BANCA D'ITALIA

EUROSISTEMA

Temi di discussione

(Working Papers)

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Number 1362

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Number 1362 - February 2022

ISSN 1594-7939 (print)
ISSN 2281-3950 (online)

Printed by the Printing and Publishing Division of the Bank of Italy

NOWCASTING THE STATE OF THE ITALIAN ECONOMY: THE ROLE OF FINANCIAL MARKETS

by Donato Ceci** and Andrea Silvestrini**

Abstract

This paper compares several methods for constructing weekly nowcasts of recession probabilities in Italy, with a focus on the most recent period of the Covid-19 pandemic. The common thread of these methods is that they use, in different ways, the information content provided by financial market data. In particular, a battery of probit models are estimated after extracting information from a large dataset of more than 130 financial market variables observed at a weekly frequency. The predictive accuracy of these models is explored in a pseudo out-of-sample forecasting exercise. The results demonstrate that nowcasts derived from probit models estimated on a large set of financial variables are, on average, more accurate than standard probit models estimated on a single financial covariate, such as the slope of the yield curve. The proposed approach performs well even compared with probit models estimated on single time series of real economic activity, such as industrial production, or on composite PMI indicators. Overall, the financial indicators used in this paper can be easily updated as soon as new data become available on a weekly basis, thus providing a reliable real-time dating of the Italian business cycle.

JEL Classification: C22, C25, C53, E32.
Keywords: financial markets, probit models, factor-augmented probit models, model confidence set, penalized likelihood, forecast evaluation.
DOI: 10.32057/0.TD.2022.1362

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** Bank of Italy, Directorate General for Economics, Statistics and Research.

1 Introduction[1]

Assessing the likelihood of a recession in a timely and objective manner has, for decades, been one of the main topics in business cycle analysis (Stock and Watson, 1993). It has become increasingly important nowadays, with the spread of the SARS-CoV-2 virus in 2020 and the simultaneous lockdown measures imposed by several governments, which led to a sharp decline in global economic activity worldwide. Gauging the state of the economy in real time, as well as predicting when the recovery will materialise, has thus gained centre stage in the current debate on economic policy (Lewis et al., 2020, 2021).

The aim of this paper is to investigate the information content provided by a large dataset of weekly financial variables in order to nowcast the recessionary and expansionary phases of the Italian business cycle,[2] which correspond to turning points in real GDP, with a focus on the most recent period affected by the Covid-19 pandemic. The latter represents one of the most severe recessions in the postwar period, which has questioned the ability of standard econometric models to provide reliable forecasts.

The interest in assessing the role of financial variables as indicators of recession probability is motivated by several compelling factors. Firstly, available evidence from the global financial crisis has highlighted that financial and credit conditions are important drivers of the business cycle, significantly contributing to the propagation of economic shocks (Gilchrist and Zakrajšek, 2012). The theoretical framework of Bernanke et al. (1999) and Kiyotaki and Moore (1997) can help explain how endogenous developments in financial markets amplify shocks to the real economy (Miglietta and Venditti, 2019; Aprigliano and Liberati, 2021). A rapidly flourishing literature has also found that financial variables are well suited to track the tail growth rate of real GDP and of other

[1]The views expressed herein are those of the authors and do not necessarily reflect those of the Bank of Italy or the Eurosystem. The authors are grateful to two anonymous reviewers, Valentina Aprigliano, Lorenzo Braccini, Fabio Busetti, Paolo Del Giovane, Davide Delle Monache, Simone Emiliozzi, Danilo Liberati, Taneli Mäkinen, Karel Mertens, Claudia Pacella, Jae Sim, Marco Taboga, Alex Tagliabracci and Fabrizio Venditti for very useful comments and suggestions on a previous draft. The authors wish to thank Arianna Miglietta and Luca Moller for providing the Italian Financial Condition Index data.

[2]The term "nowcasting", meaning "the prediction of the present, the very near future and the very recent past" (Bańbura et al., 2013, p. 196), is usually employed in the framework of real GDP forecasting. In this paper, the expression "nowcasting the state of the economy" is used as a synonym of real-time dating of the business cycle.

macroeconomic variables (Adrian et al., 2019; Degiannakis, 2021), suggesting an important connection between financial conditions and real business cycles. The interaction between financial factors and real economic activity has thus assumed a pivotal role in econometric tools for modelling and forecasting purposes (Claessens et al., 2012; Silvestrini and Zaghini, 2015; Paccagnini, 2019; Borio et al., 2020; Crump et al., 2021).

Secondly, since financial markets data incorporate expectations and reactions to macroeconomic and policy news, they are presumed to yield leading recession signals, almost in real time. Moreover, unlike national accounts aggregates, which are usually available every quarter and published with a delay (Golinelli and Parigi, 2007), and differently from other monthly economic indicators such as the industrial production indices or the purchasing managers' indices (PMI) for both manufacturing and services, financial markets data are released on a daily basis, and even at an intra-daily frequency. Besides, they are not revised, whereas most macroeconomic time series are often based on preliminary data and are subject to revisions (Moneta, 2005). As a result, if used in conjunction with appropriate econometric techniques, they can provide significant benefit to policymakers who – for instance, in the most recent period due to the ongoing pandemic – need timely forecasts of the economic cycle to immediately assess the extent of the recession, adopt timely economic policy measures and monitor the intensity and speed of the recovery.[3]

Traditional business cycle/coincident indicators are based on the observation of real economic-activity variables sampled at a quarterly or a monthly frequency (Altissimo et al., 2010; Frale et al., 2011; Aprigliano and Bencivelli, 2013; Marcellino et al., 2016; Bencivelli et al., 2017),[4] with the addition of a few financial variables (e.g., the slope of the yield curve and a broad equity index). Despite this, the interest in using higher frequency data for tracking economic developments is not novel. Aruoba et al. (2009) proposed to

[3]For a very recent attempt to anticipate the behaviour of the output gap before the release of real GDP data see Berger et al. (2020), who proposed a mixed-frequency Bayesian VAR to nowcast the US output gap during the Covid-19 pandemic.

[4]The dataset of the €-coin indicator developed by the Bank of Italy (Altissimo et al., 2010), which provides a summary index of the current economic situation in the euro area, also includes daily observations temporally aggregated at a monthly frequency.

estimate a dynamic factor model in a mixed-frequency framework for measuring economic activity at high frequency, potentially in real time. More recently, Lewis et al. (2021) developed the Weekly Economic Index (WEI) of US real economic activity, drawing on a dataset of 10 weekly series, capturing important dimensions of the pulse of the economy, such as retail-sales consumer confidence, unemployment insurance claims, steel production, fuel sales, electricity output and rail traffic, among others. Borrowing from the methodology proposed by Lewis et al. (2021), Delle Monache et al. (2020) proposed the Italian Weekly Economic Index (ITWEI), which is a timely indicator developed for monitoring the GDP growth rate on a weekly basis, working with a dataset containing real variables at a weekly and monthly frequencies. However, no financial variables were included in their databases. Yet, since the seminal contributions of Estrella and Hardouvelis (1991), Estrella and Mishkin (1998) and Stock and Watson (2003), it has been acknowledged in the literature that financial variables such as the slope of the yield curve tend to possess predictive power for future recessions, especially at horizons beyond one quarter, often outperforming other commonly used variables and tools.[5] Very recently, though, Fendel et al. (2021) highlighted that the predictive power of the term spread might be compromised at the zero lower bound. Hence, they suggested a modified version of the term spread which uses a shadow policy rate, rather than the 3-month rate, as the front leg of the spread.

Several approaches have been proposed in the literature for predicting downturns (Hamilton, 2011). On the one hand, it is possible to build standard linear or nonlinear time-series models to forecast future values of the growth rates of GDP or industrial production and then draw inferences about recessions (see, among others, Stock and Watson, 2002a,b). The class of Markov Switching models (Kim and Nelson, 1998, 2017; Aprigliano and Liberati, 2021) has also been traditionally employed for estimating re-

[5]Estrella and Mishkin (1997) show that these results, mostly pertaining to the US, are obtained to some extent in a European context as well, an exception being Italy. An ensuing literature has provided additional evidence on the usefulness of the term spread for predicting recession risks and on its stability over time as a regressor, see among others Dueker (1997), Chauvet and Potter (2001), Chauvet and Potter (2002), Estrella et al. (2003), Duarte et al. (2005), Wright (2006), Rudebusch and Williams (2009) and Nevasalmi (2021).

cession/expansion probabilities in real time (see Nalewaik, 2012, and Carstensen et al., 2020, for two recent contributions). Another option is employing binary response models (Horowitz and Savin, 2001) in which relevant explanatory variables are used to directly forecast the probability of whether the economy is in a recession (e.g., Kauppi and Saikkonen, 2008; Ng, 2012; Karnizova and Li, 2014; Ercolani and Natoli, 2020; Nevasalmi, 2021). This approach to turning point forecasting (Del Negro, 2001) – pioneered by Estrella and Hardouvelis (1991) and then followed by Estrella and Mishkin (1998) – is also used in this paper, which compares a number of alternative methods to construct weekly indicators for nowcasting recession probabilities in Italy. Besides standard probit models in which financial variables are incorporated directly as single or multiple regressors, after being selected using the Model Confidence Set (MCS) procedure of Hansen et al. (2011), other binary response models are employed in this work and their predictive performance evaluated. Specifically, relying on the data-rich environment offered by a database that gathers more than 130 financial market variables observed at a weekly frequency, probit models are augmented with common factors extracted by implementing the dynamic factor approach, in the same spirit of Chen et al. (2011). These authors introduced the probit-dynamic factor methodology to model and forecast recession probabilities in the US, working with a large dataset of monthly macroeconomic time series. In a similar vein, Bellégo and Ferrara (2012) and Bellégo and Ferrara (2017) used factor-augmented probit models to evaluate the ability of 12 financial variables to predict business-cycle turning points in the Euro area since the early 1970s, but restricted their analysis to monthly data. Very recently, Galvão and Owyang (2020) proposed a mixed-data sampling probit model to produce high-frequency recessions forecasts using a bunch of financial variables/indices such as the yield curve spread and the Chicago Fed's National Financial Condition Index (NFCI).

The present paper adds to the existing literature by monitoring business cycle developments at high frequency, using weekly data, and significantly expanding the set of financial variables included in the dataset. This is grounded on the fact that data-rich environments have been found to be helpful for both nowcasting and forecasting purposes, providing useful coincident and leading indicators of economic activity (Stock and Watson, 2002b; Bok et al., 2018).

As a preview of the results, nowcasts obtained using binary response models estimated on the whole dataset of weekly financial variables deliver more accurate forecasts compared to binary response models estimated on a single financial regressor, such as the slope of the yield curve, and according to standard forecast-evaluation criteria. This can be rationalized by the fact that the proposed approach employs many potential predictors selected from a large set of financial variables, including yield curve spreads, providing a broader information content than single financial variables alone. Furthermore, the proposed binary response models behave reasonably well, even compared to models featuring as an explanatory variable manufacturing and services Purchasing Managers Index (PMI) data, compiled from survey questions, or on single economic variables, such as the industrial production, which are well-known to be very difficult to beat in forecast competitions. Another benefit of the approach put forward in this paper is that the financial indicators used can be easily updated on a weekly basis as soon as new data become available, thus providing a timely dating of the business cycle turning points.

The rest of the paper proceeds as follows. Section 2 presents the econometric framework. Section 3 describes the dataset, which contains more than 130 weekly financial market variables. Section 4 illustrates the in-sample analysis and the out-of-sample forecast exercise aimed at predicting recessions at weekly frequency. A sensitivity analysis is also presented and discussed. Section 5 contains some concluding remarks.

