A Vector Error Correction Model to Forecast the United States' Vaccination Rate

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Introduction

The Coronavirus (COVID-2019) pandemic introduced a novel problem that did not pertain to other infectious diseases in recent history. Large numbers of people could be infected but be asymptomatic spreaders of COVID-19. More specifically, many of the asymptomatic could be *pre-symptomatic* spreaders of COVID-19. Whether asymptomatic or pre-symptomatic, this constituted a dangerous scenario in which significant portions of populations could contract COVID-19 unknowingly and only later realize it when local hospitals overfilled.

The delayed onset of COVID-19's symptoms meant that policymakers would often be making decisions based off of dated information. Those who went to test for COVID-19 and those who showed symptoms would often only do so after days had elapsed since their initial exposure. Because of this, public health officials worldwide urged governments to be cautious, to encourage isolation or to mandate quarantine for at least 14 days after suspected or confirmed contact with COVID-19, with 14 days after contact being when most people actually infected would show symptoms.

As countries around the world underwent some form of social distancing program and suffered significant socioeconomic impacts from doing so, a yearning for a return to normalcy placed hope upon vaccination. If enough of a population were to be vaccinated against COVID-19, resulting herd immunity would allow for people to live more normally. A question then comes to mind:

When will enough of a population be vaccinated such that it would be safe to relax social-distancing restrictions?

The answer to this question can be partially found through time series forecasting. Various time series methods are already used to forecast the spread of COVID-19 (Papastefanopoulos et. al). Also, there is existing literature on using an Autoregressive Integrated Moving Average (ARIMA) approach to forecasting vaccination rates (Cihan 2021). However, there is a paucity of literature that relies on Vector Error Correction Models (VECM) to forecast vaccination rates. To this end, this paper explores the effectiveness of using a VECM to forecast future rates of vaccination in the United States.

Data and Descriptive Statistics

This paper relies entirely on daily time series data from Our World in Data, which keeps a comprehensive dataset on statistics relevant to COVID-19 for most countries. This paper considers a subset of Our World in Data's "Covid-19 Dataset." Only rows for the United States are kept and the following columns are used in modeling:

- date
- people_fully_vaccinated_per_hundred
- new_vaccinations_smoothed

- new_deaths_per_million

```
> df %>% summary();
     date           people_fully_vaccinated_per_hundred new_vaccinations_smoothed new_deaths_per_million
 Length:699         Min.   : 0.00                       Min.   :   4421           Min.   : 0.000
 Class :character   1st Qu.:13.70                       1st Qu.: 704732           1st Qu.: 1.487
 Mode  :character   Median :46.87                       Median :1052470           Median : 2.950
                    Mean   :36.35                       Mean   :1330219           Mean   : 3.672
                    3rd Qu.:55.16                       3rd Qu.:1750259           3rd Qu.: 5.203
                    Max.   :61.00                       Max.   :3505960           Max.   :13.343
                    NA's   :326                         NA's   :327               NA's   :38
```

The NA's represent how "people_fully_vaccinated_per_hundred," "new_vaccinations_smoothed," and "new_deaths_per_million" do not have observations for all dates. "people_fully_vaccinated_per_hundred" and "new_vaccinations_smoothed" are not measured until very late in 2020, when vaccines were first introduced. The first date that all 3 variables have observations for is 14 December 2020. Before this day, observations for 1 or more of the variables are not available. Thus, the data considered range from 14 December 2020 to 20 December 2021, 372 days' worth of observations. In other words, there are 372 time periods.

"people_fully_vaccinated_per_hundred" constitutes vaccination rate and thus serves as the dependent variable. "people_fully_vaccinated_per_hundred" is renamed as "vacc_rate" and is henceforth interpreted as the vaccinate rate. "ln_newvacc," which is the natural log of "new_vaccinations_smoothed," and "new_deaths_per_million" have been selected to serve as explanatory variables.

Initially, this paper considered 3 daily time series from FRED:

- DOW Jones Industrial Index
- New Job Postings on Indeed in the United States
- Economic Policy Uncertainty Index for the United States

However, these 3 time series failed the test for granger-causality on "ln_newvacc" and/or had NA's such that they could not be used alongside the time series data from Our World in Data.

Methodology

The data from Our World in Data is utilized in two stages. In both stages, the order of the variables is as follows: "vacc_rate," "new_deaths_per_million," and "ln_newvacc."

In Stage 1, a VECM is used to forecast an in-sample prediction. Observations from 21 November 2021 onwards, the 343rd day since 14 December 2020, are excluded. The last 30 days' worth of observations are excluded. The observations prior are used as training data for the VECM, the VECM predicts 30 periods (days) ahead, and the excluded 30 days' vaccination rate observations are compared to the predictions.

In Stage 2, a VECM is used to forecast an out-of-sample prediction. The 362 days' worth of observations from 14 December 2020 to 20 December 2021 are used as training data for the VECM. Then, the vaccination rate for the 30 days after 12 December 2021, the last day of data, is forecasted for. In other words, the vaccination rate is forecasted for from 21 December 2021 to 19 January 2022.

Discussion of Econometric Analysis

ARIMA, Vector Autoregression (VAR), and VECM are all commonly used methods for time series forecasting. ARIMA uses the autoregressive behavior of a time series to predict for future values of itself. VAR and VECM differ from ARIMA in that they incorporate two or more time series, such that the explanatory time series influence the forecasts of the dependent time series. When a time series influences the forecasts of another time series, there is Granger-causality. Whether a time series Granger-causes another time series can be tested for.

Stage 1

The explanatory variables each undergo a Granger-causality test to demonstrate they granger-cause the dependent variable. Both "new_deaths_per_million" and "ln_newvacc" granger-cause "vacc_rate," the dependent variable.

"vacc_rate," "new_deaths_per_million," and "ln_newvacc" each undergo an augmented Dickey-Fuller test. There is strong evidence that "vacc_rate" is stationary while both "new_deaths_per_million" and "ln_newvacc" are non-stationary. "vacc_rate," "new_deaths_per_million," and "ln_newvacc" are visualized in figure 1.

The Akaike Information Criterion recommends this paper's model include up to 10 lags.

The Johansen Technique based on Vector Autoregression (VAR) is performed on this paper's three variable model. At a p-value cutoff of 0.05, there is strong evidence for two cointegrating relationships within the model. It follows that a VECM approach is applicable.
The VECM model is tested for serial correlation, heteroskedasticity in the residuals, and normal distribution of the residuals. There is strong evidence of serial correlation, heteroskedasticity in the residuals, and a non-normal distribution of the residuals.

