Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company’s public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Assessing the impact of COVID-19 on price Co-movements in China

Yingying Xu\textsuperscript{a}, Donald Lien\textsuperscript{b,}\textsuperscript{*}

\textsuperscript{a} School of Humanities and Social Science, Beihang University, Beijing, China
\textsuperscript{b} Alvarez College of Business, University of Texas at San Antonio, TX, United States

\textbf{ARTICLE INFO}

\textbf{JEL:}
C32
E31
F30
G15

\textbf{Keywords:}
COVID-19
Price co-movement
Inflation
Uncertainty
Network

\textbf{ABSTRACT}

The COVID-19 crisis has caused violent fluctuations in prices, and government responses to the pandemic further intensify the uncertainty of price changes. This study evaluates the dynamic price co-movement of main consumption categories within an Additive Bayesian Network (ABN) framework, which shows dramatically fluctuating price risks during the pandemic period. The global fears for COVID-19 affects price co-movements in China negatively with a direct linkage. By contrast, confirmed cases in China, confirmed cases around the world, and fears for the domestic pandemic situation are indirectly related with price co-movements through financial markets. The exchange rate and international hedging assets such as gold play important intermediary roles in such relationships. Meanwhile, volatile international markets including crude oil and Bitcoin are also indirectly linked with price changes in China. Comparing with the situation in China, the global pandemic appears to be a more important factor influencing the price stability in China. Overall, the impacts of COVID-19 on price co-movements are empirically demonstrated, which highlights the importance of prudent policies in response to the pandemic.

1. Introduction

Finding the aggregate sources of changes in goods’ prices is one of the goals of macroeconomics (Reis and Watson, 2010). The world has been gripped by the Coronavirus Disease-19 (COVID-19) since the first half of 2020, resulting in tremendous economic damage. Under various public intervention policies and regulations aiming to facilitate reductions in the number of confirmed cases, such as social distancing measures and unprecedented monetary and fiscal responses, heterogenous and fluctuating prices emerged for different sectors. Is COVID-19 driving the co-movements of prices, or is it merely producing an indirect effect through influencing the macroeconomy? This study attempts to assess the effect of COVID-19 on the co-movement of prices in China and offer policy suggestions.

The economic implications of COVID-19 are extensive and uncertain, with different effects being expected on demand and supply sides of various sectors and markets. For example, social distancing measures such as lockdowns and related restrictions may lead to a shortage of labor force, which simultaneously drives up the prices of many labor-intensive products. By contrast, changing preferences for specific goods such as protective clothes and masks on the part of consumers could shift the demand structure. To understand the potential impact of COVID-19 on prices, it is important to comprehend the transmission channels through which the shocks affect the economy. Three possible transmission channels exist according to the literature (see, e.g., Carlsson-Szlezak, Reeves, and Swartz,

\textsuperscript{*} Corresponding author.

\textit{E-mail address: Don.Lien@utsa.edu} (D. Lien).

https://doi.org/10.1016/j.intfin.2022.101602
Received 11 November 2021; Accepted 8 June 2022
Available online 11 June 2022
1042-4431/© 2022 Elsevier B.V. All rights reserved.
2020a, b): direct impact through reducing consumptions, indirect impact through financial market shocks, and supply-side disruptions. While supply and demand forces co-exist (Balleer et al., 2020), many studies argue that demand shortages dominate in the short run which result in a declining aggregate consumption price. Nevertheless, a decline in the aggregate price does not necessarily denote a synchronized decrease in the consumption across different categories. Additionally, the pandemic itself and corresponding policy responses may have undesirable effects on consumer prices (Banerjee, Mehrotra, and Zampolli, 2020). In fact, while the injection of liquidity into economies worldwide may cause excess demand and thus stimulate inflation (Blanchard, 2020), the collapse in commodity prices induced by stumbling oil prices is likely to decrease goods’ prices.

As the first economy to be hit by the pandemic, to contain it and to resume work and production, China is an ideal target for studying the impact of COVID-19 on price co-movements1. Since March 2020, the COVID-19 pandemic has tripped the world economic into a severe recession. China encountered the greatest impact on the macroeconomy in the first quarter of 2020, whereas the rest of the world in subsequent quarters, for example, the United States, the United Kingdom, and Russia in the second quarter of 2020 and many other emerging markets in the second half of the year (Liu, Liu, and Yan, 2020). Therefore, the research on the Chinese market provides useful implications for the other economies with the reasonable speculation that the economic recovery of other countries will basically follow China with certain lags. Within three months, China had gradually resumed production, the supply chain has basically recovered, and the growth of the secondary industry has returned to positive. Nevertheless, China’s GDP witnessed a – 6.8% growth in the first quarter, and the urban unemployment rate remained at around 6.0%. Despite the severe impact on both supply and demand sides of the Chinese economy in the first quarter, the supply side has recovered and the demand side had improved in the following quarter when China entered a phase of regular pandemic prevention and control. The supply had recovered faster than the demand, leading to a steady decline in price growth. Extraordinary macroeconomic policies were implemented to deal with the impact of COVID-19, such as increasing refinancing and reducing the required reserve ratio and interest rates to ensure sufficient growth in broad money supply and aggregate financing (Liu, Sun, and Zhang, 2020). As a consequence, China’s financial markets remained relatively stable, major asset prices rose steadily, and debt risks were better mitigated.

Impacts of the pandemic are likely to be heterogeneous for different channels. Given various goods in the real economy, shocks of the pandemic can result in both proportionally and relative price changes in different products (Reis and Watson, 2010). Nevertheless, the effects of demand and supply shocks generated by COVID-19 differ from each other, leading to uncertain impacts on the price co-movements. We attempt to specify whether and how the pandemic induces changes in price co-movements. First, we measure the dynamic co-movement index of eight consumption categories within the Additive Bayesian Network (ABN) framework through a rolling window approach. Using Bayesian Network, we describe the dependency structure between price changes of eight consumption categories before and after the pandemic. Then, we evaluate the overall effect of COVID-19 on the co-movement index considering possible impacts of important economic variables. Specifically, following Salisu, Akanni, and Raheem (2020), we test two measures of the pandemic, i.e., the number of confirmed cases in China and worldwide, and the global and China’s fear index for COVID-19. Finally, the ABN is used again to capture the network of the price co-movement index and various macroeconomic and pandemic-related factors. Robustness checks are also provided.

Our contributions to the literature are three-folds. First, based on the measurement of Price Co-movement Index (PCI), we note fluctuating price risks after the pandemic because of volatile price co-movements. Second, through measuring the global fear index for COVID-19 and the domestic fear index in China for the first time, we quantitatively estimate the effect of the pandemic on price co-movements in China. The empirical results suggest a significant negative effect of COVID-19 on price co-movements in China. Moreover, the pandemic is exerting heterogeneous impacts on prices of different categories and should be considered in forecasting inflation and analyzing the macroeconomic effects of COVID-19. Finally, the direct and indirect relationships between pandemic-related factors and price co-movements are revealed. Overall, the theoretical impact of the pandemic on inflation is ambiguous because of unidentified effects from demand and supply sides, which motivates the empirical estimation of this study. Our findings offer useful information for policy responses to the pandemic, particularly for economies that are at the height of the pandemic.

The remainder of this paper is organized as follows. Section 2 is a literature review. Section 3 explains the method used to measure price co-movement and empirical approaches used to analyze the effect of COVID-19 on price co-movements. Section 4 summaries the data, presents the empirical results, and discusses implications. Section 5 provides robustness checks, and Section 6 concludes this study.

2. Literature review

This study belongs to the rapidly expanding literature of the economics of COVID-19. Pandemics are anything but new (Brodeur et al., 2021). Nevertheless, investigations based on historical data might not be relevant in this case because COVID-19 has created large spikes of uncertainty that have no historical parallels (Baker et al., 2020). Different sectors are interconnected, making the modern economy a complex web. Everyone is someone else’s employee, consumer, etc. (Gourinchas, 2020). Consequently, the impact of COVID-19 and subsequent policy responses on the macroeconomy interrupts the circular flows and may result in cascading effects (Baldwin, 2020).

Macroeconomic impacts of the pandemic are pervasive. For example, some studies investigate the recovery process from economic crisis, which is not expected to be straightforward. The pattern for the COVID-19 economic recovery can be “V-shaped”, “U-shaped”,

---

1 Unfortunately, the Omicron COVID brought up new cases in March 2022. Shanghai and other cities in China were forced into lockdowns.
“L-shaped”, or “K-shaped” (Carlsson-Szlezak, Reeves, and Swartz, 2020a). Some studies focus on the aggregate economic costs of COVID-19. For instance, McKibbin and Fernando (2021) treat the pandemic as a positive shock to government expenditure and a negative shock to financial markets and labor supply in a hybrid DSGE/CGE model. According to the study, there are seven different scenarios for the increase in mortality and the fall in GDP. Eppinger et al. (2020) quantify the shocks of the pandemic on global value chains and find that China suffered a 30% welfare loss with moderate spillover to other economies. Mulligan (2020) extrapolates the welfare losses to be approximately $7 trillion per year of shutdown which stems from nonmarket activities, fiscal stimulus, and black market activities.

Under the high uncertainty caused by the pandemic, consumers’ expectations for prices become more divergent and their spending patterns change significantly during the crisis period according to the survey in the United States (Coibion, Gorodnichenko, and Weber, 2020). Significant changes in prices stem from many sources, including labor supply abruptions, debt responses, government sales and taxes, and consumption pattern changes. Specifically, Bonadio et al. (2021) note that a contraction in labor supply due to the global lockdown produces approximate 30% GDP drop in 64 sample countries. In addition, they find that the participation in global supply chains generally alleviates the pandemic-induced contraction in labor supply, but the extent varies across different countries. Elenev, Landvoigt, and Van Nieuwerburgh (2020) model the equilibrium dynamics of macroeconomic prices under the fall in worker productivity. They find that the pandemic under the combo policy used in the United States generates a cumulative 22% loss in consumption in the long run. Additionally, consumption and investment growth rates are much more volatile. According to Clemens and Veuger (2020), although the consumption declines are similar for goods and services, there are considerable variations across each sub-category. Such shocks transmit to personal income and government taxes. Unlike previous recessions, during this pandemic consumption decreases more than income.

