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Forecasting the effective reproduction number during a pandemic: COVID-19 R_t forecasts, governmental decisions and economic implications

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This research empirically identifies the best-performing forecasting methods for the Effective Reproduction Number R_t of coronavirus disease 2019, the most used epidemiological parameter for policymaking during the pandemic. Furthermore, based on the most accurate forecasts for the United Kingdom, we model the excess exports and imports during the pandemic (using World Trade Organization data), whilst simultaneously controlling for governmental decisions, i.e. lockdown(s) and vaccination. We provide empirical evidence that the longer the lockdown lasts, the larger the cost to the economy is, predominantly for international trade. We show that imposing a lockdown leads to exports falling by 16.55% in the United Kingdom; without a lockdown, the respective decrease for the same period would be only 1.57%. On the other hand, efforts towards fast population vaccination improve the economy. We believe our results can help policymakers to make better decisions before and during future pandemics.

Keywords: forecasting; COVID-19; pandemic; effective reproduction number; trade; lockdown; vaccination.

1. Introduction and motivation

On 11 March 2020, the World Health Organization declared coronavirus disease 2019 (COVID-19) to be a pandemic[1]. The impact of the pandemic has been devastating, with, as of 14 September 2023, a total of 695,289,957 confirmed cases and 6,915,596 deaths reported worldwide. Governments and policymakers around the world have imposed several interventions to manage the COVID-19 pandemic that have succeeded at temporarily slowing the spread of COVID-19 (Chinazzi *et al*., 2020; Ferguson *et al*., 2020; Hsiang *et al*., 2020), but have harmed both society and the economy (see Atkenson, 2020; Craighead *et al*., 2020). Different countries have decided on different strategies as to when and if to impose or lift the interventions, and to that end, policymakers, via working closely with scientists—predominantly epidemiologists, could benefit from simulating potential scenarios based on epidemiological models and big data (Ray *et al*., 2020). Academia has been at the forefront of developing such tools

[1] https://www.euro.who.int/en/health-topics/health-emergencies/coronavirus-covid-19/news/news/2020/3/who-announces-covid-19-outbreak-a-pandemic.

(Rostami-Tabar *et al.*, 2024; Nikolopoulos *et al.*, 2021a, 2021b; Nikolopoulos, 2021) and is fully engaged and motivated to keep on producing more. This is our main motivation for this research.

We contribute and corroborate to the aforementioned stream of research; we empirically identify the best predictive analytics models (Petropoulos *et al.*, 2014, 2022), in order to forecast the effective reproductive number R_t at the country level. The R_t is an epidemiological metric used to describe the contagiousness or transmissibility of infectious agents and is affected by numerous biological, socio-behavioural and environmental factors that govern pathogen transmission. It is usually estimated by various types of complex mathematical models, which can make the R_t easily misrepresented, misinterpreted and misapplied (Dietz, 1993). Most governments have used monitoring R_t as a tool for decision-making and in policy interventions during the ongoing pandemic[2].

In epidemiology, the basic reproduction number R_0 is used to measure the transmission of a disease[3]; however, a population will often not be totally susceptible to an infection as some contacts will be immune because of prior infection, immunization or just natural immunity. Therefore, the number of secondary cases per infectious case will be lower than R_0, and thus R_t is considered a better measure as it accounts for both susceptible and non-susceptible hosts. If $R_t > 1$, the number of cases will increase, whereas if $R_t < 1$ there will be a decline. R_t can be estimated as the product of the basic reproductive number and the fraction of the host population that is susceptible N_s:[3]

$$R_t = R_o N_s.$$

To the best of our knowledge, this is the first paper that investigates the predictability of R_t in a time series fashion, with operational research time forecasting methods (Makridakis *et al.*, 2020). The latter forecasts are an essential tool for healthcare management decision-making during the pandemic, as it projects when there is an outbreak of the disease ($R_t > 1$) and when the disease is slowing down ($R_t < 1$). Furthermore, building on these forecasts, we model the excess exports and imports during the pandemic to examine the effects of governmental decisions, i.e. lockdown and population vaccination on them.

The rest of the paper is structured as follows: in the next section, we present the background literature, followed by the empirical forecasting competition and then the modelling exercise for the respective international trade implications. In the last section, we provide our conclusion, limitations, implications for the theory and practice of Production and Operations Management and a roadmap for future research.

2. Background literature

2.1. *Forecasting for pandemics*

The conventional infection rates do not provide any clear indication of the timing of policy (Nsoesie *et al.*, 2013). The majority of the literature focuses on COVID-19 infection rate predictability. Makridakis & Petropoulos (2020) were the first authors to introduce an approach to predicting COVID-19 using a simple but powerful method in what is now considered a seminal paper that has received 325 citations in less than a year. Following that, Nikolopoulos *et al.*, (2021a, 2021b) used data from the first wave of the pandemic and forecasted COVID-19's growth rate using statistical and machine-learning univariate models. They further proposed a new hybrid forecasting method based on nearest neighbours and

[2] https://www.nature.com/articles/d41586-020-02009-w
[3] https://www.healthknowledge.org.uk/public-health-textbook/research-methods/1a-epidemiology/epidemic-theory

clustering. They then simulated (controlling for lockdown periods) the excess demand for critical products and services using auxiliary data (Nikolopoulos *et al*., 2021a, 2021b).

