0.05								
	(0.02)	(0.03)					(0.03)								

TABLE 4 (Continued)

Predictor variables	Spain $Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$	Greece $Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$	Belgium $Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
UNEM (10)		−0.41	−0.58	−0.31	−1.34			−0.61	−0.74	−1.89	−0.38	−0.65	−0.30		
		(0.28)	(0.17)	(0.15)	(0.27)			(0.31)	(0.29)	(0.43)	(0.19)	(0.20)	(0.30)		
CPI (11)	−0.34									−1.75	−0.20				
	(0.13)									(0.42)	(0.15)				
PPI (12)									0.17						
									(0.08)						
CONPROD (13)															
LONGR (14)										3.75					
										(1.43)					
STOCK (15)						0.05				−0.07	0.03	0.02			0.05
						(0.02)				(0.03)	(0.01)	(0.01)			(0.02)
LEAD (16)	0.28										0.17	0.15	0.14	0.09	0.39
	(0.08)										(0.06)	(0.05)	(0.05)	(0.05)	(0.23)

Panel B

Predictor variables	Finland $Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$	Sweden $Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$	Norway $Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
α	−1.26	−0.26	0.24	0.92	1.42	−0.47	0.07	0.61	1.18	2.01	−0.10	0.10	0.67	1.37	2.21
	(0.21)	(0.16)	(0.14)	(0.15)	(0.13)	(0.24)	(0.14)	(0.10)	(0.17)	(0.14)	(0.12)	(0.15)	(0.15)	(0.16)	(0.39)
$RGDP_{t-1}$ (1)					−0.30				−0.21	−0.77	−0.67	−0.54	−0.42	−0.59	−0.97
					(0.11)				(0.11)	(0.09)	(0.14)	(0.18)	(0.13)	(0.13)	(0.18)
$RGDP_{t-2}$ (2)						−0.36				−0.25	−0.55	−0.44	−0.24	−0.35	−0.35
						(0.16)				(0.07)	(0.09)	(0.13)	(0.12)	(0.10)	(0.45)
$RGDP_{t-3}$ (3)	0.21	0.25	0.23	0.18						−0.14					−0.279
	(0.07)	(0.08)	(0.08)	(0.07)						(0.05)					(0.18)
$RGDP_{t-4}$ (4)						0.06									
						(0.09)									
OIL (5)	0.06									−0.01					
	(0.01)									(0.01)					
WUI (6)					−0.01	0.01				−0.01			−0.01	−0.01	−0.01
					(0.01)	(0.01)				(0.01)			(0.01)	(0.01)	(0.01)

(Continues)

TABLE 4 (Continued)

Panel B

Predictor variables	Finland $Q_{0.10}$	Finland $Q_{0.25}$	Finland $Q_{0.50}$	Finland $Q_{0.75}$	Finland $Q_{0.90}$	Sweden $Q_{0.10}$	Sweden $Q_{0.25}$	Sweden $Q_{0.50}$	Sweden $Q_{0.75}$	Sweden $Q_{0.90}$	Norway $Q_{0.10}$	Norway $Q_{0.25}$	Norway $Q_{0.50}$	Norway $Q_{0.75}$	Norway $Q_{0.90}$
WPI (7)	−0.23	−0.17			0.26	−0.64	−0.10				−0.31	−0.24			−0.22
	(0.05)	(0.14)			(0.06)	(0.06)	(0.09)				(0.04)	(0.14)			(0.36)
RPROD (8)					0.30					0.35					0.38
					(0.16)					(0.15)					(0.30)
CREG (9)	0.01				−0.04								0.03	0.01	0.04
	(0.01)				(0.01)								(0.01)	(0.01)	(0.03)
UNEM (10)						0.54					−0.35				
						(0.30)					(0.41)				
CPI (11)					0.49	−0.26							−0.19	−0.51	−0.42
					(0.31)	(0.23)							(0.15)	(0.16)	(0.28)
PPI (12)						−0.57						−0.09			
						(0.20)						(0.11)			
CONPROD (13)	0.02				−0.01										
	(0.01)				(0.01)										
LONGR (14)															
STOCK (15)	0.03				0.02		0.03		0.03						
	(0.03)				(0.01)		(0.01)		(0.02)						
LEAD (16)	0.11	0.29	0.23	0.15	0.16	0.59	0.20	0.23	0.17	0.44	0.21	0.23	0.26	0.14	0.41
	(0.15)	(0.11)	(0.11)	(0.12)	(0.10)	(0.11)	(0.07)	(0.06)	(0.09)	(0.11)	(0.06)	(0.07)	(0.08)	(0.14)	(0.12)

Predictor variables	Denmark $Q_{0.10}$	Denmark $Q_{0.25}$	Denmark $Q_{0.50}$	Denmark $Q_{0.75}$	Denmark $Q_{0.90}$	Netherlands $Q_{0.10}$	Netherlands $Q_{0.25}$	Netherlands $Q_{0.50}$	Netherlands $Q_{0.75}$	Netherlands $Q_{0.90}$	USA $Q_{0.10}$	USA $Q_{0.25}$	USA $Q_{0.50}$	USA $Q_{0.75}$	USA $Q_{0.90}$
α	−0.70	−0.45	0.38	0.70	1.49	−0.63	−0.26	0.27	0.65	1.97	−1.58	−0.44	0.04	0.68	1.54
	(0.16)	(0.26)	(0.11)	(0.10)	(0.15)	(0.14)	(0.14)	(0.17)	(0.08)	(0.21)	(0.22)	(0.23)	(0.19)	(0.20)	(0.17)
$RGDP_{t-1}$ (1)					−0.53		0.48			−0.84					
					(0.07)		(0.13)			(0.13)					
$RGDP_{t-2}$ (2)	−0.16					−0.31	−0.22			−0.73					
	(0.15)					(0.11)	(0.08)			(0.27)					
$RGDP_{t-3}$ (3)	0.33	0.25		0.15		0.27	0.42	0.26	0.24			0.19			
	(0.10)	(0.13)		(0.07)		(0.07)	(0.05)	(0.35)	(0.07)			(0.08)			

TABLE 4 (Continued)

	Denmark					Netherlands					USA				
Predictor variables	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
$RGDP_{t-4}$ (4)															
OIL (5)						0.03				0.01	0.06				−0.02
						(0.01)				(0.01)	(0.01)				(0.01)
WUI (6)	0.01				−0.01				−0.01		0.01				
	(0.01)				(0.01)				(0.01)		(0.01)				
WPI (7)	−0.37	−0.46			0.17	−0.54	−0.57	−0.14	−0.09	−0.31	−0.24	−0.21			
	(0.03)	(0.05)			(0.07)	(0.03)	(0.03)	(0.38)	(0.06)	(0.27)	(0.04)	(0.18)			
RPROD (8)	−0.10									0.12	0.60	0.50	0.69	0.55	
	(0.08)									(0.16)	(0.41)	(0.29)	(0.29)	(0.24)	
CREG (9)															0.04
															(0.03)
UNEM (10)														0.18	0.37
														(0.11)	(0.16)
CPI (11)	−0.62												−0.75	−0.98	−1.40
	(0.25)												(0.38)	(0.33)	(0.34)
PPI (12)												0.06	0.22	0.24	0.33
												(0.04)	(0.09)	(0.07)	(0.08)
CONPROD (13)									−0.02						
									(0.01)						
LONGR (14)	0.55														
	(0.37)														
STOCK (15)		0.05			0.06		0.02	0.04	0.02						
		(0.03)			(0.03)		(0.02)	(0.02)	(0.01)						
LEAD (16)	0.57		0.23			0.21				0.31	0.25		0.16	0.17	
	(0.15)		(0.14)			(0.04)				(0.11)	(0.11)		(0.10)	(0.09)	

Note: The table reports the parameter estimates and the standard errors of the predictor variables in the quantile regression model specification for the analyzed real GDP growth based on the sample period (from 2001:Q2 to 2021:Q3). The predictor variables are the real GDP growth lagged once ($RGDP_{t-1}$), the real GDP growth lagged twice ($RGDP_{t-2}$), the real GDP growth lagged thrice ($RGDP_{t-3}$), the real GDP growth lagged four times ($RGDP_{t-4}$), the WTI oil price (OIL), the World Uncertainty Index (WUI), the World Pandemic Uncertainty Index (WPI), the real productivity growth (RPROD), the change in car registrations (CREG), the rate of unemployment (UNEM), the growth in the Consumer Price Index (CPI), the growth in the Producer Price Index (PPI), the Construction Volume Index of Production (CONPROD), the long-run interest rate (LONGR), the stock index return (STOCK), and the change in the OECD Leading Indicator (LEAD).

of unemployment, on average. The quantile regression analysis (Table 4, panel A) reveals some interesting features; the median is only affected by the autoregressive term at Lag 4 and the rate of unemployment, while other predictor variables impact the tails (lower and upper quantiles) of the RGDP growth distribution. For instance, the WPI, real productivity growth, the change in car registrations, the growth in the CPI, and the change in the OECD Leading Indicator are important predictors primarily for the lower tail quantiles.

Greek RGDP growth can be explained, on average, by the WPI, and the rate of unemployment. Quantile regression analysis, however, (Table 4, panel A) reveals that several predictors affect the lower and/or the upper tail quantiles. For example, the autoregressive terms at Lags 3 and 4, and the WPI affects mainly the lower quantiles, while a large number of predictors, that is, the autoregressive term at Lag 1, the WTI oil price, the unemployment rate, real productivity growth, the growth in the CPI, and long-run interest rates, are important predictors for the upper tail quantiles. The equity market is a significant predictor for both the 10th and the 90th quantiles.

Belgian RGDP growth is explained by the autoregressive term at Lags 1 and 2, the WPI, real productivity growth, and the change in the OECD Leading Indicator, on average. Quantile regression analysis (Table 4, panel A) shows that the autoregressive parameters at Lags 1 and 3 affect mainly the 90th quantile, while the rate of unemployment and the WPI are significant predictors for the lower quantiles. There are other variables such as the autoregressive term at Lag 2 and the equity market return that impact the tails of the RGDP growth distribution. Finally, the change in the OECD Leading Indicator is a significant factor for most of the analyzed quantiles.

Similar in spirit results emerge from the analysis of the rest of the countries considered in our analysis. For example, based on the quantile regression analysis (Table 4, panel B), the RGDP growth of Finland, Sweden, Norway, Denmark, and the Netherlands is explained by several autoregressive terms at different lags for different quantiles. In addition, WPI affects mainly the lower tail quantiles and, in some cases, the upper quantiles of the RGDP growth distribution along with the OECD Leading Indicator that seems to be a significant predictor at different quantiles.

All in all, the findings stress the usefulness of quantile regression models for exploring the impact of several RGDP predictors at different points of the underlying distribution and reveals potential differences in predictor effects across different quantiles. In particular, it was shown that there are several predictors that affect the lower or/and the upper quantiles of every country's RGDP growth distribution, and therefore, interesting relations between RGDP growth and the predictor variables were uncovered. Quantile regression models appear to be an appropriate modeling approach, that produces robust inferences regarding RGDP growth, especially in the presence of outliers and non-linearities, or in case of non-normal distributions, caused by various economic, geopolitical and other random events and/or shocks, such as market crises, economic downturns, the COVID-19 pandemic, or the recent war in the Ukraine.

