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Working Paper

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DIW Discussion Papers, No. 1861

Provided in Cooperation with:

German Institute for Economic Research (DIW Berlin)

Suggested Citation: Kholodilin, Konstantin A.; Rieth, Malte (2020) : Viral shocks to the world economy, DIW Discussion Papers, No. 1861, Deutsches Institut für Wirtschaftsforschung (DIW), Berlin

This Version is available at:

<https://hdl.handle.net/10419/218982>

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1861

Discussion Papers

Deutsches Institut für Wirtschaftsforschung

2020

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IMPRESSUM

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<http://www.diw.de>

ISSN electronic edition 1619-4535

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Viral shocks to the world economy

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April 7, 2020

Abstract

We construct a news-based viral disease index and study the dynamic impact of epidemics on the world economy, using structural vector autoregressions. Epidemic shocks have persistently negative effects, both directly and indirectly, on affected countries and on world output. The shocks lead to a significant fall in global trade, employment, and consumer prices for three quarters, and the losses are permanent. In contrast, retail sales increase. Country studies suggest that the direct effects are four times larger than the indirect effects and that demand-side dominate supply-side contractions. Overall, the findings indicate that expansionary macroeconomic policy is an appropriate crisis response.

Keywords: Coronavirus, Covid 19, text analysis, world economy, structural vector autoregressions, epidemics.

JEL codes: C32, E32, F44, I18.

1. Introduction

The worldwide spreading of the coronavirus in 2020 is a large risk for human lives and for the world economy. It is likely to cause severe economic disruptions in both the production and the service sectors due to mortality and morbidity, quarantines, travel restrictions, as well as changes in investor and consumer behavior. Practitioners and policy makers face difficulties in understanding the pandemic and forecasting its economic fallout. These difficulties reflect a lack of empirical evidence on the global economic dynamics of epidemics.

In this paper, we construct a news-based viral disease index for the monthly frequency and study the effects of epidemic shocks on the world economy, using structural vector autoregressions. We analyze the text of over 500 million documents by counting words like ‘coronavirus’ or ‘swine flu’, following the approach of Baker et al. (2016) for measuring economic policy uncertainty. Our indices track closely the retrospective onset and ending of pandemics and epidemics as defined by the World Health Organization (WHO). They are more timely than official data on affected cases or deaths as there are no reporting lags, they are less subject to diverse reporting practices and quality around the globe, and they are available at the monthly frequency for between 30-100 years, depending on the media considered. Moreover, they implicitly weigh the epidemiological characteristics of different diseases, such as attack rates, case-fatality rates or mortality rates, and summarize the intensity of each disease in one metric, making the diseases comparable for an economic analysis. Finally, they reflect the public awareness of infectious diseases, which is crucial for private investment and consumption decisions as well as for the public policy responses to the outbreaks.

We use the viral disease indicators to trace out the global economic impact of epidemic shocks. First, we estimate and compare the worldwide output effects of two major virus outbreaks in the 21st century, the severe acute respiratory syndrome coronavirus (SARS-CoV) outbreak in East Asia in 2002/03 and the swine flu pandemic (influenza A/H1N1) of North America in 2009/10. The findings suggest that both shocks significantly reduce economic activity in the country of origin, in many other countries, and globally for two quarters or more. We contrast these findings with the dynamic impact of seasonal influenza shocks to assess a recent popular contention that Covid-19 might have just the same impact as a flu. The estimated effects of regular flu, while statistically significant, are only short-lived and much smaller.

Then, we construct an aggregate news-based index for influenza-like diseases and assess the international repercussions and transmission of epidemic shocks. World output falls immediately in response to such shocks and remains below trend for several quarters. It recovers only gradually and there is no evidence of overshooting, suggesting that epidemics entail permanent output losses. The shocks also lead to a sharp drop in the airport arrivals of

foreigners, while residents fly home. World trade declines significantly for about six months, mostly driven by lower imports and exports of advanced economies. World equity prices and employment also fall significantly and persistently. Despite a temporary increase in world retail sales, consumer prices decline globally. To gauge the direct and indirect effect of the shocks, we conduct two detailed country studies. We compare Hong Kong, which was most affected by SARS, and Germany, a small open economy that was only indirectly hit by epidemic shocks before Covid-19. Qualitatively, the responses of both economies to the shocks are similar, mirroring the dynamics of world aggregates. However, the economic damage for Hong Kong is about four times larger than for Germany.

Finally, we externally validate the evidence for the world economy with a historical analysis of epidemic shocks in the United States since 1920 using an alternative media sample and index. This time span adds the influenza outbreak of 1929, the Asian flu of 1957/58, and the Hong Kong flu of 1968/69 to the sample, among other smaller influenza outbreaks. The findings confirm the evidence for the world economy based on the more recent sample. Production drops significantly for about half a year in response to the adverse health shock and consumer prices fall significantly.

In microeconomics, there is a tradition of empirical work on the economic impact of viral diseases. The studies largely focus on individual outcomes or single countries. For example, Almond (2006) estimates the effect of the 1918 Spanish flu pandemic on long-term cohort outcomes in the U.S. Karlsson et al. (2014) assess the impact of Spanish flu on economic performance in Sweden. Adda (2016) investigates the interaction between viral diseases and economic activity in France. In macroeconomics, the literature on epidemics is thin and largely confined to model-based analyses. McKibbin et al. (2006), Dixon et al. (2010), and Verikios et al. (2016) use computable general equilibrium models for quarterly or annual frequencies. While these models facilitate a detailed analysis of different sectors and countries, they are originally designed to study comparative-statics. For a short-run dynamic analysis of epidemics in individual countries, Keogh-Brown et al. (2010) employ a semi-structural model for the U.K. and Eichenbaum et al. (2020) develop a dynamic-stochastic general equilibrium model for the U.S. An advantage of the model-based approaches over empirical work is that they allow for counterfactual and policy analyses. Limitations are that

they require behavioral and parametric assumptions to derive general equilibrium effects as well as calibrated shocks to mimic the intensity of epidemics, the shock sizes involving yet further assumptions. An empirical approach is adopted by Barro et al. (2020), who estimate the global macroeconomic impact of the Spanish flu using annual flu death rates.

To the best of our knowledge, this is the first empirical paper that constructs a news-based index for viral diseases and estimates the global dynamic effects of epidemic shocks. We provide three novel stylized facts. First, the economic damage of epidemics is larger and lasts longer than that of seasonal influenza. The cumulative output loss is about 20 times larger. This result suggests that the popular saying that the coronavirus disease Covid-19 is just another flu is a fallacy. Second, the economic disruptions in countries directly affected by an epidemic are about four times larger than the harm to countries indirectly affected via supply chains, trade, financial markets, or confidence. This finding underscores the long-run importance of having transparent multilateral surveillance and health cooperation systems, such as the WHO, that prevent the spreading of infectious diseases across countries. Third, the negative demand effects of an epidemic dominate the adverse supply-side impacts such that economic activity and prices drop simultaneously. This pattern indicates that there is no short-run trade-off for central banks between stabilizing prices and output when responding to epidemic shocks and that demand stimulus is the appropriate reaction. The same holds for fiscal policy.

2. Data and empirical model

2.1. News-based viral disease indices

We measure the occurrence and intensity of viral diseases through news-based indices. To construct them, we use automated text analysis of two online media archives. The first one is the database Genios.¹ It includes about 2200 high-quality German-speaking media between January 1990 and February 2020 with the total number of documents exceeding 500 million. The database contains a wide variety of media, including daily press, specialized weekly journals, and magazines for general public as well as publications devoted to specific

¹www.genios.de.

firms and persons. The second source is the archive of The New York Times (NYT), which spans the period 1851 to February 2020.² We search for the following five keywords that capture pandemics or internationally important epidemics during the sample period: ‘SARS,’ ‘swine flu’ (‘Schweinegrippe’ in German), ‘MERS,’ ‘Coronavirus,’ and ‘Influenza’ (‘Grippe’ in German). We count the monthly occurrences of these keywords.

Given that the number of texts collected in the databases changes over time, we normalize the plain counts. We divide them by the number of occurrences of the word ‘der’, which is the most widely used word in German language, in the case of Genios, and by the occurrences of the word ‘new’ for the NYT archive, since the word ‘the’ is not searchable in that database. Thus, the index for keyword i is computed as follows:

$$A_t^i = 1000 \times \frac{N_t^i}{N_t^{\text{word}}}$$

where N_t^i is the number of occurrences of the i -th keyword in month t and N_t^{word} is the number of occurrences of the normalizing word. The resulting value is a relative frequency of use of the keyword in the media. The normalization renders the values comparable over time and across diseases.

Our news-based indices of viral diseases have several advantages over clinical measures. The number of infected people is subject to drastically varying testing and reporting practices around the world. Statistics on laboratory-confirmed cases often do not reflect the real scale of an epidemic as many cases remain uncovered or are discovered only with substantial lag due to initially low testing capacities, or an outright failure of ill persons from being tested. Moreover, such data are available only annually for longer samples, or they are weekly/monthly but cover at most 10 years and are confined to the developed countries.³ These measurement problems due to testing procedures are somewhat less relevant for fatalities, which are easier to count, but there are still manifold reporting practices both over time and across countries. Furthermore, typically there is a substantial time lag between the

²<https://www.nytimes.com/search?>

³For example, the U.S. Center for Disease Control and Prevention publishes time series of reported cases only for seasonal diseases, such as flu.

outbreak of an epidemic and the associated deaths. On the other hand, Google Trends is available at high frequency. But data are only available since 2004. Finally, a main argument for using news-based indices is that they capture the public awareness of contagious diseases. This awareness, in turn, determines the response of the private sector and of public authorities to the outbreaks.

Figure 1 shows the news-based disease indicators. These reflect both the timing of the public awareness of epidemics (when the news about it start appearing in the media) and the intensity of media coverage (the height of the series). Shaded areas denote the retrospective dating of the epidemic or pandemic by the WHO. The indices track those definitions closely. Media coverage reflects the relevance of the disease from the standpoint of reporting media, summarizing all publicly available concurrent information about the likely severity of a disease. Online Appendix B provides a detailed overview of the influenza-like diseases in the sample.

The deadliest diseases contained in the sample are avian flu and MERS. The mortality rates are about 60% and 36%, respectively. SARS and Covid-19 have, at the time of writing, expected case-fatality rates of roughly 10% and <1%, respectively (Fauci et al., 2020). Swine and seasonal flus, on the other hand, are estimated to be deadly for 0.4% and 0.1% of the infected, respectively. The propagation speed also differs markedly across diseases. The estimated reproduction number, which measures the transmissibility defined as the expected number of infected cases generated by one infected case, for SARS, Covid-19, swine flu, seasonal influenza, avian flu, and MERS is 3, 2-3, 1-2, 1, <1, and <1, respectively.

