BANCA D'ITALIA
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FORECASTING ITALIAN GDP GROWTH WITH EPIDEMIOLOGICAL DATA

by Valentina Aprigliano*, Alessandro Borin*, Francesco Paolo Conteduca*, Simone Emiliozzi*, Marco Flaccadoro*, Sabina Marchetti* and Stefania Villa*

Abstract

The COVID-19 epidemic affected the ability of traditional forecasting models to produce reliable scenarios for the evolution of economic activity. We combine macroeconomic variables with epidemiological indicators to account for the COVID-19 shock and predict the short-term evolution of Italian GDP growth. In particular, we use a mixed-frequency dynamic factor model together with a sophisticated susceptible-infectious-recovered epidemic model featuring endogenous policy responses. First, we simulate different scenarios of economic growth depending on the course of the pandemic in Italy. Second, we evaluate the forecast performance of the model for the period August 2020-March 2021. We find that taking epidemiological indicators into consideration is important for obtaining reliable projections.

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1. Introduction[1]

In early 2020, the Covid-19 shock hit the world economy unexpectedly and severely from both the supply and the demand. Governments imposed restrictions on citizens' mobility and economic activity to mitigate the spread of the contagion; at the same time, people and firms adapted their behavior by limiting many activities; uncertainty peaked, financial markets tumbled, and triggered a negative spiral which not only deepened the recession but will weigh on the recovery.

Forecasters faced a perfect storm which impaired the standard mean-reverting models routinely used to track the economy (Locarno and Zizza, 2020). Academics and policy makers rushed to set up the forecasting tools able to cope with the abrupt break and the unprecedented macroeconomic fluctuations. Covid-19 reignited the debate over whether predictive distributions may be more appropriate than point forecasts to track the economy during an extreme episode as unprecedented as the pandemic (Ioannidis et al., 2020; Taleb et al., 2020). Several strategies were suggested.

First, in order to improve predictions' accuracy, some researchers (e.g. Antolin-Diaz et al., 2021) proposed to explicitly address tail-risk and include non-linearities, drawing from the literature on forecasting macroeconomic risks (Adrian et al., 2019; Carriero et al., 2020a; Carriero et al., 2020b; Adams et al., 2021) and on stochastic volatility and time-varying-coefficient models (Clark and Ravazzolo, 2015; Carriero et al., 2016; Chiu et al., 2017).

Within a second framework, Schorfheide and Song (2020) ask whether the extreme observations should be treated as outliers, and then excluded from the estimation of the parameters, or as a structural shift in the dynamics of the time-series affecting the parameters of the forecasting model (a standard mixed-frequency VAR). Foroni et al. (2020) consider combinations of MIDAS and UMIDAS models,[2] but adjust their forecasts during the pandemic times using as a benchmark the forecasting errors made during the Global Financial Crisis and the following recovery.

Third, Lenza and Primiceri (2020) choose, in contrast, to explicitly model a break in the shock volatility during the pandemic to limit the distortions of the parameter estimates caused by extreme observations. Primiceri and Tambalotti (2020) predicted the economic effects of the pandemic by defining a synthetic Covid-19 shock, combining only macroeconomic disturbances and tilting their propagation to take into account the impact of the pandemic shock.[3]

[1] We are grateful to Fabio Busetti, Pietro Catte, Stefano Neri, Giovanni Veronese, Giordano Zevi, Roberta Zizza and Francesco Zollino for useful comments and suggestions.

[2] MIDAS (Mixed Data Sampling) regressions allow to estimate dynamic equations that explain low frequency variables by using the information contained in high frequency series and their lags. UMIDAS (unrestricted MIDAS) regressions employ unrestricted lag polynomials in MIDAS regressions. For more details see Andreou et al. (2010) and Foroni et al. (2011).

[3] At the same time, the Covid-19 fostered the collection of novel and high-frequency data (see Chetty et al., 2020 for a comprehensive survey), whose combination proves effective to track the short-run dynamics of the activity (Delle Monache et al., 2021; Lewis et al., 2021).

Fourth and finally, another strand of the literature takes into account more explicitly the epidemic propagation channels to evaluate the impact on macroeconomic aggregates (Acemoglu et al., 2020; Baqaee and Farhi, 2020; Baqaee et al., 2020; Eichenbaum et al., 2020a; Eichenbaum et al., 2020b; Favero et al., 2020; Ng, 2021).

Following this latest approach, we adapt the mixed frequency Dynamic Factor Model (DFM), traditionally used to forecast the short-run evolution of the Italian economy (Marcellino, Venditti and Porqueddu, 2016),[4] to deal with the exceptional macroeconomic fluctuations during the pandemic. This model combines macroeconomic variables with pandemic indicators as well as a measure of stringency of the restrictions enforced by the central and local governments in Italy as constructed in Conteduca (2021). Following the intuition in Ng (2021), we proceed in two steps: first, we purge economic data from the influence of the pandemic shocks and obtain stable estimates of the "pure common economic factors". In the second step, these economic factors along with the pandemic variables employed as exogenous regressors, are used to nowcast and forecast one-step-ahead the quarterly growth rate of the Italian GDP (GDP q-o-q, henceforth). We use the Kalman filter to estimate the missing values of the explicative variables at the end of the sample (the so called ragged-edge problem due to the asynchronous release of the macroeconomic indicators) and to make the predictions, similarly to Angelini et al. (2010).

We draw real-time information from a rich basket of macroeconomic indicators collected by the Bank of Italy in its economic analysis and forecasting rounds. As for the pandemic variables, we use official data from *Istituto Superiore di Sanità* (ISS, the Italian National Institute of Health)[5] and *Protezione Civile* (DPC, Civil Protection Department)[6] on daily hospitalizations, deaths and Covid-19 reported cases. We then employ the predicted scenarios on the monthly evolution of the pandemic in the third quarter of 2021– based on a Susceptible-Infectious-Recovered (SIR) model with endogenous policy responses developed by the Bank of Italy (Borin, Marchetti et al., 2021) – to envisage the possible evolutions of the economic activity.

This paper contributes to the literature along two main dimensions. First, our model is meant to provide stable and reliable projections of the economic growth even in the aftermath of the Covid-19 crisis, when the informative contribution of the pandemic variables will fade and the "pure economic common factors" will end up accounting for the most part of the comovement among the macroeconomic indicators. Second, we exploit the complementarity between the epidemic model, targeted to simulate the pandemic development in Italy, and the forecasting models commonly used in economics and based solely on macroeconomic information. In fact, a forecasting model not dealing with the developments of the pandemic has a poor chance to grasp the evolution of the economy, especially for forecast horizons longer than a few weeks.

[4] The performance of the DFM has always been monitored to ensure its reliability and accuracy, which was valuable before the pandemic (see the last report before the pandemic, Aprigliano et al. 0257638/19 of 26th February 2019).

[5] Data are provided by ISS thanks to a collaboration agreement signed with Banca d'Italia in 2020.

[6] Data can be downloaded from https://github.com/pcm-dpc/COVID-19.

The forecasting performance of our model (dubbed Covid-model; CM henceforth) is assessed for the period August 2020 – March 2021.[7] CM is compared with its counterpart, which does not take into account the pandemic variables explicitly (no-Covid model; NCM henceforth), with the official predictions of the Bank of Italy and ECB and with the Italian weekly economic indicator (ITWEI), constructed by Delle Monache et al. (2021).