The direct impact of the pandemic on prices displays mainly on consumption pattern changes. Consumer behavior and consumption pattern change significantly showing distinctive features for different sectors. Using transaction data and online shopping history, many studies report panic buying behaviors in the initial period of the pandemic and find that households increase their spending in specific sectors. For example, Chang and Meyerhoefer (2021) analyze consumers’ online food shopping decisions using transaction data from the largest online platform selling agri-food products in Taiwan. They find that the pandemic increases online food shopping in Taiwan by 5.7% per additional confirmed case. In a typical week during the pandemic, the sales increase by 18% and the number of online consumers grows by 16%. However, such increases are not uniform across food categories. The variety of food products purchased from this platform increases during the pandemic period, which is possibly a result from the substitution effects of foods. Consumer shifts are demonstrated to be driven by Google searches and newspaper reports of COVID-19, which indicates that the media affects consumers’ decisions. Based on high frequency credit and debit transactions data, Cavallo (2020) re-estimates the basket weights of consumptions in the United States and documents changes after the outbreak of COVID-19. Specifically, the weights of food at home, alcoholic beverages, housing, education, and communication rise for the month of April 2020, while weights of apparel, medical care, transportation, recreation, food away from home, and other goods and services decline. Six out of ten categories show increases in prices, and the remaining four categories have falling prices. Most of the changes in spending come from food and fuel. The investigations for 17 additional countries suggest that the consumption baskets during the pandemic are very different across economies. Seiler (2020) resorts to debit card transactions to quantify changes in consumer spending in Switzerland and finds that the consumer spending changes for 12 consumption categories are quite small before the pandemic. However, after the declaration of the extraordinary situation by the Swiss Federal Council on March 16, 2020, the cumulative expenditure changes abruptly and has remained violently fluctuating since then.

The debate about factors driving changes in prices of different consumption categories focuses on the prevalence of demand versus supply sides. Shapiro (2020) tests the sensitivity of 124 categories of consumption in the United States. Sensitive categories, in which either price or quantity changes significantly following the onset of the pandemic, make up approximately two-thirds of the 124 expenditures in the core personal consumption expenditures (PCE) index. Within sensitive categories, shifts in supply should move quantities and prices in opposite directions, whereas demand shocks should move prices and quantities in the same direction. Based on such microeconomic analysis, Shapiro (2020) finds that very few categories experience a clear supply or demand shift. That is, for most of the categories where prices are sensitive to the pandemic, there are some combinations of supply and demand shifts. Focusing on firms’ pricing decision, Riggi et al. (2021) survey firms to investigate how COVID-19 shock influence firms’ pricing choices and inflation expectations. Their study suggests that while most firms perceive the pandemic as a demand shock, the demand-supply narrative is not that relevant in shaping their pricing strategies. Instead, the expected persistence of the pandemic and competitors’ behaviors are driving factors in determining the direction of planned price changes. Some other studies also note that both demand and supply side shocks affect inflation during the pandemic period, e.g., Maital and Barzani (2020), Armantier et al. (2021), and O’Brien, Dumoncel, and Goncalves (2021).

To mitigate the negative effects of the pandemic on the economy and public health, governments around the world have implemented many policies, including monetary, fiscal, and financial policies (Gourinchas, 2020). Such policies have both direct and indirect effects on prices. For instance, the injection of liquidity may increase the amount of money in circulation and thus cause excess demand and corresponding inflation. Similarly, panic buying of various goods induced by uncertainties about the COVID-19 is likely to stimulate inflation in some categories (Ebrahimi, Igan, and Peria, 2020). The survey conducted by Binder (2020) suggests that consumers associate graver concerns about COVID-19 with higher unemployment expectations and inflation expectations. Nevertheless, when respondents are informed about the interest rate cuts of the Fed, they tend to be more optimistic about inflation and unemployment. Given that expectations will affect consumers’ investing, consuming, and saving behaviors (Xu et al., 2017; Xu et al., 2021), prices are inevitably impacted by policy disclosures.
3. Methodology

3.1. Measuring price co-movements with Additive Bayesian Network

The Bayesian Network (BN) is a particularly useful approach to understand the underlying structure of data, which is designed to sort out directed related variables from all available variables. The Additive Bayesian Network (ABN) is a data-driven method which does not rely on expert knowledge (Lewis and Ward, 2013). Meanwhile, the ABN can handle a blend of variable distributions and supports variables adjustment.

Using a BN to study observational data can be traced back to Pearl (1985). For a set of random variables \( X = \{X_1, X_2, \ldots, X_n\} \), a directed acyclic graph (DAG) \( G = (V, E) \) is generated by a BN. In the DAG, \( V \) is a finite set of vertices which are the nodes denoting the random variables, and \( E \) is a finite set of directed edges representing the statistical conditional dependences between two nodes. If the edge set \( E \) contains an edge from node \( i \) to node \( j \), the index node \( X_i \) is named as the parent of node \( j \). If there are more than one parent node, we use \( Pa_j \) to denote the set of parents for node \( j \). Conversely, \( Ch_i \) represents the set of children nodes for node \( i \). The Markov Blanket (MB) of a node fully characterizes an index node, including the set of parents, children, and co-parents (the parents of the specified children) nodes.

In a BN, an index node \( X_j \) is assumed to be dependent solely on its parent nodes \( Pa_j \). Put differently, each node is parameterized by a local probability distribution \( P(X_j|Pa_j) \). Thus, the global probability distributions are given by the Markov property.

\[
P(X) = \prod_{j=1}^{n} P(X_j|Pa_j) \tag{1}
\]

where \( n \) denotes the total number of nodes. The ABN encodes the conditional independences among codes using graphical separation. If two nodes are d-separated by one or more nodes, the corresponding random variables are conditionally independent for the given set of variables (Verma and Pearl, 1988). Score-based approaches are used to parametrize the BN.

An ABN model extends the usual generalized linear model (GLM) to multiple dependent variables and assumes that each node is characterized by a GLM where the parent indices constitute the covariates. For the index node \( X_j \) and a set of parents \( Pa_j \), \( P(X_j=s|Pa_j = c) \) denotes the probability that \( X_j = s \), given the \( c \)-th parent configuration of \( Pa_j \). Then, the joint probability distribution factorizes into:

\[
P(X|\theta_b, S) = \prod_{j=1}^{n} P(X_j|Pa_j = c, \theta_{b_j}) \tag{2}
\]

where \( \theta_b \) represents the set of local probability distributions for all variables in the Bayesian network, \( \mathcal{N} \) denotes the structure of the DAG, and \( \theta_{b_j} \) is the set of local probability distributions regarding node \( X_j \).

We use the classical exponential family parametrization following Kratzer et al. (2019):

\[
P(X_j|Pa_j) = \frac{\exp(\eta(T, H)) T(X_j, Pa_j) - A(T, H)}{dH(X_j, Pa_j)} \tag{3}
\]

where \( \theta \) incorporates the configuration of the parents' node and functions \( \eta \), \( T \), \( A \), and \( H \) can depend on the nodes. The distributions of variables can be different. Similarly, score-based approaches are useful in identifying ABN. Given that the number of possible networks increases super-exponentially with the number of nodes, we follow Kratzer et al. (2019) and use a decomposable score which is additive to the network’s nodes and depends solely on the parent nodes. Scores such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Minimum Description Length (MDL; see Daly, Shen, and Aitken, 2011) can be used in maximizing the posterior probability. Additionally, if some parts of the network are known, it is possible to impose such structure to the ABN methodology.

To measure price co-movements, we use the sum of identified arcs within a DAG with the weights being the correlations of each node according to Gómez (2019), i.e., the Price Co-movement Index (PCI). To be more specific, \( PCI = \sum \beta_{X_i,X_j} \), where \( \beta_{X_i,X_j} \) denotes the coefficients of \( X_i \) for the node \( X_j \) within an ABN. For a set of random variables \( X = \{X_1, X_2, \ldots, X_n\} \), \( \beta_{X_i,X_j} \) denotes the conditional dependence between two variables and therefore satisfies \(-1 \leq \beta_{X_i,X_j} \leq 1\). The interpretation of this measurement is intuitive which denotes the overall possibility of co-movements between different categories. Given that the COVID-19 pandemic has cast significant effects on prices, we resort to the rolling window estimation of ABN to measure dynamic co-movements of prices. Specifically, we adopt a fixed window size of 60 days, which is approximately two months, and use another window of 90 days for robustness tests.

3.2. Test the effect of COVID-19 on price co-movements

According to the theoretical framework of inflation decomposition, the effect of COVID-19 on price co-movements can result in both pure inflation changes and relative inflation changes. For example, an increase in money supply is anticipated all around the world following the pandemic (Brodeur et al., 2021), which will lead all price-setters to raise prices in the same proportion and thus result in pure inflation. By contrast, the quantity of money supply increase is partly unanticipated, to which some firms respond and others do not, leading to changes in relative-price changes. Therefore, it is necessary to control important economic variables to specify
whether the effect of the pandemic on price co-movements results in pure inflation, relative inflation, or idiosyncratic inflation.

To quantitatively determine the effect of COVID-19 on price co-movements, we investigate the relationship between four indices for the pandemic and the price co-movement index using regression methods. To obtain the net effect of the pandemic on price co-movement, we control important economic variables. In response to the outbreak of COVID-19, Chinese government adopted many monetary policy instruments, including lowering the required reserve ratio for three times to release 1.75 trillion RMB of long-term liquidity and raising the amount of refinancing and rediscount to guide the overall market interest rates. Thereby, we consider two daily available monetary policy instrument variables, i.e., the overnight SHIBOR (Shanghai Interbank Offered Rate) and 10-year treasury yields. Meanwhile, commodity prices are an important channel through which policies transmit to consumption prices. For example, changes in interest rates inevitably affect demands for investment products such as gold and Bitcoin. Thus, price changes in gold, oil, and Bitcoin are considered in our analysis. Finally, the financial market is another channel through which the policy changes affect consumption prices. We consider the Shanghai securities composite index (SSCI) and the exchange rate of Chinese Yuan quoted in the United States Dollar, i.e., USD/CNY.

The following empirical model is used to measure the effect of COVID-19 on price co-movement.

\[
P_{CI} = \alpha + \beta_{COVID} + \Gamma_{PCA} + \epsilon_i
\]

where \(P_{CI}\) denotes the price co-movement index measured through the framework of ABN, COVID, represents an index measuring the pandemic, and \(PCA_i\) is the principal components of important policy variables determined by the Scree Test Criterion. Furthermore, given possible correlations between COVID\(_t\) and \(PCA_i\), we also test the effect of the orthogonalized COVID\(_t\) to eliminate potential effects of policy changes.