2.2. Conceptual and empirical framework

Viral disease outbreaks can affect economic activity through a number of transmission channels. On the supply-side, there is direct absenteeism from work due to mortality, people who die, and morbidity, those who are infected and/ or are in quarantine. Quarantine is likely to reduce output despite new technologies facilitating online collaboration. There might also be prophylactic and indirect absenteeism because people avoid going to work where they might become infected, because they need to care for others who are ill, or because schools are shuttered. Public authorities might also close workplaces. A reduction of business trips

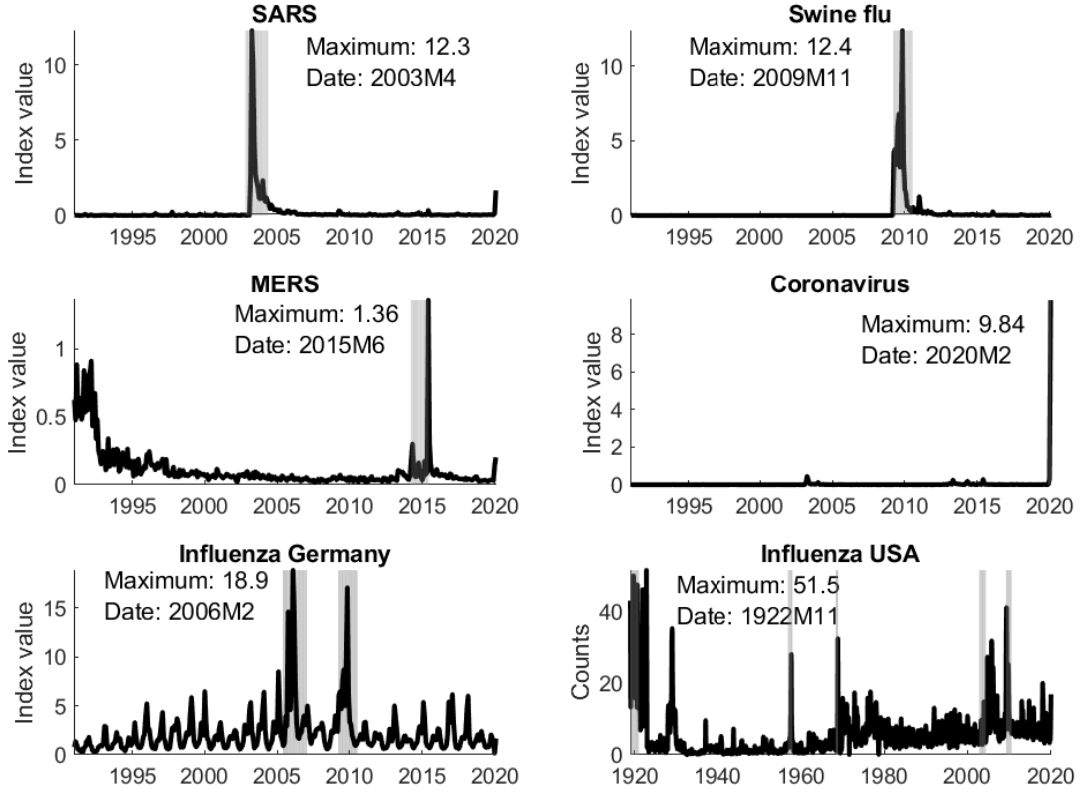


Figure 1: News-based disease indices. *Notes:* The figure shows news-based disease indicators based on text analysis of the Genios and NYT media archives. The frequency of keyword appearances are normalized. Each subplot also lists the maximum of each series and the corresponding months. The shaded areas indicate the retrospective definition of the WHO of start and ending dates of an epidemic or pandemic.

can lead to fewer contracts being concluded and, thus, to fewer orders. The closing of borders disrupts international value chains and, more generally, falls in production in certain regions lead to negative supply chain shocks worldwide, which result in decreased international trade and output.

On the demand-side, there are direct and indirect effects as well. Due to mortality and morbidity, consumption demand will decline immediately. The closing of workplaces, shops, and more general curfews lower actual consumption of products of the affected branches and sectors. Losses of social consumption (tourism, going to restaurants, attending public or social events) are likely to be permanent. Moreover, consumers and investors wait-and-see when faced with higher uncertainty, while purchases of durable goods and other investment decisions could be postponed. Financial investors are likely to reduce their exposure to risky

assets. Finally, a crucial determinant of the overall impact of an epidemic is the response of fiscal and monetary policy. Public authorities might aim at stabilizing demand and ensure that a lack of liquidity does not turn into insolvency.

To identify and trace out the economic impact of epidemic shocks, we use the following vector autoregression (VAR) for a monthly frequency:

$$y_t = c + \Pi(L)y_{t-1} + u_t.$$

The $k \times 1$ vector c includes constant terms, the matrix $\Pi(L)$ in lag polynomials captures the autoregressive part of the model, and the vector u_t contains k serially uncorrelated reduced form shocks, with $u_t \sim N(0, \Sigma)$.

We employ different specifications for the endogenous variables in y_t . In the baseline VAR, y_t includes a news-based disease index and the logarithm of industrial production in China, South Korea, Germany, Canada, the U.S., and the world, respectively. In extended specifications, y_t includes the baseline variables plus one additional variable, which changes across specifications, ranging from measures of inflation and employment to financial variables, fiscal variables, and others, both for the world and for single countries. Adding one additional variable at a time follows the approach of Beaudry and Portier (2014) and Gertler and Karadi (2015), which is particularly flexible and does not require a Bayesian perspective, a panel VAR, or factor structure to deal with the curse of dimensionality.

Depending on the variables considered in the specification, the usual lag length selection criteria typically suggest 1-3 lags. Throughout the following, we set the lag length to six to obtain reliable predictions for the annual horizon. The results are similar when changing the lag length (Figure A.7). The typical sample is 1991M1 to 2020M1 when using disease indicators based on the Genios archive and analyzing the world economy. The sample changes somewhat across specifications, depending on the variables included. When using the influenza index in a model for the U.S., the sample is 1923M1-2020M1. Although data on U.S. industrial production are available from 1919 onwards, we start the sample in 1923M1 to eliminate the loud noise in the influenza index at the very beginning of the sample (see Figure 1). Online Appendix A lists the variable definitions and construction. The macroeconomic

data are downloaded through Macrobond.

The innovations u_t are assumed to be linearly driven by an epidemic shock ϵ_t^e , which we aim to identify, and other structural shocks ϵ_t^* , which are of no interest for this paper:

$$u_t = b^e \epsilon_t^e + B^* \epsilon_t^*.$$

The $k \times 1$ vector b^e captures the impulse vector to an epidemic shock of size 1. To identify this shock, we rely on a Choleski decomposition of $\Sigma = BB'$, with $B = [b^e, B^*]$ a lower triangular matrix and where we have normalized the variances of the structural shocks to one, $\epsilon_t \sim N(0, I_k)$. Inference is based on a standard fixed-design residual wild bootstrap with 1000 replications.

We order the disease index first to identify economy-wide health shocks. The key identifying assumption is that the news-based index is contemporaneously exogenous to economic activity at the monthly frequency. The argument is that news about viral disease outbreaks in media reports are faster moving than production processes. Moreover, there is no consensus in health economics about the effect of economic activity on health status. While in the long-run there seems to be a positive relationship between GDP per capita and public health (Pritchett and Summers, 1996), others argue that mortality decreases during recessions because smoking and obesity declines (Ruhm, 2000) or because fewer people are traveling, thus reducing interpersonal contact and the spreading of infectious diseases (Adda, 2016). If the latter two arguments hold at the monthly frequency, our estimates would reflect a conservative estimate of the adverse impact of viral disease outbreaks on economic activity. In addition, in the sensitivity analysis, we show using a weekly version of our news-based disease index that reverse causality is unlikely to be a concern (Figure A.6). As we are only interested in the health shock, the ordering of the remaining variables is irrelevant for the analysis.

Another potential source of endogeneity is omitted variables. However, this issue is unlikely to meaningfully affect the results because the baseline model already contains world production. We confirm this notion in the sensitivity analysis, where we add a large number of additional variables to the model, one at a time, and the results hold (Figures A.2-A.4).

Finally, the news-based disease indices could measure the true latent health shocks with error. Therefore, we show in the robustness analysis that the results are insensitive to using the instrumental variable approach of Stock and Watson (2012) and Mertens and Ravn (2013) that accounts for various forms of errors-in-variables (Figure A.5).

3. The economic dynamics of epidemic shocks

The presentation of the core results proceeds in three steps. First, we analyze major epidemic shocks in the base sample individually and contrast them with seasonal influenza shocks (Section 3.1). Then, we construct an aggregate news-based disease index and estimate the average effects of epidemic shocks on the world economy and on individual countries (Section 3.2). Finally, we conduct a historical analysis based on the extended sample for the U.S. and cross-validate the results for the world economy (Section 3.3).

3.1. The impact of SARS, swine flu and seasonal influenza

We analyze the two major adverse health shocks in the base sample separately. According to the maximum index values, these are the SARS epidemic of 2002/03 and the swine flu pandemic of 2009/10 (see Figure 1). The estimated dynamic effects on production in main economies and on world output are shown in the first two columns of Figure 2. Each column is based on a separate model where we order either the SARS index or the swine flu index first, while keeping the other variables constant for comparison. Each shock is scaled such that the maximum index response corresponds to the peak value of the index in the sample. Thus, the responses measure the estimated economic damage of each viral disease outbreak.

Both shocks entail significant adverse effects on output in major economies and around the world as a whole. The SARS shock led to a significant drop of industrial production in China by a maximum of about 2%. Output recovers within two quarters. As the quality of Chinese data is unclear and because production data for Hong Kong, another epicenter of the epidemic, are not available, we also look at production in South Korea, which is a main trading partner of China. The impact of the SARS shock indeed appears stronger according to this metric. Economic activity falls by up to 10% one quarter after the shock. For Germany, the effects are of similar order of magnitude but milder, and they are again smaller for the

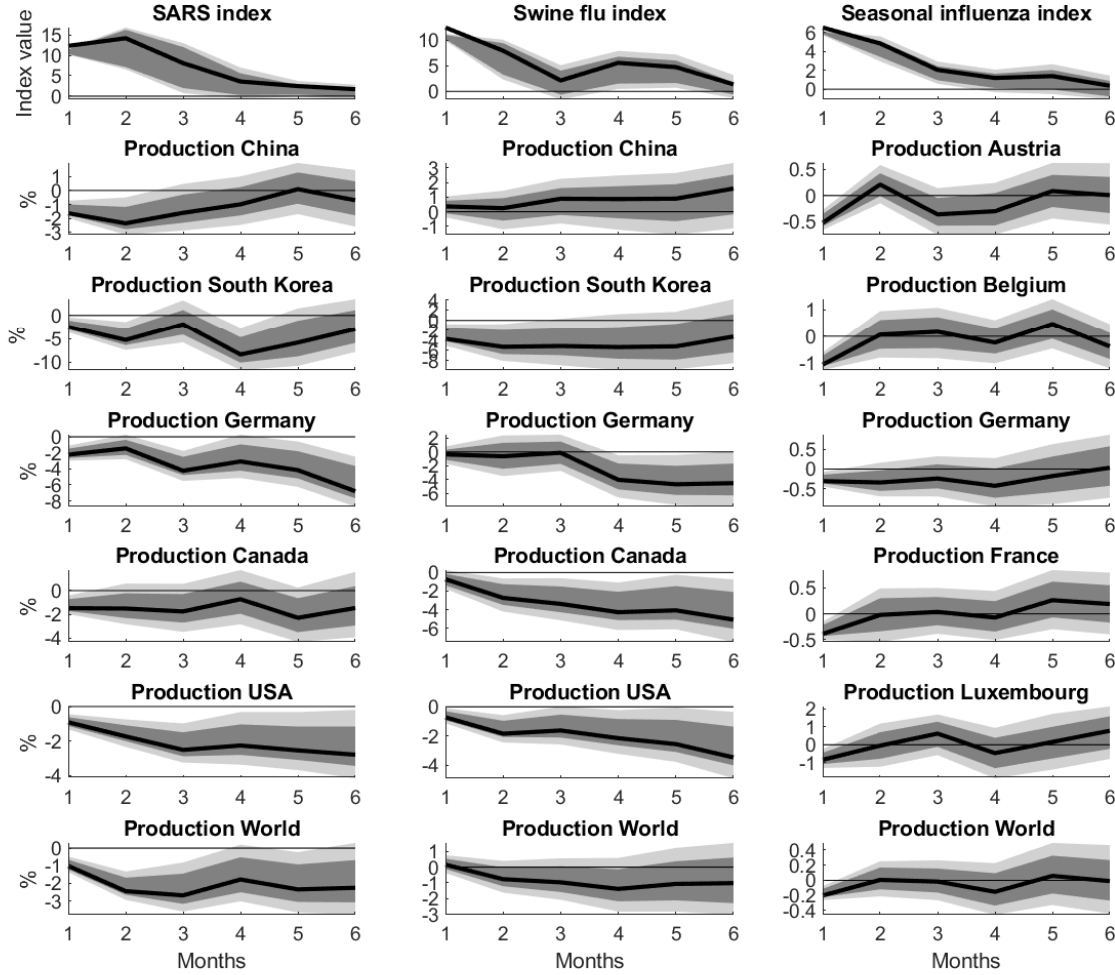


Figure 2: SARS, swine flu, and seasonal influenza shocks. *Notes:* The figure shows the dynamic impact of a SARS shock (column 1), a swine flu shock (column 2), and a seasonal influenza shock (column 3), obtained from three SVAR models, on production in single countries and globally over 6 months, along with 68% and 90% bootstrapped confidence bands.