2 The econometric models

2.1 Binary response models for predicting recessions

This section introduces univariate binary response models that will be used in the sequel for estimating and nowcasting recession probabilities for the Italian economy on a weekly basis, conditionally on a large set of financial variables or factors extracted from these variables. In these models the dependent variable is a dummy that equals one if the economy is in recession and zero otherwise. A classification of economic activity in recessions and expansions is therefore needed, such as that compiled by the National Bureau of Economic Research for the United States.

An official dating of the Italian business cycle was produced by ISCO-ISAE-Istat from the postwar period onwards; see ISTAT (2011) for details. Yet this chronology of business cycle turning points has not been updated in recent years, and therefore it is no longer available nor usable in the present study. As a consequence, it is necessary to employ an alternative classification procedure to obtain such a dating.

For this purpose, a recession is defined as two consecutive quarters of negative growth rates of real GDP, the so-called "rule of thumb" on GDP (Shiskin, 1974).[6] Consequently, the corresponding binary dependent variable y_t, observed at a weekly frequency, is equivalent to one if week t belongs to a recession quarter and zero otherwise, according to the following rule:[7]

$$\begin{aligned} g_{t_q} &= \frac{GDP_{t_q}}{GDP_{t_q-1}} - 1, \quad t_q = 1, \ldots, T_q, \\ y_t &= 1 \iff t \in (t_q - 1, t_q) \ \mid \ g_{t_q-1} \wedge g_{t_q} < 0, \quad t = 1, \ldots, T, \end{aligned} \tag{1}$$

where GDP_{t_q} is seasonally adjusted quarterly real GDP, g_{t_q} is its quarterly growth rate, subscript t_q refers to a quarter, T_q is the final quarter for which observations are available, while the time index t indicates the weekly sampling frequency and T is the final week in the sample.[8]

[6]The Bry and Boschan (1971) dating algorithm, extended by Harding and Pagan (2002) for quarterly data, produces a very similar chronology. Further results are available from the authors upon request.

[7]As for the CEPR Euro Area Business Cycle Dating Committee, the general definition of recession as proposed by Shiskin (1974) is followed. The committee defines a recession as "*a significant decline in the level of economic activity, spread across the economy of the euro area, usually visible in two or more consecutive quarters of negative growth in GDP, employment and other measures of aggregate economic activity for the euro area as a whole*" (https://cepr.org/content/business-cycle-dating-committee-methodology). See Pacella (2021) for an interesting discussion on the evaluation of dating the euro-area business cycle.

[8]Note that a given week can be in principle associated to two different quarters whenever a week covers more than one month (for instance, the week from August 30 to September 5, 2021, covers both August and September). This is almost always the case given that the number of days in a month is seldom divisible by seven. Since weekly financial data correspond to prices observed on Friday, weekly observations are conventionally associated to the quarter in which Friday occurs.

A univariate binary response model is assumed for the conditional distribution of the binomial variable y_t in (1) given a vector of financial-related regressors,

$$\Pr(y_t = 1 \mid \boldsymbol{x}_t) = \Phi(\boldsymbol{x}_t'\boldsymbol{\beta}), \tag{2}$$

where $\Phi(\cdot)$ represents the cumulative distribution function of a continuous random variable assuming values between 0 and 1, while $\boldsymbol{x}_t$ is a K-dimensional column vector of financial variables or factors. In principle, any continuous probability distribution $\Phi(\cdot)$ can be employed in (2). Typically, the cumulative distribution function of a standard normal distribution $\Phi(s) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{s} \exp\left\{-\frac{t^2}{2}\right\} dt$ has been adopted in many studies. In this empirical application the same functional form will be used. Given estimated values of the parameters and the observed predictors, the probit equation in (2) provides the conditional recession probability in week t.

In forecast applications probit models can be estimated either with a single regressor or with multiple regressors. To account for the large number of available variables, in this paper model (2) will be augmented by using estimated factors (also-called composite financial indicators) as predictive variables. This form of data reduction gives rise to factor-augmented probit specifications, see Chen et al. (2011) and Bellégo and Ferrara (2012).

The parameters of the probit model in (2) can be estimated using traditional maximum likelihood (ML) methods, which maximize the joint probability distribution of the data expressed as a function of the unknown parameters; see for instance McFadden (1974). The resulting ML estimator is consistent and asymptotically efficient, see Horowitz and Savin (2001). The maximization of the log-likelihood function is a nonlinear optimization problem that can be solved by using standard numerical methods.

2.2 Factor models for data reduction

In the last two decades Dynamic Factor Models (DFMs) have become increasingly popular in the econometric literature as a solution to the curse of dimensionality problem.

These models offer a parsimonious and realistic representation of the data in the presence of co-movements among a large set of variables. Several papers present strong evidence about the usefulness of DFMs when dealing with a data-rich environment for macroeconomic forecasting (Stock and Watson, 2016; Kim and Swanson, 2018; Goulet Coulombe et al., 2020).

In this paper, estimation of factors is therefore carried out as a tool to achieve dimensionality reduction. The resulting estimated factors will also be implemented in a forecasting model and thus employed for nowcasting purposes (Boivin and Ng, 2005).

The principle at the basis of DFMs is that the common dynamics of a large number of time series originate from a small number of unobserved common factors, which in turn evolve over time. Therefore, DFMs assume that a vector of time series is the sum of two unobservable orthogonal components, i.e., a common component driven by latent factors and an idiosyncratic component. More formally, let $\{\mathbf{X}_t = (x_{1t}, \ldots, x_{Nt})' \mid t = 1, \ldots, T\}$ be an N-dimensional column vector of weekly time series with zero mean, unit variance and positive-definite covariance matrix $\mathbf{\Omega}$. This vector includes all financial variables in the dataset. DFMs posit that the following representation holds:

$$\underset{(N\times 1)}{\mathbf{X}_t} = \underset{(N\times 1)}{\boldsymbol{\chi}_t} + \underset{(N\times 1)}{\boldsymbol{\xi}_t} \tag{3}$$

The process $\boldsymbol{\chi}_t = (\chi_{1,t} \ldots \chi_{N,t})'$ is called the common component of $\mathbf{X}_t$. The process $\boldsymbol{\xi}_t = (\xi_{1,t} \ldots \xi_{N,t})'$ represents the idiosyncratic component of $\mathbf{X}_t$. The common component $\chi_{i,t}$ is usually interpreted as the part of $x_{i,t}$ stripped from the measurement error, which is contained in $\xi_{i,t}$. This latter can be interpreted as the cause of variation of the variables in $\mathbf{X}_t$ that is specific to one (or just a few) variable(s).

Depending on the functional form supposed for the common component, it is possible to distinguish between *dynamic* (Forni et al., 2000, 2005, Forni and Lippi, 2001) and *static* (Stock and Watson, 2002a, Bai and Ng, 2002, 2007) representation of DFMs. In this paper the focus is on the *static* representation of DFMs, in which the common component can be expressed as follows:

$$\begin{cases} \underset{(N\times 1)}{\boldsymbol{\chi}_t} = \underset{(N\times K)}{\boldsymbol{\Lambda}} \underset{(K\times 1)}{\mathbf{F}_t} \\ \underset{(K\times K)}{\mathbf{A}(L)} \underset{(K\times 1)}{\mathbf{F}_t} = \underset{(K\times q)}{\mathbf{M}} \underset{(q\times 1)}{\mathbf{u}_t} \end{cases} \tag{4}$$

where $\mathbf{F}_t \in \mathbb{R}^K$ is a vector of common factors, $K << N$ and $\mathbf{A}(L) = \mathbf{I}_K - \mathbf{A}_1 L - \ldots - \mathbf{A}_p L^p$ is a matrix polynomial in the lag operator L in which p is the order of the VAR(p) process for $\mathbf{F}_t$. The terms $\xi_{i,t}$ and $\mathbf{u}_t$ are assumed to be orthogonal for all $i = 1, \ldots, N$, so that $\xi_{i,t}$ and $\chi_{j,t}$ are orthogonal for all $i, j = 1, \ldots, N$. Moreover, given that the number of dynamic shocks in $\mathbf{u}_t$ is $q \leq K$, the VAR process in the factors $\mathbf{F}_t$ is singular.

Focusing on the *static* representation, among the different methods proposed in the literature for estimating DFMs this paper follows Stock and Watson (2002a,b), who suggested to use static Principal Component Analysis (PCA) to recover the factors. PCA is an important method often employed in statistics to perform dimension reduction in the presence of many variables, since it is able to catch co-movements among time series and provides a good predictive performance. The first step of PCA consists in the estimation of $\boldsymbol{\Omega}$. After computing the eigenvectors of $\hat{\boldsymbol{\Omega}} = T^{-1} \sum_{t=1}^{T} \mathbf{X}_t \mathbf{X}_t'$, the first K principal components of $\mathbf{X}_t$ are obtained as $\hat{\mathbf{F}}_t = \mathbf{P}' \mathbf{X}_t$, where $\mathbf{P}$ is the $(N \times K)$ matrix composed by $\mathbf{P}_j$ $(j = 1, \ldots, K)$, which are the eigenvectors corresponding to the j-th largest eigenvalues of $\hat{\boldsymbol{\Omega}}$. These K principal components are considered as estimates of the (*static*) factors $\mathbf{F}_t$. Most of the literature focuses on the estimation of the DFM with $\mathbf{X}_t$ being stationary, possibly after removing trends or taking differences of non-stationary variables. For a general discussion on these issues and on the estimation techniques to be used in the presence of integrated factors (and non-stationary variables) see Barigozzi et al. (2016, 2020, 2021).

Note that the factors $\mathbf{F}_t$ are not identified per se: even if factors are orthonormal, for any orthogonal matrix $\mathbf{R}$ the following equivalence can be established:

$$\begin{aligned}\mathbf{X}_t &= \mathbf{\Lambda}\mathbf{F}_t + \boldsymbol{\xi}_t \\ &= \mathbf{\Lambda}\mathbf{R}'\mathbf{R}\mathbf{F}_t + \boldsymbol{\xi}_t\end{aligned}$$

so that the couples $(\mathbf{\Lambda}, \mathbf{F}_t)$ and $(\bar{\mathbf{\Lambda}} := \mathbf{\Lambda}\mathbf{R}',\ \bar{\mathbf{F}}_t := \mathbf{R}\mathbf{F}_t)$ are observationally equivalent. However, since PCA provides a consistent estimator for the space of the common component $\boldsymbol{\chi}_t$, it is not necessary to impose restrictions for identifying factors. In turn, the number K of unobserved factors can be estimated by using information criteria like the ones proposed by Alessi et al. (2010) and Bai and Ng (2002).

For the purpose of the paper, results are robust to a different estimation technique, which is the *likelihood approach* developed by Doz et al. (2011, 2012), who showed that a consistent estimator of both latent factors and the idiosyncratic component can be obtained by using the Kalman Filter based on the state-space representation associated with the DFM.

2.3 Forecast design

This section describes three alternative procedures used in the empirical application for dating recession probabilities in real-time.

The first approach is termed *unsupervised*, in that it only exploits information in the variables in $\mathbf{X}_t$ to nowcast the crisis probability; however, no information on the binary dependent variable is used to this purpose. More in detail, the *unsupervised* approach requires to estimate the DFM in (3)–(4) and extract K static factors from the whole set of N financial variables by means of PCA. The estimated factors are then employed as predictors $\boldsymbol{x}_t$ in the probit model in (2), which is used to nowcast recessions. The resulting *factor-augmented probit model* approach has already been implemented by Stock and Watson (1993) and Bellégo and Ferrara (2017), among others, in the framework of recession forecasting.

