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GREEK GDP REVISIONS AND SHORT-TERM FORECASTING

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ABSTRACT

Indicators of economic activity, such as gross domestic product (GDP), are usually published with a significant delay, meaning that central banks and ministries rely on estimates or predictions of the key economic indicators in order to conduct monetary and fiscal policy. The econometric methodology that is commonly used to provide a timely estimation of the current state of the economy is referred to as nowcasting and is based on the use of economic indicators that are published earlier and at a higher frequency than the target variable. This study focuses on the Greek economy and particularly on Greek GDP and examines the effect of GDP data revisions on the out-of-sample forecasting outcome of alternative nowcasting models, by utilising real-time GDP data. To that end, we construct a real-time GDP database and we compare the predictive ability of alternative nowcasting models using both last vintage and real-time databases. The empirical results for an out-of-sample period of ten years (2007-2017) show that usually a model with a small set of real variables and the PMI can consistently produce good GDP forecasts as we move closer to the GDP publication date; most importantly, this result is not affected by the GDP revisions and holds true using both the last vintage GDP and the real-time GDP data.

Keywords: Nowcasting, Bayesian shrinkage, real-time data, Greek crisis

JEL classification: C11, C22, C53

ΑΝΑΘΕΩΡΗΣΕΙΣ ΤΟΥ ΕΛΛΗΝΙΚΟΥ ΑΕΠ ΚΑΙ ΒΡΑΧΥΠΡΟΘΕΣΜΕΣ ΠΡΟΒΛΕΨΕΙΣ

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ΠΕΡΙΛΗΨΗ

Οι δείκτες οικονομικής δραστηριότητας, όπως το ακαθάριστο εγχώριο προϊόν (ΑΕΠ), δημοσιεύονται συνήθως με σημαντική χρονική υστέρηση, γεγονός που σημαίνει ότι οι κεντρικές τράπεζες και τα υπουργεία στηρίζονται σε εκτιμήσεις ή προβλέψεις των κύριων οικονομικών δεικτών προκειμένου να ασκήσουν νομισματική και δημοσιονομική πολιτική. Η οικονομετρική μεθοδολογία που χρησιμοποιείται για την παραγωγή έγκαιρων προβλέψεων για το τρέχον επίπεδο οικονομικής δραστηριότητας ονομάζεται nowcasting και βασίζεται στη χρήση οικονομικών δεικτών που δημοσιεύονται πιο έγκαιρα αλλά και με μεγαλύτερη συχνότητα από ό,τι η μεταβλητή που επιθυμούμε να προβλέψουμε. Η παρούσα μελέτη επικεντρώνεται στην ελληνική οικονομία και πιο συγκεκριμένα στο ελληνικό ΑΕΠ και επιχειρεί να εξετάσει αν οι εκτός δείγματος βραχυχρόνιες προβλέψεις οι οποίες παράγονται από οικονομετρικά υποδείγματα nowcasting επηρεάζονται από τις αναθεωρήσεις του ΑΕΠ. Για το σκοπό αυτό, κατασκευάζουμε μια βάση δεδομένων σε πραγματικό χρόνο για το ΑΕΠ και συγκρίνουμε την προβλεπτική ικανότητα εναλλακτικών υποδειγμάτων nowcasting χρησιμοποι-

ώντας τόσο τα τελευταία αναθεωρημένα στοιχεία όσο και τα δεδομένα πραγματικού χρόνου. Τα εμπειρικά αποτελέσματα για μια εκτός δείγματος περίοδο δέκα ετών (2007-2017) δείχνουν ότι συνήθως ένα υπόδειγμα που χρησιμοποιεί ένα μικρό σύνολο πραγματικών μεταβλητών καθώς και το δείκτη PMI μπορεί να παράγει με συνέπεια ποιοτικές προβλέψεις για το ΑΕΠ καθώς πλησιάζουμε προς την ημερομηνία δημοσίευσης. Το πιο σημαντικό όμως εύρημα είναι ότι το αποτέλεσμα αυτό δεν επηρεάζεται από τις αναθεωρήσεις του ΑΕΠ, καθώς ισχύει είτε χρησιμοποιούμε τα τελευταία διαθέσιμα στοιχεία είτε τη βάση δεδομένων σε πραγματικό χρόνο.

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1 INTRODUCTION

Indicators of economic activity, such as gross domestic product (GDP), are usually published with a significant delay. Thus, institutions involved in policy making, such as central banks and ministries, conduct monetary and fiscal policy without knowing with certainty the current state of the economy. In some cases, where the publication lag exceeds a period of two months, policy makers set their policies without even knowing the level of GDP in the previous quarter. Therefore, in practice, real-time economic policy is conducted in an uncertain environment of incomplete information, where policy makers rely on estimates or predictions of the current state of the economy.

The methodology that is widely used to provide a timely estimation of the current state of the economy is referred to as nowcasting, which is a portmanteau term from "now" and "forecasting". Nowcasting was introduced in economics by Giannone et al. (2008) and the term is usually used to describe the prediction of next, current and previous quarter GDP or some other economic indicator before its official release. Nowcasting techniques are widely based on the use of economic indicators that are published earlier and at a higher frequency than the target variable (see Bańbura et al. (2013) for an excellent review of nowcasting methods). Monthly economic indicators such as industrial production, retail sales, unemployment, prices, etc., financial variables (e.g. interest rates, stock indices) or "soft" data including survey-based indicators (e.g. economic sentiment indicators) are usually the main inputs in nowcasting models for GDP. The key point in nowcasting is to exploit the information content of these coincident or leading indicators of economic activity, which are usually published in a more timely fashion than the target variable, resulting in a timely prediction of current GDP. Thus, in real-time nowcasting processes, the forecaster has to work with an unbalanced data set due to the mixed frequencies of the variables (quarterly and monthly) and the so-called "ragged" or "jagged" edge problem, which refers to the non-synchronous publication of the various indicators resulting in missing observations at the end of the sample.

This study concentrates on the Greek economy and particularly on Greek GDP and aims to examine, among other things, the effect of GDP data revisions on the forecasting outcome of alternative nowcasting models, by utilising real-time GDP data.[1] The use of real-time data in forecasting studies is not new in the literature (see e.g. Clements (2016) and Louzis (2018) for recent examples and references therein), but it may be crucial in terms of forecasting and policy analysis since macroeconomic data series are typically heavily revised over time and these revisions may contain new valuable information that was not available at initial release (Orphanides 2003). Therefore, it is important to assess the forecasting ability of nowcasting models, using data available at each point in time and not the fully revised data as is the case in pseudo out-of-sample forecasting exercises. Overall, in a real-time forecasting exercise, the researcher tries to replicate as closely as possible the information available to the decision maker when she forecasts GDP in real time (Antolin-Diaz et al. 2017).

Unfortunately, a real-time macroeconomic database is not available for Greece, unlike

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1 In a recent contribution by Lamprou (2016), the author also assesses the impact of data revisions on nowcasting Greek GDP. Our work differs from hers in three main points: (i) we use a real-time data set rather than only two data vintages (2013 and 2015); (ii) we use both hard and soft indicators as predictors instead of only hard indicators; and (iii) we rely on Bayesian techniques for the estimation of the models.

what is the case with a number of major economies such as the US, the UK and the euro area.[2] Therefore, we follow the recent contribution of Bragoli and Fosten (2018) and we construct real-time vintages for GDP using publicly available information from the website of the Hellenic Statistical Authority (hereinafter ELSTAT). In particular, we use the ELSTAT archive of GDP press releases dating back to 2005:Q1 and the data history available in each of these to reconstruct a real-time GDP database. Then, as already mentioned, we use the real-time GDP vintages to perform out-of-sample nowcasting and compare its results with a pseudo out-of-sample exercise using only the last vintage GDP data.