5.2.3 | Robustness analysis

In this section, alternative model selection approaches and techniques are presented with the aim to examine the sensitivity of the findings of the Bayesian approach to inference with respect to the predictor variables that affect/predict RGDP growth. A variety of model selection methods is employed: (i) a parametric approach to inference by using information criteria based on the likelihood function, such as the AIC and the Schwarz (1978) BIC; (ii) the best subset regression approach, an automated model selection procedure that exhaustively explores the model space by using all possible subsets of predictor variables in the regression models (and employed in model building) to identify a useful subset of predictors; (iii) the penalized likelihood regression methods, such as the ridge, the LASSO, and the elastic net regularization techniques that impose shrinkage in the regression coefficients and allow for automatic variable selection. Finally, the MCS approach of Hansen et al. (2011) that allows the identification of a subset of superior models containing the best model(s) at a given level of confidence is implemented.[7]

As a first step, the predictive linear and quantile regression model specifications that were obtained by applying the stepwise approach (STEP), the AIC, and the Schwarz (1978) BIC, as well as the MP model, are reported in the Tables A5 and A6, respectively, by taking into account the collection of all 2^K competing regression models. It is evident that the stepwise, the BIC and the MP models result to almost the same set of predictors for the conditional mean and for the quantiles under consideration, for each individual country's RGDP growth series, while, as expected, the AIC-based best model includes more predictor variables compared with the other approaches. This is probably due to AIC's tendency to overfit.

Then, the best subset regression approach is implemented, and in Table 5, the best *k*-subset predictive linear regression model specifications for the RGDP growth of each of the analyzed countries is presented. Interesting results emerge from the specific analysis; the WPI

TABLE 5 Best subset predictive linear regression model specifications regarding the real GDP growth for the analyzed countries.

Best *k*-subset predictors	**Germany**	**France**	**Italy**	**Spain**
1 predictor	7	8	10	7
2 predictors	2 7	2 8	7 10	2 7
3 predictors	2 7 9	2 7 8 (*)	1 2 7	1 2 7
4 predictors	1 2 7 16	2 3 7 8	1 2 7 16	1 2 7 10
5 predictors	1 2 7 10 16 (*)	2 3 4 7 8	1 2 3 7 16 (*)	1 2 4 7 10 (*)
6 predictors	1 2 7 10 15 16	1 2 3 7 8 16	1 2 3 7 11 16	1 2 4 7 9 10
7 predictors	1 2 7 10 11 15 16	1 2 3 7 8 12 16	1 2 3 7 8 11 16	1 2 4 7 9 10 12
8 predictors	1 2 7 10 11 13 15 16	1 2 3 7 8 9 12 16	1 2 3 6 7 10 11 16	1 2 4 6 7 9 10 12
Best *k*-subset predictors	**Greece**	**Belgium**	**Finland**	**Sweden**
1 predictor	7	7	16	7
2 predictors	7 10 (*)	2 7	7 15	7 15
3 predictors	7 10 11	2 7 8	3 7 16 (*)	1 7 16
4 predictors	7 10 11 12	1 2 7 8	3 7 12 16	1 2 7 16 (*)
5 predictors	3 7 10 11 12	1 2 7 8 16 (*)	1 3 7 12 16	1 2 7 8 16
6 predictors	1 3 7 9 10 11	1 2 7 8 10 16	1 3 7 8 12 15	1 2 7 8 9 16
7 predictors	1 3 7 9 10 11 12	1 2 7 8 9 10 16	1 3 7 8 12 13 15	1 2 7 8 9 12 16
8 predictors	1 3 6 7 9 10 11 12	1 2 7 8 10 12 15 16	1 3 7 8 12 13 15 16	1 2 7 8 9 12 15 16
Best *k*-subset predictors	**Norway**	**Denmark**	**The Netherlands**	**USA**
1 predictor	7	7	7	8
2 predictors	2 7	7 15	2 7	8 16
3 predictors	1 2 7	1 7 15	1 2 7	7 8 16
4 predictors	1 2 7 16	1 2 7 16	1 2 7 16	7 8 12 16
5 predictors	1 2 7 9 16 (*)	1 2 7 15 16 (*)	1 2 7 15 16 (*)	3 7 8 12 16
6 predictors	1 2 7 9 11 16	1 2 7 13 15 16	1 2 7 10 15 16	3 7 8 9 10 12 (*)
7 predictors	1 2 6 7 9 11 16	1 2 3 7 13 15 16	1 2 3 7 10 15 16	3 7 8 9 10 11 12
8 predictors	1 2 6 7 9 11 12 16	1 2 3 7 9 13 15 16	1 2 3 4 6 7 15 16	3 7 8 9 10 11 12 16

Note: The table reports the best subset predictive linear regression model specifications of real GDP growth for the analyzed period, from 2001:Q2 to 2021:Q3. Model specifications are identified by the numbers associated with the corresponding predictor variables. Thus, 1 is the real GDP growth lagged once ($RGDP_{t-1}$), 2 is the real GDP growth lagged twice ($RGDP_{t-2}$), 3 is the real GDP growth lagged thrice ($RGDP_{t-3}$), 4 is the real GDP growth lagged four times ($RGDP_{t-4}$), 5 is the WTI oil price (OIL), 6 is the World Uncertainty Index (WUI), 7 is the World Pandemic Uncertainty Index (WPI), 8 is real productivity growth (RPROD), 9 is the change in car registrations (CREG), 10 is the rate of unemployment (UNEM), 11 is the growth in the Consumer Price Index (CPI), 12 is the growth in the Producer Price Index (PPI), 13 is the change Construction Volume Index of Production (CONPROD), 14 is the long-run interest rates (LONGR), 15 is the stock index return (STOCK), and 16 is the change in the OECD Leading Indicator (LEAD).

appears to be the single best predictor for eight of the 12 countries, that is, Germany, Spain, Greece, Belgium, Sweden, Norway, Denmark, and the Netherlands; real productivity growth (RPROD) is the best predictor for France and the United States, the rate of unemployment (UNEM) is the best predictor for Italian GDP, while the change in the OECD Leading Indicator (LEAD) for Finnish RGDP growth. The MP model specification identified by the Bayesian stochastic search belongs to a best *k*-subset regression model and is denoted by an asterisk in Table 5. Furthermore, in most of the cases, the second or the third MP model found by the Bayesian stochastic search algorithm appears to be in the set of best subset models, indicating that the stochastic search algorithm provides models in the area of "best" model specifications.

Next, penalized likelihood regression models, such as the ridge (Hoerl & Kennard, 1970), the LASSO (Tibshirani, 1996), and the elastic net (Zou & Hastie, 2005) techniques, are implemented. The corresponding results from the LASSO, the ridge, and the elastic net approach are presented for reasons of space in Tables A7–A9, respectively. The number of predictors identified by the penalized techniques is larger than the competing

TABLE 6 Model confidence set metrics for the most probable predictive linear model specifications for the analyzed countries.

Models	$pv_{max,M}$	$pv_{R,M}$	Models	$pv_{max,M}$	$pv_{R,M}$
Germany			France		
1 2 7 10 16	0.903	0.741	2 7 8	0.800	0.997
1 2 7 10 15 16	1.000	0.995	2 3 7 8	1.000	0.999
1 2 7 10 11 15 16	1.000	0.993	2 4 7 8	1.000	1.000
1 2 7 10 11 16	1.000	0.984	2 7 8 12	0.996	0.999
1 2 7 15 16	0.983	0.964	2 6 7 8	0.992	0.999
Italy			Spain		
1 2 3 7 16	0.958	0.992	1 2 4 7 10	1.000	0.997
1 2 3 7 11 16	1.000	0.997	1 2 4 7 9 10	1.000	0.999
1 2 3 7 8 16	1.000	0.986	1 2 4 7 10 12	1.000	0.996
1 2 3 6 7 16	1.000	0.995	1 2 4 7 9 10 12	1.000	1.000
1 2 3 7 15 16	0.998	0.996	1 2 4 5 7 10	1.000	0.999
Greece			Belgium		
7 10	0.988	0.980	1 2 7 8 16	0.922	0.498
7 10 11	1.000	0.980	1 2 7 8 10 16	1.000	0.996
7 10 11 12	1.000	0.988	1 2 7 8 9 16	1.000	0.940
7 10 12	1.000	0.980	1 2 7 8 10	0.945	0.978
4 7 12	1.000	0.957	1 2 7 8 15 16	1.000	0.638
Finland			Sweden		
3 7 16	0.985	0.999	1 2 7 16	0.712	0.842
3 7 12 16	0.999	0.996	1 2 7 8 16	0.997	0.834
1 3 7 8 12 13 15	1.000	0.994	1 2 7 8 9 16	1.000	0.925
1 3 7 8 12 15	1.000	0.992	1 2 7 15 16	1.000	1.000
3 7 15 16	0.998	0.997	1 2 7 9 16	0.957	0.764
Norway			Denmark		
1 2 7 9 16	1.000	0.972	1 2 7 15 16	1.000	0.998
1 2 7 11 16	0.999	0.920	1 2 7 16	1.000	0.980
1 2 7 16	0.441	0.807	1 3 7 9 15	1.000	0.999
1 2 7 9 11 16	1.000	0.999	1 3 7 15	0.996	0.979
1 2 7 9 12 16	1.000	0.998	7 15	0.999	0.999
The Netherlands			USA		
1 2 7 15 16	0.999	0.661	3 7 8 9 10 12	0.845	0.579
1 2 7 16	0.717	0.859	7 8 12 16	1.000	0.936
1 2 7 10 15 16	1.000	0.868	3 7 8 12	1.000	1.000
1 2 3 7 15 16	1.000	0.998	3 7 8 9 10 11 12	0.937	0.859
1 2 7 11 15 16	1.000	0.995	3 7 8 12 16	1.000	0.848

Note: This table reports results of the model confidence set approach applied to the in-sample squared errors of the fitted values obtained from the most probable predictive linear model specifications identified by the Bayesian Stochastic search algorithm. In particular, the *p*-values of the $T_{R,M}$ and $T_{max,M}$ test statistics are reported together with the five most probable model specifications. Model specifications are identified by the numbers associated with the corresponding predictor variables. Thus, 1 is the real GDP growth lagged once ($RGDP_{t-1}$), 2 is the real GDP growth lagged twice ($RGDP_{t-2}$), 3 is the real GDP growth lagged thrice ($RGDP_{t-3}$), 4 is the real GDP growth lagged four times ($RGDP_{t-4}$), 5 is the WTI oil price (OIL), 6 is the World Uncertainty Index (WUI), 7 is the World Pandemic Uncertainty Index (WPI), 8 is real productivity growth (RPROD), 9 is the change in car registrations (CREG), 10 is the rate of unemployment (UNEM), 11 is the growth in the Consumer Price Index (CPI), 12 is the growth in the Producer Price Index (PPI), 13 is the change Construction Volume Index of Production (CONPROD), 14 is the long-run interest rates (LONGR), 15 is the stock index return (STOCK), 16 is the change in the OECD Leading Indicator (LEAD).

methods. For example, the LASSO variable selection, apart from the autoregressive GDP growth terms, the WUI, real productivity growth (RPROD), the rate of unemployment (UNEM), the stock index return (STOCK), and the change in the OECD Leading Indicator (LEAD), includes, in many cases, additional predictor variables, such as the WUI, the CPI, the PPI, and the CONPROD. The parameter coefficients of some predictors, that is, that of the WUI or of the change CONPROD, are shrinked towards zero, while other predictors are forced to have zero coefficients. In this sense, the LASSO technique may impose a shrinkage, or, according to Buhlmann and Mandozzi (2014), a screening operator in order to reduce the predictor space, and then work with reduced dimension. It is evident that the predictor variables identified by the Bayesian stochastic search algorithms for the conditional mean and the quantile regression models, and the alternative classical methods are included in the model specifications found by the LASSO technique, and in this sense, there is some degree of consistency regarding the predictive variables included in the regression models.

