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Shock Infections through Global Value Chains

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Abstract

We examine how the Covid-19 shock was transmitted from the foreign, upstream parts of value chains to domestic (downstream) production. After categorizing global value chains based on their home-producer industry and country, we quantify the multiplier effect of the transmitted shock on the entire value chain by considering changes in home production. The upstream shock was measured using world input-output data, and our analysis relies on the upstream dependence on the early shock in China during 1-4/2020, employing a differences-in-differences research setup. Our findings reveal that the impact was large: For every percentage point of dependence on the Chinese value chain, there was a 1.3 percent larger contraction in domestic production. In essence, the multiplier effect of the manufacturing contraction amplified the direct foreign shock by an order of magnitude. These effects varied across industries and regions, with the most substantial multiplier effects observed in highly digitalized, high-R&D industries, particularly in the EU and North America. Furthermore, we provide evidence on the dynamics of adjustment.

Tiivistelmä

Sokkitartunnat globaaleissa arvoketjuissa

Tässä artikkelissa tutkimme, miten koronan aiheuttama tuotantohäiriö välittyi arvoketjujen kautta eri maiden välillä. Luokittelemme globaalit arvoketjut lopputuottajan teollisuuden ja maan mukaan ja mittaamme, miten alkuvuoden 2020 sokki Kiinassa kertautui kulkiessaan arvoketjun läpi. Difference-in-differences -menetelmään perustuvat tuloksemme paljastavat, että kerrannaisvaikutus oli suuri. Kotimaisen tuotannon pudotuksessa suoran ulkomaisen sokin vaikutus oli kymmeniä kertoja suurempi kuin alkuperäinen sokki, joka mitattiin hankkeessa hyödyntäen panos-tuotostaulukoita sekä Kiinan tuotantotietoja. Vaikutukset vaihtelivat toimialoittain ja alueittain. Merkittävimmät kerrannaisvaikutukset havaittiin pitkälle digitalisoiduilla ja korkean t&k-toiminnan aloilla, erityisesti EU:ssa ja Pohjois-Amerikassa. Artikkelissa osoitamme myös, että kärsineet arvoketjut ovat lisänneet myöhemmin kotimaista tuotantoaan ja rajoittaneet Kiinan arvoketjuriippuvuuksiaan.

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Keywords: Global value chains, Shock, Infection, Covid-19, Transmission, Transmit, Linkage

Asiasanat: Globaalit arvoketjut, Sokki, Covid-19, Arvoketjukytkennät

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1 Introduction

The Covid-19 crisis revealed the vulnerability of economic activities that rely on global value chains (GVCs). In early 2020, infections spread rapidly in the Hubei province in China and were quickly followed by contagions in Italy and other countries. As a consequence, a number of factories and other facilities were closed, either due to infections or restrictions set by authorities, resulting in a local supply shock. However, many of these plants had manufactured components and other intermediate products that other companies around the globe had used in their operations. Through these value-chain linkages, the supply shock spread rapidly to other countries and industries.

In this research, we investigate how the initial impact of Covid-19 in China spread through the foreign, upstream segments of Global Value Chains (GVCs) to affect domestic production. By categorizing GVCs based on the industry and home country, we measure the ripple effect of the transmitted shock on the entire value chain, stemming from changes in domestic production. We demonstrate that the strength of the foreign Covid-19 shock on domestic production depends on the extent to which home industries relied on foreign value chains before the pandemic. Our primary focus is on the initial shock originating in China and subsequent adjustments in the value chains. Methodologically, our approach aligns with the common difference-in-difference framework, but with variations in treatment intensity (see, e.g., Angrist and Pischke,2008). These variations arise from the interplay between the Covid-19 shock and the structure of GVCs.

According to the results, industries with a high exposure to imports from China contracted more than other industries. It is important, however, to notice that bilateral imports or exports only take direct trade between two countries into account, ignoring indirect trade through other countries. This indirect trade may represent a substantial role in trade as, for example, the results of Ali-Yrkkö and Kuusi (2020) showed. This is especially important when trying to quantify the propagation effects of the local shocks.

We contribute to the previous literature in several ways. *First,* we calculate the transmission of the initial shock in 2020 from the foreign, upstream parts of the value chains to home production in a way that, as far as we know, has not yet been done previously. Whereas existing literature has typically assessed the dependence of domestic production on imports, this study brings together the external component of the Chinese value chain, and studies its impact on the home production.[1] Second, we use data on the initial shock in terms of value-added contraction in China to measure its direct shock impact and study the

[1] The estimates are based on the world input–output tables (TiVA) and the average (pre-pandemic) dependence of home production in each country and industry on the upstream value chain contributions of other countries and their industries. Once the value chain dependencies have been calculated, the foreign production disruptions due to Covid-19 are isolated statistically, they are weighted by the dependencies, and finally the totalled disruptions are related to changes in home production.

multiplier effects that it has had in the value chains. Third, we study the heterogeneity of these effects across industries and regions. Finally, we show evidence on adjustment dynamics.

