Forecasting the COVID-19 Economic Recovery in Switzerland: a VAR-X / LSTM Approach

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Abstract

This paper forecasts the evolution of consumption, stock market, unemployment, electricity, mobility, bankruptcies, air pollution, and GDP growth for the end of the COVID-19 crisis in Switzerland. Predictions are created using two high-frequency models: a Vector Autoregression with Exogenous variables (VAR-X) and Long-term Short-term Memory neural network (LSTM). The results suggest that a strong and swift economic recovery is possible but relies heavily on the evolution of political restrictions and number of COVID-19 cases. Consumer behavior could go back to pre-pandemic levels in a 3-months time period given a significant decrease of COVID-19. The number of bankruptcies is expected to increase in this scenario, together with an economic growth of 2.8% with respect to 2019. We find no systematic evidence of an impact of COVID-19 on electricity consumption and NO_2 levels.

JEL Classification: E27, E37, E66

Keywords: COVID-19, economic recovery, forecast, VAR-X, LSTM

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1 Introduction

In this paper we study how to best forecast the evolution of macroeconomic variables in Switzerland in the context of the COVID-19 economic recovery. Using data on consumption, stock market, electricity, unemployment, mobility, bankruptcies, air pollution, COVID-19 cases, and stringency between January 2020 and May 2021, we predict the same variables for the June-August 2021 period depending on 3 scenarios. Using these forecasts, we also estimate GDP evolution using an economic activity proxy for the same period.

Predicting the evolution of the Swiss economy is of the utmost importance for policymakers and public economists who need to anticipate future macroeconomic developments. For this reason many models and prediction methods have been created for short-term forecasting in Switzerland by organizations such as the KOF (2021a), SECO (2021c), CREA (2021), and SNB-affiliated authors (Lack 2006, Galli, Hepenstrick, and Scheufele 2019). However, these models were created before COVID-19 and may lack predictive power in this unprecedented and specific crisis. Other models have been created for this purpose, such as the ones from Castle, Doornik, and Hendry (2021), Foroni, Marcellino, and Stevanovic (2020), Gharehgozli et al. (2020), or Khurshid and Khan (2021). Unfortunately, these models are often centered on the US and UK, and are trained to predict a restricted set of variables such as GDP, unemployment, or climate variables. As such, we built the first model to be fully trained, tested and used on the COVID-19 crisis time period, in Switzerland, and with a broader set of variables.

We use two different models to provide those forecasts in order to avoid the biases linked to the usage of a single specific method. First, we use a Vector Autoregression with Exogenous variables (VAR-X), which is one of the most widely used forecasting method due to its simplicity and predictive power. Secondly, we use a Long Short-Term Memory model (LSTM), which is a more unusual method of forecasting that relies on supervised learning from trained artificial intelligence. Both models provided rather similar results.

The paper is organized as follows. Section 2 introduces the data and general forecasting strategy. Section 3 presents the first VAR-X model together with its results while Section 4 presents the second LSTM model with its results. In Section 5 we analyze these predictions and extrapolate GDP forecasts. Section 6 concludes.

2 Methodology

2.1 Data

The variables presented below are used to capture multiple aspects of the Swiss economic activity through a multivariate time series. We focus on the underlying variables used to compute the SECO Weekly Economic Index (SECO 2021a), as they are likely to capture a variety of impacts from COVID-19. In order to create a model specialized in predicting COVID-19 related variables, we use data from 01.01.2020 (right before the start of COVID-19 cases in Switzerland) up to 02.05.2021 (when this paper was written). Given the nature of VAR-X and LSTM models, together with the short time frame of available data, we use daily observations in order to have enough inputs for training. The data is available with a 3-days lag, and the model can be updated accordingly to reflect recent economic development following this paper. Correlations between variables is presented in figure A5.

Some variables, such as air pollution, are prone to major yearly patterns. As such, we use 2016-2021 data for selected variables to remove the seasonal component with the Seasonal and Trend using Loess algorithm (STL) from Cleveland et al. (1990), as presented in figure A3. The autocorrelation and partial autocorrelation functions, presented in figure A2 also reveal a weekly pattern in some variables. As such, we use the HP-filter of Hodrick and Prescott (1997) to remove the weekly cyclical components of selected variables, by decomposing the data into a trend (x_{it}^T) and cycle component through the minimization problem given in equation 1. An illustration of this filter is presented in figure A1.

$$min_{x_{it}^T} \sum_{t=1}^{T} \left(x_{it} - x_{it}^T\right)^2 + \lambda \sum_{t=2}^{T-1} \left((x_{i,t+1}^T - x_{it}^T) - (x_{it}^T - x_{i,t-1}^T)\right)^2 \tag{1}$$

Consumption: Retrieved from Monitoring Consumption Switzerland (2021), consumption measures the total daily spending in Switzerland by aggregating debit cards, credit cards, mobile payments, and ATM withdrawals. Given the strong seasonality under the Christmas period, a deseasonalized trend was necessary to measure the model. However, daily data was only measured from 01.01.2019 onwards, which is not enough to quantify the correct yearly trend. As such, we use monthly data from SNB (2021) to estimate and remove the seasonal component of the daily data using an STL algorithm. Given the weekly patterns of consumption, an HP-filter is then used to remove the weekly trend.

SMI: Retrieved from SIX (2021), the SMI is the main stock market index of Switzerland, measuring the market capitalization of the 20 largest publicly listed companies of the country, such as Nestlé, Novartis, and Roche. No data transformation are used on this variable.

Unemployment proxy: Retrieved from SECO (2021b), this proxy measures the number of job seekers which are registered as actively looking for a position on job-room.ch, one of the main job board of Switzerland. Indeed, unemployment data is not measured daily, which is why a proxy is required. No data transformation are used on this variable.

Electricity: Retrieved from Swissgrid (2021), this variable measures end-user electricity consumption in GwH. Given the peak of electricity use in winter, we remove the seasonal component of the data using an STL algorithm. Given the weekly patterns of electricity consumption, an HP-filter is then used to remove the weekly trend.

Mobility: Retrieved from Google (2021), this variable measures the average percentage change in Google users mobility due to COVID-19, as measured from their smartphones localization. No data transformation are used on this variable.

Net new firms: Retrieved from SHAB (2021), this variable measures the net change in firm creation in Switzerland. In other words, it removes the daily number of bankruptcies from the daily number of companies created. Given the weekly patterns in announcing bankruptcies and announcing the creation of firms, an HP-filter is used to remove the weekly trend.

Air pollution: Retrieved from FOEN (2021), this variable measures the daily levels of nitrogen dioxide (NO_2) in Switzerland by averaging the levels in Bern, Lausanne and Zurich. Air pollution is indeed made of many types of particles, one of the most prominent being NO_2. What separates NO_2 from more famous pollutants such as CO_2 is the fact that NO_2 mainly results from human activity such as fuel combustion (Shon, Kim, and Song 2011). As such, it is one of the best measure of man-made air pollution change resulting from COVID-19. Moreover, there are multiple evidence suggesting NO_2 to be a factor of COVID-19 spread and lethality (Ogen 2020; Copat et al. 2020), furthering the relevance of this specific indicator. Given the drop of air pollution in summer, we remove the seasonal component of the data using an STL algorithm. Given the weekly patterns of NO_2, an HP-filter is then used to remove the weekly trend.

Stringency: Retrieved from KOF (2021b), this index measures the severity of political restrictions resulting from COVID-19 (such as quarantine, curfew, and lockdown) on a scale from 0 to 100. We average the stringency of every canton (Swiss states), weighted by their respective GDP, into a single Swiss index of average stringency. No further data transformation are used on this variable.

COVID-19 cases: Retrieved from FOPH (2021), this variable reports the daily number of laboratory-confirmed COVID-19 cases, measured through the various COVID-19 tests available such as PCR tests. Given the lack of testing available before October 2020, the number of cases is underestimated for the early phase of the pandemic. As a result, we correct the early COVID-19 cases (January - October 2021) by multiplying the number of positive cases (c_t) by the ratio of tests carried out (z_t) with respect to the average number of tests carried out in the later phase of the pandemic (November 2021 - today), as seen in equation 2. The corrected result is presented in figure A4. Given the weekly patterns of testing and case reporting by the local health offices, an HP-filter is used to remove the weekly trend.

$$c_t^{corr} = \begin{cases} c_t \dfrac{z_t}{\frac{1}{T}\sum_{i=271}^{T} z_i} & \forall\ 0 < t \leq 270 \\ c_t & \text{otherwise} \end{cases} \tag{2}$$

Weekly Economic Activity: Retrieved from SECO (2021a), this experimental composite indicator measures economic growth in Switzerland on a weekly basis, as opposed to GDP which is measured quarterly. The measurement is in percentage difference from the Q4 2019 level. Even though it is not meant as a measurement of GDP, it follows its path rather accurately. Given how this component is measured weekly and given the multicolinearity resulting from the other data which are underlying variables of this index, we do not use this indicator in our model. Instead, it is forecasted after the other variables in Section 5. No further data transformation is used on this variable.

2.2 Forecasting strategy

Our strategy is based on three main assumptions. The first is that past values of the variables are relevant to predict their future. The second is that correlations apply in both directions, in the sense that the economic recovery behavior corresponds to the inverse of the crisis behavior. The third is that the variables chosen are relevant, cointegrated, and provide an extensive view on multiple aspect of the Swiss economy.

The forecasts are provided using two approaches, a VAR-X model and a LSTM model. On one hand, the VAR-X model is expressed as a linear combination of past observation of itself and others variables. On the other hand, the LSTM model is non-linear. As such, the two models take two distinctively different approaches to the same purpose (Dissanayake et al. 2021). Using two methods allows us to evaluate if the computed forecasts converge or diverge between the models, reducing the bias linked to using one specific approach. Overall, forecasting performance from multiple model techniques is higher than from a single model (Chang, Lee, and Li 2012). This strategy allows for a better decision-making and gives further confidence in the forecasts provided.