The second approach is a *supervised* one, given that it utilises both the information contained in the independent variables in $\mathbf{X}_t$ and in the dependent crisis variable to make predictions. This approach relies on the Model Confidence Set (MCS) procedure of Hansen et al. (2011) to form a narrower subset of the original 132 regressors based on the best in-sample fit. Specifically, the MCS is a sequence of statistical tests that permits to construct a set of superior models in which the null hypothesis of equal predictive accuracy is not rejected at a given statistical confidence level. MCS requires the definition of a loss function associated with the model in each period $t = 1, \ldots, T^{in}$, where T^{in} is the length of the in-sample period. Dealing with a probit model, an appropriate loss function has to be employed: in the framework of binary response models, Alessi and Detken (2009) and Sarlin and von Schweinitz (2021) proposed a specific loss function to be used for the purpose of crisis prediction, which is based on the relative preference of false negative (FN) and false positive (FP) predicted events. Consistently, the following loss function is used for each week t: $\mathcal{L}(\mu, t) = \mu FN(t) + (1-\mu)FP(t)$, where μ is a preference parameter to be fixed ex ante. This loss function is applied (setting $\mu = 0.8$) to N different probit models (2) estimated on a single regressor variable, i.e. $\boldsymbol{x}_t = x_{i,t}$ $(i = 1, \ldots N)$. The value of $\mu = 0.8$ reflects the fact that a policymaker is especially interested in knowing when the economy enters a recession. See Drehmann and Juselius (2014) for an analysis of classification abilities of early warning indicators in the framework of macroprudential policies.

With a total of 132 financial variables in the dataset, there are 132 of such probit models. A superior set of models with equal predictive accuracy is then obtained at a significance level of 5%. To further reduce the number of variables selected, standard information criteria such as AIC (Akaike Information Criterion) and BIC (Bayes, or Schwarz, Information Criterion) are employed in order to select a subset of variables among those with lower loss function in the set of superior models.[9] Finally, these variables are jointly used as regressors in the probit model in (2).

The third procedure corresponds to a *mixed* approach between the former two. It

[9]AIC and BIC tend to select the same variables. When this is not the case, the set of variables selected using the AIC is employed.

requires to perform DFM-PCA on all variables in the superior set of models obtained by applying the MCS technique. As in the *unsupervised* procedure, a subset of $K << N$ static factors is extracted by means of PCA. Then, the resulting estimated K factors enter as predictors $\boldsymbol{x}_t$ in the probit model in (2), which is subsequently used for nowcasting purposes.

For each of these three approaches two different prediction methods, termed *static* and *dynamic*, are used to make nowcasts. In the *static* prediction method, a fixed start date is set for the out-of-sample period, used to evaluate forecasting performance: the models are then estimated in the in-sample period and nowcasts/forecasts produced for the entire out-of-sample. Thus, with the *static* prediction method estimation and nowcasting is conducted only once for the entire out-of-sample.

Conversely, in the *dynamic* prediction method, each time new information becomes available the start date of the out-of-sample period is shifted forward, new data enters the information set used for parameter estimation and model selection and nowcasts are produced for the out-of-sample. Then, the in-sample is extended again (using an expanding estimation window), and the exercise is repeated applying a recursive scheme.

Both the *static* and *dynamic* prediction methods are performed in a pseudo real-time environment, i.e., the nowcast of the recession probability for week t is obtained following the real-time data flow and therefore is based exclusively on the information available up to time t. Given that the financial variables in $\boldsymbol{x}_t$ are available on a weekly basis with no delay and revisions, the main challenge of the pseudo real-time exercise lies in dealing with the discrepancy between the sampling frequency of the state of the economy, which is quarterly, and the nowcast frequency, which is weekly.

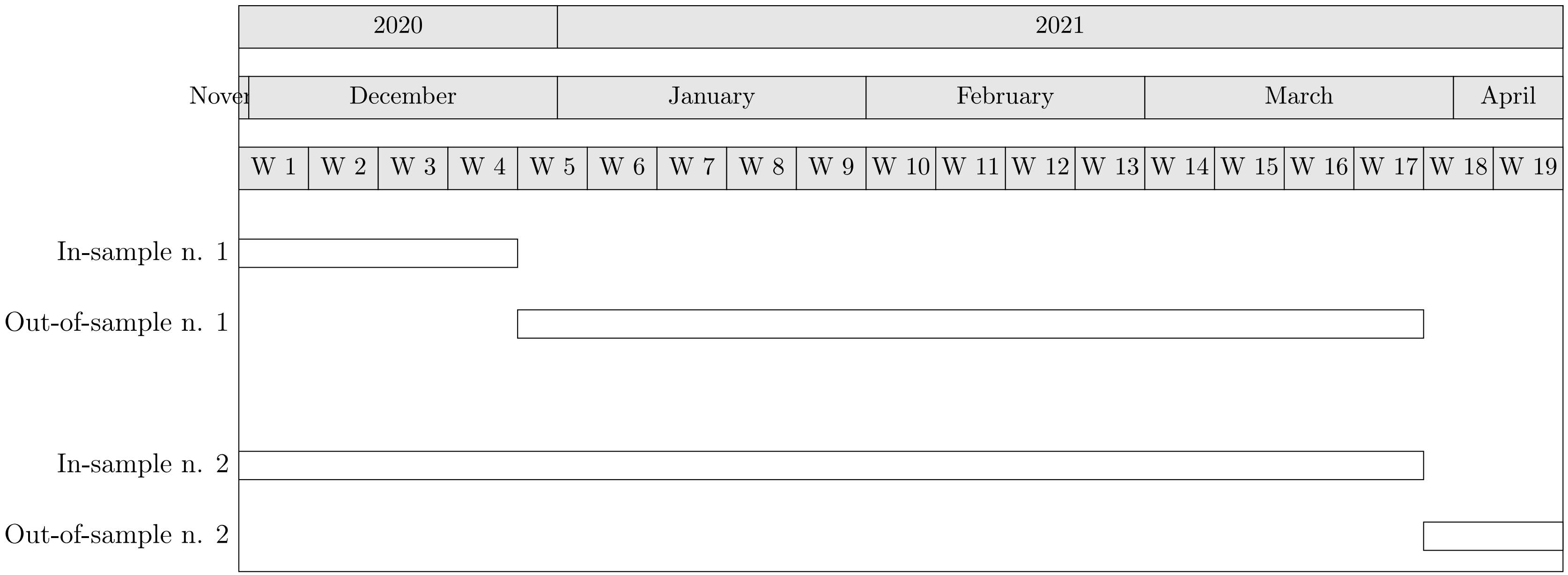
An additional issue is related to the definition of the information set used for estimation and prediction purposes. More specifically, given that the state of the economy (recession or expansion) in quarter t_q is observed only at the end of the same quarter,[10]

[10]In a pseudo real-time exercise, researchers need to consider that macroeconomic data are released with a substantial delay with respect to the reference period. For instance, the growth rate of real GDP, g_{t_q}, is not observed at the end of quarter t_q but only with some delay (the Italian National Institute of Statistics, Istat, publishes a preliminary estimate of GDP at 30 days from the end of the quarter and a second estimate that follows at 60 days). However, in this paper, it is assumed that for each week

the model can not incorporate this information when predicting the weekly recession probability in that quarter, i.e., for $y_t \mid t \in t_q$. Thus, the last observation included in the in-sample period has to be the last week of the previous quarter (for both *static* and *dynamic* prediction methods). In formal terms, denoting by t^* the first week of the out-of-sample and t_q^* the quarter it belongs to, the information set used for parameter estimation is defined as $I_{t^*} = \{\boldsymbol{x}_{1:t^\dagger}, g_{1:t_{q-1}^*}\}$, where $t^\dagger$ denotes the last weekly observation of quarter t_{q-1}^*, owing to the fact that $y_\tau \mid \tau \in t_q^*, \tau \leq t^*$ is not observed by the forecaster. As a consequence, in the *dynamic* prediction method the in-sample period remains unchanged when nowcasting all weeks $t \in t_q^*$, while it is expanded to include also $(\boldsymbol{x}_t, g_{t_q^*}) \mid t \in t_q^*$ only when nowcasts for the first week of t_{q+1}^* have to be produced. As an illustration, in Table 1 the start date of the out-of-sample t^* is set to 01 January 2021 (week 5). The information set includes only data until 25 December 2020 when producing nowcasts of weeks from 5 to 17. Data from the latter are included in the information set only when nowcasting recession probabilities for weeks belonging to the following quarter, i.e., from week 18 onwards.

$t \in t_{q+1}$ we can at least infer the sign of g_{t_q}, which is what is needed in order to define the weekly binary recession variable y_t in (1).

Table 1: Dynamic estimation method: in-sample and out-of-samples



In contrast, the *static* prediction method – which is implemented only once for the entire out-of-sample – never includes in the information set the weeks of quarter t_q^*. As an illustration, in Table 2 the start date of the out-of-sample t^* is set at 11 January 2021 (week 7): then, the information set used for parameter estimation must incorporate only data until 27 December 2020; on the other hand, weeks 5 and 6 are not part of this information set since they belong to the first quarter of 2021, which in this example contains t^*.

Table 2: Static estimation method: in-sample and out-of-sample when t^* is set at W7

	2020					2021		
Nover	December					January		
	W 1	W 2	W 3	W 4	W 5	W 6	W 7	W 8
In-sample								
Out-of-sample								

2.4 Assessing predictive performance in classification tasks

Forecast evaluation involves the measurement of predictive accuracy of competing models. Two different criteria are used in this paper to evaluate forecast performance when dealing with the two-class prediction problem at hand (or binary classification case).

The first criterion for evaluation of binary forecasts, often employed in the context of recession predictions, is based on the Receiver Operating Characteristic (ROC) curve, see Berge and Jordá (2011). The ROC curve represents in the space $[0,1] \times [0,1]$ the set of possible combinations of true positive (TP) and false positive (FP) events as a percentage of all binary occurrences (crisis/non-crisis). In the case under examination, false positive events correspond to periods of expansion mistakenly classified as recessions, while true positive events are recession periods correctly classified:

$$\begin{aligned} TP\ rate &= \frac{TP}{TP+FN} \\ FP\ rate &= \frac{FP}{FP+TN} \end{aligned}$$

where FN stands for false negative events (expansion periods incorrectly classified) and TN indicates true negative events (expansion periods correctly classified). The TP rate, also called "sensitivity", measures what proportion of the positive class (recessions) got correctly classified; on the other hand the FP rate, which is also linked to the concept of "specificity", gauges the proportion of the negative class (expansions) which got incorrectly classified.

A summary of all the trade-offs contained in the ROC curve and a commonly used measure of overall classification ability is the area under the ROC curve (AUROC):

$$AUROC = \int_0^1 ROC(c)dc. \tag{5}$$

A perfectly informative crisis classifier has an AUROC equal to 1. Conversely, a completely uninformative indicator has $AUROC = 0.5$, no better than chance occurrence.

The second evaluation criterion of binary forecasts is the Quadratic Probability Score

(QPS, Brier 1950), which is defined in terms of squared forecast errors:

$$QPS = \frac{1}{T^{out}} \sum_{t=1}^{T^{out}} (y_t - \hat{y}_{t|t^*})^2, \tag{6}$$

where T^{out} is the length of the out-of-sample and t^* is its start date. As for the standard mean squared prediction error, the better the model's forecast accuracy the lower the QPS (or Brier score). Given that all squared forecast errors in (6) lie between 0 and 1, the QPS statistics calculated with the above formula lies in the [0,1] interval, where a model with perfect skill has a score of 0 and the worst has a score of 1.

3 The dataset

This section presents a brief description of the database assembled for the empirical analysis. It also provides information on the data sources used.