U.S. Both countries rely heavily on inputs from East Asia into their value chains. The impact on Canada, the country with the third most cases beyond China (including Hong Kong) and Taiwan, is roughly -2% .

The estimated effect of the swine flu outbreak is by and large similar, with several notable exceptions. Output in China is not significantly affected, while production in Canada and the U.S. drops by more than in the case of SARS. This is plausible as both countries were, along with Mexico, the epicenter of this pandemic. The impact on production in South Korea is roughly similar to the effect of the SARS shock. For Germany, there is a delayed response,

consistent with the notion that the pandemic influenza shock affects Germany mainly through supply chain and trade disruptions.

In summary, world production declines by an average of 2% in the first year following an epidemic shock. The effect is persistent. There is no evidence of overshooting, suggesting that the output losses of health crises are permanent. This finding adds to the evidence presented by Cerra and Saxena (2008), who show that the output costs of financial and political crises, ranging between 4% and 12% over several years, are typically not recuperated.

The last column estimates the impact of seasonal influenza shocks on production. We use the flu index for Germany (see Figure 1), but winsorize the series at the 95th percentile to chop the spikes related to avian and swine flu and to concentrate on the typical influenza effects. There are nine non-epidemic peaks in the range between 4 and 6.5 in the series. We scale the shock to the largest of these values, that is, to 6.5, which corresponds to January 2000. As the disease index is constructed from German-speaking media, we include output of Austria, output of a set of neighboring countries of Austria and Germany, which have roughly similar climate and hence seasonal influenza courses, and world production into the model. The disease index is significantly positive for about one quarter, reflecting the typical duration of regular influenza. Production falls significantly in all countries individually and globally. In the single countries, the fall is between 0.5% and 1% and one-off. Production returns to its initial level already in the second month after the shock. Again, there is no overshooting.

For the world as a whole, the drop is 0.2%. This magnitude seems plausible as Europe accounts for a significant fraction of world production and since influenza cycles are correlated across the Northern hemisphere. Comparing the impact of the influenza shock to the average effect of the SARS and the swine flu shock shows that the latter two are much more damaging. Their cumulative output loss, that is, the area between the zero line and the point estimate, is on average 19 times larger for the first half year alone.

3.2. The global macroeconomic impact of epidemic shocks

We now study the international propagation of epidemic shocks. For this, we construct an aggregate epidemic index by summing over the individual indices for coronavirus (essen-

tially capturing SARS, MERS, and Covid-19 reports), SARS, and swine flu. We focus on these subindices as the underlying viral diseases are comparable in terms of mortality and propagation speed (see Section 2.1). The results for the baseline model are similar to (an average over) the first two columns of Figure 2 and, therefore, are relegated to Figure A.1. To analyze the international propagation of epidemic shocks, we use the baseline model with two modifications. First, we use the aggregate index ordered first. Second, we add one global variable at a time to the model.

Figure 3 shows the results. We scale the shock to the maximum of the aggregate index in the sample, which is 12.8 and corresponds to the height of the SARS epidemic in April 2003. The arrival of foreigners at airports drops upon impact by 5%. The decline is statistically significant for more than a quarter, but even after three quarters the fall is not fully redeemed. In contrast, airport arrivals of residents increase sharply one month after the shock as people fly home. Imports of emerging market economies drop by about 3%, possibly reflecting shuttered factories requiring fewer inputs, but the effect is short-lived. It is passed-through to exports of emerging market economies with a delay of about one quarter. Exports of advanced economies drop immediately and significantly, while their imports respond to the shock with some lag but then decline by roughly the same amount and similarly persistently. Overall, world trade falls significantly by about 2% for more than two quarters.

Following declines in production and trade, world employment falls by 0.5% two quarters after the shock. It recovers only gradually. Simultaneously, consumer prices decline significantly. They show similar dynamics as employment with a trough response of 0.4% after six months and slowly returning towards the level where they would have been without the shock after three quarters. On the other hand, world retail sales increase significantly for several months, probably reflecting panic buying. World equity prices, measured by the MSCI world index, fall upon impact and decline further as economic activity remains depressed. Finally, included into the model as a gauge of the global response of monetary policy, the Federal Reserve lowers the federal funds rate by about 50 basis points.

To obtain an impression of the direct and indirect effects of epidemic shocks, we now conduct two detailed country studies. First, we look at Hong Kong, which was most affected by SARS in terms of the clinical attack rate and mortality rate of the working population.

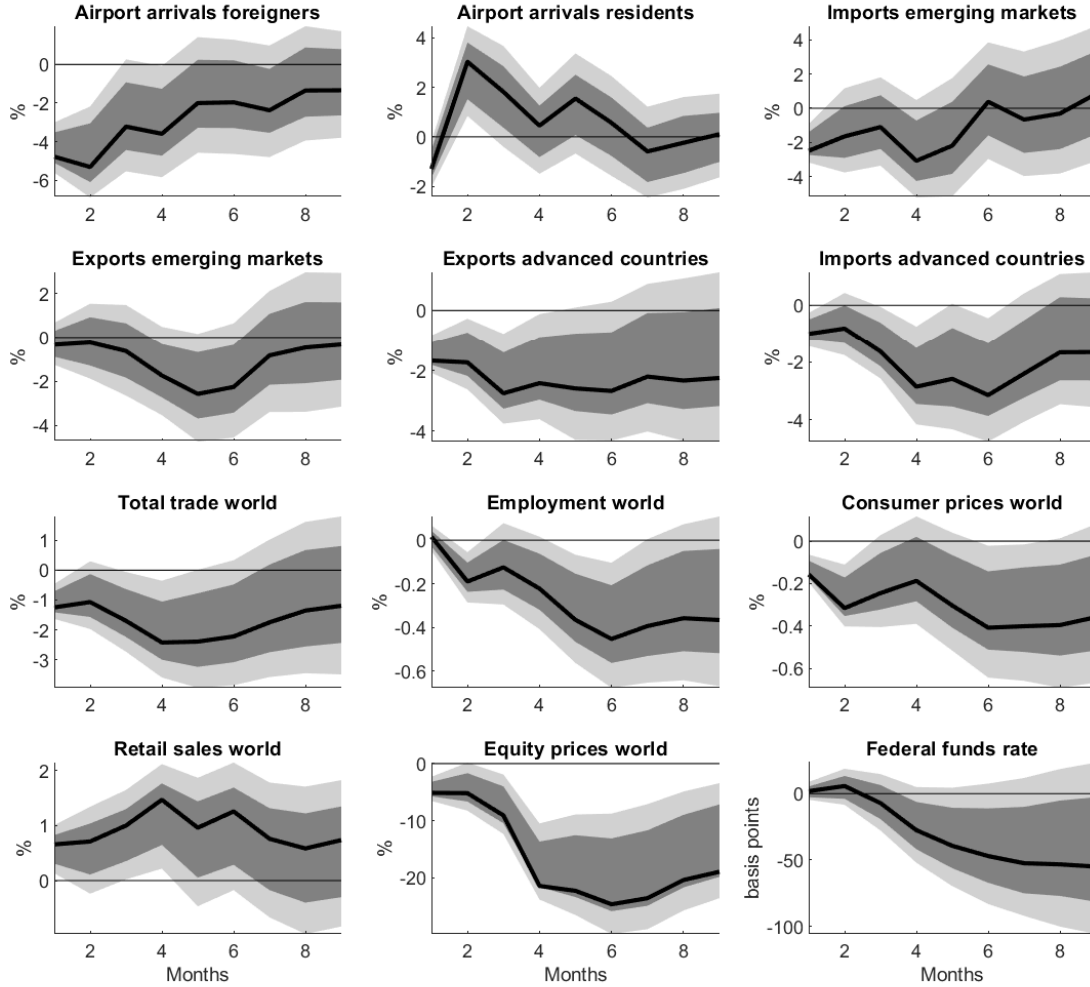
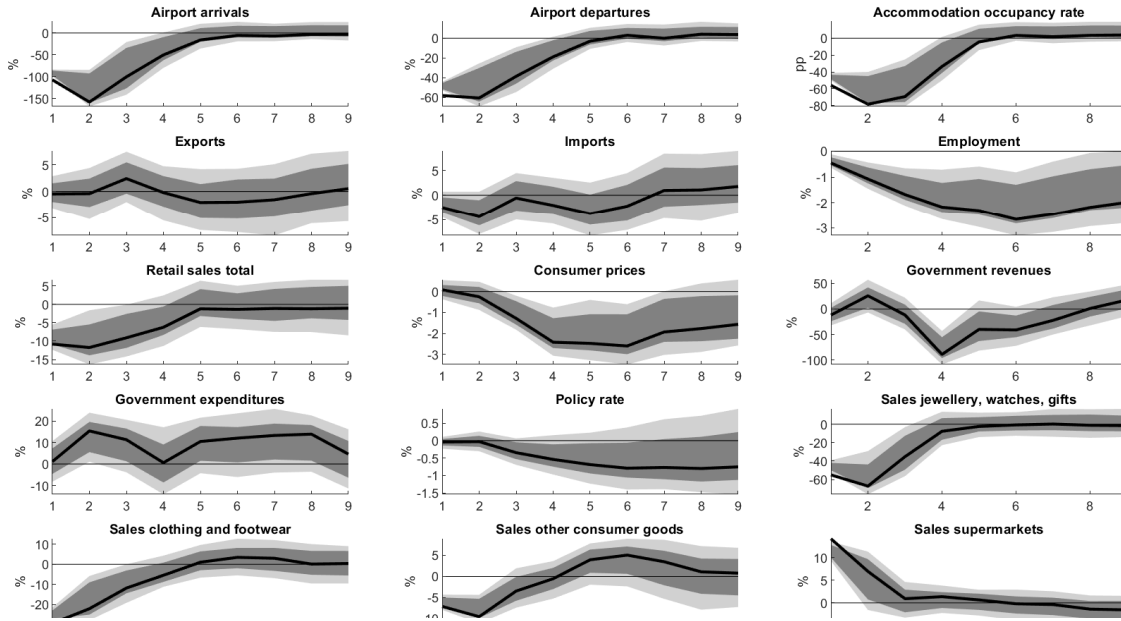


Figure 3: The international propagation of epidemic shocks. *Notes:* The figure shows the response of global variables to an epidemic shock of size 12.8 over 9 months along with 68% and 90% confidence bands.