Finally, the MCS approach introduced by Hansen et al. (2011) is implemented. This approach is based on a sequence of tests that permits the construction of a set of superior models, where the null hypothesis of equal predictive ability is not rejected at a certain confidence level. Thus, the algorithm allows the researcher to identify a subset of superior models containing the best model(s) at a given level of confidence, where best is defined in terms of a criterion, or a loss function that is specified by the analyst, which means that it is possible to test models on various aspects depending on the chosen loss function. The MCS approach can be used either to assess the forecasting ability of several competing models using an out-of-sample scheme or to perform an in-sample evaluation of competing regression models.

In our study, the MCS approach is applied to evaluate the predictive linear regression models based on the in-sample squared error (squared loss function) of the actual RGDP growth series and the corresponding fitted values obtained from different model specifications. Due to the enormous number of possible competing models, the MCS procedure (Bernardi & Catania, 2018) is implemented for the fifty MP model specifications found by the Bayesian stochastic search algorithm, in order to assess the performance of the selected models. Table 6 presents the results of the MCS approach applied to the MP predictive linear model specifications for each one of the RGDP growth series of the analyzed countries. In particular, the p-values of the $T_{R,M}$ and $T_{max,M}$ test statistics are reported together with the five MP model specifications. For both tests, high p-values are observed, which indicates that the MP regression models selected by the Bayesian stochastic search algorithm belong to the set of superior models and, therefore, confirms the efficiency of the Bayesian approach to pinpoint the "area" of most superior models.

6 | CONCLUSION

The primary goal of this study was to assess the impact of a severe unanticipated shock, such as the global outbreak and spread of the COVID-19 pandemic, on real economic activity in Greece and seven other euro area countries, namely, Belgium, Finland, France, Germany, Italy, the Netherlands, and Spain, as well as three Scandinavian countries (Denmark, Norway, and Sweden), and the United States. The standard linear and quantile regression models were employed to investigate the ability of numerous economic, financial, and COVID-19-related factors to capture and predict the footprint of the aggregate shock on the economy.

A Bayesian approach to model selection that accommodates an automatic determination of the predictor variables that explain/predict RGDP growth is introduced. More specifically, a MCMC stochastic search algorithm has been designed that explores the model space, provides posterior model probabilities, and takes into account model uncertainty, using BMA.

The use of quantile regression models in particular is quite interesting, as they allow the identification of the factors that impact the RGDP growth distribution at different points. Closely linked is the determination of the sign and magnitude of the estimated parameters, as well as the underlying consistency across different quantiles of the RGDP growth distribution. The specific modeling framework accommodates more effective modeling of the nature and non-linear characteristics of the underlying macroeconomic series.

A set of explanatory and/or predictor variables that are perceived to be common for all countries is used in the regression framework, as it is supposed to capture global effects, given the universal nature of the COVID-19 pandemic. The set of common factors includes variables, such as the oil price, and an economic uncertainty index. The rationale is to employ factors that reflect the economic effects of a significant unexpected impact, such as the outbreak of the COVID-19 pandemic. Apart from the economic-financial common factors, an additional COVID-19 specific factor was included in the analysis, the WPI. Even though the pandemic had asymmetric effects on different continents-regions of the world, a global measure could provide significant insights regarding the scale and spread of the pandemic and its likely impact on the world economy. In addition, country-specific factors were employed; the initial set of explanatory/predictive variables contains 32 macroeconomic and financial market-related indicators, the majority of which are widely followed by both policy makers and practitioners, and have been used in the existing literature for nowcasting and/or business cycle predictability. In general, the forecasting variables are representative of categories related to output and productivity, the labor market, the housing market, orders and inventories, money and credit, interest rates, prices, the financial markets, and business and consumer confidence surveys.

As anticipated, even though there is limited overlap, in general, different explanatory/predictive factors are important for different economies. A core and solid conclusion, however, is that the outbreak of the COVID-19 pandemic has had a profound impact on real economic activity across regions and countries, as a shock of such magnitude caused an immediate rise in overall uncertainty, as reflected by the WPI, that spread rapidly across all sectors of the global economy, as the specific shock had a forceful impact that was more sizeable compared with that of the 2008 GFC, the most recent severe disruption in the global economic and financial system. Having said that, the impact of the COVID-19 pandemic was not symmetric across the economies under study. Surprisingly, the extent of the impact was lower than initially expected in Greece, given the underlying structure of the Greek economy. More specifically, considering the asymmetric effects of the pandemic on the different economic sectors/industries, for a country like Greece that tourism is of paramount importance, it would be rational to project that the outbreak of COVID-19 would have a larger impact relative to other countries, due to the imposition of international travel bans and local lockdowns, especially during the initial phases of the pandemic. The same expectation applies in the cases of Spain and Italy, also economies with a large exposure to the tourism and hospitality sector. Indeed, the results show that the specific economies had the highest exposure to the repercussions caused by the pandemic.

Last, but not least, the quantile regression models reveal that there are several predictors that affect the lower or/and the upper quantiles of each country's RGDP growth distribution and, thus, uncover interesting relations of RGDP growth with the predictor variables. Quantile regression models appear to be an appropriate modeling approach that produces robust inferences for RGDP growth, especially in the presence of outliers and non-linearities, or in cases of non-normal distributions, caused by various economic, geopolitical, and other random events/shocks, such as market crises, economic downturns, the COVID-19 pandemic, or the recent war in the Ukraine.

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DATA AVAILABILITY STATEMENT

The data for the World Uncertainty Index (WUI), the World Pandemic Index (WPI), and the West Texas Intermediate Crude Oil price (OIL) are publicly available on the Federal Reserve Bank of St. Louis' FRED database webpage. Likewise, the data related to the US economy were also obtained from the FRED database, with the exception of that regarding the Real Productivity series (RPROD) that is available on the US Bureau of Labor Statistics' web page. In addition, data on Norwegian Passenger Car Registrations (CREG) are accessible on the FRED Database. Data related to the eight Eurozone countries, namely, Belgium, Finland, France, Germany, Greece, Italy, the Netherlands, and Spain, as well as the three Nordic countries (Denmark, Norway, and Sweden), are publicly available on the Eurostat and OECD databases.

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ENDNOTES

[1] See, for example, Hoeting et al. (1999), Chipman et al. (2001), Koop and Potter (2004), Vrontos et al. (2008), Meligkotsidou et al. (2009), and Vrontos (2012).

[2] The WUI is a measure that tracks uncertainty across the world; for more details, please refer to https://worlduncertaintyindex.com/.

[3] The WPI is the percent of the word "uncertain," and its variants, that appear near the pandemic terms in Economist Intelligence Unit country reports. For more details, please refer to https://worlduncertaintyindex.com/.

[4] For more details, please refer to https://www.ravenpack.com/solutions/research/coronavirus-media-monitor.

[5] It is noteworthy that the majority of the autoregressive coefficients carry a negative sign. This seems counter-intuitive but is consistent with the characteristics and the structure of the underlying data. A plausible economic interpretation could be that the period under study coincides with a severe economic drawdown (recession), the 2008 GFC, with protracted and significant repercussions that could have altered past relations.

[6] For reasons of space, only the results based on the "Stochastic Search" approach are reported; however, the results based on the "Exact" approach are almost identical. In addition, the posterior model probabilities estimated by the stochastic search algorithm are almost equal across different number of iterations, pointing to rapid MCMC algorithm convergence.

[7] The MCS approach of Hansen et al. (2011) and/or the complete subset regression approach of Elliott et al. (2013) can be implemented in a forecasting scheme, that combines forecasts from several possible regression models in order to produce more accurate predictions; see, for example, Samuels and Sekkel (2017), Meligkotsidou et al. (2021), among several others.

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APPENDIX A: Forecasting GDP growth: the economic impact of COVID-19 Pandemic

TABLE A1 Set of predictor variables—Overview.

Code	Predictor variables	Transformation
1	Real GDP growth—Lag 1 ($RGDP_{t-1}$)	Δln, quarter-on-quarter % change
2	Real GDP growth—Lag 2 ($RGDP_{t-2}$)	Δln, quarter-on-quarter % change
3	Real GDP growth—Lag 3 ($RGDP_{t-3}$)	Δln, quarter-on-quarter % change
4	Real GDP growth—Lag 4 ($RGDP_{t-4}$)	Δln, quarter-on-quarter % change
5	WTI oil (OIL)	Δln, quarter-on-quarter % change
6	World Uncertainty Index (WUI)	Δlv
7	World Pandemic Index (WPI)	Δlv
8	Real Productivity (RPROD)	Δln, quarter-on-quarter % change
9	Car Registrations (CREG)	Δln, quarter-on-quarter % change
10	Rate of Unemployment (UNEM)	Δlv
11	Consumer Price Index (CPI)	Δlv
12	Producer Price Index (PPI)	Δlv
13	Construction Volume Index of Production (CONPROD)	Δln, quarter-on-quarter % change
14	Long-Term Interest Rates (LONGR)	Δlv
15	Stock index return (STOCK)	Δln, quarter-on-quarter % change
16	OECD Leading Indicator (LEAD)	Δln, quarter-on-quarter % change

Note: The table reports detailed information about the set of predictor variables and the corresponding transformation used in the analysis; Δln denotes first differences of logarithms, and Δlv denotes first differences.

TABLE A2 Descriptive statistics.