The various nowcasting models implemented in this study are based on the bridge equations methodology that has been widely used by central banks and is currently used as a benchmark in most of the nowcasting studies (Foroni and Marcellino 2014; Luciani and Ricci 2014; Bragoli and Fosten 2018). In brief, in the bridge equation approach we deal with the "jagged" edge problem of the monthly indicators by employing auxiliary, typically autoregressive models to produce forecasts for the missing observations. Then, using monthly variables aggregated at the quarterly frequency, we estimate a regression with the target variable, e.g. the GDP growth rate, being the independent variable and monthly indicators being the explanatory variables.

The alternative models employed here differ from each other in terms of the set of explanatory variables used. Thus, we first examine whether the information content of survey indicators, nominal (e.g. price indices) and financial variables (e.g. stock indices) helps improve the accuracy of Greek GDP forecasts. To this end, we first use a standard baseline nowcasting model consisting of a small set of real variables and then compare its nowcasting ability with models that also include survey and/or nominal/financial variables.[3] Real variables, also known as "hard" indicators, are considered to generate more accurate signals for the current state of economic activity, but suffer from large publication lags.[4] On the other hand, survey and financial indicators are less accurate, but are typically much timelier. Nonetheless, the empirical evidence in the literature regarding the predictive ability of nominal, financial and survey indicators is generally inconclusive and the results depend largely on the economy or the methods used.[5] Second, we also assess the information content of the disaggregate or sectoral subindices of the real and survey indicators. The literature suggests that a "medium-scale" set of disaggregate variables typically provides the best forecasting results (see e.g. Alvarez et al. 2012), but given the small set of explanatory variables in our application we proceed with a large model that uses all the available subindices.

Recent advances in Bayesian macroeconometrics suggest that Bayesian shrinkage is a prerequisite for exploiting the information content of nearly collinear regressors (see Bańbura et al. 2010; Giannone et al. 2015; Carriero et al. 2016; D'Agostino et al. 2015 among others). Therefore, we depart from the recent literature on bridge equation modelling, which uses classical estimation techniques and simple averages across alternative univariate models (see e.g. Luciani and Ricci 2014; Bragoli and Fosten 2018), and we use Bayesian techniques to estimate the forecasting regressions

2 Publicly available macroeconomic real-time databases are the Archival Federal Reserve Economic Data (ALFRED) of the Federal Bank of St. Louis and the Real Time Data Set for Macroeconomists (RDTSM) of the Federal Bank of Philadelphia for the US economy; the Euro Area Business Cycle Network (EABCN) Real Time Database for the euro area and major European economies; and the OECD real-time database.

3 As thoroughly presented in Section 3, the real variables used in the model are the Industrial Production index, the Retail Sales index and the number of unemployed.

4 E.g. the Industrial Production index is published with a two-month delay.

5 For example, Giannone et al. (2005) find that prices and monetary indicators do not improve GDP nowcasts, while Forni et al. (2003) for the euro area and Stock and Watson (2003) for the US find mixed results for the financial variables. On the other hand, Bańbura and Rünstler (2011) find that survey-based and financial indicators contain valuable information for GDP prediction in the euro area, but this can be revealed only if the more timely publication of the monthly indicators is taken into account properly. Another example is the study of Bragoli and Fosten (2018), who document that nominal and financial variables contribute to GDP forecasting in the developing economy of India.

in the spirit of Carriero et al. (2016).[6] This approach may also be considered as a benchmark method for nowcasting studies that propose a new model or method.

To sum up, this study contributes to the nowcasting/forecasting literature by (i) constructing a real-time database for Greek GDP using publicly available data; (ii) examining the information content of survey, nominal/financial and disaggregate real and survey indicators in nowcasting Greek GDP using both real-time and pseudo real-time GDP data; and (iii) extending the standard bridge equations methodology using Bayesian shrinkage methods to account for the overparameterisation problem.

The empirical application involves estimating all competing models and producing forecasts/nowcasts for the 2007:Q4-2017:Q4 out-of-sample period, using both real-time and pseudo real-time GDP data so as to detect possible differences in the forecasting quality of the competing models. It is worth noting that the out-of-sample period is rather challenging in terms of forecasting, because it contains the severe sovereign crisis period of 2008-2013 and the current weak recovery period starting approximately in 2014 (see Chart 1) with the GDP series being possibly subject to structural breaks. Given the importance of the accuracy of short-term GDP estimates in conducting economic policy, examining the predictive ability of the various models in real time is a policy-relevant exercise. That is, models whose forecasting performance deteriorates in a real-time out-of-sample exercise compared with a pseudo out-of-sample exercise may be inappropriate for decision making due to lower forecasting quality in a real-time environment.[7]

The remainder of the paper is organised as follows: Section 2 presents the econometric methodology, while Section 3 describes the construction of the real-time GDP data, the variables used as regressors and the competing models. In Section 4, we present the forecasting results using both real-time and pseudo real-time GDP data. Section 5 provides some robustness checks, while Section 6 summarises and concludes.

2 ECONOMETRIC METHODOLOGY

2.1 BRIDGE EQUATIONS MODELLING

This section describes the standard nowcasting methodology of bridge models, which tackles the mixed frequency of the data and the "ragged" edge of the sample. Bridge modelling is one of the first attempts to utilise mixed frequency variables in order to provide an estimate of the current and short-term developments of low frequency (e.g. quarterly) variables, such as GDP, which are usually published with a considerable time lag, using high-frequency (e.g. monthly) indicators such as industrial production, retail sales, etc. (see e.g. Baffigi et al. 2004). This is a relatively simple technique which largely relies on a linear regression of the following general form:

$$y_t^Q = c + \alpha(L) y_t^Q + \Sigma_{i=1}^{n} \beta_i(L) x_{i,t}^Q + \varepsilon_t^Q, \ \varepsilon_t^Q \sim N(0, \sigma_\varepsilon^2) \quad (1)$$

where y_t^Q is the quarterly target variable, x_t^Q is the monthly indicator aggregated at the quarterly frequency, n is the number of regressors, $a(L) \stackrel{\text{def}}{=} a_1 L + \ldots + a_p L^p$ and $\beta_i(L) \stackrel{\text{def}}{=} \beta_{i,0} + \beta_{i,1} L \ldots + \beta_{i,q} L^q$ are lag polynomials, $L^l\, y_t = y_{t-l}$ is the standard backshift operator, ε_t^Q is the error term distributed as iid Normal with zero mean and constant variance and T is the number of quarters in the sample.

There are a couple of points here that should be discussed. First, the quarterly aggregates of the monthly indicators are defined as the simple monthly averages, $x_{i,t}^Q = \Sigma^3{}_{m=1} \frac{1}{3} x_{m,t}^i$ where $x_{m,t}$ is the monthly indicator observed in month m of quarter t.[8]

6 The authors use the insights of the Minnesota prior (Litterman 1986) to impose Bayesian shrinkage and estimate mixed frequency regressions for nowcasting purposes.
7 As mentioned above, economic policy is conducted in a real-time environment.
8 For flow variables, one may sum high-frequency variables over a lower-frequency period.

Second, it is obvious that equation (1) uses not only lags of the monthly indicators, but also their contemporaneous value, i.e. it uses the term $\beta_{i,0}\, x^Q_{i,t}$ on the right-hand side of the equation. This implies that x^Q_t, or alternatively $\{x_{t,m}\}^3_{m=1}$, should be available to generate an estimate of the target variable at quarter t, $\hat{y}^Q_t$. However, monthly indicators are not always available for all $m=1,...,3$ due to publication lags, thus we use an auxiliary "bridging" autoregressive (AR) model to produce forecasts over the remainder of the quarter. It should also be noted that, depending on the publication lag of each monthly indicator, the forecasting horizon for each monthly variable may differ. The number of lags in the AR model is usually selected on the basis of some information criterion, which, here, is the Bayesian Information Criterion (BIC) using a maximum number of 12 lags.