The impulse response functions (Fig. 2, 3) of the explanatory variables on the dependent variable show that:

- "vacc_rate" experiences a positive shock less than 5 percent in response to impulses by "new_deaths_per_million"; and
- "vacc_rate" experiences a negative and positive shocks, depending on which period ahead, less than 5 percent in magnitude in response to impulses by "ln_newvacc."

The forecast error variance decomposition of the model (Fig. 4) shows that "new_deaths_per_million" and "ln_newvacc" explain less than 5% of the forecast error variance of "vacc_rate." Notably, the forecast error variance of "vacc_rate" explained by "new_deaths_per_million" and "ln_newvacc" actually increases the further ahead forecast error variance decomposition is calculated. In other words, on any given day, "new_deaths_per_million" and "ln_newvacc" will exert a lagged effect on "vacc_rate" that will take place increasingly on later days.

The VECM model (Fig. 5) is used to forecast 30 days ahead with a 95% confidence interval (Fig. 6). In other words, the VECM model forecasts the vaccination rate of the United States from 21 November 2021 to 20 December 2021. Notably, the actual vaccination rate of the United States from 21 November 2021 to 20 December 2021 falls within the upper and lower bounds of the forecast.

Stage 2

The results of the diagnostic tests for Granger-causality, stationarity, cointegration rank, serial correlation, heteroskedasticity of the residuals, and normality of the residuals are roughly identical to in stage 1. In other words, 21 November 2021 to 20 December 2021 did not feature any drastic shocks that would have changed the results of the diagnostic tests from Stage 1. Similarly, the impulse response plots and the forecast error variance decomposition plots for stage 2's more complete dataset highly resemble the plots of stage 1 (Fig. 2, 3, 4).

The same VECM model (Fig. 10), except with observations from 21 November 2021 to 20 December 2021 included, is used to forecast the vaccination rate with a 95% confidence interval for the 30 days after 20 December 2021 (Fig. 11). In other words, the vaccination rate is forecasted for from 21 December 2021 to 19 January 2022.

Implications

In stage 1, it was observed through impulse response functions that on any given day, "new_deaths_per_million" and "ln_newvacc" will exert a lagged effect on "vacc_rate" that will take place increasingly on later days. This reflects the trouble policymakers experience when reacting to COVID-19, the fact that they are reacting to COVID-19 related measurements from days ago as opposed to those same measurements in the present day.

Nevertheless, in this paper's VECM model, "vacc_rate" explains the vast majority of the variance of forecasts of "vacc_rate." This is not unexpected, as once vaccinated against COVID-19, somebody cannot become not vaccinated against COVID-19. Given that forecasting accurately for "vacc_rate" can be done solely with "vacc_rate," in terms of forecast accuracy it may be sufficient to forecast "vacc_rate" with an ARIMA model.

The VECM model used in this paper was able to make in-sample predictions of the United States' vaccination rate which contained the actual vaccination rate within the lower and upper bound. In particular, "vacc_rate" was the most important variable in forecasting "vacc_rate" such that it would be quite feasible to reduce the model to a single-variable ARIMA model relying solely upon "vacc_rate." Nevertheless, time series forecasting has great potential for supporting policymakers in making educated predictions on the state of vaccinations 30 days into the future, *et ceteris paribus*.

References

Cihan, P. (2021, July 14). *Forecasting fully vaccinated people against COVID-19 and examining future vaccination rate for herd immunity in the US, Asia, Europe, Africa, South America, and the world*. Science Direct. Retrieved December 23, 2021, from https://www.sciencedirect.com/science/article/pii/S1568494621006293?via%3Dihub#!

Covid-19 data explorer. Our World in Data. (n.d.). Retrieved December 23, 2021, from https://ourworldindata.org/explorers/coronavirus-data-explorer?zoomToSelection=true&facet=none&pickerSort=asc&pickerMetric=location&Interval=New%2Bper%2Bday&Relative%2Bto%2BPopulation=true&Align%2Boutbreaks=false&country=~USA&Metric=Confirmed%2Bcases

Johansen test for cointegrating time series analysis in R. QuantStart. (n.d.). Retrieved December 23, 2021, from https://www.quantstart.com/articles/Johansen-Test-for-Cointegrating-Time-Series-Analysis-in-R/

Papastefanopoulos, V., Linardatos, P., & Kotsiantis, S. (2020, June 3). *Covid-19: A comparison of time series methods to forecast percentage of active cases per population*. MDPI. Retrieved December 23, 2021, from https://www.mdpi.com/2076-3417/10/11/3880