Dependent variable	Mean	StDev	Median	Q1	Q3	Skewness	Kurtosis	Min	Max
RGDP—Germany	0.26	1.80	0.44	−0.12	0.80	−1.73	23.43	−10.53	8.66
RGDP—France	0.28	2.65	0.35	0.03	0.66	0.87	32.69	−14.46	17.04
RGDP—Italy	0.01	2.47	0.21	−0.23	0.41	0.47	28.32	−13.50	14.85
RGDP—Spain	0.27	2.95	0.58	−0.01	0.90	−2.12	34.53	−19.42	15.53
RGDP—Greece	−0.09	2.48	0.14	−0.78	1.05	−2.51	15.60	−14.44	5.22
RGDP—Belgium	0.38	1.99	0.43	0.21	0.69	−1.35	32.55	−12.37	11.23
Predictors—Common factors	**Mean**	**StDev**	**Median**	**Q1**	**Q3**	**Skewness**	**Kurtosis**	**Min**	**Max**
OIL (5)	1.03	17.30	3.92	−5.36	10.99	−1.22	6.19	−70.10	38.01
WUI (6)	−0.26	35.38	−4.24	−21.57	29.09	−0.06	2.52	−80.60	68.15
WPI (7)	0.16	2.12	0.00	−0.00	0.00	2.85	25.64	−8.68	13.37
Predictors—Germany specific factors	**Mean**	**StDev**	**Median**	**Q1**	**Q3**	**Skewness**	**Kurtosis**	**Min**	**Max**
RPROD (8)	0.21	0.79	0.26	−0.05	0.57	−1.38	10.19	−3.62	2.65
CREG (9)	−0.27	11.11	0.08	−2.26	2.64	0.54	15.40	−46.45	58.52
UNEM (10)	−0.05	0.23	−0.10	−0.20	0.10	0.32	2.51	−0.50	0.50
CPI (11)	0.01	0.47	−0.04	−0.25	0.27	0.26	4.52	−1.47	1.610
PPI (12)	0.03	0.73	0.06	−0.28	0.42	−1.08	8.16	−3.45	1.80
CONPROD (13)	3.50	25.50	4.89	−14.72	17.70	0.53	3.04	−37.85	80.00
LONGR (14)	−0.06	0.26	−0.10	−0.25	0.16	0.15	2.36	−0.58	0.53
STOCK (15)	0.63	8.67	1.64	−2.93	6.46	−1.18	4.98	−31.83	15.04
LEAD (16)	−0.06	2.09	−0.07	−1.06	1.06	0.29	4.76	−5.79	6.62
Predictors—France specific factors	**Mean**	**StDev**	**Median**	**Q1**	**Q3**	**Skewness**	**Kurtosis**	**Min**	**Max**
RPROD (8)	0.21	0.91	0.17	-0.08	0.49	2.34	25.92	−3.63	6.09
CREG (9)	−1.18	18.25	1.05	−7.57	6.20	0.30	9.72	−70.42	82.62
UNEM (10)	−0.01	0.29	−0.03	−0.13	0.13	1.80	12.99	−0.83	1.57
CPI (11)	0.00	0.44	0.01	−0.26	0.26	−0.30	4.12	−1.49	1.08
PPI (12)	0.04	1.24	0.00	−0.68	0.82	−0.03	5.61	−4.61	4.09
CONPROD (13)	0.30	9.07	1.98	−10.11	7.65	−0.25	2.08	−17.00	22.25
LONGR (14)	−0.05	0.38	−0.10	−0.25	0.19	−0.02	4.00	−1.20	1.12
STOCK (15)	0.40	7.85	1.99	−3.00	6.25	−1.27	4.64	−27.01	11.83
LEAD (16)	−0.15	1.75	0.15	−1.41	1.01	−0.27	3.68	−4.81	4.84
Predictors—Italy specific factors	**Mean**	**StDev**	**Median**	**Q1**	**Q3**	**Skewness**	**Kurtosis**	**Min**	**Max**
RPROD (8)	0.02	0.74	0.02	−0.40	0.41	0.15	3.55	−2.01	2.10
CREG (9)	−0.61	13.13	0.15	−3.21	2.90	1.83	22.76	−51.22	80.66
UNEM (10)	0.00	0.44	0.00	−0.20	0.20	0.05	9.07	−1.90	1.80
CPI (11)	−0.02	0.42	−0.04	−0.25	0.17	−0.15	4.14	−1.31	1.21
PPI (12)	0.04	1.26	0.03	−0.66	0.73	−1.36	10.96	−6.58	3.21
CONPROD (13)	0.55	11.29	−0.71	−9.86	10.92	0.29	2.23	−18.77	35.11
LONGR (14)	−0.06	0.33	−0.05	−0.29	0.19	0.07	3.04	−0.87	0.94
STOCK (15)	−0.26	8.60	1.52	−5.05	5.92	−1.12	4.12	−30.39	11.44
LEAD (16)	−0.06	1.57	−0.01	−0.97	0.88	0.16	5.03	−4.48	5.84

TABLE A2 (Continued)

Predictors—Spain specific factors	Mean	StDev	Median	Q1	Q3	Skewness	Kurtosis	Min	Max
RPROD (8)	0.14	1.26	0.21	−0.30	0.66	−1.99	20.91	−7.45	5.36
CREG (9)	−0.38	10.19	−0.20	−2.90	3.28	1.56	18.80	−38.37	59.61
UNEM (10)	0.06	0.69	−0.10	−0.40	0.43	1.47	6.70	−1.10	2.80
CPI (11)	−0.02	0.78	−0.07	−0.48	0.38	0.02	3.92	−2.45	1.97
PPI (12)	0.05	1.71	0.00	−0.99	0.97	−0.21	5.57	−6.53	5.39
CONPROD (13)	−0.06	10.47	1.80	−7.24	7.93	−0.60	3.27	−33.28	21.47
LONGR (14)	−0.05	1.54	−0.09	−0.44	0.29	−0.89	11.86	−7.53	5.70
STOCK (15)	−0.04	8.54	1.06	−2.85	5.62	−0.85	3.64	−23.44	17.43
LEAD (16)	−0.09	1.57	0.04	−1.12	0.85	−0.41	3.51	−4.41	3.91
Predictors—Greece specific factors	**Mean**	**StDev**	**Median**	**Q1**	**Q3**	**Skewness**	**Kurtosis**	**Min**	**Max**
RPROD (8)	−0.12	3.07	−0.21	−1.30	1.33	−0.70	12.63	−15.75	11.99
CREG (9)	−0.55	18.75	0.76	−4.18	4.04	0.67	22.46	−93.57	107.91
UNEM (10)	0.05	0.81	−0.10	−0.43	0.30	0.66	3.70	−1.90	2.40
CPI (11)	−0.04	0.75	−0.06	−0.44	0.34	0.36	3.85	−1.83	2.13
PPI (12)	0.04	3.54	−0.05	−2.16	2.12	0.12	4.84	−11.94	11.24
CONPROD (13)	2.79	30.05	10.81	−26.16	24.05	−0.35	2.22	−58.38	74.73
LONGR (14)	−0.06	0.26	−0.07	−0.23	0.15	−0.23	3.31	−0.84	0.54
STOCK (15)	−1.55	13.71	−0.70	−9.19	8.87	−0.59	3.57	−47.93	24.40
LEAD (16)	0.01	1.18	0.08	−1.00	1.10	−0.19	1.90	−2.38	2.27
Predictors—Belgium specific factors	**Mean**	**StDev**	**Median**	**Q1**	**Q3**	**Skewness**	**Kurtosis**	**Min**	**Max**
RPROD (8)	0.21	0.92	0.20	−0.09	0.66	−0.29	12.49	−4.19	4.33
CREG (9)	−0.18	10.37	0.09	−3.15	3.94	0.48	11.50	−36.16	50.38
UNEM (10)	0.00	0.41	0.00	−0.30	0.23	0.16	2.91	−0.80	1.00
CPI (11)	−0.01	0.68	−0.02	−0.34	0.37	−0.59	4.23	−2.10	1.43
PPI (12)	0.11	2.63	0.12	−1.38	1.18	0.67	4.93	−6.17	9.05
CONPROD (13)	0.62	10.13	3.45	−6.26	8.35	−0.55	2.01	−17.83	17.20
LONGR (14)	−0.06	0.28	−0.11	−0.23	0.15	0.07	2.59	−0.72	0.63
STOCK (15)	0.49	8.17	1.84	−1.85	5.49	−1.73	7.77	−37.02	12.77
LEAD (16)	−0.05	2.10	−0.07	−1.10	0.63	0.47	4.68	−5.64	7.13
RGDP—Finland	0.32	1.48	0.35	−0.20	1.00	2.04	13.19	−6.70	4.89
RGDP—Sweden	0.52	1.48	0.66	0.14	1.17	−1.82	19.56	−8.10	6.75
RGDP—Norway	0.41	1.28	0.30	−0.07	0.98	−0.21	6.58	−4.77	4.39
RGDP—Denmark	0.32	1.28	0.34	−0.11	0.74	−0.70	14.40	−6.27	5.92
RGDP—Netherland	0.33	1.50	0.40	0.02	0.63	−1.65	23.43	−8.75	7.23
RGDP—USA	0.32	1.48	0.35	−0.20	1.00	−2.04	13.16	−6.70	4.89
Predictors—Common factors	**Mean**	**StDev**	**Median**	**Q1**	**Q3**	**Skewness**	**Kurtosis**	**Min**	**Max**
OIL (5)	1.03	17.30	3.92	−5.36	10.99	−1.22	6.19	−70.10	38.01
WUI (6)	−0.26	35.38	−4.24	−21.57	29.09	−0.06	2.52	−80.60	68.15
WPI (7)	0.16	2.12	0.00	−0.00	0.00	2.85	25.64	−8.68	13.37

(Continues)

TABLE A2 (Continued)

Predictors—Finland specific factors	Mean	StDev	Median	Q1	Q3	Skewness	Kurtosis	Min	Max
RPROD (8)	0.22	0.98	0.14	−0.39	0.89	−0.25	4.13	−3.16	2.95
CREG (9)	−0.02	16.8	0.77	−3.58	3.71	−0.97	13.20	−83.08	66.37
UNEM (10)	−0.01	1.29	0.40	−0.75	1.00	−0.78	2.31	−2.70	2.00
CPI (11)	−0.01	0.55	0.03	−0.21	0.26	−0.57	5.64	−2.18	1.51
PPI (12)	0.07	1.31	−0.00	−0.81	0.95	−0.34	5.43	−5.14	3.60
CONPROD (13)	1.03	23.83	9.91	−5.78	16.03	−0.98	2.33	−45.96	31.07
LONGR (14)	−0.06	0.25	−0.08	−0.23	0.16	0.09	2.47	−0.66	0.50
STOCK (15)	0.24	9.83	2.52	−4.02	6.77	−1.45	5.22	−34.82	13.69
LEAD (16)	−0.03	1.34	0.14	−0.59	0.57	0.09	4.26	−3.48	3.70
Predictors—Sweden specific factors	**Mean**	**StDev**	**Median**	**Q1**	**Q3**	**Skewness**	**Kurtosis**	**Min**	**Max**
RPROD (8)	0.34	1.18	0.23	−0.30	1.07	0.23	6.13	−3.35	5.13
CREG (9)	0.20	13.15	0.85	−2.19	5.60	−1.58	13.19	−67.89	48.13
UNEM (10)	0.06	0.86	0.10	−0.40	0.70	−0.12	2.62	−1.70	1.90
CPI (11)	0.004	0.60	0.09	−0.26	0.32	−0.53	4.03	−1.84	1.43
PPI (12)	0.05	1.07	0.14	−0.72	0.76	−0.01	2.54	−2.29	2.70
CONPROD (13)	0.91	17.06	−0.57	−11.68	15.19	−0.10	2.20	−38.62	32.82
LONGR (14)	−0.05	0.29	−0.03	−0.27	0.15	−0.32	3.15	−0.93	0.57
STOCK (15)	1.48	8.31	2.61	−2.07	6.61	−1.20	5.24	−28.97	17.01
LEAD (16)	−0.08	1.65	0.04	−0.81	0.63	0.12	4.58	−4.12	5.35
Predictors—Norway specific factors	**Mean**	**StDev**	**Median**	**Q1**	**Q3**	**Skewness**	**Kurtosis**	**Min**	**Max**
RPROD (8)	0.13	1.25	0.04	−0.47	0.84	−0.07	3.70	−3.36	3.56
CREG (9)	0.62	9.46	−0.05	−2.52	4.28	0.50	5.78	−24.86	38.13
UNEM (10)	0.02	0.35	0.00	−0.20	0.30	0.04	2.59	−0.80	0.80
CPI (11)	−0.09	0.88	−0.04	−0.50	0.42	0.13	4.27	−2.64	2.38
PPI (12)	0.03	1.35	0.03	−0.74	0.80	−0.10	4.07	−3.79	3.80
CONPROD (13)	0.67	7.09	−0.93	−5.23	6.11	0.62	2.07	−10.47	15.73
LONGR (14)	−0.56	0.31	−0.07	−0.24	0.13	−0.02	2.67	−0.81	0.67
STOCK (15)	2.27	9.98	3.84	−1.51	7.88	−2.09	11.56	−50.96	19.97
LEAD (16)	−0.07	1.70	0.11	−1.05	0.93	−0.87	4.46	−5.61	3.95
Predictors—Denmark specific factors	**Mean**	**StDev**	**Median**	**Q1**	**Q3**	**Skewness**	**Kurtosis**	**Min**	**Max**
RPROD (8)	0.28	1.13	0.34	−0.27	0.76	0.31	5.61	−2.91	4.67
CREG (9)	0.63	11.11	1.44	−4.24	5.54	−0.25	8.38	−44.42	45.28
UNEM (10)	0.02	0.61	0.10	−0.60	0.45	0.24	2.68	−1.20	1.80
CPI (11)	−0.02	0.42	−0.03	−0.27	0.25	−0.24	3.88	−1.26	1.05
PPI (12)	0.01	0.84	0.01	−0.49	0.57	−0.76	5.20	−3.46	1.52
CONPROD (13)	0.40	6.48	0.16	−4.54	5.95	−0.16	2.28	−14.07	15.70
LONGR (14)	−0.07	0.28	−0.08	−0.25	0.17	0.03	2.37	−0.65	0.51
STOCK (15)	1.94	8.37	3.33	−1.55	7.58	−1.80	9.07	−39.43	15.39
LEAD (16)	−0.05	1.23	0.05	−0.58	0.76	−0.64	4.79	−3.92	3.25

