Time-Varying Impact of Pandemics on Global Output Growth

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Abstract

This paper analyses the dynamic impact of uncertainty due to global pandemics (SARS, H5N1, H1N1, MERS, Ebola, and COVID-19) on global output growth for the quarterly period of 1996:Q1 to 2020:Q1, using a time-varying parameter structural vector autoregressive (TVP-SVAR) model. Besides the index based on the discussion about pandemics which appear in Economist Intelligence Unit (EIU) country reports, our model contains the growth rate of the United States (US), advanced economies excluding the US, and emerging market countries. We find that the negative effect of the coronavirus on the growth rate of output is unprecedented, with the emerging markets being the worst hit. We also find that since 2016, the comovement among the growth rates has increased significantly. Our results imply that policymakers would need to undertake massive expansionary policies, but it is also important to pursue well-coordinated policy decisions across the economic blocs.

Keywords: Pandemics-related uncertainty, output growth, TVP-SVAR
JEL Codes: C32, D80, E23, E32

1. Introduction

Theoretically, heightened economic uncertainty leads to the postponement of consumption and investing decisions by economic agents, and this "wait and see" approach results in lower aggregate demand, and hence a negative impact on output (see, for example, Bernanke (1993), Dixit and Pindyck (1994), and recently, Bloom (2009)). In this regard, the recent COVID-19 pandemic, that started as a localized shock in China, has triggered a massive spike in global uncertainty associated with every aspect of human life ranging from health to livelihood, extending the impact of this health crisis to the overall economy. Given the uncertainty this health crisis has created for economic fundamentals, the objective of our paper is to assess the role of uncertainty related to pandemics i.e., infectious diseases of various types the world has witnessed over the last two decades for example, severe acute respiratory syndrome (SARS), Avian or Bird Flu (H5N1), Swine Flu (H1N1), Middle East respiratory syndrome (MERS), Ebola, and of course the Coronavirus) on global output growth. It goes without saying, that this is clearly an issue of importance for not only policymakers for fiscal and monetary policy implementation, but also firms in their future planning decisions.

In this process, a necessary first step is to quantify the uncertainty related to infectious diseases in a way that it would act as suitable input into a statistical model for measuring the impact on output growth. In this regard, we use the recently developed aggregate index of discussion about pandemics which appear in Economist Intelligence Unit (EIU) country reports, as constructed by Ahir et al., (2018). This index is then fed into a time-varying parameter-structural vector autoregressive (TVP-SVAR) model to analyse the evolution of the impact of various recent pandemics on economic growth of the United States (US), advanced economies

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excluding the US, and emerging market countries over the quarterly period of 1996:Q1 to 2020:Q1.

It must be noted that quite a few recent academic studies, which deserve mentioning, have used static (VAR) models to analyse the contractionary impact of COVID-19 by translating information on financial market volatility and cost of deadly disasters on output growth of the US (Baker et al., 2020; Ludvigson et al., 2020; Salisu et al., 2020) and the overall world (Caggiano et al., forthcoming). Baker et al., (2020) indicated of the possibility of a year-on-year contraction in US real GDP of nearly 11% as of 2020:Q4 (and this value extending to a nearly 20 percent contraction with a 90 percent confidence interval). Ludvigson et al., (2020) study the dynamic responses of the US economy to a sequence of large shocks to show a cumulative loss in industrial production of 12.75% and in service sector employment of nearly 17% over a period of ten months. At the same time, Maliszewska et al., (2020) used a computable general equilibrium (CGE) model to simulate the size of the negative impact of the virus on output (and trade) growth of developing and industrialised countries as a shock involving underutilization of labour and capital, an increase in international trade costs, a drop in travel services, and a redirection of demand away from activities that require proximity between people. They showed that Gross Domestic Product (GDP) would fall by 2% below the benchmark for the world, 2.5% for developing countries, and 1.8% for industrial countries. Using a time series-based approach Caggiano et al., (forthcoming) found a peak (cumulative over one year) negative response of world output of 1.6% (14%), with the biggest decline quite close to the estimate of Maliszewska et al., (2020). Finally, Salisu et al., (2020) was more concerned about forecastability using a mixed frequency model, and showed that daily stock market volatility due to infections, can indeed be used to accurately predict the future path of monthly industrial production growth and quarterly real GDP growth of the US.

