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**SHORT TERM FORECASTS OF ECONOMIC ACTIVITY:
ARE FORTNIGHTLY FACTORS USEFUL?**

by Libero Monteforte* and Valentina Raponi**

Abstract

A short term mixed-frequency model is proposed to estimate and forecast the Italian economic activity fortnightly. Building on Frale et al. (2011), we introduce a dynamic factor model with three frequencies (quarterly, monthly and fortnightly), by selecting indicators that show significant coincident and leading properties and are representative of both demand and supply. We find that high-frequency indicators improve the real time forecasts of Italian GDP. Moreover, the model provides a new fortnightly indicator of GDP, consistent with the official quarterly series. Our results emphasize the potential benefit of the high frequency series, providing forecasting gains beyond those based on monthly variables alone.

JEL Classification: C53, E17, E32, E37.
Keywords: factor models, Kalman filter, temporal disaggregation, mixed frequency data, forecasting.

Contents

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1. Introduction[1]

Estimating the current state of the economy and forecasting future values of macroeconomic variables are extremely important tasks. Institutions need to improve the timeliness of policies and market makers need to anticipate asset price changes. Gross Domestic Product (GDP), the most important indicator of economic activity, has official figures that are typically reported quarterly, with a delay of at least one month. Therefore accurate and timely predictions of GDP are necessary to get an insightful idea of the current and future state of the economy.

The increasing search and availability of non-structured data sets, based on big data and experimental data, suggest that high frequency series should contain additional information about the business cycle and therefore should be considered as relevant for both macroeconomic nowcasting and forecasting.
The problem in using these data is that they are typically available at different frequencies and with a ragged edge structure. This requires the use of models able to incorporate this heterogeneity in terms of frequency, number of variables and time durations. In particular, taking advantage of indicators available in real time requires an efficient tool in order to face two main challenges. First, how to handle the mixing-frequency features of the available data, matching for example daily financial data with monthly variables and other quarterly indicators. The second issue concerns how to extract useful information, i.e. how to identify the main common components from the cross-section of the available indicators.

A convenient approach to address both issues is to use mixed-frequency factor models, that are suited to estimating the economic activity using indicators available at different time frequencies, possibly higher than the observable data. This idea has two advantages. On the one hand, it allows us to exploit more information, in order to extract an unobserved state of the economy and create a new coincident index. On the other hand, these models provide timely updates of the key macroeconomic variables and produce accurate forecasts.

Mixed-frequency factor models are not new in the literature. Extending the Stock and Watson (1991) US coincident index, Mariano and Murasawa (2003) propose a dynamic factor model that combines quarterly GDP and monthly business cycle indicators. Interesting early applications on macroeconomic series can be found in Mariano and Murasawa (2010),

[1]This paper represents the authors personal opinions and does not reflect the view of the Bank of Italy. We are grateful to Fabio Busetti, Cecilia Frale, Eric Ghysels, Roberta Zizza and Francesco Zollino for their helpful comments and conversations. Routines are coded in Ox 3.3 by Doornik (2001) and are based on the programs realized by Tommaso Proietti for the Eurostat project on EuroMIND: the Monthly Indicator of Economic Activity in the Euro Area.

Giannone et al. (2008), Banbura and Runstler (2011), Frale et al. (2010, 2011), Proietti and Moauro (2006), Aruoba et al. (2009), Marcellino et al. (2016), Andreou et al. (2017), Bragioli and Modugno (2017),Schorfheide and Song (2015), and McCracken et al. (2015).

The macroeconomic literature on forecasting with mixed-frequency factor models has mainly focused on monthly and quarterly frequencies. The EUROMIND indicator of Frale et al. (2011) or the dynamic factor model with stochastic volatility of Marcellino et al. (2016) are, among others, empirical illustrations on how to track and forecast GDP every month, possibly in real time. Recently, Andreou et al. (2017) propose a novel grouped factor analysis valid for large panels and identify industrial production as the dominant factor for the US economy.

In this paper we estimate and forecast the Italian GDP once every two weeks, i.e. fortnightly. In particular, we propose a one-factor model with three frequencies (namely quarterly, monthly and fortnightly), by selecting indicators that have significant coincident and leading properties in predicting Italian economic activity and, at the same time, are representative of both demand and supply. We adopt the small-scale approach of Mariano and Murasawa (2003), in view of the results of Boivin and Ng (2006). We cast the model using a state-space representation. In particular, we generalize the state-space form (SSF) proposed by Frale et al. (2011) to take into consideration the constraints imposed by the temporal aggregation of three (or more) different frequencies. The modified SSF is defined in terms of partially cumulated high-frequency series subject to missing observations, and a Kalman filter and a smoother are then applied to estimate missing values and generate forecasts via maximum likelihood[2].

From a methodological point of view, our work is close to Aruoba et al. (2009), who propose a framework to track economic activity in real time, using data available at a variety of different frequencies. However, while their paper mainly focuses on the extraction and forecast of *latent* business activity, in our paper high-frequency indicators are exploited to disaggregate the quarterly values of GDP at higher frequency. This allows us to obtain timely updates of the GDP values which are, at the same time, consistent with the quarterly official releases provided by statistical agencies.

We find that the use of high-frequency indicators significantly contributes to improving the estimates and the forecasts of Italian GDP. These results are in line with the findings of Casals et al. (2009), who show theoretically how temporal aggregation affects the predictive accuracy of the models estimated with low frequency data (see also Marcellino, 1999). To

[2] In the context of a large dataset (Forni et al., 2000), a computationally feasible maximum likelihood approach has been proposed by Banbura and Modugno (2014) and Jungbacker et al. (2011).

assess the performance and forecasting ability of our model in real time, we conduct an out-of-sample exercise and compare our results with other alternative models which do not include the fortnightly frequency. We show that our fortnightly model outperforms other benchmark models and provides smaller RMSEs, with the gain being statistically significant especially for nowcasting.

In principle, our model is able to deal with data available at higher frequencies, including daily, as proposed in Aruoba et al. (2009). However, we think that daily data could induce noise in the model estimates, as they are strongly affected by seasonal components, that would require specific treatments, out of the scope of this work.[3]

The rest of the paper is organized as follows. In Section 2 we briefly revise the mixed-frequency factor model of Frale et al. (2011) and show how its representation can be generalized to handle data available at more than two frequencies. Section 3 presents an empirical application that delivers a fortnightly indicator of the Italian economic activity. Section 4 concludes.

2. The model framework

This section describes our mixed-frequency factor model. The econometric framework was originally developed in Frale et al. (2011) to obtain a monthly coincident index for the euro area, considering a model with two frequencies (i.e., quarterly and monthly). We extend this framework to the case of multiple frequencies. We start by introducing the main notation and assumptions and then provide an overview of the statistical treatment of the model. The SSF and its generalization to the case of more than two frequencies, including other filtering and estimation details, are reported in the Appendix.

Let $\mathbf{y}_t$ denote an $N \times 1$ vector of time series at time t, which we assume to be integrated of order one, or $I(1)$. In our context, for example, $\mathbf{y}_t$ can collect the GDP series and other economic indicators, eventually available at different frequencies. The dynamic factor model assumes that the series in $\mathbf{y}_t$ can be modeled as the sum of two components. The first component is represented by the common factor, f_t. The second one, $\boldsymbol{\gamma}_t$, captures instead the idiosyncratic behaviour of each series[4]. We assume that both components are difference

[3] It is worth noting that estimation at a daily (or weekly) basis would introduce the further problem of time-varying temporal aggregation due to the different lengths of months. A fortnightly frequency, instead, allows us to set two pre-specified (and time-constant) intervals in each month. The first interval is represented by the first 15 days of the month, while the second fortnight coincides with the last day of each month (whether it has 28, 29, 30 or 31 days).

[4] A multiple factor representation is also possible using this framework. A very interesting application

stationary and subject to autoregressive dynamics. Finally, let $\boldsymbol{\theta}$ be an $N \times 1$ vector of loadings. Then, the factor model (Stock and Watson, 1991) has the following representation:

$$\begin{array}{lcll} \mathbf{y}_t & = & \boldsymbol{\vartheta} f_t + \boldsymbol{\gamma}_t + \boldsymbol{B}\boldsymbol{X}_t, & t = 1, 2, .., n \\ \phi(L)\Delta f_t & = & \eta_t, & \eta_t \sim NID(0, \sigma_\eta^2) \\ \boldsymbol{D}(L)\Delta\boldsymbol{\gamma}_t & = & \boldsymbol{\delta} + \boldsymbol{\eta}_t^* & \boldsymbol{\eta}_t^* \sim NID(\mathbf{0}, \boldsymbol{\Sigma}_{\eta^*}) \end{array} \tag{1}$$

where $\phi(L)$ is an autoregressive polynomial of order p with stationary roots,

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - ... - \phi_p L^p,$$

and the polynomial matrix $\boldsymbol{D}(L) = \text{diag}\,[d_1(L), d_2(L), ..., d_N(L)]$ is diagonal with $d_i(L) = 1 - d_{i1}L - d_{i2}L^2 - ... - d_{ip_i}L^{p_i}$. The disturbances η_t and $\boldsymbol{\eta}_t^*$ are mutually uncorrelated at all leads and lags and $\boldsymbol{\Sigma}_{\eta^*} = \text{diag}(\sigma_1^2, \sigma_2^2, ..., \sigma_N^2)$. The $k \times 1$ vector $\boldsymbol{X}_t$ eventually contains the value of k deterministic regressors at time t, that are common to all series (e.g. trading days and moving festivals regressors), while $\boldsymbol{B}$ is the associated $N \times k$ matrix of regression coefficients. The estimation of both model parameters and the common factor, together with the disaggregated GDP values, is carried out by using a state space approach which is described in the Appendix.

