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Pandemics and their impact on oil and metal prices

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Abstract: We examine the effect of pandemics on selected commodity prices—in particular, those of zinc, copper, lead, and oil. We set up a vector autoregressive model and analyse data since the mid-nineteenth century to determine how prices reacted to pandemics such as the 1918 Spanish Flu, 1957 Asian Flu, and 1968 Hong Kong Flu. We control for demand and supply fundamentals to generate forecasts from the point of outbreak, and we consider whether any pattern can be deduced in reactions to adverse global shocks. Results are varied, depending on choice of commodity and magnitude and type of response. No clear conclusions are possible from past pandemics, and we conclude that at the time of writing, forecasts are difficult to make in the ongoing current pandemic too. We conclude by estimating impulse response functions to assess likely impact and the subsequent response of commodity prices to the shock.

Key words: pandemics, commodity prices, global shocks, vector autoregressive model (VAR)

JEL classification: C22, Q02, Q32

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1 Introduction

According to the World Health Organization (WHO), in late December 2019 China reported a number of cases of pneumonia clustered in Wuhan, located in Hubei Province, leading to the identification of a novel coronavirus. By March 2020, the WHO, alarmed by the severity of the spread of the virus, declared that COVID-19 could be characterized as a pandemic. At the time of writing, the pandemic remains a concern for governments and policy-makers as it has inflicted recessions worldwide. As the impact of this virus on lives and livelihoods grows, the serious global slowdown is likely to affect oil and metal commodities. This paper aims to document the impact of past pandemics on commodities and determine whether inferences can be drawn to help understand the impact that the current pandemic may have on them.

Commodity prices are known to be highly volatile (Deaton and Laroque 1992), and soon after the start of the COVID-19 pandemic, oil prices had already started to drop, reaching a low level by April 2020. However, since then, prices have started to recover and are now increasing, albeit at a decreasing rate. Similar patterns, but with different degrees of variability, have been observed for metals such as copper, lead, and zinc—where prices fell, reaching a trough in April or May, before showing signs of recovery. If the data are observed at an aggregate level, as in data measured on a quarterly basis, then prices are still lower in the second quarter of 2020 than they were a year ago in the second quarter of 2019. Before COVID-19, prices of oil and metals were already in decline from the start of 2020, mainly driven by trade tensions between the US and China. One can conclude that pandemics can impact on commodity prices, as we know that such shocks can affect supply (e.g., through disruption to industrial production, closure of operations, reduced labour supply leading to lower production rates) and demand (e.g., due to the unavoidable recession, lockdown measures, and restricted travel). Oil and metal commodities are affected by such a slowdown or recession given the high income elasticity of demand (Baffes et al. 2020).

The COVID-19 pandemic has led to a plethora of uncertainties in various aspects of life. On the one hand are lives, the uncertainties of contracting the flu, and the mortality; on the other hand are the impact on livelihoods, uncertainties of the economy, unemployment, loss of income. Policy-makers are faced with not just the uncertainty that lies in the capacity of health care systems to meet the extraordinary challenge of carrying out testing and tracing as well as containing the virus before a vaccine is deployed, but also the challenges of the economic impact over different time horizons in the short to medium term, the time taken to recover from such shocks, and the role and effectiveness of government policy.

The severe impact of COVID-19 on the economy has spread with alarming speed (Baker et al. 2020), and as countries around the world react (some of them more slowly than others), imposing restrictions that have had a profound impact on economic activity, the damage to the economy is likely to be at a scale that has not been seen for decades. The June 2020 *Global Economic Prospects* published by the World Bank paints a grim picture of the consequences of the COVID-19 pandemic for economic growth in the short and medium term. The baseline forecast depicts a substantial contraction of global GDP of 5.2 per cent in 2020, using market exchange rate weights. An area where we have seen an immediate and serious impact of COVID-19 is in commodity prices, in particular oil and metal prices. As new investments stall, especially in manufacturing, travel, and construction, we are likely to see a consequent depressing effect on commodity prices. While governments around the world are making concerted efforts to counter the downturn using both fiscal and monetary policies, it is unlikely that they will be able to prevent the outcomes of depressed economic growth and the slowing down of commodity production in the face of investment risks.

Baker et al. (2020) note that there are no close historic parallels to the current COVID-19 crisis on the basis of which to assess the severity of the effect of the current shock on the economy. While the Spanish Flu pandemic that occurred a hundred years ago may provide a benchmark for the widespread toll on human life (Barro et al. 2020), the pandemic took place in a different time and different measures were put in place. For example, many countries were emerging from the ravages of the First World War; the world was not as interconnected as it is today; and the large strides made in the field of medical science were to happen some decades later. The Asian Flu of 1957 and the Hong Kong Flu of 1968 had a comparatively smaller impact in terms of loss of human lives, measured by absolute numbers of excess deaths. However, if one were to compare the effects on the US population in terms of excess mortality rates calculated by scaling the population size, one would be led to figures showing that the Asian and Hong Kong Flu had approximately the same rates of mortality as COVID-19 has had so far (Altig et al. 2020). The response to tackling the pandemic by government was relatively more muted in the cases of the Asian Flu and Hong Kong Flu, compared with the current response to COVID-19. However, what is common across these examples is that during the pandemics there has been uncertainty about the speed of transmission, and about the rate of infection and mortality, all of which causes economic uncertainty. Using a vector autoregressive (VAR) framework, Altig et al. (2020) show greater uncertainty in response to the pandemic and the economic fallout. As the impact on lives is uncertain, so is the impact on livelihoods.

It is well documented that uncertainty shocks have a significant negative impact on the macroeconomy (Baker et al., 2016; Bloom, 2009; Bloom et al. 2007; Caldara et al. 2016; Favero et al. 1994; Jurado et al. 2015). These studies tend to conclude that an increase in economic uncertainty has an adverse effect on industrial production, employment, and investment and stock markets. Uncertainty about the return to investment at a micro level may create cyclical fluctuations in aggregate investment at the macro level (Bernanke 1983). Under such conditions, investors may be prepared to wait and update their information set and forgo current returns, as investments are irreversible. In these conditions, oil and manufacturing firms are likely to delay their production if commodity prices are volatile, causing the price elasticity of commodity production to be low (Bredin et al. 2011; Elder and Serletis 2010; Kellogg 2014). Further, the price elasticity of demand for a commodity such as oil can be low during uncertain times (Guiso and Parigi 1999). Alternatively, price futures for commodities can cause the price elasticity of commodity demand and supply to be low as their physical purchases are hedged (Baumeister and Peersman 2013). Joëts et al. (2017) consider a large sample of commodities and assess whether the effect of macroeconomic uncertainty on commodity price returns depends on the degree of uncertainty. Making use of a structural threshold VAR model, they show that agricultural and industrial commodities are affected by the level of macroeconomic uncertainty. More recently, a selection of empirical studies have been carried out regarding the impact of uncertainty on the volatility of commodity prices (Bakas and Triantafyllou 2018; Joëts et al. 2017; van Robays 2016). Bakas and Triantafyllou (2018) employ a VAR model to show that macroeconomic uncertainty increases volatility in commodity markets. Their results show that there is a direct relationship between uncertainty in the macroeconomy and the volatility of commodity prices. In a more recent study, Bakas and Triantafyllou (2020) empirically investigate the impact on oil and gold price volatility of uncertainty in the macroeconomy related to global pandemics. Analysing data from 1996 to 2020, they find an inverse relationship between oil price volatility and uncertainty, whereas the relationship is a direct one in the case of gold prices.