Third, we depart from the literature and estimate equation (1) using Bayesian methods to deal with the overparameterisation problem. Specifically, the number of parameters in equation (1) is $k=(p+1)+n\times(q+1)$ and obviously can grow very large so that $k \gg T$. This may lead to increased parameter uncertainty and poor forecasting performance and inference if we rely on standard (e.g. ordinary least squares, OLS) estimation methods.[9] Bayesian estimation uses informative priors that shrink regression coefficients towards a specific prior mean, thus mitigating the overparameterisation problem (see Giannone et al. (2015) and the references therein for a related discussion). We will not give the full computational details of the posterior distribution in this paper, and the interested reader is referred to Koop (2003) for a textbook treatment. Here, it suffices to say that we follow Carriero et al. (2016) and use a Normal-diffuse prior for the regression parameters and the variance of the residuals with the prior on the regression coefficients being:

$$b \sim N(b_0, V_b)$$

where b is a $k\times1$ vector collecting all the regression coefficients, b_0 is $k\times1$ vector of prior means and V_b is the $k\times k$ prior diagonal covariance matrix. We set all elements of b_0 equal to zero except for the autoregressive coefficient of the first own lag, which is set equal to 0.8 to account for the persistence of the GDP growth rate. The prior covariance matrix is elicited by using the insights of the Minnesota prior (see e.g. Litterman 1986). Specifically, the prior standard deviation (sd) for the intercept is:

$$sd^{int}_b = 100\sigma_y$$

For the l-th lag of the dependent variable, the prior sd is:

$$sd^y_{b,l} = \lambda_1 / l \text{ with } l=1,\dots,p$$

Finally, for the l-th lag of the x monthly regressor, the prior sd is formulated as:

$$sd^x_{b,l} = \frac{\sigma_y}{\sigma_x}\frac{\lambda_1\lambda_2}{(l+1)}, \text{ with } l=0,\dots,p$$

where σ_y and σ_x are the residual standard deviations of an AR(1) model for the y^Q_t and $\{x^Q_{i,t}\}^n_{i=1}$ variables, respectively. Hyperparameter λ_1 controls for the overall tightness of the prior, while λ_2 controls for the tightness of the prior on the coefficients of the lagged regressors (Carriero et al. 2016). The structure of the covariance matrix implies that the prior variances become tighter around the prior mean, b_0, as the lag length increases. The rationale is that the long-lagged variables are less important than the short-lagged ones, thus the prior distribution should be tighter around its prior mean, which is set to zero by default. In general, as the hyperparameters approach zero, the prior becomes very tight around zero, meaning that prior beliefs play a crucial role in the estimation. On the other hand, the higher the value of the hyperparameters, the looser the prior, meaning that posterior estimates depend more on the data. We discuss the choice for the value of the hyperparameters, λ_1 and λ_2, in Section 3.2. Finally, we use a flat prior on the intercept of the regression equation.

9 For example, if we use $p=1$ lag for the lagged dependent variable, $q=4$ lags for the various regressors and a small number of regressors, e.g. $n=4$, then we have to estimate $k=21$ parameters.

2.2 AN ILLUSTRATIVE EXAMPLE OF THE FORECASTING PROCEDURE

The following example aims to shed some light on the forecasting procedure described in Section 2.1. Let us assume that there are two available indicators of monthly frequency, namely $CI_{t,m}$ and $IP_{t,m}$, which denote a confidence indicator (CI) and the Industrial Production (IP) index with one and two months of publication lag, respectively. Let us also assume that the quarterly target variable is the gross domestic product, i.e. GDP_t, which is released two months after the reference quarter. In this hypothetical exercise, we are interested in forecasting the *third quarter of 2010* (2010:Q3) figure with all the information available till the end of *September*, i.e. the end of Q3. This means that for the two monthly indicators the sample ends in August and July of 2010 (2010:M8 and 2010:M7), respectively, due to publication lags. Assume also that the sample of this hypothetical exercise begins in 2000:Q1 and ends in 2010:Q2 for the quarterly GDP variable, while for the two monthly variables, IP and CI, the sample spans from 2000:M1 to 2010:M7 and from 2000:M1 to 2010:M8, respectively. Given this information, we proceed with the following two-step procedure.

First, we estimate the two AR models for each of the monthly indicators producing 1- and 2-step ahead forecasts for the CI and IP indicators, respectively. In this way, we produce estimates of the missing observations till the end of the reference quarter, that is September 2010. More specifically, we use the sample 2000:M1-2010:M7 (2000:M1-2010:M8) for the IP (CI) variables to estimate an AR(p) model, where the number of lags, p, is determined by the BIC metric. Then, using the estimated parameters, we produce forecasts for August and September for the IP index and only for September for the CI index.

Second, we aggregate the monthly indicators at the quarterly frequency and use the available sample, i.e. 2000:Q1-2010:Q2, to estimate the model in equation (1) assuming that $L=1$, i.e. we estimate the following equation:

$$y_t^Q = c + a_1 y_{t-1}^Q + \beta_{CI,0} CI_t^Q + \beta_{CI,1} CI_{t-1}^Q + \beta_{IP,0} IP_t^Q + \beta_{IP,1} IP_{t-1}^Q + \varepsilon_t^Q$$

where CI_t^Q and IP_t^Q are the monthly indicators aggregated at the quarterly frequency. Once the model is estimated, we use its estimated parameters, i.e. the posterior medians, to produce the nowcast of interest as follows:

$$GDP_{2010:Q3} = \hat{c} + \hat{a}_1 GDP_{2010:Q2} + \hat{\beta}_{CI,0} \widehat{CI}^Q_{2010:Q3} + \hat{\beta}_{CI,1} CI^Q_{2010:Q2} + \hat{\beta}_{IP,0} \widehat{IP}^Q_{2010:Q3} + \hat{\beta}_{IP,1} IP^Q_{2010:Q2}$$

where $\widehat{CI}^Q_{2010:Q3} = 1/3(\widehat{CI}_{2010:M9} + CI_{2010:M8} + CI_{2010:M7})$

and $\widehat{IP}^Q_{2010:Q3} = 1/3(\widehat{IP}_{2010:M9} + \widehat{IP}_{2010:M8} + IP_{2010:M7})$

and $\widehat{CI}_{2010:M9}$, $\widehat{IP}_{2010:M9}$ and $\widehat{IP}_{2010:M8}$ are the corresponding forecasts obtained in the first step.

3 THE DATA SET

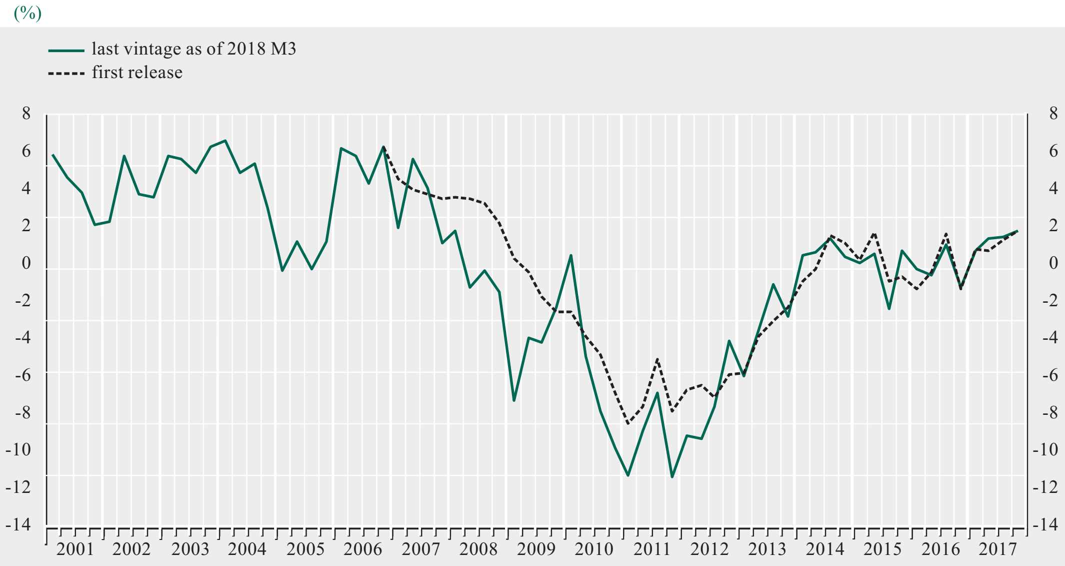
3.1 A REAL-TIME GDP DATABASE

The target variable of this study is the real GDP growth rate, which is produced and published quarterly by ELSTAT with a delay of nearly two months. This means, for example, that for the last quarter of each year (October to December) the first GDP figure is officially released in early March – usually within the first 5 to 10 calendar days – while for the first quarter of each year (January to March) the first release for GDP is within the first days of June, etc.[10]