This is not the first time that academics have tried to forecast pandemics. Soebiyanto *et al*. (2010) proposed using ARIMA models for the one-step-ahead forecasting of weekly influenza cases. Andersson *et al*. (2008) proposed using regression methods to predict the peak time and volume of cases in a pandemic and provided promising empirical evidence to that end using seven outbreaks in Sweden. Shaman & Karspeck (2012) used the Kalman filter-based SIR epidemiological model to forecast the peak time of influenza and claimed that the peak could be predicted 6–7 weeks in advance.

2.2. *Supply chain and economic disruptions during pandemics*

Over the last few decades, globalization has led to the progressive liberalization of cross-border transactions, advances in production technology and improvements in transportation logistics that have provided firms with the ability to fragment the production processes and geographically delocalize them. This is where cost reduction is achieved in global supply chains and strategies because of intermediate goods being produced in several developing countries (Guda *et al*., 2021; Karimi *et al*., 2021). The relationship between international trade and the supply chain is bidirectional. The COVID-19 pandemic has caused unprecedented disruption to the global economy and World Trade as production and consumption have been scaled back across the globe because of the disrupted supply chain.

Naude & Cameron (2020) found that the COVID-19 pandemic has significantly impacted export opportunities for Portugal. They used large UN-COMTRADE and CEPII BACI datasets and identified that these opportunities are worth € nearly 287 billion in untapped revenue potential. Antràs (2020) stated that the world economy had entered a phase of deglobalization. He offered a speculative thought on the future of global chains in the post-COVID-19 age. He concluded that the challenge for future globalization and value chains is more institutional and political than technological. The health crisis will lead to policy tensions across the involved countries. Our paper contributes to this literature with a different methodological approach because it is the first paper that evaluates different time series forecasting methods for R, reproduction number and quantifies the implementation of government decisions to excess imports and exports.

Araz *et al*. (2020) claimed that COVID-19 is the most severe disruption to the global supply chains since 2010. Ivanov (2020) considered the pandemic and the respective supply chain risks and provided a simulation model for the global supply chain disruption from the COVID-19 pandemic. He also predicted its impact on supply chain performance. Team IHME COVID-19 Health Service Utilization Forecasting and Murray (2020a,b) predicted that COVID-19 would place unprecedented stress on hospitals, ICUs and ventilators. The load will be beyond the current capacity of the healthcare system. They suggested using non-clinical measures such as social distancing to delay the demand for healthcare resources and gain time for capacity building in the USA. The ability of countries to adapt and intervene to unprecedented pandemic conditions, especially imposing lockdowns, has a significant impact on their overall success in the sustainability of the economy. Our paper further advances this literature by examining the effect of the pandemic on imports and exports and, therefore, the respective global supply chains too.

3. Forecasting the effective Reproduction number of the pandemic

Following the suggestions for future research by Petropoulos and Makridakis (2020) and especially the empirical methodological setting by Nikolopoulos *et al*., (2021a, 2021b), we decided to set the level of granularity of our analysis at the country level and focus our analysis—without loss of generality—to

Table 1 *Forecasting time series models*

Category	Method
Time-series	Naïve, Moving Average-MA(2), MA(3), MA(4), MA(7), Error Trend Seasonal(ETS), ARIMA(1,1), Theta Method, Holt—Trend, GARCH (1,1), Exponential-GARCH(1,1) model (E-GARCH), Naïve-drift-0.1, Naïve-drift-0.2, Naive-drift-0.3.

only one country: the United Kingdom. The selection of countries was based on (a) the availability of trade data (exports and imports) at a monthly level, (b) the impact of the pandemic (as of 31 December 2021) and (c) the strategic response to the pandemic. The UK is the most affected country in Europe and the one with the most casualties in Europe and one of the highest death rates (1873 deaths per 1M of the population). The UK had reported 4,460,446 cases in total and 127,716 deaths. The UK is also of interest as it has the largest public healthcare system in Europe and is the second-largest single-payer healthcare system globally. It is also the first Western country that approved the vaccines by Pfizer and the University of Oxford and adopted a very ‘aggressive’ approach offering the first dose of the available vaccines to as many people as possible without reserving a second dose in advance. The UK started vaccinations on 7 December 2020 and 4 January 2021, respectively, with the first two available vaccines.

The goal of the next section is the following: initially, we use the COVID-19 cases, and we construct the reproduction number, *R*, monthly for each country. To do the latter action, we used the EpistEm toolbox from R software. Our next step is to evaluate several time-series forecasting techniques to find the best three of them for the prediction of R. Then, we use the estimate of a simple linear regression model with the actual R produced by the EPistem to find its effect on the excess imports and exports of several industries for several months. Then, we use the estimated parameters to provide counterfactuals using the forecasted R values having different government decisions like lockdowns and vaccination programmes.

3.1. *Data and country-level forecasting using time series forecasting models*

The time series forecasting models we have empirically evaluated are reported in Table 1 (for a detailed description of the methods, the reader may revisit Nikolopoulos *et al.*, 2021a, 2021b and a brief mathematical description follows hereafter too).

