THE ECONOMICS OF COVID-19

Edited by Badi H. Baltagi,
Francesco Moscone and Elisa Tosetti

CONTRIBUTIONS TO ECONOMIC ANALYSIS

VOLUME 296

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PREFACE

Quoting from the UN's Framework for the Immediate Socio-Economic Response to the COVID 19 Crisis: 'The COVID-19 pandemic is far more than a health crisis: it is affecting societies and economies at their core. [...] Development trajectories in the long-term will be affected by the choices countries make now and the support they receive'. The global health crisis, exacerbated by the COVID-19 outbreak, has challenged all sectors of society, including health, economics, finance and social inequality. The threats and complexities from the COVID-19 pandemic shock are the subject of this book. Obviously, one cannot cover all economic and health aspects of this pandemic in one book. A lot of research is carried out globally on the effects of this virus. Enclosed are selected contributions of the effects of this pandemic covering macroeconomics, computable general equilibrium models, financial markets, the reduction in seismic noise due to the slowdown in traffic and economic activities caused by the spread of the virus, and the rapid surge in the digital transformation of production and consumption. Also included are health studies proposing to improve the traditional epidemic models, the effects of the pandemic on mental health, as well as on Minority Ethnic Groups (MEG) in the UK. The book concludes with a study that discusses the challenges and the limitations faced during the COVID-19 pandemic by the Lombardy region in Italy which was a hot spot for the virus.

Billio, Casarin and Corradin study the effects of the COVID-19 pandemic on a number of macroeconomic variables for the US and the EU, using a factor model. The authors extract a set of instability measures and perform a macroeconomic scenario analysis to better understand the factors associated with economic instability.

Roson and Van der Vorst survey the recent and rapidly expanding literature that analyses the economic impacts of the COVID-19 pandemic by means of Computable General Equilibrium models. They review recent contributions in this field, specifically looking at advantages and disadvantages of the proposed technique within the COVID context.

Massacci discusses several methodological challenges that could arise when analysing data on financial markets in periods of high economic and financial turbulence, such as the COVID-19 pandemic. The author discusses the high nonlinearity in asset returns and proposes possible approaches to properly account for such nonlinearity.

The COVID-19 pandemic exacerbated the need for policy makers to obtain accurate and timely economic data to monitor the state of the economy. Recent advances in information technology allowed the collection, storage and analysis of several new sources of information related to human behaviour and activity that could be used as proxies for economic conditions. Tiozzo Pezzoli and Tosetti explore the use of seismic data to predict variations in Gross Domestic Product for a set of States in the US over the period 2015–2021. The authors show a remarkable reduction in seismic noise due to the slowdown in traffic and economic activities during the coronavirus economic crisis.

Tabaghdehi explores the structure of the digital supply and digital consumption and the opportunities and challenges in promoting the economy, given the rapid surge in the digital transformation of production and consumption since the COVID-19 outbreak.

A number of chapters in this book focus on the health and healthcare aspects of the pandemic as well as on the statistical modelling of the spread of the virus. Among these, Arbia, Nardelli and Ghiringhelli study how to improve traditional epidemic models by proposing a stochastic version of SIR (Susceptible, Infectious or Recovered) models. In line with the specific features of the current COVID pandemic, the authors propose to augment the usual categories of individuals considered in SIR models with additional categories of hospitalised and critical care patients.

Rienzo reviews the literature on the effect of the COVID-19 pandemic on mental health, with a special focus on the differences observed across various demographic groups. The author points out the high degree of heterogeneity within demographic groups, with women, younger people and poorer households being more affected.

Madia, Nicodemo and Redding present a summary of existing evidence on the effects of the COVID-19 pandemic on Minority Ethnic Groups (MEGs) in the UK. The authors show a deterioration in the mental health of MEG, and in particular MEG women. They also observe a higher probability for certain ethnic groups to contract the infection and die, as well as a lag in receiving their first dose of the vaccine.