3 VAR-X approach

3.1 Model

The vector autoregression (VAR) is the standard model of multivariate time series analysis in macroeconomics (Sims 1980). Even though these models have identification problems, they remain some of the most powerful and reliable tools for forecasting purposes (Stock and Watson 2001). Relying on the method from Pfaff (2008b), we use a VAR with exogenous variables (VAR-X) to create multiple forecasting scenarios depending on the evolution of COVID-19, and treat it as an exogenous shock on the economy. As such, the VAR-X model presented in equation 3 uses COVID-19 cases and Stringency as exogenous variables (vector z_t), together with Consumption, SMI, Unemployment, Electricity, Mobility, New firms, and Air Pollution as endogenous variables (vector x_t).

$$x_t = \alpha + \sum_{p=1}^{5} A_p x_{t-p} + \sum_{p=1}^{5} B_p z_{t-p} + e_t \tag{3}$$

The lag of 5 periods used in the model is supported by the HQ (Hannan and Quinn 1979) and Bayesian (Schwarz 1978) criteria. It's also partially supported by the AIC (Akaike 1973) and FPE (Akaike 1969) criteria which point to a slightly larger lag of 7 periods. These four indicators are the most relevant selection criteria to select the lag of a VAR model (Liew 2004). Based on the Akaike criterion tendency to select lags too big for VAR purposes (Hyndman and Athanasopoulos 2018), we use 5 periods instead of 7. The practical implementation of the model is carried out using packages *vars* (Pfaff 2008a), *tsm* (Kotze 2020), *mFilter* (Balcilar 2019) and *urca* (Pfaff 2008a).

We test for the presence of unit roots, drift term, and trend term using an augmented Dickey-Fuller test (Dickey and Fuller 1981) on equation 4. The results outlined in table A1 suggest the presence of unit roots, drift terms, and time trends in the data. Heteroscedasticity and serial autocorrelation of the data are also confirmed by an ARCH Lagrange-multiplier test (Engle 1982) and adjusted Portmanteau test (Breusch 1978), as seen in table A2.

$$\Delta x_{i,t} = a_0 + \gamma x_{i,t-1} + a_1 t + e_t \tag{4}$$

These elements make the VAR-X model biased. Indeed, non-stationarity from unit roots is usually a problem for VAR, which can easily be resolved by taking the first difference of the series (Enders 2014). However, this bias correction is only needed to make causal inference from the model, and non-stationarity does not impair short-term forecasting purposes (Hatemi-J 2004). On the contrary, differencing the data would even reduce the predictive power of the model (Allen and Fildes 2001).

However, one condition for the use of a VAR model with non-stationary data for forecasting purposes is for the variables to be cointegrated (Fanchon and Wendel 1992). We test for cointegration with a Johansen test (Johansen 1991), using the Vector Error Correction Model (VECM) form of our VAR-X presented in equation 5. By testing the rank of the coefficient matrix Π, separated from the differentiated coefficient matrices Γ_p, as presented in table A4, we confirm the strong cointegration of the variables, thus validating the use of our VAR-X model.

$$\Delta \tilde{x}_t = \Pi \tilde{x}_{t-1} + \sum_{p=1}^{4} \Gamma_p \Delta \tilde{x}_{t-p}, \quad \tilde{x}_t \equiv \begin{bmatrix} x_t \\ z_t \end{bmatrix} \tag{5}$$

Serial autocorrelation and heteroskedasticity are a result of the non-stationarity of the data. As such, the same thinking applies and serial autocorrelation does not need to be corrected for the forecasting purpose of the VAR (Hendry and Mizon 1978). Moreover, a simple log-transformation of the data is not enough to correct the heteroskedasticity of the model, as seen in table A2. As a result, a solution to heteroskedasticity would be to use a multivariate GARCH volatility model (Engle 2002). Notwithstanding the added complexity of such models, many of the added benefits of simple VAR processes for forecasting purposes outlined by Stock and Watson (2001) would unfortunately be lost in this case. Moreover, the comparative forecasting advantages of these models would be more likely to be relevant for long-term forecasting, rather than for the short-term purpose of our analysis (Hoffman and Rasche 1996). Finally, the strong cointegration of all variables implies that a consistent estimation is possible with a VAR even if the endogenous variables are correlated with the error term, a property known as superconsistency in Cochrane (1997). Overall, the power of VAR models lies in their ability to predict variables accurately, not in their identification abilities (Clément and Germain 1993). These elements further confirm the use of our VAR-X model despite these biases which prevent causal inference, but not forecasting power.

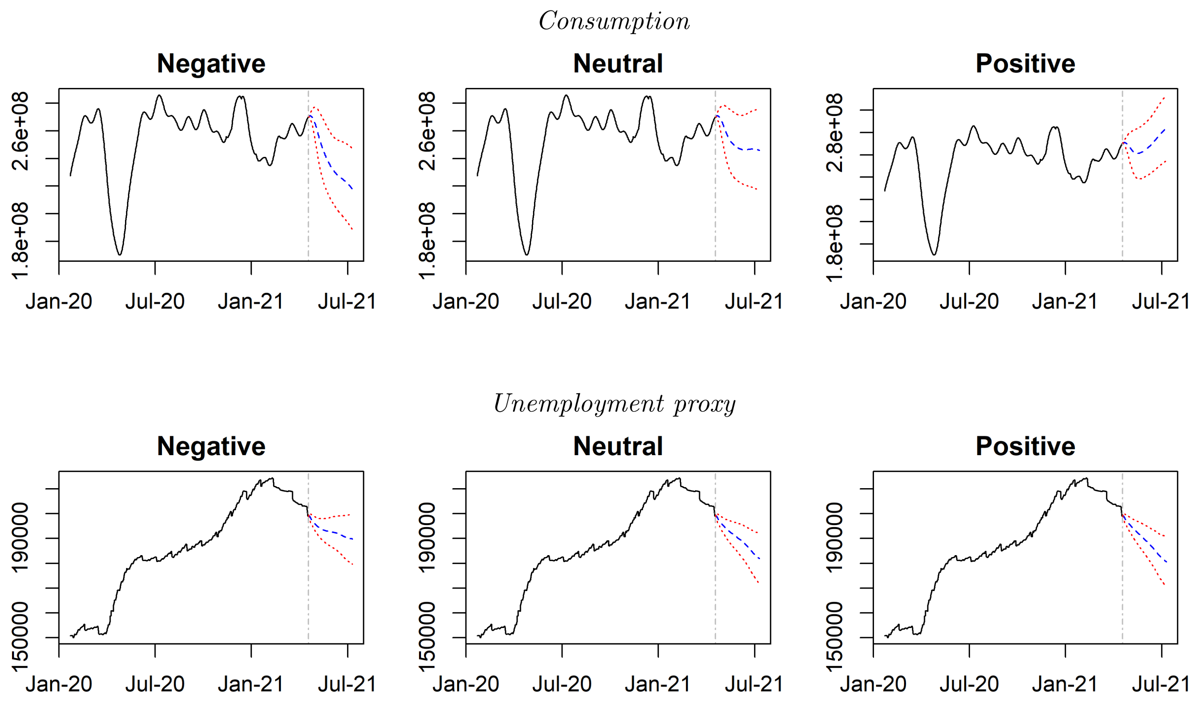
Impulse response functions (IRF) of COVID-19 shocks and Stringency shocks are presented in tables A7 and A8. Following the method from Lütkepohl (2005), we treat both variables as endogenous for this point to calculate the moving-average form and impulse responses of our model. However, one must be careful when looking at those results, as these IRF merely represent correlations and not causal evidence. Despite the lack of identification, these IRF still give useful insights in how the model works and, most importantly, how the shocks correlate to other variables over time.

3.2 Results

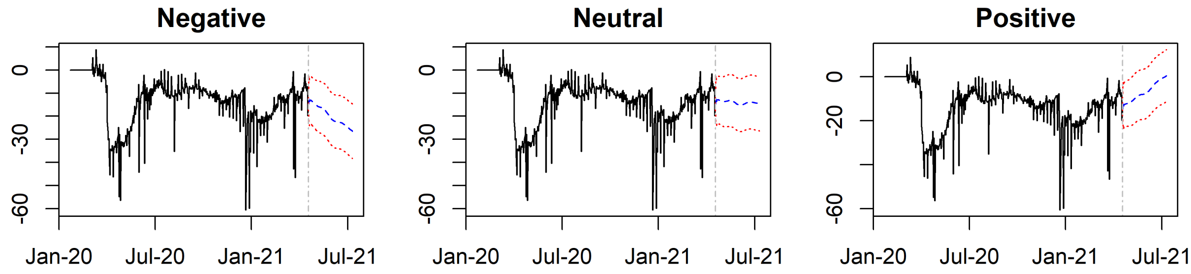
Following the method from Pesaran (2015), we compute 90-days forecasts from 03.05.2021 to 01.08.2021 in figure 1. We provide a descriptive analysis of the results, but further analysis and interpretation of the forecasts is provided in section 5. These predictions are based on 3 scenarios conditioning the future values of the exogenous variables using a linear interpolation from the last known value to the targeted value. On 03.05.2021, daily COVID-19 cases stands approximately at 1300 while stringency stands approximately at 52.

- Positive scenario: COVID-19 goes down to 100 new daily cases, and stringency goes down to 10.
- Neutral scenario: COVID-19 stays at 1300 new daily cases, and stringency stays at 52.
- Negative scenario: COVID-19 goes up to 5500 new daily cases, and stringency goes up to 80.

Figure 1a: Consumption-side VAR-X 90-days forecasts with 90% confidence intervals



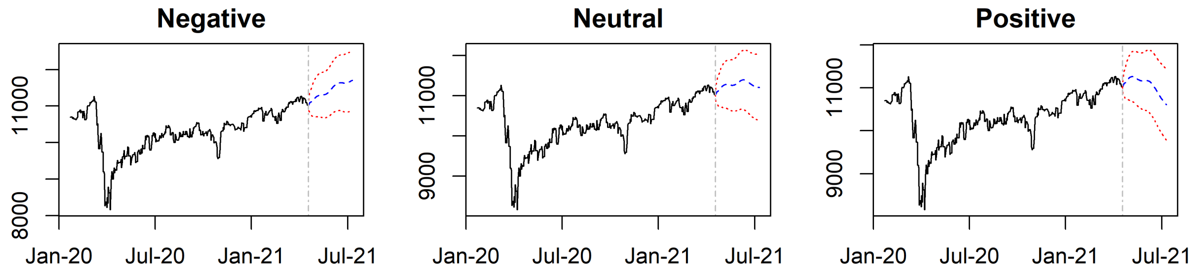
Mobility



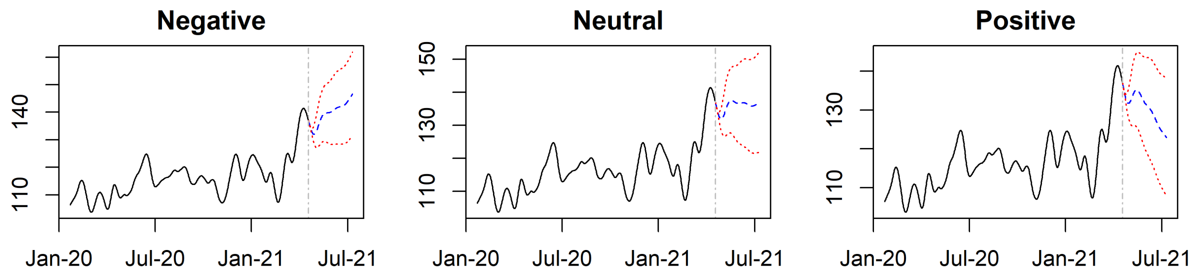
Variables on the consumption-side reacted as anticipated to COVID-19 shocks. Higher number of cases and higher stringency were met with a lower consumption, lower mobility, and higher unemployment.