Four indices are used to proxy COVID\(_t\): the growth rate of confirmed cases in China (\(CASE_{China}\)) and around the world (\(CASE_{global}\)), the global COVID-19 Fear Index (GFI), and the COVID-19 Fear Index in China (CFI). Following Salisu, Akanni, and Raheem (2020), we measure COVID-19 Fear Index through combining two components: the Reported Cases Index (RCI) and the Reported Deaths Index (RDI) with equal weights. RCI and RDI measure how far the general expectations from reported and death cases 14 days ago (the start of the incubation period) veered from current day’s infections or deaths, respectively. Specifically, \(RCI = 100 \times c_t / (c_t + c_{t-14})\), where \(c_t\) denotes the reported cases globally in day \(t\), and \(RDI\) is measured analogously. Then the fear index (CFI or GFI) is measured by \(0.5 \times RCI + 0.5 \times RDI\).

4. Data and empirical results

4.1 Data

To reveal the effect of COVID-19 on price co-movements, we use the internet-based Consumer Price Indices (iCPI) calculated by Liu et al. (2019). We use \(100 \times (iCPI, -iCPI_{t-1})\) to measure price changes. There are two main reasons that we adopt iCPI instead of the CPI provided by the Official Statistics Department. First, the pandemic has resulted in large shifts in households spending, thus making the weights of official CPI biased as demonstrated by many studies such as Cavallo (2020). Second, official CPI is available at monthly basis, which leads to insufficient data for this study. By contrast, iCPI is available at the daily basis and is generated from on online prices of most goods and services consumed by urban and rural Chinese. Eight main categories of consumption are studied, i.e., food, tobacco, and alcohol (iCPI1), clothing (iCPI2), residence (iCPI3), household articles and services (iCPI4), transportation and communication (iCPI5), education, culture, and recreation (iCPI6), health cares (iCPI7), and miscellaneous goods and services (iCPI8). Items for each category are the same as that in the official CPI basket. For economic variables, we use logarithmic growth rates of gold, oil, Bitcoin, and SSCI prices. To capture the effect of international trading and monetary policies from major economies, we consider the exchange rate of Chinese Yuan quoted in the United States Dollar, i.e., USD/CNY.

To fully reveal the effect of the pandemic, the sample period ranges from approximately one year before the outbreak of COVID-19 in China to current date with available data, i.e., November 1, 2018 to April 19, 2021. The selection of the sample period also helps to

### Table 1

Descriptive statistics (November 1, 2018 to April 19, 2021).

| iCPI1 | iCPI2 | iCPI3 | iCPI4 | iCPI5 | iCPI6 | iCPI7 | iCPI8 | CFI | GFI |
|-------|-------|-------|-------|-------|-------|-------|-------|-----|-----|
| Mean  | 0.010 | 0.017 | 0.035 | 0.025 | 0.006 | 0.020 | 0.017 | 0.033 | 40.115 | 55.407 |
| Median| 0.001 | 0.009 | 0.033 | 0.004 | 0.004 | 0.004 | 0.021 | 0.005 | 32.714 | 51.907 |
| Max.  | 2.852 | 2.982 | 2.665 | 5.422 | 0.438 | 2.764 | 3.600 | 7.995 | 100.000 | 100.000 |
| Min.  | -2.015 | -2.438 | -2.982 | -3.608 | -0.352 | -3.366 | -4.146 | -6.467 | 0.000 | 0.000 |
| Std. Dev. | 0.410 | 0.397 | 0.563 | 0.629 | 0.069 | 0.504 | 0.593 | 0.998 | 24.953 | 14.403 |
| Skewness | 0.431 | 0.990 | -0.279 | 0.916 | 0.555 | 0.176 | -0.139 | 0.570 | 0.853 | 1.447 |
| Kurtosis | 9.139 | 16.242 | 7.944 | 18.382 | 7.861 | 10.272 | 15.103 | 19.427 | 2.788 | 6.209 |
| Mean | 0.010 | 0.017 | 0.035 | 0.025 | 0.006 | 0.020 | 0.017 | 0.033 | 40.115 | 55.407 |
| Median | 0.001 | 0.009 | 0.033 | 0.004 | 0.004 | 0.004 | 0.021 | 0.005 | 32.714 | 51.907 |
| Max. | 2.852 | 2.982 | 2.665 | 5.422 | 0.438 | 2.764 | 3.600 | 7.995 | 100.000 | 100.000 |
| Min. | -2.015 | -2.438 | -2.982 | -3.608 | -0.352 | -3.366 | -4.146 | -6.467 | 0.000 | 0.000 |
| Std. Dev. | 0.410 | 0.397 | 0.563 | 0.629 | 0.069 | 0.504 | 0.593 | 0.998 | 24.953 | 14.403 |
| Skewness | 0.431 | 0.990 | -0.279 | 0.916 | 0.555 | 0.176 | -0.139 | 0.570 | 0.853 | 1.447 |
| Kurtosis | 9.139 | 16.242 | 7.944 | 18.382 | 7.861 | 10.272 | 15.103 | 19.427 | 2.788 | 6.209 |

Notes: Max. and Min. represent the maximum and minimum values; Std. Dev. denotes the standard deviation; J-B is the Jarque-Bera normality test and probabilities in parentheses; Obs. denotes the number of observations.
ease possible effects of the China-United States trade war (Xu and Lien, 2020). Table 1 summarizes the descriptive statistics of price changes and four COVID-19 variables. For brevity, the descriptive statistics for the other factors are summarized in Appendix Table A1. All eight categories show large fluctuations according to the wide range between maximum and minimum values and the standard variations (Std. Dev.). Among eight categories, iCPI8 (miscellaneous goods and services) is the most fluctuating one. The COVID-19 fear index show different statistical characteristics for China and globally. For example, the mean and median values of CFI are smaller than 50, showing that peoples’ fear for the pandemic in China should not be very severe. By contrast, the fear index around the world exceeds 50 for both mean and median values, indicating that the global pandemic should cause great concern among people. However, both CFI and GFI reached 100 at some periods, meaning that the pandemic in China and around the world should have caused extreme panic. Comparatively, the GFI has more extremely high values than CFI, implying that fear for the progress of pandemic around the world should exceed that in China, which is in line with reality.

4.2. Inflation networks before and after COVID-19

We first explore the price networks based on the ABN for eight consumption categories before and after the outbreak of COVID-19. Network analysis can portray the interplay among prices and measure their co-movements. Interconnectedness shown by networks is the key to understanding systemic price risks. By comparing the networks before and after the pandemic, we can better understand the situations when price distress in one category subsequently raises the likelihood of price distress in other categories because of their common risk sources and interconnected flow of production factors. In line with Xu and Lien (2022), we set December 27, 2019 as the date of the outbreak of COVID-19 according to the white paper of State Council Information Office of China.

The ABN attempts to model potential dependencies between all categories through the representation of the joint probability. Eight nodes represent eight categories, and edges denote the conditional dependencies that are statistically significant. It should be noted that the edges denote parent nodes and children nodes rather than implications of causal impacts.

According to Fig. 1, there are connections for seven categories except for iCPI6 (recreation). In this case, iCPI7 (health cares) has direct relationships with all the other six categories, including food, tobacco, and alcohol (iCPI1), clothing (iCPI2), residence (iCPI3), household articles and services (iCPI4), transportation and communication (iCPI5), and iCPI8 (miscellaneous goods and services). Similarly, iCPI8 (miscellaneous goods and services) is directly related with iCPI1 (food, tobacco, and alcohol), iCPI3 (residence), iCPI4 (household articles and services), and iCPI7 (health cares). Therefore, iCPI8 is indirectly related with clothing (iCPI2) and transportation and communication (iCPI5). Correspondingly, such network indicates that the information of iCPI8 (miscellaneous goods and services) can pass to all the other categories except for iCPI6 (recreation), and the information of iCPI7 (health cares) can pass to five categories (iCPI1, iCPI2, iCPI3, iCPI4, and iCPI5). The price change of iCPI8 (miscellaneous goods and services) has an influence on iCPI7 (health cares), which then affects price of food, tobacco, and alcohol (iCPI1), clothing (iCPI2), residence (iCPI3), household articles and services (iCPI4), and transportation and communication (iCPI5). Similarly, by a reverse argument, changes in all categories except for iCPI6 (recreation) will influence the price of iCPI8 (miscellaneous goods and services). Clearly, iCPI8 (miscellaneous goods and services) and iCPI7 (health cares) are the key categories in connecting price co-movements before the pandemic.

Nevertheless, the network structure changes dramatically after the outbreak of COVID-19. First, iCPI6 (recreation) is no longer separated from the other categories. It is directly linked with iCPI8 (miscellaneous goods and services). Second, connections between price changes become more complex. For instance, we find a longer chains of connections among clothing (iCPI2), health cares (iCPI7), residence (iCPI3), miscellaneous goods and services (iCPI8) and recreation (iCPI6). Although iCPI8 (miscellaneous goods and services) remains vital in coordinating price co-movements after the outbreak of the pandemic, it is no longer the determining node. In other words, information can be transferred across many categories even if iCPI8 (miscellaneous goods and services) is in a stationary state, i.e., other categories are still connected in some ways. Overall, the price co-movement has changed dramatically after the outbreak of

Fig. 1. Networks of price changes before and after the pandemic (left: pre-pandemic; right: post-pandemic).
Fig. 2. Dynamic Price Co-movement Index (PCI) for eight categories and the fear index for COVID-19 in China (CFI) and globally (GFI) during December 5, 2018-April 19, 2021.