The analysis covers quarterly real GDP observations for Italy over the time period between 2003Q1 and 2021Q1. Recessions are defined as two consecutive quarters of negative growth of Italy's real GDP, which is sourced from Istat (quarter-on-quarter growth rates of chained, seasonally and calendar adjusted volumes).[11] The dataset also contains 132 weekly financial variables starting from February 7, 2003.[12] The last observation is for July 16, 2021. Financial data are taken from Bloomberg, Refinitiv Eikon, ICE and the ECB Statistical Data Warehouse. The complete list of variables is reported in the Appendix (Tables A.1, A.2, and A.3).

Table 3 lists the weekly financial time series used in the empirical analysis, grouped into 7 categories. Commodities comprise West Texas Intermediate (WTI) and Brent crude oil spot prices, both quoted in US dollars per barrel. Gold, silver and copper future prices are also included. A second category is money market rates, namely the 3-month EUR Euribor and the 3-month Eonia swap rates, which are used to calculate Euribor-OIS

[11]The Istat website has been accessed on July 21, 2021.

[12]The dataset starts in January 2003, but a single series (Bloomberg ID GTITL20Y GOVT) is only available as of February 7, 2003.

differentials. Then there are 12 series measuring corporate credit risk for banks and firms, which issue bonds for financing their business. Specifically, these series measure the yield-to-maturity and the option-adjusted spread for baskets of bonds issued by US, euro-area and Italian banks as well as non-financial corporations. The largest category comprise 67 Morgan Stanley Capital International (MSCI) equity indexes and forward price-to-earnings ratios for worldwide, US, Italy and euro-area companies. Several sectoral stock market indexes (for banks and firms, these latter disaggregated in broad industry sectors such as basic materials, industrial goods, consumer goods, etc.) as well as stock market volatilities for the US and the euro area (VIX, VSTOXX) are also included. The main euro foreign exchange rates (US dollar, sterling, yen, etc.) constitute the exchange rates category, which consists of 12 series. Another large group of time series (25 in all) contains ten-year government bond spreads for US, UK and the main euro-area countries and yields of Italian government bonds with maturity at 3 and 6 months as well as 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20, and 30 years, allowing to estimate the Italian government bond term structure. Lastly, a residual group of series includes the main items on the asset side of the Eurosystem balance sheet (in EUR millions), such as gold, securities holdings, other claims, etc. Concerning data transformations, all series – which are mostly yields or growth rates – are taken in levels.

Table 3: Variables included in the dataset

Group	Variables	N. series
Commodities	Gold, oil (WTI, brent), silver, copper prices	5
Money Market	Euribor, OIS rates	2
Corp. Credit Risk	Yields and OAS spreads on bonds issued by banks and firms (IT, EA, US)	12
Stock Market	Equity indices, dividend yields, expected earnings and volatility indices (IT, EA, US)	67
Exchange Rates	\$/€, £/€, ¥/€ exchange rate futures	12
Sovereign Bonds	10yrs yields IT, DE, FR, BE, ES, PT, GR, IE, UK, US Term structure of IT government bonds	25
Others	Selected items of Eurosystem's balance sheet	9
Total		132

Source: Bloomberg, Refinitiv Eikon, ICE, and ECB Statistical Data Warehouse.
Sample: 07/02/2003 – 16/07/2021.

4 Empirical analysis

This section presents the empirical application and forecast exercise aimed at predicting recession probabilities in Italy at a weekly frequency. It first interprets the principal components extracted from the data (Section 4.1) and then discusses the in-sample analysis (Section 4.2). Subsequently, given that in-sample predictive content does not necessarily guarantee out-of-sample predictive ability, Section 4.3 makes a step forward and presents the out-of-sample forecast results. The final section (Section 4.4) undertakes a sensitivity analysis.

4.1 Interpretation of principal components

This section first analyses the principal components of the dataset described in Section 3. It then correlates all variables included in the database with the main principal components extracted. The purpose is to interpret these latter in terms of the original

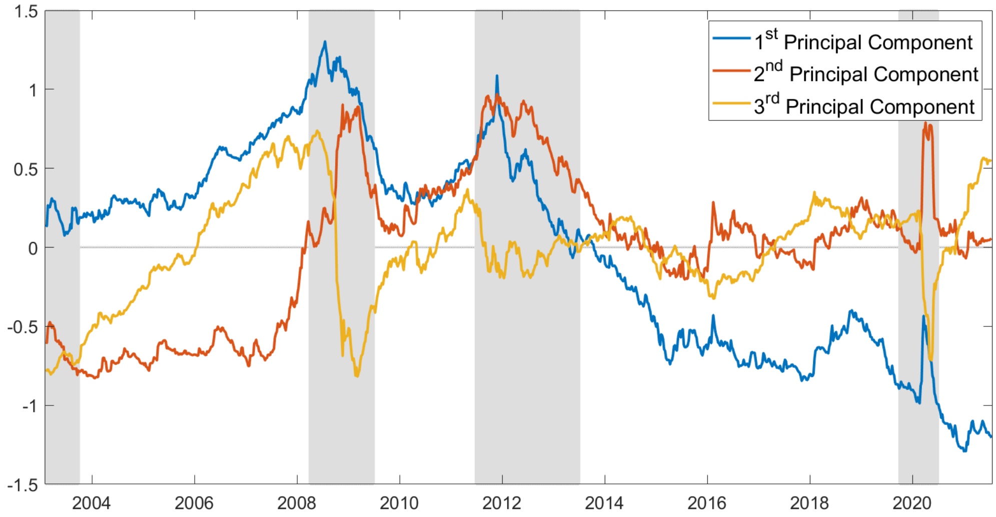


Figure 1: Three first principal components accounting for 74% of total variation, sample: 07/02/2003–16/07/2021.

variables, owing to the fact that principal components are statistical artefacts with no clear economic significance.

Figure 1 displays the first three estimated principal components, which explain 74% of variance in the bulk of the data. More specifically, the first principal component accounts for 41% of total variation, while the second and the third explain, respectively, 22% and 11% of the variance. Grey-shaded areas in the chart indicate the weeks belonging to recession quarters. The first and the third principal components decrease rapidly at the onset of (or during) each recession, and then rise gradually again, when the recession subsides. In contrast, the second one traces an opposite pattern, particularly through recession quarters. These sharp trends during recession periods suggest that, potentially, the first three principal components contain useful predictive information in crisis times.

To form an overall picture of the correlation structure between the first three principal components and the explanatory variables in the dataset, Figure 2 shows three histograms displaying these correlations (in absolute value). Explanatory variables are grouped in seven categories, as in Table 3. Figure 2 (a) focuses on the correlations between the first principal component and the explanatory variables. It can be appreciated that variables belonging to the sovereign bond category present, on average, the highest correlation values, closely followed by variables in the corporate credit risk subset. Table 4 displays the ten highest correlated variables with the first principal component together with the corresponding correlation coefficients, always taken in absolute value. It appears that the yield-to-maturity of bonds issued by banks and firms, respectively, in the eurozone and Italy, present correlation coefficients above 0.95, while a bunch of Italian government bond yields (at different maturities) have correlation coefficient values in the range of 0.92–0.94. This fact signals that the first principal component largely co-moves with the Italian government bond term-structure.[13]

Figure 2 (b) turns to correlation coefficients with the second principal component. In this case the correlation pattern differs, in that the stock-market bloc of variables is, on average, the most correlated with the second principal component extracted from the dataset. Table 5 also reflects this, in that several equity market indices – for instance some components of the MSCI Italy index – appear to have correlation coefficients between 0.80 and 0.90. Interestingly, even ICE BofA Option-Adjusted Spreads (OASs) of euro-area and Italian banks have correlation coefficient values higher than 0.90. Significant correlation clusters with stock market variables emerge also when examining the third principal component, as revealed by Figure 2 (c). However, it can also be noted that correlation values tend to be on average lower than in the previous two charts. Table 6 investigates further this correlation structure and shows indeed that EMU stock market indices along with world stock market ones are highly correlated with the third principal component, suggesting that the latter contains information on the global stock market price dynamics.

[13]Specifically, results available from the authors upon request show that the first principal component has a correlation coefficient of roughly 0.96 with the time series of a well-diversified portfolio of Italian bonds observed since July 2012 (represented by the Exchange Traded Funds Ishares Italy Government Bond series sourced from Eikon).

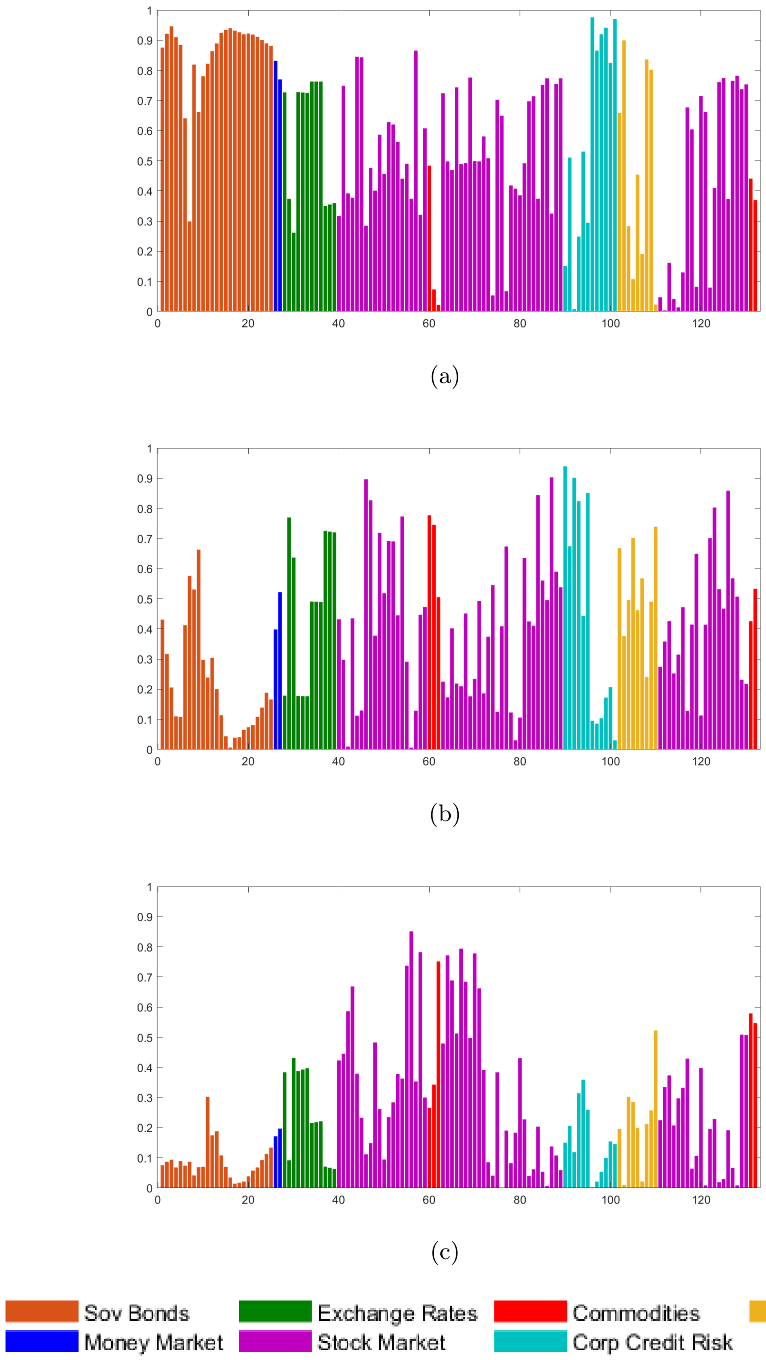


Figure 2: Correlation coefficients of each variable with first (a), second (b) and third (c) principal components (absolute values), sample: 07/02/2003–16/07/2021.