TABLE A2 (Continued)

Predictors—Netherlands specific factors	Mean	StDev	Median	Q1	Q3	Skewness	Kurtosis	Min	Max
RPROD (8)	0.17	0.98	0.22	−0.36	0.73	−0.51	4.69	−3.32	2.86
CREG (9)	−0.26	45.61	9.41	−19.34	19.76	−0.81	4.74	−155.33	123.98
UNEM (10)	0.02	0.45	0.00	−0.33	0.23	0.84	4.47	−0.70	1.80
CPI (11)	−0.02	0.45	−0.03	−0.28	0.22	−0.32	3.43	−1.33	0.86
PPI (12)	0.07	2.32	0.09	−0.93	1.18	−0.63	6.37	−9.86	6.11
CONPROD (13)	0.29	10.47	3.59	−7.39	7.95	−0.56	2.03	−19.38	16.80
LONGR (14)	−0.06	0.25	−0.10	−0.24	0.15	0.02	2.60	−0.72	0.51
STOCK (15)	0.22	8.62	1.76	−2.66	5.78	−2.09	9.75	−41.89	13.39
LEAD (16)	−0.10	1.95	−0.07	−1.05	0.96	0.01	5.50	−5.85	6.93
Predictors—US specific factors	**Mean**	**StDev**	**Median**	**Q1**	**Q3**	**Skewness**	**Kurtosis**	**Min**	**Max**
RPROD (8)	0.50	0.76	0.47	−0.004	0.83	1.28	7.35	−1.04	3.99
CREG (9)	−1.00	9.39	−1.67	−3.61	2.98	−0.21	10.71	−43.27	37.06
UNEM (10)	0.02	1.19	−0.10	−0.20	0.07	5.14	46.19	−4.13	9.17
CPI (11)	0.02	0.87	0.05	−0.37	0.37	−0.06	7.85	−3.54	3.10
PPI (12)	0.14	3.70	0.07	−1.45	1.83	0.05	6.95	−14.01	13.60
CONPROD (13)	0.80	2.63	1.44	−1.06	2.66	−0.61	2.98	−6.58	6.40
LONGR (14)	−0.04	0.34	−0.02	−0.26	0.17	−0.02	2.86	−0.83	0.72
STOCK (15)	0.52	0.58	0.59	0.33	0.81	−1.67	9.40	−2.32	1.81
LEAD (16)	−0.10	1.68	0.24	−1.00	0.76	−0.77	5.22	−5.82	4.16

Note: The table reports summary statistics for the dependent variables (individual country real GDP growth rates), as well as the common and country-specific predictor variables.

TABLE A3 Probabilities of inclusion of the predictor variables in the linear regression model specifications for the real GDP growth series for different countries.

Predictor variables	Germany	France	Italy	Spain	Greece	Belgium
$RGDP_{t-1}$ (1)	0.96	0.35	0.91	1.00	0.36	0.75
$RGDP_{t-2}$ (2)	0.99	0.99	1.00	0.99	0.32	0.99
$RGDP_{t-3}$ (3)	0.37	0.44	0.67	0.38	0.44	0.36
$RGDP_{t-4}$ (4)	0.37	0.37	0.36	0.53	0.41	0.37
OIL (5)	0.39	0.30	0.35	0.37	0.32	0.36
WUI (6)	0.40	0.34	0.37	0.35	0.34	0.36
WPI (7)	0.99	0.99	1.00	1.00	1.00	1.00
RPROD (8)	0.37	0.99	0.40	0.35	0.30	0.99
CREG (9)	0.39	0.35	0.40	0.47	0.42	0.37
UNEM (10)	0.58	0.33	0.46	0.99	0.50	0.52
CPI (11)	0.41	0.32	0.41	0.33	0.46	0.41
PPI (12)	0.39	0.36	0.34	0.40	0.44	0.48
CONPROD (13)	0.40	0.33	0.39	0.35	0.29	0.38
LONGR (14)	0.35	0.32	0.32	0.34	0.35	0.35
STOCK (15)	0.55	0.32	0.37	0.34	0.31	0.41
LEAD (16)	0.96	0.37	0.89	0.35	0.33	0.48
Predictor variables	**Finland**	**Sweden**	**Norway**	**Denmark**	**The Netherlands**	**USA**
$RGDP_{t-1}$ (1)	0.50	0.96	0.90	0.60	0.98	0.30
$RGDP_{t-2}$ (2)	0.29	0.86	0.95	0.45	0.99	0.31
$RGDP_{t-3}$ (3)	0.66	0.34	0.33	0.46	0.49	0.54
$RGDP_{t-4}$ (4)	0.29	0.33	0.30	0.30	0.37	0.30
OIL (5)	0.37	0.34	0.34	0.29	0.36	0.37
WUI (6)	0.35	0.35	0.40	0.33	0.40	0.30
WPI (7)	0.62	0.98	0.86	0.91	0.99	0.82
RPROD (8)	0.49	0.49	0.34	0.30	0.33	0.86
CREG (9)	0.27	0.46	0.54	0.39	0.35	0.45
UNEM (10)	0.28	0.35	0.29	0.29	0.39	0.50
CPI (11)	0.31	0.35	0.41	0.33	0.36	0.38
PPI (12)	0.46	0.40	0.39	0.30	0.36	0.58
CONPROD (13)	0.34	0.36	0.29	0.33	0.35	0.28
LONGR (14)	0.29	0.34	0.29	0.28	0.33	0.29
STOCK (15)	0.52	0.46	0.37	0.60	0.65	0.31
LEAD (16)	0.53	0.96	0.69	0.44	0.75	0.55

Note: The table reports the probabilities of inclusion of each predictor variable in the linear regression model specification for the analyzed real GDP growth, obtained from the Bayesian stochastic search algorithm, based on the sample period (from 2001:Q2 to 2021:Q3). The predictor variables are the real GDP growth lagged once ($RGDP_{t-1}$), the real GDP growth lagged twice ($RGDP_{t-2}$), the real GDP growth lagged thrice ($RGDP_{t-3}$), the real GDP growth lagged four times ($RGDP_{t-4}$), the WTI oil price (OIL), the World Uncertainty Index (WUI), the World Pandemic Uncertainty Index (WPI), the real productivity growth (RPROD), the change in car registrations (CREG), the rate of unemployment (UNEM), the growth in the Consumer Price Index (CPI), the growth in the Producer Price Index (PPI), the Construction Volume Index of Production (CONPROD), the long-run interest rate (LONGR), the stock index return (STOCK), and the change in the OECD Leading Indicator (LEAD).

TABLE A4 Probabilities of inclusion of the predictor variables in the quantile regression model specifications for the real GDP growth series for different countries.

	Germany					France				
Predictor variables	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
$RGDP_{t-1}$ (1)	0.58	0.38	0.47	0.87	0.99	0.50	0.38	0.32	0.40	0.51
$RGDP_{t-2}$ (2)	0.55	0.56	0.64	0.97	0.99	0.91	1.00	0.55	0.43	1.00
$RGDP_{t-3}$ (3)	0.97	0.59	0.40	0.35	0.62	0.48	0.39	0.36	0.37	0.55
$RGDP_{t-4}$ (4)	0.70	0.29	0.33	0.41	0.46	0.64	0.84	0.42	0.32	0.41
OIL (5)	0.82	0.39	0.31	0.32	0.39	0.34	0.33	0.28	0.30	0.40
WUI (6)	0.51	0.45	0.39	0.39	0.46	0.35	0.30	0.28	0.29	0.34
WPI (7)	1.00	0.55	0.32	0.37	0.43	1.00	1.00	0.58	0.33	0.48
RPROD (8)	0.51	0.51	0.45	0.43	0.50	0.65	0.49	0.56	0.72	0.97
CREG (9)	0.67	0.30	0.40	0.43	0.42	0.37	0.32	0.29	0.29	0.36
UNEM (10)	0.46	0.35	0.38	0.50	0.57	0.36	0.30	0.30	0.29	0.46
CPI (11)	0.47	0.33	0.32	0.36	0.53	0.35	0.36	0.28	0.29	0.48
PPI (12)	0.53	0.31	0.31	0.39	0.50	0.33	0.32	0.30	0.28	0.35
CONPROD (13)	0.43	0.30	0.33	0.37	0.43	0.37	0.31	0.27	0.30	0.34
LONGR (14)	0.57	0.28	0.37	0.40	0.59	0.33	0.33	0.41	0.41	0.35
STOCK (15)	0.50	0.49	0.58	0.44	0.50	0.35	0.39	0.57	0.53	0.56
LEAD (16)	0.64	0.82	0.91	1.00	0.99	0.73	0.81	0.51	0.39	0.38
	Italy					**Spain**				
Predictor variables	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
$RGDP_{t-1}$ (1)	0.55	0.40	0.34	0.43	0.96	0.63	0.78	0.44	0.39	1.00
$RGDP_{t-2}$ (2)	0.85	0.96	0.55	0.42	0.99	0.71	0.77	0.31	0.36	1.00
$RGDP_{t-3}$ (3)	0.52	0.41	0.43	0.42	0.98	0.78	0.95	0.59	0.46	1.00
$RGDP_{t-4}$ (4)	0.50	0.49	0.33	0.29	0.80	0.99	0.98	0.68	0.44	0.36
OIL (5)	0.43	0.35	0.27	0.28	0.43	0.42	0.35	0.28	0.29	0.37
WUI (6)	0.35	0.32	0.30	0.38	0.43	0.38	0.36	0.29	0.28	0.60
WPI (7)	1.00	1.00	0.84	0.56	0.86	1.00	0.99	0.45	0.30	0.52
RPROD (8)	0.39	0.41	0.30	0.26	0.41	0.60	0.57	0.31	0.31	0.69
CREG (9)	0.37	0.37	0.28	0.34	0.47	0.62	0.57	0.33	0.29	0.38
UNEM (10)	0.54	0.33	0.32	0.29	0.54	0.71	0.69	0.86	0.59	0.85
CPI (11)	0.47	0.38	0.30	0.35	0.77	0.46	0.37	0.28	0.31	0.42
PPI (12)	0.53	0.62	0.32	0.33	0.40	0.38	0.34	0.34	0.28	0.35
CONPROD (13)	0.42	0.34	0.30	0.30	0.43	0.37	0.31	0.29	0.28	0.33
LONGR (14)	0.37	0.34	0.29	0.29	0.41	0.35	0.41	0.30	0.32	0.36
STOCK (15)	0.44	0.41	0.36	0.36	0.57	0.42	0.36	0.35	0.31	0.45
LEAD (16)	0.91	0.94	0.64	0.46	0.92	0.64	0.49	0.34	0.33	0.38
	Greece					**Belgium**				
Predictor variables	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
$RGDP_{t-1}$ (1)	0.52	0.34	0.28	0.34	0.61	0.43	0.41	0.31	0.40	0.97
$RGDP_{t-2}$ (2)	0.37	0.51	0.60	0.44	0.49	0.98	0.99	0.55	0.54	0.97
$RGDP_{t-3}$ (3)	0.85	0.77	0.49	0.35	0.41	0.42	0.43	0.32	0.31	0.94
$RGDP_{t-4}$ (4)	0.62	0.40	0.33	0.31	0.50	0.46	0.52	0.30	0.33	0.84