Moreover, it provides more detailed economic data at the monthly frequency than China or Taiwan, the other two epicenters of SARS, allowing for a more granular view. We take these estimates as an approximation of the direct effects of influenza-like disease outbreaks on an economy. We contrast these findings with estimates for Germany. This is a small open economy heavily relying on international value chains. At the same time, it had low attack and mortality rates for both SARS and swine flu, such that the largest effects on the German economy arguably occurred through indirect trade and confidence effects. Moreover, the country provides rich economic data at the monthly frequency.

Panel (a) of Figure 4 shows the results for Hong Kong. They are based on the model in

Panel (a): Direct effects of epidemic shocks on Hong Kong



Panel (b): Indirect effects of epidemic shocks on Germany

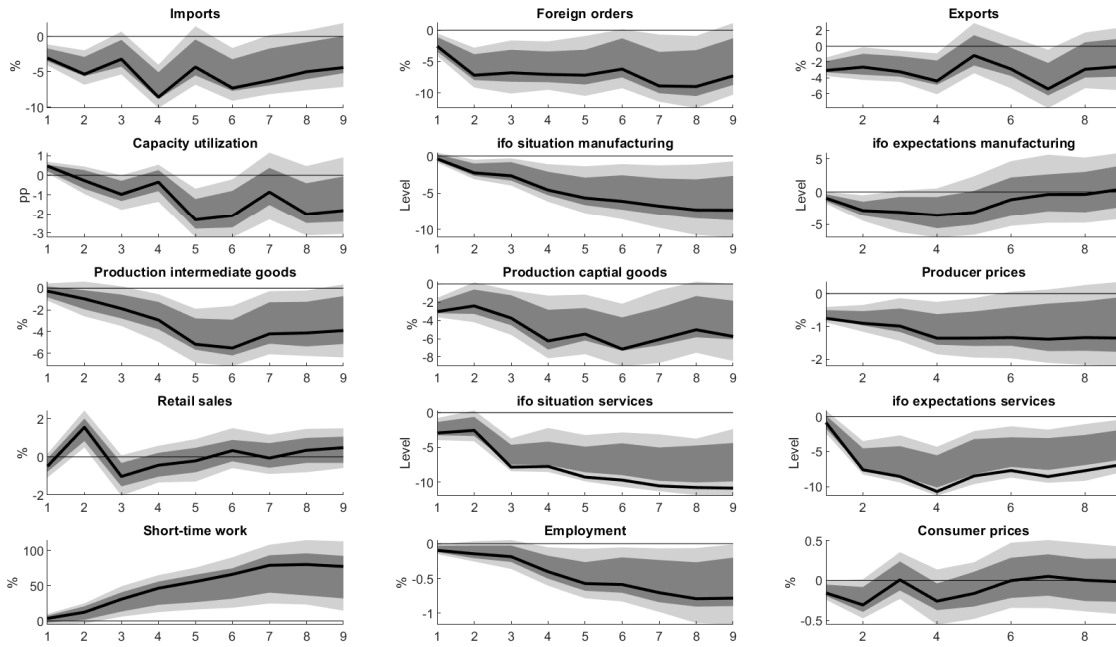


Figure 4: Direct and indirect effects of epidemic shocks. *Notes:* Panel (a) shows the response to a SARS shock of Hong Kong-specific variables individually added to the SVAR of the first column of Figure 2. Panel (b) depicts the response to an epidemic shock of Germany-specific variables individually replacing production in France, one at a time, in the baseline SVAR underlying Figure A.1. The shaded areas denote 68% and 90% confidence bands.

the first column of Figure 2 with the SARS index, and adding one additional Hong Kong-specific variable at a time. As before, the shock is scaled to the maximum of the SARS index. In response to the epidemic shock, airport arrivals essentially come to a halt. It takes six months before they return to their pre-shock trend. Airport departures drop by 60%, also needing two quarters before recovering. Business and tourism travel also take a hard hit. The hotel room occupancy rate drops by 60 percentage points upon impact and by nearly 80 percentage points after two months. In contrast, exports and imports are only mildly affected as the manufacturing sector is outside the city center in Pearl River Delta and it largely relies on immigrant workers with few potentially infectious ties to the main community. Unfortunately, there are no production data for Hong Kong at the monthly frequency. Nevertheless, the significant fall of employment by more than 2% suggests that the overall effect of the shock on the economy is severely negative.

Indeed, retail sales fall by 10% and for more than one quarter. The strong decline of demand for travel, tourism, and retail goods is reflected in a sustained fall of consumer prices by more than 2%. The collapse of economic activity is also associated with a pronounced, lagged fall of government revenues. Public expenditure policy and monetary policy are expansionary but cannot offset the demand contraction. Finally, when looking at selected subcomponents of domestic trade to see which sectors suffer most, we observe the largest declines for retail sales of jewellery, watches, and valuable gifts (−60%), clothing, footwear, and allied products (−30%) and sales of other consumer goods (−10%). The typical domestic trade contraction lasts for about one quarter and the foregone sales are largely permanently lost. Only for other consumer goods is there some indication of catching-up. The notable exception from these patterns are supermarket sales. They increase drastically by 14% as consumers stockpile necessities, substitute restaurant visits, and more generally refrain from social consumption activities outside their homes.

Next, we analyze the impact of epidemic shocks on Germany to obtain a quantitative impression of their indirect effects. We return to the aggregate viral disease index and add to the model one Germany-specific variable at a time. The responses of the latter are shown in Panel (b) of Figure 4. The shock is scaled to the maximum of the aggregate disease index (12.8). The composition of variables differs somewhat from the selection for Hong Kong

as more economic data series for the monthly frequency are available. But we also include employment to compare the economic effects across countries quantitatively.

The figure shows that imports decline significantly upon impact and subsequently fall further as inputs into German supply chains are not shipped. Foreign orders also drop immediately and by similar amounts. Exports, on the other hand, fall less as companies can partially replace imported inputs by domestic products, either out of their stocks or from home companies. However, substitution seems imperfect and capacity utilization declines. More generally, firms are more pessimistic about their current and expected future situation, as judged by the ifo business survey for the manufacturing sector. Looking at the broad subcategories of industrial production shows that, in particular, intermediate and capital goods suffer, potentially due to a disruption of international supply chains. Overall, producer prices fall by 1% in response to the lower demand for their goods.

As for Hong Kong, the decline in economic activity is not universal. Retail sales increase significantly one month after the shock, potentially reflecting panic buying and consumption substitution. However, in general the service sector is also persistently negatively affected by the shock, as the corresponding decline in the ifo index current situation and in the expectation component show. Hence, overall, short-time work increases strongly (although from a typically very low level) and employment falls significantly by more than 0.5%. Comparing the employment decline to that of Hong Kong suggests that the indirect impact of epidemic shocks is about one-fourth of the direct effect. Finally, the economic contraction in Germany is associated with lower consumer prices.

3.3. Historical analysis of epidemic shocks for the U.S.

The last part of the main analysis is an estimation of the average impact of epidemic shocks on the U.S. economy using historical data. This serves two purposes. First, it is an external validation of the previous results for the world economy, which are based on news-indices from the Genios media data, using an alternative news data source, the NYT archive. Second, the NYT data extend further back in time and, hence, contribute several (global) influenza outbreaks that are interesting in their own right to the sample. Specifically, the data cover the epidemic influenza of 1929, the 1957/58 pandemic Asian flu (H2N2 virus),

and the 1968/69 pandemic Hong Kong flu (H3N2 virus) (see Figure 1).

To exploit as many of these additional observations as possible, we only include variables in the model that are available at the monthly frequency at least from before the first of these episodes, that is, from before the influenza pandemic of 1929. Hence, the model includes the influenza index, the logarithm of industrial production, oil and gas production, the S&P 500, and consumer prices, respectively, as well as the three-month rate on AA-rated commercial papers as a proxy for monetary policy. As before, the model contains six lags and we scale the shock to the maximum of the flu index for the U.S., which is 41 and corresponds to the peak of the pandemic influenza in May 2009. The peaks of the other flu outbreaks are between 27 and 35, and, as such, roughly comparable.

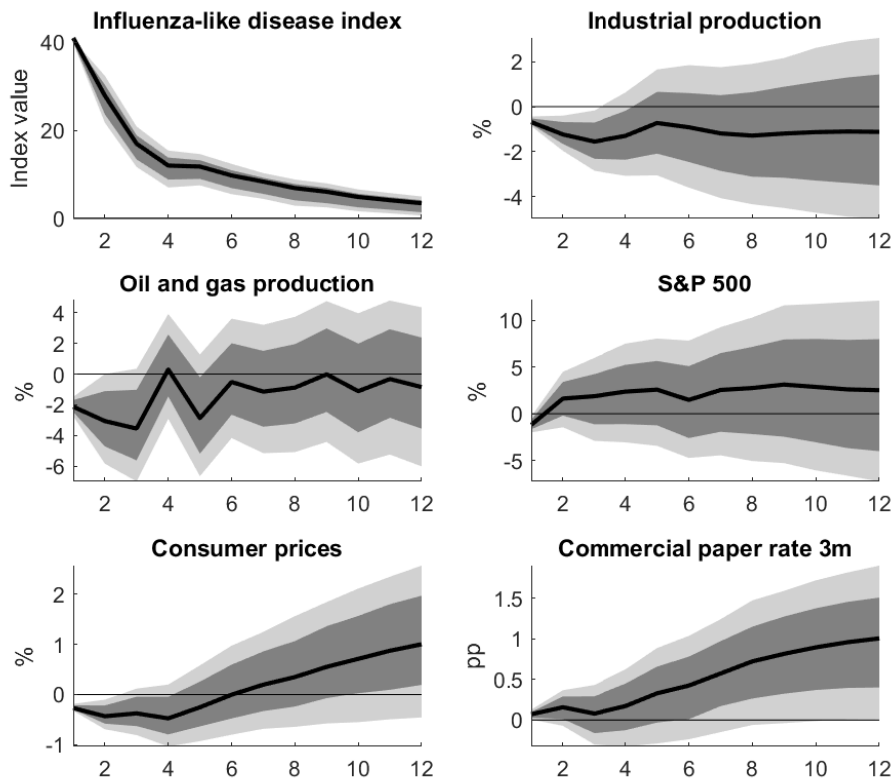


Figure 5: The impact of influenza-like disease shocks on the U.S. economy. *Notes:* The figure shows the responses of the endogenous variables to an influenza-like disease shock of size 41 over 12 months based on a SVAR for the U.S., along with 68% and 90% confidence bands.

Figure 5 shows that the influenza index increases significantly upon impact and remains elevated for about one year. This suggests that the identified shocks largely reflect pandemic

or epidemic flu outbreaks, that is, the outliers in Figure 1, rather than unexpectedly severe seasonal influenza episodes. While the former typically last 6 to 18 months, the latter are typically short-lived and confined to the winter months. In response to the influenza-like disease shock, industrial production declines significantly upon impact and falls further for another two months. Thereafter, it gradually returns to trend and the response becomes indistinguishable from zero. The trough is -1.6% . Oil and gas production also falls upon impact, by more than industrial production. It also bottoms one quarter after the shock and then recovers. Equity prices drop significantly by 1.2% and then overshoot slightly. Consumer prices decline by 0.2% initially. They fall further, to -0.4% . After two quarters, there is evidence of overshooting as well. Finally, somewhat surprisingly given the disinflation in the first two quarters, the three-month rate tends to increase (although the response is largely insignificant at the 90% level). This positive reaction can mirror an anticipation of monetary policy of the future price increase.