Figure 1b: Production-side VAR-X 90-days forecasts with 90% confidence intervals

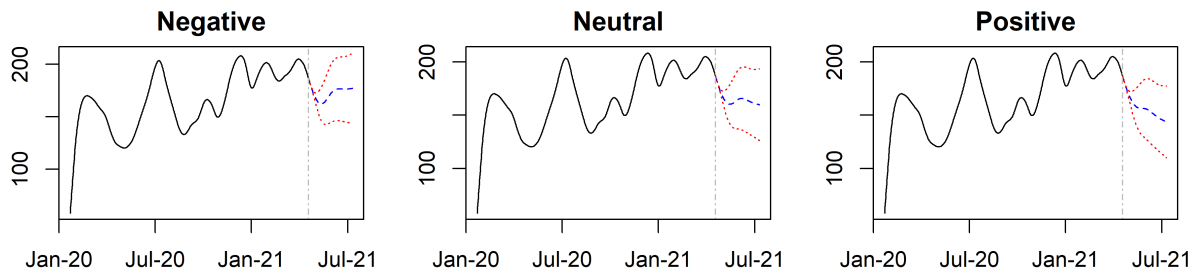
SMI



Electricity



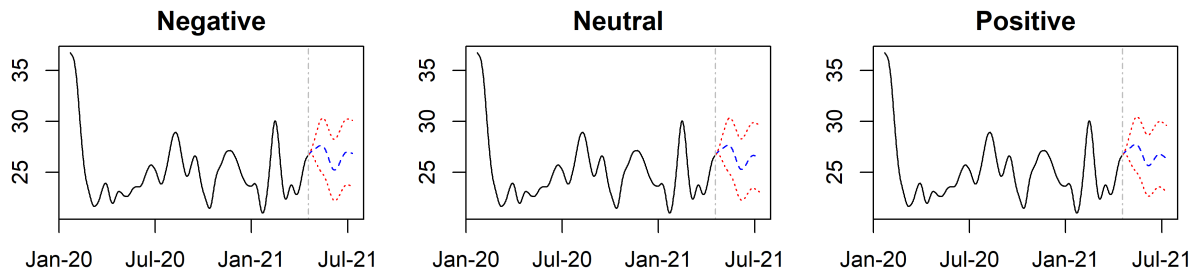
Net new firms



Variables on the production-side reacted in a more unexpected way to COVID-19 shocks. Higher number of Covid cases and higher stringency were met with an higher stock market, higher electricity consumption, and higher net new firms (i.e. lower bankruptcies).

Figure 1c: Pollution VAR-X 90-days forecasts with 90% confidence intervals

Air pollution



Our model predicts no correlation between the incidence of COVID-19 and air pollution levels.

These results are further analyzed in section 5. One limitation to the model remains that alternative scenarios where COVID-19 cases and Stringency go in opposite direction would produce biased results, due to the lack of causal estimation.

Empirical validation of the model is provided in figure A9, which gives the forecasting results of the VAR-X model fitted without the last 90 values. These imply that the model performs relatively well in predicting most variables. Some estimates, such as Unemployment or Electricity are weaker for the last 30 days of the prediction, but the model remains an overall powerful forecasting tool, which gives further confidence in the forecasts displayed above.

4 LSTM approach

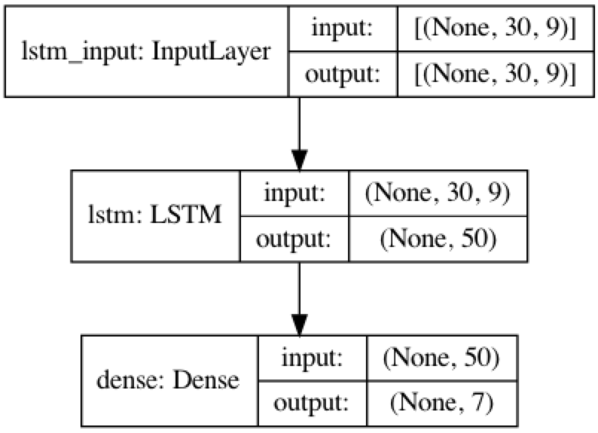
4.1 Model

The Long Short-Term Memory model (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning. The LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. The cells are designed to have memory over arbitrary time intervals and to process data sequentially by keeping its hidden state through time. The three remaining gates regulate the flow of information into and out of the cell (Hochreiter and Schmidhuber 1997). These elements allow for the model to be used in the context of multivariate time series, providing accurate forecasting results (Sagheer and Kotb 2019).

We use a first LSTM model to train our data set in order to compute the connections weights between the nodes of the model. Then, we copy the weights of the first model into a second same LSTM model with *stateful* mode. Since we use a recursive method to compute forecasts and due to the small amount of data observations (488 days), the *stateful* mode provides better results because it allows the second model to save the state of the neurons for the next training session instead of resetting it (Elsworth and Güttel 2020).

As for the VAR-X model, the LSTM models use COVID-19 cases and Stringency as exogenous variables and Consumption, SMI, Unemployment, Electricity, Mobility, New firms, and Air Pollution as endogenous. The hyper-parameters of our models are 50 hidden neurons, 1000 Epochs with an early stop and a lag of 30 days. The structure of the algorithm is composed of one input layer of size 9x30, an LSTM layer of 50 hidden neurons and a dense layer of size 7x1 with linear activation, as shown in figure 2.

Figure 2: Structure of the LSTM neural network



The process is divided into three parts : Training, testing and forecasting. First, we split the data set in order to use the last 90 days of data for validation and testing. Then, the first LSTM model trains on the remaining data in order to compute connections weights between the nodes by using all the nine variables as inputs and the seven endogenous variables as outputs. Then, the algorithm tests if the predicted values of the computed model fit with the real values in the test set, as shown in figure A10. Then, we evaluate the model by minimizing the Mean Absolute Error (MAE) function given in equation 6, where $\hat{y}_i$ is the predicted value, y_i the real value and n the number of observations during the evaluation.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{6}$$

The evaluation shown in A11 gives further confidence in the fitted model due to its performance, as the MAE drops under 10% and stays stable between 3% and 5%. This supports that our model fits the data-set appropriately and is well-trained.

In the last part, we use the second LSTM model with *stateful* mode to forecast 90 days out-of-sample data. This second model has the same structure and connections weights as the first one. Forecasts are computed using a recursive method :

$$\hat{y}_t = model(y_{t-1}, y_{t-2}, ..., y_{t-30})$$

$$\hat{y}_{t+1} = model(\hat{y}_t, y_{t-1}, y_{t-2}, ..., y_{t-29})$$

$$\vdots$$

$$\hat{y}_{t+90} = model(\hat{y}_{t+89}, \hat{y}_{t+88}, \hat{y}_{t+87}, ..., \hat{y}_{t+60})$$

where $\hat{y}_i$ is the predicted out-of-sample value and y_i is the in-sample observation value.

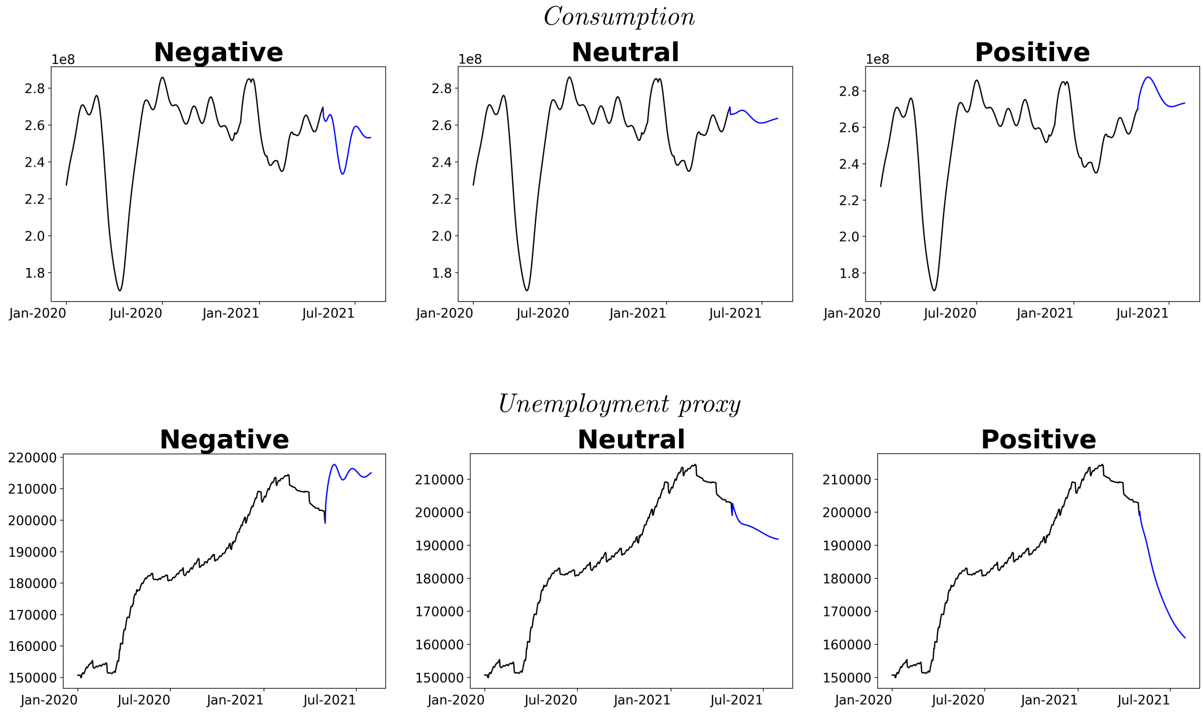
Finally, in order to compute three different scenarios (Positive, Neutral and Negative), we concatenate predicted values (size 7x1) with fixed values of Covid-19 cases and Stringency (size 2x1) so this vector can be used as an input in the second LSTM model with the recursive method. The practical implementation of the model is carried out using packages *keras* (Chollet et al. 2015), *tensorflow* (Abadi et al. 2015) and *scikit-learn* (Pedregosa et al. 2011).

