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A shot for the US economy

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\textbf{A B S T R A C T}

While previous literature examines the effects of increasing COVID-19 incidences and fatality rates on economic activity, the impact of vaccination roll-outs on public health and the economy is not yet well understood. We examine the effect of a vaccination shock in the United States on various pandemic and economic indicators. By employing a BVAR model to overcome the short data sample, we show that an increase in vaccinations is not only associated with declining incidences, reproduction and fatality rates, but also increases mobility, which dampens the effect on public health indicators in the medium term. With respect to the economy, a vaccination shock is associated with lower unemployment, higher GDP growth and also reduces uncertainty in financial markets.

1. Introduction

Starting in January 2020, the COVID-19 pandemic spread across the world leading to a globally unprecedented public health crisis. The resulting deep global recession had a severe negative impact on the United States’ (US) economy, with collapsing stock markets and strongly rising unemployment. Less than twelve months later, the first vaccine against COVID-19 was administered in the US outside of a clinical trial. While previous literature examines the effects of increasing incidences and fatality rates on economic activity, the impact of vaccination roll-outs on various economic indicators is not yet well understood, also because of limited data availability. In this context, the following letter aims to identify the effect of a positive vaccination shock in the US on the effective reproduction rate of COVID-19, its incidence, fatality, mobility, the S&P500 index and its volatility, as well as the most relevant economic indicators, i.e. unemployment and gross domestic product (GDP).

Following the global spread of the COVID-19 pandemic, the US faced a severe economic downturn leading to an unseen spike in initial unemployment claims and rising unemployment rates, which was mirrored by a severe drop in the S&P500 index and a significant increase in stock market volatility. Existing research so far has mostly focused on the initial effects of the pandemic on the economy and stock markets. In this context, Dreger and Gros (2021) find that a tightening of social distancing policies exerts a strong and immediate impact on initial unemployment claims, followed by a shortly delayed increase in unemployment rates. On the contrary, various health indicators – such as incidences or case fatalities – are found to be only marginally important for the development of the unemployment rate. In a similar vein, Kong and Prinz (2020) examine the impact of various shutdown policies on unemployment by using Google searches for claiming unemployment as a proxy. By exploiting the differential timing of the
introduction of the shutdown policies across states, the authors are able to quantify the share of overall growth in unemployment during the COVID-19 pandemic that can directly be attributed to shutdown measures. Other papers focus on modeling the rise and subsequent (projected) decline in US unemployment as a result of the pandemic (see, for instance, Larson and Sinclair, 2021; Şahin et al., 2020; Petrovsky-Nadeau and Valletta, 2020) and highlight the importance of distinguishing between temporary and permanent unemployment in this specific pandemic situation (Gallant et al., 2020). Baker et al. (2020b) emphasize the important role of uncertainty induced by the pandemic. The authors use three different uncertainty indicators to estimate the effects of the pandemic on real GDP, with half of the projected output contraction reflecting the negative effect of pandemic-related uncertainty.

With respect to the financial sector, previous studies point to a strong reaction of stock markets to the start of the pandemic (Baker et al., 2020a; Zhang et al., 2020), with a detrimental effect of the pandemic on financial performance and financial stability indicators (Elnahass et al., 2021). Earlier literature also suggests a positive link between new infections or fatality rates and stock market volatility (Albulescu, 2021; Haroon and Rizvi, 2020), with significant contagion effects across countries both for stock market returns and volatility (Okorie and Lin, 2021). Thereby, the findings by Zaremba et al. (2020) suggest that containment measures by governments play the main role in increasing volatility, rather than pandemic indicators such as incidences or fatality rates. On the contrary, most studies find no direct effect on stock returns (see, for instance, Onali, 2020). Furthermore, a rise in Google search queries for COVID-19 has both a direct and indirect effect on implied stock volatility, with the latter being enforced by stock returns reflecting increased risk aversion under pandemic conditions (Papadamou et al., 2020).

While there is abundant literature on the effects of the pandemic on economic activity and stock markets in the early phase of the crisis, previous work lacks analysis on the effect of key recovery factors, such as vaccines, on stock markets, unemployment and GDP. Gros and Gros (2021), for instance, look at the relationship between vaccination progress and infection numbers in light of new virus mutations, but do not link the results to economic indicators. Turner et al. (2021) go one step further by comparing the effects of vaccinations to the impact of various containment measures, concluding that quick vaccination would limit the economic costs related to the pandemic. With respect to financial markets, Yu et al. (2021) find that the correlation between pandemic-related anxiety and stock markets becomes weaker after the announcement of the development of COVID-19 vaccines.