Appendix

Figure 1

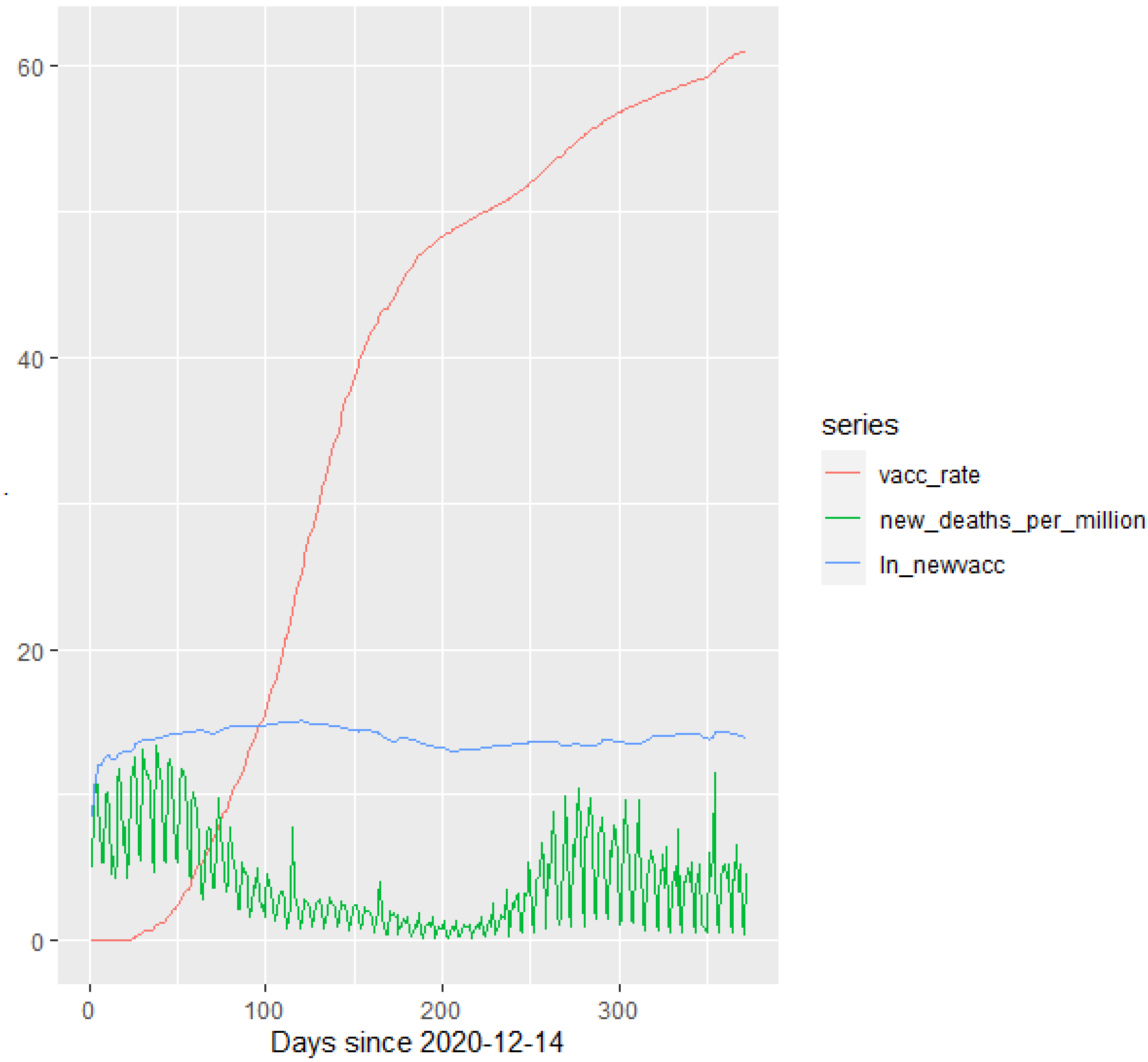


Figure 2

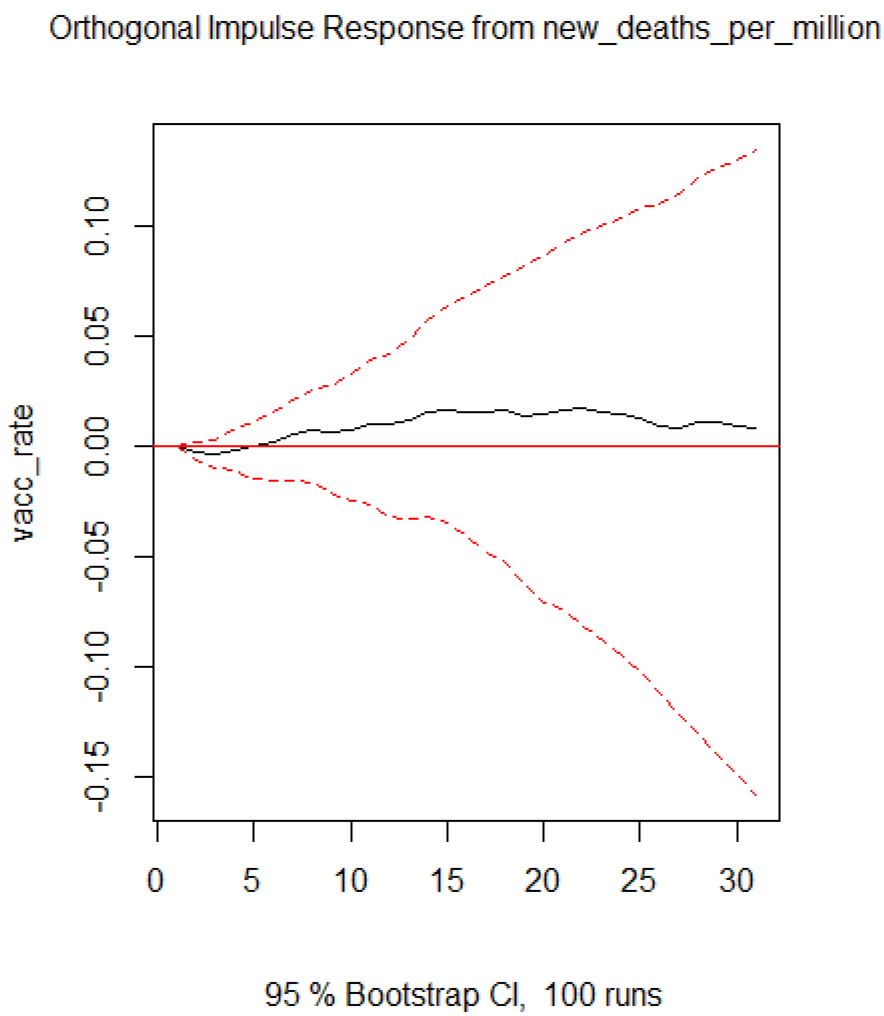

Orthogonal Impulse Response from new_deaths_per_million
vacc_rate
-0.15
-0.10
-0.05
0.00
0.05
0.10
0
5
10
15
20
25
30
95 % Bootstrap CI, 100 runs