When dealing with mixed-frequencies, the SSF of the model needs to be modified in order to account for the different timeliness of the data. Once the base-frequency is established, the model can be defined in terms of partially observed cumulated series and the temporal aggregation issue is converted into a missing values problem as follows.

Formally, suppose that $\mathbf{y}_t$ (expressed in levels) can be partitioned into S groups, i.e. $\mathbf{y}_t = \left[\mathbf{y}'_{1,t}, \mathbf{y}'_{2,t}, ..., \mathbf{y}'_{S,t}\right]'$, where the first group (of dimension N_1) contains the variables available at the highest frequency (i.e. the *base* frequency), while the remaining $(S-1)$ blocks (with dimension $N_2 + ... + N_S$) gather the set of flow-variables which are subject to temporal disaggregation. For example, assume that we have observations available at $S = 3$ different frequencies, namely fortnightly ($\mathbf{y}_{Ft}$), monthly ($\mathbf{y}_{Mt}$) and quarterly ($\mathbf{y}_{Qt}$), so that $\mathbf{y}_t = \left[\mathbf{y}'_{Ft}, \mathbf{y}'_{Mt}, \mathbf{y}'_{Qt}\right]'$. If the base frequency of the model is the fortnightly one, then all the variables in $\mathbf{y}_{Ft}$ do not need to be disaggregated. However, since the monthly and quarterly

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of a grouped factor model can be found in Andreou et al. (2017). Assuming that there could be sector-specific shocks affecting the US economy, they allow for the presence of three types of factors. The first group of factors explains the variation common to all the sectors in the economy (economy-wide factors); the second type includes factors exclusively pertaining to the IP sector, while the third one identifies factors that exclusively affect the non-IP sector.

data are not available at the fortnightly frequency (due to time aggregation), both $\mathbf{y}_{Mt}$ and $\mathbf{y}_{Qt}$ are not directly observable. Instead, the monthly data arises at the sum of $\lambda_m = 2$ consecutive fortnightly (twice per month) values, while the quarterly aggregates can be viewed as the sum of $\lambda_q = 6$ consecutive fortnightly measures.

Using a more general notation, we can define the vector $\mathbf{y}^*_\tau = [\mathbf{y}^{*\prime}_{1\tau}, \mathbf{y}^{*\prime}_{2\tau}, ..., \mathbf{y}^{*\prime}_{s\tau}]'$ which represents the set of the observed aggregated variables available at time $\tau = 1, 2, ..., [T/\lambda_s]$, with λ_s being the aggregation level corresponding to the s-th group of variables. Than, the temporal aggregation constrains impose that:

$$\mathbf{y}^*_{s\tau} = \sum_{j=0}^{\lambda_s - 1} \mathbf{y}_{s,\tau\lambda_s - j}, \qquad s = 1, 2, ..., S \qquad \tau = 1, 2, ..., [T/\lambda_s]$$

Note that λ_1 will be always equal to 1 in our framework, since it represents the aggregation level of the model base frequency.

One of the key features for the treatment of this set-up is the introduction of a cumulator variable into the state space model (see Harvey, 1989). To facilitate the intuition behind this mechanism, consider first the simplest case with only one temporal aggregation constraint and just two sets of variables, as in Frale et al. (2011). Let λ be any specified aggregation level and assume $\mathbf{y}_t = [\mathbf{y}'_{1t}, \mathbf{y}'_{2t}]'$, with $\mathbf{y}_{2t}$ being the set of indicators subject to temporal aggregation. Then, the cumulator variable, $\mathbf{y}^c_{2t}$, is defined as:

$$\mathbf{y}^c_{2t} = \psi_t \mathbf{y}^c_{2,t-1} + \mathbf{y}_{2t}$$

where ψ_t is an indicator variable such that:

$$\psi_t = \begin{cases} 0 & t = \lambda(\tau - 1) + 1, \quad \tau = 1, 2, ..., [n/\lambda] \\ 1 & \text{otherwise} \end{cases}$$

In other words, at times $t = \lambda\tau$ the cumulator variable coincides with the observed aggregate series (e.g. the observed quarterly value of the GDP), otherwise it contains the partial cumulative value of the aggregate in a smaller time interval (e.g. months). When dealing with $S > 2$ different frequencies, a more general version of this framework is required. In particular, for each s-th time-frequency ($s = 2, ..., S$), we define a corresponding cumulator variable, $\mathbf{y}^c_{s,t}$, as follows:

$$\mathbf{y}^c_{s,t} = \psi_{s,t} \mathbf{y}^c_{s,t-1} + \mathbf{y}_{s,t} \qquad s = 2, 3, ..., S \tag{2}$$

with

$$\psi_{s,t} = \begin{cases} 0 & t = \lambda_s(\tau - 1) + 1, \quad \tau = 1, 2, ..., [n/\lambda_s] \qquad s = 2, 3, ..., S \\ 1 & \text{otherwise.} \end{cases} \tag{3}$$

where now the indicator variable $\psi_{s,t}$ is also frequency-specific. As an example, consider again a model at a bimonthly base-frequency that uses also monthly and quarterly aggregated data. In this case, we can easily specify two different aggregation levels. The first level ($\lambda_M = 2$) allows us to disaggregate monthly values into two fortnightly measures, while the second level ($\lambda_Q = 6$) decomposes each quarter into six fortnightly values. We can then introduce two different indicator variables, $\psi_{M,t}$ and $\psi_{Q,t}$, defined as in (3), so that we can set the two sequences $\psi_M = \{0,1,0,1,0,...\}$ and $\psi_Q = \{0,1,1,1,1,1,0,1,1,1,1,1,...\}$, with the corresponding cumulator variables as follows

$$\mathbf{y}^c_{M,t} = \begin{cases} y^c_{M,1} = & y_{M,1}, & t=1 \\ y^c_{M,2} = & y_{M,1}+y_{M,2}, & t=2 \\ y^c_{M,3} = & y_{M,3}, & t=3 \\ y^c_{M,4} = & y_{M,3}+y_{M,4}, & t=4 \\ y^c_{M,5} = & y_{M,5}, & t=5 \\ y^c_{M,6} = & y_{M,5}+y_{M,6}, & t=6 \\ \vdots & & \vdots \end{cases}, \mathbf{y}^c_{Q,t} = \begin{cases} y^c_{Q,1} = & y_{Q,1}, & t=1 \\ y^c_{Q,2} = & y_{Q,1}+y_{Q,2}, & t=2 \\ y^c_{Q,3} = & y_{Q,1}+y_{Q,2}+y_{Q,3}, & t=3 \\ y^c_{Q,4} = & y_{Q,1}+y_{Q,2}+y_{Q,3}+y_{Q,4}, & t=4 \\ y^c_{Q,5} = & y_{Q,1}+y_{Q,2}+y_{Q,3}+y_{Q,4}+y_{Q,5}, & t=5 \\ y^c_{Q,6} = & y_{Q,1}+y_{Q,2}+y_{Q,3}+y_{Q,4}+y_{Q,5}+y_{Q,6}, & t=6 \\ y^c_{Q,7} = & y_{Q,7} & t=7 \\ \vdots & & \vdots \end{cases}$$

It is worth noting that, using this setup, λ_s $(s = 1,..,S)$ could be in principle a time-varying variable since, for example, some months have 28 days, some have 29, and others 30 or 31. For ease of notation we ignore this possible issue at the moment and prefer to keep the variable time-constant. The extension to the time-varying case is however straightforward.

The result of the above framework is an alternative state space representation, the derivation of which is given in the Appendix. Under the normality assumption of the disturbances distribution, the model parameters can be estimated via maximum likelihood, using the prediction error decomposition performed by the Kalman filter. Maximum likelihood estimation is carried out by a quasi-Newton algorithm, such as the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm. Given the parameter estimates,the Kalman filter and the smoother provide the minimum mean-square estimates of the state $\boldsymbol{\alpha}^*_t$ (see Harvey, 1989) and, therefore, the missing values in $\mathbf{y}^c_t = [\mathbf{y}^c_{2t},...,\mathbf{y}^c_{S,t}]'$ can be optimally estimated. Finally, estimates of the vector $\mathbf{y}_t = [\mathbf{y}_{2t},...,\mathbf{y}_{S,t}]'$ can be trivially obtained, by using the following "decumulator" variable:

$$\mathbf{y}_{s,t} = \mathbf{y}^c_{s,t} - \psi_{s,t}\mathbf{y}^c_{s,t-1} \tag{4}$$

3. Empirical application: a bimonthly indicator for the Italian GDP

In order to show the practical relevance of the model described above, we present an empirical application that uses data available at three frequencies, namely quarterly, monthly and fortnightly (the latter being our chosen base-frequency, as defined in Section 2). As a final result, the model delivers a fortnightly coincident indicator of Italian economic activity and allows us to obtain more timely estimates (i.e. twice per month) of Italian GDP. A crucial aspect of the application concerns the identification of the appropriate set of indicators, which should in principle satisfy the properties of relevance, availability and timeliness. We investigate the predictive ability of the model, with an out-of-sample rolling exercise. To show the potential benefits of using high-frequency data, we compare the forecasts of our model with those provided by other models that do not include the fortnightly frequency. We find that our fortnightly model delivers significantly smaller errors in short term forecasting.