(Continues)

TABLE A4 (Continued)

Predictor variables	Germany $Q_{0.10}$	Germany $Q_{0.25}$	Germany $Q_{0.50}$	Germany $Q_{0.75}$	Germany $Q_{0.90}$	France $Q_{0.10}$	France $Q_{0.25}$	France $Q_{0.50}$	France $Q_{0.75}$	France $Q_{0.90}$
OIL (5)	0.44	0.34	0.28	0.35	0.43	0.42	0.38	0.28	0.28	0.38
WUI (6)	0.39	0.31	0.33	0.30	0.37	0.36	0.32	0.28	0.32	0.45
WPI (7)	1.00	0.98	0.56	0.40	0.35	1.00	1.00	0.72	0.55	0.81
RPROD (8)	0.45	0.31	0.28	0.32	0.59	0.54	0.65	0.52	0.59	0.92
CREG (9)	0.46	0.49	0.45	0.33	0.45	0.39	0.35	0.29	0.36	0.41
UNEM (10)	0.50	0.53	0.54	0.67	0.99	0.59	0.55	0.36	0.28	0.34
CPI (11)	0.39	0.35	0.32	0.30	0.66	0.47	0.35	0.33	0.31	0.37
PPI (12)	0.36	0.32	0.31	0.49	0.60	0.42	0.44	0.29	0.30	0.37
CONPROD (13)	0.42	0.34	0.31	0.33	0.32	0.35	0.34	0.28	0.27	0.43
LONGR (14)	0.35	0.30	0.29	0.38	0.74	0.35	0.32	0.27	0.32	0.40
STOCK (15)	0.75	0.41	0.30	0.31	0.53	0.67	0.53	0.48	0.51	0.61
LEAD (16)	0.33	0.33	0.31	0.35	0.39	0.79	0.78	0.52	0.46	0.76
$RGDP_{t-1}$ (1)	0.42	0.33	0.32	0.48	0.95	0.38	0.33	0.35	0.81	1.00
$RGDP_{t-2}$ (2)	0.40	0.35	0.27	0.33	0.43	0.90	0.37	0.33	0.41	0.73
$RGDP_{t-3}$ (3)	1.00	0.94	0.78	0.53	0.37	0.42	0.32	0.34	0.41	0.78
$RGDP_{t-4}$ (4)	0.44	0.29	0.29	0.31	0.37	0.53	0.31	0.31	0.38	0.49
OIL (5)	0.99	0.40	0.29	0.32	0.50	0.34	0.32	0.38	0.40	0.49
WUI (6)	0.40	0.37	0.34	0.38	0.55	0.72	0.30	0.29	0.35	0.49
WPI (7)	0.99	0.63	0.30	0.52	0.99	1.00	0.53	0.32	0.35	0.56
RPROD (8)	0.44	0.35	0.41	0.45	0.66	0.46	0.32	0.33	0.49	0.60
CREG (9)	0.45	0.31	0.29	0.40	0.63	0.39	0.31	0.32	0.36	0.37
UNEM (10)	0.42	0.34	0.29	0.35	0.43	0.72	0.28	0.28	0.35	0.46
CPI (11)	0.37	0.39	0.31	0.37	0.59	0.49	0.36	0.31	0.40	0.43
PPI (12)	0.41	0.43	0.35	0.30	0.37	0.96	0.32	0.33	0.37	0.39
CONPROD (13)	0.61	0.32	0.30	0.31	0.52	0.37	0.30	0.29	0.35	0.41
LONGR (14)	0.36	0.30	0.33	0.30	0.45	0.36	0.33	0.31	0.42	0.58
STOCK (15)	0.60	0.34	0.40	0.40	0.51	0.37	0.66	0.43	0.49	0.53
LEAD (16)	0.72	0.74	0.67	0.72	0.92	0.99	0.95	0.97	0.93	1.00

Predictor variables	Norway $Q_{0.10}$	Norway $Q_{0.25}$	Norway $Q_{0.50}$	Norway $Q_{0.75}$	Norway $Q_{0.90}$	Denmark $Q_{0.10}$	Denmark $Q_{0.25}$	Denmark $Q_{0.50}$	Denmark $Q_{0.75}$	Denmark $Q_{0.90}$
$RGDP_{t-1}$ (1)	0.85	0.89	0.86	1.00	1.00	0.42	0.31	0.28	0.40	0.99
$RGDP_{t-2}$ (2)	0.99	0.98	0.70	0.68	0.66	0.49	0.33	0.30	0.33	0.59
$RGDP_{t-3}$ (3)	0.40	0.38	0.35	0.33	0.42	1.00	0.47	0.43	0.56	0.40
$RGDP_{t-4}$ (4)	0.36	0.39	0.36	0.31	0.41	0.41	0.35	0.38	0.35	0.34
OIL (5)	0.38	0.35	0.39	0.42	0.38	0.48	0.30	0.30	0.30	0.37
WUI (6)	0.35	0.32	0.38	0.52	0.62	0.53	0.34	0.29	0.33	0.52
WPI (7)	0.99	0.75	0.34	0.32	0.40	1.00	0.62	0.31	0.36	0.57
RPROD (8)	0.45	0.39	0.36	0.43	0.60	0.39	0.40	0.36	0.47	0.44
CREG (9)	0.44	0.46	0.59	0.64	0.72	0.56	0.38	0.29	0.31	0.35
UNEM (10)	0.49	0.33	0.28	0.33	0.36	0.38	0.29	0.30	0.30	0.38
CPI (11)	0.35	0.38	0.49	0.72	0.72	0.82	0.48	0.36	0.37	0.37

TABLE A4 (Continued)

Predictor variables	Germany $Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$	France $Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
PPI (12)	0.36	0.42	0.45	0.34	0.44	0.37	0.31	0.39	0.37	0.37
CONPROD (13)	0.38	0.30	0.27	0.32	0.36	0.38	0.35	0.29	0.29	0.40
LONGR (14)	0.36	0.32	0.28	0.30	0.35	0.40	0.28	0.30	0.30	0.37
STOCK (15)	0.37	0.38	0.35	0.37	0.36	0.52	0.59	0.42	0.44	0.85
LEAD (16)	0.89	0.93	0.73	0.57	0.99	0.88	0.66	0.49	0.45	0.35

Predictor variables	Netherlands $Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$	USA $Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
$RGDP_{t-1}$ (1)	0.69	0.65	0.34	0.38	0.99	0.38	0.31	0.34	0.35	0.34
$RGDP_{t-2}$ (2)	0.57	0.58	0.33	0.39	0.99	0.51	0.36	0.32	0.32	0.37
$RGDP_{t-3}$ (3)	1.00	0.99	0.61	0.74	0.41	0.56	0.85	0.57	0.40	0.42
$RGDP_{t-4}$ (4)	0.55	0.57	0.28	0.30	0.40	0.39	0.32	0.30	0.37	0.40
OIL (5)	0.65	0.39	0.28	0.34	0.69	0.93	0.39	0.30	0.31	0.53
WUI (6)	0.43	0.35	0.37	0.43	0.39	0.50	0.30	0.44	0.41	0.39
WPI (7)	1.00	0.99	0.44	0.45	0.90	1.00	0.75	0.34	0.33	0.42
RPROD (8)	0.40	0.37	0.43	0.34	0.54	0.52	0.59	0.67	0.63	0.42
CREG (9)	0.35	0.33	0.28	0.28	0.36	0.46	0.39	0.31	0.36	0.47
UNEM (10)	0.37	0.36	0.29	0.33	0.42	0.40	0.37	0.45	0.63	0.87
CPI (11)	0.37	0.33	0.28	0.36	0.35	0.42	0.35	0.42	0.73	1.00
PPI (12)	0.44	0.35	0.28	0.31	0.42	0.48	0.42	0.57	0.83	1.00
CONPROD (13)	0.45	0.40	0.31	0.34	0.36	0.42	0.28	0.34	0.39	0.37
LONGR (14)	0.55	0.35	0.28	0.30	0.36	0.35	0.34	0.29	0.29	0.35
STOCK (15)	0.66	0.75	0.74	0.60	0.44	0.40	0.37	0.31	0.32	0.37
LEAD (16)	0.74	0.48	0.48	0.59	0.96	0.76	0.37	0.41	0.48	0.37

Note: The table reports the probabilities of inclusion of each predictor variable in the quantile regression model specification for the analyzed real GDP growth, obtained from the Bayesian stochastic search algorithm based on the sample period from 2001:Q2 to 2021:Q3. The predictor variables are the real GDP growth lagged once ($RGDP_{t-1}$), the real GDP growth lagged twice ($RGDP_{t-2}$), the real GDP growth lagged thrice ($RGDP_{t-3}$), the real GDP growth lagged four times ($RGDP_{t-4}$), the WTI oil price (OIL), the World Uncertainty Index (WUI), the World Pandemic Uncertainty Index (WPI), the real productivity growth (RPROD), the change in car registrations (CREG), the rate of unemployment (UNEM), the growth in the Consumer Price Index (CPI), the growth in the Producer Price Index (PPI), the Construction Volume Index of Production (CONPROD), the long-run interest rate (LONGR), the stock index return (STOCK), and the change in the OECD Leading Indicator (LEAD).

TABLE A5 Predictive linear regression model specifications obtained by different model selection approaches for the real GDP growth series of each analyzed country.