Figure 3

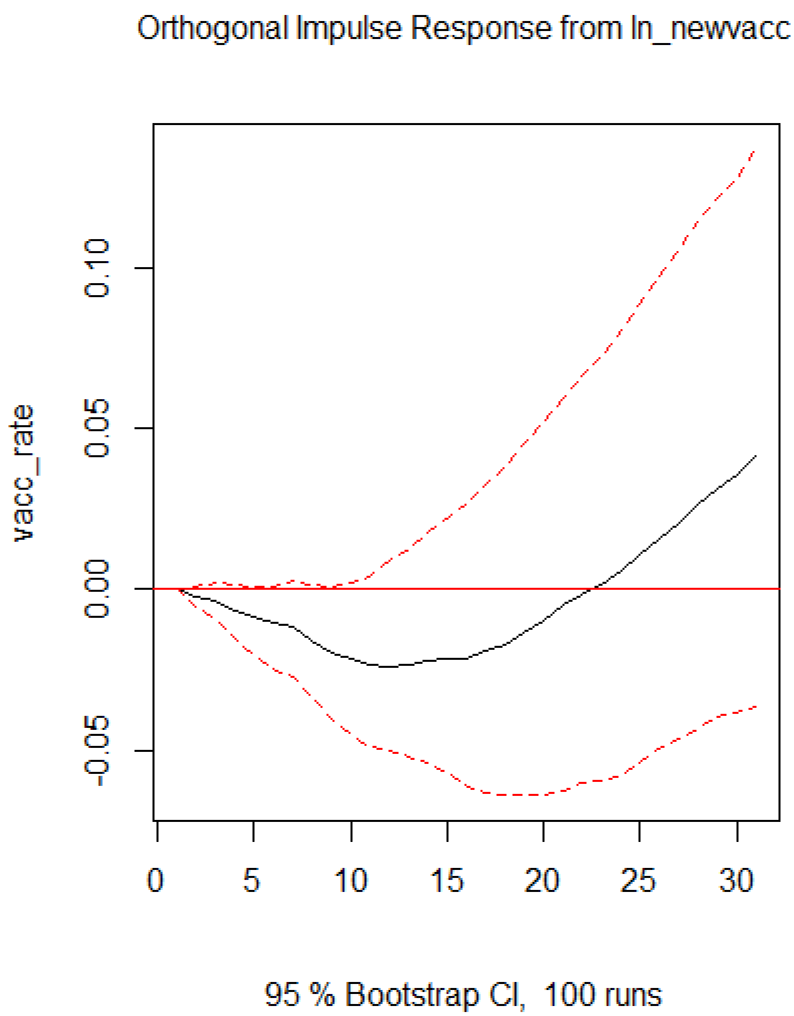

Orthogonal Impulse Response from ln_newvacc
vacc_rate
0.10
0.05
0.00
-0.05
0
5
10
15
20
25
30
95 % Bootstrap CI, 100 runs

Figure 4

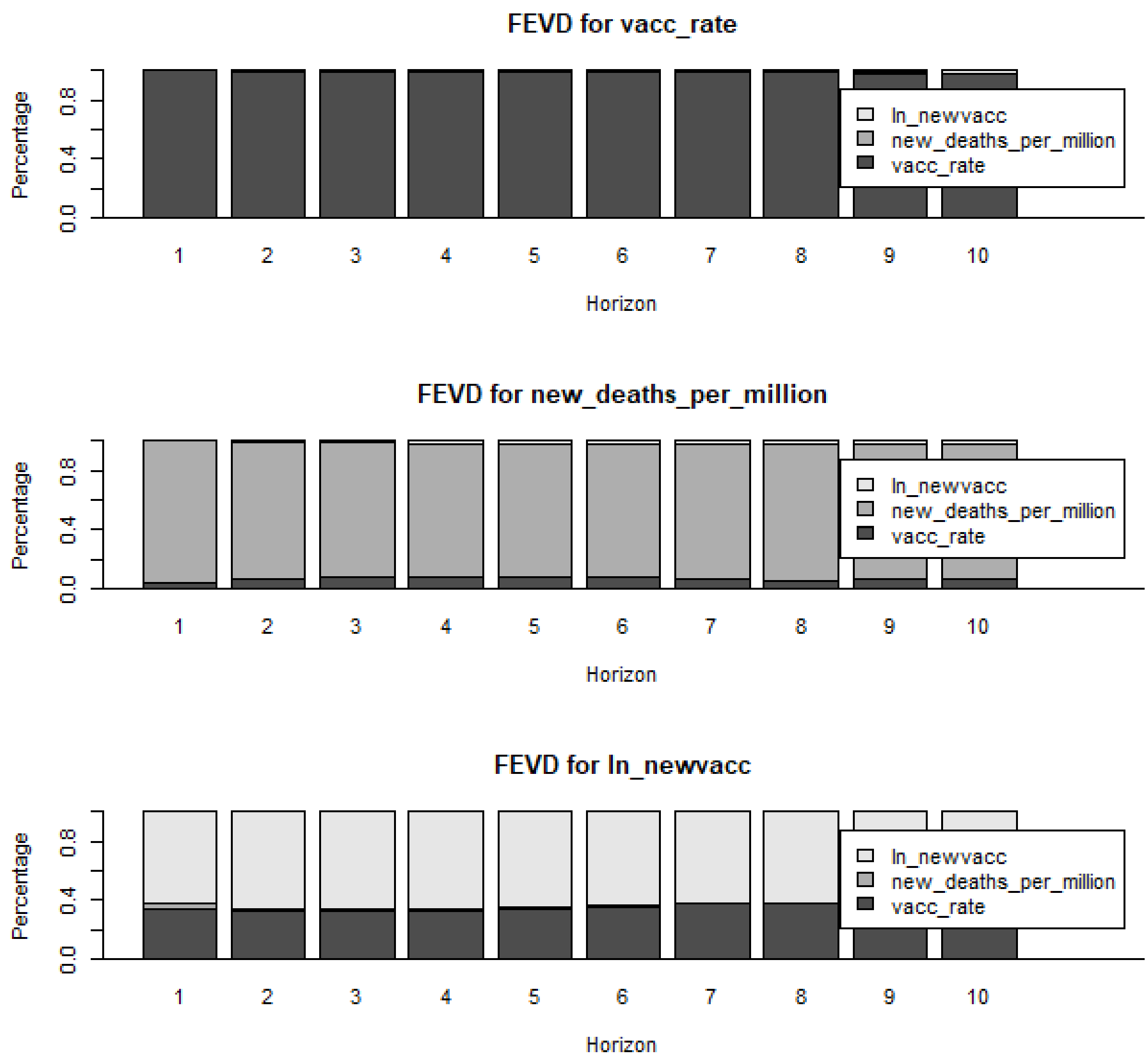
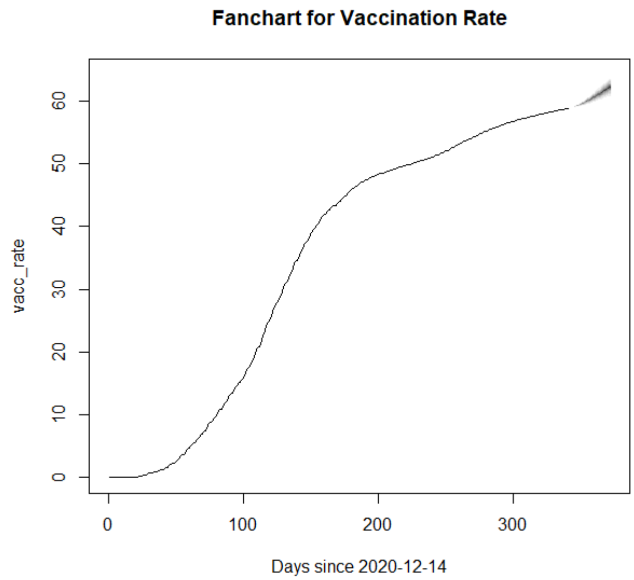