Finally, Angelici, Berta and Vittadini discuss the challenges and the limitations faced during the COVID-19 pandemic by the Lombardy region (Italy), one of the most heavily affected regions by the virus worldwide. The excess mortality in the Lombardy region indicates that the region did not manage the spread of the virus in an effective way. Surprisingly, when examining non-COVID patients, their results show that the healthcare system was able to guarantee the same level of quality in treatment as that provided in pre-COVID periods, particularly for those pathologies requiring treatments that could not be deferred in time or a strong continuity of care.

We hope these sample of contributions spur much needed research in the effects of COVID on the global economy, the health and financial sectors as well as development and growth and economic inequality, to mention a few.

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UNDERSTANDING ECONOMIC INSTABILITY DURING THE PANDEMIC: A FACTOR MODEL APPROACH

Monica Billio, Roberto Casarin and Fausto Corradin

ABSTRACT

This chapter studies the effects of the COVID-19 pandemic on the economic structure of the US and EU economies by measuring its impact on some reference macro-economic variables. We use a factor model approach on a set of variables available at different frequencies (daily, weekly, monthly, and quarterly) and provide evidence of instability in the primary factors driving the economy. A sequential analysis of the factors allows us to evaluate the model's forecasting performance and extract some instability measures based on the factor model's eigenvalues. Finally, we show how to use COVID-related variables, such as policy, economic, and health indicators, to compute conditional forecasts with factor models, and perform a scenario analysis on the variables of interest to understand economic instability.

Keywords: COVID-19; factor models; forecasting; scenario analysis; uncertainty; vector autoregressions

1. INTRODUCTION

Despite the relevance of the topic, the impact of COVID-19 on economic systems has been investigated in only a few papers. Much attention has been paid to possible recovery patterns and how they can be driven by more sustainable choices. The multiple positive effects of lockdowns on the environment and society, including biodiversity (Prakash & Verma, 2020) have been analysed, but

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as Ibn-Mohammed et al. (2020) argue, it is helpful to diagnose the danger of relying on pandemic-driven benefits to achieving sustainable development. Ibn-Mohammed et al. (2020) also emphasizes the need for a decisive, fundamental structural change to the dynamics of how we live. Also, in Battiston, Billio, and Monasterolo (2020), there are several analyses of the possible economic impacts of COVID-19 from different perspectives. Battiston et al. (2020) discuss how 'business as usual' recovery strategies may jeopardize mid-to-long-term sustainability and financial stability objectives. Strengthening socio-economic resilience against future pandemics (as well as other shocks) calls for recovery measures that are fully aligned with sustainability and climate change objectives and global corporate taxation policies; tackling these long-term objectives is not more costly than funding the current short-term measures.

Among the possible consequences of the pandemic, the shock to the labour market is certainly one of the most relevant, and it should be managed in a manner that does not leave a post-COVID-19 world more disastrous (Aberinpoka Awafo, Kwame Morgan, & Quartey, 2020). The impact of COVID-19 on event businesses is also relevant (Madray, 2020). The relationship between the COVID-19 pandemic and the financial markets has been investigated (Sansa, 2020) in the context of various factors, such as lockdown approaches, moratoriums, different impacts on banking, financial services, and the insurance sector (Ramasamy, 2020). The effect of the pandemic has already been examined in the context of Chinese economics (Liu, 2021), the short-term global economy (McKibbin & Roshen, 2021), and across industries and countries (Fernandes, 2020), and attempts have been made to investigate the possible mechanisms of economic contagion (McKibbin & Vines, 2020).

The purpose of this chapter is to study how the COVID-19 pandemic has changed economic structures, focusing on the US and EU economies. We aim to measure its effects on the main economic variables and to study this issue from a structural point of view. Therefore, we use a dimensionality reduction approach on a set of variables available at different frequencies.