In this paper, we examine the impact of demand and supply on metal and oil prices over a long period spanning from the mid-nineteenth century to the present, so that we can compare and contrast the periods of previous pandemics such as the Spanish Flu, the Asian Flu, and the Hong Kong Flu. The paper is empirical in nature and examines the effect of these pandemics on commodity prices, with the aim of quantifying the impact of pandemics on selected metal and oil prices based on a VAR modelling approach. We determine how prices react to these pandemics by making a forecast of the counterfactual—that is, if there were no pandemic, how prices would evolve over time based on the past history of prices and the market fundamentals of demand and supply. This allows us to trace out the deviation between what prices would have been without the pandemic and how prices actually evolved after the outbreak of the pandemic. The deviations between actual and forecasted prices are studied for the three pandemics to examine if there are any patterns that we can observe for selected metal and oil prices. The results that we obtain from past pandemics are mixed and vary widely based on the type of commodity and the specific pandemic, making it difficult to obtain any clear conclusions. Finally, we carry out an innovation accounting exercise on the commodity prices to trace out the response of commodity prices to a projected severe downturn in the world economy as forecasted by experts. Based on our results from previous pandemics, it is important to note that the results of this paper are meant not to be a prediction of commodity prices as a result of COVID-19 but to give an idea of the time path that commodity prices might follow in light of the severe downturn that the world economy is facing. The results need to be treated with caution, as the COVID-19 pandemic is still prevalent and the estimated downturn in the world economy may change.

2 A review of past pandemics

In this section, we provide a narrative about the major pandemics since the early twentieth century, focusing on how they started, spread, and affected the population, the workforce, and hence global demand. One can expect that pandemics would have an impact on the workforce, with miners falling sick and thus affecting global supply of metals and minerals. The impact on global demand and supply of commodities can influence commodity prices. In this paper we are concerned to see how the market fundamentals affected commodity prices during major pandemics such as the Spanish Flu of 1918, the Asian Flu of 1957, and the Hong Kong Flu of 1968.

The Spanish Flu started in the spring of 1918. The place of origin is unclear, but it certainly was not Spain; rather, the pandemic was reported by Spain, a neutral country at the time following the First World War. It is claimed that the outbreak of the flu might have begun in March 1918 in the US and the Western Front but was suppressed to preserve the morale of soldiers fighting the war (The Week 2020). While the estimated number of deaths as a result of this virus vary, it is widely acknowledged as having had a devastating effect on the world population, affecting at least 500 million people—a third of the world population at the time—and causing approximately 50 million deaths. It was dubbed the 'greatest medical holocaust in history' (Waring 1971). The pandemic is believed to have arrived in three distinct waves: the first wave started in the spring of 1918, the second wave in autumn 1918, and a third wave in the spring of 1919 (Johnson and Mueller 2002). Clearly, the Spanish Flu had a devastating effect, as medical technology was far less advanced a century ago (Gordon 2020). While the second wave affected the US the most and was responsible for most of the deaths recorded globally, the economy did not take a major hit. Gordon (2020) puts forward two reasons for this: first, the war was not over in the spring of 1918 and therefore production was still going on. Second, a large number of people lacked the substantial savings or wealth to protect themselves. In the US, for instance, unemployment insurance did not begin until 1932, and therefore at the outbreak of the Spanish Flu people had to continue working (Gordon 2020). The cumulative death rate in the US was 0.5 per cent; this was low compared with the death rates of some other countries with large populations. India, with its huge population, was badly affected by the pandemic: Barro et al. (2020) estimate that between 1918 and 1920 there were 16.7 million flu deaths in India, out of the world total of 39.0 million—that is, 43 per cent of the total. South Africa came next with 3.4 per cent of deaths, followed by Indonesia with 3.0 per cent.

Though China recorded a large number of deaths, because its population was very high this did not equate to a large cumulative percentage of total deaths (see Gordon 2020). With such a large number of deaths and cases, one can expect some impact on global demand and production of commodities.

Some studies have examined the impact of pandemics on the economy. Velde (2020) examines historical data on industrial production compiled by Miron and Romer (1990), to observe sharp falls in industrial production from mid-1918 to the end of 1919 and, after a brief rebound, a further drop from about March 1920 to mid-1921. A similar pattern is noted by Velde (2020) for employment, where a sharp downward swing occurs from 1918 to early 1919, followed by a brief recovery and then a sharp and substantial fall until early 1921. If the monthly series on industrial production and employment were to be aggregated, one would notice an overall decline in industrial production from about 1918 to 1921. Burns and Mitchell (1946) use a vast array of monthly economic time series data to note a peak-to-trough movement from 1918 to 1919. The period surrounding the Spanish Flu epidemic is complex, as there were several other events, including the First World War prior to the pandemic and then the Great Depression of the early 1930s, that had a major impact on the world economy. Barro and Ursúa (2008) note that beside the two world wars and the Great Depression, the Spanish Flu may have been the next most important cause of economic shock. In a more recent study, Barro et. al (2020) find that the war may have played a more substantive role than the Spanish Flu pandemic in contracting economic growth. However, what is notable according to their calculations is that the largest contraction in economic growth took place in 1921, the time after the Spanish Flu peaked. While their regressions do not point to any lagged effect, the sample size chosen in their regression is small, and therefore the possibility of the pandemic being linked to the large contraction cannot be completely ruled out. What seems to be suggested is that the pandemic resulted in an economic slowdown, albeit a brief downswing in economic activity. The question is whether such a drop in economic activity lowered demand, and whether the rise in unemployment caused commodity production to be cut back, thereby affecting the price of commodities—especially those that are used in industrial production and manufacturing sectors, such as metals and oil.

Forty years after the outbreak of the Spanish Flu, a new strain emerged in 1957 to cause another flu pandemic. This pandemic started in the Yunnan province of China (Pyle 1986) and then spread across Japan and the Pacific Rim countries before spreading globally to other countries. This strain came to be known as the Asian Flu. The economic impact was small, estimated to have affected industrial production in North America by about 1 per cent on average (Henderson et al. 2009). There was limited use of interventions such as closing schools or imposing travel restrictions, the banning of mass gatherings, or quarantine (Trotter et al. 1959). These restrictions were considered inappropriate due to the mild nature of symptoms; however, the pandemic served as a reminder of the threat posed by the global spread of diseases (Saunders-Hastings and Krewski 2016). The Asian Flu coincided with a short-lived recession in the US, also known as the Eisenhower Recession. During this period, there was a drop in personal consumption expenditure not only in the US but also in Asian countries where the virus had originated, such as China, South Korea, and Japan.

The next global pandemic, named the Hong Kong Flu, occurred within a decade of the Asian Flu. This strain set itself apart from the previous pandemics in the manner in which it spread: at an accelerated pace due to extensive air travel (Cockburn et al. 1969). The virus was first detected in Hong Kong, thereafter spreading to the US via Vietnam War veterans (Cockburn et al. 1969). While this flu transmitted quickly, it was milder than the Asian Flu virus (Saunders-Hastings and Krewski 2016). The geographic impact of this pandemic was heterogeneous, and the overall economic impact was small. For instance, when the pandemic reached its peak in December 1968 there were hardly any school closures or businesses being shut, despite the fact that *The New York Times* described the pandemic as 'one of the worst in the Nation's history' (Honigsbaum 2020).

In very different times, in an interconnected world, we are now facing a global pandemic—COVID-19. The spread of COVID-19 has resulted in a considerable slowdown in economic activity. This contraction is substantial and will have far-reaching consequences. The outlook does not look good, with the virus expected to persist until the spring of 2021 if not longer. For example, at the time of writing, many countries are not ruling out the possibility of a further complete lockdown. Varying levels of lockdowns are being implemented in various countries, such as overnight curfews, regional tiered lockdowns, etc. Several measures such as social distancing and reduced business hours are still in place, adding to uncertainty, which contributes to the gloomy forecasts. COVID-19 has affected both demand for and supply of commodities (World Bank 2020a). The lockdowns aimed at containing the spread of the virus have caused disruption to supply chains, which has had a direct impact on commodity prices, especially those of industrial commodities and oil. Further, the sharp global decline in demand will have had an indirect impact on commodity prices (World Bank 2020a).