3.1.1. *Forecasting methods.* The **Naïve method** is the simplest forecasting approach and assumes the last know value of the time series will be the forecast for the next immediate period:

$$\hat{F}_t = y_{t-1}$$

where $\hat{F}_t$ is the forecast for time period *t*, calculated at time $t-1$ (one step ahead forecast).

The **Naïve method with drift** is the simplest forecasting approach with the addition of a constant trend term:

$$\hat{F}_t = y_{t-1} + d$$

where *d* can be any fixed value but quite often is selected to be a percentage of the linear regression trend over time of the series (in our empirical investigation 0.1, 0.2 and 0.3, respectively).

Moving Averages (MA): MA computes a simple moving average smoother of a given time series. The MA smoother averages the nearest order periods of each observation. As neighbouring observations of a time series are likely to be similar in value, averaging eliminates some of the randomness in the data, leaving a smooth trend-cycle component.

$$\hat{F}_t = \frac{1}{m}\sum_{j=-k}^{k} y_{t+j}$$

where $k = \frac{m-1}{2}$.

When an even order is specified, the observations averaged will include one more observation from the future than the past (k is rounded up). In R package 'Forecast' that was used in this investigation, for the *ma* function, if centre is TRUE, the value from two MAs (where k is rounded up and down, respectively) is averaged, centring the MA. Package used in R is forecast.

ARIMA: Different definitions of ARMA models have different signs for the AR and/or MA coefficients. The definition used here has

$$\hat{F}_t = a_1 y_{t-1} + \ldots + a_p y_{t-p} + e_t + b_1 e_{t-1} + \ldots + b_q e_{t-q}$$

In our implementation, the order of AR and MA is equal to 1, $p = q = 1$, and the same R package 'Forecast' is used that automatically estimates the model parameters.

ETS*:* ETS is based on the classification of methods as described in Hyndman *et al*. (2008). The methodology is fully automatic. The only required argument for *ets* is the time series. The model is chosen automatically (if not specified). This methodology performed extremely well on the M3-competition data (see Hyndman *et al*., 2002).

Theta Method: *theta* from the same R package 'Forecast' creates forecasts for the basic version of the theta method. The basic version of the theta method of Assimakopoulos & Nikolopoulos (2000) as used in the M3-competion has a similar mathematical equation to simple exponential smoothing with drift. Nevertheless, the optimization of the method parameters is very different than the latter (Nikolopoulos *et al*., 2011). The series is first tested for seasonality. If deemed seasonal, the series is seasonally adjusted using a classical multiplicative decomposition before applying the theta method. The resulting forecasts are then reseasonalized.

The model is based on modifying the local curvatures of a time series. This change is achieved via a Θ coefficient that is applied directly to the second differences of the time series. Following this procedure, a set of new time series, the so-called Theta-lines are constructed noted as $L(\Theta)$. Each of the Theta-lines is extrapolated separately and the forecasts are combined either equally weighted or through a weight optimization procedure. Any forecasting method can be used for the extrapolation of $L(\Theta)$. In the M3-competition, exponential smoothing was used for the extrapolation of $L(\Theta)$.

If we consider one of the simplest cases in which the initial time series

$$y = \{y_1, \ldots, y_n\}$$

is decomposed into two $L(\Theta)$, $L(\Theta = 0)$ and $L(\Theta = 2)$, then the algebra can be significantly simplified:

$$y_t = ½\,(L_t\,(\Theta = 0) + L_t\,(\Theta = 2)),\ \forall\, t = 1 \ldots n =>$$
$$y_t = ½\,(\mathrm{LRL}_t + L_t\,(\Theta = 2)) =>$$
$$Lt\,(\Theta = 2) = 2\,y_t—\mathrm{LRL}_t,$$

where LRL is the linear regression line of the data over time.

Formula-wise, Theta model extrapolations in this specific case may look like SES-d, but there are two fundamental differences: (a) the drift is predefined as being equal to half of the regression slope and (b) the smoothing parameter is optimized on $L(\Theta = 2)$ and not the original data as anybody would expect in any SES-with-drift approach (Nikolopoulos *et al.*, 2011).

Holt trend: The Holt trend Exponential Smoothing model builds on the Simple Exponential Smoothing model by adding one more equation for controlling the evolution of trend of the series. The forecast equation for the one-step-ahead forecast is as follows:

$$\hat{F}_t = \ell_t + b_t.$$

where ℓ_t is the level of the data at time t and b_t the trend element of the dta a time t. For many steps ahead the forecasting equation becomes:

$$\hat{F}_{t+h} = \ell_t + h\, b_t$$

Level equation$\ell t = \alpha\ yt + (1 - \alpha)\ (\ell t - 1 + bt - 1)$
Trend equation $bt = \beta\ (\ell t - \ell t - 1) + (1 - \beta)\ bt - 1,$

where α is the smoothing coefficient for the level and b is the smoothing coefficient for the trend and both can be optimized via an OLS. We use the implementation of the method in the R package 'Forecast'.