4. Sensitivity analysis

We perform an extensive sensitivity analysis that we briefly summarize here. Online Appendix C contains the details and the results which show that our main conclusions hold. First, we address three potential sources of endogeneity: omitted variables, measurement error and reverse causality. Then, we conduct several more technical robustness tests by changing the number of lags, including trends or month dummies, winsorizing the epidemic index and extending the model for the U.S.

5. Conclusions

We construct news-based viral disease indices and estimate the dynamic macroeconomic impact of coronavirus and other epidemic influenza outbreaks at the monthly frequency. We analyze the global effects and propagation, complementing this evidence with detailed country studies and a historical analysis of epidemics in the U.S. since 1920. The estimates provide three stylized facts. First, the macroeconomic damage of epidemic shocks is an order of magnitude larger than that of seasonal influenza shocks. Second, the adverse impact of

epidemic shocks lasts for about three quarters and is roughly four times larger for epicenter countries than for countries indirectly affected through supply chain disruptions, global trade, or sentiment. Third, epidemic shocks lead to a simultaneous fall of consumer prices with economic activity.

The results have several implications. First, they suggest that epidemics are disparately more economically damaging than regular influenza, thus questioning a popular view that Covid-19 is just another flu. Furthermore, they indicate that epidemics are costly tail events that are roughly comparable to financial or political crises. At the time of writing, the value of the aggregate news-based disease index suggests that the current shock is roughly four times larger than the one identified and used for the estimates for the world economy presented above. The costs also reflect containment measures, such as school closures, lockdowns, and other means of social distancing, which are taken to reduce the number of cases because the public health system has limited shock absorption capacities. In the long-run, these costs must be weighed against the short-run gains of trimming public health systems as more resilient systems would potentially allow for softer forms of disease control in the case of tail events.

Second, the results indicate that transparency in the testing and reporting of cases world-wide and multilateral containment policy coordination are key. In this way, the spreading of viral diseases across borders can be reduced, thereby reducing the direct economic costs of epidemic shocks to countries.

Third, the findings suggest that the negative demand effects of epidemic shocks on businesses, consumers, and investors are larger than the negative supply effects. Epidemic shocks are both contractionary and deflationary. This, in turns, points toward expansionary monetary and fiscal policy as the appropriate short-run response to epidemic shocks

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Online appendix to ‘Viral shocks to the world economy’

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April 7, 2020

Appendix A. Data definitions and sources

The news data are from the Genios and The New York Times archives. All other data are downloaded through Macrobond. All data refer to the monthly frequency. We use seasonally adjusted real data, where available. Otherwise we make these adjustments ourselves. When constructing world aggregates ourselves, we confine the set of countries to strike a reasonable balance between having a sufficient number of countries and time-series observations to avoid changing compositions.

Variable	Definition and transformation
News-based disease indices	We measure the occurrence and intensity of viral diseases through news-based indices. To construct them, we use automated text analysis of two online media archives. The first one is the database Genios (www.genios.de). It includes about 2200 high-quality German-speaking media between January 1990 and February 2020 with the total number of documents exceeding 500 million. The second source is the archive of the New York Times (NYT), which spans the period January 1910 to February 2020 (www.nytimes.com/search?). We search for the following five keywords that capture pandemics or internationally important epidemics during the sample period: ‘SARS’, ‘swine flu’ (Schweinegrippe), ‘MERS’, ‘Coronavirus’, and ‘Influenza’ (Grippe). We count the monthly occurrences of these keywords. Given that the amount of texts collected in the databases changes over time, we normalize the plain counts. We divide them by the number of occurrences of the word ‘der’, which is the most widely used word in German language, in the case of Genios, and by the occurrences of the word ‘new’ for the NYT archive, since the word ‘the’ is not searchable in that database. The aggregate news-based index for viral diseases sums of the the subindices for SARS, coronavirus and swine flu within months.
Global macroeconomic variables	
Industrial production	World Bank, Global Economic Monitor, Industrial Production, Total, Constant Prices, SA, USD, logarithm. Countries: world, China, South Korea, Germany, Canada, USA, Austria, Belgium, France, Luxembourg
Airport arrivals foreigners	Italy, International Arrivals, Holiday and Other Short-Stay Accommodation, Camping Grounds, Recreational Vehicle Parks and Trailer Parks, Foreign Countries, SA, Germany, Arrivals, Total, Foreigners [sa. X-11 ARIMA], Canada, CANSIM, Number of International Travellers Entering or Returning to Canada by Type of Transport, Canada, Total International Travellers [sa. X-11 ARIMA], Japan, Arrivals, Total Foreign Visitors [sa. X-11 ARIMA]. Logarithm of monthly sum.
Airport arrivals residents	Germany, Arrivals, Total, Residents [sa. X-11 ARIMA], Italy, International Arrivals, Holiday and Other Short-Stay Accommodation, Camping Grounds, Recreational Vehicle Parks and Trailer Parks, Italy, SA, New Zealand, Arrivals, By Type, NZ-Resident Travellers, Actual Counts [sa. X-11 ARIMA]. Logarithm of monthly sum.
Imports emerging markets	Foreign Trade, CPB World Trade Monitor, SA, Index, Emerging Markets, Import, Volume. Logarithm

Exports emerging markets	Foreign Trade, CPB World Trade Monitor, SA, Index, Emerging Markets, Export, Volume. Logarithm
Exports advanced countries	Foreign Trade, CPB World Trade Monitor, SA, Index, Advanced Economies, Export, Volume. Logarithm
Imports advanced countries	Foreign Trade, CPB World Trade Monitor, SA, Index, Advanced Economies, Import, Volume. Logarithm
Total trade world	Foreign Trade, CPB World Trade Monitor, SA, Index, World, Total, Volume. Logarithm
Employment world	Germany, Employment, Total, Domestic Concept, SA (X13 JDemetra+); United States, Employment, National, 16 Years and Over, SA; Austria, Employment, Employed Persons, Total, Persons in Dependent Employment [sa. X-11 ARIMA]; Japan, Employment, Employed Persons, Total, National, Males and Females, SA; United Kingdom, Employment, Aged 16-64, SA; Canada, Employment, Women and Men, 15 Years and Over, SA; Taiwan, Employment, Total [sa. X-11 ARIMA] ; Australia, Employment, Total, SA; South Korea, Labor Force Statistics, Economically Active Persons, Employed Persons [sa. X-11 ARIMA]; Hong Kong, Employment, Total [sa. X-11 ARIMA]. Logarithm of monthly sum.
Consumer prices world	World Bank, Global Economic Monitor, Prices, Consumer Price Index, SA, Index. Logarithm
Retail sales world	Austria, Domestic Trade, Retail Trade, Turnover, Total, Excluding Trade in Motor Vehicles, Constant Prices, Index; Germany, Domestic Trade, Retail Trade, Turnover, Total, Excluding Vehicle Trade, Calendar Adjusted (X13 JDemetra+), Constant Prices, SA (X13 JDemetra+), Index; Australia, Domestic Trade, Retail Trade, By Industry, Total, Current Prices, SA, AUD; Japan, Domestic Trade, Retail Trade, Total, JPY [sa. X-11 ARIMA] ; Hong Kong, Domestic Trade, Retail Trade, Total Sales, Value, HKD [sa. X-11 ARIMA] ; Singapore, Domestic Trade, Wholesale and Retail Trade, Retail Sale, Total, Constant Prices, SA, Index; Mexico, Domestic Trade, Retail Trade, Total, Constant Prices, SA, Index; Sweden, Domestic Trade, Retail Trade, Total except Fuel, SA, Index; Canada, Domestic Trade, Retail Trade, Total, SA, CAD; Portugal, Domestic Trade, Retail Trade, Total, Excluding Fuel, Index [sa. X-11 ARIMA] ; United States, Domestic Trade, Retail Trade, Retail Sales, Total, Calendar Adjusted, SA, USD. Aggregation of individual growth rates using fixed-GDP weights as of 2010. Logarithm of aggregate index.
Equity prices world	Equity Indices, MSCI, Large Cap, Index, Total Return, Local Currency; World. Logarithm
Federal funds rate	United States, Policy Rates, Effective Rates, Federal Funds Effective Rate

Macroeconomic variables for Hong Kong

Airport arrivals	Arrivals, Total [sa. X-11 ARIMA]. Logarithm
Airport departures	Departures, By Border Checkpoint, Total [sa. X-11 ARIMA]. Logarithm
Accommodation occupancy rate	Accommodation, Occupancy, Hotels, Room Occupancy Rate, All Hotels [sa. X-11 ARIMA]
Exports	Foreign Trade, Total Exports, Quantum, Index [sa. X-11 ARIMA]. Logarithm
Imports	Foreign Trade, Imports, Quantum, Index [sa. X-11 ARIMA]. Logarithm
Employment	IMF IFS, Real Sector, Labor, Employment, Persons [sa. X-11 ARIMA]. Logarithm
Unemployment rate	IMF IFS, Real Sector, Labor, Unemployment Rate
Retail sales total	Hong Kong, Domestic Trade, Retail Trade, Total Sales, Value, HKD [sa. X-11 ARIMA]. Logarithm
Consumer prices	Consumer Price Index, Index. Logarithm
Government revenues	Government Fiscal Operations, Revenues, Provisional, HKD [sa. X-11 ARIMA]. Logarithm
Government expenditures	Government Fiscal Operations, Expenditures, Provisional, HKD [sa. X-11 ARIMA]. Logarithm
Policy rate	Policy Rates, Central Bank Policy Rate, End of Period
Sales jewellery, watches, gifts	Domestic Trade, Retail Trade, Jewellery, Watches and Clocks, and Valuable Gifts, Total, Per CPI, HKD [CPI index Oct. 2014 - Sep. 2015 = 100, sa. X-11 ARIMA]. Logarithm
Sales clothing and footwear	Domestic Trade, Retail Trade, Clothing, Footwear and Allied Products, Total, Per CPI, HKD [CPI index Oct. 2014 - Sep. 2015 = 100, sa. X-11 ARIMA]. Logarithm
Sales department stores	Domestic Trade, Retail Trade, Department Stores, Total, Per CPI, HKD [CPI index Oct. 2014 - Sep. 2015 = 100, sa. X-11 ARIMA]. Logarithm
Sales other consumer goods	Domestic Trade, Retail Trade, Other Consumer Goods, Total, Per CPI, HKD [CPI index Oct. 2014 - Sep. 2015 = 100, sa. X-11 ARIMA]. Logarithm
Sales consumer durables	Domestic Trade, Retail Trade, Consumer Durable Goods, Total, Per CPI, HKD [CPI index Oct. 2014 - Sep. 2015 = 100, sa. X-11 ARIMA]. Logarithm
Sales supermarkets	Domestic Trade, Retail Trade, Supermarkets, Total, Per CPI, HKD [CPI index Oct. 2014 - Sep. 2015 = 100, sa. X-11 ARIMA]. Logarithm

Macroeconomic variables for Germany

Imports	Foreign Trade, Total, Calendar Adjusted (X13 JDemetra+), SA (X13 JDemetra+), EUR, Imports. Logarithm
Foreign orders	Foreign orders, real, SA. Logarithm
Exports	Foreign Trade, Total, Calendar Adjusted (X13 JDemetra+), SA (X13 JDemetra+), EUR, Exports. Logarithm