The overall impacts of past pandemics may differ, and this is what we are planning to analyse in this study. One can expect that the first impact of a pandemic is the sudden and drastic drop in production. The severity and timing of the pandemic can affect production in many ways. For example, while the Spanish Flu had a devastating impact on peoples' lives, production may not have contracted at the outbreak of the pandemic as a war was still going on. However, a fall in production can be a result of people falling sick, or people missing work in fear of falling sick. Wren-Lewis (2020) notes how school closures can impact upon GDP. According to Wren-Lewis (2020), school closures force members of the workforce to take time off to look after children, thereby leading to a reduction in labour supply, which in turn can impact upon GDP with multiplier effects up to a factor of three. However, as Wren-Lewis (2020) further argues, the economy may be in a position to revert to its original level once the pandemic is over. This is because people have information as to why there was a loss of output, and the revival should take place once these causes are removed. As we have mentioned, the Eisenhower Recession was short-lived, and the Asian Flu pandemic was marked by limited use of interventions such as school closures. Barro et al. (2020) conclude that the interventions implemented during 1918 Spanish Flu pandemic were not maintained for a long enough period to reduce the overall incidence of death. Interventions such as school closures and prohibitions of public gatherings had a mean duration of only 36 days, whereas the mean duration of quarantine/isolation was 18 days. The upshot is that the combination of both demand shocks (where households cut back on consumption expenditure in fear of exposing themselves to the virus) and supply shocks (where people withdraw their supply of labour and cut back on production) leads to a recession, and depending on the severity of these shocks, the recession may be deep and persistent. Governments and policy-makers react to the evolving nature of a pandemic and make interventions dependent on the severity of the virus. Accordingly, we review three pandemics: the Spanish Flu, followed by the relatively milder Asian Flu, and then by the Hong Kong Flu, which was relatively milder again. We trace out the impact that these shocks had on the market fundamentals of selected commodities and make a prediction of the prices of these commodities in the medium term. From these results, we try to draw parallels with the ongoing COVID-19 pandemic to see if we can draw lessons for the future.

3 Econometric methodology

We adopt the VAR model proposed by Sims (1980), in which all the variables under study are considered endogenous and treated symmetrically, meaning that we can obviate the 'incredible identification restrictions'. The variables chosen are ΔY_t, ΔQ_t, and P_t, which denote world economic growth, the rate of change of commodity production, and commodity prices respectively. The structural model can be described as follows:

$$\Delta Y_t = -b_{12}\Delta Q_t - b_{13}P_t + b_{10} + \sum_{i=1}^{p}\beta_{11(i)}\Delta Y_{t-i} + \sum_{i=1}^{p}\beta_{12(i)}\Delta Q_{t-i} + \sum_{i=1}^{p}\beta_{13(i)}P_{t-i} + \varepsilon_{Yt}$$

$$\Delta Q_t = -b_{21}\Delta Y_t - b_{23}P_t + b_{20} + \sum_{i=1}^{p}\beta_{21(i)}\Delta Y_{t-i} + \sum_{i=1}^{p}\beta_{22(i)}\Delta Q_{t-i} + \sum_{i=1}^{p}\beta_{23(i)}P_{t-i} + \varepsilon_{Qt}$$

$$P_t = -b_{31}\Delta Y_t - b_{32}\Delta Q_t + b_{30} + \sum_{i=1}^{p}\beta_{31(i)}\Delta Y_{t-i} + \sum_{i=1}^{p}\beta_{32(i)}\Delta Q_{t-i} + \sum_{i=1}^{p}\beta_{33(i)}P_{t-i} + \varepsilon_{Pt}$$

The above set of equations can be set up as a three-variable structural vector autoregressive (SVAR) model. Accordingly, the SVAR model can be written as:

$$\mathbf{B}_0\mathbf{x}_t = \mathbf{c} + \textstyle\sum_{i=1}^{p}\mathbf{B}_i\mathbf{x}_{t-i} + \boldsymbol{\varepsilon}_t \qquad (1)$$

where $\mathbf{x}_t = [\Delta Y_t \quad \Delta Q_t \quad P_t]'$ is the vector of endogenous variables, and $\mathbf{B}_0 = \begin{bmatrix} 1 & b_{12} & b_{13} \\ b_{21} & 1 & b_{23} \\ b_{31} & b_{32} & 1 \end{bmatrix}$ and $\mathbf{B}_i = \begin{bmatrix} \beta_{11(i)} & \beta_{11(i)} & \beta_{11(i)} \\ \beta_{11(i)} & \beta_{11(i)} & \beta_{11(i)} \\ \beta_{11(i)} & \beta_{11(i)} & \beta_{11(i)} \end{bmatrix}$ are square coefficient matrices. The vector $\mathbf{c}$ denotes a vector of constants. The matrices $\mathbf{B}_0$ and $\mathbf{B}_i$ are square coefficient matrices of dimension 3×3, and $\boldsymbol{\varepsilon}_t$ is a vector of structural innovations which are white noise. The lag length p is determined according to the Akaike information criterion (AIC).

The SVAR model given by Equation 1 is pre-multiplied by $\mathbf{B}_0^{-1}$ to obtain the reduced-form VAR model in standard form as follows:

$$\mathbf{x}_t = \boldsymbol{\alpha} + \textstyle\sum_{i=1}^{p}\boldsymbol{\Gamma}_i\mathbf{x}_{t-i} + \mathbf{v}_t \qquad (2)$$

where the reduced-form coefficient matrices are $\boldsymbol{\Gamma}_i = \mathbf{B}_0^{-1}\mathbf{B}_i$, the reduced-form vector of deterministic terms is given by $\boldsymbol{\alpha} = \mathbf{B}_0^{-1}\mathbf{c}$, and the reduced-form error terms by $\mathbf{v}_t = \mathbf{B}_0^{-1}\boldsymbol{\varepsilon}_t$. The covariance matrix of the reduced-form errors $\Sigma = E(\mathbf{v}_t\mathbf{v}_t')$ so that $\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_2^2 & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_3^2 \end{bmatrix}$ are composites of the structural errors $\Sigma_\varepsilon = \begin{bmatrix} \sigma_{\Delta Y}^2 & \sigma_{\Delta Y.\Delta Q} & \sigma_{\Delta Y.P} \\ \sigma_{\Delta Q.\Delta Y} & \sigma_{\Delta Q}^2 & \sigma_{\Delta Q.P} \\ \sigma_{\mathrm{P}.\Delta Y} & \sigma_{P.\Delta Q} & \sigma_P^2 \end{bmatrix}$, and therefore we can obtain

$\Sigma = \mathbf{B}_0^{-1}\Sigma_\varepsilon \mathbf{B}_0^{-1\prime}$. Since Σ is symmetric—that is, $\sigma_{12} = \sigma_{21}$, $\sigma_{13} = \sigma_{31}$, and $\sigma_{23} = \sigma_{32}$—we have only six independent equations to determine nine unknowns in the Σ_ε matrix. We would therefore need to make the three restrictions on $\mathbf{B}_0^{-1}$ to exactly identify the system.

On estimating the standard VAR, we can proceed to test for Granger causality. We conduct this test by determining whether the lags of a variable are significant in the equation for another variable. For example, in our three-equation VAR with p lags, P_t does not Granger-cause ΔQ_t if $\sum_{i=1}^{p} \beta_{23(i)} = 0$. By concluding that P_t does not Granger-cause ΔQ_t we imply that P_t does not improve the forecasting performance of ΔQ_t. Assuming that all the endogenous variables in the vector are stationary, the direct way of testing Granger causality is to set the null hypothesis, H_0: $\sum_{i=1}^{p} \beta_{23(i)} = 0$. Rejecting the null hypothesis implies that current and past values of P_t can be used to forecast future ΔQ_t. If we cannot reject the null, this would imply that there is no Granger causality from P_t to ΔQ_t. It needs to be noted that this is not a test for exogeneity, where we would require that P_t does not contemporaneously affect ΔQ_t. Since lagged variables are involved, we are measuring under Granger causality whether current and past values of a variable (say P_t) affect a future variable (say ΔQ_t) in the system.

Once the VAR is estimated it can be used as a multi-equation forecasting model. For example, in the above VAR model given by Equation 2, we can estimate the coefficients in $\boldsymbol{\alpha}$ and $\boldsymbol{\Gamma}_i$. Assuming that we allow the data to run through to a certain time period T in the sample, we can obtain the one-step-ahead forecasts using the relation $E_T\mathbf{x}_{T+1}$ (where E_T denotes the conditional expectation), which will be a function of the estimated $\boldsymbol{\alpha}$ and $\boldsymbol{\Gamma}_i$ coefficients. Using recursive methods, we can obtain j-steps-ahead forecasts (where $j > 1$) that will be based on a combination of the $\boldsymbol{\alpha}$ and $\boldsymbol{\Gamma}_i$ coefficients. As we continue to recursively make forecasts further into the future, the number of coefficient estimates increases. The number of estimated parameters can also increase with the lag length of the VAR. Since the unrestricted VAR is over-parameterized, the resulting forecasts may be unreliable. A method to obviate this problem is to drop the insignificant parameter estimates and obtain a 'near-VAR' using seemingly unrelated regression estimation (SURE) (Enders 2014).