GARCH and EGARCH: The GARCH (1,1) model used is $y_t = \beta_1 + \beta_2 x_{2t} + ... + \beta_k x_{kt} + u_t$, $u_t \sim N(0, \sigma_t)$ where

$$\sigma_t = \alpha u_{t-1} + \beta \sigma_{t-1} + \varepsilon_t$$

It is based on the fGarch toolbox in the software of R.

The E-GARCH is formulated as the above GARCH (1,1) with difference in the variance equation that is equal

$$\log\left(\sigma_t^2\right) = \omega + \beta \log\left(\sigma_{t-1}^2\right) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\,u_{t-1}\,|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right]$$

The package used to forecast it was rugarch in R.

3.1.2. *Data and software.* The data on COVID-19 were collected from the Johns Hopkins Coronavirus Resource Center (https://coronavirus.jhu.edu/), for the period of 22 January 2020 to 31 December 2021. The training data used ranged from 22 January (the first case of COVID-19) until 31 July. The remaining data are used as test data (in a rolling evaluation fashion), and we focus our analysis on monthly frequencies. We work on monthly frequencies because the data for imports and exports are on a monthly level. Using data of lower granularity could introduce more noise to the analysis and render its implementation more difficult. On the other hand, data of higher granularity would display clearer patterns, being fewer in terms of observations and probably missing important details.

We used the software developed by epidemiologists Cori *et al.* (2013) and the EpiEstim package in the R programming language to calculate R_t (noted both as R_e or R_t in the literature—see Gostic *et al.*, 2020). Their method implements a Bayesian approach for quantifying transmissibility overtime during an epidemic. More specifically, it allows estimating the instantaneous and case reproduction numbers during an epidemic, in our case COVID-19, for which a time series of incidence is available and the distribution of the serial interval (time between symptoms onset in a primary case and symptoms onset in the second case) is approximately known. We produced the instantaneous reproduction number at a weekly and monthly level using the daily infection rates of COVID-19.

As in Cori *et al*. (2013), the chosen window time has an important role. Small values of the time window were chosen to lead to rapid detection of changes in transmission but also more statistical noise. On the other hand, large values lead to more smoothing and a reduction in statistical noise. As a result, by producing weekly and monthly R_t, we shall be able to identify the right forecasting techniques for it.[4]

The effective reproductive number R_t quantifies how many people are infected on average by an infected person. R_t is often encountered in epidemiology and public health literature (see Anderson & May, 1982). It has been described as one of the most fundamental metrics in studying infectious disease dynamics (see Anderson & May, 1985). Epidemiologists use this measure for decision-making. The interpretation of R_t is typically straightforward; an outbreak is expected to continue if the R_t has a value > 1. It ends if the R_t is <1 and close to 0. Figure 1 shows the evolution of R_t for the period of the sample that we investigate, which is the 24 months of the years 2020–2021. We present four countries from each continent. For instance, the United States, Argentina, Mexico and Brazil from America, Senegal, Nigeria, South Africa and Algeria from Africa, China, Japan, United Arab Emirates and Vietnam from Asia and finally, Italy, France, Sweden and the United Kingdom from Europe. It is easy to notice that in all countries, the peak month for the transmission of the disease is the 3rd month of the year, March 2020 and, more generally, the year 2020. For the rest of the analysis, we focus on the continent of Europe and, in particular, the United Kingdom.

We selected Mean Absolute Scaled Error (MASE) because it is scale-independent and a widely accepted metric for forecast evaluations (Hyndman & Koehler, 2006; Nikolopoulos *et al*., 2021a, 2021b). We used the simple average of forecasts since it is one of the most effective methods for combining forecasts (Makridakis & Winkler, 1983; Nikolopoulos *et al*., 2021a, 2021b). The list of the competing models is illustrated in Table 1.[5]

3.2. *Country-level pandemic forecasting results*

As mentioned above, we used the EpiEstim package in the R software and produced the effective reproduction number at a monthly level using the daily infection rates of COVID-19. We also calculated the Mean Error, Mean Absolute Error, Root Mean Squared Error, MASE and Symmetric Mean Absolute Percentage Error (SMAPE) for each iteration (Makridakis *et al*., 2020). Following the strategy of Punia *et al*. (2020), we calculated the relative errors by dividing the corresponding errors of each method with those of the naïve method. To keep the length of this article reasonable, we only used Table 2 to report the relative (to naïve) medians of the two chosen error-metrics of MASE (RelMdMASE) and SMAPE (RelMdMAPE). [6]

We are interested in finding the most suitable time series forecasting technique across the competing methods for predicting R. Consequently, we evaluated the methods used across the four countries simultaneously. To do so, we produced forecasts for each country's competing methods at a weekly and monthly level. Then we calculated the median forecasting errors across all countries.

[4]For details about the calculation of R_t the reader should study the supplementary material of Cori et al. (2013).

[5]The reader can find out more details on these popular methods by revisiting either the article on the latest forecasting competition (the M4 competition—Makridakis *et al*., 2020) or by reading the free online forecasting textbook by Hyndman and Athanassopoulos (https://otexts.com/fpp3/).

[6]In the appendix, Table A1 shows the relative mean errors of the forecasting techniques which they produce identical conclusions with those of Table 2.