Against this background, our paper significantly contributes to the existing literature on the COVID-19 pandemic as it moves past assessing the impact of the pandemic, but instead focuses on the currently ongoing economic recovery. By applying Bayesian Vector Autoregression (BVAR) techniques, we are able to overcome the issue of the relatively short time series and consider the main pandemic indicators, including vaccinations, and both economic and financial market variables in a simple model. We show that a positive vaccination shock is associated with increasing stock returns as well as declining levels of stock market volatility. The impact on economic activity (as measured by unemployment and GDP) is positive and both statistically and economically significant.

The paper is structured as follows. Section two describes the data set and the empirical strategy. Section three presents our main results, while section four draws some conclusions.

2. Data & empirical methods

We use a daily data set for the US running from 20 December 2020 to 1 June 2021, based on Krispin (2021) and Arroyo-Marioli et al. (2021). Our model includes the (logarithm) of the effective reproduction rate, the incidence, the number of deaths associated with COVID-19 per 100,000 inhabitants (death/100k) and the number of vaccines administered (vaccines). Additionally, we measure lockdowns by considering Google COVID mobility data (Arias et al., 2021). To capture how these COVID-19 related series dynamically interact with macroeconomic and financial quantities, we include a daily proxy of unemployment (obtained from Google trends, henceforth labeled Google Unemployment Hits3) as well as stock market data relating to the S&P500 and VIX closing. Since vaccinations do not have an immediate effect on health related quantities, all health and mobility variables are lagged forward by 21 days, i.e. vaccinations affect health quantities with a lag of at least 21 days in our empirical model.

To capture dynamic interactions between our set of variables, we propose a simple VAR model. Let \( Y_t \), denote a \( M = 3 \)-dimensional vector which stores the economic quantities and \( H_t \) is a vector which contains the \( N = 4 \) health-related time series. Finally, we let \( \epsilon_t \), denote the vaccinations in time \( t \). Our vector of endogenous variables is given by \( Y_t = (H'_{t-1}, \epsilon_t, Y'_{t-1})' \). We assume that \( Y_t \) evolves according to a VAR model:

\[
Y_t = A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + \epsilon_t,
\]  

with \( A_j \) being coefficient matrices associated with the \( j \)th lag of \( Y_t \) and \( \epsilon_t \) is a Gaussian shock with error variance \( \Sigma \).

The variables in \( Y_t \) are characterized by different persistence properties. From a frequentist perspective, this requires appropriate transformation of the time series under consideration and calls for either a model in (log) differences (if no cointegration between the elements in \( Y_t \) is present) or directly estimating a vector error correction model. Using a Bayesian stance to inference, Sims et al. (1990) suggest that transforming models to stationary form (either through differencing or explicitly taking into account cointegration) in cases when the data appears to be cointegrated (which might arise in our dataset) is not necessary. We follow their recommendation by remaining agnostic on this issue but specify a prior which is capable of detecting, in a data-based fashion,
whether the data should be differenced (capturing the case of no cointegration) or whether cointegration is present in the data and the time series evolve around a stochastic trend.

Our prior builds upon the well-known class of natural conjugate Minnesota priors. The classical Minnesota prior shrinks the model towards a standardized prior model which, in our case, is a random walk and captures the notion that higher lag orders are less relevant for explaining $Y_t$. Following Sims and Zha (1998) and Giannone et al. (2015), we refine the prior to be consistent with cointegration by adding a so-called dummy initial observation prior which, in the limit (i.e. the prior being imposed dogmatically) implies that the variables are either at their unconditional mean or the system features an unknown number of unit roots without drift. The second prior we consider is the sum-of-coefficients prior. This specification allows for assessing whether the variables should enter the model in first differences (and thus ruling out long-run relations) or in log-levels.

This implies that we combine three priors (in combination with an inverted Wishart prior on $\Sigma$) and multiply them with the likelihood of the model. This yields the posterior distribution which is available in closed form (conditional on a low dimensional set of hyperparameters). We follow Giannone et al. (2015) and estimate the hyperparameters alongside the remaining model coefficients using a Markov chain Monte Carlo simulation algorithm. This is carried out using the BVAR package in R (Kuschnig and Vashold, 2019). Several papers (e.g., Koop, 2013; Carriero et al., 2015) show that this prior works well in forecasting applications.