Capacity utilization	Capacity Utilization, Manufacturing, Total, SA (X-13 ARIMA)
Retail sales	Retail sales, real, SA. Logarithm
Domestic orders	Domestic orders, real, SA. Logarithm
ifo situation manufac- turing	ifo situation manufacturing
ifo expectations manu- facturing	ifo expectations manufacturing
ifo situation services	ifo situation services
ifo expectations ser- vices	ifo expectations services
Short-time work	Short-time work. Logarithm
Employment	Employment, total, SA. Logarithm
Production intermedi- ate goods	Industrial Production, By Goods, Calendar Adjusted (X13 JDemetra+), Constant Prices, SA (X13 JDemetra+), Index, Production intermediate goods. Logarithm
Production capital goods	Industrial Production, By Goods, Calendar Adjusted (X13 JDemetra+), Constant Prices, SA (X13 JDemetra+), Index, Production capital goods. Logarithm
Production non- durables	Industrial Production, By Goods, Calendar Adjusted (X13 JDemetra+), Constant Prices, SA (X13 JDemetra+), Index, Production non-durables goods. Logarithm
Production consumer goods	Industrial Production, By Goods, Calendar Adjusted (X13 JDemetra+), Constant Prices, SA (X13 JDemetra+), Index, Production consumer goods. Logarithm
Producer prices	Producer Price Index, Industrial Products, Total, Calendar Adjusted, SA, Index. Logarithm
Consumer prices	Consumer Price Index, Total, Calendar Adjusted, SA, Index. Logarithm

Macroeconomic variables for the United States

Industrial production	Industrial Production, Constant Prices, SA, Index, Total. Logarithm
Employment	Employment, Payroll, SA, Nonfarm, Total. Logarithm
S&P 500	Equity Indices, S&P, 500, Index, Total Return, End of Period, USD. Logarithm
Consumer prices	Consumer Price Index, SA. Logarithm
Retail sales	OECD MEI, Sales, Retail Trade, SA, Total Retail Trade, Volume, Index. Logarithm
Commercial paper rate 3m	Commercial Paper Rates, Rates, AA Nonfinancial, 3 Month, Yield
Oil and gas production	EIA, Oil and Gas, Crude Oil, Production, Total, Barrels. Logarithm

Appendix B. List of epidemics and additional results

This section provides details on the epidemics in the base sample and additional estimation results. *SARS*. The outbreak of this disease caused by the SARS coronavirus (SARS-CoV) originated in Foshan, China in November 2002 and lasted until May 2004. Between November 1, 2002, and July 31, 2003, 8,096 people were infected and at least 774 of them died worldwide. The most affected regions were Mainland China with 5,327 cases and Hong Kong with 1,755 cases.⁴ In Figure 1, the index peaks in April 2003; that is, half a year after the outbreak of the disease. Another, much smaller peak, in February 2020, is related to the comparison of Covid-19 to SARS in the media.

Swine flu. The swine flu was an influenza pandemic caused by the H1N1/09 virus. It was first recognized in California and Texas in March 2009. The pandemic lasted from April 2009 to July 2010.⁵ In terms of the number of confirmed deaths, the pandemic affected mostly the USA, Brazil, India, and Mexico. By July 2009, there were 94,512 confirmed cases, including 429 deaths.⁶

MERS. The ‘Middle East respiratory syndrome’ is caused by the betacoronavirus (MERS-CoV). As the name suggests, the epidemic originated in the Middle East, specifically, Saudi Arabia, where approximately 80% of cases were identified. The first laboratory-confirmed case was reported in Saudi Arabia in April 2012. The first large outbreak of MERS started in March 2014 and ended in July 2015. Since then, and through November 2019, there were 2,494 laboratory-confirmed cases, including 858 deaths.⁷

COVID-19. The disease is caused by the SARS-CoV-2 coronavirus. Its outbreak was identified in December 2019 in the city of Wuhan, Hubei province, China. By March 2020, there are about 1 million confirmed cases, including more than 50,000 deaths.⁸ The corresponding index started to rise in January 2020. Already at this early stage, the intensity of media coverage is close to that of SARS or swine flu at their peaks, and much stronger than for MERS.

Influenza. The figure also contains indices of influenza for Germany based on the Genios database and for the U.S. based on the NYT archive. For the overlapping period, the correlation between the indicators is 0.64. Both have recurrent medium-sized peaks, typically during the winter. For Germany, milder courses of the disease are associated with peaks of 2-3, while the largest non-epidemic spike is at 7. For the U.S., typical seasonal peaks are close to, but below, 10 and the largest non-epidemic spike is at 20. In addition, both indices have several outliers. They capture

⁴The WHO summary of probable SARS cases with onset of illness is from November 1, 2002, to July 31, 2003; https://www.who.int/csr/sars/country/table2004_04_21/en/.

⁵European Centre for Disease Prevention and Control, Timeline on the pandemic (H1N1) 2009; <https://www.ecdc.europa.eu/en/seasonal-influenza/2009-influenza-h1n1-timeline>.

⁶World Health Organization, Human infection with pandemic (H1N1) 2009 virus: updated interim WHO guidance on global surveillance, p. 7, 2009.

⁷World Health Organization, MERS situation update, November 2019.

⁸World Health Organization, Coronavirus disease 2019 (COVID-19), Situation Report - 45, 2020.

epidemic or pandemic influenza. For Germany, they correspond to the global avian flu (H5N1 virus) and swine flu outbreaks in 2005 and 2009, respectively. For the U.S., where the sample starts much earlier, the large spikes correspond to the domestic epidemic influenza of 1929, to the 1957/58 pandemic Asian flu (H2N2 virus), to the 1968/69 pandemic Hong Kong flu (H3N2 virus), as well as to the avian and swine flus that are also present in the German series.

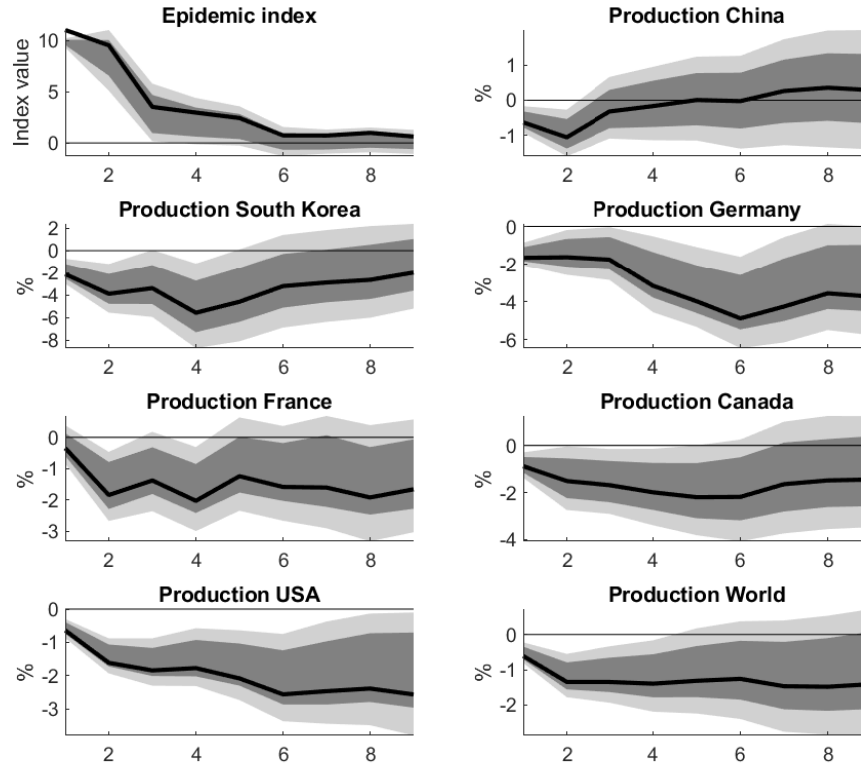


Figure A.1: Global output effects of epidemic shocks. *Notes:* The figure shows the response of industrial production to an epidemic shock of size 12.8 over 9 months along with 68% and 90% confidence bands.

Appendix C. Sensitivity analysis

This section summarizes an extensive sensitivity analysis and the main results.

Appendix C.1. Addressing potential sources of endogeneity

First, we aim at addressing three potential sources of endogeneity. To investigate the effect of potentially omitted variables, we compute the responses of the baseline variables in the model for the world economy (Figure A.1) when replacing the production in France by the additional variables shown in Figures 3-4. The main results hold (see Figures A.2-A.4). This finding reflects that the baseline model already contains output of the world as a whole and of main economies individually such that the potential for omitting important variables is low in the first place.

Figure A.2: Robustness to adding further global variables. *Notes:* The figure shows the responses of the endogenous variables to an epidemic shock of size 11 over a horizon of 8 months based on a SVAR(6). The 68% and 90% confidence bands refer to the baseline specification. The solid lines show the point estimates of the baseline variables in the augmented models where the variables shown in Figure 3 are added one at a time.