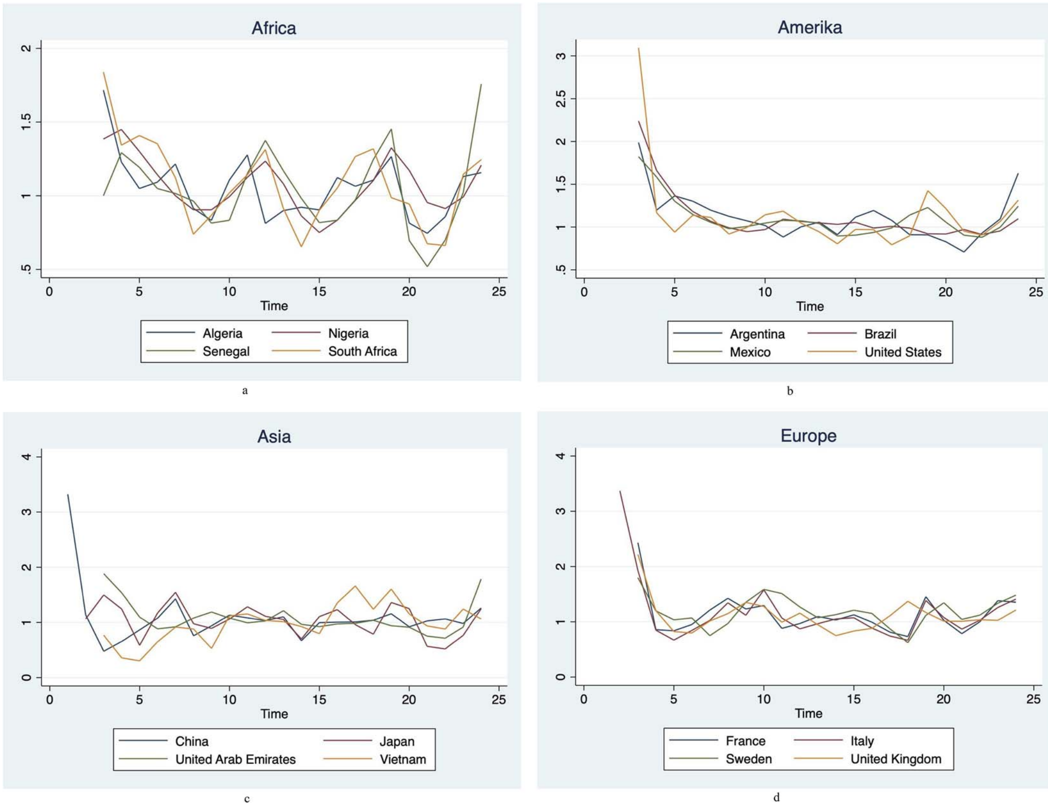

Fig. 1 Evolution of R_t during the years 2020–2021 at a monthly level at continent level ((a) Africa; (b) America; (c) Asia; (d) Europe).

Table 2 illustrates the results of the Relative median errors for the forecasting techniques for the prediction of R. We can observe from Table 2 that the performance of the naïve method is the best amongst the other competing methods for the monthly effective reproduction number. We noted that GARCH (1,1) and theta are ranked next. In particular, we noticed that the theta method produced less of a forecasting error for the monthly data. Consequently, it is important to highlight the decisions because of government policy and the forecasting method, which depends on the decision of whether it is related to the period or not.

From Table 2, we can observe that the performance of the naïve method was very hard to beat by other popular time series methods. Taking the naïve method to the next level, an improvement was made by adding drift (Nikolopoulos *et al.*, 2016). Naïve with different levels of drift α performed best amongst all of the studied methods. This is the 'winner' amongst our chosen empirical forecasting competition from the other methods. Most of the relative errors were <0.5, indicating a large performance improvement over naïve using the proposed methodology. Looking at the detailed results of the forecasting, it is also evident that the GARCH (1,1) model, theta and EGARCH (1,1) can be important techniques for forecasting the Reproduction number of infections, R_t. Summarizing the best three forecasting techniques for the UK are Naïve with drift 0.2, Naïve with drift 0.3 and theta.

Table 2 *The median relative errors for each forecasting method for R for UK used in this analysis*

	RelMdMASE monthly	**RelMdSMAPE**
MA(2)	2.07	2.03
MA(3)	4.32	4.35
MA(4)	7.83	8.41
MA(7)	2.28	2.35
ARIMA(1,1)	2.10	2.15
ETS	2.78	2.67
GARCH(1,1)	1.22	1.24
EGARCH(1,1)	1.37	1.46
Naïve with drift 0.1	0.80	0.75
holt—trend	1.29	1.32
Naïve with drift 0.2	0.98	0.94
Naïve with drift 0.3	0.78	0.70
Theta	0.75	0.69

4. Modelling the excess international trade for critical products

Forecasting has a crucial role in decision-making (Thomassey, 2010). Governments and policymakers can use it for planning and management. Forecasting an epidemic has an important role in saving lives and providing them with the necessary resources for living (Zhu *et al*., 2021; Cakici, 2020). As a result, accurate prediction of a pandemic is crucial for the necessary resources needed by international trade.