This Section is organized as follows. The list of the selected indicators is provided in Section 3.1. The fortnightly estimates of the Italian GDP, together with all the model parameter estimates, are shown in Section 3.2. Finally, Section 3.3 presents a real-time rolling exercise and assesses the forecasting ability of the model.

3.1. Data description

Our data set includes quarterly, monthly and fortnightly series, from 1991Q1 to 2017Q1. We consider all the variables expressed in levels.

As an empirical application is concerned, the selection of the most relevant and representative indicators plays a crucial role in the analysis. In order to identify variables that can be defined as representative of Italian economic activity and, importantly, not subject to our discretionary choice, we first follow Camacho and Martinez-Martin (2015) criteria, which include high statistical correlation with GDP growth and a short publication lag. Even though, of course, this does not provide a complete procedure for selecting indicators, it represents an important prerequisite in the context of multivariate factor models. We also consider variables which have already been used (and found to be significant) in the applied literature on forecasting the Italian business cycle (see, e.g, Altissimo et al., 2000; Bulligan et al., 2012). In selecting indicators we also try to represent different markets, such as manufacturing, financial market, external trade and consumption. The combination of all these requirements leads to a final set of 9 indicators[5]: (1) Electricity consumption, which is available bimonthly and has been found to have a strong coincident correlation in the empirical literature, especially for

[5]It is worth noting that, in order to provide a realistic picture of economic activity we preliminarily analyse a vast list of timely and potentially relevant indicators like, e.g., other survey indicators, consumers and

countries that have a high exposure to the industrial sector, like Italy (see, e.g, Bulligan et al., 2012); (2) the Italian Stock Market Index (FTSE MIB), available daily or even at a higher frequency; (3) the monthly Italian Industrial Production Index for paper and other paper products (as in Altissimo et al., 2000) ; (4) the monthly Italian Volume Index of Foreign Orders; (5) the monthly Italian Index of Total Exports for goods; (6) the monthly CPB's World Trade Volume Index; (7) the monthly Confidence Index for the manufacturing sector; (8) the monthly Industrial Production Index and (9) the monthly Total Industrial Orders. All the series use 2010 as the base year and are seasonally adjusted. The list of selected indicators, their frequency and availability, together with the correlation coefficient of each variable with quarterly GDP, in terms of growth rates, is reported in Table 1. The last column of the table also displays the chosen lag of each variable considered in the model. The coincident/leading properties of the variables are also depicted in Figure 1, which shows the co-movement between quarterly GDP dynamics and each indicator at the chosen lag. As expected, all the indicators considered in our sample show quite a strong and positive correlation with GDP, at least up to the lag of order 1 (one quarter), confirming the potential coincident and leading properties of all the variables.

3.2. Estimation results

Using the set of indicators listed in Section 3.1, we use our mixed-frequency factor model to track and forecast Italian GDP. The model also derives fortnightly values for GDP, which are consistent with the official quarterly series.

Before presenting estimation results, we briefly discuss the main identification assumptions required for model identifiability. First, to avoid identification issues, which in turn could affect the estimation of auto-regressive effects (see Proietti and Moauro, 2006), the idiosyncratic component of GDP is specified as a random walk with drift. As for the parametric assumptions of the model, it is standard in the literature to assume that the coincident index will follow an autoregressive (AR) process. According to selection criteria (like, e.g, the standard BIC and AIC) we found empirical evidence for the common factor to follow an AR(1) process. As a further identification assumption, we set $\sigma_\eta^2 = 1$. Moreover, following the dynamic factor model representation formulated in Section 2, we assume that each of the series is stationary in first differences. Finally, to conclude our model specification, the vector $\mathbf{X}_t$ in

business confidence indexes, Markit Italy Services PMI and other financial and monetary flows. However, we did not find evidence of any significant contribution in terms of loadings on the common factor and the nine variables described above produced the model with the smallest BIC and AIC. Results are available upon request.

model (1) contains regressors at time t which are common to all series and essentially accounts for calendar effects (trading days, Easter holidays and length of each fortnight).

The estimates of model parameters for the sample $1991Q1$ - $2017Q1$ are reported in Table 2. The loadings of the common factor are significant for all variables (except for the stock price index), confirming that all the indicators contribute significantly to explaining the dynamics of Italian economic activity.

The estimates of the fortnightly GDP are displayed in Figure 2. The red lines in Panels (A) and (B) of Figure 2 show the GDP estimates disaggregated at the fortnightly frequency provided by our model, both in levels (panel (A)) and in growth rates (panel (B)). The blue lines represent the disaggregated estimates obtained by using polynomial interpolations of the quarterly values. Panels (C) and (D) show, instead, the (observed) official GDP at the quarterly frequency, respectively in levels and growth rates. The difference between the two methods shows up clearly in Panel (B), where the disaggregation obtained by polynomial fitting appears very smooth compared with the one produced by the factor model which, instead, seems to capture actual GDP volatility much better. Moreover, as an interpolation technique, the polynomial fitting produces a disaggregated series which does not satisfy the temporal aggregation constraints. This is, instead, automatically guaranteed by the factor model, through the constraints imposed by the cumulator variable in (2).

Finally, in order to show how the common factor is able to represent the co-movement among the series, in Figure 3 we report all the series in levels (disaggregated at the fortnightly frequency) and the extracted fortnightly common factor (represented by the solid black line in Figure 3). As we can easily see from the figure, the common factor properly summarizes the dynamics of most of the variables and thus looks consistent with the Italian business cycle.

3.3. Model performance and forecasting ability in real time

We analyse the short-term forecasting ability of the model by conducting an out-of-sample rolling exercise. Our objective is twofold. On the one hand we would like to assess whether the inclusion of high-frequency indicators improves the performance of the model; on the other, we would like to evaluate the model performance in (pseudo) real time, that is adjusting our information set as new information becomes available, tracking the exact timeliness (and delay) of the various indicators. As regards the question of improved performance of the model, we consider three alternative models. The first two models are mixed-frequency one-factor models specified at the monthly level, which consider the same quarterly and monthly variables of our fortnightly model. In particular, the first factor model ("Monthly FM1", hereafter) excludes the two fortnightly indicators from the analysis, i.e. it considers 7 monthly indicators, plus quarterly GDP. The second factor model ("Monthly FM2"), instead, does consider the two fortnightly variables, but they are aggregated at the monthly level. Finally, the third competing model ("MIDAS") provides quarterly forecasts of GDP by using the MIDAS regression (Ghysels et al., 2005) and considers the same monthly indicators of "Monthly FM2" as explanatory variables. Let Q_T denote the last observable quarter in the sample and let Q_{T+1} be the one-quarter ahead, which is of course not yet available. In order to properly mimic the availability of our data, for each model described above we provide forecasts of the GDP level up to one-quarter ahead, using three different scenarios:

(a) *Month 1*: at this point in time we only have information for the first month in the latest quarter. Therefore, due to publication lags we still do not know the value of GDP[6] in the previous quarter. Hence, at time T, we need also to forecast GDP at quarter Q_{T-1}. Despite publication delays, however, all the other monthly (and fortnightly) indicators are already available for each month, since we mainly consider one-quarter lagged variables in the analysis.

(b) *Month 2*: the set of indicators is updated up to the second month within the quarter. The value of the GDP at Q_{T-1} is now available, and the information set is updated in order to obtain a better forecast of the GDP at either time Q_T and Q_{T+1}.

(c) *Month 3*: all the values available within the quarter are now available and the forecasts are based on the richest information set.

Each of the three different scenarios is then considered to perform an out-of-sample rolling exercise. We consider a rolling window of 312 fortnights (i.e a testing period of 13 years), starting from the period in the interval 15 January 1990 - 31 December 2002. Hence, starting from 15 of January 2003, the four models are estimated at the highest frequency-level (i.e. fortnightly for the fortnightly model, monthly for the other two competing factor models) and the quarterly forecasts of the GDP are then computed by summing up the fortnightly (or monthly) figures. Then, the forecast origin is shifted one fortnight ahead and the estimation process is repeated until the end of the sample is reached. The root mean square forecast errors (RMSFEs) performed by each model are presented in Table 3. In order to disentangle the effect of the most recent crisis on model performance, we conducted our analysis on two different sample periods. The first sample (results reported in Panel A) covers the whole period, from 2003Q1 up to 2017Q1, while the second one (in Panel B) excludes the double

[6]Official estimates of Italian GDP are typically released with a delay of about 45 days. Starting from May 2018, GDP measures will be available more timely, with a publication lag of 30 days.

dip recession of the Italian economy. In all cases, the RMSFE is in favour of our fortnightly model since, at each forecast horizon, its value is always smaller than in the other three models.

As expected, for all the models, the RMSFE increases as the forecast horizon increases, reflecting the higher degree of uncertainty when computing forecasts at longer time horizons. In particular, it seems that high-frequency indicators are particularly useful for nowcasting (i.e the forecast of the current value of GDP, not yet released by statistical agencies), since in Q_{T-1} and Q_T we observe the highest difference between the RMSFEs of the fortnightly model compared to the other three competitive models. Also, if we evaluate the performance of each of the four models across the three months, the RMSFEs tend to decrease significantly from Month 1 to Month 3, when we refer to forecasts in Q_T. The dominance of the fortnightly model is even more evident if we exclude the period of the recent crisis (see Panel B); the smaller RMSFEs in Panel B (compared to Panel A) are expected and reasonably reflect the high volatility of the endogenous variable during the crisis.