In order to analyse the dynamic relationships between the variables in the VAR, we transform the standard VAR to a vector moving average (VMA) form. Using iteration methods, we can transform the standard VAR to the following VMA:

$$\begin{bmatrix} \Delta Y_t \\ \Delta Q_t \\ P_t \end{bmatrix} = \begin{bmatrix} \mu_{Yt} \\ \mu_{Qt} \\ \mu_{Pt} \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} \phi_{11}(i) & \phi_{12}(i) & \phi_{13}(i) \\ \phi_{21}(i) & \phi_{22}(i) & \phi_{23}(i) \\ \phi_{31}(i) & \phi_{32}(i) & \phi_{33}(i) \end{bmatrix} \begin{bmatrix} \varepsilon_{Yt} \\ \varepsilon_{Qt} \\ \varepsilon_{Pt} \end{bmatrix}$$

where the column vector $[\mu_{\Delta Yt} \quad \mu_{\Delta Qt} \quad \mu_{Pt}]'$ denotes the mean of the corresponding vector of endogenous variables $[\Delta Y_t \quad \Delta Q_t \quad P_t]'$. Note that the structural errors are introduced in the VMA by replacing the reduced-form errors, using the relation $\mathbf{v}_t = \mathbf{B}_0^{-1}\boldsymbol{\varepsilon}_t$. The coefficients ϕ_{ij} are obtained using the product of the coefficient matrices from the reduced-form model and the matrix $\mathbf{B}_0^{-1}$. These coefficients ϕ_{ij} can be used to generate the effects of structural innovations on the entire time paths of the ΔY_t, ΔQ_t, and P_t variables. The elements $\phi_{ij}(0)$ are the impact multipliers. For example, $\phi_{32}(0)$ is the instantaneous impact on P_t of a one-unit change in $\varepsilon_{\Delta Qt}$. In the same way, $\phi_{32}(1)$ is the response of P_t after one period in the future (in this case, one year) as a result of the shock $\varepsilon_{\Delta Qt}$ in the current period (year). All of the coefficients $\phi_{ij}(i)$ comprise the impulse response functions. In order to identify the estimated VAR, we use the Cholesky decomposition so that the reduced-form errors are:

$$\begin{bmatrix} v_{1t} \\ v_{2t} \\ v_{3t} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ b_{21} & 1 & 0 \\ b_{31} & b_{32} & 1 \end{bmatrix}^{-1} \begin{bmatrix} \varepsilon_{\Delta Yt} \\ \varepsilon_{\Delta Qt} \\ \varepsilon_{Pt} \end{bmatrix}$$

We set restrictions on the matrix $\mathbf{B}_0^{-1}$ so that the matrix is lower triangular, or in other words we make a Cholesky decomposition of the matrix. Following Stuermer (2018), we construct a commodity demand shock, a commodity supply shock, and a commodity-specific demand shock. We assume that economic growth is not affected contemporaneously by commodity production or commodity prices. Commodity production is not affected contemporaneously by prices; but prices are contemporaneously affected by economic growth and commodity production.

4 Data and empirical results

In order to measure the immediate and subsequent effects of the pandemic on the economy, one would prefer to choose data measured at a monthly or bi-monthly frequency (Velde 2020). However, in order to measure the impact of past pandemics on commodity prices using market fundamentals, obtaining the data is problematic. To analyse the history of commodity prices along with global demand and supply variables prior to the first pandemic we consider—that is, the Spanish Flu—we need reliable continuous data, and these are only found at an aggregate level measured at an annual frequency. In the analysis that follows, we employ three variables: world economic growth, change in commodity production, and commodity prices, denoted by ΔY_t, ΔQ_t, and P_t respectively. The data are measured on an annual basis and span the period from 1850 to 2019. All details of the data on world GDP and commodity production are obtained from Stuermer (2018).[1] Economic growth is the transformed variable of world GDP, obtained by taking the difference of the logarithm of world GDP. The real GDP data measured on an annual basis are sourced from the Maddison Project Database from 1850 to 1950 and the subsequent years from the Conference Board. The copper production data are from Schmitz (1979) and various releases by the International Copper Study Group; tin production data are from Neumann (1904), the Bundesanstalt für Geowissenschaften und Rohstoffe (BGR; Federal Institute for Geosciences and Natural Resources), and the International Tin Research Institute; zinc production data are from Schmitz (1979), Metallgesellschaft, BGR, and the International Lead and Zinc Study Group; lead production data are from Neumann (1904), BGR, and the International Lead and Zinc Study Group. Crude oil production data are sourced from Mitchell (2007) and British Petroleum plc. Details of the data sources are available on Martin Stuermer's website. We use the same sources to update the data to the current period, 2019. The real price data from 1850 to 2019 are obtained from Jacks (2019).[2] Following Jacks (2019), the prices are expressed in US dollars, deflated by the US Consumer Price Index (CPI), and supplemented by updates taken from the Bureau of Labor Statistics (BLS). While there has been some debate about the choice of the deflator, we find that there is a strong correlation between alternative deflators such as the UK CPI or the Producer Price Index (PPI) from the UK or US. A plot of all the metal and oil prices is shown in Figure 1.

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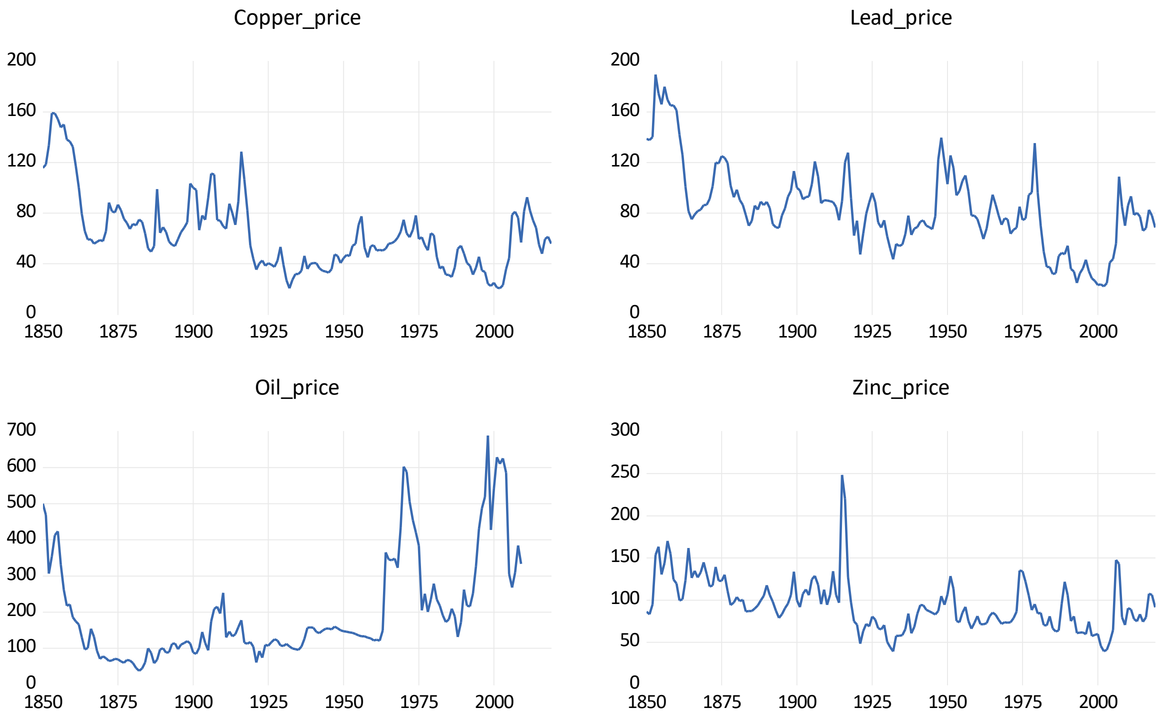
[1] Special thanks to Martin Stuermer for making his data available on his webpage: https://sites.google.com/site/mstuermer1/research-1.