FEVD for vacc_rate
Percentage
0.0
0.4
0.8
1
2
3
4
5
6
7
8
9
10
Horizon
ln_newvacc
new_deaths_per_million
vacc_rate
FEVD for new_deaths_per_million
Percentage
0.0
0.4
0.8
1
2
3
4
5
6
7
8
9
10
Horizon
ln_newvacc
new_deaths_per_million
vacc_rate
FEVD for ln_newvacc
Percentage
0.0
0.4
0.8
1
2
3
4
5
6
7
8
9
10
Horizon
ln_newvacc
new_deaths_per_million
vacc_rate

Figure 5

```
> vecm1 %>% summary();
#############
###Model VECM
#############
Full sample size: 342   End sample size: 331
Number of variables: 3  Number of estimated slope parameters 99
AIC -4710.367   BIC -4326.353   SSR 323.2995
Cointegrating vector (estimated by ML):
       vacc_rate new_deaths_per_million ln_newvacc
r1  1.000000e+00                      0  -20.28973
r2 -2.775558e-17                      1  -21.15123


                                ECT1                ECT2                Intercept           vacc_rate -1        new_deaths_per_million -1
Equation vacc_rate              -0.0004(0.0001)***  -0.0002(0.0003)     -0.1346(0.0899)     0.7949(0.0702)***   -0.0021(0.0019)
Equation new_deaths_per_million 0.0023(0.0033)      0.0240(0.0105)*     7.2652(2.9061)*     3.2127(2.2700)      -0.7881(0.0618)***
Equation ln_newvacc             -0.0002(8.7e-05)**  0.0008(0.0003)**    0.1737(0.0755)*     -0.0215(0.0590)     -0.0053(0.0016)***
                                ln_newvacc -1      vacc_rate -2       new_deaths_per_million -2 ln_newvacc -2       vacc_rate -3
Equation vacc_rate              -0.1500(0.0858).   0.0671(0.0885)     -0.0002(0.0023)           0.0695(0.1024)      -0.1152(0.0725)
Equation new_deaths_per_million 2.4452(2.7736)     -0.3536(2.8606)    -0.7332(0.0756)***        2.9357(3.3125)      -2.4546(2.3439)
Equation ln_newvacc             0.6707(0.0721)***  0.1038(0.0743)     -0.0046(0.0020)*          -0.0002(0.0861)     -0.0327(0.0609)
                                new_deaths_per_million -3 ln_newvacc -3       vacc_rate -4       new_deaths_per_million -4 ln_newvacc -4
Equation vacc_rate              0.0037(0.0026)            -0.1061(0.0921)     0.0194(0.0396)     -0.0011(0.0028)           0.0798(0.0782)
Equation new_deaths_per_million -0.6098(0.0853)***        -4.3309(2.9802)     0.5687(1.2793)     -0.5942(0.0908)***        -1.6621(2.5305)
Equation ln_newvacc             -0.0041(0.0022).          -0.0504(0.0775)     0.0306(0.0332)     -0.0058(0.0024)*          -0.0788(0.0658)
                                vacc_rate -5        new_deaths_per_million -5 ln_newvacc -5       vacc_rate -6        new_deaths_per_million -6
Equation vacc_rate              -0.0602(0.0395)     -0.0001(0.0029)           -0.0493(0.0648)     0.0455(0.0396)      0.0008(0.0028)
Equation new_deaths_per_million -0.5400(1.2763)     -0.6053(0.0925)***        1.5241(2.0946)      0.6584(1.2794)      -0.4349(0.0919)***
Equation ln_newvacc             -0.0360(0.0332)     -0.0059(0.0024)*          0.1471(0.0544)**    0.0337(0.0333)      -0.0043(0.0024).
                                ln_newvacc -6      vacc_rate -7        new_deaths_per_million -7 ln_newvacc -7       vacc_rate -8
Equation vacc_rate              0.0310(0.0659)     0.8448(0.0396)***   0.0006(0.0028)            -0.1776(0.0626)**   -0.6756(0.0744)***
Equation new_deaths_per_million 0.5951(2.1314)     0.0052(1.2796)      0.2656(0.0892)**          -3.9046(2.0234).    -2.3180(2.4050)
Equation ln_newvacc             0.0099(0.0554)     -0.0798(0.0333)*    -0.0041(0.0023).          -0.1896(0.0526)***  0.0850(0.0625)
                                new_deaths_per_million -8 ln_newvacc -8      vacc_rate -9        new_deaths_per_million -9 ln_newvacc -9
Equation vacc_rate              0.0021(0.0026)            0.1150(0.0618).    -0.1282(0.0890)     0.0009(0.0023)            0.0070(0.0618)
Equation new_deaths_per_million 0.2070(0.0839)*           3.1362(2.0001)     0.0481(2.8790)      0.1071(0.0741)            2.5411(1.9988)
Equation ln_newvacc             -0.0007(0.0022)           0.1612(0.0520)**   -0.1229(0.0748)     -2.9e-05(0.0019)          -0.0454(0.0520)
                                vacc_rate -10      new_deaths_per_million -10 ln_newvacc -10
Equation vacc_rate              0.1211(0.0684).    -0.0040(0.0019)*           -0.0272(0.0334)
Equation new_deaths_per_million 2.5821(2.2121)     0.0354(0.0612)             -2.8332(1.0798)**
Equation ln_newvacc             0.0351(0.0575)     -0.0013(0.0016)            -0.0437(0.0281)
```

Figure 6




```
> forecast1$fcst$vacc_rate;
          fcst    lower    upper         CI
 [1,] 58.98547 58.92499 59.04596 0.06048529
 [2,] 59.04024 58.92100 59.15948 0.11923976
 [3,] 59.11171 58.93067 59.29275 0.18104184
 [4,] 59.19748 58.95673 59.43822 0.24074380
 [5,] 59.29156 58.99259 59.59053 0.29897097
 [6,] 59.37325 59.02067 59.72584 0.35258573
 [7,] 59.43533 59.03187 59.83879 0.40346223
 [8,] 59.50438 59.03036 59.97840 0.47401685
 [9,] 59.59458 59.04007 60.14909 0.55450728
[10,] 59.70309 59.06600 60.34018 0.63708931
[11,] 59.83055 59.11301 60.54808 0.71753063
[12,] 59.96434 59.16948 60.75921 0.79486437
[13,] 60.07859 59.21225 60.94493 0.86633982
[14,] 60.17146 59.23773 61.10518 0.93372358
[15,] 60.26946 59.25685 61.28206 1.01260497
[16,] 60.38573 59.28810 61.48335 1.09762318
[17,] 60.52056 59.33669 61.70443 1.18386646
[18,] 60.67544 59.40731 61.94356 1.26812460
[19,] 60.83316 59.48345 62.18286 1.34970484
[20,] 60.96600 59.53982 62.39219 1.42618810
[21,] 61.07447 59.57517 62.57377 1.49930265
[22,] 61.18629 59.60593 62.76664 1.58035357
[23,] 61.31444 59.64825 62.98063 1.66618885
[24,] 61.46125 59.70856 63.21393 1.75268184
[25,] 61.62911 59.79175 63.46648 1.83736545
[26,] 61.79742 59.87775 63.71709 1.91967194
[27,] 61.93696 59.93952 63.93440 1.99744192
[28,] 62.05031 59.97801 64.12262 2.07230479
[29,] 62.16545 60.01255 64.31835 2.15289899
[30,] 62.29577 60.05859 64.53294 2.23717094
```