Strategies	Germany Models	France Models	Italy Models
STEP	1 2 7 10 16	2 7 8	1 2 3 7 16
AIC	1 2 7 10 11 13 15 16	1 2 3 7 8 16	1 2 3 7 8 11 16
BIC	1 2 7 10 16	2 7 8	1 2 3 7 16
MP	1 2 7 10 16	2 7 8	1 2 3 7 16
Strategies	**Spain Models**	**Greece Models**	**Belgium Models**
STEP	1 2 4 7 10	7 10	1 2 7 8 16
AIC	1 2 4 7 9 10 12	1 3 7 9 10 11 12	1 2 3 4 7 8 10 11 12 15 16
BIC	1 2 4 7 10	7 10	1 2 7 8 16
MP	1 2 4 7 10	7 10	1 2 7 8 16
Strategies	**Finland Models**	**Sweden Models**	**Norway Models**
STEP	3 7 12 16	1 2 7 16	1 2 7 9 16
AIC	1 3 7 8 12 13 15 16	1 2 7 8 9 12 15 16	1 2 6 7 9 11 16
BIC	3 7 16	1 2 7 16	1 2 7 9 16
MP	3 7 16	1 2 7 16	1 2 7 9 16
Strategies	**Denmark Models**	**The Netherlands Models**	**USA Models**
STEP	1 3 7 9 15	1 2 7 15 16	7 8 12 16
AIC	1 2 3 7 13 15 16	1 2 3 7 10 15 16	3 7 8 9 10 11 12
BIC	1 2 7 15 16	1 2 7 15 16	3 7 8 9 10 12
MP	1 2 7 15 16	1 2 7 15 16	3 7 8 9 10 12

Note: The table reports the linear regression model specifications that predict real GDP growth, obtained from four model selection approaches, namely, stepwise regression (STEP), the Akaike (1973) information criterion (AIC), the Schwarz (1978) Bayesian information criterion (BIC), and the Bayesian stochastic model search most probable (MP) model based on the sample period (from 2001:Q2 to 2021:Q3). Model specifications are identified by the numbers associated with the corresponding predictor variables. Thus, 1 is the real GDP growth lagged once ($RGDP_{t-1}$), 2 is the real GDP growth lagged twice ($RGDP_{t-2}$), 3 is the real GDP growth lagged thrice ($RGDP_{t-3}$), 4 is the real GDP growth lagged four times ($RGDP_{t-4}$), 5 is the WTI oil price (OIL), 6 is the World Uncertainty Index (WUI), 7 is the World Pandemic Uncertainty Index (WPI), 8 is real productivity growth (RPROD), 9 is the change in car registrations (CREG), 10 is the rate of unemployment (UNEM), 11 is the growth in the Consumer Price Index (CPI), 12 is the growth in the Producer Price Index (PPI), 13 is the change Construction Volume Index of Production (CONPROD), 14 is the long-run interest rates (LONGR), 15 is the stock index return (STOCK), and 16 is the change in the OECD Leading Indicator (LEAD).

TABLE A6 Predictive quantile regression model specifications obtained by different model selection approaches for the real GDP growth for the analyzed countries.

Countries	Quantiles	AIC	BIC	MP
Germany	$Q_{0.10}$	1 2 3 5 7 8 9 10 11 14 15 16	3 5 6 7 8 9 13 16	3 5 6 7 8 9 13 16
	$Q_{0.25}$	2 3 6 7 11 16	2 3 7 16	2 3 7 16
	$Q_{0.50}$	1 2 6 9 10 12 15 16	1 2 15 16	1 2 15 16
	$Q_{0.75}$	1 2 3 4 10 12 13 16	1 2 10 16	1 2 10 16
	$Q_{0.90}$	1 2 3 4 6 7 8 11 12 13 14 15 16	1 2 4 8 10 11 13 14 16	1 2 4 8 10 11 13 14 16
France	$Q_{0.10}$	1 2 4 7 8 16	2 4 7 16	2 4 7 16
	$Q_{0.25}$	2 4 7 8 16	2 4 7 16	2 4 7 16
	$Q_{0.50}$	2 4 7 8 15 16	2 4 7 8 16	2 4 7 8 16
	$Q_{0.75}$	1 2 8 15	2 8	2 8
	$Q_{0.90}$	1 2 3 5 7 8 10 12 15	1 2 3 7 8 15	1 2 3 7 8 15
Italy	$Q_{0.10}$	1 3 4 7 8 10 11 12 16	2 7 10 15 16	2 7 10 15 16
	$Q_{0.25}$	2 3 4 7 8 9 11 12 16	2 7 12 16	2 7 12 16
	$Q_{0.50}$	2 3 4 7 15 16	2 7 16	2 7 16
	$Q_{0.75}$	1 2 7 15 16	3 7	3 7
	$Q_{0.90}$	1 2 3 4 5 6 7 11 13 14 15 16	1 2 3 4 7 9 11 16	1 2 3 4 7 9 11 16
Spain	$Q_{0.10}$	1 2 3 4 7 8 9 10 11 15 16	1 3 4 7 8 9 11 16	1 3 4 7 8 9 11 16
	$Q_{0.25}$	1 2 3 4 7 8 9 10 16	1 2 3 4 7 8 9 10	1 2 3 4 7 8 9 10
	$Q_{0.50}$	1 3 4 7 10 15	4 10	4 10
	$Q_{0.75}$	3 4 10	10	10
	$Q_{0.90}$	1 2 3 6 7 8 10 12 14 15	1 2 3 6 8 10	1 2 3 6 8 10
Greece	$Q_{0.10}$	1 3 4 5 7 8 13 15	1 3 4 7 15	1 3 4 7 15
	$Q_{0.25}$	2 3 7 9 10 11	2 3 7 9	2 3 7 9
	$Q_{0.50}$	2 3 7 9 10 11 16	2 10	2 10
	$Q_{0.75}$	1 2 8 10 12	10 12	10 12
	$Q_{0.90}$	1 4 5 8 9 10 11 12 14 15	1 4 5 8 10 11 14 15	1 4 5 8 10 11 14 15
Belgium	$Q_{0.10}$	2 4 7 10 11 15 16	2 4 7 10 11 15 16	2 4 7 10 11 15 16
	$Q_{0.25}$	2 7 8 10 12 15 16	2 7 8 10 15 16	2 7 8 10 15 16
	$Q_{0.50}$	2 7 8 10 12 16	2 7 8 10 16	2 7 8 10 16
	$Q_{0.75}$	1 2 3 7 8 15 16	2 7 8 16	2 7 8 16
	$Q_{0.90}$	1 2 3 4 5 6 7 8 12 13 15 16	1 2 3 4 7 8 15 16	1 2 3 4 7 8 15 16
Finland	$Q_{0.10}$	1 3 4 5 6 7 8 9 11 12 13 15 16	3 5 7 9 13 15 16	3 5 7 9 13 15 16
	$Q_{0.25}$	2 3 6 7 10 11 12 16	3 7 16	3 7 16
	$Q_{0.50}$	1 3 8 13 15 16	3 16	3 16
	$Q_{0.75}$	1 2 6 7 8 9 11 13 15 16	3 16	3 16
	$Q_{0.90}$	1 2 5 6 7 8 9 11 12 13 15 16	1 6 7 8 9 11 13 15 16	1 6 7 8 9 11 13 15 16
Sweden	$Q_{0.10}$	2 4 6 7 10 11 12 16	2 4 6 7 10 11 12 16	2 4 6 7 10 11 12 16
	$Q_{0.25}$	5 7 15 16	7 15 16	7 15 16
	$Q_{0.50}$	5 15 16	16	16
	$Q_{0.75}$	1 2 3 4 5 6 8 14 15 16	1 15 16	1 15 16
	$Q_{0.90}$	1 2 3 5 8 13 14 15 16	1 2 3 5 6 8 16	1 2 3 5 6 8 16

(Continues)

TABLE A6 (Continued)

Countries	Quantiles	AIC	BIC	MP
Norway	$Q_{0.10}$	1 2 7 9 10 16	1 2 7 10 16	1 2 7 10 16
	$Q_{0.25}$	1 2 4 7 9 12 16	1 2 7 12 16	1 2 7 12 16
	$Q_{0.50}$	1 2 4 8 9 12 15 16	1 2 6 9 11 16	1 2 6 9 11 16
	$Q_{0.75}$	1 2 6 9 11 16	1 2 6 9 11 16	1 2 6 9 11 16
	$Q_{0.90}$	1 2 3 6 7 8 9 11 14 16	1 2 3 6 7 8 9 11 16	1 2 3 6 7 8 9 11 16
Denmark	$Q_{0.10}$	2 3 6 7 8 11 14 16	2 3 6 7 8 11 14 16	2 3 6 7 8 11 14 16
	$Q_{0.25}$	2 3 7 8 11 15 16	3 7 15	3 7 15
	$Q_{0.50}$	8 11 12 16	16	16
	$Q_{0.75}$	1 3 8 9 11 15 16	3	3
	$Q_{0.90}$	1 3 5 6 7 8 11 15	1 6 7 15	1 6 7 15
The Netherlands	$Q_{0.10}$	1 2 3 4 5 6 7 8 14 15 16	2 3 5 7 16	2 3 5 7 16
	$Q_{0.25}$	1 2 3 4 6 7 8 12 13 14 15 16	1 2 3 7 15	1 2 3 7 15
	$Q_{0.50}$	1 2 3 7 8 15 16	3 7 15	3 7 15
	$Q_{0.75}$	3 6 7 13 15	3 6 7 13 15	3 6 7 13 15
	$Q_{0.90}$	1 2 5 7 8 15 16	1 2 5 7 8 16	1 2 5 7 8 16
USA	$Q_{0.10}$	1 2 3 5 7 8 12 13 14 15 16	5 6 7 8 16	5 6 7 8 16
	$Q_{0.25}$	3 5 7 9 10 11 15	3 7 8 12	3 7 8 12
	$Q_{0.50}$	3 8 11 12 16	8 11 12 16	8 11 12 16
	$Q_{0.75}$	2 6 8 10 11 12 16	8 10 11 12 16	8 10 11 12 16
	$Q_{0.90}$	3 5 9 10 11 12 13	5 9 10 11 12	5 9 10 11 12

Note: This table reports the quantile regression model specifications that predict the real GDP growth, obtained from three model selection approaches, namely, Akaike (1973) information criterion (AIC), Schwarz (1978) Bayesian information criterion (BIC), and Bayesian "Exact" method that calculates the posterior model probabilities. These metrics (AIC, BIC, and posterior model probabilities) calculated for the collection of all 2^K competitive models and then "single" best models were derived based on the sample period from 2001:Q2 to 2021:Q3. Model specifications are identified by the numbers associated with the corresponding predictor variables. Thus, 1 is the real GDP growth lagged once ($RGDP_{t-1}$), 2 is the real GDP growth lagged twice ($RGDP_{t-2}$), 3 is the real GDP growth lagged thrice ($RGDP_{t-3}$), 4 is the real GDP growth lagged four times ($RGDP_{t-4}$), 5 is the WTI oil price (OIL), 6 is the World Uncertainty Index (WUI), 7 is the World Pandemic Uncertainty Index (WPI), 8 is real productivity growth (RPROD), 9 is the change in car registrations (CREG), 10 is the rate of unemployment (UNEM), 11 is the growth in the Consumer Price Index (CPI), 12 is the growth in the Producer Price Index (PPI), 13 is the change Construction Volume Index of Production (CONPROD), 14 is the long-run interest rates (LONGR), 15 is the stock index return (STOCK), and 16 is the change in the OECD Leading Indicator (LEAD).