Table 2
The effect of COVID-19 on price co-movements (rolling window of 60 observations).

|            | M1       | M2       | M3       | M4       | M5       | M6       | M7       | M8       |
|------------|----------|----------|----------|----------|----------|----------|----------|----------|
| c          | 3.966*** | 3.272*** | 2.836*** | 2.840*** | 4.211*** | 3.325*** | 3.190*** | 3.187*** |
|            | (0.390)  | (0.133)  | (0.100)  | (0.101)  | (0.431)  | (0.129)  | (0.129)  | (0.128)  |
| CFI        | -0.068***| -0.058***| -0.038** | -0.033** | -0.025** | -0.025** | -0.025** | -0.025** |
|            | (0.020)  | (0.021)  | (0.018)  | (0.014)  | (0.012)  | (0.012)  | (0.012)  | (0.012)  |
| GFI        | -0.080***| -0.033** | -0.038** | -0.038** | -0.025** | -0.025** | -0.025** | -0.025** |
|            | (0.011)  | (0.014)  | (0.018)  | (0.018)  | (0.012)  | (0.012)  | (0.012)  | (0.012)  |
| CASE_{China} | -0.033** | -0.033** | -0.033** | -0.033** | -0.033** | -0.033** | -0.033** | -0.033** |
|            | (0.014)  | (0.014)  | (0.014)  | (0.014)  | (0.014)  | (0.014)  | (0.014)  | (0.014)  |
| CASE_{global} | -0.025** | -0.025** | -0.025** | -0.025** | -0.025** | -0.025** | -0.025** | -0.025** |
|            | (0.012)  | (0.012)  | (0.012)  | (0.012)  | (0.012)  | (0.012)  | (0.012)  | (0.012)  |
| PCA 1      | 0.063    | 0.036    | 0.103**  | 0.105**  | 0.063    | 0.036    | 0.103**  | 0.105**  |
|            | (0.048)  | (0.065)  | (0.049)  | (0.049)  | (0.048)  | (0.065)  | (0.049)  | (0.049)  |
| PCA 2      | -0.176** | -0.122*  | -0.132*  | -0.130*  | -0.176** | -0.122*  | -0.132*  | -0.130*  |
|            | (0.075)  | (0.064)  | (0.068)  | (0.068)  | (0.075)  | (0.064)  | (0.068)  | (0.068)  |
| PCA 3      | 0.472*** | 0.338*** | 0.473*** | 0.476*** | 0.472*** | 0.338*** | 0.473*** | 0.476*** |
|            | (0.057)  | (0.088)  | (0.059)  | (0.059)  | (0.057)  | (0.088)  | (0.059)  | (0.059)  |
| R²         | 0.038    | 0.087    | 0.001    | 0.001    | 0.129    | 0.109    | 0.104    | 0.105    |

Notes: This table summarizes the effects of COVID-19 on price co-movements and adjusts the residual error with HAC to eliminate the effects of heteroscedasticity. In this table, GFI and CFI represent global and China fear index, respectively. CASE_{global} and CASE_{China} are the growth rate of confirmed cases of COVID-19 globally and in China, respectively. Standard errors of the coefficients are in the parentheses. *** , ** , and * denote 1%, 5%, and 10% significance levels, respectively. PCA1, PCA2 and PCA3 denote the first three principal components of seven important macroeconomic and financial variables. All variables are stationary without unit root.
resort to regression analysis based on Eq. (4) to investigate this issue. As shown in Table 2, we consider four COVID-19 variables: the COVID-19 fear index in China (\( \text{CASE}_{\text{China}} \)) and globally (\( \text{CASE}_{\text{Global}} \)), and confirmed case growth rate in China (\( \text{GFI}_{\text{China}} \)) and globally (\( \text{GFI}_{\text{Global}} \)).

Nevertheless, it is not clear which is the driving factor for such changes, the pandemic itself or corresponding policy responses. We consider the orthogonalized variables to account for the possible factors. The orthogonalized variables are selected based on the Scree Test Criterion. The results of Principal Component Analysis are reported in Appendix Table A2. According to the results from Augmented Dickey-Fuller unit root test (1981, ADF) and Phillips and Perron’s test (1988, PP), all variables used in the empirical analysis are stationary without unit root.

### 4.3. The effect of COVID-19 on price co-movements

Based on the rolling window estimation of ARB, we calculate dynamic price co-movements for the window of 60 days. As shown in Fig. 2, the overall price co-movement index (PCI) of eight categories fluctuates during the sample period. Before the outbreak of the pandemic, i.e., from December 5, 2018 to December 27, 2019, the price co-movement is generally lower than that during the post-pandemic period with the average PCI being 2.145. Nevertheless, after the outbreak of COVID-19, the average price co-movement increases to 2.834. In the pre-pandemic period, the average number of arcs is 3.29, whereas it is 4.40 after the pandemic, thus indicating more nodes are connected to other nodes in the post-pandemic period. In addition, the trends of price co-movements have distinct periodical characteristics. During December 27, 2019 to January 19, 2020, when the pandemic in China is in the incubation stage (see, e.g., Xu and Lien, 2022), the PCI drops abruptly from 4.51 to 2.99. Then, when China entered the fever stage (January 20, 2020 to March 17, 2020), the PCI further drops and reaches a low point of 1.22 in early March 2020. The PCI declines again during March 18, 2020 to April 28, 2020. At the end of the moderation stage, i.e., April 28, 2020, the PCI decreases to below one. Thereafter, the pandemic in China was generally under control and entered the normalization stage with more fluctuating price co-movements. October 2020 marks another changing point with the price co-movement index increasing from 1.72 to 5.99 within two months. One possible explanation for such abrupt change is the relaxed pandemic prevention policy during the National Day Golden Week (October 1 to October 7) which is vital for the tourist industry and economic growth in China. Significant changes in PCI during the pre-pandemic period and the normalization period after the pandemic indicate that COVID-19 in China is not the only factor driving price co-movements.

An important observation from Fig. 1 is that changes in price co-movements are affected by the development of COVID-19. Nevertheless, it is not clear which is the driving factor for such changes, the pandemic itself or corresponding policy responses. We resort to regression analysis based on Eq. (4) to investigate this issue. As shown in Table 2, we consider four COVID-19 variables: the COVID-19 fear index in China (\( \text{CFI}_{\text{China}} \)) and globally (\( \text{GFI}_{\text{Global}} \)), and confirmed case growth rate in China (\( \text{CASE}_{\text{China}} \)) and globally (\( \text{CASE}_{\text{Global}} \)).

Table 3

| Dependent Variable: Price Co-Movement Index (PCI) | M9 | M10 | M11 | M12 |
|-----------------------------------------------|----|-----|-----|-----|
| \( c \)                                        | 3.199*** | 3.199*** | 3.199*** | 3.199*** |
| \( \text{CFI}^{-1} \)                          | -0.058*** | -0.058*** | -0.058*** | -0.058*** |
| \( \text{GFI}^{-1} \)                          | -0.038** | -0.038** | -0.038** | -0.038** |
| \( \text{CASE}_{\text{China}}^{-1} \)         | 0.042   | 0.042   | 0.042   | 0.042   |
| \( \text{CASE}_{\text{Global}}^{-1} \)        | 0.024   | 0.024   | 0.024   | 0.024   |
| \( \text{PCA} 1 \)                            | 0.101** | 0.101** | 0.101** | 0.101** |
| \( \text{PCA} 2 \)                            | -0.139* | -0.139* | -0.139* | -0.139* |
| \( \text{PCA} 3 \)                            | 0.469*** | 0.469*** | 0.469*** | 0.469*** |
| \( R^2 \)                                     | 0.129 | 0.109 | 0.104 | 0.105 |

Notes: This table adjusts the residual error with HAC to eliminate the effects of heteroscedasticity. In this table, \( \text{CFI}^{-1} \) and \( \text{GFI}^{-1} \) are orthogonalized global and China fear index, respectively. \( \text{CASE}_{\text{Global}} \) and \( \text{CASE}_{\text{China}} \) are the orthogonalized growth rate of confirmed cases of COVID-19 globally and in China, respectively. Standard errors of the coefficients are in the parentheses. ***, **, and * denote 1%, 5%, and 10% significance levels, respectively. \( \text{PCA} 1, \text{PCA} 2 \) and \( \text{PCA} 3 \) denote the first three principal components of seven important macroeconomic and financial variables. All variables are stationary without unit root.
co-movements tend to be weakened. The one-tail \( t \)-statistics comparing the coefficients of \( \text{CFI} \) and \( \text{GFI} \) and that comparing \( \text{CASE}_{\text{China}} \) and \( \text{CASE}_{\text{global}} \) are \(-1.130\) and \(0.685\), respectively. Therefore, the pandemic situations in China and globally appear to show no difference in driving price co-movements in China if no other factors are considered.

To control potential effects of policy changes, we add the first three principal components of important economic variables in the model and report the results in M5-M8 of Table 2. The coefficients of \( \text{CASE}_{\text{China}} \) and \( \text{CASE}_{\text{global}} \) are no longer significant, whereas the coefficients of \( \text{CFI} \) and \( \text{GFI} \) maintain statistically negative. While the effects of growth rates of confirmed cases in China and around the world on price co-movement are transferring through the channel of policy responses, the fear for the pandemic have additional net impacts. In line with the estimation of M1-M2, the coefficients of \( \text{CFI} \) and \( \text{GFI} \) in M5-M6 are negative, indicating that the fear for the pandemic are accompanied by lowered price co-movements. Meanwhile, the effects of policy changes denoted by \( \text{PCA}_1 \), \( \text{PCA}_2 \) and \( \text{PCA}_3 \) are generally significant as expected. The coefficients of \( \text{PCA} \) are close to each other for M5-M8, thus showing the robustness of our empirical estimates. Upon comparing the coefficients, when considering the effects of macroeconomic variables, the fear for the pandemic in China appears to cause similar concern with global COVID-19 because of the insignificant one-tail \( t \)-statistic comparing these two coefficients in M5 and M6. Although the Chinese government’s quick response to the pandemic has helped to control COVID-19 in China and bring the economy back to normal, sporadic and frequent outbreaks of regional COVID-19 cases induce significant policy changes nationwide. Therefore, the pandemic around the world also has inevitable impacts to Chinese economy and prices through import and export trades, commodity prices, etc.

As a robustness test, we estimate the impact of orthogonalized COVID-19 variables to eliminate possible effects from \( \text{PCA} \) and report the results in Table 3. Similar with the findings from Table 2, while the orthogonalized \( \text{CASE}_{\text{China}} \) and \( \text{CASE}_{\text{global}} \) are statistically insignificant in explaining price co-movements, orthogonalized \( \text{CFI} \) and \( \text{GFI} \) have negative effects. Meanwhile, the coefficients of \( \text{CFI} \) and \( \text{GFI} \) stay the same regardless of orthogonalization or not. Therefore, we provide solid evidence for the negative effects of fears for the pandemic on price co-movements in China.