Our results show that the CM tracks the short-term growth of real GDP more closely than the models that do not feature the epidemiological factors: not including them would result in a peculiar omitted variable bias that generates instabilities in both nowcasts and forecasts. Most noteworthy, the CM turns out to be as accurate as the official projections of the Bank of Italy, which were published in the Economic Bulletin during this period. In terms of nowcasting performance, the latter are seldom over-performed because they result from a model averaging which also takes into account soft information from the Bank of Italy staff' judgment. However, Bank of Italy's forecasting models do not include so far any indicator referring to the pandemic explicitly; therefore, they rely only on the interaction among the macroeconomic indicators, that, albeit timely and reliable, explain partially the forces driving the economy during the pandemic turmoil. Finally, the CM scores well even in comparison with ITWEI, which captures the exceptional fluctuations of Italian economic activity during the pandemic using high frequency indicators.

The rest of the paper is organized as follows. Section 2 describes the dataset. Section 3 deals with the empirical application, by introducing the econometric model and the real time simulations. Section 4 presents the SIR model. Section 5 discusses the main empirical results. Section 6 shows the scenario analysis. Finally, Section 7 briefly concludes.

2. Dataset

Our dataset spans from February 2003 to June 2021. The starting date is dictated by the availability of the series of freight traffic and retail payment data. The last date is motivated by the objective of this work, i.e. to assess the forecasting performance of epidemiological data during the Covid-19 pandemic.

The dataset includes 16 macroeconomic and financial monthly variables that are already used in the Economic Outlook Division of the Bank of Italy, and extensively described by Aprigliano et al. (2019) and Aprigliano et al. (2020). These series are selected according to the researcher's experience and to their coincident and leading properties with respect to the Italian GDP. Table 1 lists all the variables and their transformations as follows: (1) no transformation; (2) month-on-month percentage change; (3) year-on-year percentage change; and (4) log difference. All series are seasonally adjusted.

In addition to the indicators traditionally used in conjunctural analysis, such as industrial production, some proxies of demand (i.e., payment data and new car registrations) and confidence indicators (Purchasing Managers Indexes and business and consumers' confidence surveys), we include five additional sets of variables, which are suitable for their timeliness and reliability. In particular we add: (i) a series recording the financial intermediation services

[7] For a thorough description of the models used in the Economic Outlook Division of the Bank of Italy to produce real-time short-term forecasts of the economic activity for Italy, see https://www.bancaditalia.it/compiti/ricerca-economica/modelli-macroeconomici/.

provided by the banking sector (indirectly measured); [8] (ii) the two main components - expenditures on goods and services (variables 11 and 12 in Table 1) – of the indicator of households' consumption computed by Confcommercio,[9] which is timelier than the Istat retail sales counterpart and shows an appreciable forecasting ability; (iii) the import VAT to capture the effects of trade on the Italian economy; (iv) data on leasing contracts for capital goods and commercial vehicles, which provide timely information on investment dynamics and contribute significantly to improving forecasting;[10] (v) as a financial variable, the weighted average earnings per share (EPS) for the next t+2 fiscal year, which tracks effectively the short-term evolution of the GDP.[11]

We also explore a large information set of pandemic-related indicators such as the epidemiological series provided by *Istituto Superiore di Sanità* (ISS, the Italian National Institute of Health) and *Protezione Civile* (Civil Protection Department, CPD), and a stringency index measuring the degree of restrictiveness of central and local policy responses, which differs from the OxCGRT (Oxford Covid-19 Government Response Tracker) released by Hale at al. (2021) as it is tailored for Italy (Conteduca, 2021).[12] In particular, we tested the forecasting ability of the monthly series for deaths, admissions to hospitals and intensive care units, new cases, and a principal component combining the last two series with the stringency index.[13] Within this pandemic dataset, the variable *new cases* turned out to be the best predictor and it was then included in our model.[14] The level of this epidemiological variable is subject to obvious caveats related to mismeasurements and reflects the testing capacity and accuracy, as stated in Manski and Molinari (2020). Notwithstanding this, its monthly growth rate proves effective in anticipating the Government's decision on the restrictions and individuals' voluntary responses to reduce the risk of infections.

The epidemiological shock, v_t, is therefore defined as the log difference of $V_t, i.e.$ the monthly series of new cases:

$$v_t = \log\left(\frac{V_t}{V_{t-1}}\right).$$

[8] It is approximated by the difference between the interest rate paid on loans times the stock of loans minus the interest rate paid on deposit times the stock of deposits for households and firms.

[9] Data from Confcommercio are taken from the website https://www.confcommercio.it/comunicati-stampa.

[10] In Italy, leasing accounts for 1.7% of total GDP and more than 35% of its value is used to finance investments in the manufacturing sector. 22% of the investments spurred by Industry 4.0 and 70% of the incentives planned in the "Nuova Sabatini" where financed by leasing. Data are kindly provided by Assilea, https://www.assilea.it/default.do.

[11] The EPS is weighted by the average number of ordinary shares over the reporting period because the number of shares can change over time. We are indebted to Taneli Makinen for suggesting us this financial variable. Please note that our "standard" forecasting models have been changed along a number of dimensions to provide reliable forecasts during the pandemic.

[12] The stringency index relies on the information obtained from central and local governments' provisions, issued since January 1, 2020. The regulations are coded into a set of categorical variables and used to construct a series of sub-indicators, which are then collapsed into a nationwide stringency index, similarly to Hale et al. (2021). Differently from them, when constructing the stringency index, Conteduca (2021) accounts for the reach of the local measures by taking a population-weighted average.

[13] *Istituto Superiore di Sanità* and *Protezione Civile* provide, at the daily level, data on deaths, admissions to hospitals and intensive care units, and cases. Daily data are aggregated, at a monthly level, to obtain variables suitable for the forecasting exercise.

[14] The results from the alternative specifications of the model based on the other Covid-19 proxies are available upon request.

Table 1 – The dataset

	Definition	Treatment[a]	Source
1	Industrial Production (Manufacturing) - Italy	2	Istat
2	Industrial Production: Germany	2	Destatis
3	Freight traffic – truck	2	ASPI[b]
4	New Passenger Car Registrations	2	Anfia[c]
5 6	PMI Manufacturing PMI Services – Business Activity	1 1	Markit
7	CS[d] – Consumer Confidence	1	Istat
8	CS – Unemployment Expectations, next 12 months	1	Istat
9	Target2 retail – total	1	Bank of Italy
10	Target2 retail – crossborders	1	Bank of Italy
11	Consumption of services	2	Confcommercio
12	Consumption of goods	2	Confcommercio
13	Financial intermediation services	2	Bank of Italy
14	VAT – import	1	Bank of Italy
15	Stipulated leasing contracts (no.) – capital goods	1	Assilea[e]
16	Weighted average earnings per share	3	IBES MSCI
	EPIDEMIOLOGICAL DATA		
17	New hospitalized in standard and intensive care units	4	ISS/CPD
18	New hospitalized in intensive care	4	ISS/CPD
19	New deaths	4	ISS/CPD
20	New positive case	4	ISS/CPD
21	Stringency index	2	Conteduca (2021)

Note: (a) Code 1: no transformation; 2: month-on-month percentage change; 3: year-on-year percentage change; 4: log difference; (b) *Autostrade per l'Italia*; (c) *Associazione Italiana Filiera Industria Automobilistica*; (d) Consumer Surveys; (e) *Associazione Italiana Leasing*.