The coefficients in the VAR are typically of little relevance for the researcher. In the vast majority of applications, interest centers on non-linear functions of the parameters such as impulse responses, historical and forecast error variance decompositions or forecast distributions. In this paper, our focus will be on impulse responses. To compute impulse response functions, we identify the model using short-run restrictions. Given the ordering in $Y_t$, we compute the Cholesky decomposition of $\Sigma$ and use this to back out the structural representation of the model. The ordering in $Y_t$ implies that daily economic variables are allowed to react immediately to vaccine shocks, while health quantities react with a time lag of $r = 21$ periods (i.e. days).

Since we only include a proxy of unemployment, we map the responses of this proxy back to actual unemployment and output growth. To this end, we estimate two bi-variate regressions over the period 2004 : Q1 to 2021 : Q2 between Google queries and the growth rate of US GDP and the US unemployment rate, respectively. The corresponding slope coefficients are then used to obtain responses of GDP growth and the unemployment rate.

3. Results

Our findings suggest that a positive one standard deviation shock to administered vaccines in the US leads to a significant decrease in the reproduction rate, the incidence as well as the number of deaths associated with COVID-19. Naturally, with a positive shock to the number of people vaccinated, we also observe an increase in individuals’ mobility, leading to a weakening effect of vaccinations on the above mentioned public health indicators in the medium term.

The effect on economic outcomes is sizeable and intuitively appealing. We find that the S&P 500 increases, while stock market volatility decreases. This suggests that an unexpected increase in administered vaccines has a benign effect on financial markets by reducing uncertainty and the likelihood of further lockdown measures. With respect to unemployment queries, we find that a positive vaccination shock significantly reduces Google search queries for the term “unemployment”, which is directly related to important economic indicators such as unemployment and GDP.

Assessing the Impulse Response Functions (IRFs) displayed in Fig. 1, we observe that a positive one standard deviation shock to administered vaccines in the US leads to a decrease in the COVID-19 reproduction rate, with the effect peaking after approximately 25 days. Similarly, we observe a decrease in the incidence rate and the rate of death per 100'000 people, with the effect slightly deferred by a few days relative to the reproduction rate. Yet, the impact on the pandemic indicators is counteracted by a simultaneous increase in individuals’ mobility, peaking approximately 30 days after the vaccination shock hit the system. This reaction naturally dampens the effect of additional vaccinations on the reproduction rate, incidences and case fatalities to some extent in the medium term. Our results are well in line with our expectations. With an increased number of people being vaccinated, the chance of an individual contracting COVID or passing away in association with COVID-19 related symptoms decreases.

Considering the IRFs of the economic variables, we observe that a positive vaccination shock exerts a pronounced and immediate impact on both the closing price of the S&P500 and expected stock market volatility, as measured by the VIX. Since the shock can be interpreted as an unexpected increase in vaccinations, the positive reaction in stock markets is well in line with our expectations. One possible explanation could be that the increased rate of vaccinations may reduce the uncertainty related to new waves of infections, with a negative effect on the VIX and a positive impact on stock market returns.

Additionally, we find that a positive vaccination shock decreases Google queries related to the term “unemployment”. Taking into account that an increased proportion of vaccinated people and hence lower incidence and reproduction rates, combined with higher mobility, are associated with a rise in demand for goods and services, it is not surprising to observe a decline in Google queries for the term “unemployment”.

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5 For the interested reader, we include a table showing the posterior mean and standard deviations of the coefficients in the empirical appendix. While many of the (reduced-form) coefficients are not statistically significant, the standard VAR analysis focuses on functions of the parameters, such as impulse responses (see also Stock and Watson, 2001). As shown in the following section, the dynamics in the VAR (i.e. the endogenous variables being driven by own and cross lags of the other variables) result in impulse response functions that are highly statistically significant.

6 Please note that all health (and mobility) indicators are lagged forward by 21 days in our model. For instance, the effect on the reproduction rate in panel (a) peaks after 4 days, i.e. the empirical model suggests the strongest effect after 21+4 days. Please also note that the economic variables are not forward lagged, i.e. the results in the IRF can be directly interpreted.
Fig. 1. Impulse response functions to a one standard deviation vaccination shock across variables. Notes: The figures show the impulse responses to a one standard deviation vaccination shock identified through zero restrictions. The black line denotes the median while the light gray lines refer to the 16th and 84th percentiles of the posterior distribution. All results are based on sampling 10,000 draws from the posterior of the IRFs.