There are many channels through which the pandemic affects inflation, making the impact of COVID-19 on price co-movements uncertain because of simultaneous shocks on demand and supply. For example, the government responses to COVID-19, including social distancing measures and market closures, will reduce households’ income and then their demand for some goods and services such as transport, entertainment, restaurant, etc. Nevertheless, the pandemic itself induces panic buying of various goods including oil, food, and toilet paper (Ebrahimy, Igan, and Peria, 2020). Therefore, the negative effect of the pandemic on price co-movement is explainable.

Summarizing Tables 2 and 3, \( \text{CFI} \) and \( \text{GFI} \) affect price co-movements additional to \( \text{PCA} \), thus indicating that the pandemic leads to relative price changes across categories. Such finding is quite reasonable that the effect of the pandemic on different sectors is disproportional. From the perspective of commodity attributes, import and export goods are more affected by the pandemic than domestic products. For example, industrial products which account for up to 94% of China’s export products are affected by the increased transaction costs and risks caused by the pandemic. With the spread of the pandemic within China in 2020, industrial enterprises across the country have delayed the resumption of production, and transportation, logistics, warehousing, and other supporting industries are also restricted, which reduced the productivity of exporters in the short run. From the perspective of essential productive factors, labor-intensive products are more affected in the initial stage of COVID-19 than other products. Personnel flow control measures, implemented by local governments in China, added up the influence of confirmed cases, further increased the difficulty of labor-intensive industries to resume work.
4.4. The network of PCI and factors during the pandemic period

The evidence from regression analysis shows that COVID-19 has significant effects on the price co-movement of eight categories, even after controlling the effect of various macroeconomic variables. Undoubtedly, the pandemic has exerted enormous impacts on many aspects of the global economy, including unemployment, trading, commodity prices, monetary policies, fiscal expenditures, etc. (Brodeur et al., 2021), which changes consumption patterns in China and around the world. To further reveal the channel through which the pandemic affects price co-movements, we use the ABN method to capture the network of pandemic variables, PCI, and various macroeconomic variables. Arc direction is omitted in Fig. 3 because only statistical dependency is relevant for the ABN analysis.

In line with the regression analysis, four pandemic variables are considered here, i.e., CFI (COVID Fear Index in China), GFI (Global COVID Fear Index), growth rates of confirmed cases in China and globally, i.e., case (China) and case (global). Using the ABN approach, it is possible to evaluate both “direct” and “indirect” relations of price co-movements and potential factors. In Fig. 3, an arc between two variables indicates a direct relationship, whereas an indirect relationship is denoted by two arcs connected two variables with an intermediate variable. Therefore, focusing on PCI, we find that GFI, exchange rate (USD/CNY) and the returns of gold and stock markets (SSCI) have direct relationships with the consumption price co-movements. All the remaining factors, i.e., returns of treasure bonds, bitcoin, and WTI crude oil, interest rates in China (SHIBOR), CFI and confirmed cases in China and globally, are indirectly related with PCI.

For the four variables that have direct relationships with PCI, GFI has a negative effect, whereas all the other three factors are positively related with PCI. Such finding is in line with the results of Tables 2-3, which shows a negative relationship between GFI and PCI. Fig. 3 suggests that, the pandemic has both direct and indirect effects on price co-movements, which agrees with theoretical analysis of many studies such as Brodeur et al. (2021). Compared with the pandemic in China, the global situation appears to be more important for China’s price changes given that three out of four direct linked factors are international variables, i.e., GFI, gold returns and exchange rate. CFI is related to PCI mainly through indirect effects of gold return and exchange rates. Also, confirmed cases in China and globally are not directly related with PCI, thus indicating that labor supply is not an important factor in driving price changes in China. Instead, they affect PCI through GFI and gold return. Such finding reveals that the global pandemic rather than the COVID situation in China is more important in understanding price changes in China.

Under significant uncertainty, international safe-haven assets such as gold becomes key intermediaries of price movements considering the risk aversion of investors. The close relationships between financial markets and price co-movements are in line with Baker et al. (2020) that COVID-19 has caused massive spikes in uncertainty that have no close historical parallels. Another important factor that is closely related with uncertainty is inflation expectations. For virtually most major advanced economies, the markets expect highly accommodative policies to continue for the next two years (Federal Reserve Board, 2021). Such expectation may trigger significant rises in price risks if inflation expectations are unanchored. Through the intermediary effects of international financial
markets, policy changes in other countries are easily to transmit to Chinese consumer market and lead to increased price risks. Rapidly rising inflation rates in European countries at the end of the year 2021 strengthen such concern.

5. Robustness checks

To ensure the robustness of our empirical results, we resort to some different checks. First, the Granger-causality tests suggest that there is no significant reverse causality between PCI and PCA (please refer to Appendix Table A3). Second, we use the Structural Vector Autoregression (SVAR) model to re-test the effect of pandemic variables on PCI. Third, we adopt a different rolling window in calculating PCI. Finally, we replace explanatory variables. The results of robustness test show that the effect of COVID-19 on price co-movements in China is robust.

Table 4
The effect of COVID-19 on price co-movements (rolling window of 90 observations).

| Dependent Variable: Price Co-movement Index (PCI) | M1          | M2          | M3          | M4          | M5          | M6          | M7          | M8          |
|-------------------------------------------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| c                                               | 6.371***    | 3.966***    | 3.282***    | 3.286***    | 5.578***    | 3.703***    | 3.077***    | 3.080***    |
| (0.337)                                         | (0.112)     | (0.085)     | (0.085)     | (0.419)     | (0.111)     | (0.108)     | (0.109)     |
| CFI                                             | -0.177***   | -0.177***   | -0.138***   | -0.138***   | -0.138***   | -0.138***   | -0.138***   | -0.138***   |
| (0.017)                                         | (0.017)     | (0.022)     | (0.022)     | (0.029)     | (0.022)     | (0.022)     | (0.022)     |
| GFI                                             | -0.119***   | -0.241***   | -0.022***   | -0.022***   | -0.022***   | -0.022***   | -0.008***   | -0.008***   |
| (0.007)                                         | (0.036)     | (0.003)     | (0.003)     | (0.003)     | (0.003)     | (0.003)     | (0.002)     |
| CASEChina                                      | 0.188***    | 0.105**     | 0.284***    | 0.284***    | 0.284***    | 0.284***    | 0.138**     | 0.138**     |
| (0.049)                                         | (0.051)     | (0.039)     | (0.039)     | (0.039)     | (0.039)     | (0.039)     | (0.051)     |
| PCA 1                                           | 0.138**     | 0.138**     | 0.155***    | 0.155***    | 0.155***    | 0.155***    | 0.155***    | 0.155***    |
| (0.061)                                         | (0.059)     | (0.051)     | (0.051)     | (0.051)     | (0.051)     | (0.051)     | (0.051)     |
| R²                                              | 0.184       | 0.228       | 0.019       | 0.022       | 0.243       | 0.243       | 0.176       | 0.176       |

Notes: This table summarizes the effects of COVID-19 on price co-movements and adjusts the residual error with HAC to eliminate the effects of heteroscedasticity. In this table, GFI and CFI represent global and China fear index, respectively. CASEglobal and CASEChina are the growth rate of confirmed cases of COVID-19 globally and in China, respectively. Standard errors of the coefficients are in the parentheses. ***, **, and * denote 1%, 5%, and 10% significance levels, respectively. PCA1 and PCA2 denote the first two principal components of seven important macroeconomic and financial variables. All variables are stationary without unit root.

Table 5
The effect of orthogonalized COVID-19 variables on price co-movements (rolling window of 90 observations).

| Dependent Variable: Price Co-movement Index (PCI) | M9          | M10         | M11         | M12         |
|-------------------------------------------------|-------------|-------------|-------------|-------------|
| c                                               | 3.079***    | 3.079***    | 3.051***    | 3.051***    |
| (0.105)                                         | (0.110)     | (0.105)     | (0.105)     |
| CFI⊥                                            | -0.138***   | -0.101***   | -0.089***   | -0.008***   |
| (0.022)                                         | (0.009)     | (0.024)     | (0.002)     |
| GFI⊥                                            | -0.119***   | -0.241***   | -0.022***   | -0.008***   |
| (0.007)                                         | (0.036)     | (0.003)     | (0.003)     |
| CASE⊥China                                      | 0.188***    | 0.105**     | 0.284***    | 0.284***    |
| (0.049)                                         | (0.051)     | (0.039)     | (0.039)     |
| PCA 1                                            | 0.284***    | 0.284***    | 0.293***    | 0.293***    |
| (0.042)                                         | (0.040)     | (0.038)     | (0.038)     |
| PCA2                                             | 0.138**     | 0.155***    | 0.155***    | 0.155***    |
| (0.061)                                         | (0.059)     | (0.051)     | (0.051)     |
| R²                                              | 0.243       | 0.243       | 0.176       | 0.176       |

Notes: This table adjusts the residual error with HAC to eliminate the effects of heteroscedasticity. In this table, GFI⊥ and CFI⊥ are orthogonalized global and China fear index, respectively. CASE⊥global and CASE⊥China are the orthogonalized growth rate of confirmed cases of COVID-19 globally and in China, respectively. Standard errors of the coefficients are in the parentheses. ***, **, and * denote 1%, 5%, and 10% significance levels, respectively. PCA1 and PCA2 denote the first two principal components of seven important macroeconomic and financial variables. All variables are stationary without unit root.
we consider seven macroeconomic and financial variables, the PCI, and a pandemic variable in constructing the SVAR model. Specifically, we rule out the possibility that COVID-19 variables react to shocks of macroeconomic and financial indices systematically because the pandemic is exogenous. Also, we assume that the PCI reacts contemporaneously to shocks of all other variables including COVID-19 variables. As shown in Table 4, all four COVID-19 variables exert statistically negative effects on PCI. For the selected macroeconomic and financial variables, we compare the results with different restrictions on the contempora neous effects and find that the responses of PCI to COVID-19 variables are insensitive to the order choice. Therefore, we report the results based on the order of COVID-19 variables, Bitcoin, Gold, WTI, Bond, SSCI, SHIBOR, USD/CNY, and PCI, with the restrictions being that the variables at the top are not contemporaneously affected by those at the bottom. Fig. 4 shows the results of the impulse-response of PCI to shocks of CASE\textsubscript{China}, CASE\textsubscript{global}, CFI, and GFI, respectively. We use the wild bootstrap approach to determine the significance of impulse-responses and set the time horizon to be 20 days. The results of 90% confidence intervals (CI) are based on 1,000 bootstraps.