Figure 7

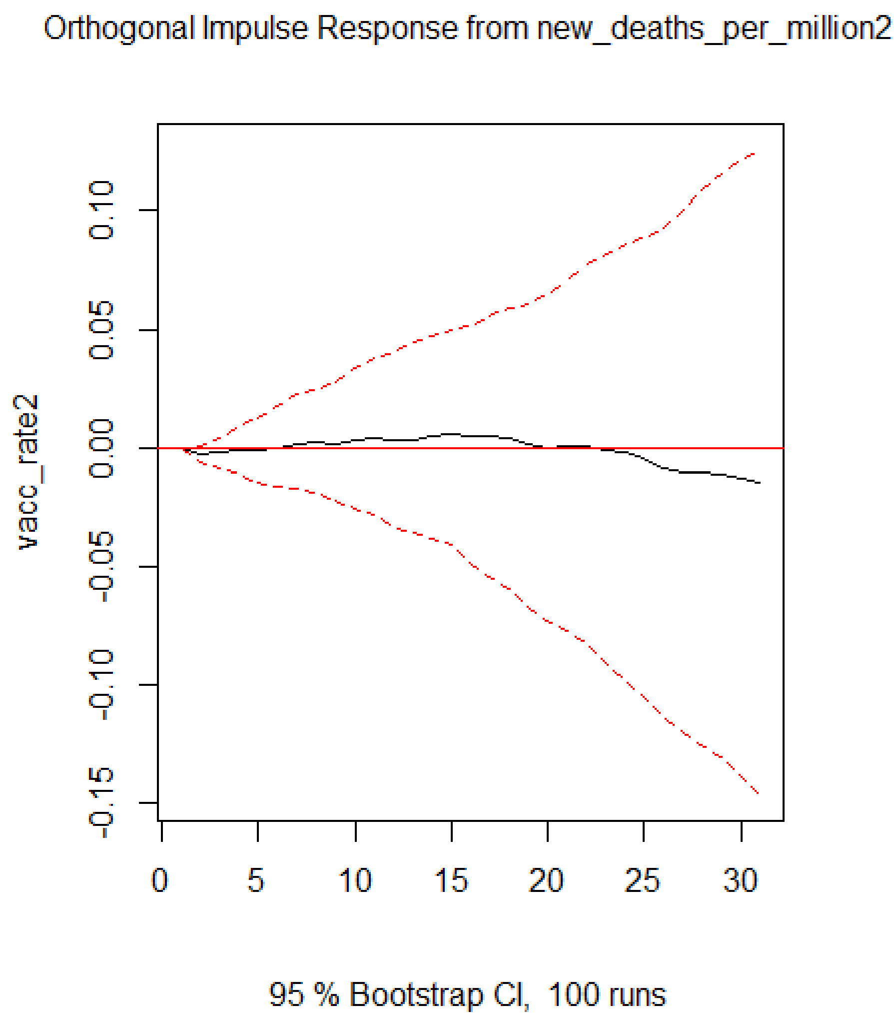

Orthogonal Impulse Response from new_deaths_per_million2
vacc_rate2
0.10
0.05
0.00
-0.05
-0.10
-0.15
0
5
10
15
20
25
30
95 % Bootstrap CI, 100 runs

Figure 8

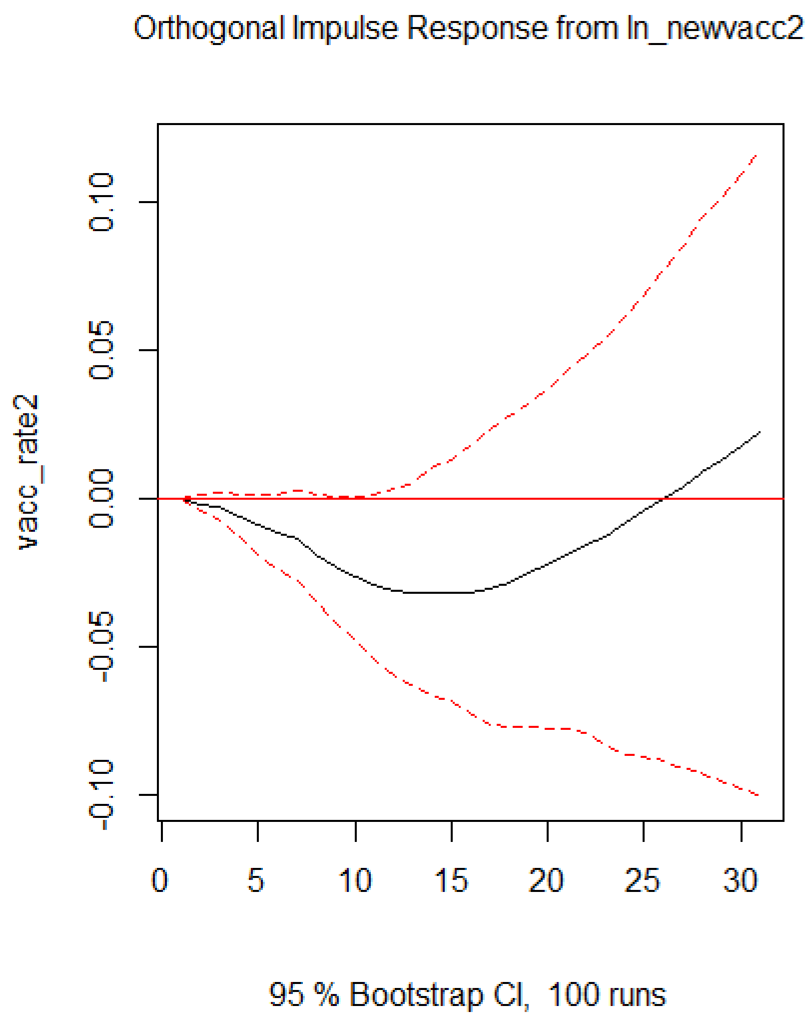

Orthogonal Impulse Response from ln_newvacc2
vacc_rate2
0.10
0.05
0.00
-0.05
-0.10
0
5
10
15
20
25
30
95 % Bootstrap CI, 100 runs