In this section, we used the prediction of our models from Section 2, and we modelled the excess exports and imports for several products during the COVID-19 pandemic and investigated its effect on them. These industries, like many others, were affected during the pandemic. In normal conditions, the exports and imports for these industries will be similar to those of previous years without exhibiting complex patterns. However, during a pandemic, we expect significant changes in the exports and imports of a country, given the needs of the consumers and the governments because of the anticipation of lockdowns concerning the purchasing and overstocking of products.

4.1. *Modelling excess exports and imports for critical products*

In this analysis, we estimate the specification below to be able to fit the data that we have and to incorporate the effect of the pandemic. In particular, we considered the following equation as our model.

$$T_t = aR_t + nD_t + u_t \tag{1}$$

where T_t is the amount of dollars of the 'excess' exports or imports of country i at time t;Rt is the reproduction rate of the incidents of COVID-19 that happened at time t. Parameter a captures the effect of R_t on T. We introduced a dummy that took the value of 1 after the month that the government imposed a lockdown and 0 before, D. The lockdown could generate further anxiety, and as a result, consumer behaviour could change.

4.2. *Forecasting the excess international trade for critical products*

For the estimation of the exports and imports measured in thousands of dollars, we used the monthly data from World Trade Organization as a proxy for the two different sectors (groceries/beverages and pharmaceutical) for the UK, given that they are the most critical sectors.[7]

For the values of R_t in Equation (1), we used the average of the top three forecasts prepared in Section 3. We used two different methods of estimation. The first was the ordinary least square to estimate the coefficients used in Equation (1). In this estimation, we used a dependent variable of either monthly excess exports or imports and independent monthly values for R_t. Consequently, we want to find the appropriate estimates for robust simulations. We modelled the excess exports and imports over and above the average of the years 2017–2019 exports and imports. In other words, to construct this variable, we have subtracted from each month (from January to August) of the year 2020 the average imports or exports from the same month of the previous 2 years. As shown in Fig. 1, the main period of interest is 2020, when most countries needed to make decisions for the economy and healthcare sector. We made the implicit assumption that for the critical products we were looking at more or less stable average exports or imports could be observed in the long run. Our sample has only eight observations.[8] In particular, we estimate Equation (1) for the months of January–August 2020. The key interest of this analysis was the impact of COVID-19 on international trade. We focused only on short-term changes because of this exogenous shock. We essentially assumed that the pandemic leads to an intermittent demand pattern over and above the mainstream demand (Nikolopoulos *et al*., 2021a, 2021b).

The UK imposed restrictions on social mobility in the form of lockdowns involving curfews or travel bans during the period that we analyzed using our data compared with other countries like Sweden that avoided any curfews to reach herd immunity like Sweden. On the contrary, additional variable—*lockdown*—was incorporated as a binary classifier with values of 0 = no travel ban or curfew, and 1 = curfew or travel ban in place for the UK in Table 3.[9]

Both tables show very interesting results. First, we found that the R_t reproductive number had a tremendous and significant effect on the imports and exports of different products and industries in all countries. We noticed a similar result for lockdown (see Table 3). The latter result was consistent with the results of Nikolopoulos *et al*., (2021a, 2021b). They presented that lockdown affects the supply chain of several products negatively. Contrary to their paper, we found that the lockdown also had a positive and significant result on the pharmaceutical industries in the UK. Third, we noticed that the coefficients of the parameters on the estimation of the theoretical model were very similar and independent of R_t and its lagged value used.

The latter result allowed us to use the parameters of R_t when the estimation method of Equation (1) is OLS. We provided simulations only for the UK (Nikolopoulos *et al*., 2021a, 2021b). We analyzed only the exports of the groceries/beverage industry and the imports of the pharmaceutical industry in the UK.

[7]There are other sectors quite interesting for the United Kingdom like the automobile and the oil sector. However, these two sectors are hugely affected since there were traffic curfews during the first wave of COVID-19.

[8]We try to estimate our model with the simplest way given then the restriction of the time span of our analysis. There are some caveats in the specification that they could be addressed in a future research in the part of the methodology like non-linear models, including interaction terms and others in the sample size by introducing a panel data.

[9] Table A2 replicates the results of Equation 1 including a variable Google provide an overview of what its mobility trends represent and how it is measured here: https://support.google.com/covid19-mobility/answer/9824897?hl=en&ref_topic=9822927 and we include as a control how many visitors went to grocery and pharmaceutical. We construct this variable at a monthly level and as an average from all the countries to capture potential demand for groceries and pharmaceutical equipment.