However, to the best of our knowledge, this is the first attempt to provide a full-fledged time-varying analysis of the impact of uncertainty due to various pandemics on real Gross Domestic Product (GDP) growth of the US, other advanced countries barring the US, and emerging economies. The remainder of the paper is organized as follows: Section 2 outlines the data and the econometric model, with Section 3 presenting the results, and Section 4 concluding the paper.

2. Data and Methodology

Our analysis involves four variables, the real GDP of the US, other advanced barring the US (Advanced) and emerging market (Emerging) economies, with the latter two treated as economic blocs, and a metric for pandemics-related global uncertainty. The real GDP data is obtained from the Global Economic Database maintained by the Federal Reserve Bank of Dallas, which is available for download from https://www.dallasfed.org/institute/dgei/gdp.aspx.[1] As far as the uncertainty related to global pandemics is concerned, we use the aggregate (global) index of discussion about pandemics as

[1] The reader is referred to Grossman et al., (2014) for further details. Data on 18 advanced (excluding the US, Japan, Germany, the United Kingdom (UK), France, Italy, Spain, Canada, South Korea, Australia, Taiwan, The Netherlands, Belgium, Sweden, Austria, Switzerland, Greece, Portugal, and Czech Republic, in order of Purchasing Power Parity (PPP)-adjusted GDP shares in 2005) and 21 emerging (China, India, Russia, Brazil, Mexico, Turkey, Indonesia, Poland, Thailand, Argentina, South Africa, Colombia, Malaysia, Venezuela, Philippines, Nigeria, Chile, Peru, Hungary, Bulgaria, and Costa Rica, in order of PPP-adjusted GDP shares in 2005) countries are used to compile the aggregates for these blocs, by using trade weights with the US in weighting the country-level data.

developed by Ahir et al., (2018). The index is constructed by counting the number of times a word related to pandemics is mentioned in the EIU country reports. Specifically, the index is the percent of the words related to pandemic episodes in EIU country reports, multiplied by 1,000. A higher number means higher discussions about pandemics and vice versa. The world Discussion about Pandemics related Uncertainty Index (DPI) is a simple average of the 143 countries for which data is available on the issue of pandemics, with the data available publicly at https://worlduncertaintyindex.com. Note that, these countries account for 99 percent of world GDP. We work with the natural logarithmic form of DPUI, while, we use year on year growth rate of the real GDP. The sample period of our quarterly dataset is from 1996:Q1 to 2020:Q1. The data has been plotted in Figure A1 in the Appendix of the paper.

In order to examine the time-varying relationship between the pandemic-related uncertainty and the growth rates, we estimate the TVP-SVAR model of Akram and Mumtaz (2019) using the Bayesian approach.[2]

$$\begin{bmatrix} Y_{1,t} \\ Y_{2,t} \end{bmatrix} = C_t + \begin{bmatrix} B_{1,t}(L) & 0 \\ B_{2,t}(L) & B_{3,t}(L) \end{bmatrix} \begin{bmatrix} Y_{1,t} \\ Y_{2,t} \end{bmatrix} + \varepsilon_t \tag{1}$$

where $Y_{1,t}$ is an exogenous variable capturing the pandemic-related uncertainty index (i.e., DPI); $Y_{2,t}$ is a vector of three endogenous variables measuring real GDP growth rates of the US, developed economies (excluding the US) and emerging economies, respectively, ordered assuming a Cholesky decomposition. This ordering is understandable as it allows us to capture the fact that US growth rate impacts growth rates of the other two blocs within the same quarter, while advanced economies and emerging countries have a delayed impact on the growth rate of the US. In addition, just like the US, advanced economies too are assumed to contemporaneously impact emerging markets, but the feedback is delayed by a quarter. In other words, the variables are included in the model in decreasing order of exogeneity, with DPI being treated, understandably, as completely exogenous, which would not be possible if we used a recursive ordering for all the four variables. $B_{i,t}(L)$ denotes a lag polynomial, with L representing the length of lags.[3] C_t is a vector of time-varying intercepts. The covariance matrix of the innovations ε_t is defined as:

$$Var\ (\varepsilon_t) = \Omega_t = A_t^{-1}\Sigma_t(A_t^{-1})' \tag{2}$$

where time-varying A_t is the lower triangular matrix with ones on the diagonal. Σ_t is defined as diag($h_{1,t}, h_{2,t}, \ldots h_{i,t}$), while $h_{i,t}$ follows a geometric random walk process as follows:

$$Ln(h_{i,t}) = Ln(h_{i,t-1}) + \eta_t \tag{3}$$

Let a_t be the vector of non-zero and non-one elements of the matrix A_t (stacked by rows) and B_t be the vector that stacked all the time-varying coefficients on the right-hand side of equation (1). Both a_t and B_t are assumed to evolve as driftless random walks:

$$a_t = a_{t-1} + \xi_t \tag{4}$$

$$B_t = B_{t-1} + v_t \tag{5}$$

All innovations in the model are assumed to be jointly normally distributed (i.e., $V = [\varepsilon_t', \eta_t', \xi_t', v_t'], V \sim N(0, H)$, with the following assumptions on the covariance matrix H:

$$H = Var\left(\begin{bmatrix} \varepsilon_t \\ \eta_t \\ \xi_t \\ v_t \end{bmatrix}\right) = \begin{bmatrix} \Omega_t & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & G \end{bmatrix} \tag{6}$$

[2] In particular, a Gibbs sampling algorithm is used to approximate the posterior distribution. The number of replications is 10000 and the size of burn-in is 1000.

[3] Akram and Mumtaz (2019) set L to 2 following the parsimony rule.

where Ω_t is an identity matrix; Q, S, and G are positive definite matrices.

The dynamic correlation measuring the time-varying co-movement between two variables (i.e., variables i and j) at time t is defined as follows:

$$\rho_{ij,t} = \frac{\hat{c}_{i,j}(w)}{\sqrt{\hat{f}_t^{ii}(w)\hat{f}_t^{jj}(w)}} \tag{7}$$

where $\hat{c}_{i,j}(w)$ is the cospectrum between the two variables at frequency w. $\hat{f}_t^{ii}(w)$ and $\hat{f}_t^{jj}(w)$ are the model implied spectral density matrices of variables i and j, and can be calculated at each point in time as: $\hat{f}_t(w) = (I - F_t e^{-iw})^{-1} \frac{\Omega_t}{2\pi} [(I - F_t e^{-iw})^{-1}]'$. The dynamic correlation has a range from -1 to 1. It is equal to 1 when variables i and j are perfectly synchronised at a given frequency.

3. Empirical Results

In this section, we use the TVP-SVAR model to study possible changes in time-varying correlations between the variables in the system, with a special focus on the co-movements between the DPI and output growth rates of the US, developed economies (excluding the US) and emerging economies.