[2] Special thanks to David Jacks for sharing his updated dataset on real primary commodity prices from 1850 to 2019. Details are available in the Appendix of Jacks (2019) and on his website: www.sfu.ca/~djacks/data/index.html.

Figure 1: Commodity prices



Source: authors' construction based on Jacks (2019) and BLS updates.

Over the last 150 years, commodity prices have exhibited a large amount of variability. As expected, we see the preponderance of upward spikes, which is a common feature of commodity prices (Deaton and Laroque 1992). From a visual inspection of the data alone, it is not clear whether the prices show any signs of trend or mean reversion. The issue of whether commodity prices contain stochastic trends remains contentious, and conclusions about such dynamic properties can only be made once unit root tests are carried out. The results of such tests are dependent on the sample size and can change with time (Ghoshray 2013). Given that commodity prices are autocorrelated and are generally skewed with heavy tails (Deaton and Laroque 1992), this is not surprising.

Accordingly, as a prelude to estimating the VAR, we first conduct unit root tests to determine whether the commodity prices are stationary, to satisfy the conditions needed to conduct the subsequent econometric procedures and tests. This is of significance because the issue of whether commodity prices are persistent or not is contentious and the evidence is mixed (Ghoshray 2011). We conduct the unit root tests specified by Elliot et al. (1996) and Ng and Perron (2001), which are powerful versions of the standard unit root tests.[3] The null hypothesis for both of these tests is a unit root against the alternative hypothesis of stationarity. The estimation takes place over the entire sample period and then in three subperiods, for reasons explained earlier, i.e. because the results can be sensitive as the sample size increases. The first subperiod is from 1850 to the start of the Spanish Flu epidemic; the second subperiod is from 1850 to the start of the Asian Flu epidemic; and finally the last subperiod is from 1850 to the start of the Hong Kong Flu epidemic. The results of the unit root test are given in Table 1.

[3] We ignore structural breaks, as we are examining the data in subsamples and therefore there can be an issue of power when the sample size is small.

Table 1: Unit root tests

Price	ERS	MZa	MZt
Oil price	–1.58	–4.90	–1.52
Zinc price	–3.77***	–28.01***	–3.73***
Lead price	–3.78***	–27.83***	–3.70***
Copper price	–3.49**	–24.21***	–3.44***
1850 to 1918 (period up to the Spanish Flu)			
Oil price	–0.38	–0.30	–0.17
Zinc price	–1.94	–10.21	–2.25
Lead price	–2.44	–14.83*	–2.59
Copper price	–2.16	–8.87	–2.01
1850 to 1956 (period up to the Asian Flu)			
Oil price	–1.09	–3.12	–1.16
Zinc price	–2.27	–10.72	–2.31
Lead price	–3.06**	–19.59**	–3.04**
Copper price	–2.88*	–18.47**	–2.91**
1850 to 1967 (period up to the Hong Kong Flu)			
Oil price	–1.14	–3.13	–1.20
Zinc price	–2.81*	–15.42*	–2.77*
Lead price	–3.54**	–24.92***	–3.47***
Copper price	–3.15**	–20.64**	–3.11**

Note: ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% levels respectively. ERS (Elliot, Rothenberg and Stock test) denotes the GLS (generalized least squares) version of the standard Dickey-Fuller test specified by Elliot et al. (1996); MZa and MZt denote the M-type (modified) versions of the unit root test specified by Ng and Perron (2001).

Source: authors' construction based on own calculations.

For the entire sample period we find that except for oil prices, we can reject the null hypothesis of a unit root for the prices of the commodities under consideration at the 1 per cent significance level at least. This implies that apart from oil, all the commodity prices are stationary. For the subsample for the period up to the outbreak of the Spanish Flu, we find that we cannot reject the unit root null in any of the prices except for lead at the 10 per cent significance level. This result is not unusual, as it is well known that the null hypothesis of a unit root is under-rejected for smaller sample sizes. In other words, the power of unit root tests is lower, thereby making it more difficult to reject the null hypothesis of a unit root. In the second subsample, for the period up to the outbreak of the Asian Flu, we find that apart from for oil and zinc, we can reject the unit root null hypothesis at the 5 per cent significance level. We find oil prices to remain persistent to shocks, as we cannot reject the unit root null for the entire sample as well as for subsamples. Zinc prices are stationary only for the entire sample, not for the shorter subsamples. For the remaining variables (that is, world GDP and oil, zinc, copper, and lead production), we do not report the unit root test results as these variables are transformed in the differenced logarithm, so that they are represented in growth form. Where we find cases in which the unit root null is not rejected for certain price variables, we transform these variables to be stationary. In other words, these variables for which the null hypothesis of a unit root is not rejected are first-differenced to achieve stationarity and therefore appear in growth form in the VAR model. Since the unrestricted VAR is over-parameterized, the resulting forecasts may be unreliable. As discussed earlier, we obviate this problem by purging the insignificant parameter estimates and obtaining a 'near-VAR' using SURE. We first consider the results by conducting forecasts based on the subsample 1850 to 1917—that is, the period up to the Spanish Flu.

Table 2: Forecasts based on the SURE model for the 1850–1917 sample period

			Zinc price			Oil price
	Actual	*Forecast*	*Error*	*Actual*	*Forecast*	*Error*
1918	97.14339	158.5878	−61.4444	215.3049	135.1532	80.15171
1919	74.92017	120.5975	−45.6773	196.2682	173.4667	22.80143
1920	70.96728	62.50597	8.461307	253.3864	224.6008	28.78566
1921	48.2714	64.75494	−16.4835	129.8774	280.6898	−150.812
1922	63.24454	53.59352	9.65102	146.2899	117.6419	28.64796
			Lead price			Copper price
	Actual	*Forecast*	*Error*	*Actual*	*Forecast*	*Error*
1918	91.65184	126.4595	−34.8077	82.22767	102.6423	−20.4146
1919	62.01797	122.5447	−60.5268	54.31645	81.70759	−27.3911
1920	73.98741	118.3774	−44.39	43.80484	54.08472	−10.2799
1921	47.24434	114.7056	−67.4612	35.11093	43.60063	−8.4897
1922	63.64443	111.6728	−48.0283	40.11332	34.94271	5.170605

Note: ‘actual’ denotes the actual price and ‘forecast’ denotes the forecasted price from the SURE. The error is calculated as (actual − forecast). Prices in US dollars (real).

Source: authors’ calculations.

Forecasting five periods ahead from 1918 (the point of outbreak of the Spanish Flu), we find a widely varying pattern for the selected metal and oil prices. In the case of lead, the forecasted price is above the actual price for the entire time horizon—that is, five years after the pandemic broke out. This implies that lead prices were well below the expected price (based on the history), and that the pandemic caused prices to be depressed over the chosen horizon. In the case of copper, a somewhat similar picture emerges. While the forecasted price is above the actual price for most of the time horizon, the magnitude of the error is relatively smaller than that for lead prices. In addition, towards the end of the horizon the forecasted price falls below the actual price. For zinc, the forecasted price is above the actual price only for the duration of the pandemic. By 1920 the forecasted price drops below the actual price. Thereafter, the wedge between actual and forecasted price remains small and shows signs of fluctuation, as a result of forecasted prices rising above or falling below actual prices. This implies that the Spanish Flu pandemic caused only a short-lived depression in zinc prices. In the case of oil the gap between actual and forecasted prices is different to those for metals, with actual prices being greater than forecasted prices for most of the time horizon. The deviations are quite large and seem to fluctuate widely, with no consistent pattern at all, which indicates the highly volatile response of oil prices after the pandemic. In general, the large variation of the metal and oil prices could be driven by the demand for these metals especially in the aftermath of the First World War.

The same exercise is repeated for the second subsample, the time up to the outbreak of the Asian Flu in 1957. The results of the forecasts using the SURE model are shown in Table 3.

The effects of the Asian Flu pandemic on metal prices are quite varied. For example, both lead and copper prices remain quite depressed compared with their forecasts, thereby implying that the pandemic may have caused this depressing effect. However, the effect on oil prices seems to be relatively negligible, with the wedge between actual and forecasted prices fluctuating between positive and negative values. This shows that the forecasted and actual prices cross over each other, with no substantial gaps in general. A similar fluctuating pattern in forecasts is found for zinc prices, except that the magnitude of the errors is relatively larger than those for oil.