Table 3 *Excess imports and exports for the UK grocery and pharmaceutical sectors*

	Grocery/beverage/exports		Grocery/beverage/imports		Pharmaceutical/exports		Pharmaceutical/imports	
	α	n	α	n	α	n	α	n
UK	−10,461.35***	−11,437.86***	−12,197.83***	−191,683.7***	−113,523.6***	−19,882.38***	105,665.1***	105,154.7***
(R_t)	(96.053)	(150.961)	(151.88)	(243.41)	(4074.563)	(6537.766)	(5401.151)	(48,511.48)
	R^2=0.98		R^2=0.98		R^2=0.98		R^2=0.98	
UK	−7879.93***	−17,437.04***	−9157.38***	−160,490.7***	−84,890.66***	−85,829.3***	98,288.89***	140,300***
(R_t −1)	(1215.067)	(4192.76)	(1385.099)	(74,064.18)	(12,316.58)	(35,417.67)	(7542.98)	(23,043.44)
	R^2=0.97		R^2=0.93		R^2=0.93		R^2=0.97	

Model : Trade $\sim aRt + n$Lockdown $+ u$, In the second row, we alternate the model to Model : Trade $\sim aRt - 1 + n$Lockdown $+ u$

Notes. Robust standard errors used in the parenthesis

Table 4 *Comparison of the forecasts and average exports and imports in the UK from 2016 to 2019*

Months	Exports of groceries in the UK		Imports of pharmaceutical products in the UK	
	% change with lockdown	% change with no lockdown	% change with lockdown	% change with no lockdown
September	−12.81	−2.04	14.16	5.47
October	−16.55	−1.59	17.06	5.96
November	−19.73	−1.67	13.31	4.24
December	−15.53	−1.17	14.67	5.25
January	−11.23	−0.93	17.32	6.80

Notes. This table compares the forecasted exports produced by Equation (1) and the average exports and imports in the UK from 2017 to 2019.

We have provided two types of simulations/counterfactuals. In the first counterfactual, we compare the changes in the imports and exports that could be caused because of the scenario of imposing a lockdown or not (only because of the virus) for a specific month. In particular, we calculate the change in the exports and imports that COVID-19 causes with the one that would be expected. We assume that there are no other factors that could potentially affect trade changes given the average of the last 2 years for the same months (see Table 4 in Columns 3 and 5). In other words, we calculated the exports of groceries and imports of pharmaceutical sectors using Equation (1). Then we compared them with the expected exports and imports for the same months. To measure the last ones, we used the average exports of groceries and beverages and imports in the UK from 2017 to 2019 in the same months. For instance, let us consider that the 3rd month of our counterfactual is November. We use Equation (1) to predict the groceries exports for this month. Then we compared this prediction with the average exports of groceries and beverages in the UK for the last 5 years, which was 760,075 pounds. Considering that the UK has not imposed a lockdown, the existence of COVID-19 has damaged exports by 1.59% in October, which is tiny.

We do something similar, taking into account that the government impose a lockdown in parallel with the spread of the virus. For instance, imposing a lockdown and curfew reduces COVID-19 infections means that the damage will be 16.55% in October in the UK (see Table 4). We found similar results for the imports of the pharmaceutical companies. We found that the damage of the lockdown is almost

10 times larger. We found that the longer the lockdown remains, the larger the number of imports arriving in the UK market. In economic terms, the balance of payments through trade is negative. Consequently, the larger the duration of the lockdown, the larger the economic deficit will be expected.

We then considered another experiment. We imposed different scenarios in the two industries to investigate the effect of the vaccination's timing on the population and the economy. These counterfactuals aim to quantify the time of improving the economy/international trade through the achievement of herd immunity because of vaccination. The epidemiological literature considers that herd immunity assumes that the vaccines induce solid immunity against infection and that the populations' mix at random, consistent with the simple herd immunity threshold for random vaccination of $Vc = (1–1/R_0)$ using the symbol Vc for the critical minimum proportion to be vaccinated (assuming 100% vaccine effectiveness) (see Vynnycky & White, 2010; Anderson & May, 1982, 1985). The literature has also discussed the complexities of imperfect immunity, heterogeneous populations and non-random vaccinations (see Keeling & Rohani, 2007).

The effective Reproduction number can be simply written as a function of Reproduction number (R_0) and the share of Susceptible to the total population.[10] We forecast the Reproduction number (R_0) using the top three performed forecasting methods and we forecast the susceptible population. Then, we consider that every person that has been inoculated is removed from the group of persons that they like to be infected with. Consequently, the effective reproduction number decreases as many people are vaccinated each month. In other words, we consider the following equation in our counterfactuals where θ is the percentage of people who are not vaccinated. The θ is between 0 and 1, which means that if it takes the value of 0, there is no virus given that everybody is vaccinated, and it reaches the value equally, which means that all the population is not inoculated. Our idea is inspired by Eyre *et al.* (2021), who show that vaccinations cause a decrease in transmission.

The announcements of different pharmaceutical companies like Pfizer Moderna and AstraZeneca on the effectiveness of their vaccines and the unknown effects because of the heterogeneous population led us to make some assumptions. First, we assumed that the vaccine was 95% effective. Second, we considered that the time taken for it to be effective, in other words, to generate T-cells and antibodies against the virus, is a month. Another concern is that there is enough supply of the vaccine for the entire population.

We used two scenarios in our simulations. Initially, we presented the case of no vaccinations, with the case of vaccination from the 1st month being effective without a lockdown. Then, we consider the scenario of no vaccination with the vaccination to be effective from the first month with the country being in lockdown, depending on the R_t value. Specifically, if R_t is $>$ or $<$ 1, the country imposes lockdown or no lockdown, respectively.