3. The empirical application

We employ a mixed frequency dynamic factor model with the Kalman filter as in Angelini et al. (2010) to forecast GDP q-o-q based on a monthly information set. We build the model in two steps. First, we follow Ng (2021) to estimate the common macroeconomic factors during the pandemic. Denote with $X_N^T = (x_{it})_{i=1,\dots,N;t=1,\dots,T}$ an array of observations for N economic variables over T periods. Within a general factor model framework, these variables are assumed to have a factor structure:

$$X_{it} - \mu_i = \Lambda_i' f_t + \xi_{it} \quad (1)$$

$$f_{t+1} = \sum_{s=1}^{p} A_i f_{t-s+1} + B\eta_{t+1} \quad (2)$$

where μ_i is the sample average of each variable i; $f_t = (f_{1t}, \dots, f_{rt})'$ is the vector of r common economic factors that account for the bulk of the comovement between the variables Xs; Λ_i is the matrix of factors' loadings and ξ_{it} is the idiosyncratic factor.[15] Equation (2) describes the law of motion of the economic factors that are assumed to follow an autoregressive process of order p driven by q-dimensional white noise η_{t+1}, where B is an r x q matrix.

As the Covid-19 pandemic starts at T_0 = February 2020, extracting f_t from the full sample $X_t - \mu$, where μ is the vector of the μ_is and $t = 1, \dots, T$, would be misleading and statistically inefficient. In fact, these common factors would not only represent the economic forces driving

[15] The vector of idiosyncratic components $\xi_t = (\xi_{1t}, \dots, \xi_{Nt})$ is distributed as $N(0, \Sigma_\xi)$.

the comovement among the variables, but they would also account for the common pandemic shock V_t . Moreover, the factors extracted without purging data from Covid-19 would change their shape significantly after T_0 and this would make forecasting problematic when the effects of the pandemic shock on the economy become less huge. We thus extract the common economic factors from a sample adjusted differently before and after the outbreak of the epidemic

$$x_{it} = \begin{cases} X_{it} - \mu^0{}_{it} & t < T^0 \\ X_{it} - \mu^1{}_{it} & t \geq T^0 \end{cases} \tag{3}$$

where $\mu^0{}_{it} = \mu_i$ for all $t = 1, \dots, T_0 - 1$ and $\mu^1{}_{it}$ is the mean of the Xs affected by the Covid-19. The latter is recovered as follows. Firstly, we use v_t and the post-Covid-19 data to estimate the parameters in the regression:

$$X_{it} = d_i + \gamma 1_{t=T_0} + \sum_{s=1}^{l} \beta_{is} v_{t-s} + \varepsilon_{it} \tag{4}$$

where d_i is a constant; $\gamma 1_{t=T_0}$ is a dummy for February 2020, arguably the start of the Covid-19 pandemic in Italy; v_t represents the Covid-19 shock lagged by $l = 2$ months.[16] Therefore, the estimate of $\mu^1{}_{it}$ is obtained as follow:

$$\hat{\mu}^1{}_{it} = \hat{d}_i + \hat{\gamma} 1_{t=T_0} + \sum_{s=1}^{l} \hat{\beta}_{is} \hat{v}_{t-s}, \qquad t \geq T_0$$

The adjusted variables x_{it} from (3) are standardized[17] before estimating the factors with the principal components.

Once we have disentangled the economic factors from the pandemic ones, their interaction is exploited in the second step of the analysis to forecast the short-term evolution of the economic activity. Let $Y_t^Q = (Y_{1t}^Q, \dots, Y_{Mt}^Q)$ be the vector of the quarterly targets, i.e. only GDP in this case, therefore we can define the monthly counterpart:

$$Y_t^m = \begin{cases} Y_t{}^Q & \text{for } t = 1st \text{ month of Q} \\ n.a. & \text{otherwise} \end{cases}$$

to deal with the mixed-frequency data. The monthly growth rates, $\gamma_t = \ln Y_t^m - \ln Y_{t-1}^m$ are assumed to be related to the monthly common factors and to the 1-month lagged[18] Covid-19 proxy by the equation:

$$\gamma_t = c + Bf_t + Wv_{t-1} + u_t, \qquad u_t \sim N(0, \Sigma_u). \tag{5}$$

[16] The lag structure for the Covid-19 shock captures the delay between the diffusion of the diseases and its economic consequences.

[17] Although all the series x_{it} have a mean of zero in their respective subsamples, their mean is not necessarily zero over the full sample.

[18] In particular, the relationship between the recording of the new positive cases (our Covid-19 proxy) and the dynamics of the economy is not contemporaneous.

Following Mariano and Murasawa (2003), the quarterly growth rates, $\gamma_t^Q = \ln Y_t^Q - \ln Y_{t-1}^Q$ can be recovered as a function of the three-month growth rates defined as

$$\gamma_t^{(3)} = \gamma_t + \gamma_{t-1} + \gamma_{t-2}$$

i.e.:

$$\gamma_{3k}^Q = \frac{1}{3}\left(\gamma_{3k}^{(3)} + \gamma_{3k-1}^{(3)} + \gamma_{3k-2}^{(3)}\right) \quad (6)$$

where $k = 1,2,\dots,[T/3]$.[19] Equation (6) is implemented in a suitable recursive way:

$$Q_t = C_{t-1}Q_{t-1} + \frac{1}{3}\gamma_t^{(3)} \quad (7)$$

with $C_{t-1} = 0_{M\,x\,M}$ in the first month and $C_{t-1} = I_M$ otherwise.

Equations (1), (2), (5), (6), and (7) are cast in a state-space form to run the Kalman filter's recursions (see the Appendix for the matrix-representation of the model).

The model is estimated with an expanding window in pseudo real-time to produce the out-of-sample projections. Therefore, the last available vintage of data (i.e. March 2021) is taken and cut month-by-month being careful to replicate the pattern of missing values at the end of the sample in each month. The first pseudo real-time vintage is August 2020, because we need a minimum number of observations on the pandemic for the estimation. The first nowcast is then on 2020Q3 and the first one-step-ahead forecast is on 2020Q4. The last pseudo real-time vintage is June 2021, when the model delivers the nowcast on 2021Q2 and the forecast on 2021Q3. We further perform a scenario analysis for the 2021Q3 GDP forecast conditioning on different paths (mild, baseline, severe) for the monthly series of the new cases calibrated using the epidemiological model of Borin et al. (2021).

4. Forecasting epidemic outcomes with endogenous mitigation measures application

Passing the generated epidemic indicators as exogenous variables to the forecasting model requires projecting the future evolution of the pandemic. Statistical predictive models, as those traditionally employed in time series analysis, are neither suited to describe biological processes such as the spread of the contagion, nor to handle the specific determinants that steer the containment measures imposed by public authorities (for instance, the emergence of more transmissible variants of the virus and the progress of the vaccination campaign). In order to account for this specificity, projections on epidemic outcomes are based on the epidemiological model developed by Borin, Marchetti, et al. (2021) to track the transmission of SARS-CoV-2 in Italian regions.

The model extends the traditional compartmental Susceptible-Infected-Recovered (SIR) framework to take into account some key aspects, such as the stratification by different age groups, administration of different vaccines, diffusion of new variants[20] as well as seasonal- and regional-specific effects. Moreover, it is augmented with a component to replicate the framework implemented by the Italian Government to determine the level of restriction in force

[19] This notation considers $t = 1$ as the first month in the first quarter.

[20] Although the model features two different main virus variants, the Delta variant was estimated to account for over 4 cases out of 5 by the end of July 2021, with the remaining infections generated by other strains including the Alpha variant.

on a weekly basis. We refer to the Appendix A3 and Borin, Marchetti, et al. (2021) for additional information on the framework.