ELSTAT typically revises GDP because of incoming new information in later quarters, changes in the methodology, e.g. changes in the European System of Accounts (ESA), or

10 See the ELSTAT calendar of press releases: http://www.statistics.gr/documents/20181/12044283/elstat_press_releases_calendar_2019_en.pdf.

Chart 1 First release versus fully revised year-on-year GDP growth for Greece



Source: Hellenic Statistical Authority (ELSTAT).

statistical changes such as a change of base years or seasonal weights; methodological changes are usually referred to as *benchmark revisions* and should be carefully treated in out-of-sample exercises (Aruoba 2008).[11] A real-time database for the Greek GDP is not currently available, not even in the OECD database.[12] Thus, we follow the recent contribution of Bragoli and Fosten (2018) and construct a real-time data set for Greek GDP from the press releases of ELSTAT which are publicly available on its website.[13]

More specifically, starting from the 2005:Q1 vintage, we construct a real-time database for the non-seasonally adjusted real GDP figure (chain-linked volumes) for Greece. The first available vintage, i.e. 2005:Q1, includes data from 2001:Q1 to 2004:Q4, the second available data vintage, i.e. 2005:Q2, includes data from 2001:Q1 to 2005:Q1, etc. We choose to work with the non-seasonally adjusted figures because the seasonally adjusted figures are not available in each and every press release. Nonetheless, this is not a problem, since we work with year-on-year (y-o-y) growth rates, which account for seasonality (Bragoli and Fosten 2018).

Chart 1 presents the last vintage data as of March 2018, which for the purposes of our study are considered as the fully revised GDP, and the first release data which are available from 2007:Q1. Obviously, during the first years of the sovereign debt crisis 2007-2012, there are substantial differences between the first-release and the fully revised data. The latter are almost always far lower than the former, implying that mostly downward revisions occurred during that period. The crucial question that this article tries to address is whether these differences in real-time and last vintage data affect the overall forecasting output of standard econometric methods.

3.2 PREDICTORS OF GDP

The first column of Table 1 shows the set of input *monthly* variables used to predict the

11 ELSTAT currently uses the ESA 2010 with reference year 2010.
12 See the OECD Main Economic Indicators, Revisions Analysis Dataset – Infra-annual Economic Indicators at https://stats.oecd.org/ Index.aspx?DataSetCode=MEI_ARCHIVE#. The real-time OECD database has currently real-time data for the Industrial Production Index, the Consumer Price Index and Unemployment and for vintages starting from 2015, which obviously are not useful for the present analysis.
13 See http://www.statistics.gr/el/statistics/-/publication/SEL84/- .

Table 1 GDP predictors, publication lags, transformations and sources

Indicator	Baseline	Model 1	Model 2	Model 3	Publication lag	Unit/ Trans-formation	Source
Industrial Production Index (IP index)	X	X	X	X	2 months	Index/ y-o-y %	ELSTAT
IPI sectoral indices				X	2 months	Index/ y-o-y %	ELSTAT
Retail Sales (RS) volume	X	X	X	X	2 months	Index/ y-o-y %	ELSTAT
RS sectoral indices				X	2 months	Index/ y-o-y %	ELSTAT
Unemployed	X	X	X	X	3 months	Thousands/ y-o-y %	ELSTAT
Purchase Managers' Index (PMI)		X	X	X	Current	Index/ none	Markit
PMI disaggregate indices				X	Current	Index/ none	Markit
Consumer Price Index (CPI)			X		1 month	Index/ y-o-y %	ELSTAT
M1 Money supply			X		1 month	Millions / y-o-y %	BoG
Athens Stock Exchange Index			X		Current	Index/ y-o-y %	Datastream

Note: BoG stands for the Bank of Greece.

real GDP growth rate. This set includes three main categories of variables widely used in the recent nowcasting/forecasting literature (see e.g. Lucianni and Ricci 2014; Carriero et al. 2015; Marcellino et al. 2016; Antolin-Diaz et al. 2017; Bragoli and Fosten 2018 among others). More specifically, we use: (a) real or *hard* indicators, such as the Industrial Production Index (IP), the volume of retail sales (RS) and the number of unemployed persons in Greece; (b) survey or soft indicators, such as the Purchase Managers' Index (PMI); (c) nominal/financial variables such as the Consumer Price Index (CPI), M1 money supply and the Athens stock exchange index. It is worth mentioning that the choice of the variables is also partially dictated by data limitations, given that many of the other potential predictors of GDP are not available at the monthly frequency or their sample is not long enough for an out-of-sample exercise.[14] Moreover, all real variables and the CPI are generally subject to revisions; however, the construction of a real-time database from the ELSTAT data is infeasible, thus we rely on the fully revised data for these indicators.

In Table 1, we also show the different models employed in this study depending on the set of regressors used in equation (1). In particular, the *Baseline* model uses only the real variables, while *Model 1* uses the real variables and the manufacturing PMI, a survey index that is widely monitored by economic agents due to its timeliness and its ability to depict accurately the current state of the economy (see e.g. Antolin-Diaz et al. 2017). The third model, *Model 2*, uses the variables of *Model 1* plus the nominal/financial indicators (prices, M1 money supply and the stock exchange index),

14 Survey indicators could also include the Economic Sentiment Indicator (ESI) and its disaggregate indices published by the European Commission. We experimented with the ESI as an input variable in all models and found that it does not lead to any forecasting improvements, thus we decided to exclude the ESI from the analysis. Moreover, we also decided to exclude the 10-year Greek government bond yield to avoid the distortion of our results because of the outliers during the sovereign debt crisis. To circumvent this problem, one can use the Dynamic Factor Model (DFM) in the spirit of Antolin-Diaz et al. (2017), which can deal with missing values due to outliers.

while *Model 3* uses the variables of *Model 1* plus the disaggregate and sectoral subindices for the IP, RS and PMI indices.[15] Obviously, the choice of the variables in each model serves the purspose of our analysis which, among other things, is to assess the information content of nominal/financial and disaggregate indicators in nowcasting/forecasting the real GDP growth rate in Greece.

Before proceeding to the forecasting analysis of the alternative models, we briefly discuss the choice of the shrinkage hyperparameters, λ_1 and λ_2, which play an important role in forecasting (Bańbura et al. 2010). Based on the theoretical results of De Mol et al. (2008), Bańbura et al. (2010) (see also Giannone et al. 2015) argue that the degree of prior shrinkage should be chosen in relation to the size of the model, i.e. the number of the explanatory variables, in order to extract the valuable information carried by the near-collinear covariates. Therefore, following Carriero et al. (2016) among others, we set the overall shrinkage hyperparameter, λ_1, equal to 0.5 for the small *Baseline* model and *Model 1*, while we apply a tighter prior for *Model 2* and *Model 3* that include a larger number of variables, by setting $\lambda_1=0.2$. Finally, hyperparemeter λ_2 is set equal to 0.2 across all models (Carriero et al. 2016). Nonetheless, in the empirical section we also experiment with a looser degree of overall shrinkage by setting $\lambda_1=0.5$ for the largest models, i.e. *Model 1* and *Model 2*, thus examining also the effect of the Bayesian shrinkage on our results.