Fig. 4 suggests that the responses of PCI to shocks of CASE\textsubscript{China} and CASE\textsubscript{global} are statistically insignificant, agreeing with the findings of M7-M8 in Table 2. By contrast, CFI has comparatively long-lived negative impacts on PCI. In other words, a positive shock of CFI is likely to induce significant decreases in price co-movements in China after approximately 11 days. Although shocks of GFI also have negative impacts on PCI, such effects are statistically insignificant. When comparing the responses of PCI to CFI and GFI, one can find that CFI tends to exert stronger effect than GFI, which is in line with the greater coefficient of CFI in M7 than that of GFI in M8.

### 5.2. Results based on a different rolling window

To provide further robustness checks for the empirical results, we expand the rolling window to 90 days in calculating PCI. The other variables including pandemic variables and macroeconomic variables are accordingly date-adjusted. Two principal components are selected here according to the Scree Test Criterion. Similar with Tables 2-3, Tables 4-5 report the results of the effects of four different COVID-19 variables on PCI. As shown in Table 4, all four COVID-19 variables exert statistically negative effects on PCI. For M1 and M2, the one-tail \(t\)-statistic is \(-3.356\), thus indicating that the effect of CFI is much stronger than that of GFI. Similarly, the growth rate of reported cases in China has a larger effect on PCI than that around the world with the one-tail \(t\)-statistic being \(-6.021\). The results of M5-M8 which consider the effects of macroeconomic variables are in line with Table 2, showing that CFI and GFI have significant negative effects on PCI. Meanwhile, for the 90-days rolling window, the negative effects of CASE\textsubscript{China} and CASE\textsubscript{global} remain statistically significant when controlling the impacts of various macroeconomic variables.

Similarly, when we consider the orthogonalized COVID-19 variables, Table 5 shows that orthogonalized CFI and GFI have significant negative effects on PCI. Considering that prices may move together in response to common macroeconomic shocks, we resort to the SVAR model to re-test the effect of pandemic variables on PCI. SVAR models are popular in studying the relationships among multiple variables. The impulse-response functions can be used to identify the effects of pandemic variables on price co-movements. In line with the regression analysis, we construct seven macroeconomic and financial variables, the PCI, and a pandemic variable in constructing the SVAR model. Specifically, we rule out the possibility that COVID-19 variables react to shocks of macroeconomic and financial indices systematically because the pandemic is exogenous. Also, we assume that the PCI reacts contemporaneously to shocks of all other variables including COVID-19 variables. For the selected macroeconomic and financial variables, we compare the results with different restrictions on the contempora neous effects and find that the responses of PCI to COVID-19 variables are insensitive to the order choice. Therefore, we report the results based on the order of COVID-19 variables, Bitcoin, Gold, WTI, Bond, SSCI, SHIBOR, USD/CNY, and PCI, with the restrictions being that the variables at the top are not contemporaneously affected by those at the bottom. Fig. 4 shows the results of the impulse-response of PCI to shocks of CASE\textsubscript{China}, CASE\textsubscript{global}, CFI, and GFI, respectively. We use the wild bootstrap approach to determine the significance of impulse-responses and set the time horizon to be 20 days. The results of 90% confidence intervals (CI) are based on 1,000 bootstraps.

### 5.1. Results based on SVAR models

Considering that prices may move together in response to common macroeconomic shocks, we resort to the SVAR model to re-test the effect of pandemic variables on PCI. SVAR models are popular in studying the relationships among multiple variables. The impulse-response functions can be used to identify the effects of pandemic variables on price co-movements. In line with the regression analysis, we consider seven macroeconomic and financial variables, the PCI, and a pandemic variable in constructing the SVAR model. Specifically, we rule out the possibility that COVID-19 variables react to shocks of macroeconomic and financial indices systematically because the pandemic is exogenous. Also, we assume that the PCI reacts contemporaneously to shocks of all other variables including COVID-19 variables. As shown in Table 4, all four COVID-19 variables exert statistically negative effects on PCI. For the selected macroeconomic and financial variables, we compare the results with different restrictions on the contempora neous effects and find that the responses of PCI to COVID-19 variables are insensitive to the order choice. Therefore, we report the results based on the order of COVID-19 variables, Bitcoin, Gold, WTI, Bond, SSCI, SHIBOR, USD/CNY, and PCI, with the restrictions being that the variables at the top are not contemporaneously affected by those at the bottom. Fig. 4 shows the results of the impulse-response of PCI to shocks of CASE\textsubscript{China}, CASE\textsubscript{global}, CFI, and GFI, respectively. We use the wild bootstrap approach to determine the significance of impulse-responses and set the time horizon to be 20 days. The results of 90% confidence intervals (CI) are based on 1,000 bootstraps.

Fig. 4 suggests that the responses of PCI to shocks of CASE\textsubscript{China} and CASE\textsubscript{global} are statistically insignificant, agreeing with the findings of M7-M8 in Table 2. By contrast, CFI has comparatively long-lived negative impacts on PCI. In other words, a positive shock of CFI is likely to induce significant decreases in price co-movements in China after approximately 11 days. Although shocks of GFI also have negative impacts on PCI, such effects are statistically insignificant. When comparing the responses of PCI to CFI and GFI, one can find that CFI tends to exert stronger effect than GFI, which is in line with the greater coefficient of CFI in M7 than that of GFI in M8.

### 5.2. Results based on a different rolling window

To provide further robustness checks for the empirical results, we expand the rolling window to 90 days in calculating PCI. The other variables including pandemic variables and macroeconomic variables are accordingly date-adjusted. Two principal components are selected here according to the Scree Test Criterion. Similar with Tables 2-3, Tables 4-5 report the results of the effects of four different COVID-19 variables on PCI. As shown in Table 4, all four COVID-19 variables exert statistically negative effects on PCI. For M1 and M2, the one-tail \(t\)-statistic is \(-3.356\), thus indicating that the effect of CFI is much stronger than that of GFI. Similarly, the growth rate of reported cases in China has a larger effect on PCI than that around the world with the one-tail \(t\)-statistic being \(-6.021\). The results of M5-M8 which consider the effects of macroeconomic variables are in line with Table 2, showing that CFI and GFI have significant negative effects on PCI. Meanwhile, for the 90-days rolling window, the negative effects of CASE\textsubscript{China} and CASE\textsubscript{global} remain statistically significant when controlling the impacts of various macroeconomic variables.

Similarly, when we consider the orthogonalized COVID-19 variables, Table 5 shows that orthogonalized CFI and GFI have significant negative effects on PCI. Considering that prices may move together in response to common macroeconomic shocks, we resort to the SVAR model to re-test the effect of pandemic variables on PCI. SVAR models are popular in studying the relationships among multiple variables. The impulse-response functions can be used to identify the effects of pandemic variables on price co-movements. In line with the regression analysis, we consider seven macroeconomic and financial variables, the PCI, and a pandemic variable in constructing the SVAR model. Specifically, we rule out the possibility that COVID-19 variables react to shocks of macroeconomic and financial indices systematically because the pandemic is exogenous. Also, we assume that the PCI reacts contemporaneously to shocks of all other variables including COVID-19 variables. As shown in Table 4, all four COVID-19 variables exert statistically negative effects on PCI. For the selected macroeconomic and financial variables, we compare the results with different restrictions on the contempora neous effects and find that the responses of PCI to COVID-19 variables are insensitive to the order choice. Therefore, we report the results based on the order of COVID-19 variables, Bitcoin, Gold, WTI, Bond, SSCI, SHIBOR, USD/CNY, and PCI, with the restrictions being that the variables at the top are not contemporaneously affected by those at the bottom. Fig. 4 shows the results of the impulse-response of PCI to shocks of CASE\textsubscript{China}, CASE\textsubscript{global}, CFI, and GFI, respectively. We use the wild bootstrap approach to determine the significance of impulse-responses and set the time horizon to be 20 days. The results of 90% confidence intervals (CI) are based on 1,000 bootstraps.

Fig. 4 suggests that the responses of PCI to shocks of CASE\textsubscript{China} and CASE\textsubscript{global} are statistically insignificant, agreeing with the findings of M7-M8 in Table 2. By contrast, CFI has comparatively long-lived negative impacts on PCI. In other words, a positive shock of CFI is likely to induce significant decreases in price co-movements in China after approximately 11 days. Although shocks of GFI also have negative impacts on PCI, such effects are statistically insignificant. When comparing the responses of PCI to CFI and GFI, one can find that CFI tends to exert stronger effect than GFI, which is in line with the greater coefficient of CFI in M7 than that of GFI in M8.

### 5.2. Results based on a different rolling window

To provide further robustness checks for the empirical results, we expand the rolling window to 90 days in calculating PCI. The other variables including pandemic variables and macroeconomic variables are accordingly date-adjusted. Two principal components are selected here according to the Scree Test Criterion. Similar with Tables 2-3, Tables 4-5 report the results of the effects of four different COVID-19 variables on PCI. As shown in Table 4, all four COVID-19 variables exert statistically negative effects on PCI. For M1 and M2, the one-tail \(t\)-statistic is \(-3.356\), thus indicating that the effect of CFI is much stronger than that of GFI. Similarly, the growth rate of reported cases in China has a larger effect on PCI than that around the world with the one-tail \(t\)-statistic being \(-6.021\). The results of M5-M8 which consider the effects of macroeconomic variables are in line with Table 2, showing that CFI and GFI have significant negative effects on PCI. Meanwhile, for the 90-days rolling window, the negative effects of CASE\textsubscript{China} and CASE\textsubscript{global} remain statistically significant when controlling the impacts of various macroeconomic variables.