As far as it concerns restrictions, since November 2020 the Italian Government has implemented a tier-system that classifies regions into four different tiers (white, yellow, orange, and red) based on their epidemic risk.[21] The original implementation derived mechanically from a set of epidemic indicators, including the reproduction number (Rt), the incidence of new weekly infections in the population, and the hospital/ICU occupancy rate. Such framework has been successively revised several times to change the relative importance of the indicators.[22] The current mechanism, in force since the end of July 2021, appoints the occupancy rates of hospital and intensive care unit beds as the main epidemic indicator for the determination of the zones. The outlined policy mechanism is embedded in the epidemiological model, to account for the interplay between contagion dynamics and mitigation policies imposed by public authorities. As in the real world, previous weeks' epidemic indicators obtained from the model (e.g. infection incidence, congestion rates in hospitals etc.) define the new containment policies. These, in turn, affect infections' dynamics over the ensuing weeks. The effect of containment policies on the transmission of the virus is based on past empirical evidence (e.g. Manica et al., 2021). When this is not available due to changes in the regulatory framework or other exogenous variations, we rely on reasonable hypotheses or we consider a range of possible outcomes to take into account the uncertainty of the effects.[23]

The epidemic model is used to predict epidemiological outcomes and the evolution of restrictions in the second half of 2021 up to the end of the third quarter of 2021. A key assumption behind the simulation results is that the policy mechanism in place when we calibrate the relevant parameters will not be substantially modified over the projection period.

Modelling simultaneously the dynamics of epidemic variables and that of containment measures not only improves the accuracy of epidemic projections but also provides an assessment on the future pattern of social distancing restrictions which deeply affect economic activity (see, among others, Caselli et al., 2020; Rodano, 2021).

The future evolution of the pandemic is subject to many sources of uncertainty. Some events can be hardly identified ex-ante (e.g. the insurgence of a new variant); in other cases, we may be aware of the presence of a given factor but it may be extremely difficult to provide a quantitative assessment its effect on the virus transmission (e.g. changes in individuals' behaviours). Nonetheless, for some epidemic determinants we can define a plausible range of variation that can be used to draw different scenarios basing on the information set available in a given moment. In particular, here we focus on three main scenarios reflecting different hypotheses about the Delta variant, in terms of i) regional prevalence levels at initialization, ii) increase in transmissibility, iii) severity of the symptomatic disease, and iv) vaccine escape probabilities.[24] The evolution of notified cases and restrictions predicted by the model at national level under the different scenarios is depicted in Figure 1a and Figure 1b.

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[21] Each category entails specific provisions in terms of individual mobility, economic activities, school opening levels, etc.

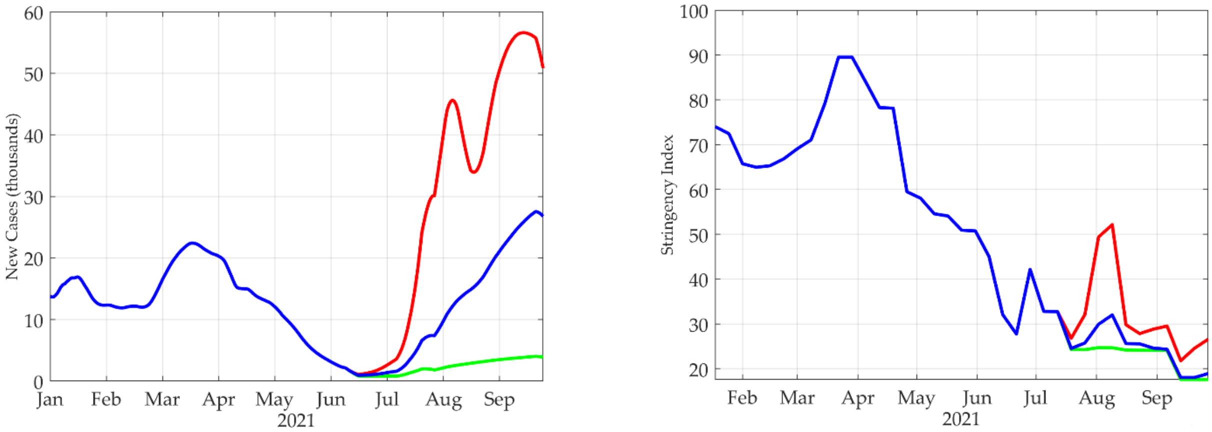
[22] While we account for weekly changes in restrictions at the regional level given the policy framework, we do not consider endogenous shift of the framework itself. So far, those have been minor and slow, often going beyond the target forecast horizon considered in this note.

[23] For instance, we assumed that the reopening of the indoor service in bars and restaurants would have had a limited impact on the contagion since a vaccine certificate (the so called "green pass") was required to access this service.

[24] Many other possible sources of uncertainty, which are not taken into account in the simulation results, may affect epidemic and policy outcomes. Extensive sensitivity analysis was run on such sources, which include the effect of schools closure and re-openings and of increased temperatures throughout the summer period. See Borin, Marchetti et al. (2021) for details.

Figure 1: Projections on infections and restrictions in Italy

Number of new notified cases (*7-day moving average*) **Weekly Modified *Oxford Stringency Index***



Note: The blue curve represents the baseline scenario whereas red and green lines display respectively the severe and benign scenarios. Each scenario is associated with a different trajectory in terms of pattern of weekly regional tiers.

The severity of each scenario depends on the choice of parameter values characterizing the evolution of the epidemic. We either estimate these parameters or draw them from the literature. For each parameter, we take the central estimates to model our baseline, whereas we use the endpoints of the respective confidence intervals to design the pessimistic and optimistic scenarios. As far as it concerns the parameters governing the characteristics of the Delta variant, we rely on Lopez Bernal et al. (2021).

As depicted by Figure 1, each scenario defines its own pattern of restrictions over time, thanks to the endogenous policy determination mechanism.

Under more favorable hypotheses, the compounded effects of vaccination campaign, standard calendar closure of schools and the rise of atmospheric temperatures allow to contain the number of infections during the summer, while the epidemic risk increases in autumn when school reopening and less favorable climatic conditions may trigger a substantial resurgence of infections. The limited incidence of notified infections among the population and relative low hospital bed occupancy rates will support the adoption of “white” tier restrictions in all Italian regions during the 2021Q3. This is associated with a decline in the (modified) Oxford Stringency Index, which during the summer is projected to attain the minimum level since February 2020. The severe scenario points to a steep increase of infections as early as the summer with the incidence of daily cases evolving in line with those already reported in other European countries (e.g., the UK, the Netherlands, and Spain). In this case, a new tightening of restrictions may occur, but the stringency of containment policies is likely to remain well below the level reached in April 2021. Indeed, the high vaccine coverage among the elderly and other fragile individuals is expected to prevent new infections from straining substantially the healthcare system, limiting the consequences on the overall level of restrictions. Remarkably, the severe scenario triggers more stringent restrictions on mobility and activities as early as August, that in turn manage to abate the contagion by the end of the 2021Q3. As far as it concerns the baseline scenario, we observe a moderate increase of cases over the summer, which slows down at the end of the forecast horizon. However, the rise of infections does not translate into a substantial increase of restrictions thanks to the relatively low hospital bed occupancy rates. In the benign scenario, the epidemic shows a mild increase, with the number of cases always lower than those observed in the other scenarios. In line with this, the implied restrictions remain below those observed in the alternative scenarios.

5. Results of forecasting during a pandemic

In this section, we evaluate the precision of the nowcasts and the one-step-ahead forecasts of CM for GDP q-o-q against both the flash (so called "t+30") and the first estimate ("t+60") published by Istat.[25] Moreover, we exploit the projections on the evolution of the pandemic in three different scenarios (severe, baseline and less-severe), chiefly depending on the spreading of the Delta variant, to envisage the corresponding figures for GDP quarterly growth.