The increased availability of a large amount of data allows researchers to model and forecast more accurately in many fields (e.g., see Choi & Varian, 2012; Einav & Levin, 2014; Varian, 2014; Varian & Scott, 2014). However, one of the main issues when working with large datasets is over-parametrization in high-dimensional models. Various solutions have been proposed, such as regularization (Zou & Hastie, 2005), stochastic search variable selection (George, Sun, & Ni, 2008), graphical models (Ahelgebey, Billio, & Casarin, 2016a, 2016b), and random projections (Casarin & Veggente, 2021; Koop, Korobilis, & Pettenuzzo, 2017). In this chapter, we consider factor models (Banbura, Giannone, & Reichlin, 2010; Stock & Watson, 2002, 2004, 2005, 2012, 2014) with a reduced number of factors.

In this approach, relevant information is summarized through a limited number of factors, which allows us to describe the overall economic conditions and analyse the sensitivity of some key economic indicators to COVID-related variables. We study the impact of variables related to COVID-19 on factors to obtain a reasonable level of information about its effects on the number of factors and their predictability. More specifically, we use a VARX model to describe the dynamics of factors in which the exogenous variables are related to the COVID-19 information and public expenditure. In this way, we can study the conditional forecast and provide different scenarios exploring the COVID-19 impact. In the robustness analysis, we analyse how the factors have changed their composition during the period affected by the COVID-19 pandemic to identify the most sensitive variables to the COVID-19 impact.

We compare the effects of COVID-19 on the US and EU economies and decompose the impact according to various factors. Moreover, from a policy point of view, we consider the approaches of the US and EU governments to the emergency and compare the effects of health and economic interventions on the economic systems. Finally, we follow a scenario analysis and apply a conditional forecast approach to predict out of sample the following variables for both the EU and US regions: Gross Domestic Product (GDP), Unemployment rate, and Personal Consumption Expenditure (PCE) index. Three scenarios have been considered for the exogenous variables: in the first scenario, the pandemic effects vanish; in the second scenario, there is a resumption of the pandemic with a peak in April 2021; and in the third scenario, the pandemic disappears in the summer period, but contagion effects appear again in November 2021. In all scenarios, we assumed an increase in public expenditure.

The structure of the chapter is as follows. Section 2 describes the dataset. Section 3 introduces the econometric models. Section 4 provides some preliminary results and presents some valuable statistics for interpreting the latent factors and comparing the models. The focus of this section is on the impact of COVID-19 on factors and forecasting performance. Section 5 describes some scenarios for the exogenous variables, including the ECD index and the Oxford index, and presents the results of the conditional forecasting given the scenarios. Section 6 concludes the chapter.

2. DATA DESCRIPTION

We consider two datasets of macroeconomic variables related to the US and the EU economies. The series are provided by Bloomberg and are sampled from December 2001 to January 2021. The first dataset includes 42 monthly variables, and the second contains two quarterly variables. The variables considered include core and headline prices, labour market variables, imports, exports, industrial production, consumption, sales, leading indicators of interest rates, and the term structure. See Table 1 for a more detailed description.

Our models assume two alternative specifications of the exogenous variables related to COVID-19: the number of deaths, and the level of government responses to the pandemic. The first indicator is available weekly from the European Centre for Disease Prevention and Control (ECDC). It measures the number of newly reported deaths in the EU (ECD EU) and the US (ECD US).[1] We transform the weekly data into monthly data by summing the four weeks of data. The total number of deaths is then divided by the full population size of the EU and the US: 340 million and 330 million persons, respectively.

Table 1. Macroeconomic Variables for Two Major Geographical Regions, the US and EU, Sampled Either at Monthly or Quarterly Frequency from December 2001 to January 2021. In the Columns, the Series Label (*N*), the Country (*C*), a Description (Definition), a Label (*L*), the Measure Unit (MU), and the Frequency (*F*) That Is Quarterly (*Q*) or Monthly (*M*).