4.2 Results

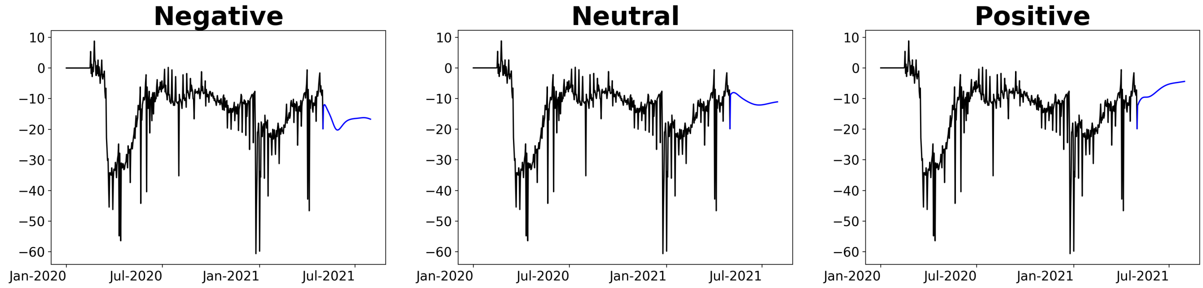
As in the VAR-X forecasts results, we computed 90-days forecasts from 03.05.2021 to 01.08.2021 and these forecasts are based on 3 scenarios conditioning the future values of the exogenous variables :

- Positive scenario: COVID-19 goes down to 100 new daily cases, and stringency goes down to 10.
- Neutral scenario: COVID-19 stays at 1300 new daily cases, and stringency stays at 52.
- Negative scenario: COVID-19 goes up to 5500 new daily cases, and stringency goes up to 80.

Figure 3a: Consumption-side LSTM 90-days forecasts



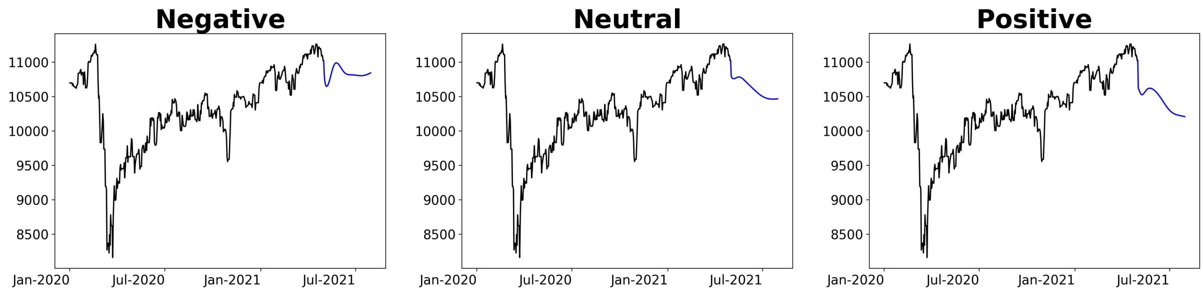
Mobility



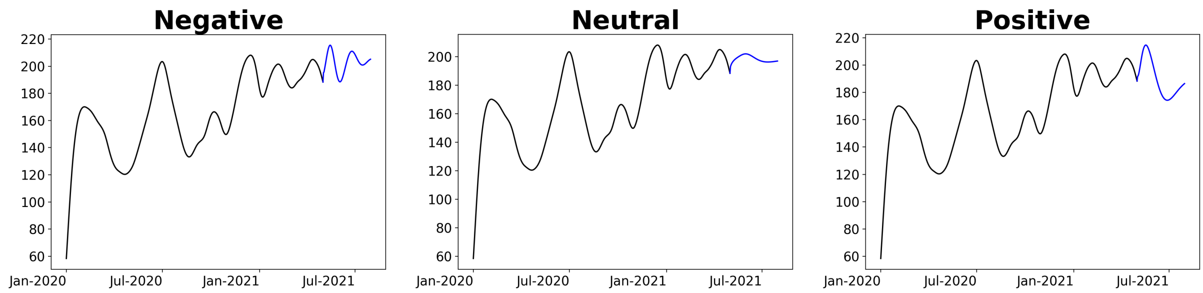
Variables on the consumption-side reacted as anticipated to COVID-19 shocks, with the LSTM results converging to the VAR-X results. Indeed, higher number of COVID-19 cases and higher stringency were met with a lower consumption, lower mobility and higher unemployment.

Figure 3b: Production-side LSTM 90-days forecasts

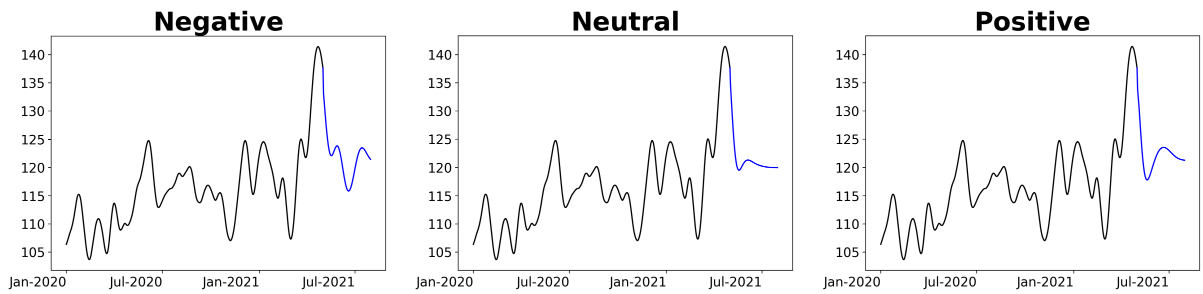
SMI



Net new firms

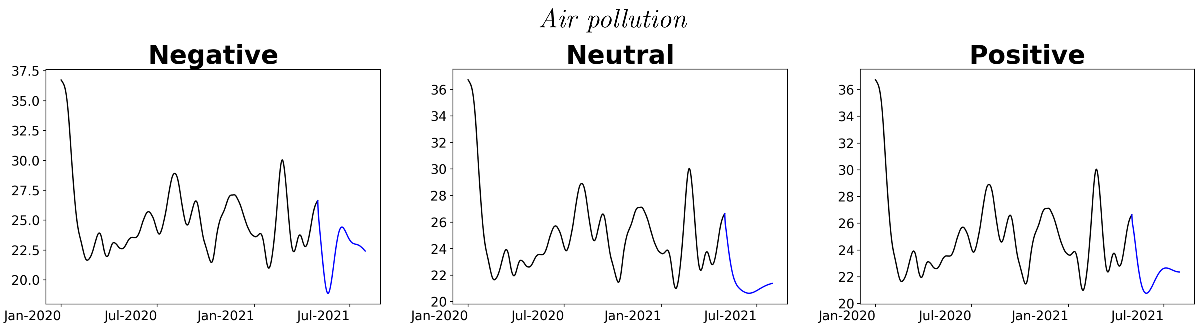


Electricity



Variables on the production-side reacted in a more unexpected way to COVID-19 shocks. Higher number of COVID-19 cases and higher stringency were met with an higher stock market and higher net new firms (i.e. lower bankruptcies). One difference with the VAR-X results is that the LSTM model predicts less correlation between COVID-19 shocks and electricity.

Figure 3c: Pollution LSTM 90-days forecasts



The LSTM model predicts close to no correlation between COVID-19 shocks and air pollution, as in the VAR-X case.

The results are further analyzed in section 5. In addition to the lack of causal identification mentioned for the VAR-X, the LSTM model also suffers from a lack of confidence intervals due to the recursive method. Evaluation and validation of the model is provided in the testing set provided in figures A11 and A10.

5 Discussion

5.1 Analysis of results

This sections further analyzes the results presented in section 3 and 4, providing potential explanations for the results and comparing the two models.

On the demand side, variables react as expected to COVID-19. Indeed, the pandemic and the related political restrictions led citizens to stay at home (lowering mobility), reduce their shopping habits due to closed shops (lowering consumption), and look for new occupations and part-time jobs given the reduction of economic activity and closure of leisure activities (increasing unemployment). Both models predict rather similar ranges for consumption and mobility. However, the sensitivity of the LSTM forecasts for unemployment to a COVID-19 shock is higher than for the VAR-X model, reducing our confidence in this specific forecast. All in all, a reduction of cases and political restrictions should be met with a swift return to pre-pandemic economic activity from Swiss citizens, as proxied through their consumption, mobility, and unemployment.

On the production side, both SMI and electricity seem to present counter-intuitive predictions, as they both increase when the situation worsen and decrease when the situation gets better. Indeed, one could expect that the decrease of economic activity impacted the biggest companies heavily (thus decreasing the SMI) and that the reduction of industrial activity and mobility decreased electricity consumption. However, this intuition is not consistent with the empirical data and the reverse situation is consistent across both models, which produce similar forecasts. Regarding the stock market, the positive effect of COVID-19 on the SMI illustrates the gap between general economic activity and the biggest Swiss firms (such as Nestlé, Roche, or Novartis) which benefited from the pandemic due to the boost in the pharmaceutical and FMCG sectors. Moreover, most stock markets saw a spike of trading volume and prices during lockdown due to an increased market participation with new investors trading from home (Chiah and Zhong 2020). These two elements could explain the positive rally of the Swiss stock market despite the negative COVID-19 shocks. Regarding electricity, Janzen and Radulescu (2020) estimate an overall decrease of electricity consumption of 4.6% in 2020 in Switzerland due to COVID-19. However, as seen in figure A3, this decrease happened following an exceptionally low year 2019. As such, electricity consumption in 2020 benefited from a rebound after this particular year which was too big to be compensated by the thin decrease due to COVID-19. We therefore find no systematic evidence of a relationship between electricity and the COVID-19 shock. Overall, these results imply that the Swiss stock market and electricity consumption should not be heavily impacted by the economic recovery.