The evaluation period runs from 2020Q3[26] until 2021Q2. The forecasting performance of CM is compared with:

1. an equivalent DFM model with no correction for the Covid-19 outbreak (NCM);
2. the Bank of Italy official nowcasts (BoI), published on the quarterly Economic Bulletin based on both econometric models and analysts' judgment;
3. the forecasts produced by Eurosystem and ECB staff, i.e. (B)MPE;[27]
4. the GDP nowcasts from ITWEI, an indicator constructed during the pandemic to track the economic growth by relying on the high-frequency information.[28]

Figure 2 shows the evolution of the monthly nowcasts of all the competing models together with the targets, i.e. the preliminary and the first official estimates of GDP q-o-q (blue and black dotted lines, respectively). Disentangling the Covid-19 shock from the economic common factors and relating the former to GDP growth directly improve the nowcast precision.[29] CM is more precise than NCM throughout the testing sample and it behaves similarly to two robust competitors such as BoI and ITWEI. In fact, the forecasts of the Bank of Italy reported in the Economic Bulletin are based on both the estimates from the battery of econometric models and on analysts' judgment, which shapes the former based on supplementary information. ITWEI is a model focused on the pandemic period and developed to address the forecasting in an extremely uncertain and volatile background like that caused by the Covid-19 shock.

Conversely, CM is meant to track the economic activity during the pandemic crisis without denting the forecasting performance in both the pre- and post-Covid eras.

In 2020Q4 the forecasts were revised downward between the first and the last month of the quarter, as the pandemic reignited gradually. Nonetheless, the outlook based on CM was less pessimistic than that of the BoI and closer to the final figure of the GDP.

In 2021Q1, the preliminary estimate of the GDP growth was revised up by 0.5 percentage points (from -0.4 to 0.1%). CM had signaled a gradual improvement of the outlook throughout the quarter as new information piled up and on average it predicted a 0.2% growth, very close to the official first estimate produced by the national statistical institute (NSI) with a more complete set of information.

[25] The out-of-sample forecasting simulation is run in pseudo real time, in that we use the last available vintage of data and we cut the sample month-by-month being careful to reproduce the pattern of the missing values at the end of the sample. However, since the iterations are few, the pseudo real-time simulation approximates the real-time one, because the macroeconomic indicators are not revised a lot in a short period.

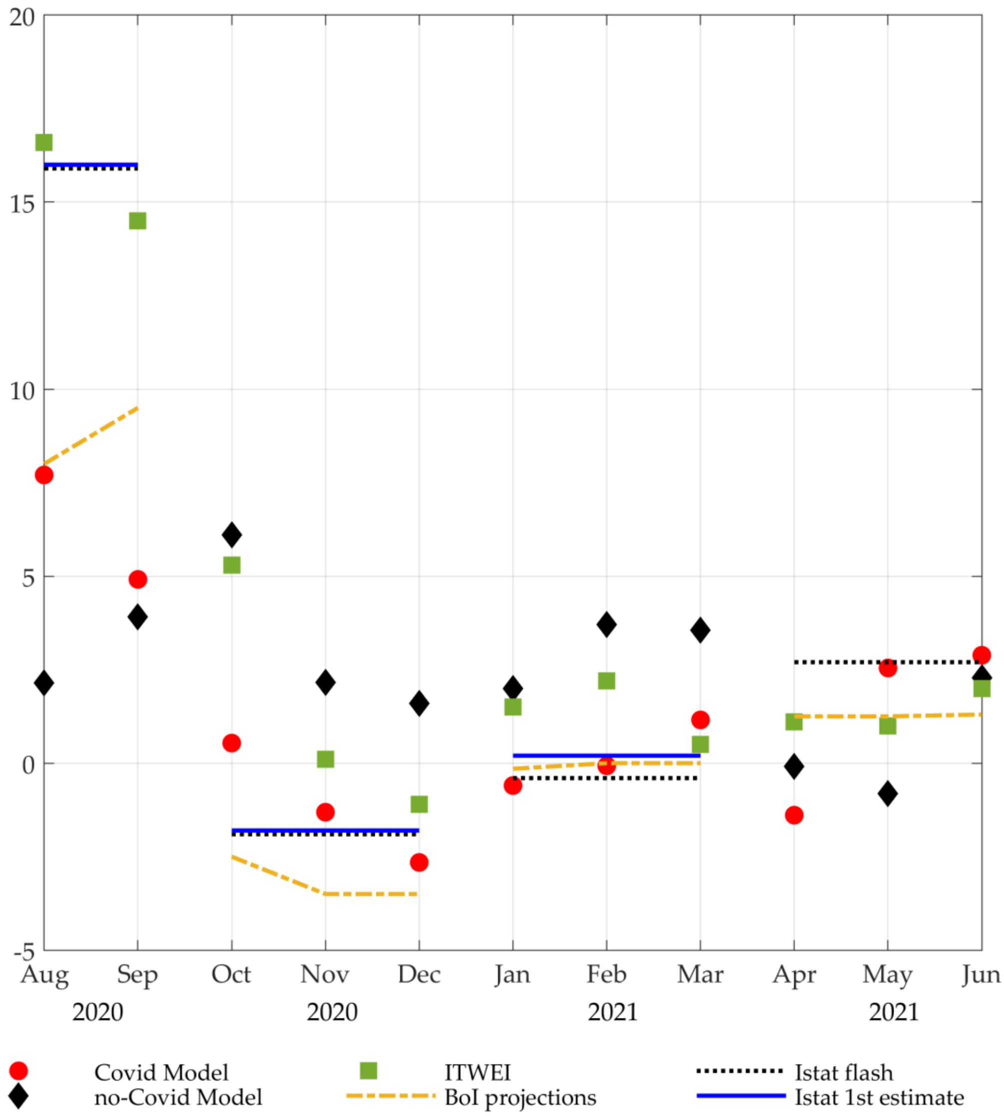
[26] A minimum number of observations should be saved for the estimation of the model during the pandemic, therefore 2020Q1 and 2020Q2 cannot be included in the evaluation sample.

[27] See https://www.ecb.europa.eu/pub/projections/html/details.en.html.

[28] For ITWEI we use the end-of-month nowcast on the Italian GDP q-o-q growth rate.

[29] Tables A1 and A2 in the Appendix report the value of the forecasts shown in Figures 1 and 2.

Figure 2 – GDP q-o-q: official estimates and nowcasts from BdI (a), Covid Model, no-Covid Model, ITWEI for the reference quarter