Figure 1. Dynamic Correlations

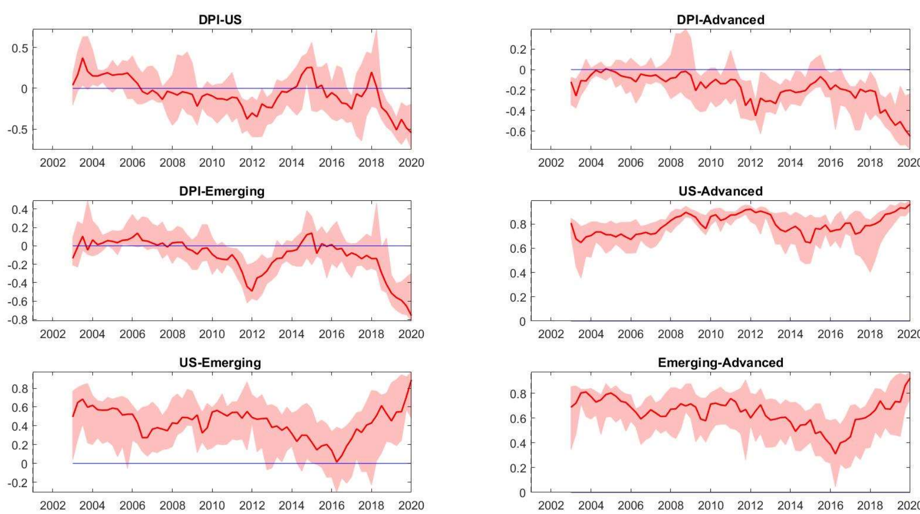

Figure 1 shows the estimated dynamic correlations between variables at the long-run frequency. The red shaded areas represent one standard deviation error bands. Note that, we use the first 26 observations as a training sample to initialise the estimation algorithm so that the starting point of our time-varying analysis corresponds to the outbreak of SARS.[4] This pre-sample and the two lags used in estimation imply that the effective sample for estimation results starts from 2003:Q1 to 2020:Q1, which covers the period including all recent global major infectious disease outbreaks, such as the SARS in 2003, Avian flu towards the end of 2003, Swine flu in 2009-2010, MERS coronavirus (MERS-CoV) in 2012-present, Bird flu in 2013, Ebola virus disease (EVD) in 2014-2016, and finally, the Coronavirus disease (COVID-19) in 2019-present.

[4] Akram and Mumtaz (2019) use initial 50 observations as a training sample, however they suggest the results are not sensitive to the length of this pre-sample used for calibrations.

We find that the dynamic correlations between economic growth activities and pandemics-related uncertainty across the US, other developed economies, and emerging countries are negative in general. Note, a negative correlation indicates that higher pandemics-related uncertainty can be associated with lower economic growth rates. We observe two sharp dips in correlations between DPI and GDP growth rates resulting from the outbreaks of MERS-CoV (in 2012-present) and the recent COVID-19 (as well as mildly from the Bird Flu in 2013, but which could be the persistent impact of MERS-CoV), highlighting a closer relationship between higher uncertainty associated with these on-going diseases and lower real economic activities. This is clear evidence that GDP growth rates highly covary with uncertainty caused by pandemics, especially in the events of disease outbreaks that have not been brought under proper control, and there are no effective vaccines or treatments for the diseases. In contrast, during the periods of SARS and Avian flu in 2003, the Swine Flu in 2009-2010, and EVD in 2014-2016 when the disease outbreaks have been quickly contained, we only observe negative and statistically significant correlations between DPI and real economic activities in advanced economies (excluding the US), and the sizes of correlations are relatively small. Furthermore, our results show that the size of the dynamic correlations reaches its highest level during the period of COVID-19 in the estimation sample period, with strongest negative value observed for emerging market economies (-0.8), followed by other advanced countries (-0.6) and the US (-0.5). The comparatively higher negative impact on developing countries is in line with the findings of Maliszewska et al., (2020), and should not come as a surprise due to the virus first hit China in late 2019, which is the biggest emerging market economy. Hence, fast and dramatic actions from policymakers around the world are needed to address the negative macroeconomic impact of uncertainty caused by the coronavirus.

Our results also show that the dynamic correlations of economic growth among the US, other developed economies, and emerging economies are positive and statistically significant throughout most of the estimation sample period. It is noteworthy that the economic growth rates between the US and advanced economies are highly correlated, and the long-run dynamic correlations are around 0.8 over the whole estimation period. In addition, the time-variation in dynamic correlations is quite stable while the associated error bands are relatively narrow. We also observe a notable decline in the long-run dynamic correlations of economic growth between emerging countries and the US and other developed economies at the beginning of MERS-CoV in 2012, and a further fall during the period of EVD in 2014-2016, but have gradually increased over time since then. The increased correlation is most likely due to the trade wars the US has been involved with many advanced and emerging markets since the start of Donald J. Trump's presidential term. This implies that in the wake of this heightened comovement around the world, policy decisions to correct for the negative impact on growth due to COVID-19 needs to be undertaken in a coordinated manner across these countries.