N	*C*	Definition	*L*	MU	*F*
1	US	Export	Ex	m/m	M
2	US	Import	Im	m/m	M
3	US	Unemployment rate	UR	%	M
4	US	Employment (Agricultural sector)	EA	thousands	M
5	US	Employment (Private sector)	EP	thousands	M
6	US	Average hourly wages	Ahw	m/m	M
7	US	PCE	PCE	y/y	M
8	US	PCE core	PCEc	y/y	M
9	US	PPI	PPI	y/y	M
10	US	Industrial Production	IP	y/y	M
11	US	Industrial Orders	IO	m/m	M
12	US	Durable goods orders	Dgo	m/m	M
13	US	Durable goods orders excluding transport	Dgoet	m/m	M
14	US	Stocks	S	m/m	M
15	US	Use of production capacity	Upc	%	M
16	US	ISM manufacturing	ISMm	level	M
17	US	Start of new construction sites	Snc	m/m	M
18	US	Constructions expenditure	Cse	m/m	M
19	US	Existing homes sale	Ehs	m/m	M
20	US	New homes sale	Nhs	m/m	M
21	US	Expenditure (real)	Er	m/m	M
22	US	Income (real)	Ir	m/m	M
23	US	Retail sales	RS	m/m	M
24	US	Conference Board	CB	level	M
25	US	Michigan Consumer Sentiment Index	MCSI	level	M
26	US	RUS10 (Int.Rate Gov.Bond 10Y US)	RUS10	Yield	M
27	US	DeltaRUS72 (=RUS7-RUS2)	DRUS72	Yield	M
28	EU	Export	Ex	m/m	M
29	EU	Import	Im	m/m	M
30	EU	Unemployment rate	UR	%	M
31	EU	HCPI	HCPI	y/y	M
32	EU	CPI core	CPIc	y/y	M
33	EU	PPI	PPI	y/y	M
34	EU	Industrial Production	IP	y/y	M
35	EU	Constructions expenditure	Cse	m/m	M
36	EU	PMI manufacturing index	PMImI	level	M
37	EU	ESI	ESI	level	M
38	EU	Leading indicator	LeIn	level	M
39	EU	Retail Sales	RS	y/y	M

Table 1. *(Continued)*

N	*C*	Definition	*L*	MU	*F*
40	EU	REMU10 (Int.Rate Gov.Bond 10Y EU)	REMU10	Yield	M
41	EU	DeltaREMU72 (=REMU7-REMU2)	DREMU72	Yield	M
42	EU/US	CEUUS	CEUUS	Ratio €/$	M
43	US	Gross Domestic Product	GDPUS	q/q	Q
44	EU	Gross Domestic Product	GDPEU	q/q	Q

The second exogenous variable is the Oxford COVID-19 Government Response Tracker (OxCGRT), released by the University of Oxford.[2] Data are collected and updated in real time by a team of over 100 Oxford students, alumni and staff and project partners. This indicator describes the government actions implemented. The higher the number, the stricter the government actions. OxCGRT collects publicly available information on 19 indicators of government responses. The indicator results from the aggregation of various policy, economic and health indicators. Eight of the policy indicators record information on containment and closure policies, such as school closures and restrictions of movement. Four of the indicators record economic policies, such as income support to citizens or the provision of foreign aid. Seven indicators record health system policies, such as the COVID-19 testing regimes, emergency investments in healthcare and most recently, vaccination policies. The OxCGRT index provides a systematic cross-national, cross-temporal measure of government responses to COVID-19, which have evolved over the period following the disease's spread. Governments have varied substantially—both across countries and often within countries—in their adopted measures and how quickly they have adopted them. Thus, this paper considers the OxCGRT index for the EU (OXL EU) and the US (OXL US). We obtain the OXL EU daily indicator by a GDP-weighted sum of the OxCGRT indicator for Italy, Germany, France, Spain, the Netherlands and Belgium. The daily OxCGRT for the US states is available as an aggregate. The monthly indicator is obtained as an average of the daily OxCGRT indicator values.

Another set of exogenous variables considered includes the public expenditure growth for the European Union and United States of America (PE EU and PE USA, or simply PE if we intend to indicate both variables); these variables are quarterly, and for every quarter value g_q, we derive three monthly values g_m using the following formula:

$$\left(1 + \frac{g_m}{100}\right)^3 = 1 + \frac{g_q}{100}$$

We perform unit root tests for all endogenous and exogenous variables using the augmented Dickey-Fuller (ADF) procedure. If necessary, variables have been differentiated to obtain a stationary time series; after this step, we normalize the series, and then extract the factors.