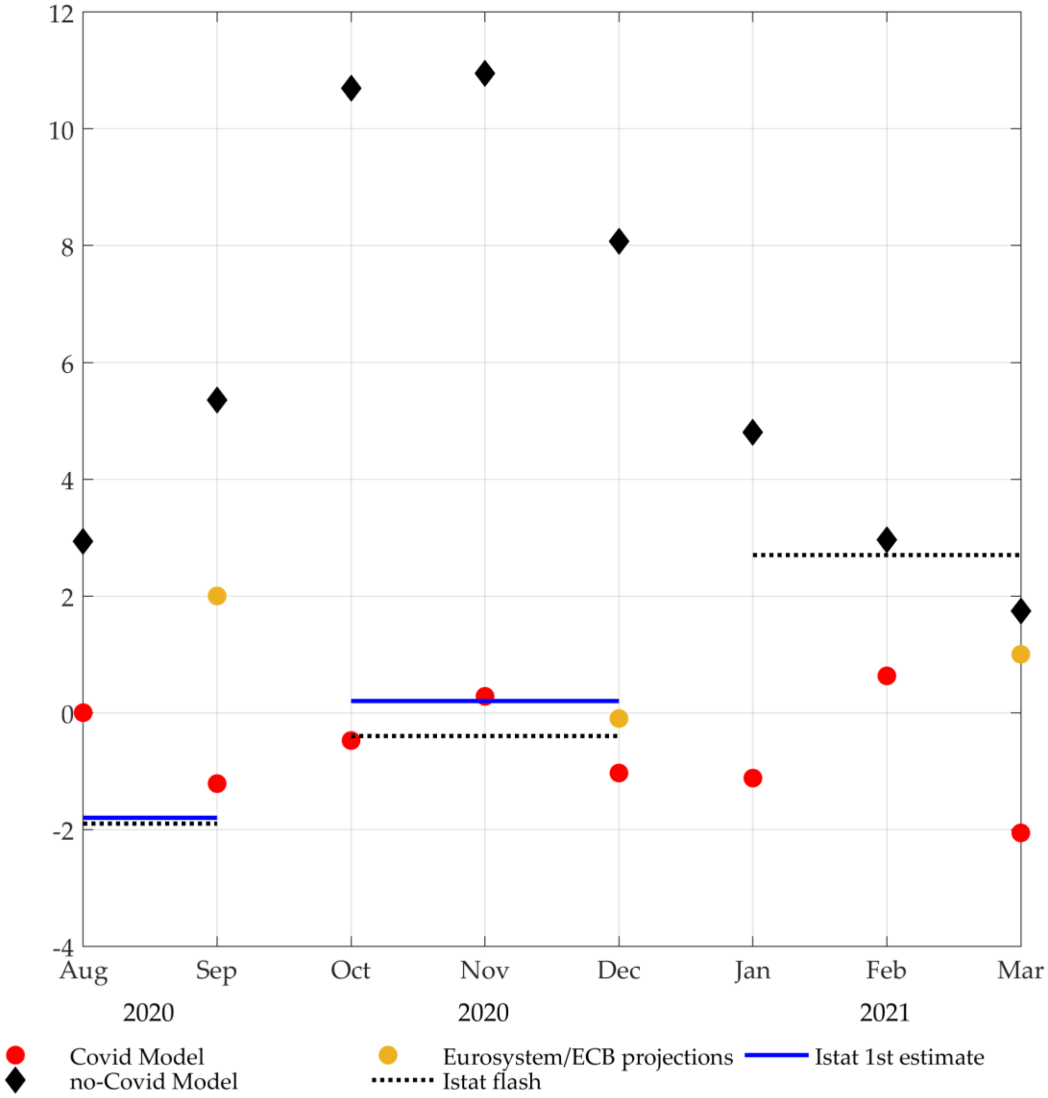


Note: (a) Estimates published in the Economic Bulletin.

In 2021Q2 CM pointed to a robust expansion of the GDP since the second month of the quarter, when BoI and ITWEI had signaled an expansion half as wide as the official estimate.
Figure 3 displays the evolution of the monthly one-step-ahead forecasts for a short out-of-sample period ranging from 2020.Q4 to 2021.Q2. Achieving a moderate degree of accuracy in one-step-ahead forecasts is a difficult task even in normal times since models information sets have less updated information: the high volatility registered during the pandemic exacerbated this forecasting exercise, so that results presented here are preliminary and have to be interpreted with caution.

The CM in August had forecasted a stagnation of the GDP in 2020.Q4 but this outlook gradually worsened in September as the contagion reignited. The final forecast for 2020.Q4 was consistent with the official GDP's figure.

Figure 3 – GDP q-o-q: official estimates and one-step-ahead forecasts from CM, NCM, Eurosystem/ECB (a)



Note: (a) (Broad) macroeconomic projection exercise. The figures represent the forecasts made in each month from August 2020 until March 2021 for the one-step-ahead quarters (i.e. 2020.Q4, 2021.Q1 and 2021.Q2).

In October, CM's forecast for 2021.Q1 was in line with the preliminary NSI's estimate (i.e. -0.4%); as new information piled up, in November CM revised upward the projection to 0.2, close to NSI's first estimate, which was corrected to 0.1%. However, in December CM got out of track, affected by the rapid increase of the contagion and the following restrictions to the mobility imposed by the Government. Nonetheless, overall CM performed better than NCM, suggesting that the pandemic factor is crucial for producing reliable forecasts.

The negative impact of the new wave of infections dragged in the first months of 2021, when CM depicted a negative outlook for the spring. CM was surprised to the upside in 2021.Q2 and failed to envisage the break in the relationship between the spreading of the Covid-19 and the economy, that was ever since less impaired thanks to the vaccination roll-out and the ensuing revision in the strategy of the restriction policies. Both factors take time to be fully accounted for in our modelling.

6. Scenario analysis for 2021 Q3 with forecasts on pandemic variables

We present a scenario analysis for the growth rate of GDP in 2021.Q3. This exercise aims at exploring how the epidemiological trends, envisaged by the SIR model presented in Section 4, contribute to shaping the economic outlook. The simulation is implemented at the end of June 2021, when the last vintage of the macroeconomic information set is available. The missing values of the epidemiological series at the end of the sample are estimated by the SIR model, while the macroeconomic indicators are extended forward by a naïve method.[30]

Figure 4 shows one-step-ahead forecast of GDP q-o-q in 2021Q3 throughout each month of the quarter (green, yellow and red boxes) and on their quarterly average (blue box).[31] Our findings underline a significant negative correlation between the pandemic variable and the projections of economic activity. The GDP q-o-q forecast is gradually revised downward (from 4.4% to 3.3% in, respectively, July and August baseline scenario), reflecting the less favorable evolution of the pandemic caused by the spreading of the "Delta" variant in July and in August (Figure 1).[32]

The intervals around the baseline forecasts (solid lines) reflect the hypothesis on both the spreading of the "Delta" variant and the containment measures to tackle the former. Overall, the dispersion around the baseline implied by the optimistic and severe scenarios is rather limited. Indeed, even if the number of cases is relatively large in the severe scenario, the policy mechanism currently in place may contain the spread of the virus. In addition, one has to consider the role of temperature and vaccines in mitigating the harm to the economic activity as the number of cases would be substantially larger than predicted without these brakes. Finally, many sectors of the economy, as well as households, adapted to Covid-19 and became more resilient to worsening pandemic perspectives. It is therefore less plausible that a revival of the infections could take a toll on GDP growth to the same extent of the outbreak in early 2020.