Table 1 also presents the publication lags of the various predictors with respect to the reference quarter, that is the number of months after the last day of quarter t that a specific monthly indicator becomes available.[16] For example, the Industrial Production index for the first quarter (January to March) of each year becomes available after two calendar months, i.e. in May, etc. Obviously, as already mentioned, survey and financial indicators become available in a more timely manner compared with hard indicators. The crucial question here is whether the former carry substantial information content as predictors of the current state of the economy. Lastly, we transform the variables to achieve stationarity, as is typically the case in the literature (e.g. Antolin-Diaz et al. 2017; Bragoli and Fosten 2018).

4 EMPIRICAL ANALYSIS

4.1 THE TIMELINE OF THE FORECASTING PROCEDURE

In this section, we provide empirical evidence regarding the forecasting ability of the various models using both pseudo real-time and "quasi" real-time out-of-sample forecasting exercises. In this study, a pseudo real-time forecasting exercise uses the last vintage, i.e. the fully revised data for both GDP and regressors, while a "quasi" real-time forecasting exercise uses the real-time vintages for GDP and the fully revised data for the regressors. A proper real-time out-of-sample exercise, as implemented for instance in Louzis (2018), also requires real-time vintages for those regressors that are usually subject to revisions (e.g. real variables and the CPI). Nonetheless, as explained in Section 3.2, real-time vintages for the regressors are not available and cannot be reconstructed from the publicly available information of ELSTAT.

The out-of-sample period is from 2007:Q4 to 2017:Q4, spanning ten years, and includes both a crisis and a recovery phase of the Greek business cycle (see Chart 1), enhancing the robustness of our empirical results. All models are estimated recursively, meaning that we first estimate the models for the initial sample 2001:Q1-2007:Q3 and then add one observation at a time as we move forward in the sample in order to generate forecasts for the full out-of-sample period.

15 Details on the disaggregate or sectoral indices are provided in the Appendix due to space considerations.

16 Publication lags are based on the press release calendar of ELSTAT.

Table 2 The timeline of the forecasting procedure

Forecast period Quarter *t*-1			Nowcast period Reference quarter *t*			Backcast period Quarter *t*+1		
Month 1	Month 2	Month 3	Month 1	Month 2	Month 3	Month 1	Month 2	Month 3
For each of the months (1, 2, 3) within the quarter, we generate GDP forecasts for the reference quarter, *t*.			For each of the months (1, 2, 3), we generate GDP nowcasts for the reference quarter, *t*.			For the first two months (1 and 2), we generate GDP backcasts for the reference quarter, *t*. The first figure of GDP is published during the first days of Month 3 of the current quarter, *t*+1.		

Following the recent literature, for a given reference quarter, we provide monthly forecasts three months before the beginning of the quarter, i.e. the "forecast period", during the reference quarter, i.e. the "nowcast period", and two months after the end of the reference quarter, i.e. the "backcast period". The aforementioned forecasting procedure is presented schematically in Table 2.

The predictive ability of the models is evaluated using two standard evaluation metrics: the root mean squared forecast errors (RMSE) and the mean absolute deviation (MAD) defined as:

$$RMSE_j = \sqrt{\frac{1}{T_{out}}\sum_{t=1}^{T_{out}}\left(GDP_t - \widehat{GDP}_{j,t}\right)^2}$$

$$MAD_j = \frac{1}{T_{out}}\sum_{t=1}^{T_{out}}\left|GDP_t - \widehat{GDP}_{j,t}\right|$$

where $j=1,\dots,m$, with m being the number of models employed in this study, T_{out} is the number of out-of-sample observations and $\widehat{GDP}_{j,t}$ is the GDP growth rate prediction produced by the j-th model. Following the standard practice in the literature, we present the relative RMSE and MAD defined as $RMSE_j/RMSE_{AR}$ and MAD_j/MAD_{AR}, respectively, where $RMSE_{AR}$ and MAD_{AR} are the evaluation metrics produced by a benchmark AR(1) model estimated with OLS. Thus, for values below 1, the j-th model outperforms the benchmark and vice versa. Finally, we also provide a rough gauge of whether the improvement in the forecasting accuracy relative to the AR model is statistically significant by implementing the Diebold and Mariano (1995) t-statistic for equal RMSE and MAD compared against normal critical values (see Louzis 2018 for a recent application and the discussion therein).

4.2 COMPARATIVE PERFORMANCE USING PSEUDO REAL-TIME AND QUASI REAL-TIME DATA

In this subsection, we compare the forecasting ability of the various models using pseudo real-time data and quasi real-time data. Table 3 presents the results of the pseudo real-time forecasting exercise, where we use the last vintage or fully revised GDP data to assess the out-of-sample forecasting ability of the alternative specifications.

Overall, the results presented in Table 3 clearly show that *Model 3* is the best performing model for the nowcast (Months 2 and 3) and backcast evaluation periods across both evaluation metrics, while *Model 2* augmented with nominal and financial variables outperforms its rivals mainly for the forecast evaluation period. Moreover, *Model 1* outperforms the *Baseline* model, highlighting the importance of the survey PMI indicator as a predictor of the current state of the Greek economy. It is also worth noting that *Model 1*, comprising only aggregate real variables and the PMI, is typically the second best performing model for the last month of the nowcast evaluation period and for the entire backcast period. Moreover, all three models outperform the benchmark AR(1) model across almost all evaluation periods and

Table 3 Forecasting results using last vintage (fully revised) GDP data

Panel A: RMSE				
Forecast period	**Baseline**	**Model 1**	**Model 2**	**Model 3**
Month 1	0.983	0.978***	**0.925*** **	0.945**
Month 2	0.963*	0.955**	**0.920*** **	0.940*
Month 3	1.008	1.000	**0.928*** **	0.960*
Nowcast period				
Month 1	0.962	0.947***	**0.906*** **	0.921**
Month 2	0.930***	0.921***	**0.902*** **	**0.888*** **
Month 3	0.937***	0.920***	**0.929*** **	**0.909*** **
Backcast period				
Month 1	0.928***	**0.903*** **	0.923***	0.905***
Month 2	0.904***	0.884***	0.916***	**0.874*** **
Panel B: MAD				
Forecast period	**Baseline**	**Model 1**	**Model 2**	**Model 3**
Month 1	0.956	0.947	**0.898** **	0.945*
Month 2	0.935	0.910**	**0.880** **	0.938
Month 3	0.998	0.990	**0.912*** **	0.975
Nowcast period				
Month 1	0.947***	0.910***	**0.877*** **	0.916**
Month 2	0.906***	0.882***	0.880***	**0.873*** **
Month 3	0.916***	0.900***	0.921***	**0.866*** **
Backcast period				
Month 1	0.903***	0.874***	0.913***	**0.859*** **
Month 2	0.880***	0.867***	0.910***	**0.838*** **

Notes: The table presents the RMSE and MAD ratios of the *Baseline* model, *Model 1, Model 2* and *Model 3* (see Section 3.2 and Table 1 for a definition of the models) relative to the RMSE and MAD of the benchmark AR(1) model. Bold-faced numbers indicate the best-performing model. Asterisks denote that the ratios are significantly below one at *10%, **5% and ***1% significance level. The out-of-sample period is from 2007:Q4 to 2017:Q4.
Source: Author's calculations.

metrics, with forecasting gains being up to 12.6% and 16.2% for the RMSE and MAD metrics, respectively.