Moreover, we can observe a negative correlation between stringency, COVID-19 cases and net new firms in both models. This might be explained by the economic measures taken by the Swiss government such as the *corona loans*. The most indebted companies have been more willing to take those loans (Brülhart et al. 2020), thus avoiding bankruptcy or at least delaying it. Indeed, there was no significant increase in bankruptcy during 2020 (Eckert, Mikosch, and Stotz 2020), and the corona loan program might also have helped young companies that might struggle to obtain funding in a normal situation (Fuhrer, Ramelet, and Tenhofen 2021), lowering the probability of bankruptcy. As such, the negative impact on bankruptcies can be explained by the numerous COVID-19 emergency schemes, which were high enough to save companies that would have otherwise closed even without the pandemic. This interpretation implies that the number of bankruptcies can be expected to increase in the recovery.

For air pollution, we find close to no correlation between NO_2 and COVID-19, which is not consistent with current literature that point to a slight decrease of air pollution (Zoran et al. 2020,Guevara et al. 2021). However, as seen in figure A6, what may be interpreted as a diminution of NO_2 at the start of the pandemic can be almost entirely explained by seasonality. However, seasonality is driven by meteorology in the case of air pollution (Grange and Hüglin 2020), which is absent from our deseasonalization strategy and might explain the lack of correlation. All in all, the actual drop in air pollution due to COVID-19 is too thin to be captured by our model given the much larger seasonality patterns. As such, we expect air pollution to only be slightly impacted by the economic recovery, and to be mainly driven by seasonality instead.

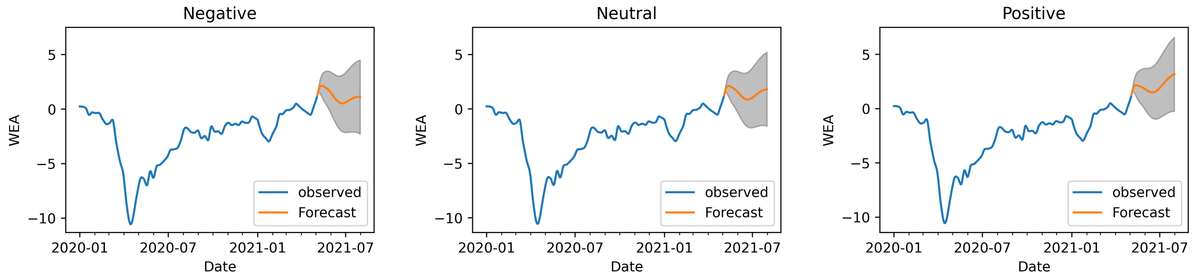
5.2 Growth forecast

To generalize our results to a single quantifiable measure of the state of the economy, we forecast the index of weekly economic activity (WEA) from the SECO (2021a). GDP is usually the variable of choice to measure the economic activity, but it remains a low-frequency variable that is published only quarterly and with a significant delay. As such, GDP is not compatible with our high frequency model. Instead, the WEA has a much higher weekly publication rate with a lower delay. Furthermore, the WEA shows a significant correlation with GDP growth, and almost replicates it. As it is a composite index partially constructed with some of our variables, we could not use it in our previous models that presupposed mutual influences and no-multicolinearity between the variables. To forecast the WEA using the results from the VAR-X and LSTM models, we used an ARIMAX model which can be interpreted as a VAR-X model with one single endogenous variable. We then used all other predictions as exogenous.

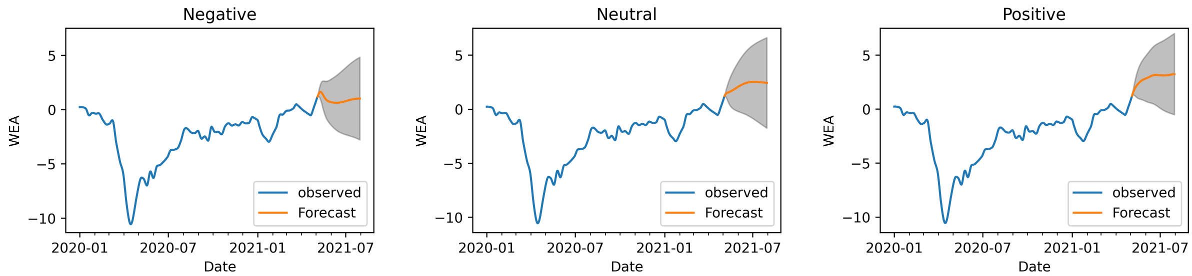
As seen in table (A3), we find that the series is non-stationary with the Augmented Dickey-Fuller test (Dickey and Fuller 1981) and KPSS test(Kwiatkowski et al. 1992). However, taking the first difference of the variable is enough to remove the unit root, making it stationary and ready to be used in the model. We use the best parameters by minimizing the AIC criterion (Akaike 1973). We find that the best model is an ARIMAX with 4 lags, integrated of order 1 and with no moving-average term. The Ljung-Box test (Ljung and Box 1978) does not reject the absence of auto-correlation in our residuals at 5% level. Given the different frequencies between the daily and weekly data, we interpolate the daily value of the WEA using an Akima spline (Akima 1970). Practical implementation of the model is carried out with the *statsmodels* (Seabold and Perktold 2010) and *pmdarima* (Smith 2017) packages.

Figure 4: WEA ARIMAX 90-days forecasts with 90% confidence interval

With VAR data



With LSTM data



The forecasts presented in figure 5.2 show the estimated GDP growth with respect to the 2019 level. Averaging the results of both models, we estimate the total growth from Q4 2019 to Q2 2021 to be 2.83% in the positive case, 1.1% in the neutral case, and 0.7% in the negative case. These forecasts suggest an overall return to pre-pandemic economic activity and growth in the second quarter of 2021, except in the case of an exceptional new wave of a magnitude even greater than the previous ones, which seems unlikely given the vaccination trend in Switzerland (FOPH 2021). Empirical validation of the model is provided in figure A12 and imply that the model performs relatively well in predicting the index.

6 Conclusion

We propose a high frequency and relatively simple model that takes into account the effect of the spread of the virus and the strength of the mitigation measures. The crisis outlined how the situation can dramatically worsen in a short period of time, increasing the need for a model that can be updated quickly. Given the empirical validation and results of the models, we believe them to be successful in reducing the uncertainty linked to the economic recovery phase of the pandemic. The model can greatly benefit policymakers to plan policies and forecast the effects of the proposed interventions, both in a general and specific way. Indeed, not only does our model allow for a general forecast of the economic situation, it can also be adapted to a specific policy analysis by adding the policy target as an exogenous variable.

The main conclusion form our study is that the economic recovery in Switzerland should occur very quickly if the sanitary situation does not worsen. As seen from consumption, unemployment, and mobility, consumer behavior can be expected to go back to pre-pandemic levels in a 3-months time frame. On the other hand, production behavior can be expected to recover more slowly and in a less sensitive way. All in all, both models gave rather similar results, which gives further confidence in the forecasts. The validation point towards the VAR-X model providing more accurate forecasts than the LSTM, most likely due to the need for larger datasets in deep learning models.

Our model exhibits some limitations. The variables are not stationary, which contrasts with the assumption that they behave in a similar way throughout the different phases of the pandemic. Moreover, as low levels of stringency are yet to be observed, the actual behavior of the agents can only be extrapolated rather than observed. Our model is still subject to the Lucas critique (Lucas 1976) because the parameters will change whenever a policy change occur. On the other hand the accuracy of the models does not rely on underlying economic assumption or on the realism of an economic model to identify the policy invariant parameters (Sims, Goldfeld, and Sachs 1982). To improve the usefulness of our model, we could thus create a structural VAR with short term restrictions (Sims 1980). Doing so would help to identify the isolated effect of each variable which can then be used for policy evaluation purposes through new exogenous variables. Such additional research would allow a better identification of the underlying mechanisms of these forecasts, thus improving the potential of the results for policymaking.

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Appendix

Table A1: Augmented Dickey-Fuller test

Test	Unit root $\gamma = 0$	Time trend $a_0 = \gamma = 0$	Drift term $a_1 = a_0 = \gamma = 0$
Consumption	-4.73	7.46***	11.19***
SMI	-2.97***	3.09	4.63
Unemployment proxy	-0.31***	2.42	2.23
Stringency	-1.95***	1.88	2.57
Electricity	-4.43	6.68***	9.93***
C19 cases	-2.36***	1.9	2.84
Mobility	-2.39***	2.04	3.02
Net new firms	-5.77	11.18***	16.75***
Air pollution	-6.16	12.74***	19.08***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A2: ARCH Lagrange-multiplier test and Portmanteau test

	Chi-squarred statistic	Degree of freedom
Test of heteroskedasticity	4872.8***	3920
Test of heteroskedasticity (log-transformed data)	4807.3***	3920
Test of serial autocorrelation	426.2***	0
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A3: ARIMAX tests on Weekly Economic Activity index (WEA)