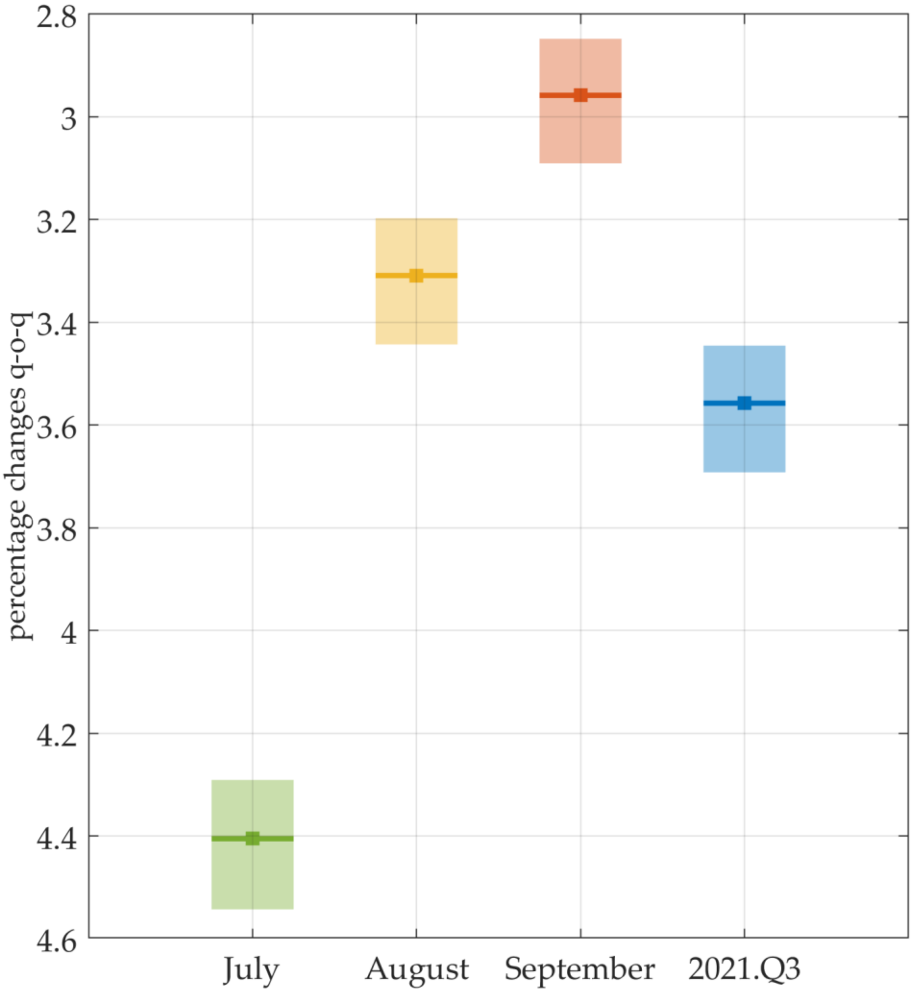
The baseline prediction of GDP q-o-q is closer to the lower limit of the interval than to the upper one. This result can be essentially explained by the fact that in July and in August the growth rate of infections is more pronounced in the severe and baseline scenarios than in the optimistic one.

[30] In this simulation, the macroeconomic time-series are projected by a constant until the end of the forecasting horizon, i.e. September 2021, differently from the Kalman filter used to estimate the missing values at the end of the sample in the rest of the forecasting exercise. In fact, when all the variables are not observed, the autoregressive component would prevail in the estimation and we know that it may be distorted given the exceptional magnitude of the oscillations ever since the beginning of the pandemic.

[31] The average over the monthly forecast provides a reliable and less noisy outlook over the quarter because the monthly predictions of GDP q-o-q cannot be properly intended as the updates of the forecasts led by a genuinely new real-time flow of information.

[32] The pandemic variable *new cases* enters the forecasting equation with one lag.

Figure 4 – Macroeconomic scenarios for 2021.Q3



Note: bold lines represent the forecast for 2021.Q3 based on the baseline projections of the epidemiological model; the shadow area represents the forecast interval ranging between the worst and best case pandemic scenario.

7. Conclusion

This note investigates whether including pandemic variables in a forecasting model, along with the macroeconomic indicators, improves its ability to track GDP q-o-q during the pandemic.

The model endowed with pandemic series, CM, proves more accurate in nowcasting GDP growth than its counterpart without epidemiological variables. Its performance is comparable with the official estimates produced by the Bank of Italy and ECB, which combine both econometric estimates and analysts' judgement. CM performs as well as ITWEI, the Italian weekly indicator suited to grasp the peculiar dynamics of real GDP during the pandemic. The model can also be used to construct macroeconomic scenarios based on different assumptions on the evolution of the pandemic.

The following caveat is in order: there are still few observations since the outbreak of the pandemic. A more accurate assessment of the forecasting performance of these models will be possible when more post-Covid observations become available.

The promising results pave the way to further analyses and improvement in the modelling framework. The model can be used to draw a comprehensive picture of the short-term evolution of the Italian economy, by nowcasting and forecasting the quarterly growth rate of the main demand and supply components of GDP (i.e., households' consumption, gross fixed investments, imports, exports, and the value added in services). This is particularly important during highly uncertain periods, when the economy is upset by forces whose strength and timing are difficult to anticipate and assess in real time. Further development may be extending the analysis to make projections for GDP in the euro area and its major countries.

Appendix

A1 Model

For the sake of simplicity, the state-space form in the following is presented for one lag p. Equations (1), (2), (5), (6), and (7) represent the transition equation of the state vector $(f_{t+1}, \gamma_{t+1}, \gamma_t, y_{t+1}^{(3)}, Q_{t+1})$. The matrix form is:

$$\begin{bmatrix} I_r & 0 & 0 & 0 & 0 \\ -B & I & 0 & 0 & 0 \\ 0 & 0 & I & 0 & 0 \\ 0 & -I & -I & I & 0 \\ 0 & 0 & 0 & \frac{1}{3}I & I \end{bmatrix} \begin{bmatrix} f_{t+1} \\ \gamma_{t+1} \\ \gamma_t \\ y_{t+1}^{(3)} \\ Q_{t+1} \end{bmatrix} = \begin{bmatrix} 0 \\ \lambda \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ Wv_{t+1} \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} A_1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & I & 0 & 0 & 0 \\ 0 & 0 & I & 0 & 0 \\ 0 & 0 & 0 & 0 & C_t \end{bmatrix} \begin{bmatrix} f_t \\ \gamma_t \\ \gamma_{t-1} \\ y_t^{(3)} \\ Q_t \end{bmatrix} + \begin{bmatrix} B\eta_{t+1} \\ u_{t+1} \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

where I is an $m\ x\ m$ identity matrix.
The observation equation is:

$$\begin{bmatrix} x_t \\ \gamma_t^Q \end{bmatrix} + \begin{bmatrix} \Lambda & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & I \end{bmatrix} \begin{bmatrix} f_t \\ \gamma_t \\ \gamma_{t-1} \\ y_t^{(3)} \\ Q_t \end{bmatrix} + \begin{bmatrix} \xi_t \\ 0 \end{bmatrix},$$

where γ_t^Q is defined only in the third month of each quarter, and skipped otherwise.

A2 Results

Table A1 and A2 show the nowcasts and the one-step-ahead forecasts of the Covid-model and its two competitors (the no-Covid model and the official projections by both the Bank of Italy and ECB).

Table A1 – Monthly nowcasts of the Covid-model compared with the no-Covid model and BoI estimates

		Covid Model (CM)	no-Covid Model (NCM)	BdI models (average)	ITWEI	BdI official estimates (a)	Istat flash estimate	Istat last estimate (b)
2020.Q3	Aug 2020	7.7	2.1	1.0	16.6	8.0	**16.1**	**16.0**
	Sep 2020	4.9	3.9	7.8	14.5	9.5	**16.1**	**16.0**
2020.Q4	Oct 2020	0.5	6.1	-2.0	5.3	-2.5	**-1.9**	**-1.8**
	Nov 2020	-1.3	2.2	0.1	0.1	-3.5	**-1.9**	**-1.8**
	Dec 2020	-2.7	1.6	-1.3	-1.1	-3.5	**-1.9**	**-1.8**
2021.Q1	Jan 2021	-0.6	2.0	-0.4	1.5	-0.2	**-0.4**	**0.2**
	Feb 2021	-0.1	3.7	0.2	2.2	0.0	**-0.4**	**0.2**
	Mar 2021	1.2	3.6	0.8	0.5	0.0	**-0.4**	**0.2**
2021.Q2	Apr 2021	-1.4	-0.1		1.1	1.3	**2.7**	-
	May 2021	2.5	-0.8		1.0	1.3	**2.7**	-
	Jun 2021	2.9	2.3		2.0	1.3	**2.7**	-

Note: (a) Estimates both published in the Economic Bulletin and prepared for the Governing Council; (b) last update 30th July 2021.