The empirical evidence presented so far is largely in line with the findings of Bańbura and Rünstler (2011), who find that survey and financial indicators contribute to the accuracy of GDP forecasts in the euro area, while the role of real variables is relatively more important during the backcast period. The good forecasting behaviour of *Model 2* during the forecast evaluation period and the first and second months of the nowcast period can be partially attributed to the significant publication lag of hard indicators, meaning that their figures are not published before the end of the reference quarter. However, the picture changes when hard indicators become gradually available, starting from the last month (Month 3) of the reference quarter and during the backcast period, when ELSTAT publishes both IP and

Table 4 Forecasting results using real-time GDP data (forecast evaluation using first release data)

Panel A: RMSE				
Forecast period	**Baseline**	**Model 1**	**Model 2**	**Model 3**
Month 1	1.007	0.974	**0.878****	0.941
Month 2	0.960	0.922	**0.856****	0.902
Month 3	0.993	0.962	**0.855*****	0.933
Nowcast period				
Month 1	0.964	0.921	**0.847*****	0.883
Month 2	0.919	0.865**	0.836***	**0.834****
Month 3	0.885**	0.851***	0.853***	**0.832****
Backcast period				
Month 1	0.875**	0.834***	0.850***	**0.800*****
Month 2	0.841***	0.807***	0.850***	**0.776*****
Panel B: MAD				
Forecast period	**Baseline**	**Model 1**	**Model 2**	**Model 3**
Month 1	0.995	0.930	**0.811****	0.933
Month 2	0.915	0.843	**0.780****	0.855
Month 3	0.957	0.903	**0.820****	0.902
Nowcast period				
Month 1	0.928	0.854	**0.794****	0.826**
Month 2	0.897	0.803**	0.792**	**0.787****
Month 3	0.839***	0.816***	0.827***	**0.789*****
Backcast period				
Month 1	0.825***	0.790***	0.825***	**0.771*****
Month 2	0.802***	0.772***	0.827***	**0.761*****

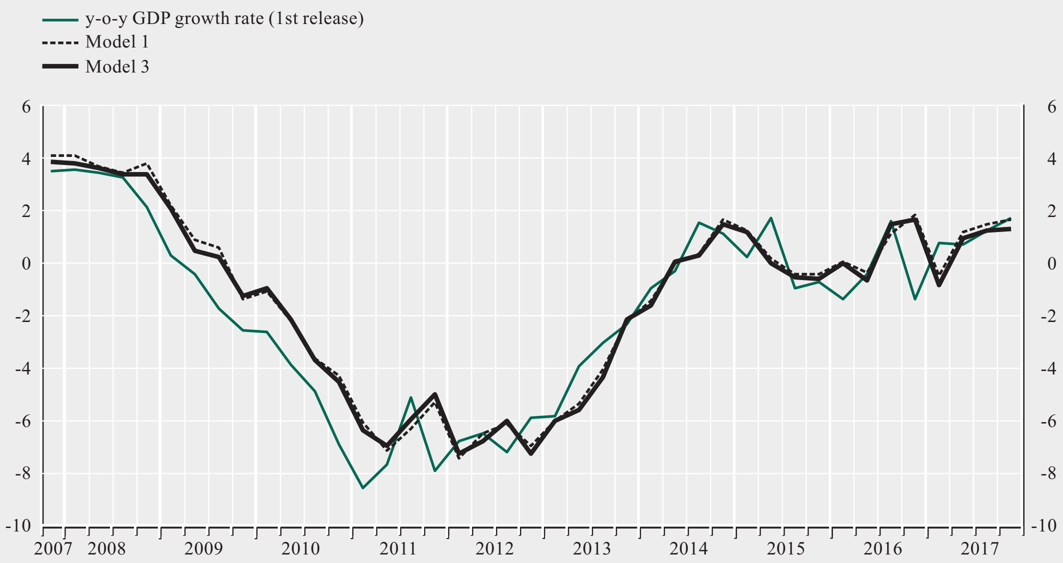
Notes: The table presents the RMSE and MAD ratios of the *Baseline* model, *Model 1, Model 2* and *Model 3* (see Section 3.2 and Table 1 for a definition of the models) relative to the RMSE and MAD of the benchmark AR(1) model. Bold-faced numbers indicate the best-performing model. Asterisks denote that the ratios are significantly below one at *10%, **5% and ***1% significance level. The out-of-sample period is from 2007:Q4 to 2017:Q4.
Source: Author's calculations.

RS indices for all three months of the reference quarter (Months 1 and 2 for the unemployed). These results clearly show that hard indicators give a precise signal for the current state of the Greek economy, and a more timely release of these indicators would possibly benefit decision making.

A policy-relevant question, here, is whether these results hold when we use real-time – or at least quasi real-time – data, because policy makers make their decisions in real time with the information available at each point in time. Large discrepancies in the forecasting quality of the various competing models between pseudo real-time and real-time data forecasting exercises may indicate that forecasting models evaluated using only fully revised data are inappropriate for policy making decisions due to their low forecasting quality. Next, we attempt to address this question by repeating the forecasting analy-

Chart 2 Year-on-year GDP growth rate forecasts at the end of the reference quarter

(%)



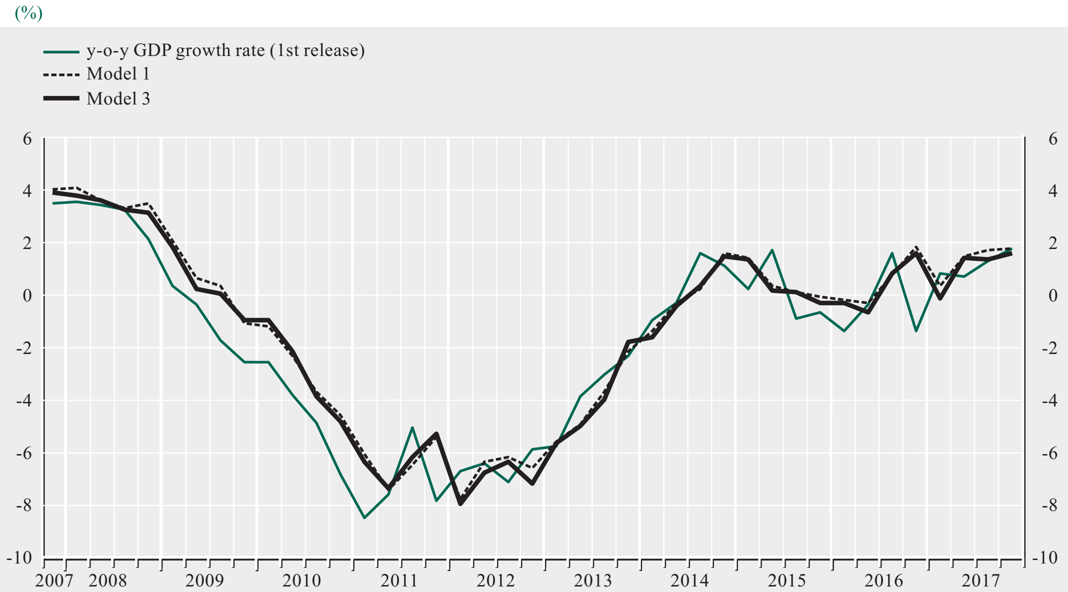
Source: Hellenic Statistical Authority (ELSTAT) and author's estimations.

sis presented in Table 3 using the real-time GDP data.