4. Conclusion

In this paper, we use a TVP-SVAR model to analyse the impact of uncertainty associated recent pandemics namely, SARS, Avian or Bird Flu, Swine Flu, MERS, Ebola, and of course the COVID-19 on output growth of the US, advanced economies (excluding the US), and emerging countries over the quarterly period of 1996:Q1 to 2020:Q1. To quantify the impact of pandemics-related uncertainty, we use the recently developed aggregate index of discussion about pandemics which appear in EIU country reports. We find that the negative effect of the coronavirus on the growth rate of output of the US, other advanced and emerging economies is unprecedented, with the only comparable, but way smaller, deterioration of output growth under MERS. Moreover, among these three output growth series considered, the emerging markets are the worst hit in the wake of the COVID-19, which is not surprising given the massive slowdown in China, where the virus was first reported. We also find that since 2016, the comovement among the growth rates of the US, other advanced and emerging countries have increased significantly. Our results have the obvious policy implication for policymakers around the world, and in particular emerging market economies, for undertaking massive expansionary policies (which governments are already implementing) to counteract the negative influence of the coronavirus on the real economy. But given the recently heightened connectedness among the US, other advanced and emerging countries, it is important for policy authorities to pursue well-coordinated policy decisions. In other words, while domestic policy changes will be important, there must be a concerted effort to ensure that the policies around the world are aligned in terms of their objectives to pull the global economy out of the deepest possible recession it currently finds itself in since the "Great Depression", with even the "Great Recession" looking pale in comparison.

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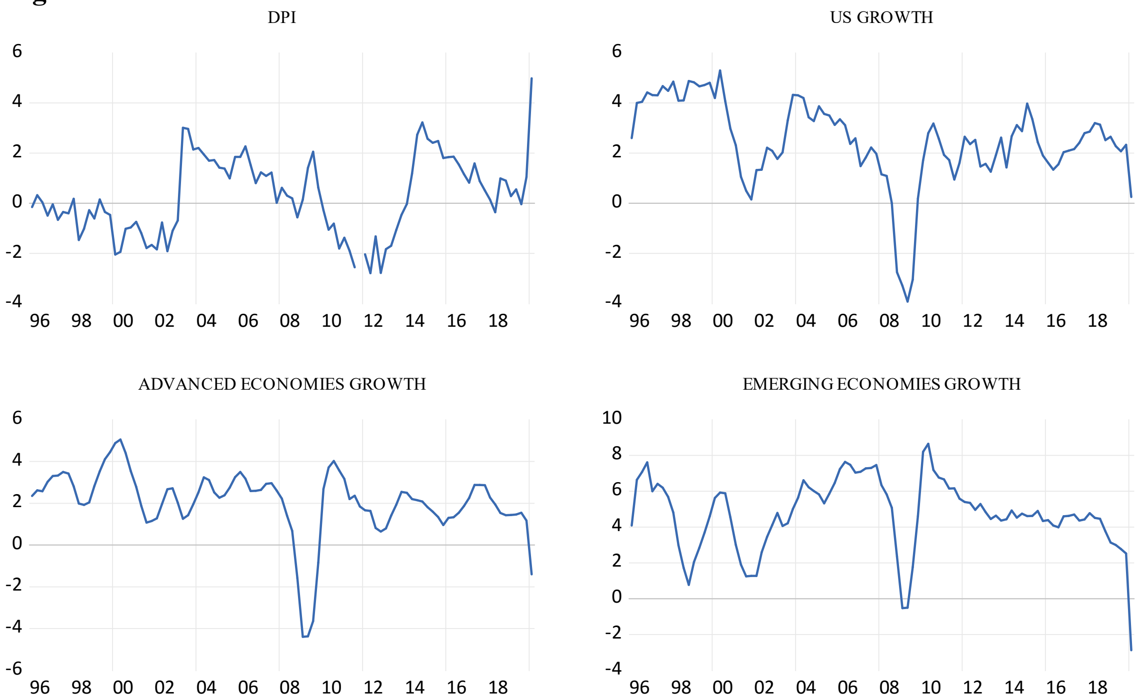
APPENDIX:

Figure A1. Data Plots



Note: DPI is the natural logarithmic values of the Discussion about Pandemics related Uncertainty Index, while the rest are year-on-year growth rates of real GDP of the US, other advanced economies excluding the US and emerging market countries.