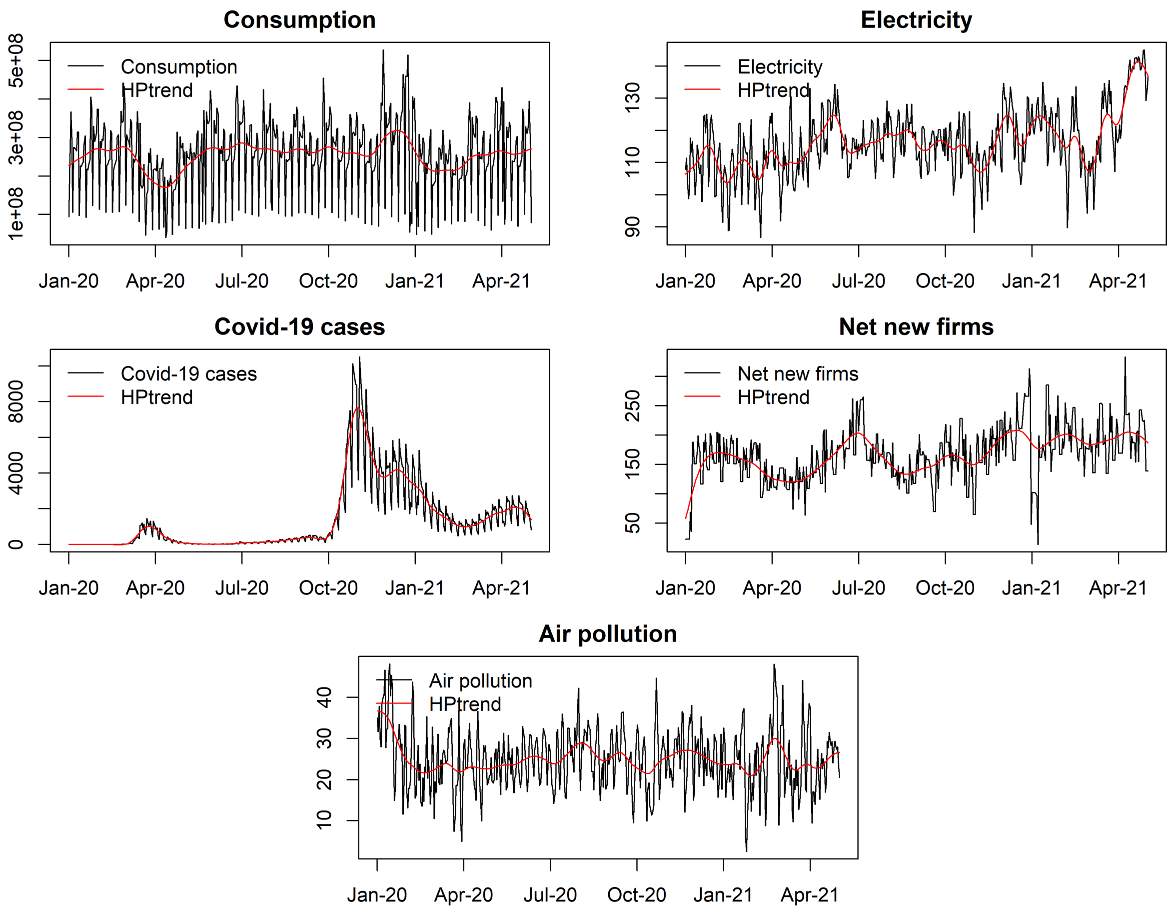
Test	Test statistic
ADF test	-1.480
KPSS test	1.180***
ADF test (d=1)	-4.177***
KPSS test (d=1)	0.29
Ljung-Box	3.18*
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A4: Johansen test of cointegration

Null hypothesis	Test statistic
$r \leq 8$	7.69*
$r \leq 7$	20.36**
$r \leq 6$	40.60***
$r \leq 5$	99.77***
$r \leq 4$	219.42***
$r \leq 3$	346.09***
$r \leq 2$	589.71***
$r \leq 1$	947.59***
$r = 0$	1394.44***

Note: *p<0.1; **p<0.05; ***p<0.01

Figure A1: HP-filter smoothing of cyclical data



Note: $\lambda_{cons} = 4000$, $\lambda_{elec} = 500$, $\lambda_{c19} = 500$, $\lambda_{firm} = 6000$, $\lambda_{air} = 2000$

Figure A2: Data persistence: autocorrelation (ACF) and partial autocorrelation (PACF)

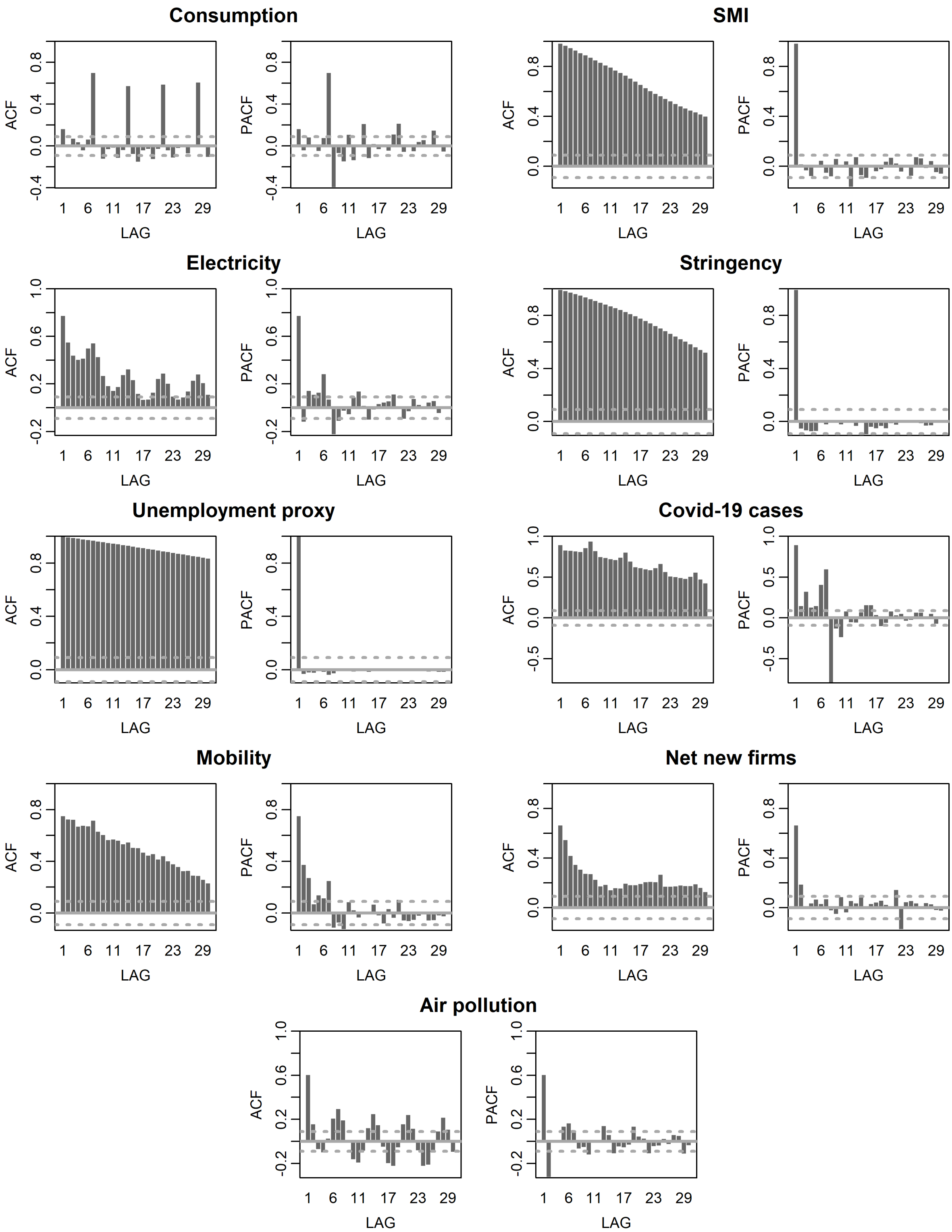
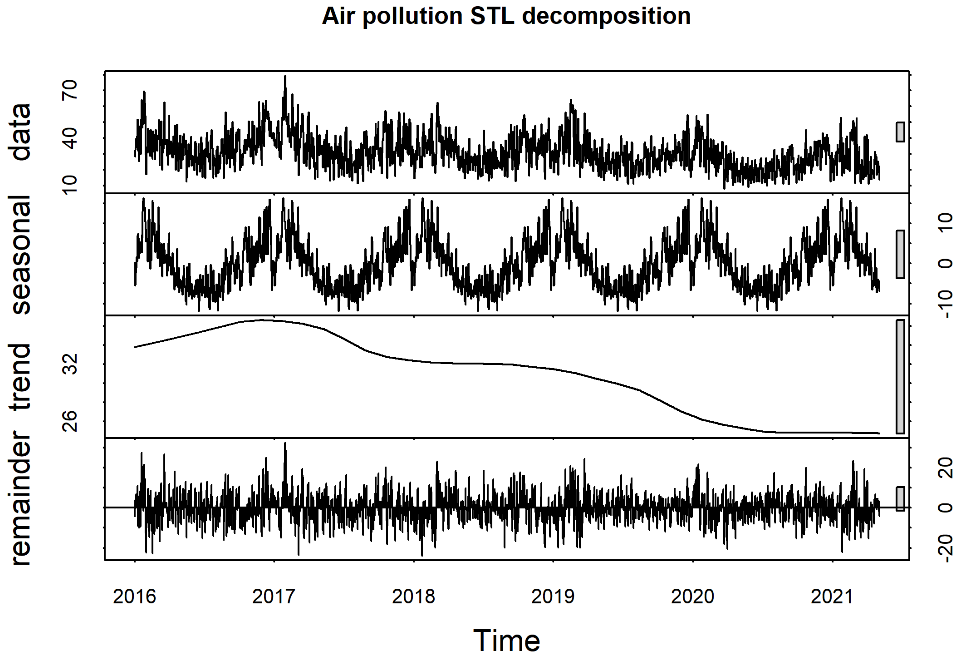


Figure A3: STL decomposition



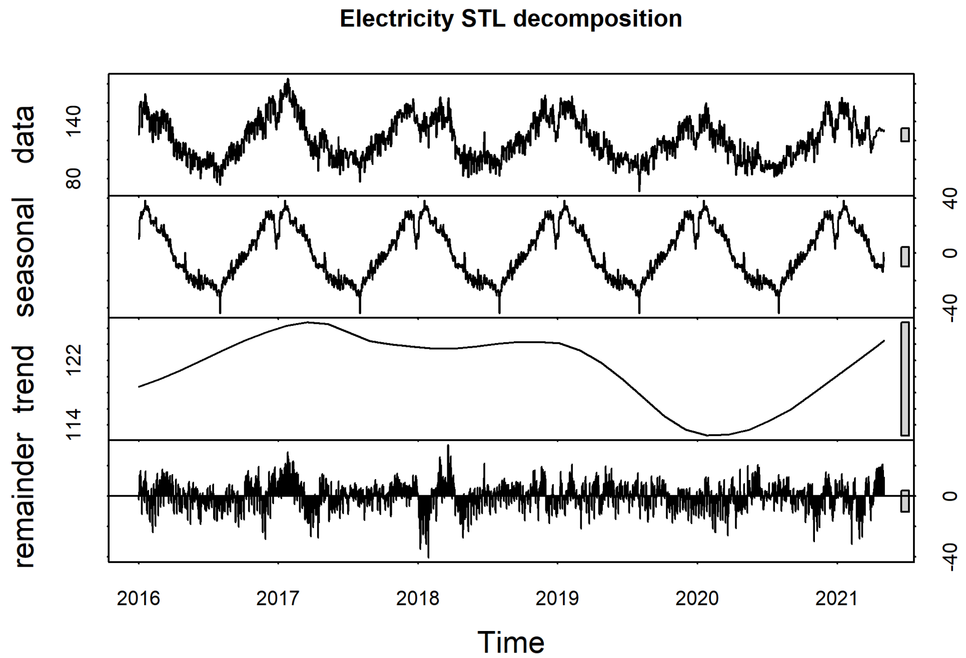


Figure A3: STL decomposition (cont'd)