Table 4: Ten highest correlation coefficients of variables with the first principal component
(absolute values)

YTM BANKS EA	0.9759
YTM FIRMS IT	0.9705
GBGB10YR INDEX	0.9464
YTM FIRMS EA	0.9414
GTITL4Y GOVT	0.9402
GTITL3Y GOVT	0.9342
GTITL5Y GOVT	0.9315
GTITL6Y GOVT	0.9265
GTITL2Y GOVT	0.9245
GTITL8Y GOVT	0.9222

Sample: 07/02/2003–16/07/2021.

Table 5: Ten highest correlation coefficients of variables with the second principal component
(absolute values)

OAS BANKS EA	0.9397
ITMSCIP(AF3PE) - MSCI ITALY	0.9031
OAS BANKS IT	0.9012
FIT1CSE(PI) - FTSE ITALIA ALL-SHR CONSUMER	0.8966
ITMSCIP(A18PE) - MSCI ITALY	0.8584
OAS FIRMS IT	0.8512
ITMSCIP(AF2PE) - MSCI ITALY	0.8440
FIT1T1E(PI) - FTSE ITALIA ALL-SHR TELECOM	0.8267
OAS FIRMS EA	0.8240
ITMSCIP(A12PE) - MSCI ITALY	0.8026

Sample: 07/02/2003–16/07/2021.

Table 6: Ten highest correlation coefficients of variables with the third principal component
(absolute values)

MSEXEM(MSPI) - MSCI EUROPE EX EMU US $	0.8515
M1EMU(AF2MN) - MSCI EMU	0.7938
MSEMKF(MSPI) - MSCI EM US $	0.7824
M1EMU(AF3MN) - MSCI EMU	0.7782
M1EMU(AF1MN) - MSCI EMU	0.7719
NHGCS00(PS) - CMX-HIGH GRADE COPPER CONT.	0.7517
MSEMUIL(MSPI) - MSCI EMU	0.7372
M1WLDF(AF1MN) - MSCI Fmr THE WORLD INDEX	0.6885
M1WLDF(AF2MN) - MSCI Fmr THE WORLD INDEX	0.6843
FIT1IDE(PI) - FTSE ITALIA ALL-SHR INDUSTRIALS	0.6688

Sample: 07/02/2003–16/07/2021.

4.2 In-sample analysis

This section presents the in-sample analysis, covering the period from 7 February 2003 to 28 December 2018 (for the *static* prediction method) and 7 February 2003 to 25 December 2020 (for the *dynamic* prediction method).

Table 7 lists the nineteen variables employed by the supervised model when applying the *static* prediction method. They mainly belong to the sovereign bonds and stock market categories. These nineteen variables are selected using the MCS procedure of Hansen et al. (2011), among those with a lower loss function; the supervised model based on these variables will be subsequently utilised in the out-of-sample forecast exercise in the next section. It should be noted that most of these variables are highly correlated with the first three principal components (refer to Tables 4-6).

Table 7: Variables selected from the MCS estimation model, static approach

ITMSCIP(A18PE) - MSCI ITALY
ITMSCIP(AF3PE) - MSCI ITALY
ITMSCIP(AF1PE) - MSCI ITALY
GTITL10Y GOVT
GBTPGR10 INDEX
M1EMU(A18PE) - MSCI EMU
ITMSCIP(A12PE) - MSCI ITALY
M1WLDF(AF3PE) - MSCI Fmr THE WORLD INDEX
M1EMU(A12PE) - MSCI EMU
FIT1U1E(PI) - FTSE ITALIA ALL-SHR UTILITIES
ITMSCIP(AF2PE) - MSCI ITALY
M1WLDF(AF2PE) - MSCI Fmr THE WORLD INDEX
FIT1IDE(PI) - FTSE ITALIA ALL-SHR INDUSTRIALS
MSEMUIL(MSPI) - MSCI EMU
GTITL20Y GOVT
M1EMU(AF1PE) - MSCI EMU
GTITL30Y GOVT
M1EMU(AF3PE) - MSCI EMU
M1EMU(AF2PE) - MSCI EMU

Sample: 07/02/2003–28/12/2020.

Figure 3 displays the estimated recession probabilities over the full in-sample produced, respectively, by the supervised, unsupervised and mixed approaches. The focus is on the *static* prediction method. For comparison purposes, the figure also reports the recession probabilities obtained when relying on the original MCS procedure of Hansen et al. (2011), which requires averaging of forecasts produced by different univariate probit specifications based on the variables included in the set of equal predictive ability. As in previous charts, grey-shaded areas indicate the weeks belonging to recession quarters. Furthermore, the horizontal dashed line marks the historical recession average over the sample (λ), which approximately equals 0.24. This latter may be considered an empirical threshold on the predicted probabilities allowing assessment of the likelihood of a recession: although in a model with two states (recession and expansion) a regime switch can be determined when the threshold of 50% is passed, the empirical proportion (λ) is much more useful since it represents the predicted probability of a constant-only model,

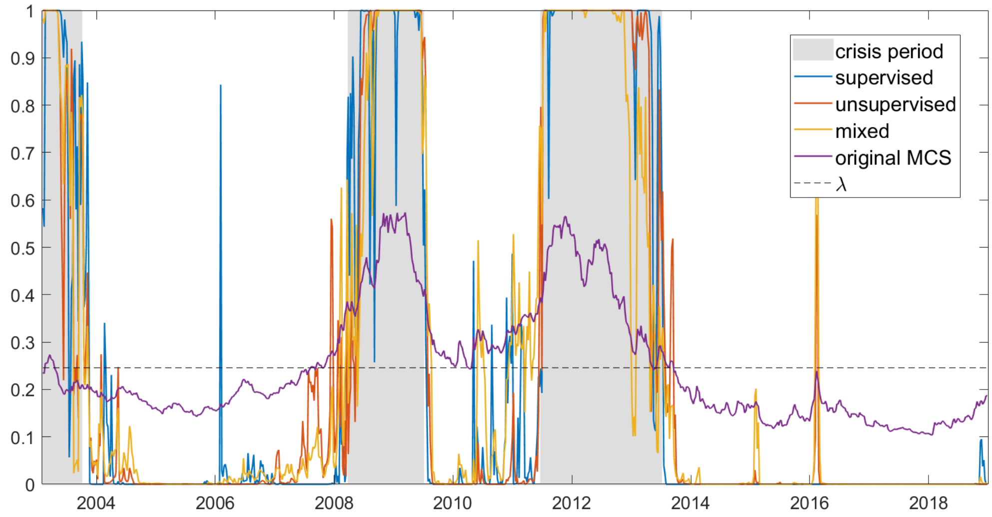


Figure 3: Static prediction method: in-sample results (07/02/2003–28/12/2018).

i.e., the empirical tossing-the-coin prediction.

Figure 3 indicates that the supervised, unsupervised and mixed models successfully replicate the observed business cycle fluctuations. Most of the times, the estimated recession probabilities match well with the reference recession dates. When examining the chart in more detail, some differences are visible though: firstly, both unsupervised and mixed models estimate fairly similar recession probabilities. Secondly, the supervised model produces more volatile estimates, but nonetheless delivers higher predicted probabilities within recession periods. It is also interesting to note that the original version of MCS produces very poor results, implying that some form of dimensionality reduction is of crucial importance in this application: the estimated predicted probabilities fluctuate around the historical recession average with two peaks during the GFC and the SDC, but seldom exceed the 50% threshold.

A quantitative analysis of the proposed models in terms of in-sample goodness of fit is presented in Table 8, displaying both AUROC and QPS results for all the multivariate models examined in Figure 3. Moreover, results for traditional univariate models are also compared. Specifically, these univariate models correspond to five probit specifications in which the regressor is, respectively, the slope of the yield curve for Germany, the slope of the yield curve for the US (which is assumed to track global financial-macroeconomic fluctuations), the slope of the yield curve for Italy, the dividend yield (DY) on the Italian stock index (along the lines of Bellégo and Ferrara, 2012, 2017) and the Italian Financial Condition Index (FCI) proposed by Miglietta and Venditti (2019). Table 8 confirms that the supervised model is the best in terms of both AUROC and QPS. Probit models with a single covariate generate the worst results instead. Among these univariate specifications, those estimated on the Italian dividend yield and on the FCI tend to be more accurate. These findings indicate that the multivariate probit specifications under scrutiny tend to provide a more accurate dating of the Italian business cycle.

Table 8: In-sample goodness of fit, static prediction method

Model	**AUROC**	**QPS**
multivariate models:		
supervised	0.99584	0.02294
unsupervised	0.99336	0.02938
mixed	0.99279	0.03166
MCS original	0.93340	0.12143
univariate models:		
YC slope (DE)	0.66162	0.17419
YC slope (US)	0.64466	0.17359
YC slope (IT)	0.75408	0.14792
DY IT	0.93816	0.09163
FCI-IT	0.93673	0.08551

Sample: 07/02/2003–28/12/2018.

We now turn to the *dynamic* prediction method, which presents results comparable to the *static* one and a similar ranking of models (see Figure 4 and Table 9). It should be noted that the last observation in the in-sample period for the *dynamic* prediction method corresponds to 25 December 2020, differently from the *static* one, for which the in-sample end date is 28 December 2018. The Covid-19 recession is included within this time window, and Figure 4 consistently displays high predicted probabilities for most of the considered *dynamic* forecasting models. However, even in this case the original MCS procedure reveals a poorer performance compared to the other multivariate specifications.

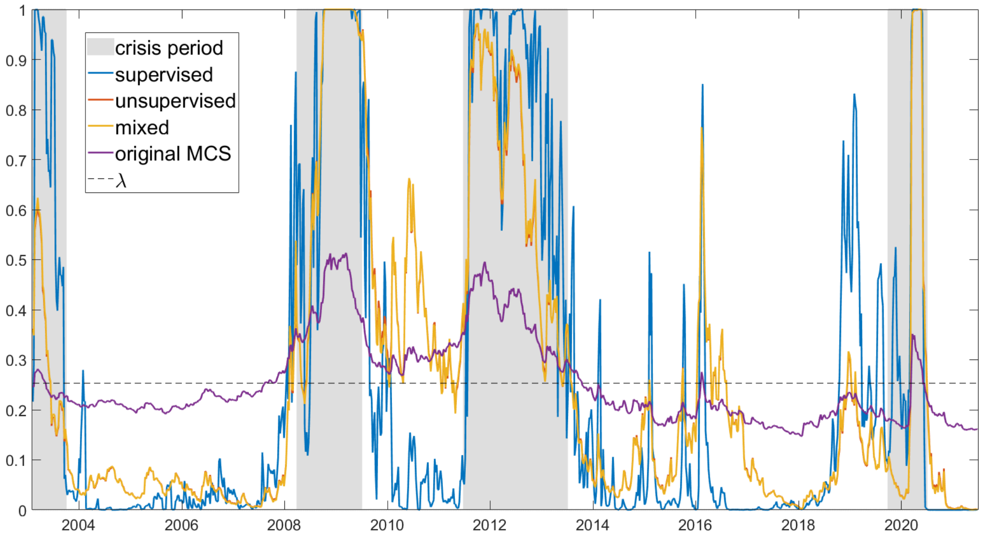


Figure 4: Dynamic prediction method: in-sample results (07/02/2003–25/12/2020).

Table 9: In-sample goodness of fit, dynamic prediction method.

Model	**AUROC**	**QPS**
multivariate models:		
supervised	0.95857	0.06806
unsupervised	0.88967	0.10082
mixed	0.89049	0.10016
MCS original	0.86353	0.14715
univariate models:		
YC slope (DE)	0.58366	0.18725
YC slope (US)	0.58873	0.18625
YC slope (IT)	0.64474	0.17781
DY IT	0.85540	0.12364
FCI-IT	0.79771	0.12654

Sample: 07/02/2003–25/12/2020.