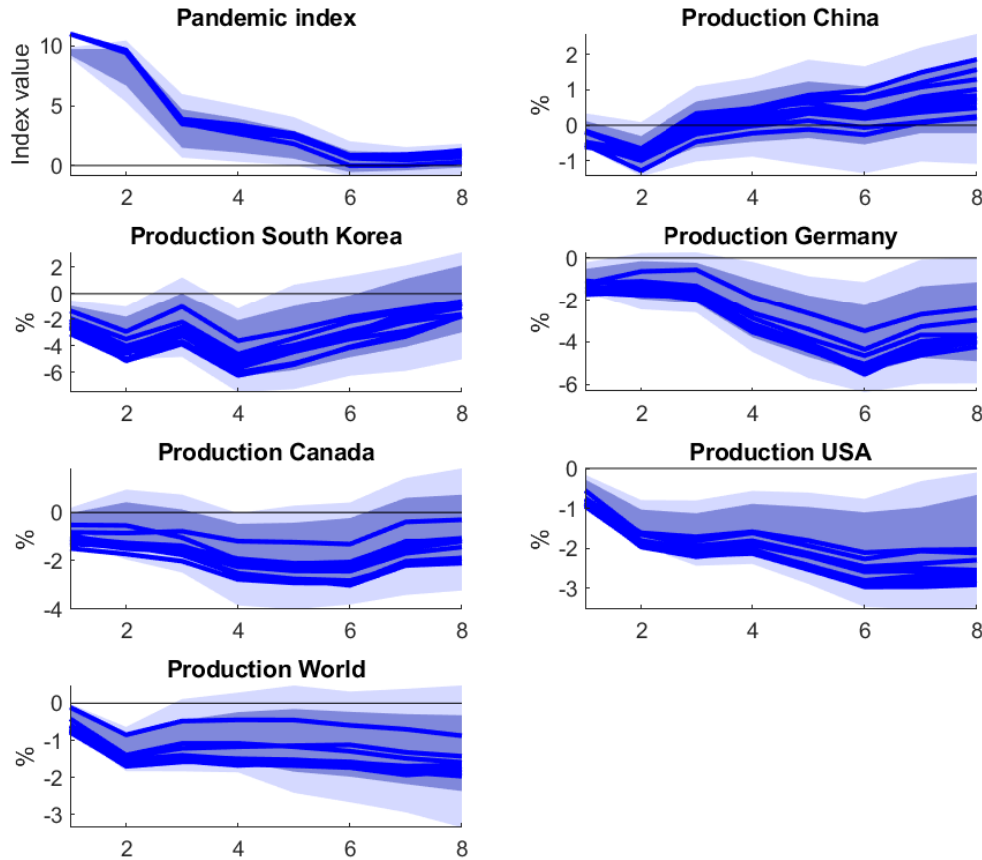
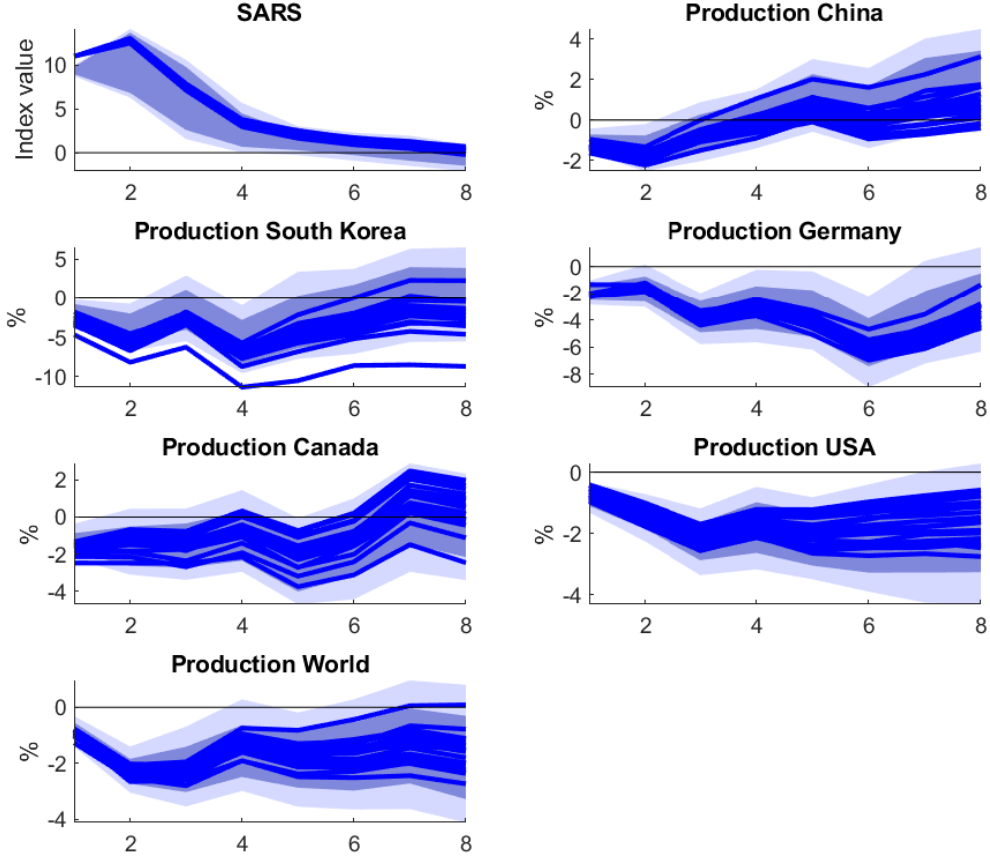


Figure A.3: Robustness to adding variables for Hong Kong. *Notes:* The figure shows the responses of the endogenous variables to an epidemic shock of size 11 over a horizon of 8 months based on a SVAR(6). The 68% and 90% confidence bands refer to the baseline specification. The solid lines show the point estimates of the baseline variables in the augmented models where the variables shown in Panel (a) of Figure 4 are added one at a time.



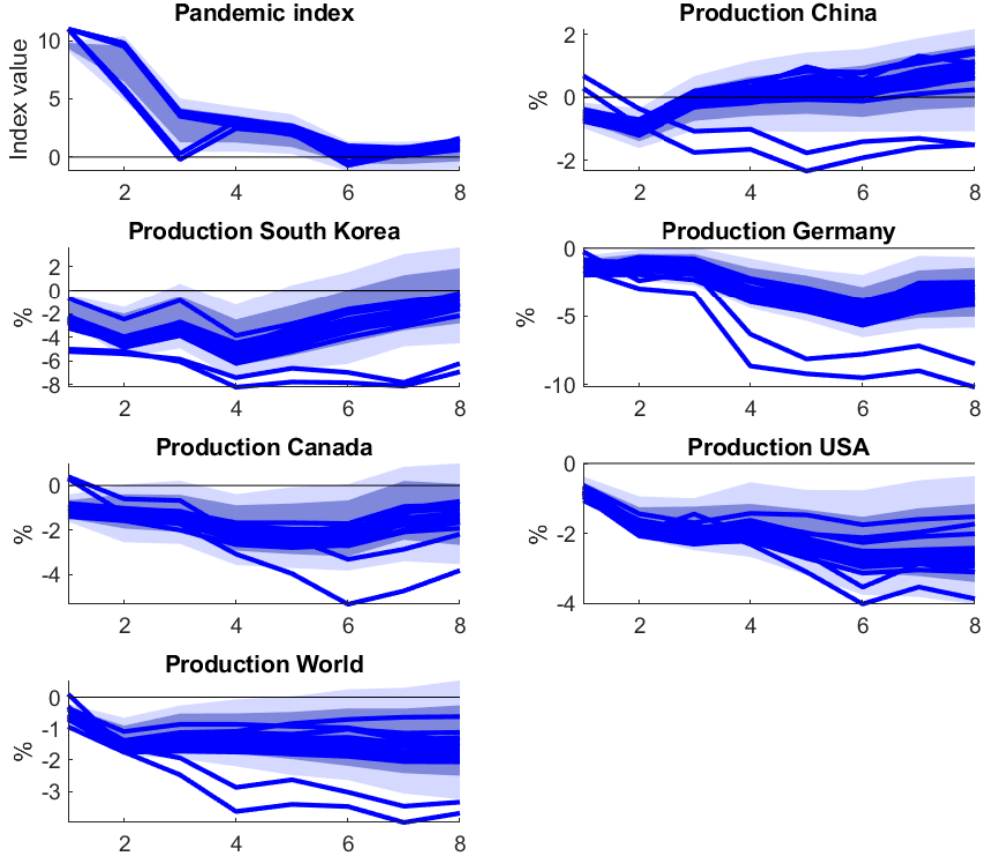
To determine if the estimates are plagued by measurement error in the aggregate news-based disease index, we follow the external instrument approach for SVARs developed in Stock and Watson (2012) and Mertens and Ravn (2013). We assume that the index is an instrumental variable s_t that is correlated with the latent epidemic shock of interest, but uncorrelated with other structural shocks and hence fulfills

$$\mathbb{E}[s_t \varepsilon_{1t}] = \phi \neq 0 \quad (\text{A.1})$$

$$\mathbb{E}[s_t \varepsilon_{jt}] = 0 \quad \forall j = 2, \dots, K, \quad (\text{A.2})$$

where ϕ is an unknown correlation between the instrument s_t and the structural shock of interest ε_{1t} . The latter is ordered first without loss of generality. In the literature, (A.1) is usually called

Figure A.4: Robustness to adding variables for Germany. *Notes:* The figure shows the responses of the endogenous variables to a pandemic shock of size 11 over a horizon of 8 months based on a SVAR(6). The 68% and 90% confidence bands refer to the baseline specification. The solid lines show the point estimates of the baseline variables in the augmented models where the variables shown in Panel (b) of Figure 4 are added one at a time.



the relevance condition and assumption (A.2) the exogeneity condition. A valid instrument satisfies both (A.1) and (A.2). It allows for recovering ε_{1t} and, hence, the corresponding response vector from the reduced form residuals. Using $B = [b_1, B^*]$, where b_1 is the response vector corresponding to ε_{1t} and B^* contains the responses of the remaining shocks, yields

$$u_t = b_1 \varepsilon_{1t} + B^* \varepsilon_t^*. \quad (\text{A.3})$$

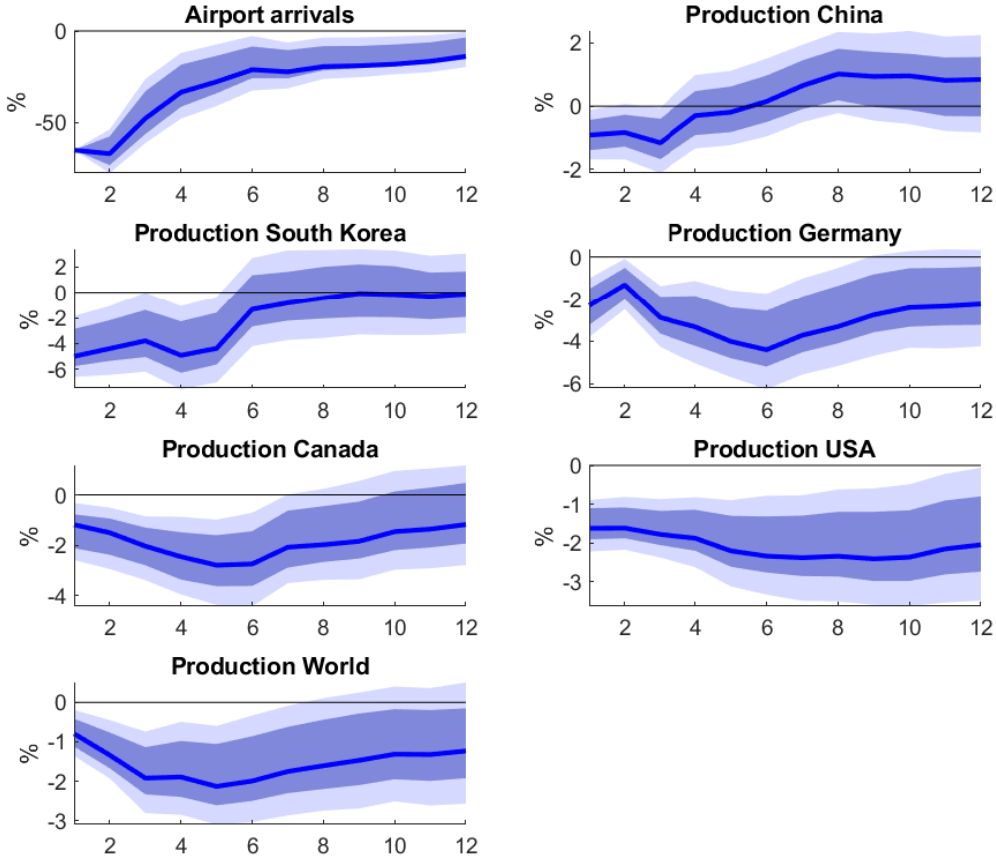
Substituting (A.3) into $\mathbb{E}(s_t u_t)$, while using (A.1) and (A.2), allows for uncovering the (relative) impact of the structural shock of interest on every variable in the system, that is, the j th element of b_1 . By using the sample moments $\hat{\mathbb{E}}(u_t s_t)$, the instrument s_t implies the following $k - 1$

identifying restrictions

$$b_1 = b_{11} \left(1, \frac{\hat{\mathbb{E}}(u_{2t} s_t)}{\hat{\mathbb{E}}(u_{1t} s_t)}, \dots, \frac{\hat{\mathbb{E}}(u_{Kt} s_t)}{\hat{\mathbb{E}}(u_{1t} s_t)} \right)', \quad (\text{A.4})$$

posing identification of shock ε_{1t} up to the scaling factor b_{11} . To scale the shock, we need an indicator variable that enters the SVAR. We use the log of the number of airport passenger arrivals in Hong Kong, which was the economy most affected in the world in terms of relative SARS cases. The news-based disease instrument is strong. It has a F-statistic of 24.9. We scale the adverse epidemic shock to lower airport arrivals by 65%. This corresponds to the drop in that series from March to April 2003. Figure A.5 shows that the main results hold.