It is worth noting that the forecasts of the two alternative monthly factor models are very similar: the inclusion of high-frequency indicators aggregated at a lower frequency may not improve forecasting ability, as asserted by the theoretical finding of Casals et al. (2009). To predict the values of a low-frequency indicator (eg. GDP, as in our case), then a model which efficiently combines low- and high-frequency data may provide better forecasts than a model which uses only low-frequency data. The MIDAS model, instead, does not seem to provide any forecasting improvement compared with factor models. This is mainly due to the fact that, by construction, MIDAS models do not exploit the information provided by the Kalman filter (as is the case in mixed-frequency factor models). Hence, in Month 1 and Month 2, factor models are provided by a more precise information set compared with MIDAS. In Month 3, the three models reach the same information set and MIDAS's performance is of the same order as the two monthly factor models.

The forecasting performance of the four models in the scenario of *Month 3* is also shown graphically in Figure 4. The actual series of GDP growth is displayed, together with the forecasts at Q_T (top panel) and Q_{T+1} (bottom panel) provided by the three competing models. The two benchmark models show a very similar behavior, which is often lagging with respect to the series of the observed GDP. The fortnightly model, instead, seems to be closer to the realized values of the target variable and to track better the turning points of the cycle. The superior performance of the fortnightly model is more evident in the top panel of the figure, where the forecasts are computed to predict the values in Q_T.

Finally, to give some insights of estimation uncertainty, in Figure 5 we show the time series of the rolling forecasts provided by our fortnightly model together with the corresponding 95%

confidence bands. As expected, forecasts seem to be more volatile during periods associated with economic crises. Uncertainty also increases with the time horizon of the forecasts.

In order to statistically assess the predictive accuracy of all the models considered, in Table 4 we report the p-values associated with the Diebold-Mariano test (Diebold and Mariano, 1995). The test is computed using the forecast errors obtained by forecasting the GDP in Q_T and Q_{T+1}, under the three different scenarios described above. The null hypothesis is that our fortnightly model has the same forecast accuracy as the three competing models. The table shows that the better performance of the fortnightly model is statistically significant, especially for nowcasting. As argued before, instead, the improvement of the fortnightly model at a longer horizon is less clear and the test does not provide any statistical evidence in favour of any of the four models, except in the case of Month 1.

4. Conclusions

Building on Frale et al. (2011), this paper has argued for the use of mixed frequency dynamic factor models to estimate and forecast Italian GDP, exploiting indicators that are released at monthly and fortnightly frequencies. The model implicitly assumes that the economic activity evolves fortnightly and that the level of GDP, which is quarterly, can be expressed as the cumulative sum of the previous six fortnights. The use of variables in levels and the cumulator variable contributes to simplifying the well-known problems related to temporal aggregation. Using this factor model setup, we addressed two main points. First, we obtained a timely coincident index of GDP. At the same time, we investigated whether the use of higher frequency indicators could improve the forecasts of the model. The empirical application on Italian data clearly shows evidence for the potential benefits of high-frequency indicators, especially in the very short-run. In particular, we found that the use of bimonthly indicators results in a significant reduction of RMSFEs for nowcasting.

Even though our empirical analysis was limited to three frequencies, with the highest being the fortnightly one, we think that multi-frequency factor models are powerful tools to track and forecast macroeconomic variables, thanks to their ability to incorporate heterogeneous information coming from different data sets. Many other extensions are of course possible. Other applications using experimental and big data, possibly using data on payments, are left for future research.

Technical Appendix

In this section we show how the mixed frequency factor model in (1) can be written in the SSF. To facilitate readability, we first start by introducing the SSF for the easiest case where all the indicators in $\boldsymbol{y}_t$ are observable at the same frequency. The generalization to the case of mixed frequency will be then straightforward.

Let $\boldsymbol{e}_{1p} = [1, 0, .., 0_p]'$ be a $p \times 1$ vector having 1 in the first position and zeros elsewhere. Define by $\boldsymbol{I}_p$ a $p \times p$ identity matrix and let $\boldsymbol{0}_p$ be a $p \times 1$ vector of zeros.

Remember that the model assumes an autoregressive process for both the factor (f_t) and each of the idiosyncratic components ($\boldsymbol{\gamma}_t = [\gamma_{1t}, ..., \gamma_{Nt}]'$) in first differences. If p denotes the autoregressive order of the common factor and p_i denotes the autoregressive order of the i-th component of $\boldsymbol{\gamma}_t$, $i = 1, .., N$, then

$$\begin{aligned} f_t &= f_{t-1} + \phi_1 \Delta f_{t-1} + \phi_2 \Delta f_{t-2} + ... + \phi_p \Delta f_{t-p} + \eta_t \\ \gamma_{it} &= \delta_i + \gamma_{i,t-1} + d_{i1} \Delta \gamma_{i,t-1} + d_{i2} \Delta \gamma_{i,t-2} + ... + d_{ip_i} \Delta \gamma_{i,t-p_i} + \eta^*_{it}, \quad i = 1, .., N. \end{aligned}$$

All the observable variables enter the model in level. Thus

$$\boldsymbol{y}_t = \boldsymbol{\vartheta} f_t + \boldsymbol{\gamma}_t + \boldsymbol{B}\boldsymbol{X}_t$$

This means that the state-space representation has to consider a state vector where all the unobserved components need to appear not only in first differences, but also in levels (f_t and $\boldsymbol{\gamma}_t$). Let us start by deriving the SSF for the common factor. Define the following $p \times 1$ vector

$$\boldsymbol{g}_t = \begin{bmatrix} \Delta f_t \\ \Delta f_{t-1} \\ \vdots \\ \Delta f_{t-p+1} \end{bmatrix}$$

such that

$$\begin{aligned} \Delta f_t &= \boldsymbol{e}'_{1p} \boldsymbol{g}_t \\ \boldsymbol{g}_t &= \boldsymbol{T}_{\Delta_f} \boldsymbol{g}_{t-1} + \boldsymbol{e}_{1p} \eta_t \end{aligned}$$

where $\boldsymbol{T}_{\Delta_f}$ is defined as

$$\boldsymbol{T}_{\Delta_f} = \begin{bmatrix} \phi_1 & \phi_2 & \cdots & \phi_p \\ & \boldsymbol{I}_{p-1} & & \boldsymbol{0}_{p-1} \end{bmatrix}.$$

Now we can define the following state vector and transition matrix associated to the common factor dynamics:

$$\boldsymbol{\alpha}_{f,t} = \begin{bmatrix} f_t \\ \boldsymbol{g}_t \end{bmatrix}, \qquad \boldsymbol{T}_f = \begin{bmatrix} 1 & \phi_1 & \cdots & \phi_p \\ \boldsymbol{0}_{p-1} & & \boldsymbol{T}_{\Delta_f} & \end{bmatrix}$$

such that the following holds:

$$\begin{aligned} f_t &= \boldsymbol{e}_{1(p+1)}\boldsymbol{\alpha}_{f,t} \\ \boldsymbol{\alpha}_{f,t} &= \boldsymbol{T}_f\boldsymbol{\alpha}_{f,t-1} + \boldsymbol{h}_f\eta_t \end{aligned}$$

where $\boldsymbol{h}_f = [1, \boldsymbol{e}'_{1p}]'$.
We can now use a similar representation to derive the SSF for the idiosyncratic component $\boldsymbol{\gamma}_t$. For the i-th component γ_{it}, we define

$$\boldsymbol{\alpha}_{\gamma_i,t} = \begin{bmatrix} \gamma_{it} \\ \Delta\gamma_{it} \\ \Delta\gamma_{i,t-1} \\ \vdots \\ \Delta\gamma_{i,t-p_i+1} \end{bmatrix}, \qquad \boldsymbol{T}_{\gamma_i} = \begin{bmatrix} 1 & d_{i1} & \cdots & d_{ip_i} \\ \boldsymbol{0}_{p_i-1} & & \boldsymbol{T}_{\Delta_{\gamma_i}} & \end{bmatrix}, \quad \text{with} \quad \boldsymbol{T}_{\Delta_{\gamma_i}} = \begin{bmatrix} d_{i1} & d_{i2} & \cdots & d_{ip_i} \\ & \boldsymbol{I}_{p_i-1} & & \boldsymbol{0}_{p_i-1} \end{bmatrix}.$$