Similarly, when we consider the orthogonalized COVID-19 variables, Table 5 shows that orthogonalized CFI and GFI have significant negative effects on PCI.
Table 7
The effects of orthogonalized COVID-19 variables on price co-movements (rolling window of 60 observations, with augmented control variables).

| Dependent Variable: Price Co-movement Index (PCI) | M17 | M18 | M19 | M20 |
|---------------------------------------------------|-----|-----|-----|-----|
| c                                                 | 3.162*** | 3.162*** | 3.162*** | 3.162*** |
| (0.163)                                           | (0.164) | (0.184) | (0.164) |     |
| CFI⊥                                              | −0.071*** |     |     |     |
| (0.022)                                           |     |     |     |     |
| GFI⊥                                              | −0.082*** |     |     |     |
| (0.022)                                           |     |     |     |     |
| CASE⊥<sub>China</sub>                            |     |     |     |     |
| (0.090)                                           |     |     |     |     |
| CASE⊥<sub>Global</sub>                           |     |     |     |     |
| 0.018                                             |     |     |     |     |
| (0.090)                                           |     |     |     |     |
| PCA 1                                             | 0.002 | 0.002 | 0.002 | 0.002 |
| (0.038)                                           | (0.036) | (0.050) | (0.036) |     |
| PCA 2                                             | −0.066 | −0.066 | −0.066 | −0.066 |
| (0.062)                                           | (0.057) | (0.069) | (0.061) |     |
| PCA 3                                             | 0.315*** | 0.315*** | 0.315*** | 0.315*** |
| (0.083)                                           | (0.079) | (0.105) | (0.084) |     |
| PCA 4                                             | 0.323*** | 0.323*** | 0.323*** | 0.323*** |
| (0.096)                                           | (0.096) | (0.104) | (0.097) |     |
| R<sup>2</sup>                                     | 0.122 | 0.116 | 0.086 | 0.086 |

Notes: This table adjusts the residual error with HAC to eliminate the effects of heteroscedasticity. In this table, GFI⊥ and CFI⊥ are orthogonalized global and China fear index, respectively. CASE<sub>Global</sub> and CASE<sub>China</sub> are the orthogonalized growth rate of confirmed cases of COVID-19 globally and in China, respectively. Standard errors of the coefficients are in the parentheses. ***, **, and * denote 1%, 5%, and 10% significance levels, respectively. PCA1, PCA2, PCA3, and PCA4 denote the first four principal components of 12 important macroeconomic and financial variables. All variables are stationary without unit root.

Table A1
Descriptive statistics of macroeconomic variables (November 1, 2018 to April 19, 2021).

|                       | Gold | SHIBOR | Bond | SSCI | USD/CNY | WTI | Bitcoin |
|-----------------------|------|--------|------|------|---------|-----|---------|
| Mean                  | 1.100| 1.923  | 3.115| 0.979| 6.861   | 0.268| 9.002   |
| Median                | 0.566| 1.949  | 3.176| 0.923| 6.903   | 3.062| 8.275   |
| Max.                  | 15.122| 2.604  | 3.431| 18.740| 7.125   | 122.042| 79.540  |
| Min.                  | −9.921| 0.931  | 2.555| −13.336| 6.460   | −93.814| −75.984 |
| Std. Dev.             | 4.153| 0.424  | 0.200| 5.309| 0.198   | 21.993| 23.509  |
| Skewness              | 0.332| −0.543 | −1.212| 0.303| −0.611  | −0.292| −0.412  |
| Kurtosis              | 3.555| 2.577  | 3.742| 3.667| 2.222   | 10.747| 3.906   |
| J-B                   | 13.503| 32.325 | 152.843| 19.326| 49.920  | 1430.812| 35.645  |
| (P-value)             | 0.001| 0.000  | 0.000| 0.000| 0.000   | 0.000| 0.000   |
| Obs.                  | 571  |        |      |      |         |      |         |

Notes: Gold, SSCI, WTI, and Bitcoin denote the log returns of gold price, Shanghai securities composite index, WTI crude oil futures price, and Bitcoin price, respectively. SHIBOR represents the overnight Shanghai Interbank Offered Rate, Bond represents the 10-year treasury yield, and USD/CNY denotes the exchange rate between the United States Dollar (USD) and Chinese Yuan (CNY). These data are available from investing.com. Max. and Min. represent the maximum and minimum values; Std. Dev. denotes the standard deviation; J-B is the Jarque-Bera normality test and probabilities in parentheses; Obs. denotes the number of observations.

statistically negative effects on PCI, agreeing with the findings of Tables 3-4. Nevertheless, the effects of orthogonalized CASE<sub>China</sub> and CASE<sub>Global</sub> are significant, which are different from Table 3 but are in line with Table 4. It appears that the effect of the pandemic on price co-movements is stronger and more robust over a longer term of 90 calendar days. Generally, both Table 3 and Table 5 support the negative effects of the pandemic situations in China and globally on price co-movements from the perspective of fear indices.

Contrast to the objective measurement of growth rates of reported cases in China and globally, CFI and GFI consider incubation expectations because of the comparison between current pandemic and the situation 14 days earlier. When the number of current daily confirmed cases and/or deaths falls below the corresponding number 14 days earlier, people in China or around the world should be less concerned with the pandemic. Undoubtedly, the numbers of COVID-19 confirmed cases and deaths constitute an integral part of media reports ever since the outbreak of the pandemic. Therefore, it is reasonable to infer that the level of panic will increase when the numbers rise. Our empirical results support that the pandemic in a country and around the world matter to domestic price risks. The worsening of the pandemic engenders palpable fear among households and investors because of its threat to the livelihood and health of the general public and thus adversely affects price stabilities within a country. Consequently, for open economies with strong connections to severely affected countries, particular attention should be given to the spillover effects through international markets and international trade when setting policies in managing price stabilities.
5.3. Changing control variables

Many other variables may also affect price movements in China; for instance, the offshore CNY exchange rate such as USD/CNH, some commodity prices, the Chinese economic policy uncertainty, etc. Therefore, we add a new set of control variables: the exchange rate of USD/CNH, the USD index (USDX), the Chinese economic policy uncertainty index (CNEPU), and three commodity indices, farm price index (FPI), non-ferrous price index (NFPI) and steel price index (SPI). Similarly, we select the first four principal components according to the results of the Scree Test Criterion. Tables 6-7 summarize the effects of four pandemic variables on PCI when using the new control variables. In line with Tables 2-5, CFI and GFI show statistically negative effects on PCI, even when using orthogonalized variables. Also, when using augmented control variables, the growth rates of reported cases in China and globally have no significant effect on PCI, which is in line with the findings of Tables 4 and 5. Overall, changes in control variables are unlikely to impact the role of COVID-19 variables in affecting price co-movements in China.

6. Conclusions

While the final effects of COVID-19 on the macroeconomy are yet to be seen, the changes in consumption patterns during the pandemic have produced significant price movements. Besides the direct impact on labor supply and demand for goods and services, the pandemic has caused various government responses including social distancing, market closures, monetary easing, etc. Such reactions to COVID-19 affects households’ demand for goods and services and need to hedge against risks through asset allocations. Consequently, based on the ABN methodology, we find fluctuating price co-movements across eight consumption categories during the pandemic period, which is negatively related with fears for COVID-19 in China and globally. Comparing with the situation in China, the global pandemic is more important in understanding the fluctuating price risks in China. Important safe-haven assets such as gold and domestic capital markets are directly related with price co-movements. Meanwhile, exchange rates which are sensitive to monetary and trading policies of major economies also play an important role in affecting price co-movements in China, acting as an

---

**Table A2**
The results of principal components analysis.

| Panel A: Eigenvalues |
|---------------------|
| Number | Value | Proportion | Cumulative Proportion |
|--------|-------|------------|-----------------------|
| 1 | 2.213 | 31.61% | 31.61% |
| 2 | 1.860 | 26.57% | 58.18% |
| 3 | 1.236 | 17.65% | 75.84% |
| 4 | 0.746 | 10.66% | 86.50% |
| 5 | 0.595 | 8.50% | 95.00% |
| 6 | 0.236 | 3.37% | 98.37% |
| 7 | 0.114 | 1.63% | 100.00% |

| Panel B: Eigenvectors (loadings) |
|----------------------------------|
| PCA1 | PCA2 | PCA3 | PCA4 | PCA5 | PCA6 | PCA7 |
| Bitcoin | 0.368 | 0.484 | −0.199 | 0.357 | 0.191 | 0.640 | 0.130 |
| Bond | 0.498 | −0.350 | 0.199 | 0.390 | −0.029 | −0.290 | 0.594 |
| Gold | −0.441 | 0.114 | 0.166 | 0.813 | 0.053 | −0.200 | −0.247 |
| SHIBOR | 0.203 | −0.532 | 0.490 | 0.052 | 0.132 | 0.460 | −0.451 |
| SSCI | −0.039 | 0.377 | 0.609 | −0.079 | −0.663 | 0.140 | 0.138 |
| USD/CNY | −0.586 | −0.150 | 0.208 | −0.098 | 0.346 | 0.348 | 0.584 |
| WTI | 0.190 | 0.427 | 0.489 | −0.203 | 0.618 | −0.337 | −0.074 |

Notes: Gold, SSCI, WTI, and Bitcoin denote the log returns of gold price, Shanghai securities composite index, WTI crude oil futures price, and Bitcoin price, respectively. SHIBOR represents the overnight Shanghai Interbank Offered Rate, Bond represents the 10-year treasury yield, and USD/CNY denotes the exchange rate between the United States Dollar (USD) and Chinese Yuan (CNY).

**Table A3**
Granger-causality tests between PCI and PCA (rolling window of 60 observations).

| Tests | $\chi^2$-Statistics | Optimal lag order | $p$-values |
|-------|---------------------|------------------|------------|
| $H_0$: PCI does not Granger cause PCA1 | 5.931 | 6 | 0.431 |
| $H_0$: PCI does not Granger cause PCA2 | 6.539 | 6 | 0.266 |
| $H_0$: PCI does not Granger cause PCA3 | 3.314 | 6 | 0.769 |
| $H_0$: PCI does not Granger cause PCA4 | 0.801 | 6 | 0.992 |
| $H_0$: PCI does not Granger cause PCA5 | 4.173 | 4 | 0.383 |
| $H_0$: PCI does not Granger cause PCA6 | 0.466 | 4 | 0.977 |

Notes: This table summarizes the Granger-causality results between PCI and PCA within the rolling window of 60 observations. In this table, PCI represents the Price Co-movement Index in China, and PCA1, PCA2 and PCA3 denote the first three principal components of seven important macroeconomic and financial variables. All variables are stationary without unit root.

5.3. Changing control variables

Many other variables may also affect price movements in China; for instance, the offshore CNY exchange rate such as USD/CNH, some commodity prices, the Chinese economic policy uncertainty, etc. Therefore, we add a new set of control variables: the exchange rate of USD/CNH, the USD index (USDX), the Chinese economic policy uncertainty index (CNEPU), and three commodity indices, farm price index (FPI), non-ferrous price index (NFPI) and steel price index (SPI). Similarly, we select the first four principal components according to the results of the Scree Test Criterion. Tables 6-7 summarize the effects of four pandemic variables on PCI when using the new control variables. In line with Tables 2-5, CFI and GFI show statistically negative effects on PCI, even when using orthogonalized variables. Also, when using augmented control variables, the growth rates of reported cases in China and globally have no significant effect on PCI, which is in line with the findings of Tables 4 and 5. Overall, changes in control variables are unlikely to impact the role of COVID-19 variables in affecting price co-movements in China.