Table 3: Forecasts based on the SURE model for the 1850–1956 sample period

			Zinc price			Oil price
	Actual	*Forecast*	*Error*	*Actual*	*Forecast*	*Error*
1957	75.09054	86.63572	−11.5452	159.8263	149.7821	10.0442
1958	66.10176	73.15515	−7.05339	155.2747	159.2472	−3.97248
1959	72.80733	67.13283	5.674497	149.6748	154.1353	−4.4605
1960	81.06701	72.92634	8.140673	147.2264	147.772	−0.54558
1961	71.51563	80.2063	−8.69067	145.7502	145.5817	0.168496
			Lead price			Copper price
	Actual	*Forecast*	*Error*	*Actual*	*Forecast*	*Error*
1957	97.00776	100.5311	−3.52332	52.83082	74.87374	−22.0429
1958	77.99915	94.57784	−16.5787	44.784	72.69186	−27.9079
1959	77.99744	92.73695	−14.7395	53.7598	70.7701	−17.0103
1960	75.15025	91.62393	−16.4737	54.40246	69.07296	−14.6705
1961	67.67357	90.8004	−23.1268	50.27778	67.57057	−17.2928

Note: ‘actual’ denotes the actual price and ‘forecast’ denotes the forecasted price from the SURE. The error is calculated as (actual − forecast). Prices in US dollars (real).

Source: authors’ calculations.

Finally, the SURE model is repeated for the third subsample—that is, the period up to the Hong Kong Flu in 1968. The results are shown in Table 4.

Table 4: Forecasts based on SURE model for the 1850–1967 sample period

			Zinc price			Oil price
	Actual	*Forecast*	*Error*	*Actual*	*Forecast*	*Error*
1968	71.92991	79.36275	−7.43283	129.5309	132.8134	−3.28246
1969	73.82429	81.5829	−7.75861	127.43	128.4103	−0.98024
1970	73.13659	83.45235	−10.3158	121.9801	125.9541	−3.97394
1971	73.83024	85.01869	−11.1884	123.5966	120.7249	2.87165
1972	78.64306	86.32622	−7.68316	121.101	122.4029	−1.30196
			Lead price			Copper price
	Actual	*Forecast*	*Error*	*Actual*	*Forecast*	*Error*
1968	70.70891	74.02529	−3.31638	60.46249	57.47228	2.990211
1969	75.6871	73.05222	2.634878	65.16749	57.40283	7.764661
1970	74.91119	73.94082	0.970369	74.69126	57.33909	17.35217
1971	63.45553	75.74682	−12.2913	63.83048	57.2806	6.54988
1972	66.89694	77.74688	−10.8499	60.81345	57.22692	3.586531

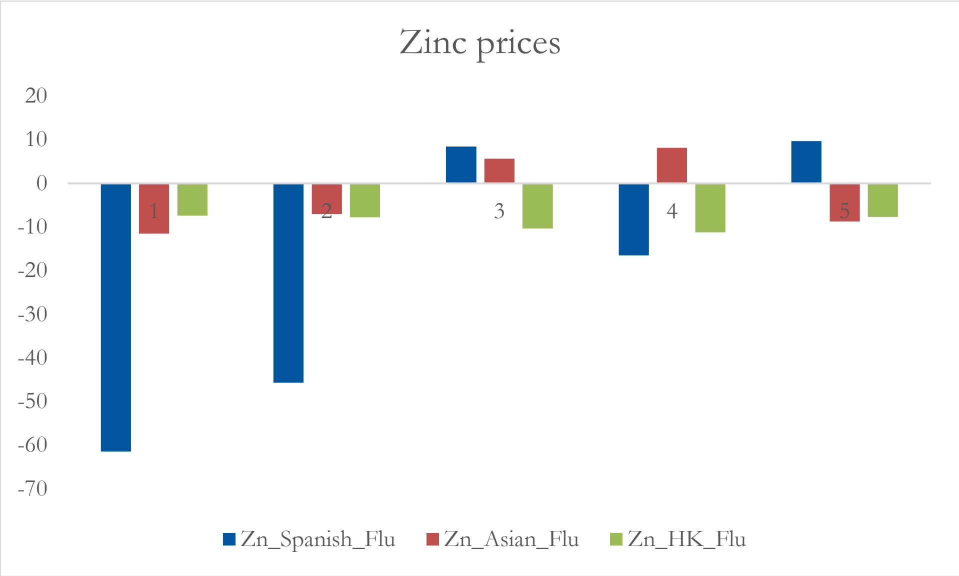
Note: ‘actual’ denotes the actual price and ‘forecast’ denotes the forecasted price from the SURE. The error is calculated as (actual − forecast). Prices in US dollars (real).

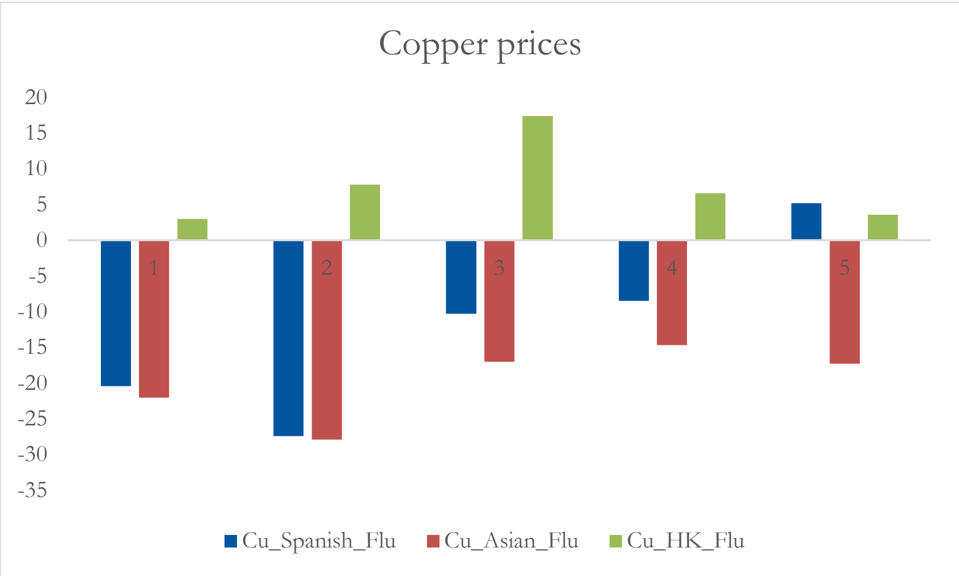
Source: authors’ calculations.

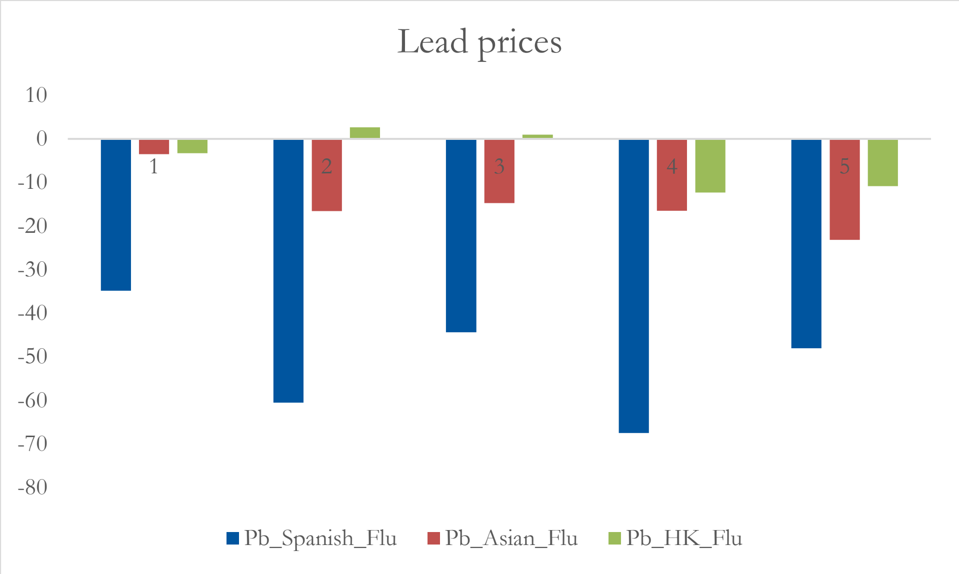
The pattern of errors changes substantially in this case. For example, for the entire five-year horizon the forecasted zinc prices this time remained above the actual prices, implying that zinc prices were more depressed than expected after the Hong Kong Flu outbreak. The opposite is the case for copper, where the forecasted prices remained below the actual prices, implying that the latter price remained buoyant during this period. Oil shows a fluctuating pattern of errors that are small in magnitude compared with those for lead, which shows a fluctuating pattern as well.