Figure 9

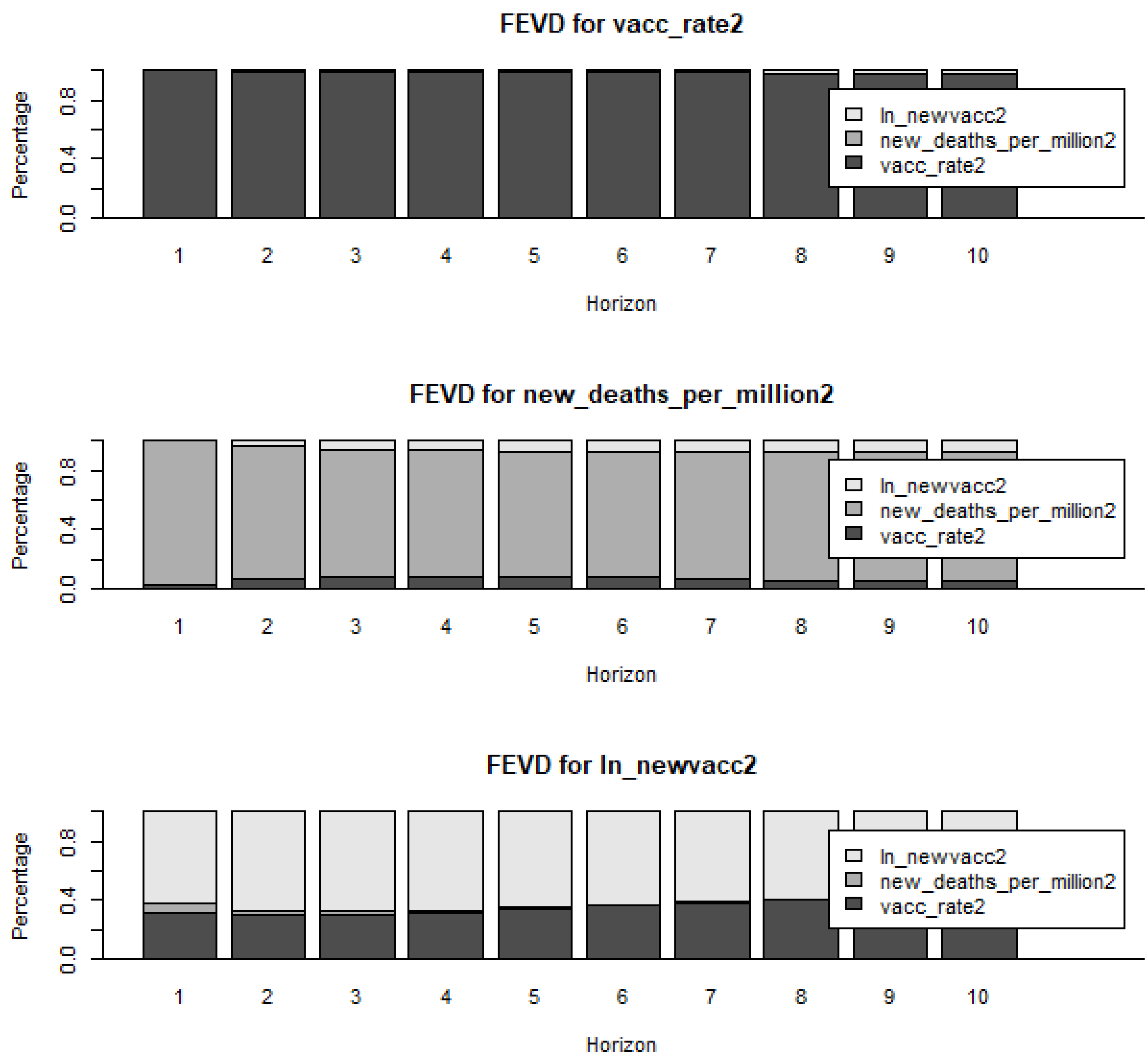
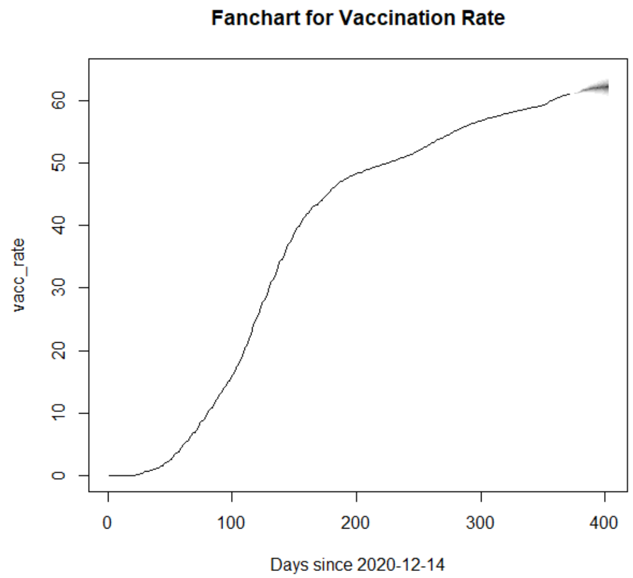

FEVD for vacc_rate2
Percentage
0.0
0.4
0.8
1
2
3
4
5
6
7
8
9
10
Horizon
ln_newvacc2
new_deaths_per_million2
vacc_rate2
FEVD for new_deaths_per_million2
Percentage
0.0
0.4
0.8
1
2
3
4
5
6
7
8
9
10
Horizon
ln_newvacc2
new_deaths_per_million2
vacc_rate2
FEVD for ln_newvacc2
Percentage
0.0
0.4
0.8
1
2
3
4
5
6
7
8
9
10
Horizon
ln_newvacc2
new_deaths_per_million2
vacc_rate2