TABLE A7 Predictors identified by LASSO predictive regression modes for the real GDP growth series.

Predictor variables	Germany	France	Italy	Spain	Greece	Belgium
α	0.496	0.120	0.095	0.770	0.063	0.931
$RGDP_{t-1}$ (1)	−0.424		−0.326	−0.480	−0.077	−0.401
$RGDP_{t-2}$ (2)	−0.510	−0.564	−0.488	−0.684		−1.199
$RGDP_{t-3}$ (3)	0.007	−0.017	−0.042		0.132	−0.115
$RGDP_{t-4}$ (4)		0.042	0.025	0.130	0.089	−0.127
OIL (5)			−0.002			0.001
WUI (6)	−0.003		−0.006	−0.002	−0.004	−0.0001
WPI (7)	−0.419	−0.612	−0.640	−1.096	−0.556	−0.936
RPROD (8)	−0.022	1.816	0.217	0.131		1.031
CREG (9)				0.044	0.015	0.015
UNEM (10)	−0.918		1.593	−1.096	−0.528	−0.700
CPI (11)	−0.132	−0.042	0.246		−0.556	0.313
PPI (12)				−0.084	0.093	−0.125
CONPROD (13)	0.004		0.015			0.016
LONGR (14)			0.076		0.428	−0.039
STOCK (15)	0.030		0.007			0.026
LEAD (16)	0.267		0.365		−0.099	0.156

Predictor variables	Finland	Sweden	Norway	Denmark	The Netherlands	USA
α	0.262	0.770	0.693	0.322	0.526	−0.018
$RGDP_{t-1}$ (1)	−0.148	−0.295	−0.362	−0.168	−0.258	
$RGDP_{t-2}$ (2)		−0.162	−0.360	−0.056	−0.360	
$RGDP_{t-3}$ (3)	0.209			0.104	0.146	0.117
$RGDP_{t-4}$ (4)					0.015	
OIL (5)						0.005
WUI (6)	−0.002	−0.0001	−0.002	−0.001	−0.002	
WPI (7)	−0.131	−0.261	−0.154	−0.188	−0.380	−0.168
RPROD (8)	0.182					0.653
CREG (9)		0.003	0.017	0.004		0.007
UNEM (10)						0.138
CPI (11)			−0.121		0.077	
PPI (12)	0.177		−0.042			0.069
CONPROD (13)	0.004	0.004		0.005	−0.006	
LONGR (14)						
STOCK (15)	0.021	0.023		0.030	0.034	
LEAD (16)	0.159	0.262	0.171	0.051	0.072	0.116

Note: The table reports the predictor variables identified by the LASSO predictive regression model for the analyzed countries. The predictor variables are: the real GDP growth lagged once ($RGDP_{t-1}$), the real GDP growth lagged twice ($RGDP_{t-2}$), the real GDP growth lagged thrice ($RGDP_{t-3}$), the real GDP growth lagged four times ($RGDP_{t-4}$), the WTI oil price (OIL), the World Uncertainty Index (WUI), the World Pandemic Uncertainty Index (WPI), the real productivity growth (RPROD), the change in car registrations (CREG), the rate of unemployment (UNEM), the growth in the Consumer Price Index (CPI), the growth in the Producer Price Index (PPI), the Construction Volume Index of Production (CONPROD), the long-run interest rate (LONGR), the stock index return (STOCK), and the change in the OECD Leading Indicator (LEAD).

TABLE A8 Predictors identified by RIDGE predictive regression modes for the real GDP growth series.

Predictor variables	Germany	France	Italy	Spain	Greece	Belgium
α	0.492	0.267	0.130	0.979	0.103	0.783
$RGDP_{t-1}$ (1)	−0.462	−0.134	−0.370	−0.521	−0.231	−0.348
$RGDP_{t-2}$ (2)	−0.549	−0.695	−0.646	−0.681	0.011	−0.919
$RGDP_{t-3}$ (3)	0.058	−0.098	−0.154	−0.028	0.226	−0.051
$RGDP_{t-4}$ (4)	0.046	0.026	0.024	0.148	0.114	−0.052
OIL (5)	0.015	0.011	−0.024	−0.005	0.002	−0.0002
WUI (6)	−0.006	0.001	−0.008	−0.005	−0.007	−0.003
WPI (7)	−0.450	−0.720	−0.744	−1.061	−0.608	−0.792
RPROD (8)	−0.213	1.736	0.285	0.280	0.088	0.856
CREG (9)	−0.007	0.006	−0.009	0.076	0.039	0.018
UNEM (10)	−1.394	0.242	1.689	−1.285	−0.712	−0.388
CPI (11)	−0.676	−0.288	0.825	−0.035	−0.719	0.161
PPI (12)	−0.263	−0.201	0.123	−0.111	0.106	−0.077
CONPROD (13)	0.008	0.009	0.026	0.012	0.002	0.010
LONGR (14)	0.098	0.182	0.129	0.053	0.614	−0.023
STOCK (15)	0.044	0.010	0.028	−0.020	−0.002	0.024
LEAD (16)	0.320	0.108	0.484	0.102	−0.267	0.110
Predictor variables	**Finland**	**Sweden**	**Norway**	**Denmark**	**Netherlands**	**USA**
α	0.243	0.920	0.672	0.362	0.566	0.111
$RGDP_{t-1}$ (1)	−0.330	−0.614	−0.426	−0.348	−0.418	−0.030
$RGDP_{t-2}$ (2)	−0.097	−0.305	−0.403	−0.185	−0.497	−0.085
$RGDP_{t-3}$ (3)	0.337	0.030	0.072	0.194	0.193	0.220
$RGDP_{t-4}$ (4)	0.082	0.025	0.008	−0.016	0.107	0.027
OIL (5)	0.001	−0.007	0.003	−0.0006	0.004	0.007
WUI (6)	−0.006	−0.002	−0.005	−0.002	−0.005	−0.002
WPI (7)	−0.180	−0.352	−0.192	−0.246	−0.430	−0.223
RPROD (8)	0.380	0.228	0.004	−0.009	0.030	0.605
CREG (9)	0.0003	0.016	0.031	0.018	−0.001	0.040
UNEM (10)	−0.049	0.019	0.394	0.147	−0.241	0.371
CPI (11)	−0.195	0.181	−0.213	−0.268	0.226	−0.226
PPI (12)	0.222	−0.138	−0.148	−0.080	−0.029	0.150
CONPROD (13)	0.008	0.007	0.009	0.028	−0.010	0.010
LONGR (14)	0.146	0.152	−0.022	−0.050	−0.269	0.010
STOCK (15)	0.030	0.033	0.005	0.039	0.048	−0.170
LEAD (16)	0.228	0.391	0.189	0.204	0.130	0.155

Note: The table reports the predictor variables identified by the RIDGE predictive regression model for the analyzed countries. The predictor variables are: the real GDP growth lagged once ($RGDP_{t-1}$), the real GDP growth lagged twice ($RGDP_{t-2}$), the real GDP growth lagged thrice ($RGDP_{t-3}$), the real GDP growth lagged four times ($RGDP_{t-4}$), the WTI oil price (OIL), the World Uncertainty Index (WUI), the World Pandemic Uncertainty Index (WPI), the real productivity growth (RPROD), the change in car registrations (CREG), the rate of unemployment (UNEM), the growth in the Consumer Price Index (CPI), the growth in the Producer Price Index (PPI), the Construction Volume Index of Production (CONPROD), the long-run interest rate (LONGR), the stock index return (STOCK), and the change in the OECD Leading Indicator (LEAD).

TABLE A9 Predictors identified by elastic net predictive regression modes for the real GDP growth series.

Predictor variables	Germany	France	Italy	Spain	Greece	Belgium
α	0.496	0.137	0.117	0.777	0.087	0.705
$RGDP_{t-1}$ (1)	−0.462		−0.373	−0.503	−0.156	−0.283
$RGDP_{t-2}$ (2)	−0.531	−0.598	−0.578	−0.674		−0.829
$RGDP_{t-3}$ (3)	0.035	−0.038	−0.101		0.180	
$RGDP_{t-4}$ (4)	0.006	0.051	0.024	0.144	0.102	
OIL (5)	0.005		−0.011	−0.002		
WUI (6)	−0.004		−0.007	−0.004	−0.005	−0.003
WPI (7)	−0.433	−0.646	−0.695	−1.079	−0.589	−0.775
RPROD (8)	−0.105	1.832	0.257	0.198	0.037	0.801
CREG (9)				0.062	0.027	0.009
UNEM (10)	−1.212		1.626	−1.179	−0.626	−0.219
CPI (11)	−0.407	−0.161	0.551	−0.006	−0.638	0.040
PPI (12)	−0.093	−0.008	0.012	−0.101	0.099	−0.033
CONPROD (13)	0.006	0.002	0.020	0.006	0.001	0.003
LONGR (14)			0.127	0.021	0.530	
STOCK (15)	0.037		0.020	−0.009		0.016
LEAD (16)	0.305	0.024	0.433	0.037	−0.181	0.074
Predictor variables	**Finland**	**Sweden**	**Norway**	**Denmark**	**Netherlands**	**USA**
α	0.261	0.868	0.690	0.358	0.555	0.005
$RGDP_{t-1}$ (1)	−0.245	−0.476	−0.385	−0.274	−0.335	
$RGDP_{t-2}$ (2)	−0.039	−0.244	−0.380	−0.136	−0.424	−0.022
$RGDP_{t-3}$ (3)	0.262	0.004	0.026	0.144	0.166	0.170
$RGDP_{t-4}$ (4)	0.006				0.069	
OIL (5)		−0.001				0.003
WUI (6)	−0.004	−0.001	−0.004	−0.002	−0.004	−0.001
WPI (7)	−0.152	−0.304	−0.171	−0.218	−0.408	−0.192
RPROD (8)	0.289	0.112				0.626
CREG (9)		0.010	0.023	0.011		0.025
UNEM (10)			0.118		−0.042	0.277
CPI (11)	−0.002	0.067	−0.151	−0.148	0.147	
PPI (12)	0.203	−0.058	−0.084	−0.002		0.083
CONPROD (13)	0.007	0.006		0.013	−0.010	
LONGR (14)	0.028					
STOCK (15)	0.026	0.028	0.003	0.032	0.040	
LEAD (16)	0.176	0.343	0.179	0.140	0.108	0.130

Note: The table reports the predictor variables identified by the elastic net predictive regression model for the analyzed countries. The predictor variables are: the real GDP growth lagged once ($RGDP_{t-1}$), the real GDP growth lagged twice ($RGDP_{t-2}$), the real GDP growth lagged thrice ($RGDP_{t-3}$), the real GDP growth lagged four times ($RGDP_{t-4}$), the WTI oil price (OIL), the World Uncertainty Index (WUI), the World Pandemic Uncertainty Index (WPI), the real productivity growth (RPROD), the change in car registrations (CREG), the rate of unemployment (UNEM), the growth in the Consumer Price Index (CPI), the growth in the Producer Price Index (PPI), the Construction Volume Index of Production (CONPROD), the long-run interest rate (LONGR), the stock index return (STOCK), and the change in the OECD Leading Indicator (LEAD).