A rather critical point in real-time forecasting exercises is the choice of the observed value of the GDP growth rate in the forecasting evaluation procedure, i.e. the actual value of GDP growth rate, GDP_t, that is used in the computation of RMSE and MAD metrics (see also the discussion in Clark 2011). Here, we follow the recent contribution of Antolin-Diaz et al. (2017) and choose the first release of the GDP figure (published approximately 2 months after the end of the reference quarter) as the actual value used in the forecasting evaluation (see also Chart 1). First release figures have two important advantages over other choices such as the fully revised data: (a) they are typically used by policy makers as benchmarks to check the accuracy of their predictions; and (b) they are usually unaffected by benchmark revisions which may distort the evaluation process. Nevertheless, in the robustness check section, we also use the second release and the fully revised data as the actual GDP growth rate to evaluate the forecasting ability of the models.

Table 4 presents the forecasting results using the real-time GDP data, constructed as described in Section 3, which are qualitatively similar to those of Table 3. Again, the large model with the disaggregate real and survey (PMI) variables is the best performing model for the last two months of the nowcast evaluation period and the full backcast period, followed by the parsimonious *Model 1* with the aggregate real and PMI variables. The information content of the price index and the financial variables proves to be useful for forecasting purposes only during the forecast period and the first two months of the nowcast period possibly exploiting the forward-looking nature of the stock exchange index, while the PMI index helps improve the forecast quality of the *Baseline* model. Moreover, all models almost always outperform the benchmark, with forecasting gains ranging approximately between 3% and 24% across evaluation metrics. It is also evident that the largest forecasting gains are generated during the last month of the backcast period when hard indicators become available, as expected. Thus, the main conclusions of the analysis based on the

Chart 3 Year-on-year GDP growth rate forecasts at the end of the backcast period



Source: Hellenic Statistical Authority (ELSTAT) and author's estimations.

results of Table 3 still hold true for the quasi real-time forecasting exercise.

Next, we proceed with a visual inspection of the nowcasts produced by *Model 1* and *Model 3* at the end of the reference quarter (Month 3 of the nowcast evaluation period) and at the end (Month 2) of the backcast period in Charts 2 and 3, respectively. Overall, the differences in the forecasts generated by the two competing models are rather small, practically following the same pattern. Nevertheless, the most striking feature of Charts 2 and 3 is that both models produce upward-biased GDP nowcasts during the first 5 years of the crisis (2007:Q4-2012:Q4), during which y-o-y GDP growth dropped abruptly from 4% in 2008:Q1 to -8.5% in 2011.[17] It is also evident that turning points are usually picked up with a lag due to the high persistence of the autoregressive parameter. These results probably indicate that constant parameter models are not capable of capturing abrupt structural changes in the unconditional mean and the volatility of the GDP time series and imply that time-varying parameter models may improve the forecasting accuracy, as shown in Carriero et al. (2016), Marcellino et al. (2016) and Antolin-Diaz et al. (2017).

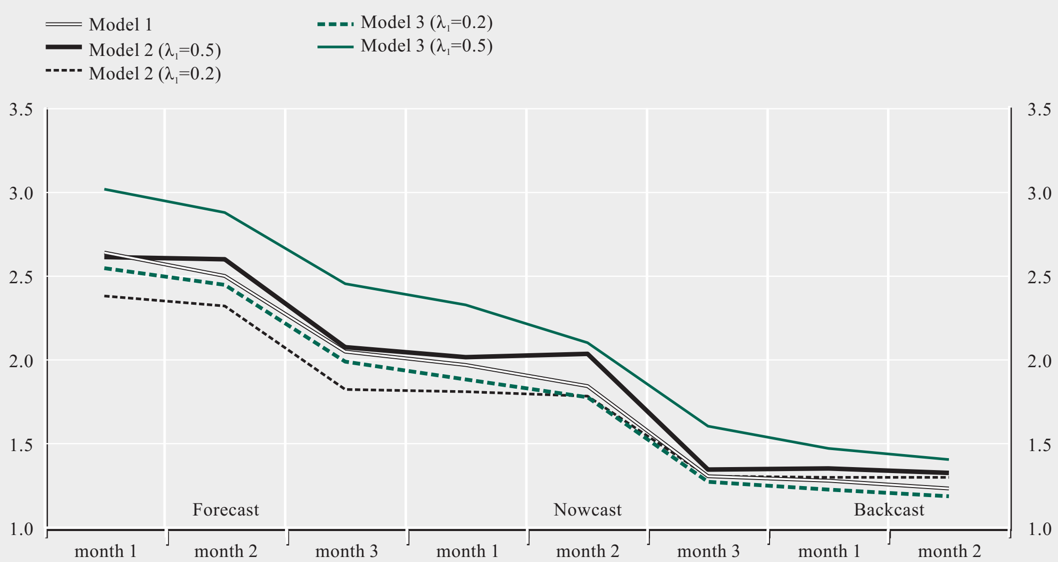
5 ROBUSTNESS CHECKS

As also mentioned in Section 3.2, an important aspect in the forecasting performance of models with a large set of regressors is the degree of Bayesian shrinkage, as expressed by hyperparameter λ_1 in our case. In the results presented so far, *Model 2* and *Model 3* use a tighter prior (λ_1=0.2) compared with the more parsimonious *Baseline* model and *Model 1* (λ_1=0.5) for reasons briefly explained in Section 3.2. Now, we investigate the role of Bayesian shrinkage by performing a sensitivity analysis with respect to λ_1. In particular, we repeat the out-of-sample exercise using the real-time GDP data and the first release data for the forecast evaluation by setting λ_1=0.5 for the large mod-

17 This result is even more striking, considering that all models use the fully revised hard indicators (e.g. IP) which are associated with the fully revised GDP that is itself considerably lower than the first release GDP figure.

Chart 4 The role of Bayesian shrinkage in forecasting GDP

(RMSE)



Source: Author's calculations.

els (*Model 2* and *Model 3*). The forecasting results are presented in Chart 4, where we plot the RMSE against the evaluation periods for five models: *Model 1*, *Model 2* with λ_1=0.2 and λ_1=0.5 and *Model 3* with λ_1=0.2 and λ_1=0.5.

The results are clear-cut as to the beneficial effects of tighter priors in large models. More specifically, both *Model 2* and *Model 3* with a higher degree of shrinkage (λ_1=0.2) – depicted with dashed lines – outperform those with a looser prior (λ_1=0.5) – depicted with solid lines – as the RMSE is consistently lower across evaluation periods.[18] A second question that Chart 4 tries to address is whether the degree of shrinkage can distort the final outcome of the specific forecasting exercise. The answer is yes, because *Model 1* would have been the best performing model across all evaluation periods (see the black solid line) if we had used λ_1=0.5 across all models. Thus, we see that Bayesian shrinkage plays a significant role in exploiting the information content of financial or disaggregate indicators in nowcasting Greek GDP, and the degree of shrinkage should be carefully chosen. However, the main drawback of such an approach is that the shrinkage hyperparameter is an ad hoc choice of the forecaster; a possible extension that circumvents this problem is to use the insights of the hierarchical Bayesian modelling and choose the degree of shrinkage optimally (see e.g. Giannone et al. 2015 and Louzis 2018, among others, for a relevant discussion on hierarchical modelling in macroeconomic forecasting).