Then, we can write

$$\gamma_{it} = \boldsymbol{e}'_{1,p_i+1}\boldsymbol{\alpha}_{\gamma_i,t}, \qquad \boldsymbol{\alpha}_{\gamma_i,t} = \boldsymbol{T}_{\gamma_i}\boldsymbol{\alpha}_{\gamma_i,t-1} + +\boldsymbol{h}_{\gamma_i}\delta_i + \boldsymbol{h}_{\gamma_i}\eta^*_{it}, \qquad i = 1, 2, ..., N$$

where $\boldsymbol{h}_{\gamma_i} = [1, \boldsymbol{e}'_{1p_i}]'$ and δ_i is the drift of the i-th idiosyncratic component. We can now combine all the blocks and define the total state vector of dimension $\kappa \times 1$, with $\kappa = (p + 1) + \sum_{i=1}^{N}(p_i + 1)$, as

$$\boldsymbol{\alpha}_t = [\boldsymbol{\alpha}'_{f,t}, \alpha_{\gamma_1,t}, \alpha_{\gamma_2,t}, \cdots, \alpha_{\gamma_N,t}]' \tag{5}$$

and the following $\kappa \times \kappa$ transition matrix $\boldsymbol{T} = \text{diag}[\boldsymbol{T}_f, \boldsymbol{T}_{\gamma_1}, \boldsymbol{T}_{\gamma_2}, \cdots, \boldsymbol{T}_{\gamma_N}]$, so that the SSF for the model in (1) can be written as

$$\boldsymbol{y}_t = \boldsymbol{Z}\boldsymbol{\alpha}_t + \tilde{\boldsymbol{X}}_t\boldsymbol{\beta} \tag{6}$$
$$\boldsymbol{\alpha}_t = \boldsymbol{T}\boldsymbol{\alpha}_{t-1} + \boldsymbol{W}\boldsymbol{\beta} + \boldsymbol{H}\boldsymbol{\eta}_t \tag{7}$$

where $\boldsymbol{Z} = [\boldsymbol{\vartheta}_0, \boldsymbol{0}_{N\times p}, \boldsymbol{E}]$, with $\boldsymbol{E} = \text{diag}[\boldsymbol{e}'_{1p_1}, \boldsymbol{e}'_{1p_2}, \cdots, \boldsymbol{e}'_{1p_N}]$ being a block-diagonal matrix of dimension $N \times \sum_{i=1}^{N}(p_i + 1)$, where each i-th diagonal block equals $\boldsymbol{e}'_{1p_i}$ and has a dimension of $1 \times p_i$. $\boldsymbol{\beta}$ is a $(2N + Nk) \times 1$ vector, where the first $2N$ elements correspond to the pair (f_{0i}, δ_i), for $i = 1, 2, ..., N$, while the last Nk elements contain the values of vec($\boldsymbol{B}$). Accordingly, $\tilde{\boldsymbol{X}}_t = [\mathbf{0}_{N\times 2N}, \boldsymbol{I}_N \otimes \boldsymbol{X}_t']$, $\boldsymbol{H} = \text{diag}[\boldsymbol{h}_f, \boldsymbol{h}_{\gamma_1}, ..., \boldsymbol{h}_{\gamma_N}]$ and $\boldsymbol{\eta}_t = [\eta_f, \eta_{1t}^*, ..., \eta_{Nt}^*]'$. $\boldsymbol{W}$ is a time-invariant matrix which selects the drift δ_i of the corresponding state element (see also Frale et al., 2011).

The relationship in (6) represents the measurement equation, which relates the vector of observable variables ($\mathbf{y}_t$) to a set of latent states ($\boldsymbol{\alpha}_t$) and some exogenous variables ($\mathbf{X}_t$), typically used to incorporate calendar effects. The relationship in (7) defines the transition equation, which mainly describes the evolution over time of the latent states, and where $\mathbf{W}$ and $\mathbf{H}$ are two time-constant matrices.

The SSF described above can be easily extended to properly accommodate for the presence of mixed-frequencies. The result is an alternative state space representation, where the state vector in (5) needs now to be augmented by the $(N_2 + ... + N_S)$-vector $\left[\mathbf{y}_{2,t}^{c'}, ..., \mathbf{y}_{S,t}^{c'}\right]'$. Notice that, using (6), (7) and (2), $\mathbf{y}_{s,t}^c$ has the following representation

$$
\begin{aligned}
\mathbf{y}_{s,t}^c &= \psi_{s,t}\mathbf{y}_{s,t-1}^c + \mathbf{y}_{s,t} \\
&= \psi_{s,t}\mathbf{y}_{s,t-1}^c + \mathbf{Z}_s\mathbf{T}\boldsymbol{\alpha}_{t-1} + [\tilde{\mathbf{X}}_{s,t} + \mathbf{Z}_s\mathbf{W}]\boldsymbol{\beta} + \mathbf{Z}_s\mathbf{H}\boldsymbol{\eta}_t \qquad s = 2, 3, ..., S
\end{aligned} \tag{8}
$$

where $\mathbf{y}_{1,t} = \mathbf{Z}_1\boldsymbol{\alpha}_t + \mathbf{X}_1\boldsymbol{\beta}$. $\mathbf{Z}_s$ has a dimension of $N_s \times \kappa$ and represents the s-th block of the measurement matrix $\mathbf{Z} = [\mathbf{Z}_1', ..., \mathbf{Z}_S']'$, and where we have partitioned the matrix $\tilde{\mathbf{X}}_t = [\tilde{\mathbf{X}}_1', , ..., \tilde{\mathbf{X}}_S']'$. Therefore, the new augmented state and observation vectors can be defined as:

$$
\boldsymbol{\alpha}_t^* = \begin{bmatrix} \boldsymbol{\alpha}_t \\ \mathbf{y}_{2,t}^c \\ \mathbf{y}_{3,t}^c \\ \vdots \\ \mathbf{y}_{S,t}^c \end{bmatrix}, \qquad \mathbf{y}_t^\dagger = \begin{bmatrix} \mathbf{y}_{1,t} \\ \mathbf{y}_{2,t}^c \\ \mathbf{y}_{3,t}^c \\ \vdots \\ \mathbf{y}_{S,t}^c \end{bmatrix} \tag{9}
$$

where $\boldsymbol{\alpha}_t$ is defined in (5) and represents the state vector of the SW factor model with no mixed- frequency data. The new state vector $\boldsymbol{\alpha}_t^*$ and the observation vector $\mathbf{y}_t^\dagger$ have a dimension of $\kappa^* = (\kappa + N_2 + N_3 + ... + N_S)$ and $N = (N_1 + N_2 + ... + N_S)$, respectively. Using this approach, therefore, the unavailable $(S-1)$ blocks $[\mathbf{y}_{2,t}, ..., \mathbf{y}_{S,t}]'$ are replaced by the corresponding augmented vectors $[\mathbf{y}_{2,t}^c, ..., \mathbf{y}_{S,t}^c]'$, which are observed at time $t = \lambda_s\tau$, while they are treated as missing values (to be estimated) at all the intermediate times.

The final SSF for the disaggregated model can be written as

$$\mathbf{y}_t^{\dagger} = \mathbf{Z}^* \boldsymbol{\alpha}_t^* + \tilde{\mathbf{X}}_t \boldsymbol{\beta}, \qquad \boldsymbol{\alpha}_t^* = \mathbf{T}^* \boldsymbol{\alpha}_{t-1}^* + \mathbf{W}^* \boldsymbol{\beta} + \mathbf{H}^* \boldsymbol{\eta}_t \tag{10}$$

where

$$\mathbf{Z}^* = \begin{bmatrix} \mathbf{Z}_1 & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_{N_2} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{I}_{N_3} & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{I}_{N_S} \end{bmatrix}, \qquad \mathbf{T}^* = \begin{bmatrix} \mathbf{T} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{Z}_2\mathbf{T} & \psi_{1,t}\mathbf{I}_{N_2} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{Z}_3\mathbf{T} & \mathbf{0} & \psi_{2,t}\mathbf{I}_{N_3} & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{Z}_s\mathbf{T} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \psi_{s,t}\mathbf{I}_{N_S} \end{bmatrix},$$

$$\mathbf{W}^* = \begin{bmatrix} \mathbf{W} \\ \mathbf{Z}_2\mathbf{W} + \mathbf{X}_2 \\ \mathbf{Z}_3\mathbf{W} + \mathbf{X}_3 \\ \vdots \\ \mathbf{Z}_s\mathbf{W} + \mathbf{X}_s \end{bmatrix}, \qquad \mathbf{H}^* = \begin{bmatrix} \mathbf{I} \\ \mathbf{Z}_2 \\ \mathbf{Z}_3 \\ \vdots \\ \mathbf{Z}_s \end{bmatrix} \mathbf{H} \tag{11}$$

Hence, the cumulator variable proposed by Harvey (1989) significantly simplifies the problem of the temporal aggregation of the lower frequency variables by using a recursive representation that requires only one state per variable, while the missing observations for each variable are linked to only one cumulator variable.

In order to convince the reader about the relevance of the proposed approach, consider the case of a fortnightly model with one quarterly, seven monthly and two fortnightly indicators in levels, as in our empirical application. Using our approach, the measurement equation is specified in such a way that monthly variables are observed every two basic fortnightly periods and quarterly variables every six periods. The missing observations for each one of the indicators will be linked to only one cumulator variable (hence, in total 7 for the various monthly indicators and 1 for the quarterly variable). In total, the size of the state vector is equal to 20.

In the absence of the cumulator variable, instead, one would need to specify a measurement equation where the quarterly variable were linked to the last six factors and the last six measurement errors. Thus, in this case, the resulting state vector would greatly increase its dimension (having a size of 67).