The rest of this paper is organized as follows. In the next section, we review the literature. Section 3 describes the methodology, while Section 4 introduces our data sources and descriptive analyses. In Section 5, we present our results based on an empirical analysis. Chapter 6 concludes and provides a discussion.

2 Previous literature

A growing body of literature examines the spread of supply disruptions in the production networks. In the field of supply-chain management, researchers have predominantly analyzed disruption propagation through simulation and optimization frameworks, aiming to offer valuable insights for prevention and mitigation (Dolgui et al., 2018; Li et al., 2021). Adjustments within various segments of the value chain can stem from two primary factors: the first is a demand-related effect caused by shifts or reductions in the demand for final products (known as backward propagation), and the second is a supply-related effect resulting from the direct operations within the value chain (termed forward propagation).

With globalized and extremely complex value chains (Baldwin, 2006; Johnson and Noguera, 2012), the ripple effects of Covid-19 across country borders have reached the macroeconomic scale. In the globalized economy, even a simple product may contain components and parts manufactured by tens of companies, located in various countries. While some enterprises possess comprehensive visibility into their entire value chains, many others lack knowledge about the origins of their primary suppliers' components, raw materials, and other intermediate inputs. This lack of visibility became a critical issue during the Covid-19 crisis, as entire industries found themselves blindsided by input shortages. These businesses had not comprehended the extent to which their value chains relied on China, Italy, and other countries where plants were closed.

Our theoretical starting point is growth accounting and its applications in the analysis of vertically integrated production processes. We use a decomposition of the global value-added contents of the outputs and contributions of industries and of the other sectors in the upstream value chain (Leontief, 1936; Wolff, 1994; Timmer, 2017; Timmer and Ye, 2020, Kuusi et al., 2022). The value chain approach makes more visible both the substantial role of upstream industries to which industries have backward linkages as well as technology and knowledge investments as a source of productivity growth in the entire value chain (for a review, see also Carvalho and Tahbaz-Salehi, 2019).

A key element of our analysis is to contrast and highlight the differences between growth accounting results and the actual measured contractions in the value chains. There is extensive, theoretical literature on the fragility of value chains suggesting that deviations from the growth accounting benchmark and larger multiplier effects may be expected (see, e.g., Bagaee and Farhi, 2019: Acemoglu and Tahbaz-Salehi, 2020; Elliott et al., 2022). In the complex production chains, the production is typically featured with customized supplier relationships and non-competitive markets. Discrete sourcing failures may result in nonlinearities or even discontinuities in complex supply networks, as disruptions can lead into shortages of essential inputs or obstruct relationship-specific factors of production.

This work relates to a large empirical literature on the value-chain implications of individual shocks. In terms of covid-19 effects, Bonadio et al. (2021) used a macroeconomic model with input linkages to study the impacts of the Covid-19 pandemic through value chains. Their results suggest that, on average, even close to one-fourth of GDP’s contraction comes from foreign shocks. According to Sforza and Steininger (2020), global linkages between countries account for a substantial but heterogeneous share of the income drop caused by Covid-19 shock. Their econometric analysis suggested that the degree of trade openness is a key factor in explaining this heterogeneity.

In contrast, our work aims to isolate the role of value chain disruptions with only few assumptions about the production structure. Thus, following, e.g., Boehm et al. (2019), Carvalho et al. (2021) and Meier and Pinto (2020), we rely on differences-in-differences methods to leverage variations in pre-crisis exposure to intermediate goods as a means of identification. While the previous literature has already shown that value chain disruptions may lead to sizable and wide-reaching effects on production, employment, and international trade, our approach is different in aiming at measuring the multiplier effects based on the comparison to the growth accounting benchmark. Moreover, our focus on the measured value chain exposures highlights the importance of indirect trade when trying to quantify the propagation effects of the local shocks (see, e.g., Ali-Yrkkö and Kuusi 2020).

3 Methodology

In this section, we outline our approach of quantifying value chain linkages in GVCs and the participation of the countries in them. We first describe our methodology for identifying the linkages and then use them to quantify the foreign, upstream value-chain shock due to the initial contraction in 2020 on home production. We also apply the methodology to analyze later adjustments of the value chains.

3.1 Measuring value chain linkages

The theoretical basis for our analysis is in the global value chain accounting approach which complements the traditional KLEMS type productivity studies (Timmer, 2017). This decomposition method is based on the analysis of the input-output, linear system of cost equations introduced by Leontief (1936). The approach uses cost shares and productivity growth and it can be empirically implemented using synthetic input-output tables. (Wolff, 1994; Timmer, 2017; Timmer and Ye, 2020, Kuusi et al., 2022).