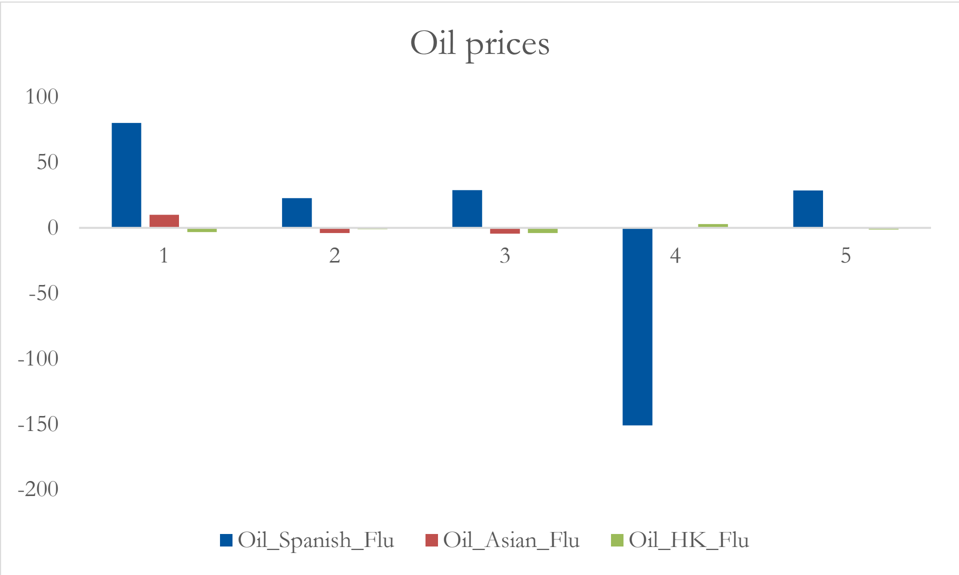
So far, we find that the Spanish, Asian, and Hong Kong Flu pandemics exerted an effect on the selected metal and oil prices. But how do they compare? The graphs in Figure 2 show how prices evolved during and following the three pandemics by comparing the errors, or in other words the gap between forecasted and actual prices.

Figure 2: Comparison of price deviations during and following the Spanish Flu, Asian Flu, and Hong Kong Flu pandemics









Note: price deviations in US dollars (real).

Source: authors' construction based on own calculations.

A number of interesting observations can be made from these graphs. While it is clear is that oil prices deviated widely from their forecasted (or expected) prices following the Spanish Flu, there is hardly any significant effect on deviations following the Asian or the Hong Kong Flu. Another striking feature is the manner in which copper prices deviated from their expected prices. Following the Spanish Flu, the deviations of copper prices from their expected prices were similar to those in the first four years following the outbreak of the Asian Flu, but in the fifth year of the projected horizon the Asian Flu seems to have had a stronger impact on copper prices than the Spanish Flu. The deviations are negative in the case of the Spanish Flu and Asian Flu but positive in the case of the Hong Kong Flu (suggesting that actual prices of copper ended up being higher than forecasted prices). For lead, the deviations are largely negative in sign, implying that actual prices were lower than expected, and the magnitude of the deviation was larger following the outbreak of the Spanish Flu than following the outbreak of the Asian Flu. In comparison, the effect of the Hong Kong Flu outbreak was much smaller. For zinc, the deviations are large and negative only in the first two years following the Spanish Flu. From then on, over the time horizon considered, we find that the deviations are relatively small and they fluctuate for all of the pandemics. The upshot is that these pandemics had a differing impact on commodity prices, and we find the deviations between actual and expected prices to be different for different commodities in terms of magnitude. No clear conclusion can be drawn about the magnitude, the persistence, or the sign (whether the deviations are negative or positive) of the impact. However, concerning the last of these, the sign, we can generally conclude the presence of a negative impact on metal prices to be discernible for the first few years following the outbreak of past pandemics. The results do not provide any pattern in terms of the effect that past pandemics had on commodity prices. At this stage, we proceed to trace out the effect on the rate of commodity production and commodity prices of a sharp drop in global aggregate demand as predicted by leading institutions.

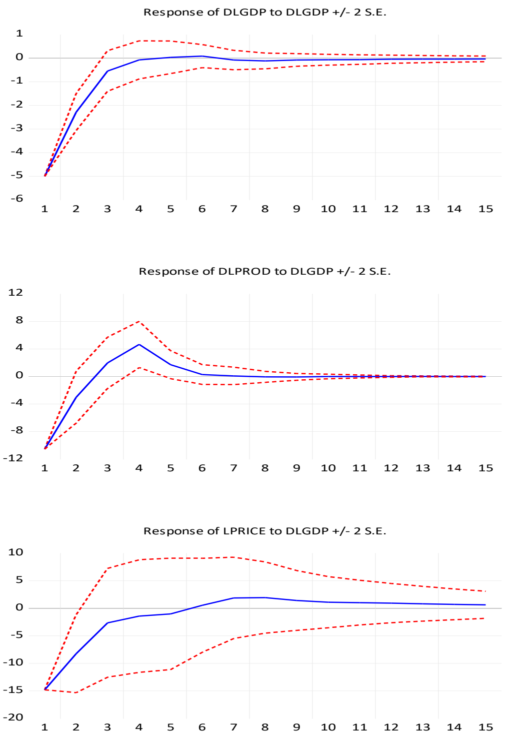
With the outbreak of COVID-19, the World Bank and the International Monetary Fund (IMF) both projected that global growth would contract by approximately 5 per cent.[4] Accordingly, we choose this contraction in global economic growth of 5 per cent to trace out the effects on commodity production and commodity prices, as well as how global economic growth responds to its own shock. To this end, impulse response analysis is employed to trace out in percentages what the impact of a global contraction would be on commodity prices as well as commodity production and global growth. The responses of the three different metal and oil prices and production are shown in Panels A to D in Figure 3.

We create an impulse of a 5 per cent contraction in global economic growth. Following this shock of global demand contraction, we find that global economic growth takes about three years to recover for all commodities chosen, both oil and metals. This recovery in global economic growth is in line with the forecasts of the IMF and the World Bank, which suggest approximately the same amount of time for global growth to recover to its previous levels. The rates of production of all four commodities face a sharp drop, with copper and zinc recording the largest contractions, followed by lead and then oil. The contraction in production is seen only as an impact shock. By the next year, the rates of production return to their original levels and stabilize. In the case of commodity prices, we find that following the forecasted global contraction, the prices of zinc and oil are likely to be adversely impacted, recording large falls, but then they are likely to recover in the next year following the global recovery of the rate of growth of production of the commodity. For lead prices, a similar adjustment takes place in response to a global contraction in demand, but it takes just a little less than a year longer than for zinc and oil for the effect of the shock to disappear. Only in the case of copper do we find that the adjustment of prices takes a very long time, suggesting that the adverse projected shock will have a long-lasting effect.