Figure 10

```
> vecm2 %>% summary();
#############
###Model VECM
#############
Full sample size: 372   End sample size: 361
Number of variables: 3  Number of estimated slope parameters 99
AIC -4997.878   BIC -4605.102   SSR 426.6115
Cointegrating vector (estimated by ML):
      vacc_rate2 new_deaths_per_million2 ln_newvacc2
r1  1.000000e+00                       0   -2.667861
r2 -1.387779e-17                       1  -15.957674


                                 ECT1                ECT2                Intercept           vacc_rate2 -1       new_deaths_per_million2 -1
Equation vacc_rate2              -0.0004(0.0001)*** -0.0006(0.0004)      -0.1094(0.0755)     0.7646(0.0665)***   -0.0009(0.0017)
Equation new_deaths_per_million2 0.0027(0.0039)      0.0196(0.0129)      4.1850(2.6916)      1.3897(2.3683)      -0.8169(0.0607)***
Equation ln_newvacc2             -0.0002(0.0001)*    0.0009(0.0003)**    0.1971(0.0714)**    -0.0492(0.0628)     -0.0052(0.0016)**
                                 ln_newvacc2 -1       vacc_rate2 -2      new_deaths_per_million2 -2 ln_newvacc2 -2      vacc_rate2 -3
Equation vacc_rate2              -0.0910(0.0761)      0.0759(0.0838)     0.0014(0.0021)             0.0395(0.0929)      -0.0842(0.0692)
Equation new_deaths_per_million2 8.5797(2.7122)**     0.2263(2.9863)     -0.7520(0.0750)***         0.7056(3.3106)      -1.0502(2.4666)
Equation ln_newvacc2             0.7709(0.0719)***    0.1419(0.0792).    -0.0044(0.0020)*           -0.0641(0.0878)     -0.0106(0.0654)
                                 new_deaths_per_million2 -3 ln_newvacc2 -3       vacc_rate2 -4      new_deaths_per_million2 -4 ln_newvacc2 -4
Equation vacc_rate2              0.0025(0.0024)             -0.1075(0.0840)      0.0147(0.0386)     -0.0004(0.0026)            0.0526(0.0730)
Equation new_deaths_per_million2 -0.5862(0.0854)***         -8.5305(2.9949)**    0.9612(1.3739)     -0.6079(0.0912)***         -1.9555(2.6029)
Equation ln_newvacc2             -0.0042(0.0023).           -0.0774(0.0794)      0.0237(0.0364)     -0.0055(0.0024)*           -0.0413(0.0690)
                                 vacc_rate2 -5        new_deaths_per_million2 -5 ln_newvacc2 -5       vacc_rate2 -6       new_deaths_per_million2 -6
Equation vacc_rate2              -0.0588(0.0384)      0.0005(0.0026)             -0.0359(0.0607)      0.0530(0.0385)      0.0008(0.0026)
Equation new_deaths_per_million2 -1.3408(1.3687)      -0.5723(0.0928)***         2.1121(2.1631)       0.6368(1.3717)      -0.4207(0.0919)***
Equation ln_newvacc2             -0.0289(0.0363)      -0.0057(0.0025)*           0.1258(0.0574)*      0.0377(0.0364)      -0.0044(0.0024).
                                 ln_newvacc2 -6       vacc_rate2 -7      new_deaths_per_million2 -7 ln_newvacc2 -7      vacc_rate2 -8
Equation vacc_rate2              0.0260(0.0611)       0.8339(0.0385)***  0.0013(0.0025)             -0.1731(0.0579)**  -0.6335(0.0708)***
Equation new_deaths_per_million2 -0.4835(2.1763)      0.1879(1.3734)     0.2666(0.0885)**           -8.4957(2.0624)*** -0.8960(2.5227)
Equation ln_newvacc2             -0.0273(0.0577)      -0.0920(0.0364)*   -0.0040(0.0023).           -0.2140(0.0547)*** 0.1328(0.0669)*
                                 new_deaths_per_million2 -8 ln_newvacc2 -8      vacc_rate2 -9      new_deaths_per_million2 -9 ln_newvacc2 -9
Equation vacc_rate2              0.0014(0.0023)             0.0943(0.0587)      -0.1466(0.0847).   0.0002(0.0020)             0.0183(0.0591)
Equation new_deaths_per_million2 0.2513(0.0832)**           5.7444(2.0922)**    -0.2818(3.0197)    0.1272(0.0713).            2.1074(2.1051)
Equation ln_newvacc2             -0.0009(0.0022)            0.1826(0.0555)**    -0.1748(0.0801)*   0.0001(0.0019)             -0.0532(0.0558)
                                 vacc_rate2 -10      new_deaths_per_million2 -10 ln_newvacc2 -10
Equation vacc_rate2              0.0995(0.0653)      -0.0024(0.0016)             -0.0188(0.0314)
Equation new_deaths_per_million2 0.5803(2.3280)      0.0265(0.0564)              -1.5942(1.1173)
Equation ln_newvacc2             0.0235(0.0618)      -0.0014(0.0015)             -0.0328(0.0296)
```

Figure 11




```
> forecast2$fcst$vacc_rate2;
          fcst    lower    upper         CI
 [1,] 61.04292 60.98287 61.10297 0.06005224
 [2,] 61.09892 60.98026 61.21758 0.11866072
 [3,] 61.15753 60.97702 61.33803 0.18050327
 [4,] 61.22740 60.98703 61.46777 0.24037179
 [5,] 61.28975 60.99114 61.58835 0.29860521
 [6,] 61.32338 60.97135 61.67541 0.35203262
 [7,] 61.38008 60.97754 61.78263 0.40254280
 [8,] 61.46426 60.99176 61.93676 0.47249567
 [9,] 61.55965 61.00722 62.11209 0.55243458
[10,] 61.63755 61.00319 62.27192 0.63436288
[11,] 61.71074 60.99658 62.42491 0.71416517
[12,] 61.76560 60.97489 62.55630 0.79070235
[13,] 61.78720 60.92596 62.64844 0.86123524
[14,] 61.81791 60.89040 62.74542 0.92751074
[15,] 61.87563 60.87054 62.88073 1.00509565
[16,] 61.94092 60.85182 63.03001 1.08909348
[17,] 61.98913 60.81474 63.16353 1.17439316
[18,] 62.02860 60.77057 63.28663 1.25802809
[19,] 62.05117 60.71194 63.39041 1.33923724
[20,] 62.04586 60.63038 63.46135 1.41548149
[21,] 62.05329 60.56487 63.54172 1.48842385
[22,] 62.08994 60.52045 63.65942 1.56948516
[23,] 62.14005 60.48422 63.79589 1.65583641
[24,] 62.17515 60.43203 63.91828 1.74312402
[25,] 62.20125 60.37218 64.03031 1.82906706
[26,] 62.21158 60.29860 64.12456 1.91297959
[27,] 62.19747 60.20500 64.18995 1.99247822
[28,] 62.19558 60.12651 64.26466 2.06907502
[29,] 62.22378 60.07219 64.37538 2.15159291
[30,] 62.26570 60.02748 64.50392 2.23822295
```