The results of the simulations indicate that earlier vaccination causes a faster drop in excess exports and a decrease in excess imports in both industries. The crucial point is that the economy's recovery through the improvement of excess exports comes 5–6 months after the population's vaccination.

We can make two recommendations based on the above results. First, policymakers need to secure high volumes of inventory for products like medicines and masks before the lockdown to decrease imports. This result is supported by the work of Nikolopoulos *et al.*, (2021a, 2021b). The decision of

[10]It is easy to forecast the susceptible population given that according to SI model, the population is divided to infected and susceptible excluding the deaths. Forecasting the infected people using COVID-19 cases and then subtracting from the total population is easy to predict the people that they might be infected from the virus. Based on the, we consider that it is likely to be reinfected from COVID-19 after the individual has been recovered from the disease. Only people that have been inoculated get strong immunity against the virus.

the date of lockdown matters concerning not only the saving lives but also the deficit of the economy. The second recommendation is that countries need to have a large stock of vaccines and large campaigns when they start vaccinating the population to achieve herd immunity and restore international trade and economy. Potential disruptions of this will imply changes to the forecasting models as well.

5. Conclusions, implications for practice and policymaking and the future

This paper has examined the predictability of R_t, which is the effective reproductive rate of the infectious disease COVID-19 in the United Kingdom. We used this predictability to investigate its effects on the short-run disruptions in international trade during the pandemic. We collected the COVID-19 infection rates and then calculated the reproduction number at a weekly and monthly level. We determined the top three performing time series forecasting methods. We used the predictions obtained from our models to estimate, calibrate and estimate a model of international trade.

Through our simulations, we were able to forecast the excess exports and imports of the UK during the pandemic. We found that the social restrictions because of the lockdown led to an extreme loss of money because of the tremendous fall in exports, which is higher than the fall in imports. We also showed that earlier vaccination causes a faster drop in excess exports and the improvement of the economy 5–6 months after the vaccination of a sufficient number of the population which ended the pandemic.

Many operational decisions are affected by our research: planning, production, shipping, stock-control (Prak *et al*., 2017), ordering and allocating resources (Nikolopoulos *et al*., 2003), to name a few. These are all decisions where an accurate forecast is an essential input, so our study is quite relevant. Moreover, governmental policies are affected by our research based on the above results.

Our results exhibit some caveats. The counterfactuals were carried out using strong assumptions like the willingness of the population to participate in vaccination and enough of a vaccine stock to achieve the herd immunity needed to end the pandemic. We have not taken into account the possibility of heterogeneity in the population and the potential negative effects of the vaccines that can delay the process. Also, the lack of data does not allow us to consider the demand and supply from the country's trade counterparties. Consequently, our results present the lowest damages that international trade can have on the economy through the studied industries.

Furthermore, this paper has considered the short-term effect of the pandemic on the economy through trade. A pandemic like COVID-19 has a long-term impact on the economy and society (Atkenson, 2020; Jordà *et al*., 2022). The continuous lockdowns will affect people's mental health and their confidence in their respective governments. Mental health and the lack of physical attendance of children in school will affect the human capital formation and as a result, economic growth (see Asharf & Galor 2011; Vasilakis, 2012). Effective vaccines and large campaigns to persuade people of their effectiveness and safety will decrease the damage of COVID-19. The focus of future research should be on the hospitalizations and death rates instead of the COVID-19 cases. Furthermore, we need better tools and more forecast-informed decisions on all fronts.

Conflict of interest

The authors declare that they had no conflict of interest while completing this study.

Data availability

All data and software can be provided by the authors upon formal written request.

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Appendices

Table A1 *The mean relative errors for each forecasting method from all of the countries used in this analysis*

	RelMeanMASE monthly	**RelMeanSMAPE**
MA(2)	2.12	2.16
MA(3)	4.33	4.34
MA(4)	7.66	8.50
MA(7)	2.34	2.35
ARIMA(1,1)	2.09	2.11
ETS	2.76	2.64
GARCH(1,1)	1.24	1.25
EGARCH(1,1)	1.34	1.53
Naïve with drift 0.1	0.79	0.74
holt – trend	1.89	1.87
Naïve with drift 0.2	0.97	0.98
Naïve with drift 0.3	0.71	0.69
Theta	0.76	0.71

Table A2 *Excess imports and exports for the UK grocery and pharmaceutical sectors*

	Grocery/beverage/exports		**Grocery/beverage/imports**		**Pharmaceutical/exports**		**Pharmaceutical/imports**	
	A	n	α	n	α	n	α	n
UK (R_t)	-10461.35^{***}	-11437.86^{***}	— 12187.83^{***}	-191653.7^{***}	-113717.9^{***}	-20793.89^{***}	105655.1^{***}	105152.7^{***}
	(96.053)	(150.961)	(150.88)	(243.41)	(4316.28)	(8286.65)	(5411.151)	(48501.48)
	R^2=0.98		R^2=0.96		R^2=0.93		R^2=0.98	
Visitors in the retail and pharmaceutical stores	0.000 (0.001)		−12.285 (13.97)		−62.557 (157.53)		−5674.307 (4387.95)	
Model : Trade $\sim aRt + nLockdown + X + u$,								

Notes: standard errors are robust.