4.3 Out-of-sample results

This section extends the analysis to an out-of-sample setting. The out-of-sample includes the period from 4 January 2019 to 16 July 2021, covering the Covid-19 pandemic and the crisis it triggered. The same competing models as in Section 4.2 are considered. Both *static* and *dynamic* prediction methods are implemented.

Figure 5 presents the recession probabilities when applying the *static* prediction method, together with the historical recession average ($\lambda = 0.29$). Nowcasts delivered by the supervised, unsupervised and mixed models track the recession periods rather well, although with some delay. However, it should be kept in mind that the Covid-19 outbreak started in the second half of February 2020, and the supervised, unsupervised and mixed models consistently signal a sharp increase in recession probabilities at the end of February 2020. Instead, the original MCS approach produces almost constant predictions, always lying below the historical average, with a single exception during the most acute phase of the pandemic. As such, it is not capable of clearly discriminating between recession and expansion periods in the out-of-sample under investigation.

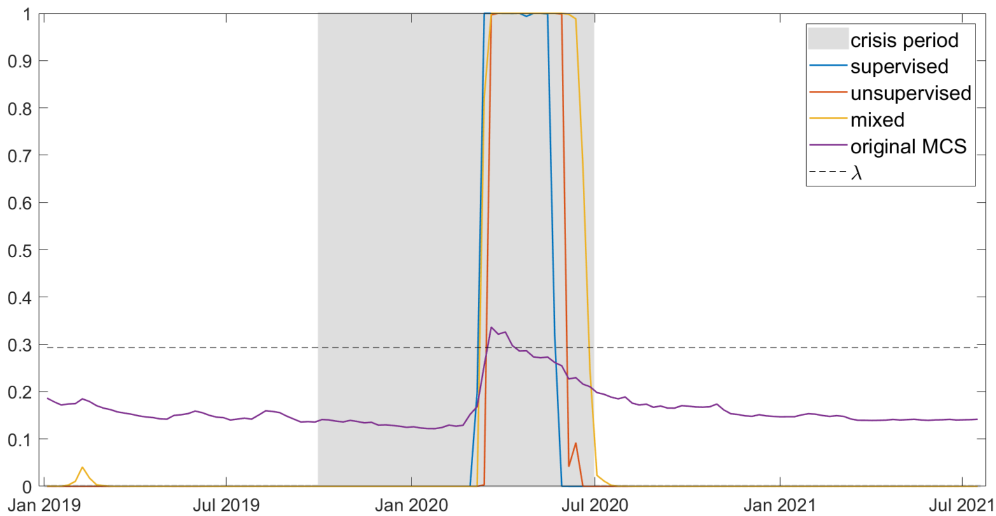


Figure 5: Static prediction method: out-of-sample forecasts (04/01/2019–16/07/2021).

Concerning out-of-sample forecast accuracy measures, Table 10 presents the AUROC and the QPS defined in Section 2.4 for all univariate and multivariate models examined in the paper. The focus is again on the *static* prediction method. Considering the multivariate specifications, the highest AUROC is achieved by the unsupervised and mixed models, closely followed by the supervised model, and a similar ranking is provided by the QPS diagnostics. Coming to the univariate models, the best out-of-sample performance is obtained by the probit with the dividend yield on the Italian stock index, while the probit models using the German and the US yield curve spreads produce worse results both in terms of AUROC and QPS statistics.

Table 10: Out-of-sample forecast accuracy measures, static prediction method

Model	**AUROC**	**QPS**
multivariate models:		
supervised	0.65385	0.21129
unsupervised	0.67949	0.20855
mixed	0.67949	0.20968
MCS original	0.45158	0.21168
univariate models:		
YC slope (DE)	0.37589	0.23022
YC slope (US)	0.37684	0.24891
YC slope (IT)	0.55728	0.24616
DY IT	0.66653	0.23392
FCI-IT	0.55101	0.22271

Out-of-sample: 04/01/2019–16/07/2021.

Figure 6 turns to the *dynamic* prediction method and displays the predicted recession probabilities together with the historical recession average over the out-of-sample. Results are similar to those presented in Figure 5. The supervised, unsupervised and mixed models track the recession and recovery periods rather well, again with some delay for the reasons already explained. In addition, the supervised model forecasts a spike in the recession probability even in summer 2020, which then abruptly fades away. Also the mixed model signals a predicted probability higher than the historical average in the same summer months, though of shorter duration. The unsupervised model produces the most accurate nowcasts in this respect, given that the corresponding predictions lie beneath the historical average soon after the beginning of July 2020. Lastly, predictions delivered by the original MCS model are always below the historical average – barring a short period during the most acute phase of the Covid-19 pandemic – and probably too stable to be of any interest.

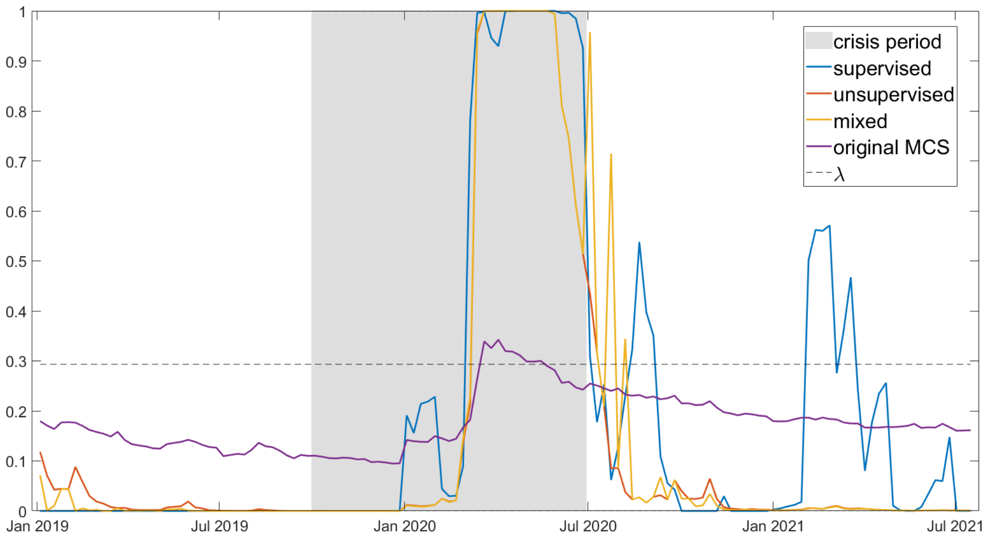


Figure 6: Dynamic prediction method: out-of-sample forecasts (04/01/2019–16/07/2021).

Table 11 reports the corresponding out-of-sample diagnostic statistics. Among the multivariate models, the supervised has the best prediction performance, followed by the mixed one. Focusing on the univariate models, AUROC values are overall lower compared to the same metrics presented in Table 10. The probit with the dividend yield on the Italian stock index is by far the most accurate. Overall, the AUROC and QPS indicators generate a similar ranking as in Table 10.

Table 11: Out-of-sample forecast accuracy measures, dynamic prediction method

Model	**AUROC**	**QPS**
<u>multivariate models:</u>		
supervised	0.71290	0.17079
unsupervised	0.62821	0.17310
mixed	0.67921	0.18284
MCS original	0.49441	0.21522
<u>univariate models:</u>		
YC slope (DE)	0.22954	0.23096
YC slope (US)	0.35038	0.24348
YC slope (IT)	0.28028	0.23560
DY IT	0.66148	0.21897
FCI-IT	0.50150	0.21219

Out-of-sample: 04/01/2019–16/07/2021.

Figure 7 takes a step forward and focuses on the variables selected by the *dynamic* prediction method in the out-of-sample, grouped by categories, using the MCS procedure of Hansen et al. (2011). This subset of predictors is used both by the supervised and mixed models, as explained in Section 2.3. In the supervised model, standard information criteria are employed to further narrow the number of variables selected. In the mixed model, static factors are extracted from this subset of regressors.

Variables in the commodities and corporate credit risk groups tend to always be included in the superior set of models applying the MCS approach, with a single exception, notably the first commodity series (gold price). Sovereign bonds variables are also frequently selected, except for the first series in the group (specifically, the 10-year government bond yield of Belgium, France and Germany). Another interesting feature that can be observed in Figure 7 is that a bunch of stock-market variables are seldom included in the superior set of models. The same holds true for a number of variables in the other category.

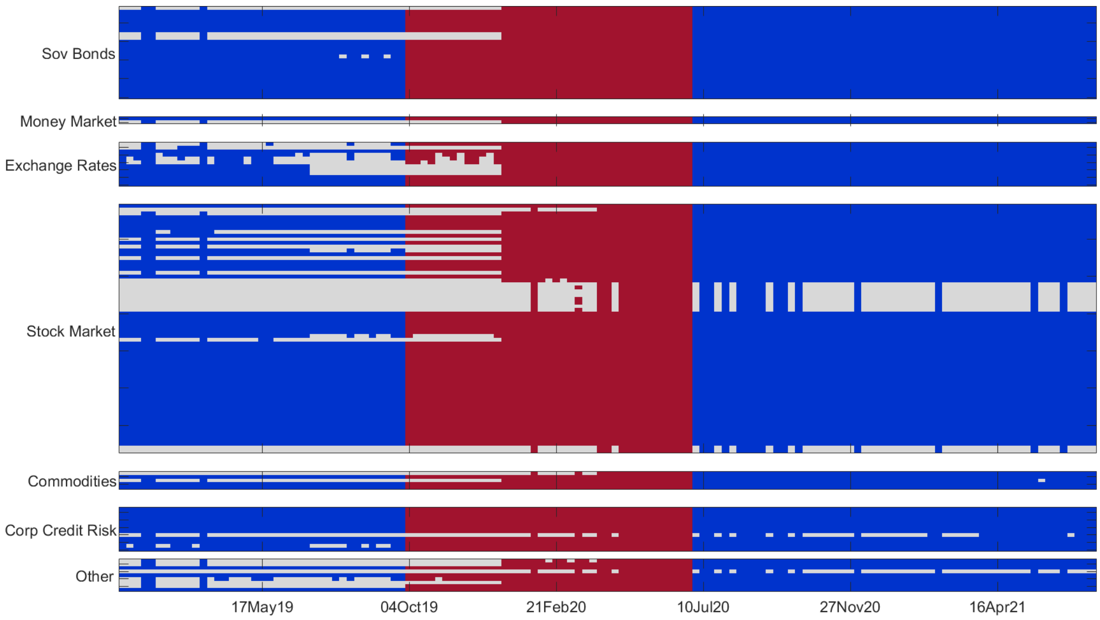


Figure 7: Dynamic prediction method: variables included according to the MCS procedure for each out-of-sample period (04/01/2019–16/07/2021) in blue (red for weeks belonging to recession quarters).

4.4 Sensitivity analysis

This section illustrates a sensitivity study on the specification of the binary response model used for dating the Italian business cycle. The probit model has been employed in the main analysis in Sections 4.2 and 4.3, following a long literature pioneered by Estrella and Mishkin (1998). An alternative approach relies on a different functional form for the cumulative distribution function $\Phi(\cdot)$ in equation (2), specifically the logistic function instead of the standard normal distribution, i.e. $\Phi(s) = \frac{e^s}{e^s+1}$. Logit models have been often used in the literature on the effectiveness of early warning systems, see for instance Jarmulska (2021), and therefore can serve as a benchmark to compare with.

Tables 12 and 13 present the forecast accuracy results when using this alternative logit specification and focusing on multivariate models. Table 12 refers to the *static* prediction method, whereas Table 13 pertains to the *dynamic* one. Results are presented both for the in-sample and the out-of-sample periods.

Results for the *static* prediction method in Table 12 are largely in line with those displayed in Tables 8 and 10. The only exception is the supervised model, which in the present case reports a worse performance both in terms of AUROC and QPS.