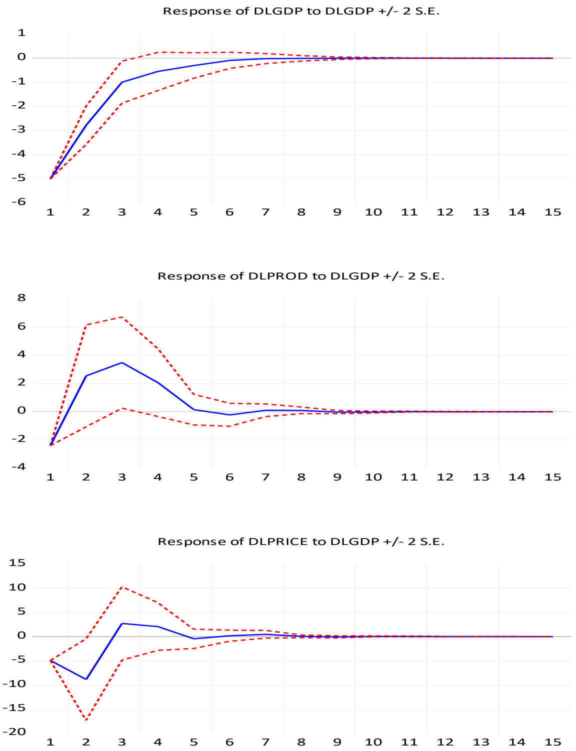
[4] At the time of writing, the contraction in global economic growth is estimated to be −5.2% according to the World Bank (2020b); according to the IMF (2020) it is estimated to be −4.9%.

Figure 3: The effect on commodity prices: response to a projected contraction in global demand

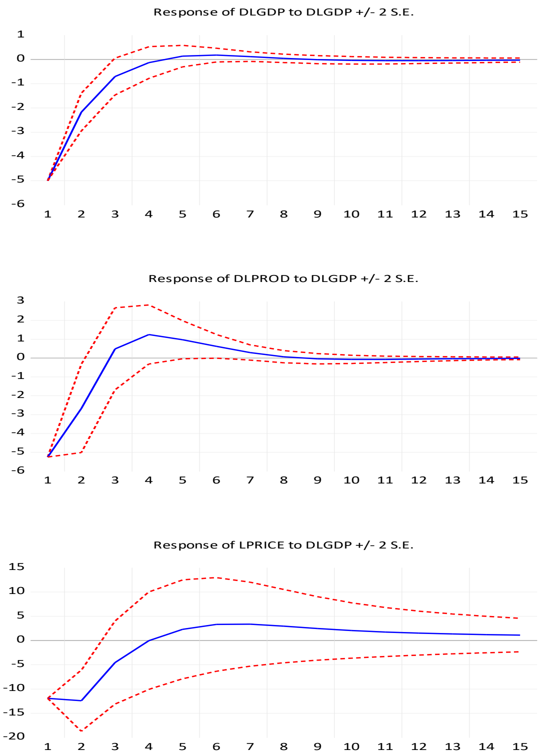
Panel A: Zinc



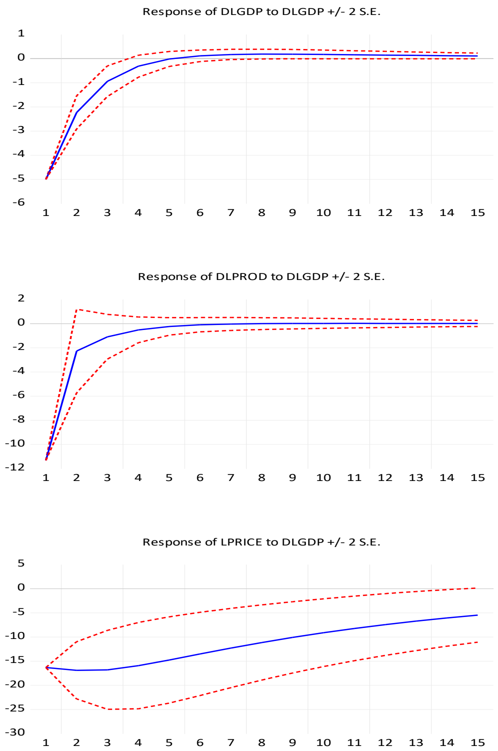
Panel B: Oil



Panel C: Lead



Panel D: Copper



Note: the broken lines denote the 95% standard error bands. DLGDP denotes world economic growth, DLPROD denotes the growth rate of production, and LPRICE denotes the natural log of prices.

Source: authors' construction based on own calculations.

5 Concluding remarks

In this study, we analyse the impact of past pandemics on a selection of commodity prices, comprising industrial metals and oil prices—those commodities that are likely to have been most affected by these pandemics. To cover the major pandemics from the twentieth century onwards, we choose a dataset that stretches over 150 years, from 1850 to 2019, that allows us to have an appropriate sample size to conduct forecasts over a chosen time horizon. To this end, we construct separate VAR models for each commodity price and the rate of production. To be specific, the VAR model uses a vector of variables that include world GDP and commodity production in growth form, and commodity prices in level or growth form, depending on whether the prices are integrated or stationary. Choosing points of time at which pandemics broke out, we make use of SURE models that generate forecasts into the future, on a five-year time horizon, to provide the counterfactual scenario. To this end, we choose the Spanish Flu of 1918, the Asian Flu of 1957, and the Hong Kong Flu of 1968. The forecasted prices are then compared with actual prices to compute the errors, or alternatively what the impact of the pandemic could have been on commodity prices. The errors vary widely by commodity and across the different pandemics, and therefore we find no general pattern in the response of commodity prices to these pandemics. Broadly, one can conclude that the Spanish Flu had a relatively larger adverse impact on commodity prices, while for the other pandemics considered—the Asian Flu and Hong Kong Flu—the impact is smaller and, for some of the industrial metals considered, not adverse but rather the contrary. A caveat to these results is that the Spanish Flu overlapped with the final stages of the First World War, and the severity of the Asian Flu and the Hong Kong Flu was not that profound compared with that of the Spanish Flu. While no clear pattern can be discerned from past pandemics, we end the study by carrying out an innovation accounting exercise on the VAR model to trace out the effect of shocks to world economic growth, world production of commodities, and commodity prices. The broad conclusion is that prices will be impacted as well as production, but the latter effect is short-lived in comparison with the former.

The broad conclusion is that the current pandemic, COVID-19, has had and will continue to have an initial impact (the pandemic is ongoing at the time of writing). To understand the full extent of this impact, we would need to know for how long this pandemic continues and how severe it is overall, and how economies around the world choose to respond to it. As we have described, the government response to past pandemics has differed, with hardly any initial response to the Spanish Flu outbreak due to the ongoing war and a lack of medical technology, and some limited response to the Asian Flu and Hong Kong Flu but with very little non-pharmaceutical intervention.

The current problem is the uncertainty surrounding COVID-19. For example, there is still debate about the infectiousness of the virus and whether it can lead to long-term debilitating conditions. At the time of writing, there is news that a vaccine may be ready by early 2021, with Pfizer-BioNTech and Moderna announcing that their vaccines are more than 90 per cent effective. By the end of November 2020, we will know more about the effectiveness of the Oxford vaccine. However, all vaccines are subject to safety checks. As a second wave seems to be emerging in countries such as the UK and other European countries, along with rising numbers of cases in countries such as the USA, Brazil, and India, policy-makers are unclear as to whether further lockdown conditions need to be imposed and if so, whether they should be at a regional or national level. If such conditions are imposed, the intention is usually to make them short term, but uncertainty shrouds the question of whether the necessity for such measures will turn out to be persistent. All of this is likely to change consumption patterns. For example, whether firms encourage working from home as opposed to using an office, or whether business travel will be curtailed, can lead to uncertainty. Uncertainty in the construction sector (e.g., over the building of office blocks) can lead a drop in demand for industrial metals used for construction, such as copper, zinc, and lead; uncertainty in the travel sector (e.g., over whether business travel is possible) can cause a drop in the price of oil. Our results show that this pandemic, in common with past pandemics, is indeed having a depressing effect on such commodity prices and that this impact varies depending on the underlying market fundamentals as well as on government intervention.

A limitation of the current study is that the modelling approach is based on macroeconomic data that are essentially backward-looking. This approach is constrained by the fact that we are analysing a very long time period that stretches back to the mid-nineteenth century to allow us to analyse demand and supply shocks using world GDP data and world commodity production, for which annual data are available. While using such data makes it possible to include the impact of past pandemics such as the Spanish Flu of 1918, such a modelling approach is not suited to swift sudden developments, such as the economy being hit by a large shock; measuring such uncertainties is only possible if one uses high-frequency data, such as daily or weekly data (Altig et al. 2020). Avenues for further research can be broadened by collecting further data that can be used as a measure of uncertainty, measured over a long period of time, and making use of procedures that allow mixed-frequency analysis in order to employ all of the information in the data.

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