Table A2 – Monthly one-step-ahead forecasts of the Covid-model compared with the no-Covid model and BoI estimates

	1-step ahead forecast	Covid Model (CM)	no-Covid Model (NCM)	BdI models (average)	ITWEI	Eurosystem/ECB forecasts (B)MPE	Istat flash estimate	Istat last estimate (b)
2020.Q4	Aug 2020	0.0	2.9	-3.1	-		**-1.9**	**-1.8**
	Sep 2020	-1.2	5.4	-4.3	-	2.0	**-1.9**	**-1.8**
2021.Q1	Oct 2020	-0.5	10.7	2.0	-		**-0.4**	**0.2**
	Nov 2020	0.3	11.0	0.6	-		**-0.4**	**0.2**
	Dec 2020	-1.0	8.1	1.0	-	-0.1	**-0.4**	**0.2**
2021.Q2	Jan 2021	-1.1	4.8		-		**2.7**	-
	Feb 2021	0.6	3.0		-		**2.7**	-
	Mar 2021	-2.1	1.7		-	1.0	**2.7**	-

Note: (a) Eurosystem/ECB staff macroeconomic projections.

A3 The epidemic model

The epidemic model used in this paper derives from Borin, Marchetti et al. (2021). It is an extension of the traditional compartmental Susceptible-Infected-Recovered (SIR) framework to take into account some key aspects, such as the stratification by different age groups, the administration of different vaccines, the diffusion of new variants as well as seasonal- and regional-specific effects. Moreover, since contagion dynamics are also affected by mitigation policies imposed by public authorities, the model replicates the framework implemented by the Italian Government to determine endogenously the level of restrictions in force. Modelling simultaneously the dynamics of epidemic variables and that of containment measures not only improves the accuracy of epidemic projections but also provides an assessment on the future pattern of social distancing restrictions which deeply affect economic activity (see, among others, Caselli et al., 2020; Rodano, 2021).

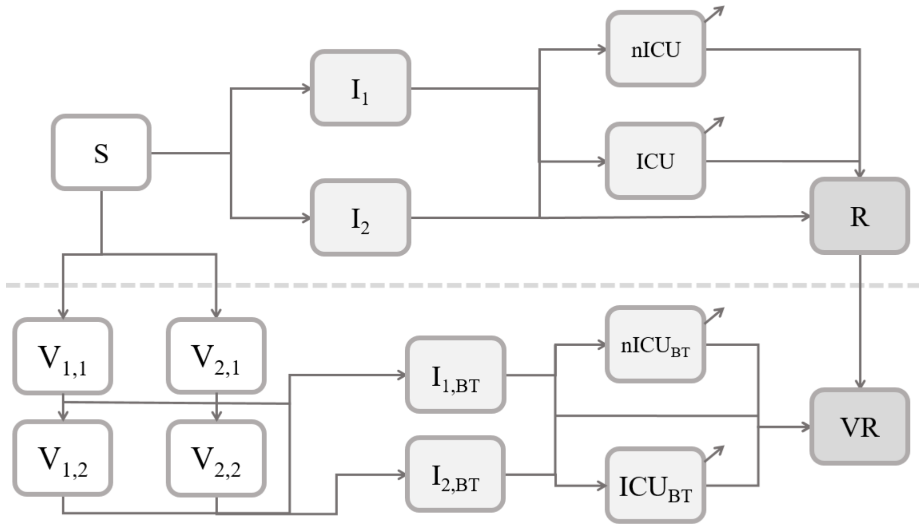
The diagram in Figure A.3.1 provides a simplified representation of the SIR model. Individuals are initially assigned to a given compartment according to the past evolution of the epidemic in each region. Transitions between compartments in each step of the simulation are governed by a system of differential equations whose parameters are calibrated to capture the characteristics of the SARS-CoV-2 infection according to the structure of people's interactions conditional upon age groups, restrictions in place, and the assumptions on the vaccine rollout. Five age groups are included: 0-12, 13-18, 19-64, 65-79, 80+. Each group is characterized by a specific contact pattern (i.e. daily number of effective interactions within and across groups), susceptibility to the disease, risk of hospitalization/ICU probability and fatality rate (IFR).

Vaccine administration capacity is assumed to progress at a pace of about 500,000 daily doses, in line with the target set by the Italian Government, up to the end of July (about 60% of the population with at least one dose). Then, the vaccine rollout is assumed to slow down partly because of the progressive reduction of eligible individuals, partly because of vaccine hesitancy. As far as it concerns the latter, we calibrate the final vaccination coverage according to the latest available results of the surveys conducted by the Imperial College London-YouGov.[33] We do not model the possible response of vaccine uptake to changes in epidemic or regulatory conditions (e.g. increase in cases/hospitalizations, introduction of the vaccine certification and related restrictions, etc.). While the model features two different main virus variants, we estimate the Delta variant to account for over 4 cases out of 5 by the end of July 2021, with the remaining infections generated by other strains including the Alpha variant.[34]

[33] See https://github.com/YouGov-Data/covid-19-tracker.

[34] In the original version of the model, a first variant was calibrated to mimic the characteristics of the "wild type" strain, whereas the second one was based on the features of the Alpha variant, which has become dominant in Italy since early-March. Also the cases associated with the Gamma variant were included in the "second variant" in the model calibration, as this variant's relative prevalence in Italy as compared to the Alpha variant has remained broadly stable in the period March-May 2021. According to the surveys conducted by the ISS and the Italian Ministry of Health, at the end of May the Alpha variant accounted for 88.1% of the cases, while 7.3% of the cases were related to the Delta variant. By the second half of June, the Delta variant was reported to account for almost one case out of 4 (22.7%).

Figure A.3.1: Flow diagram for the epidemiological SIR model



Source: Borin, Marchetti et al. (2021).
Note: Model compartments are the following: individuals susceptible to the virus (S), infectious individuals with first and second variant type virus (I_1 and I_2, respectively), hospitalised in non-intensive (nICU) or intensive care units (ICU), recovered (R), immunised with the first group of vaccines (first and second dose, respectively, $V_{1,1}$ and $V_{1,2}$), immunised with the second group of vaccines (first and second dose, respectively, $V_{2,1}$, $V_{2,2}$), breakthrough infection cases ($I_{1,BT}$ and $I_{2,BT}$ for variant types 1 and 2), hospitalisations ($nICU_{BT}$, ICU_{BT}) and recovered from breakthrough infection (VR).

The model also accounts for the rules used by public authorities to implement containment measures at a regional level. In particular, since November 2020 the Italian Government has implemented a tier-system that classifies regions into four different categories (white, yellow, orange, and red) based on their epidemic risk.[35] The original implementation derived mechanically from a set of epidemic indicators, including the reproduction number (Rt), the incidence of new weekly infections in the population, and the hospital/ICU occupancy rate. The policy mechanism has been successively revised several times to change the relative importance of the indicators.[36] The current mechanism, in force since the end of July 2021, appoints the occupancy rates of hospital and intensive care unit beds as the main epidemic indicator for the determination of the zones.

Our epidemiological model embeds the outlined policy mechanism. More specifically, the former simulates daily epidemic outcomes through a series of iterations with weekly shifts. As in the real world, previous weeks' epidemic indicators derived from the model (e.g. infection incidence, congestion rates in hospitals etc.) define the new containment policies. The latter, in turn, affect infections' dynamics over the following weeks.

[35] Each category entails specific provisions in terms of individual mobility, economic activities, school opening levels, etc.

[36] While we account for weekly changes in restrictions at the regional level given the policy framework, we do not consider endogenous shift of the framework itself. So far, those have been minor and slow, often going beyond the target forecast horizon considered in this note.

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