Specifying the model in levels, rather than in growth rates or first differences (see Bambura and Modugno, 2014 and Mariano and Murasawa, 2003) also simplifies the high-dimensionality of the problem. In fact, by applying Mariano and Murasawa (2003)'s approximation, we would end up with a state vector containing one factor, Δf_t, 10 of its lag, one innovation for each of the measurement errors $\eta^*_{i,t}$ and 10 of its lags. In total, a size of 110. A more reduced representation (with possibly only 11 states) has recently been proposed by Basselier et al. (2017) for the euro area. However, one of the drawbacks of this approach is that one cannot derive a fortnightly measure of GDP, which is one of the objectives of our paper. Our approach, therefore, combines both the concept of simplicity and parsimony. At the same time it shows how to deal with high frequency data using two simply ideas: the cumulator variable to deal with temporal aggregation, and the simplicity of mixing frequencies by using data in levels.

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Table 1

List of indicators and their coincident/leading properties.

The table shows the set of indicators included in the model. For each of the variables, we report the corresponding label used in the model, its frequency and its delay of release. We also report the correlation coefficient between quarterly GDP growth and each variable, previously aggregated at the quarterly level, from the coincident level (lag0) up to a lag of one year (lag4). The last column finally displays the selected lag of the variable used in the model.

	Label	Frequency	Delay	Correlation with quarterly GDP					Variable lag
				Lag0	Lag1	Lag2	Lag3	Lag4	
Electricity consumption	ElectrCons	Fortnightly	c.a 1 day	0.350	0.090	0.160	0.152	-0.053	0
FTSE MIB	MIB	Fortnightly	c.a 1 day	0.338	0.513	0.332	0.284	0.247	−6 fortnights
Industrial Production Index, Paper	Paper	Monthly	c.a 45 days	0.556	0.559	0.337	0.217	0.110	−3 months
Foreign Orders	ForeignOrd	Monthly	c.a. 50 days	0.411	0.429	0.275	0.138	-0.079	−3 months
Exports of goods	Exports	Monthly	c.a 45 days	0.644	0.468	0.221	0.060	-0.115	−3 months
CPB World Trade	CPB	Monthly	c.a 55 days	0.715	0.564	0.260	0.118	-0.06	−3 months
Confidence Index, manufacturing	ConfIndex	Monthly	c.a 25 days	0.561	0.616	0.273	0.229	0.022	−3 months
Industrial Production	IP	Monthly	c.a 45 days	0.834	0.563	0.288	0.097	-0.146	−3 months
Industrial Orders	Orders	Monthly	c.a 50 days	0.627	0.677	0.197	0.089	-0.156	−3 months

Table 2

Parameter estimates and standard errors.

The table shows the parameter estimates of the model described in Section 2. Standard errors are reported in brackets. Coefficients appear in boldface if significant at 10%

	Electr cons	MIB (-6)	Paper (-3)	Foreign Ord (-3)	Exports (-3)	CPB (-3)	ConfIndex (-3)	IP (-3)	Orders (-3)	GDP
θ_i	**0.035**	0.386	**0.307**	**2.747**	**1.593**	**0.373**	**0.219**	**0.311**	**1.931**	**0.192**
	(0.012)	(0.612)	(0.134)	(0.472)	(0.530)	(0.149)	(0.104)	(0.101)	(0.302)	(0.079)
δ_i	**0.012**	0.115	0.029	0.136	**0.462**	**0.127**	0.013	-0.010	0.068	**0.019**
	(0.004)	(0.249)	(0.051)	(0.192)	(0.208)	(0.027)	(0.043)	(0.038)	(0.110)	(0.008)
d_{i1}	0.304	0.454	0.799	-0.901	-0.348	0.579	0.052	0.892	-0.963	
σ_{η^*}	0.097	6.295	1.209	3.043	4.536	0.645	1.063	0.870	0.811	0.195

$$(1 + 0.591L)\Delta f_{1,t} = \eta_{1,t}, \quad \eta_{1,t} \sim N(0,1)$$

Table 3
Forecasting ability of the Fortnightly Model.

The table reports the Root Mean Square Forecast Errors (RMSFEs) of the out-of-sample rolling exercise performed by the four competing models (denoted by "Fortnightly Model", "Monthly FM1", "Monthly FM2", and "MIDAS" in the table), for each of the three scenarios described in Section 3.3 ("Month 1", "Month 2" and "Month 3", respectively). The errors are computed using the variables in levels. The experiment considers a rolling window of 312 fortnights (i.e. a testing period of 13 years). Starting from the 15th of January 2003, the three models are estimated at the highest frequency-level (i.e. bimonthly for the Bimonthly Model, monthly for the two benchmark models) and the quarterly forecasts of GDP are then computed by summing the fortnightly figures. The analysis is conducted over two different sample periods. The first period (Panel A in the table) covers the whole period, from 2003Q1 to 2017Q1. The second sample (Panel B in the table) excludes the intervals 2007Q4-2009Q2 and 2011Q3-2013Q1, in order to mitigate the forecast error due to the most recent financial crises. The lowest RMSFE of the three models in the same scenario and for the same forecast horizon is highlighted in gray.

	Panel A: $2003Q1 - 2017Q1$			Panel B: $2003Q1 - 2007Q3/2009Q3 - 2011Q2/2013Q2 - 2017Q1$		
	Month 1			**Month 1**		
	Q_{T-1}	Q_T	Q_{T+1}	Q_{T-1}	Q_T	Q_{T+1}
Fortnightly model	0.56	0.71	0.88	0.30	0.31	0.33
Monthly FM1	0.76	0.87	0.90	0.39	0.41	0.41
Monthly FM2	0.77	0.87	0.90	0.39	0.40	0.41
MIDAS	0.92	1.06	1.12	0.52	0.64	0.70
	Month 2			**Month 2**		
	Q_{T-1}	Q_T	Q_{T+1}	Q_{T-1}	Q_T	Q_{T+1}
Fortnightly model		0.58	0.79		0.27	0.31
Monthly FM1		0.76	0.89		0.39	0.42
Monthly FM2		0.79	0.89		0.39	0.42
MIDAS		0.91	0.98		0.57	0.63
	Month 3			**Month 3**		
	Q_{T-1}	Q_T	Q_{T+1}	Q_{T-1}	Q_T	Q_{T+1}
Fortnightly model		0.58	0.81		0.21	0.36
Monthly FM1		0.71	0.88		0.38	0.42
Monthly FM2		0.76	0.88		0.38	0.42
MIDAS		0.84	0.89		0.43	0.45

Table 4
Results of the Diebold-Mariano test.

The table reports the p-values associated with the Diebold-Mariano test (Diebold and Mariano, 1995). The test uses the forecast errors obtained by forecasting GDP in Q_T and Q_{T+1}, for each of the three scenarios described in Section 3.3 ("Month 1", "Month 2" and "Month 3", respectively). The null hypothesis is that the Fortnightly Model has the same forecast accuracy of the other three competing models. The p-values appear in boldface if significant at the 10% level.

	Fortnightly model versus Monthly FM1	
	Q_T	Q_{T+1}
Month 1	**0.033**	**0.044**
Month 2	**0.005**	0.054
Month 3	**0.036**	0.101
	Fortnightly model versus Monthly FM2	
	Q_T	Q_{T+1}
1 month	**0.031**	**0.042**
2 month	**0.009**	0.056
3 month	**0.036**	0.097
	Fortnightly model versus MIDAS	
	Q_T	Q_{T+1}
1 month	**0.023**	**0.008**
2 month	**0.003**	0.061
3 month	**0.004**	0.095

Figure 1
GDP and the selected indicators.

The figure shows the co-movement of the quarterly GDP growth with each indicator considered in the model, expressed in growth rates. The series of the indicators are displayed at the chosen lag, as described in Table 1.