6. Conclusions

While the final effects of COVID-19 on the macroeconomy are yet to be seen, the changes in consumption patterns during the pandemic have produced significant price movements. Besides the direct impact on labor supply and demand for goods and services, the pandemic has caused various government responses including social distancing, market closures, monetary easing, etc. Such reactions to COVID-19 affects households’ demand for goods and services and need to hedge against risks through asset allocations. Consequently, based on the ABN methodology, we find fluctuating price co-movements across eight consumption categories during the pandemic period, which is negatively related with fears for COVID-19 in China and globally. Comparing with the situation in China, the global pandemic is more important in understanding the fluctuating price risks in China. Important safe-haven assets such as gold and domestic capital markets are directly related with price co-movements. Meanwhile, exchange rates which are sensitive to monetary and trading policies of major economies also play an important role in affecting price co-movements in China, acting as an
important mediator for international markets in influencing Chinese price changes.

Although the impact of COVID-19 on price changes is underdetemined theoretically because of its double shocks on demand and supply, this study suggests an increased trend of price co-movements during the pandemic period. This highlights the necessity of paying more attention to the effects of the pandemic through the lens of asset prices, exchange rates, and investors’ sentiments. The second implication is on the importance of uncertainty caused by the pandemic. Our empirical evidence highlights the relationships between financial markets and price co-movements is likely related to the high uncertainty during the pandemic period. Thereby, forward-looking uncertainty measures should be utilized to further quantify the impacts of COVID-19 on the economy so that preventive policies can be implemented. Another implication from this study is that financial markets provide available instruments for policy makers to maintain price stability, such as precious metals, energy assets, and cryptocurrencies.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We gratefully acknowledge the support of the National Natural Science Foundation of China, China (No. 71873014).

References

Armanitier, O., Kojar, G., Pomerantz, R., Skandalis, D., Smith, K., Topa, G., van der Klauw, W., 2021. How economic crises affect inflation beliefs: Evidence from the Covid-19 pandemic. Journal of Economic Behavior & Organization 189, 443–469.

Baker, S.R., Bloom, N., Davis, S.J., Terry, S.J., 2020. COVID-induced economic uncertainty. National Bureau of Economic Research, Cambridge, MA, No. p. 26983.

Baldwin, R. 2020. Keeping the lights on: Economic medicine for a medical shock. VoxEU.ORG. Retrieved from https://voxeu.org/article/how-should-we-think-about-containing-covid-19-economic-crisis.

Banerjee, R., Mehrotra, A., Zampolli, F., 2020. Inflation at risk from Covid 19. Bank for International Settlements Bulletin, No, p. 28.

Binder, C., 2020. Coronavirus fears and macroeconomic expectations. Rev. Econ. Stat. 102 (4), 721–730.

Blanchard, O., 2020. Is there deflation or inflation in our future? VOX CEPR Policy Portal.

Bonadio, B., Huo, Z., Levchenko, A.A., Pandalai-Nayar, N., 2021. Global supply chains in the pandemic. Journal of International Economics 133, 103534. https://doi.org/10.1016/j.jie.2021.103534.

Brotetea, A., Gray, D., Islam, A., Bhuivian, S., 2021. A literature review of the economics of COVID-19. Journal of Economic Surveys 35 (4), 1007–1044.

Carlsson-Szlezak, P., Reeves, M., Swartz, P., 2020. Understanding the economic shock of Coronavirus. Retrieved from Harvard Business Review 27, https://hbr.org/2020/03/understanding-the-economic-shock-of-coronavirus.

Carlsson-Szlezak, P., Reeves, M., Swartz, P., 2020b. What coronavirus could Mean for the global economy. Retrieved from Harvard Business Review. 3 (10). https://hbr.org/2020/03/what-coronavirus-could-mean-for-the-global-economy.

Cavallo, A. 2020. Inflation with covi pdomption baskets. National Bureau of Economic Research, No. w27352. Doi: 10.3386/w27352.

Chang, H.H., Meyerhofer, C.D., 2021. COVID-19 and the demand for online food shopping services: Empirical evidence from Taiwan. Am. J. Agric. Econ. 103 (2), 448–465.

Clemente, J., Veguer, S., 2020. Implications of the Covid-19 Pandemic for State Government Tax Revenues. National Tax Journal. 73 (3), 619–644. https://doi.org/10.17310/ntj.2020.3.01.

Collison, O., Gorodnichenko, Y., & Weber, M. (2020). The cost of the Covid-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending. National Bureau of Economic Research, Cambridge, MA, No. 27141. Doi: 10.3386/w27141.

Daly, R., Shen, Q., Aiiksen, S., 2011. Learning Bayesian networks: approaches and issues. The knowledge engineering review 26 (2), 99–157.

Ebhorenyi, E., Igan, D., Peria, S.M., 2020. The impact of COVID-19 on inflation: Potential drivers and dynamics. Special Notes Series on COVID-19. IMF Research.

Elenev, V., Landvoigt, T., & Van Nieuwerburgh, S. 2020. Can the Covid bailouts save the economy? National Bureau of Economic Research, Cambridge, MA, No. 27207. Doi: 10.3386/w27207.

Eppington, P.S., Fellermayr, G., Krebs, O., & Kukharsky, B. 2020. Covid-19 shocking global value chains. Kiel Institute for the World Economy, Germany, No. 2167. Retrieved from https://www.econstor.eu/handle/10419/224061.

Federal Reserve Board, 2021. Minutes of the Federal Open Market Committee: April 27–28. Federal Reserve Board, Washington, DC.

Gómez, S., 2019. Centrality in networks: finding the most important nodes. In: Business and Consumer Analytics: New Ideas. Springer, Cham, pp. 401–433.

Gourinchas, P.-O., 2020. Flattening the pandemic and recession curves. Act Fast and Do Whatever, Mitigating the COVID Economic Crisis. Retrieved from http://viet-studies.net/kinhte/COVIDEconomicCrisis.pdf#page=38.

Gratzer, G., Lewis, P.I., Comin, A., Pittavino, M., & Furrer, R. 2019. Additive Bayesian Network Modelling with the R Package abn. arXiv preprint arXiv:1911.09006.

Lee, F.I., Ward, M.P., 2013. Improving epidemiologic data analyses through multivariate regression modelling. Emerging Themes in Epidemiology 10 (1), 1–10.

Li, X., Liu, Y., Yan, Y., 2020a. China macroeconomic report 2020: China’s macroeconomy is on the rebound under the impact of COVID-19. Economic and Political Studies 8 (4), 395–435.

Li, D., Sun, W., Zhang, Z., 2020b. Is the Chinese economy well positioned to fight the COVID-19 pandemic? The financial cycle perspective. Emerging Markets Finance and Trade 56 (10), 2259–2276.

Maqial, S., Barani, E., 2020. The global economic impact of COVID-19: A summary of research. Samuel Neaman Institute for National Policy Research 1–12.

Mckibbin, W., Femando, R., 2021. The global macroeconomic impacts of COVID-19: Seven scenarios. Asian Economic Papers 20 (2), 1–30.

Mulligan, C.B., 2020. Economic activity and the value of medical innovation during a pandemic. Journal of Benefit-Cost Analysis 12 (3), 420–440. https://doi.org/10.17310/jbca.2021.5.

Mulligan, C.B., 2020. Economic activity and the value of medical innovation during a pandemic. Journal of Benefit-Cost Analysis 12 (3), 420–440. https://doi.org/10.17310/jbca.2021.5.

O’Brien, D., Dumonceel, C., Goncalves, E., 2021. The role of demand and supply factors in HICP inflation during the COVID-19 pandemic—a disaggregated perspective. Available from: Economic Bulletin Articles 1 https://www.ecb.europa.eu/pub/economic-bulletin/articles/2021/html/ecb.ebart202101_02-7f3bd48751.en.html.

Pearl, J. 1985. Bayesian networks: A model of self-activated memory for evidential reasoning. In Proceedings of the 7th conference of the Cognitive Science Society, University of California, Irvine, CA, USA (pp. 15–17).

Pelis, R., Watson, M.W., 2010. Relative goods prices, pure inflation, and the Phillips correlation. American Economic Journal: Macroeconomics 2 (3), 128–157.

Rigg, M., Bottone, M., Conflitti, C., & Tagliabraci, A. 2021. Firms’ Inflation Expectations and Pricing Strategies During Covid-19. Bank of Italy Occasional Paper, No. 619. Available at: https://doi.org/10.2139/ssrn.3891604.

Saliu, A.A., Akanni, L., Raheem, I., 2020. The COVID-19 global fear index and the predictability of commodity price returns. Journal of Behavioral and Experimental Finance 27, 100383. https://doi.org/10.1016/j.jbef.2020.100383.
Seiler, P., 2020. Weighting bias and inflation in the time of COVID-19: Evidence from Swiss transaction data. Swiss Journal of Economics and Statistics 156 (1), 1–11.
Shapiro, A.H., 2020. Monitoring the inflationary effects of COVID-19. FRBSF Economic Letter 24, 01–06.
Verma, T., & Pearl, J. 1988. Influence diagrams and d-separation. UCLA, Computer Science Department.
Xu, Y., Lien, D., 2020. Dynamic exchange rate dependences: The effect of the US-China trade war. Journal of International Financial Markets, Institutions and Money 68, 101238. https://doi.org/10.1016/j.intfin.2020.101238.
Xu, Y., Lien, D., 2022. COVID-19 and currency dependences: Empirical evidence from BRICS. Finance Research Letters 45, 102119. https://doi.org/10.1016/j.frl.2021.102119.
Xu, Y., Liu, Z.X., Chang, H.L., Peculea, A.D., Su, C.W., 2017. Does self-fulfillment of the inflation expectation exist? Appl. Econ. 49 (11), 1098–1113.
Xu, Y., Liu, Z., Su, C.-W., Ortiz, J., 2021. Causality between actual and expected inflation in central and eastern Europe: Evidence using a heterogeneous panel analysis. Eastern European Economics 59 (2), 148–170.