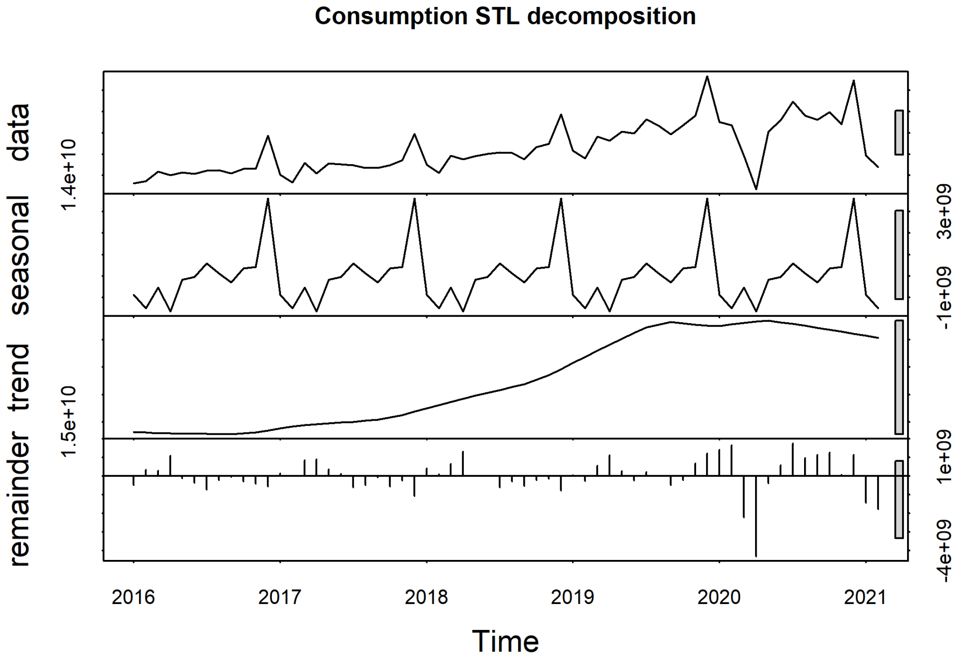


Figure A4: Early-pandemic correction of COVID-19 cases

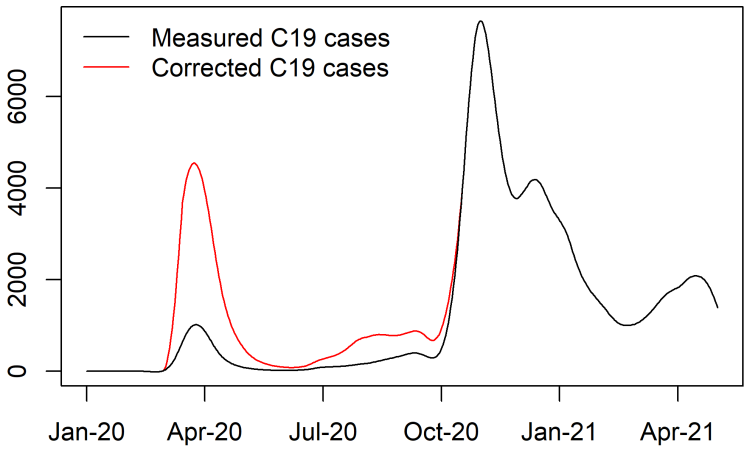


Figure A5: Correlation matrix

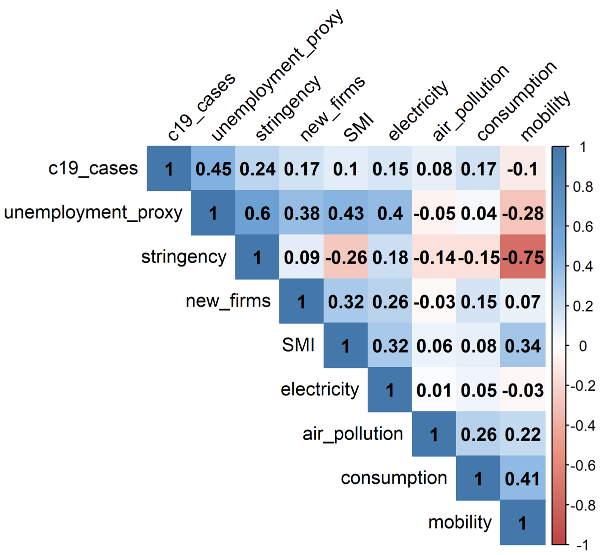


Figure A6: Evolution of air pollution and stringency 2019-2021

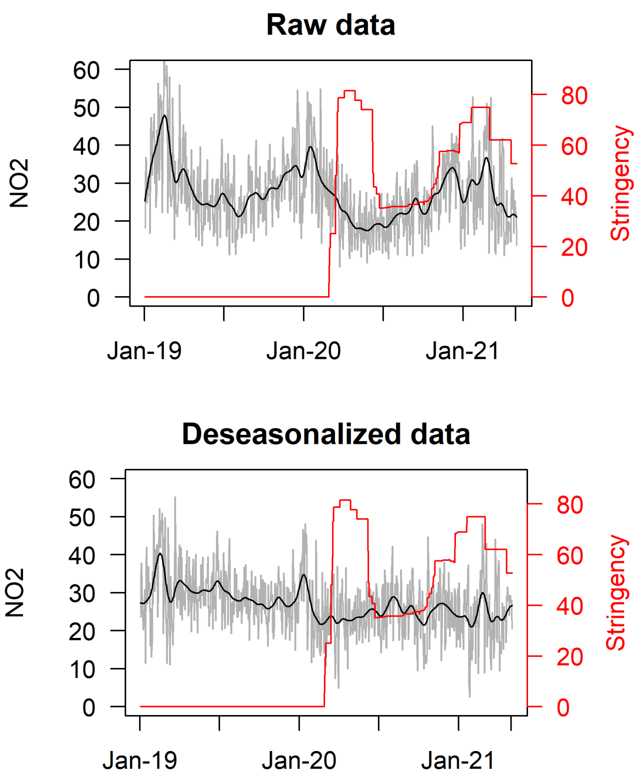


Figure A7: Impulse responses of a shock in COVID-19 cases

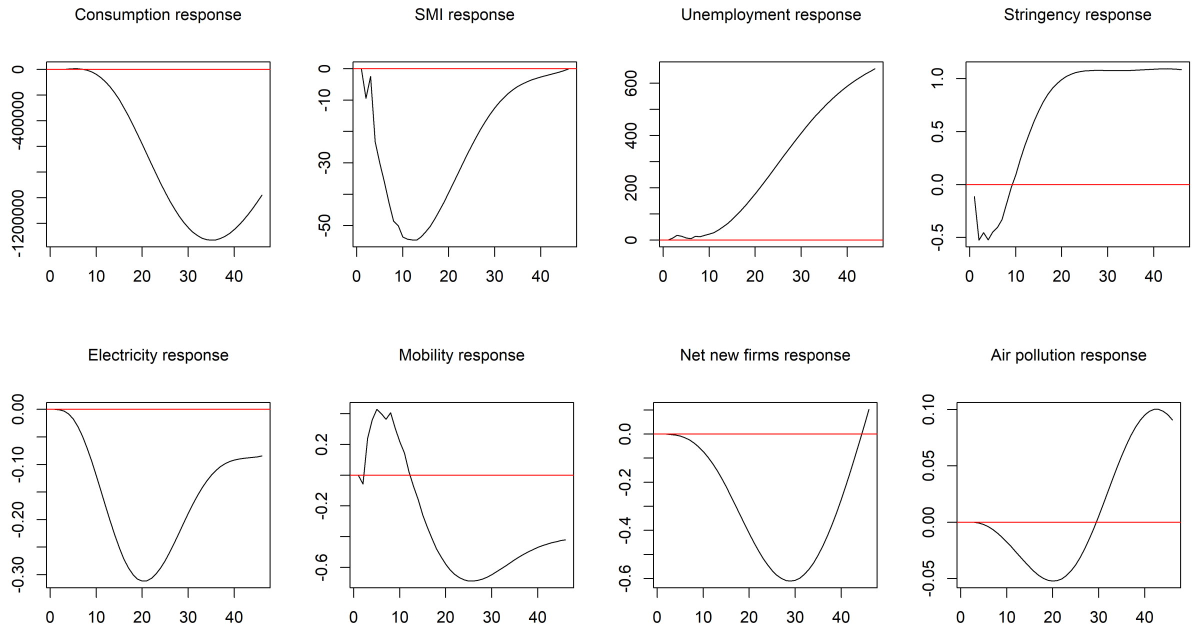