Table 12: Accuracy measures of logit model, static prediction method

Model	**In-sample**		**Out-of-sample**	
	AUROC	**QPS**	**AUROC**	**QPS**
supervised	0.99468	0.02312	0.58974	0.27707
unsupervised	0.99348	0.02952	0.67512	0.20928
mixed	0.99261	0.03195	0.68167	0.20873
MCS original	0.93698	0.11902	0.45063	0.21128

In-sample: 07/02/2003–28/12/2018. Out-of-sample: 04/01/2019–16/07/2021.

Turning to the *dynamic* prediction method, Table 13 confirms that the logit model yields similar results as the probit one (Tables 9 and 11), with marginal differences only observed for the supervised model in the out-of-sample (the deterioration in the forecast accuracy being less pronounced in the *dynamic* case).

Table 13: Accuracy measures of logit model, dynamic prediction method

Model	**In-sample**		**Out-of-sample**	
	AUROC	**QPS**	**AUROC**	**QPS**
supervised	0.96109	0.06449	0.69163	0.21022
unsupervised	0.88712	0.09934	0.68876	0.17760
mixed	0.88712	0.09934	0.68876	0.17760
MCS original	0.86407	0.14785	0.45499	0.21114

In-sample: 07/02/2003–25/12/2020. Out-of-sample: 04/01/2019–16/07/2021.

Focusing on the supervised model, another issue worth of investigation pertains to the selection of variables to be included as regressors in the binary response specification used for nowcasting. So far, the MCS procedure has been employed to select these regressors. Another option is using Least Absolute Shrinkage and Selection Operator (LASSO) regressions (Tibshirani, 1996), which can efficiently select a subset of relevant regressors from a large set of potential predictors. LASSO penalizes with a tuning parameter the size of the regression coefficients. When numerous possible predictors are present, many of which exert little influence on a target variable, this method drives the coefficient of irrelevant variables to zero and thus performs automatic variable selection.[14] Operationally, two different routes can be taken to implement this approach: either estimating a probit model with a LASSO penalty (Probit LASSO), either relying on a standard probit model in which regressors are those associated with non-zero coefficients in the Probit LASSO (Post LASSO).

Table 14 shows the corresponding diagnostic statistics for the *static* prediction method, both in-sample and out-of-sample, obtained with these two models. Since LASSO is not designed for correlated regressors, which is typical in time-series, Table 14 also displays results for probit models with Elastic Net and Ridge penalties (Zou and Hastie, 2005), called Probit Elastic Net and Probit Ridge, respectively. As in the case of Post Lasso, it is also possible to estimate standard probit models in which regressors are those associated with non-zero coefficients in Elastic Net and Ridge regressions (Post Elastic Net and Post Ridge).[15]

Whereas in-sample these models deliver an almost perfect fit, the out-of-sample performance is not as good, with an AUROC comprised between 0.57 (Post Ridge) and 0.68 (Post Lasso), only slightly lower than the values achieved by the supervised, unsupervised and mixed models in Table 10. However, these results confirm that the database of financial market variables gathered for this study can be employed conveniently for forecasting purposes even implementing simple linear regression models with regularization.

Another question worth of investigation is whether there is any gain in using financial variables to predict recession probabilities in Italy compared to models which only include real variables. Being close indicators of agents' expectations, financial variables are per se useful in this respect but it is unclear whether they have any additional predictive power compared to real activity variables. A simple way to test this hypothesis is to consider standard probit models estimated on single real economic variables, such as

[14]The associated Lagrangian multiplier for the l_1 penalty in LASSO regressions is calibrated using (K-fold) cross-validation in the in-sample.

[15]Regularized regressions (such as LASSO, Elastic Net and Ridge) are estimated on standardized covariates.

the Industrial Production index, or on composite Purchasing Managers Index (PMI) indicators which, being derived from surveys, are very strong competitors in forecast competitions.[16] The last three rows of Table 14 present some evidence on this issue. Very interestingly, it appears that all multivariate models estimated from a financial dataset largely outperform a probit model estimated on Services PMI data and are at least as accurate as a probit model with the Industrial Production index as explanatory variable. This is a surprising result, bearing in mind that the Industrial Production index is considered to be a coincident indicator of the state of the economy. Models estimated on financial variables are only outperformed by a probit estimated on Manufacturing PMI data.

Table 14: Accuracy measures of alternative models, static prediction method

Model	**In-sample**		**Out-of-sample**	
	AUROC	**QPS**	**AUROC**	**QPS**
multivariate models:				
Probit LASSO	0.99999	0.00141	0.63775	0.23815
Probit Elastic Net	0.99999	0.00160	0.64935	0.23065
Probit Ridge	0.99980	0.00204	0.67430	0.21324
Post LASSO	1	0.00000	0.68003	0.21056
Post Elastic Net	1	0.00000	0.59656	0.24061
Post Ridge	1	0.00000	0.57065	0.28486
univariate models (with PMI and IP regressors):				
Manufacturing PMI	0.96341	0.06494	0.89321	0.11650
Services PMI	0.97055	0.05755	0.47627	0.31227
Industrial Production	0.54226	0.17740	0.67103	0.19314

In-sample: 07/02/2003–28/12/2018. Out-of-sample: 04/01/2019–16/07/2021.

Lastly, Table 15 turns to the *dynamic* estimation method. No significant differences compared to Table 14 emerge in the in-sample. Focusing on the out-of-sample, regularized regression methods perform very well both in terms of AUROC and QPS statistics. Specifically, they improve upon all the multivariate models in Table 11, except for the

[16] The Purchasing Manager Indexes are published by Markit (markit.com) and downloaded from Refinitiv Eikon. The monthly Industrial Production Index is released by Istat. For both PMIs and the Industrial Production index, the weekly recession probabilities of the Italian economy are computed by imputing the monthly observations of the indices equally to each week of the month.

supervised one, which reports similar AUROC and QPS values. They also perform significantly better than all the univariate models in Table 11. Coming back to Table 15, they definitively yield better forecasts than the univariate probit models estimated with Survey PMI and Industrial Production data, both in terms of AUROC and QPS. They are slightly outperformed only by the univariate probit model with Manufacturing PMI data. Thence, it is recommended to include the financial market variables gathered for this research in the information set available to the econometrician tasked to forecast the Italian recession phases.

Table 15: Accuracy measures of alternative models, dynamic prediction method

Model	**In-sample**		**Out-of-sample**	
	AUROC	**QPS**	**AUROC**	**QPS**
multivariate models:				
Probit LASSO	0.99999	0.00134	0.76178	0.19536
Probit Elastic Net	1	0.00070	0.76418	0.19549
Probit Ridge	0.99998	0.00263	0.76418	0.19549
Post LASSO	1	0.00000	0.77837	0.17294
Post Elastic Net	1	0.00000	0.68412	0.28517
Post Ridge	1	0.00000	0.76596	0.19594
univariate models (with PMI and IP regressors):				
Manufacturing PMI	0.95690	0.07330	0.86798	0.12145
Services PMI	0.92000	0.09650	0.49509	0.30623
Industrial Production	0.54157	0.18679	0.45636	0.20580

In-sample: 07/02/2003–25/12/2020. Out-of-sample: 04/01/2019–16/07/2021.

5 Concluding remarks

This paper has estimated and predicted recession probabilities in Italy, drawing on a large dataset of more than 130 financial market variables. The focus has been on the most recent period affected by the Covid-19 pandemic, which has led to a sharp contraction of global economic activity. Compared to the extant literature, this work has significantly increased the number of financial variables included in the database and proposed a novel modelling and forecasting framework based on binary response models with many potential predictors for monitoring business-cycle developments at a high frequency.

For nowcasting recession probabilities, this paper has compared several models estimated on weekly data. Besides standard probit models in which financial variables are incorporated directly as single or multiple regressors, probit models have been augmented with common factors extracted from the large dataset of financial market variables by implementing the dynamic factor approach. In a further step, other techniques often used when many potential regressors are available have been applied in order to automatically select the most relevant variables to be included in the predictive model. Different prediction methods (*static* and *dynamic*) have been implemented to assess the impact of new data on the subsequent forecast revisions for the binary target variable.

Results show that predictions obtained using probit models – in the spirit of the turning point model proposed by Estrella and Mishkin (1998) – estimated on a large set of weekly financial variables are very accurate, both in-sample and out-of-sample. Different econometric techniques, such as common factors, the Model Confidence Set approach of Hansen et al. (2011) and regularization methods (LASSO, ridge and elastic net regressions) turn out to be effective for extracting the information contained in financial data. Furthermore, binary response models estimated on the entire dataset deliver more accurate forecasts compared to standard binary response models estimated on a single financial covariate, such as the slope of the yield curve. The proposed binary response models behave reasonably well even compared to probit models featuring as an explanatory variable manufacturing and services PMI data, compiled from survey questions, or real economic data, such as the industrial production, which are well-known to be very difficult to beat in forecast competitions. These findings are noteworthy in light of the fact that, unlike for instance in the US, Italy is a bank-based economy in which market finance and financial markets are less crucial to the financing of the private sector. Thus, a priori, it is not clear whether market indicators can tell much about the state of the real economy and have any predictive power more in general. This paper shows that this is indeed the case.

In addition, besides having the benefit of being easy to update as soon as new data points become available, these models provide a reliable real-time dating of the Italian business cycle. This empirical evidence highlights the importance of using forward-looking information as contained in financial market variables for forecasting purposes. This newly proposed approach can thus be used for monitoring recession risks in real-time and can potentially pave the way for a joint use of real and financial data for turning point detection or for predicting the growth rate of real GDP, even in a mixed-frequency framework, also using recent developments in the machine learning literature (Nevasalmi, 2021). These interesting developments are left for future research.