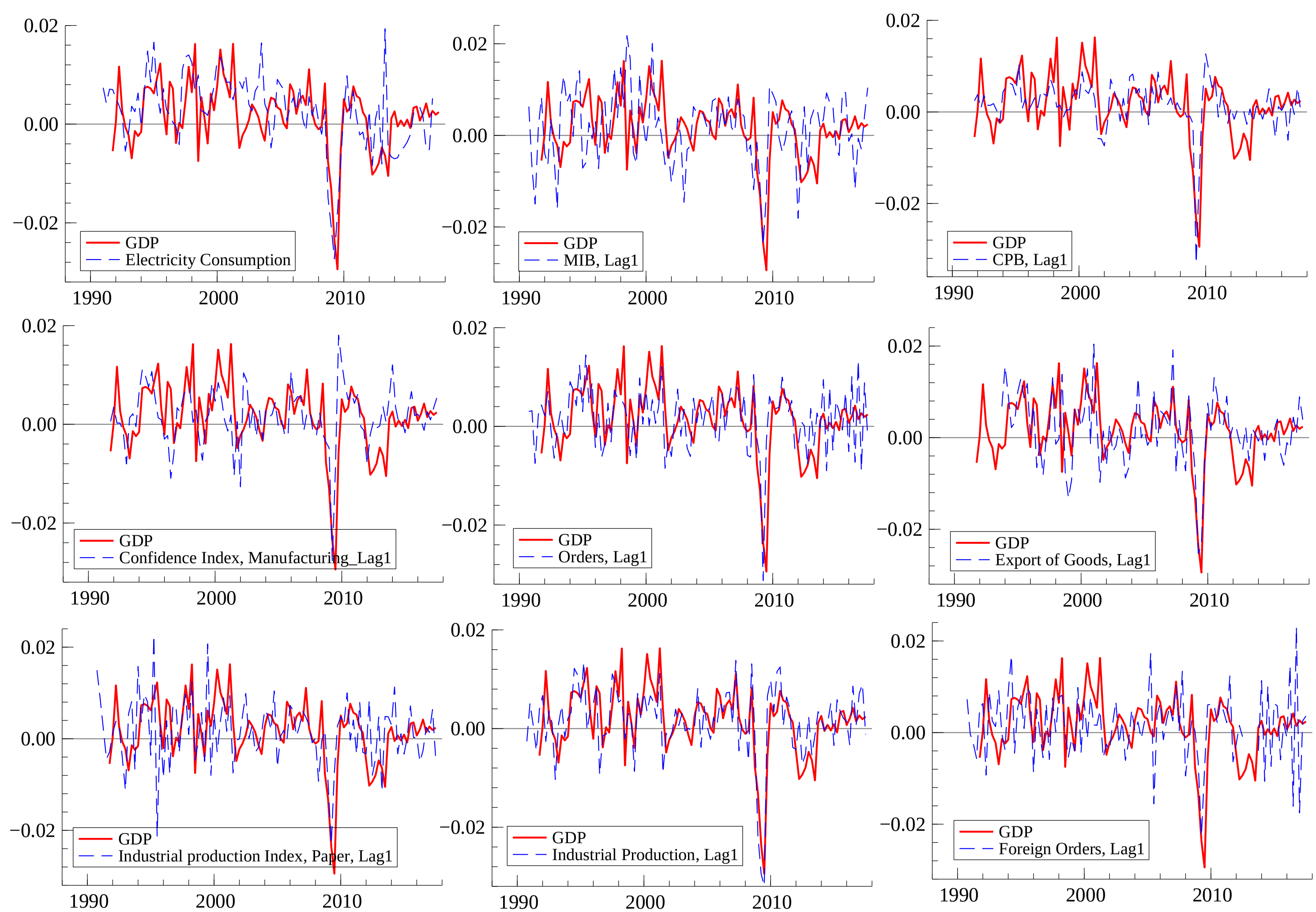


Figure 2
The fortnightly estimates of Italian GDP.

The figure shows the fortnightly estimates of Italian GDP as provided by the model. The upper panels represent the disaggregated GDP at the bimonthly frequency, both in terms of levels of the variable (Panel A) and in growth rates (Panel B). The red lines in (A) and (B) show the GDP estimates disaggregated at the fortnightly frequency provided by the fortnightly model. The blue lines represent the disaggregated estimates obtained by polynomial interpolation. Panels (C) and (D) report instead the corresponding GDP at the quarterly (observed) frequency.

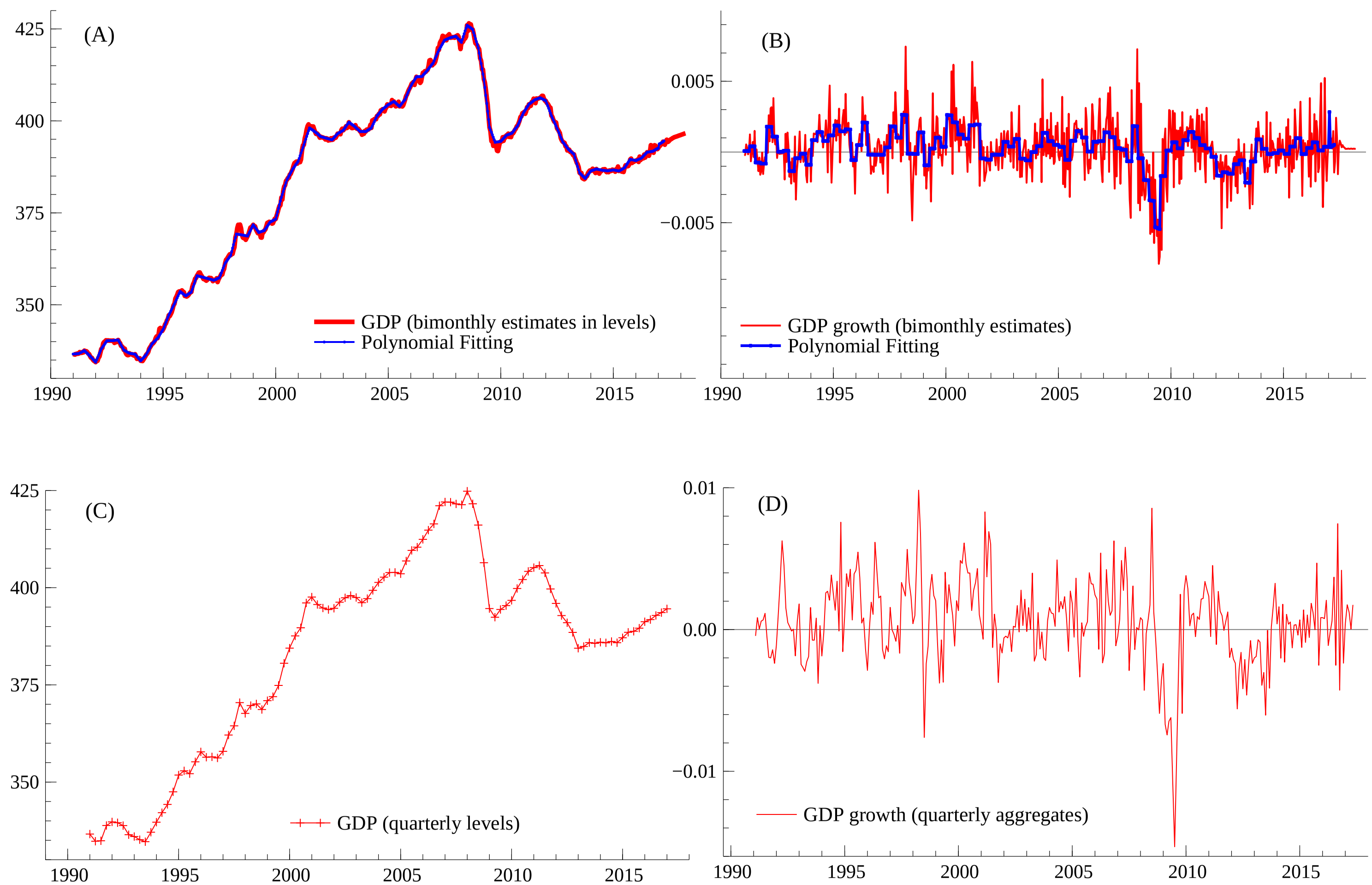


Figure 3
The common factor and Italian economic activity

The figure shows the series (in levels) of all the indicators in the model, disaggregated at the fortnightly frequency. The extracted common factor is displayed by the solid black line in the figure.

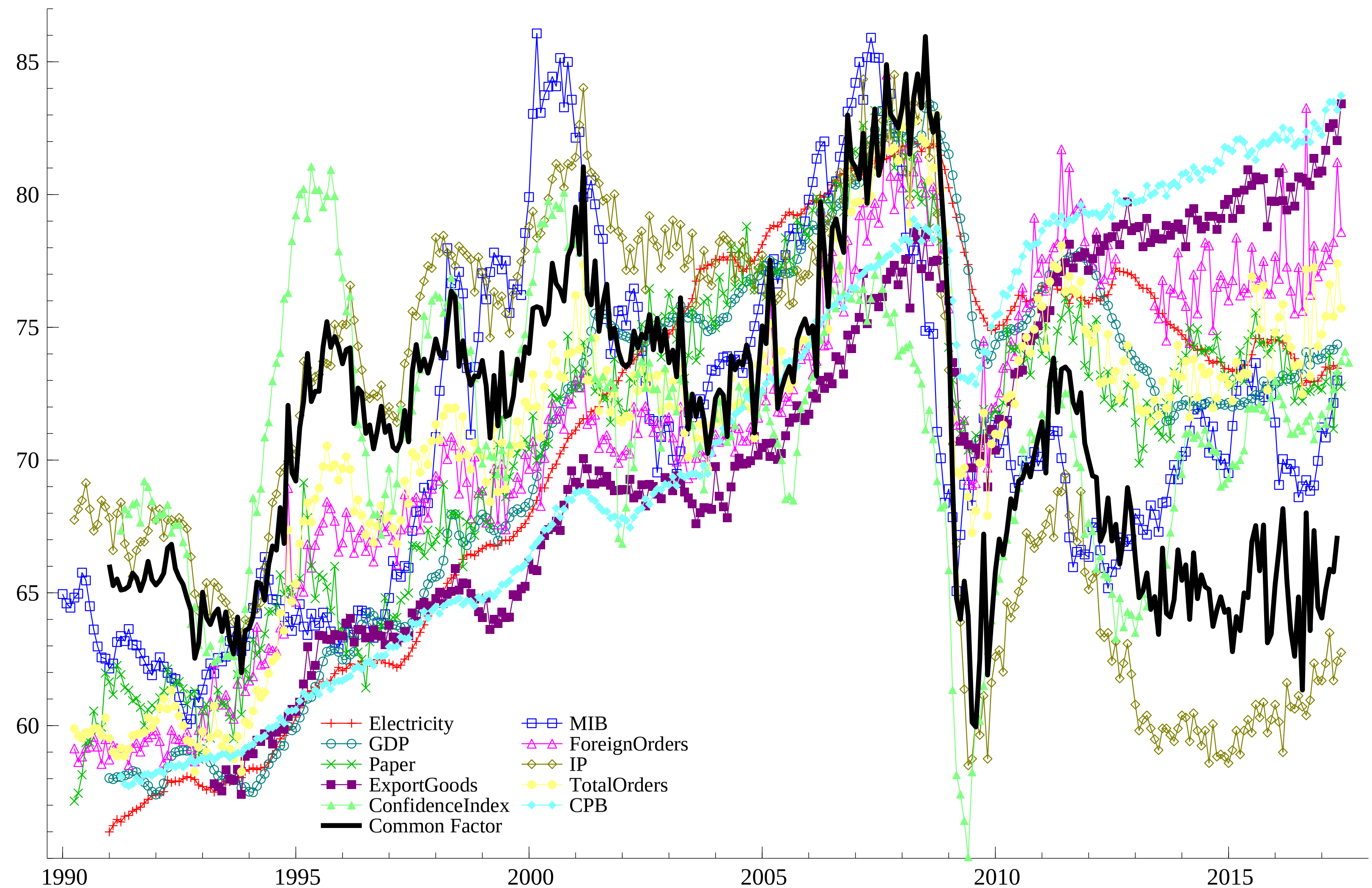


Figure 4

The forecasting ability of the fortnightly model

The figure shows the series of actual GDP growth, together with the series of the forecasts at Q_T (upper panel) and Q_{T+1} (lower panel) of the four competing models, computed at the third scenario (*Month-3 scenario*, as described in Section 3.3)