3. ECONOMETRIC MODELLING

In the following, we introduce and describe the econometric models used in the empirical analyses.

3.1 Factor Models

Let X_t, $t = 1, 2, \ldots, T$, be an $(n \times 1)$ random process. In our applications, the random process includes $n = 42$ macroeconomic variables for two major geographical regions, the United States and the European Union, sampled at a monthly frequency from December 2001 to January 2021. The time index t represents months, and the sample size is $T = 230$ (see also Section 2). We assume the process is covariance stationary with a zero mean and a standard deviation equal to one. To understand how it is possible to extract factors, let us consider the following derivations:

$$E\left[X_t X'_t\right] a_i = \Gamma_X a_i = \lambda_i a_i, \tag{1}$$

where, a_i and λ_i, $i = 1, \ldots, n$, are the eigenvectors and eigenvalues. Let A be an $(n \times n)$ orthonormal matrix with the normalized eigenvectors in the columns, also called a factor loading matrix, then:

$$\Gamma_X A = A\Lambda, \tag{2}$$

where, Λ is a diagonal matrix with elements λ_i, $i = 1, \ldots, n$, on the main diagonal such that $A'\Gamma_X A = \Lambda$ with $\Gamma_X = A\Lambda A'$. The vector of n factors $F_{n,t} = (f_{1,t}, \ldots, f_{n,t})'$ is given by the linear transformation:

$$F_{n,t} = A' X_t. \tag{3}$$

Let us denote with Γ_n the expectation of the external product of the factor, $E[F_{n,t} F'_{n,t}]$; then one obtains the following relationship between Γ_n and the eigenvector matrix Λ :

$$\Gamma_n = E\left[A' X_t X'_t A\right] = A' E\left[X_t X'_t\right] A = A' \Gamma_X A = \Lambda. \tag{4}$$

Let $F_{k,t}$ be the vector composed by the k factors, with $k < n$:

$$F_{k,t} = A'_k X_t, \tag{5}$$

where, A_k is the matrix containing the first k columns of A. Since the columns of A are orthogonal, then $A'A = I_n$ and $A'_k A_k = I_k$. The first k factors capture the following proportion of the total variance:

$$V_k = \frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{n} \lambda_i} \tag{6}$$

We also define:

$$E\left[F_{k,t}F'_{k,t}\right] = \Gamma_k = \text{diag}(\lambda_i)_k, \tag{7}$$

$$E\left[f_{i,t}f'_{i,t}\right] = \lambda_i, \tag{8}$$

for $i = 1, \ldots, k$ where $f_{i,t}$ is the kth factor.

3.2 Vector Autoregressive Models with Exogenous Variables

We use the first k latent factors, $F_{k,t} = (f_{1,t}, \ldots, f_{k,t})'$, with $k < n$, to obtain a representation of the panel data $\{X_t\}_{t=1,2,\ldots,T}$ on a lower-dimensional space. We assume that the factors follow a vector autoregressive model with exogenous variables (VARX). Using only k factors, the reconstruction of the variables derives from the approximated model:

$$X_{k,t} = A_k F_{k,t}. \tag{9}$$

Considering the dynamic part related to the k factors, our model is thus as follows:

$$X_{k,t} = A_k F_{k,t}, \tag{10}$$

$$F_{k,t} = c_k + \Phi_k F_{k,t-1} + B_{k,0}E_t + \varepsilon_{k,t},\ \varepsilon_{k,t}\text{WN}(0, \Sigma_k), \tag{11}$$

where, $B_{X,0}$ has dimensions n x l, E_t is a l-dimensional vector of exogenous variables at time t, and l is the number of exogenous variables. Our application alternatively employed the following sets of exogenous variables: the EU and US public expenditure growth, and newly reported deaths (i.e., $l = 4$); the EU and US public expenditure growth, and the COVID-19 Government Response Tracker (i.e., $l = 4$); the EU and US public expenditure growth, newly reported deaths, and the COVID-19 Government Response Tracker (i.e., $l = 6$).