Fig. 2. Impulse response functions to a one standard deviation vaccination shock: GDP growth and unemployment. Notes: The figures show the impulse responses to a one standard deviation vaccination shock identified through zero restrictions for output growth and the unemployment rate. These IRFs are obtained by scaling the responses of the Google Unemployment Hits by the coefficients of the simple OLS regression. The black line denotes the median while the light gray lines refer to the 16th and 84th percentiles of the posterior distribution. All results are based on sampling 10,000 draws from the posterior of the IRFs.
While we rely on Google search queries in our model, as real economic indicators are not available on a daily basis, it is important to interpret the effect on Google search activities in terms of more “standard” economic indicators. For this purpose, we run two simple bi-variate regressions linking Google search queries for the term “unemployment” with the actual unemployment rate on the one hand, and with GDP numbers on the other, taking into account time series data back to 2004.\textsuperscript{7} The regression results suggest that Google queries are strongly correlated with the unemployment rate, with a somewhat weaker, but still significant link to GDP growth. Subsequently, the corresponding regression coefficients allow us to map the reaction of unemployment hits to implied reactions of GDP growth and the unemployment rate. These IRFs are shown in Fig. 2. Panel (a) suggests that vaccination shocks have a positive effect on GDP growth which slowly dies out after around 20 days. Similarly, we observe that this vaccination shock decreases the unemployment rate. When interpreting the results in Fig. 2, it is important to notice that this purely relates to a simulation which implies a one-off vaccination shock. Against the background of the progress in the vaccination campaign, the US economy was confronted with repeated vaccination shocks, even on a monthly basis, i.e. the economic effect in monthly or quarterly terms would be a multiple of the effect shown in Fig. 2. While the point estimates of this simple simulation have to be taken with caution in light of the simple bivariate regressions, the mapping of our model results to more “standard” economic variables makes our empirical findings more tangible for policy-makers and shows the important role of vaccinations in the context of the ongoing economic recovery.

4. Conclusions

Following the global spread of the COVID-19 pandemic, the US economy was severely hit, with skyrocketing unemployment rates and sharply contracting stock markets. In our short paper, we model the effect of a vaccination shock on the recovery of the US economy. The model draws on BVAR methods to overcome the issue of the rather short time series since the start of the vaccination campaign in the US. We find that a one standard deviation shock to administered vaccines has a negative impact on the COVID-19 reproduction rate and its incidence, but also increases individuals’ mobility. Considering the economic variables in our model, we find evidence that a vaccination shock increases stock market returns and reduces stock volatility as measured by the VIX. Finally, we observe that a positive vaccination shock decreases the number of Google queries around the term “unemployment”, which is associated with a decrease in the US unemployment rate and an increase in US GDP. While most of the empirical results are probably not surprising, the contribution of this short paper may nevertheless be substantial in terms of policy implications.

Our study is not only the first empirical work to confirm the link between progress in vaccination programs and economic activity, but we are also able to quantify the corresponding effect with respect to important economic and financial variables. Against this background, the policy implications of our findings are rather straightforward, but of particular importance: The progress in vaccinations is not only essential to reach public health objectives and to lower case fatalities associated with COVID-19, but it is also indispensable to “restart” the economy in a sustainable manner. Against this background, our paper has the potential to serve as the backbone for further research focusing on countries with low vaccination rates, low access to vaccinations and mark the starting point for research assessing the effect of vaccinations on the economic recovery following the pandemic.

Apart from that, there are several fruitful avenues for further research. For instance, our model assumes that quantities such as the effective reproduction rate are known. However, these series are based on estimates and our model treats it as actual data. Hence, one could imagine setting up a model which enables estimating the reproduction rate alongside the other model parameters, taking into account all sources of uncertainty.\textsuperscript{8} In addition, our framework is linear and assumes that the effects of vaccination shocks are constant over time. This simplifying assumption can be relaxed by introducing non-linearities of unknown form (either through time-varying parameter or structural break models) or by assuming that the effects are driven by some signal variable (such as the lagged value of vaccinations). Finally, our focus is on US data only. In a subsequent step, one could estimate potential international spillover effects of vaccination shocks originating in the US.

Credit authorship contribution statement

\textbf{Martin Gächter:} Research idea, Study design, Methodology, Formal analysis, Writing – original draft, Writing – review & editing.
\textbf{Florian Huber:} Research idea, Study design, Methodology, Formal analysis, Writing – original draft, Writing – review & editing.
\textbf{Martin Meier:} Research idea, Study design, Methodology, Formal analysis, Writing – original draft, Writing – review & editing.