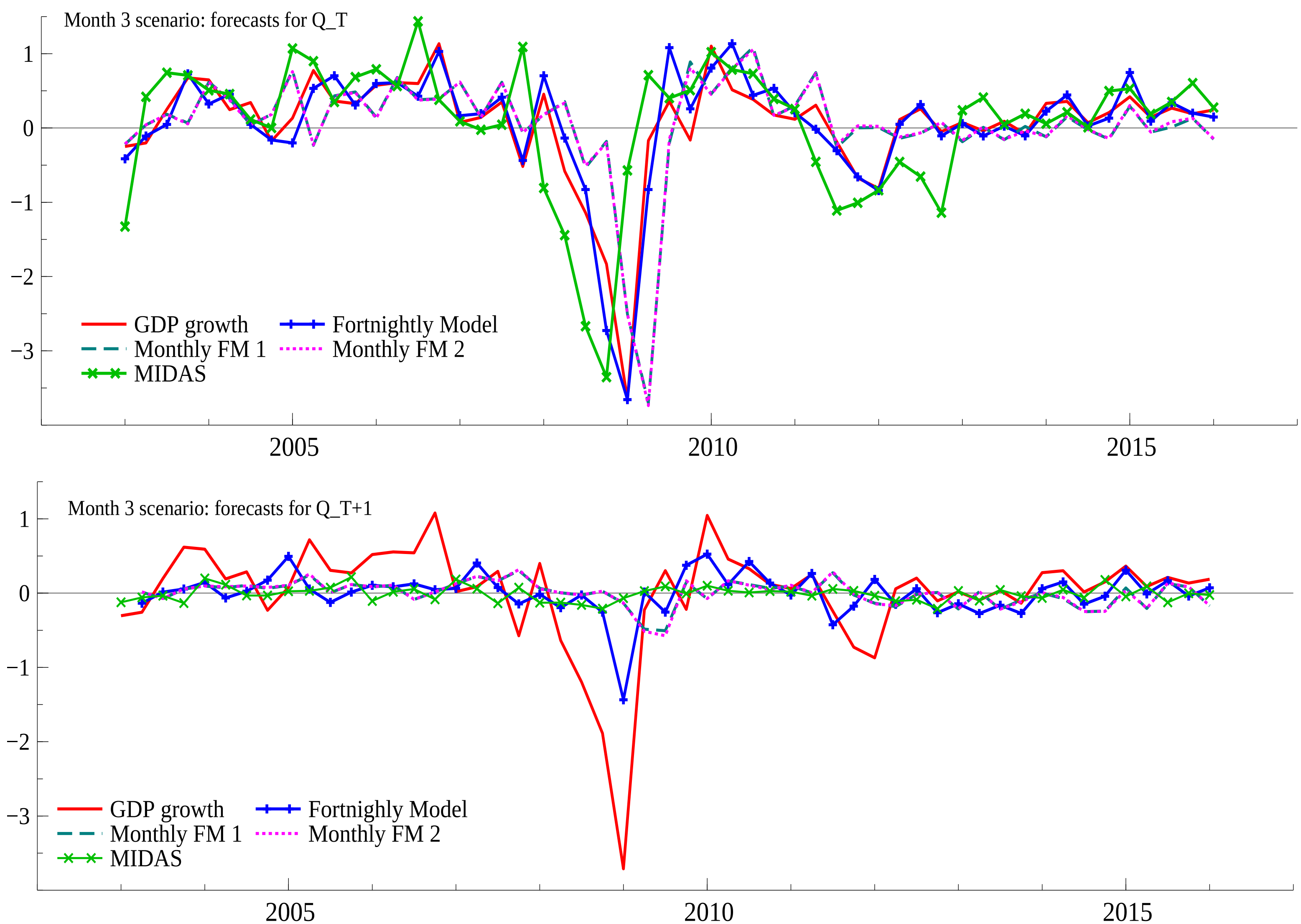
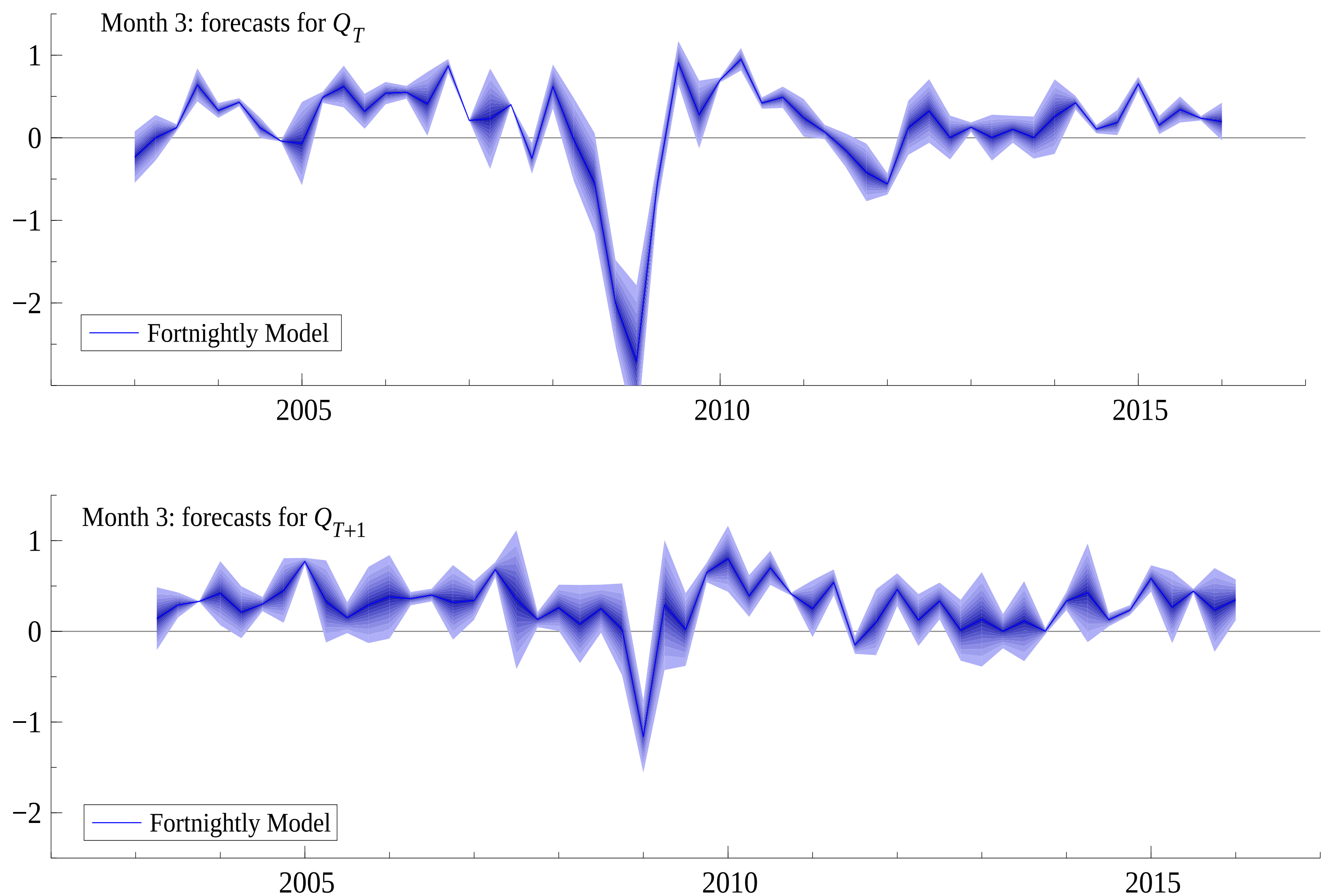


Figure 5
The forecasting performance of the fortnightly model and its confidence bands

The figure shows the series of the forecasts and the corresponding confidence bands at Q_T (upper panel) and Q_{T+1} (lower panel) of the proposed fortnightly model, computed at the third scenario (*Month 3 scenario*, as described in Section 3.3)



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