Finally, we also perform a robustness check regarding the choice of the observable value of GDP in the spirit of Antolin-Diaz et al. (2017). Tables 5 and 6 repeat the quasi real-time out-of-sample forecasting exercise, the results of which are presented in Table 4, but this time we use the second release and the last vintage GDP data (as of March 2018), respectively, for the assessment of the forecasts via the two evaluation criteria. In both tables, the forecasting results follow an almost identical pattern to the one presented in Tables 3 and 4 in Section 4.1. That is, *Model 2* enhanced with nominal and financial variables usually fore-

18 The results with the MAD criterion are qualitatively similar.

Table 5 Forecasting results using real-time GDP data (forecast evaluation using second release data)

Panel A: RMSE				
Forecast period	**Baseline**	**Model 1**	**Model 2**	**Model 3**
Month 1	1.009	0.980	**0.892****	0.948
Month 2	0.973	0.937	**0.875****	0.920
Month 3	0.992	0.963	**0.880****	0.939
Nowcast period				
Month 1	0.969	0.923	**0.864*****	0.896
Month 2	0.922	0.869**	0.853***	**0.845****
Month 3	0.895*	0.857**	0.872***	**0.835****
Backcast period				
Month 1	0.892**	0.849**	0.870***	**0.823****
Month 2	0.862**	0.822***	0.864***	**0.791*****
Panel B: MAD				
Forecast period	**Baseline**	**Model 1**	**Model 2**	**Model 3**
Month 1	0.993	0.935	**0.825****	0.927
Month 2	0.932	0.874	**0.806****	0.873
Month 3	0.976	0.922	**0.857***	0.916
Nowcast period				
Month 1	0.928	0.861	**0.824****	0.856*
Month 2	0.918	0.827**	0.817**	**0.809****
Month 3	0.837***	0.807***	0.840***	**0.803*****
Backcast period				
Month 1	0.825***	0.793***	0.833***	**0.785*****
Month 2	0.802***	0.778***	0.831***	**0.769*****

Notes: The table presents the RMSE and MAD ratios of the *Baseline* model, *Model 1, Model 2* and *Model 3* (see Section 3.2 and Table 1 for a definition of the models) relative to the RMSE and MAD of the benchmark AR(1) model. Bold-faced numbers indicate the best-performing model. Asterisks denote that the ratios are significantly below one at *10%, **5% and ***1% significance level. The out-of-sample period is from 2007:Q4 to 2017:Q4.
Source: Author's calculations.

casts well during the forecast period and the first months of the nowcast period, with *Model 3* being the overall best performing model for the last months of the nowcast period and the full backcast period.

6 SUMMARY, DISCUSSION AND CONCLUSIONS

Economic policy is conducted in an uncertain environment which requires, at least, accurate estimates for the current state of economic activity, as synopsised in the GDP figure. Thus, it is considered crucial in terms of forecasting accuracy and decision making to examine the forecasting ability of the alternative econometric models using real-time data, replicating as close as possible the situation of the policy maker who has to predict the GDP figure with information available at a given point in time.

Unfortunately, real-time GDP data are not publicly available for Greece, and the first goal of this study is to construct a real-time data-

Table 6 Forecasting results using real-time GDP data (forecast evaluation using last vintage data)

Panel A: RMSE				
Forecast period	**Baseline**	**Model 1**	**Model 2**	**Model 3**
Month 1	1.035	1.023	**0.952**	1.010
Month 2	1.006	0.987	**0.936****	0.987
Month 3	1.019	1.009	**0.941****	0.990
Nowcast period				
Month 1	0.993	0.967	**0.927*****	0.950
Month 2	0.960	0.938	0.920***	**0.916***
Month 3	0.949	0.935*	0.927**	**0.917**
Backcast period				
Month 1	0.942	0.924*	0.926**	**0.905***
Month 2	0.917*	0.897**	0.918***	**0.878****
Panel B: MAD				
Forecast period	**Baseline**	**Model 1**	**Model 2**	**Model 3**
Month 1	1.004	0.987	**0.902***	0.976
Month 2	0.958	0.935	**0.876****	0.941
Month 3	1.002	0.988	**0.906****	0.986
Nowcast period				
Month 1	0.962	0.914	**0.883*****	0.921
Month 2	0.936	0.886**	0.884***	**0.875****
Month 3	0.926*	0.903**	**0.898*****	0.905*
Backcast period				
Month 1	0.911**	0.884**	0.893***	**0.886****
Month 2	0.886**	0.863***	0.887***	**0.853*****

Notes: The table presents the RMSE and MAD ratios of the *Baseline* model, *Model 1, Model 2* and *Model 3* (see Section 3.2 and Table 1 for a definition of the models) relative to the RMSE and MAD of the benchmark AR(1) model. Bold-faced numbers indicate the best performing model. Asterisks denote that the ratios are significantly below one at *10%, **5% and ***1% significance level. The out-of-sample period is from 2007:Q4 to 2017:Q4.
Source: Author's calculations.

base for Greek GDP using publicly available information from the national statistical authority. To this end, we exploit the information available in the press releases and construct a real-time GDP database dating back to 2005:Q1. Next, we examine the information content of survey, nominal/financial and disaggregate real and survey indicators in forecasting/nowcasting Greek GDP for an out-of-sample period spanning from 2007:Q4 to 2017:Q4. We exploit the newly constructed real-time database and compare the predictive ability of the models using both real-time and pseudo real-time data. Lastly, to address the overparameterisation problem we rely on Bayesian shrinkage methods to estimate the standard bridge equations widely used in nowcasting.

Overall, we provide robust empirical evidence that a model with a small set of real variables and the PMI can consistently produce good GDP forecasts as we move closer to the GDP publication date. Its forecasting performance can be further enhanced if we account for the information content of the disaggregate subindices of the Industrial Production Index, the Retail Sales Index and the PMI survey indicator. On the other hand, nominal/financial variables such as prices, M1 money supply and the stock exchange index can improve short-term forecasting of the Greek GDP growth rate for periods of up to two months before the end of the reference quarter. However, it should be noted that a prerequisite for the two latter results is to apply appropriate Bayesian shrinkage so as to exploit the information content of the near-collinear regressors. Lastly, we show that the widely used PMI survey indicator carries significant information on the current state of the economy, since it consistently improves the forecasting ability of a model consisting of only real variables.

The most important empirical finding of this study is that these results hold true using both the last vintage GDP and the real-time GDP data. This is a policy-relevant result: in economies with a lack of real-time data sets, forecasters and policy makers usually examine the predictive ability of their models in pseudo out-of-sample forecasting exercises using fully revised data but, at the same time, they have to make decisions in real time using the available, non-revised data. Possible discrepancies in the forecasting performance of models using fully revised and real-time data may be crucial for policy decisions, because policy makers may favour a model that performs well in pseudo out-of-sample forecasting but, in practice, forecasts poorly in real time, leading to poor decision making.

Although our results are robust to the choice of different "observed" data in the forecasting evaluation procedure, they should be, in general, treated cautiously, mainly for two reasons. First, the real variables and the price index used in this study —that is, the Industrial Production Index, the Retail Sales Index, the number of unemployed and the CPI— are also subject to (relatively small) revisions. However, we could not reconstruct a real-time database for these indices and instead relied on the fully revised data. The extent to which this choice distorts the final forecasting outcome should be investigated empirically as soon as real-time data become available. Second, from a more technical point of view, the results are largely based on the appropriate choice of the degree of shrinkage, as shown in a sensitivity analysis in the robustness check section. This may be a problem for the inexperienced Bayesian user who wants to experiment with alternative sets of explanatory variables and probably implies that we should move towards more automated methods which restrict the role of subjective inputs in the setting of the priors.

In future research, the models presented here can be extended to account for structural breaks in the mean of the GDP series, as well as to consider fat-tailed and heteroscedastic error terms, thereby possibly leading to considerable forecasting improvements. Other potential avenues for further research could involve the implementation of the recent advances in mixed frequency Dynamic Factor models to nowcast Greek economic activity and also explore the role of macroeconomic uncertainty in nowcasting.

APPENDIX

Table A.1 Industrial Production, Retail Sales and PMI subindices

Indices	Subindices
Industrial Production (IP)	IP manufacturing
	IP energy
	IP intermediate goods
	IP capital goods
	IP consumer durables
	IP consumer non-durables
Retail Sales (RS)	RS excl. automotive fuel
	RS food sector
	RS non-food sector
	RS super markets
	RS department stores
	RS automotive fuel
	RS food, beverages, tobacco
	RS pharmaceutical
	RS clothing and footwear
	RS household equipment
	RS books etc.
PMI	Input prices
	New orders
	Stocks of finished goods
	New export orders

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