Appendix

See Tables 1–3.

\textsuperscript{7} The results of the two regressions are shown in Appendix.
\textsuperscript{8} For a similar non-linear state space approach, see Arias et al. (2021).
Table 1
Regression results: Google search data and its impact on unemployment and GDP growth.

| Dependent variable: | Unemployment Rate | GDP Growth Rate |
|---------------------|------------------|-----------------|
| (1)                 | (2)              |
| Google Unemployment Hits | 1.754***         | −0.479*         |
|                     | (0.159)          | (0.263)         |
| Google Unemployment Hits | 1.448***         | 1.557**         |
|                     | (0.445)          | (0.733)         |
| Constant            | 1.448***         | 1.557**         |
|                     | (0.445)          | (0.733)         |
| Observations        | 210              | 69              |
| R²                  | 0.368            | 0.047           |
| Adjusted R²         | 0.365            | 0.033           |
| Residual Std. error | 1.659 (df = 208) | 1.521 (df = 67) |
| F statistic         | 121.283*** (df = 1; 208) | 3.317* (df = 1; 67) |

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

Table 2
Posterior mean and standard deviations of the VAR coefficients.

| Y_{t-1} | Y_{t} | ROC | Incidence | death/100k | Mobility | Vaccines | Hits | S&P 500 | VIX |
|---------|-------|-----|-----------|------------|----------|----------|------|---------|-----|
|         |       |     |           |            |          |          |      |         |     |
| Constant | 0.20  | 26.21 | 0.10 | −9.30 | 0.53 | 0.42 | −0.03 | 0.41 |
| R0       | 0.17  | 25.95 | 0.49 | 7.43 | 1.96 | 1.85 | 0.06 | 0.37 |
| Incidence| −0.00 | 0.69 | −0.00 | −0.03 | −0.00 | −0.00 | −0.00 | 0.00 |
| death/100k| 0.00  | 0.09 | 0.00 | 0.02 | 0.02 | 0.01 | 0.00 | 0.00 |
| Mobility | −0.00 | −0.49 | −0.01 | 0.73 | −0.01 | −0.02 | 0.00 | −0.00 |
| Vaccines | 0.00  | 0.23 | 0.00 | 0.07 | 0.02 | 0.02 | 0.00 | 0.00 |
| Hits     | 0.00  | −0.36 | −0.01 | −0.17 | 0.23 | 0.27 | 0.00 | −0.01 |
| S&P 500  | 0.01  | 1.22 | 0.02 | 0.34 | 0.09 | 0.09 | 0.00 | 0.02 |
| VIX      | 0.01  | 2.18 | 0.04 | 0.60 | 0.17 | 0.16 | 0.01 | 0.03 |
|         | −0.01 | 3.35 | 0.08 | 0.08 | 0.09 | 0.43 | 0.01 | 0.84 |
|         | 0.02  | 3.85 | 0.07 | 1.05 | 0.28 | 0.28 | 0.01 | 0.06 |

Notes: The table shows the posterior mean of the VAR coefficients (in white rows) and the associated posterior standard deviations (in gray shaded rows). The rows refer to the different covariates while the columns refer to the different equations of the VAR.

Table 3
Summary statistics.

| Statistic          | N   | Mean  | St. Dev. | Min     | Pctl(25) | Pctl(75) | Max   |
|--------------------|-----|-------|----------|---------|----------|----------|-------|
| Effective reproduction rate | 112 | −0.078 | 0.120    | −0.342  | −0.167   | 0.043    | 0.122 |
| Incidence          | 112 | 35.340 | 22.327   | 2.501   | 18.397   | 56.266   | 90.379 |
| death/100k         | 112 | 0.633  | 0.375    | 0.063   | 0.276    | 0.971    | 1.370 |
| Mobility           | 112 | −19.824| 6.462    | −35.000 | −26.000  | −14.750  | −7.583 |
| S&P500             | 112 | 8.288  | 0.041    | 8.215   | 8.253    | 8.332    | 8.356 |
| VIX                | 112 | 3.044  | 0.165    | 2.788   | 2.912    | 3.140    | 3.617 |
| Google Unemployment Hits | 112 | −0.028 | 0.626    | −3.147  | −0.398   | 0.396    | 1.057 |
| Vaccines           | 112 | 18.115 | 1.386    | 13.278  | 17.410   | 19.251   | 19.577 |

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