Using the exogenous paths E_{t+h}, $h = 1, \ldots, 12$, we have the following conditional forecasts over 12 periods:

$$\begin{aligned} E\left[F_{k,t+h|t}\right] &= \hat{F}_{k,t+h|t} \\ &= E\left[c_k + \Phi_k F_{k,t+h-1} + B_0 E_{t+h} + \varepsilon_{k,t+h}\middle|t\right] \\ &= c_k + \Phi_k F_{k,t+h-1} + B_{k,0}E_{t+h} \end{aligned} \tag{12}$$

From Eq. (9) we have the conditional forecast for $X_{k,t+h}$:

$$X_{k,t+h|t} = A_k \hat{F}_{k,t+h|t} \tag{13}$$

To summarize, we first estimate the latent factors and then use a VARX model on factors to forecast both the factors and the variables of interest. We refer to this procedure as the factor model approach (FM). In Appendix B, we present additional details about the VARX model used.

A dynamic panel data model given by a set of independent autoregressive models with exogenous variables and equation-specific parameters is a special case of the VARX model where equation error terms of the following equations:

$$x_{i,t} = \alpha_i + \beta_i x_{i,t-1} + b_0 E_t + \varepsilon_{i,t}, \tag{14}$$

$i = 1, \ldots, n$, are independent, that is:

$$E\left[\varepsilon_{i,t}\right] = 0, \quad E\left[\varepsilon_{i,t}\varepsilon_{i,s}\right] = \begin{cases} \sigma_i^2 \text{ for } t = s \\ 0 \quad \text{otherwise} \end{cases}, \tag{15}$$

where, E_t the l-dimensional vector of exogenous variables and b_0 is a coefficient vector of dimension $1 \times l$. The conditional forecast at time $t+1$ given $x_{i,t}$ and the value of E_{t+h} with $h > 0$ can be written as follows:

$$E\left[x_{i,t+1} \middle| x_{i,t}\right] = \alpha_i + \beta_i x_{i,t} + b_0 E_{t+1}. \tag{16}$$

By iterating Eq. (16), we can compute the forecast $E[x_{i,t+h}|x_{i,t}]$ for a given horizon $h = 1, \ldots, 12$.

4. EMPIRICAL RESULTS

4.1 Estimated Factors

First, we extract factors and analyse their behaviour to understand their stability and the percentage of variance they explain. We follow a rolling window estimation approach and analyse the ability of the factors to detect crisis periods. Their forecast ability is measured using the Tracking Error (TE). We use 61 rolling windows of 170 observations each, and for every window, we extract the main factors. The first window is from December 2001 to January 2016, the second shift is one month from January 2002 to February 2016, and the 61st is

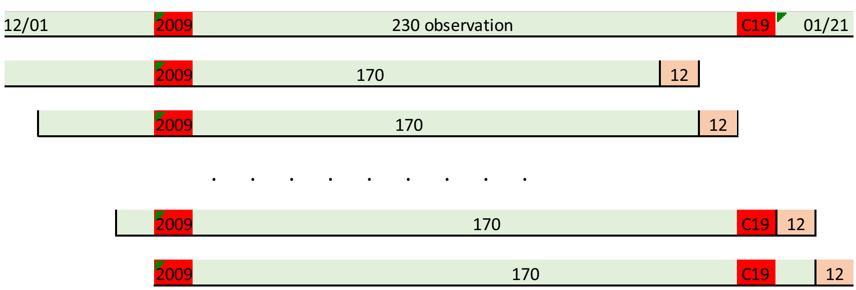

Fig. 1. Example of Rolling Windows. The Size of the Window Is 170 Observations. We Consider 61 Overlapping Windows. The First Window Is from December 2001 to January 2016 (Second Line), the Second Window Is from January 2002 to February 2016 (Third Line), and the Last Is from December 2012 to January 2021 (Last Line).