Figure A8: Impulse responses of a shock in stringency

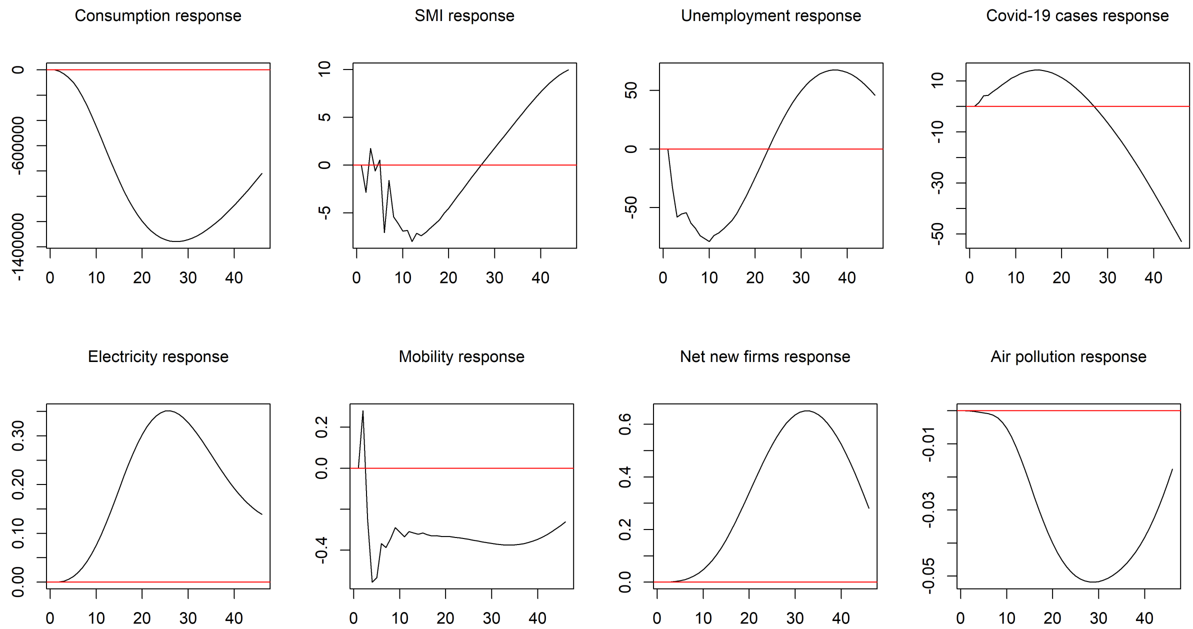


Figure A9: Empirical validation of VAR-X model: February-April 2021 forecasts

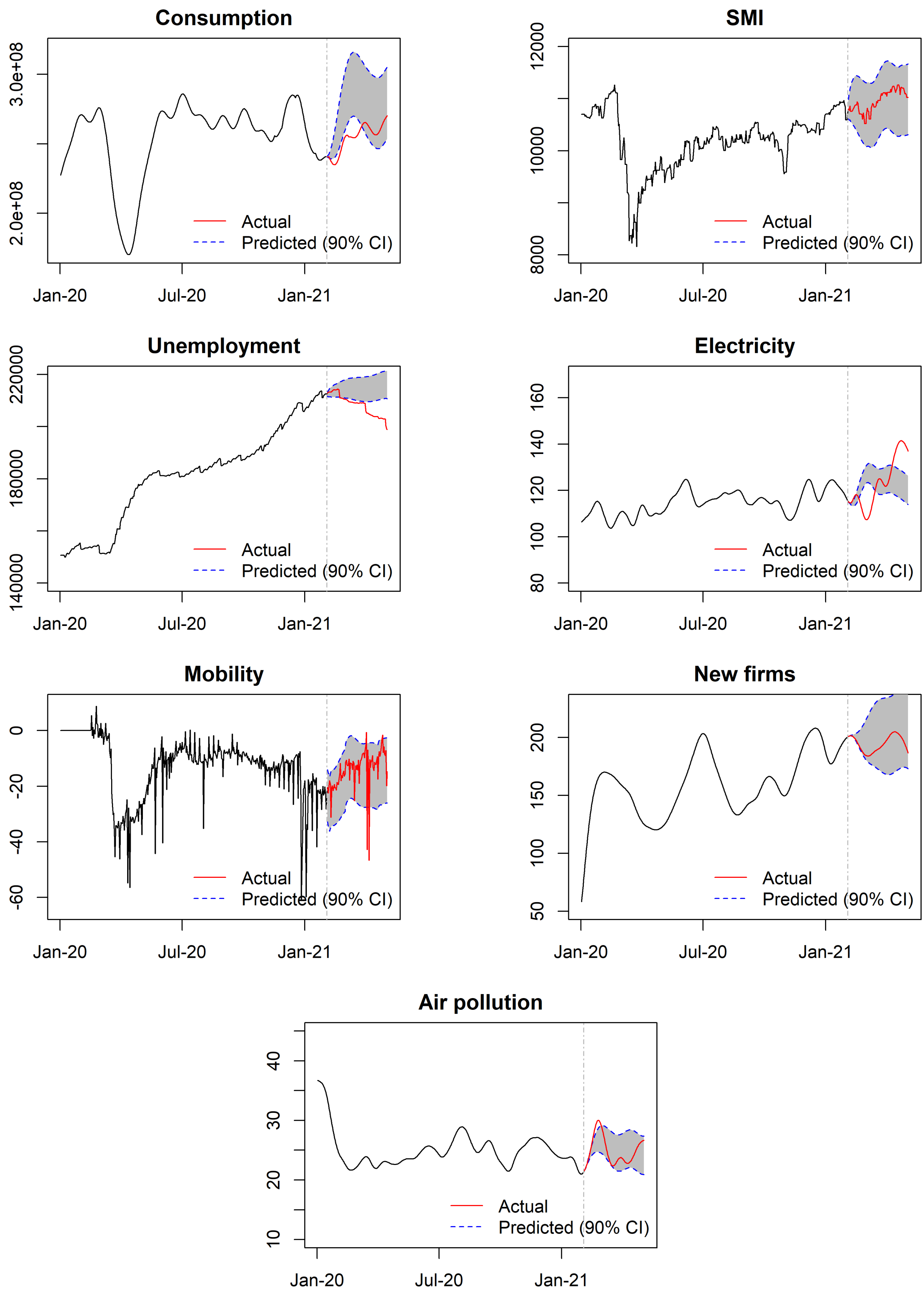


Figure A10: Empirical validation of LSTM model: testing set

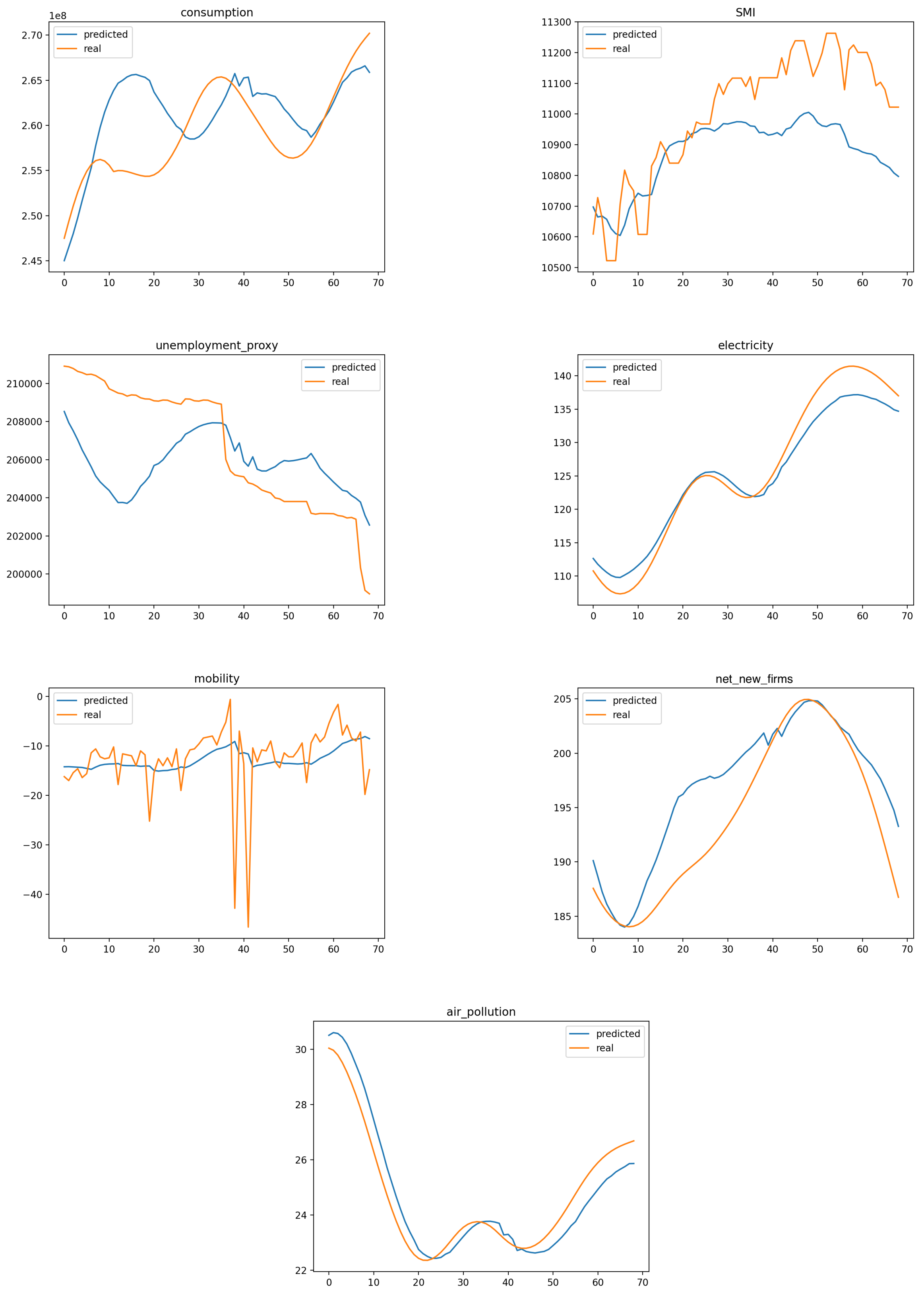


Figure A11: LSTM evaluation with MAE

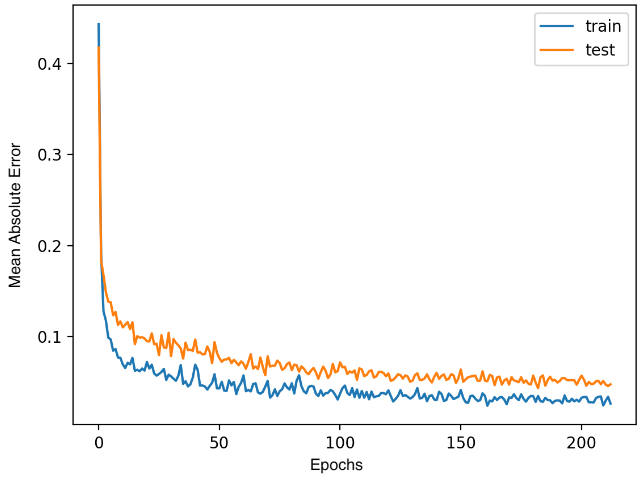


Figure A12: Empirical validation of ARIMAX model: January to May forecast