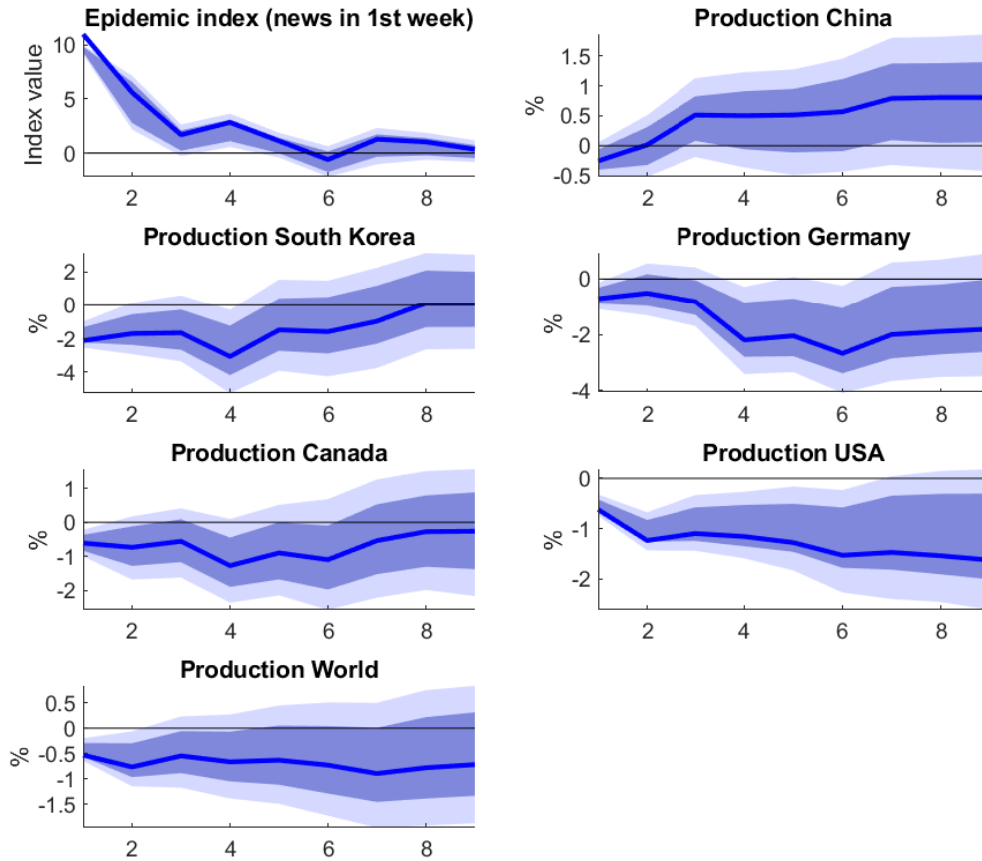
Figure A.5: Responses to an epidemic shock in a Proxy-SVAR. *Notes:* The figure shows the responses of the endogenous variables to an epidemic shock over a horizon of 12 months based on a SVAR(6) identified through an external instrument. The shaded areas are 68% and 90% confidence bands. The instrument is the pandemic index for the global model. The F-statistic for the instrument is 24.9.



For exploring whether the estimates are affected by reverse causality, we modify the aggregate news-based disease index. As the underlying data are available at the daily frequency, we

construct the subindices entering the aggregate index using keyword counts in the onset week of each month only. Then, we sum these first-week subindices to obtain an aggregate index that disregards media coverage of weeks 2-4 of each month. For the model at the monthly frequency, this implies that the contemporaneous overlap between the modified news-based disease index and industrial production is only 25%. In other words, we assume that the news-based disease index is exogenous at the weekly frequency. Figure A.6 shows that the main results hold, although the effects are estimated less precisely as there is more noise in the weekly index.

Figure A.6: Responses to an epidemic shock using a news-based disease index for the onset week of each month. *Notes:* The figure shows the responses of the endogenous variables to an epidemic shock of size 11 over a horizon of 9 months based on a SVAR(6). The shaded areas are 68% and 90% confidence bands. The news-based epidemic index is based on the counting of keywords during the first week of each month only, disregarding weeks 2-4.



Appendix C.2. Further sensitivity tests

We also conduct several more technical robustness tests. Instead of using 6 lags, we change the lag length to 3, 4, 5, 7, 8, and 9, respectively (Figure A.7). Next, we incorporate a linear trend into the model (solid lines and shaded area in Figure A.8), month dummies (dashed lines in Figure A.8), or we winsorize the epidemic index at the 95th percentile (dotted lines in Figure A.8). All-in-all, the results hold. Finally, we extend the model for the U.S. by including the logarithm of employment and of retail sales. This shortens the sample by half to start in 1955M1. The drop in prices is now more significant. Employment falls and retail sales increase, potentially reflecting stockpiling by consumers, but the responses of the two additional variables are only borderline significant.

Figure A.7: Responses to an epidemic shock using alternative lag length. *Notes:* The figure shows the responses of the endogenous variables to an epidemic shock of size 11 over a horizon of 9 months based on a SVAR(p), with $p = 3, 4, 5, 6, 7, 8, 9$, respectively. The shaded areas are 68% and 90% confidence bands and refer to the baseline specification with $p = 6$.

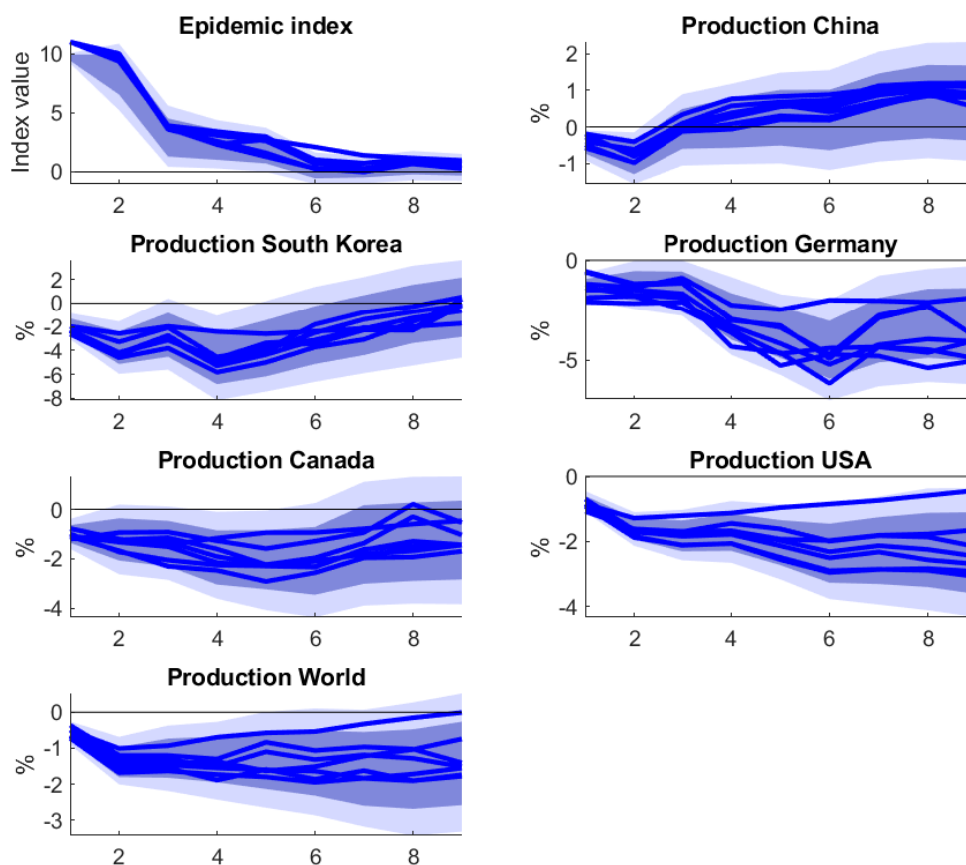


Figure A.8: Responses to an epidemic shock when including a trend, month dummies, or a winsorized epidemic index. *Notes:* The figure shows the responses of the endogenous variables to an epidemic shock of size 11 over a horizon of 9 months based on a SVAR(6). The solid lines and the shaded areas for 68% and 90% confidence bands refer to a model including a linear trend, the dashed lines to a model with month dummies, and the dotted lines to a model where we winsorize the epidemic indicator at the 95th percentile.

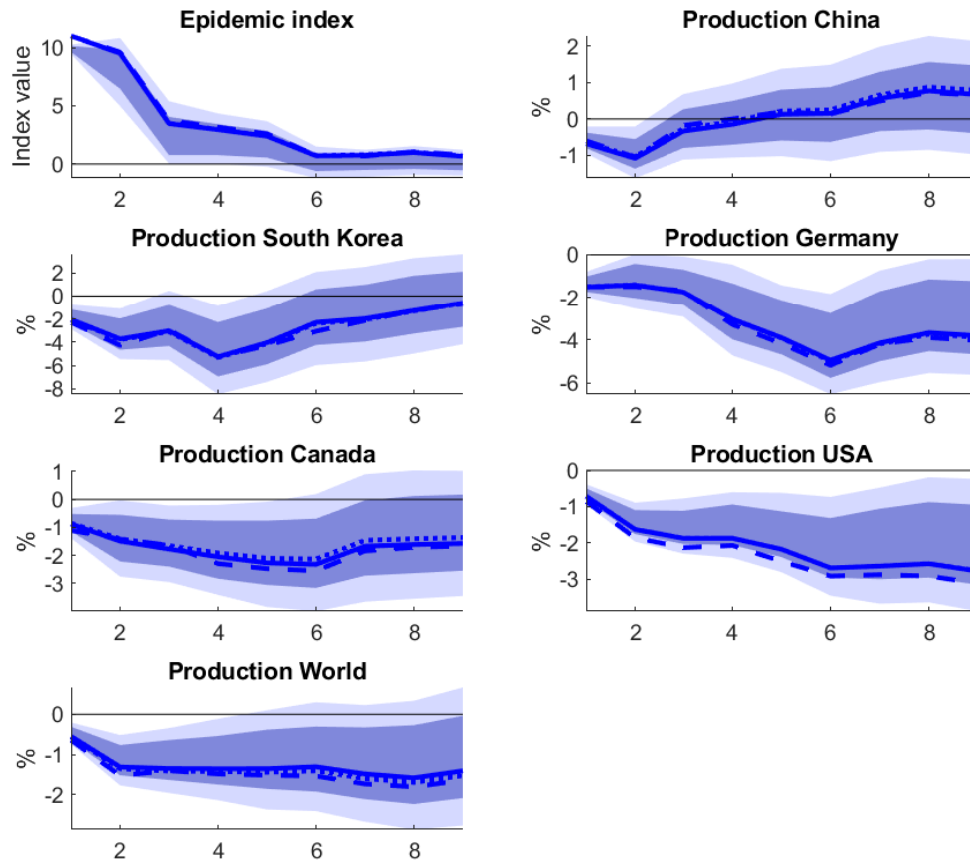


Figure A.9: Responses of U.S. variables to an influenza-like disease shock in extended model. *Notes:* The figure shows the responses of the endogenous variables to an influenza shock of size 41 over a horizon of 12 months based on a SVAR(6) for the U.S. The shaded areas indicate 68% and 90% confidence bands. The extended model includes additionally the logarithm of employment and of retail sales.