A Appendix - Data description

Table A.1: Description of financial variables

N.	VARIABLE	CATEGORY	LABEL
1	GDBR10 INDEX	EU 10y Gov Bonds	Sov Bonds
2	GFRN10 INDEX	EU 10y Gov Bonds	Sov Bonds
3	GBGB10YR INDEX	EU 10y Gov Bonds	Sov Bonds
4	GBTPGR10 INDEX	EU 10y Gov Bonds	Sov Bonds
5	GSPG10YR INDEX	EU 10y Gov Bonds	Sov Bonds
6	GSPT10YR INDEX	EU 10y Gov Bonds	Sov Bonds
7	GGGB10YR INDEX	EU 10y Gov Bonds	Sov Bonds
8	GUKG10 INDEX	EU 10y Gov Bonds	Sov Bonds
9	USGG10YR INDEX	EU 10y Gov Bonds	Sov Bonds
10	GIGB10YR INDEX	EU 10y Gov Bonds	Sov Bonds
11	GTITL3M GOVT	IT Gov Bonds	Sov Bonds
12	GTITL6M GOVT	IT Gov Bonds	Sov Bonds
13	GTITL1Y GOVT	IT Gov Bonds	Sov Bonds
14	GTITL2Y GOVT	IT Gov Bonds	Sov Bonds
15	GTITL3Y GOVT	IT Gov Bonds	Sov Bonds
16	GTITL4Y GOVT	IT Gov Bonds	Sov Bonds
17	GTITL5Y GOVT	IT Gov Bonds	Sov Bonds
18	GTITL6Y GOVT	IT Gov Bonds	Sov Bonds
19	GTITL7Y GOVT	IT Gov Bonds	Sov Bonds
20	GTITL8Y GOVT	IT Gov Bonds	Sov Bonds
21	GTITL9Y GOVT	IT Gov Bonds	Sov Bonds
22	GTITL10Y GOVT	IT Gov Bonds	Sov Bonds
23	GTITL15Y GOVT	IT Gov Bonds	Sov Bonds
24	GTITL20Y GOVT	IT Gov Bonds	Sov Bonds
25	GTITL30Y GOVT	IT Gov Bonds	Sov Bonds
26	EUR003M Index	Euribor - OIS	Money Market
27	EUSWEC Curncy		Money Market
28	USECBSP(ER) - US $ TO EURO (ECB)	Exchange Rates	Exchange rates
29	UKECBSP(ER) - UK £ TO EURO (ECB)	Exchange Rates	Exchange rates
30	JPECBSP(ER) - JAPANESE YEN TO EURO (ECB)	Exchange Rates	Exchange rates
31	TDEUR1M(ER) - US $ TO EURO 1M FWD (RFV)	Exchange Rates	Exchange rates
32	TDEUR2M(ER) - US $ TO EURO 2M FWD (RFV)	Exchange Rates	Exchange rates
33	TDEUR3M(ER) - US $ TO EURO 3M FWD (RFV)	Exchange Rates	Exchange rates
34	TDGBP1M(ER) - US $ TO GBP 1M FWD (RFV)	Exchange Rates	Exchange rates
35	TDGBP2M(ER) - US $ TO GBP 2M FWD (RFV)	Exchange Rates	Exchange rates
36	TDGBP3M(ER) - US $ TO GBP 3M FWD (RFV)	Exchange Rates	Exchange rates
37	TDJPY1M(ER) - JAPANESE YEN TO US $ 1M FWD (RFV)	Exchange Rates	Exchange rates
38	TDJPY2M(ER) - JAPANESE YEN TO US $ 2M FWD (RFV)	Exchange Rates	Exchange rates
39	TDJPY3M(ER) - JAPANESE YEN TO US $ 3M FWD (RFV)	Exchange Rates	Exchange rates
40	VSTOXXI(PI) - VSTOXX VOLATILITY INDEX	Financial Indexes	Stock Market
41	FIT1O1E(PI) - FTSE ITALIA ALL-SHR OIL & GAS	Financial Indexes	Stock Market
42	FIT1BME(PI) - FTSE ITALIA ALL-SHR BASIC MATS	Financial Indexes	Stock Market
43	FIT1IDE(PI) - FTSE ITALIA ALL-SHR INDUSTRIALS	Financial Indexes	Stock Market
44	FIT1CGE(PI) - FTSE ITALIA ALL-SHR CONSUMER GDS	Financial Indexes	Stock Market
45	FIT1H1E(PI) - FTSE ITALIA ALL-SHR HEALTH CARE	Financial Indexes	Stock Market

Table A.2: Description of financial variables (cont'd)

N.	VARIABLE	CATEGORY	LABEL
46	FIT1CSE(PI) - FTSE ITALIA ALL-SHR CONSUMER SVS	Financial Indexes	Stock Market
47	FIT1T1E(PI) - FTSE ITALIA ALL-SHR TELECOM	Financial Indexes	Stock Market
48	FIT1U1E(PI) - FTSE ITALIA ALL-SHR UTILITIES	Financial Indexes	Stock Market
49	FIT1FNE(PI) - FTSE ITALIA ALL-SHR FINANCIALS	Financial Indexes	Stock Market
50	FIT1G1E(PI) - FTSE ITALIA ALL-SHR TECHNOLOGY	Financial Indexes	Stock Market
51	FIT2B2E(PI) - FTSE ITALIA ALL-SHR BANKS	Financial Indexes	Stock Market
52	S2ESB2E(PI) - EURO STOXX BANKS E	Financial Indexes	Stock Market
53	BALTICF(PI) - Baltic Exchange Dry Index (BDI)	Financial Indexes	Stock Market
54	MSITALL(MSPI) - MSCI ITALY	Financial Indexes	Stock Market
55	MSEMUIL(MSPI) - MSCI EMU	Financial Indexes	Stock Market
56	MSEXEM$(MSPI) - MSCI EUROPE EX EMU US $	Financial Indexes	Stock Market
57	MSUSAML(MSPI) - MSCI USA	Financial Indexes	Stock Market
58	MSEMKF$(MSPI) - MSCI EM US $	Financial Indexes	Stock Market
59	MILANBC(DSDY) - MILAN COMIT GLOBAL	Financial Indexes	Stock Market
60	NGCCS00(PS) - CMX-GOLD 100 OZ CONTINUOUS	Financial Indexes	Commodities
61	NSLCS00(PS) - CMX-SILVER 5000 OZ CONTINUOUS	Financial Indexes	Commodities
62	NHGCS00(PS) - CMX-HIGH GRADE COPPER CONT.	Financial Indexes	Commodities
63	ITMSCIP(AF1MN) - MSCI ITALY	Earning per Share /Forward	Stock Market
64	M1EMU(AF1MN) - MSCI EMU	Earning per Share /Forward	Stock Market
65	M1WLDF(AF1MN) - MSCI Fmr THE WORLD INDEX	Earning per Share /Forward	Stock Market
66	ITMSCIP(AF2MN) - MSCI ITALY	Earning per Share /Forward	Stock Market
67	M1EMU(AF2MN) - MSCI EMU	Earning per Share /Forward	Stock Market
68	M1WLDF(AF2MN) - MSCI Fmr THE WORLD INDEX	Earning per Share /Forward	Stock Market
69	ITMSCIP(AF3MN) - MSCI ITALY	Earning per Share /Forward	Stock Market
70	M1EMU(AF3MN) - MSCI EMU	Earning per Share /Forward	Stock Market
71	M1WLDF(AF3MN) - MSCI Fmr THE WORLD INDEX	Earning per Share /Forward	Stock Market
72	ITMSCIP(AF1SDC) - MSCI ITALY	Earning per Share /Forward	Stock Market
73	M1EMU(AF1SDC) - MSCI EMU	Earning per Share /Forward	Stock Market
74	M1WLDF(AF1SDC) - MSCI Fmr THE WORLD INDEX	Earning per Share /Forward	Stock Market
75	ITMSCIP(AF2SDC) - MSCI ITALY	Earning per Share /Forward	Stock Market
76	M1EMU(AF2SDC) - MSCI EMU	Earning per Share /Forward	Stock Market
77	M1WLDF(AF2SDC) - MSCI Fmr THE WORLD INDEX	Earning per Share /Forward	Stock Market
78	ITMSCIP(ALTMN) - MSCI ITALY	Earning per Share /Forward	Stock Market
79	M1EMU(ALTMN) - MSCI EMU	Earning per Share /Forward	Stock Market
80	M1WLDF(ALTMN) - MSCI Fmr THE WORLD INDEX	Earning per Share /Forward	Stock Market

Table A.3: Description of financial variables (cont'd)

N.	VARIABLE	CATEGORY	LABEL
81	ITMSCIP(AF1PE) - MSCI ITALY	Earning per Share /Forward	Stock Market
82	M1EMU(AF1PE) - MSCI EMU	Earning per Share /Forward	Stock Market
83	M1WLDF(AF1PE) - MSCI Fmr THE WORLD INDEX	Earning per Share /Forward	Stock Market
84	ITMSCIP(AF2PE) - MSCI ITALY	Earning per Share /Forward	Stock Market
85	M1EMU(AF2PE) - MSCI EMU	Earning per Share /Forward	Stock Market
86	M1WLDF(AF2PE) - MSCI Fmr THE WORLD INDEX	Earning per Share /Forward	Stock Market
87	ITMSCIP(AF3PE) - MSCI ITALY	Earning per Share /Forward	Stock Market
88	M1EMU(AF3PE) - MSCI EMU	Earning per Share /Forward	Stock Market
89	M1WLDF(AF3PE) - MSCI Fmr THE WORLD INDEX	Earning per Share /Forward	Stock Market
90	OAS_BANKS_EA	ICE (OAS-YTM)	Corp. Credit Risk
91	OAS_BANKS_US	ICE (OAS-YTM)	Corp. Credit Risk
92	OAS_BANKS_IT	ICE (OAS-YTM)	Corp. Credit Risk
93	OAS_FIRMS_EA	ICE (OAS-YTM)	Corp. Credit Risk
94	OAS_FIRMS_US	ICE (OAS-YTM)	Corp. Credit Risk
95	OAS_FIRMS_IT	ICE (OAS-YTM)	Corp. Credit Risk
96	YTM_BANKS_EA	ICE (OAS-YTM)	Corp. Credit Risk
97	YTM_BANKS_US	ICE (OAS-YTM)	Corp. Credit Risk
98	YTM_BANKS_IT	ICE (OAS-YTM)	Corp. Credit Risk
99	YTM_FIRMS_EA	ICE (OAS-YTM)	Corp. Credit Risk
100	YTM_FIRMS_US	ICE (OAS-YTM)	Corp. Credit Risk
101	YTM_FIRMS_IT	ICE (OAS-YTM)	Corp. Credit Risk
102	ECB_gold	ECB BALANCE SHEET	Other
103	ECB_claims1	ECB BALANCE SHEET	Other
104	ECB_claims2	ECB BALANCE SHEET	Other
105	ECB_claims3	ECB BALANCE SHEET	Other
106	ECB_lending	ECB BALANCE SHEET	Other
107	ECB_othclaims	ECB BALANCE SHEET	Other
108	ECB_securities	ECB BALANCE SHEET	Other
109	ECB_government	ECB BALANCE SHEET	Other
110	ECB_othassets	ECB BALANCE SHEET	Other
111	ITMSCIP(A12M1C) - MSCI ITALY	Earning per Share /Forward	Stock Market
112	M1EMU(A12M1C) - MSCI EMU	Earning per Share /Forward	Stock Market
113	M1WLDF(A12M1C) - MSCI Fmr THE WORLD INDEX'	Earning per Share /Forward	Stock Market
114	ITMSCIP(A18M1C) - MSCI ITALY	Earning per Share /Forward	Stock Market
115	M1EMU(A18M1C) - MSCI EMU	Earning per Share /Forward	Stock Market
116	M1WLDF(A18M1C) - MSCI Fmr THE WORLD INDEX	Earning per Share /Forward	Stock Market
117	ITMSCIP(A12SDC) - MSCI ITALY	Earning per Share /Forward	Stock Market
118	M1EMU(A12SDC) - MSCI EMU	Earning per Share /Forward	Stock Market
119	M1WLDF(A12SDC) - MSCI Fmr THE WORLD INDEX	Earning per Share /Forward	Stock Market
120	ITMSCIP(A18SDC) - MSCI ITALY	Earning per Share /Forward	Stock Market
121	M1EMU(A18SDC) - MSCI EMU	Earning per Share /Forward	Stock Market
122	M1WLDF(A18SDC) - MSCI Fmr THE WORLD INDEX	Earning per Share /Forward	Stock Market
123	ITMSCIP(A12PE) - MSCI ITALY	Earning per Share /Forward	Stock Market
124	M1EMU(A12PE) - MSCI EMU	Earning per Share /Forward	Stock Market
125	M1WLDF(A12PE) - MSCI Fmr THE WORLD INDEX	Earning per Share /Forward	Stock Market
126	ITMSCIP(A18PE) - MSCI ITALY	Earning per Share /Forward	Stock Market
127	M1EMU(A18PE) - MSCI EMU	Earning per Share /Forward	Stock Market
128	M1WLDF(A18PE) - MSCI Fmr THE WORLD INDEX	Earning per Share /Forward	Stock Market
129	ITMSCIP(A12FE) - MSCI ITALY	Earning per Share /Forward	Stock Market
130	ITMSCIP(A18FE) - MSCI ITALY	Earning per Share /Forward	Stock Market
131	OILWTIN(P) - Crude Oil WTI Cushing U$/BBL	Oil price	Commodities
132	LLCC.01(P) - ICE-BRENT CRUDE OIL TRc1 - U$/BL	Oil price	Commodities

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