Formally, we analyze a production function (F) where final output is produced based on factor inputs only, including both domestic and foreign factors. Formally, let F be a translog production function for the industry aggregate product: $f = F(\mathbf{VA}, T)$[2], where $\boldsymbol{VA}$ is the column vector of sectoral value-added requirements for production, and T denotes technology. Under the standard assumptions of constant returns to scale and perfect input markets, the productivity decomposes into components of the different industries. The decomposition of the real gross output growth in value chain S falls into the contributions of real value-added growth and the TFP ($\boldsymbol{\pi}$) as residual is

$$\mathbf{growth_t} = \overline{\boldsymbol{\alpha}}_{\mathbf{t,s}} \mathbf{VA\ growth_t} + \boldsymbol{\Delta\pi}_{t,s}$$

where $\overline{\boldsymbol{\alpha}}_{\mathbf{t,s}}$ is a column vector of the value-added shares in the value chain, $\mathbf{VA\ growth}$ is the corresponding real value-added growth vector, and $\boldsymbol{\Delta\pi}_{t,s}$ is the multifactor productivity of the whole value chain s in period t. [3]

3.2 Empirical estimation strategy

To provide an empirical counterpart to the theoretical impact, we measure the value chain linkages, $\overline{\boldsymbol{\alpha}}(\boldsymbol{F^S})$, based on the OECD trade-in-value added (TiVA) database and the world input-output matrix for

[2] It is notable that the similar characterization can be further made for different factor inputs, i.e. $f = F(\boldsymbol{\Lambda}, \mathbf{K}, T)$, where $\boldsymbol{\Lambda}$ is the column vector of labor requirements for production, $\mathbf{K}$ is similarly a column vector of capital requirements, and T denotes technology (see, e.g., Timmer, 2017; Kuusi et al., 2022). Here, however, we focus on the overall shock in the value chain without further decomposing it.

[3] In case of further factor composition, the corresponding equation becomes $\boldsymbol{\Delta}\log(\boldsymbol{Y}_{t,\boldsymbol{F^s}}) = \overline{\boldsymbol{\alpha^L}}(\boldsymbol{F^S})\boldsymbol{\Delta}\log(\boldsymbol{\Lambda}_t) + \overline{\boldsymbol{\alpha^K}}(\boldsymbol{F^S})\boldsymbol{\Delta}\log(\mathbf{K}_t) + \boldsymbol{\Delta\pi}(\boldsymbol{F^S})$, where TFP growth contribution can be seen as a weighted average of TFP of the production in different stages, with the value-added shares of the industries in the value chain as weights (Timmer, 2017; Kuusi et al., 2022). In our form, the TFP growth contribution are considered as part of $\boldsymbol{\Delta}\log(\mathbf{VA_t})$, while the residual is considered as the unaccountable part of the growth.

the year 2018. We collect the data on value chain linkages for each TiVA country and use them in our econometric analysis as the value chain exposure variables.

We consider the *upstream* value-added fraction. A large upstream value-added fraction in domestic production indicates that that country-industry pair actively uses a foreign country as the intermediate producer of products that are assembled in the domestic country. In comparison, a large *downstream* fraction in production indicates that a domestic country-industry pair actively uses foreign countries as the final producer of products for which the domestic country produces intermediate goods and services.

After denoting the home country producer industry as *s* and the corresponding partner industry-country pair as *i*, we denote the total corresponding *upstream value-added* fraction of industry i as $\alpha_{s,t}^{i}$, where the *VA* matrix for year *t* is used. As we only consider the pre-Covid period fractions 2018, we omit the time index and simply use the notation α_{s}^{i}. We use the pre-Covid fractions instead of Törnquist weights, as the Covid period potentially suffer from endogeneity, that is, they may reflect the impact of the shock rather than causing it.

We first use a generalized differences-in-differences approach to estimate the reduced-form effects of the Chinese value chain Our estimation equation for the industry-country pairs is:

$$growth_{t,s} = \gamma_p dependence_s + \epsilon_{c,t} + \epsilon_p + \epsilon_s + \epsilon_{s,t} \quad (1)$$

In the equation, $growth_{t,s}$ is the monthly, year-on-year output growth rate of industry s as relative to its output growth 12 months before. We use p to show periods, here to pre- (2019) and post-Covid (1-4/2020 or later years) periods. $dependence_s = \sum_{CHN} \alpha_s^{CHN}$ is the dependence of the value chain on the Chinese part of the value chain before Covid (2018). We control for the periods ϵ_p, as well as country-level shocks $\epsilon_{c,t}$ and individual industry-country fixed effects, ϵ_s. The error terms $\epsilon_{s,t}$ allow for heterogeneity and are cluster-robust within the industry-country pairs.

Our main estimated variable is the multiplier γ_p. Given the theoretical decomposition of the growth impacts in the value chains, multiplier γ yields the (China-share-)weighted sum of value chain shocks $\gamma = \sum_{CHN} \frac{\alpha_{t,s}^{i}}{\sum_{CHN} \alpha_{t,s}^{CHN}} VA\ growth_{t,i}$, conditional on the control variables. Especially we focus on its value in the early months of 2020 ($\mathrm{Dependence\ 2020} = \gamma_{2020}$). We use different regional subsamples and industry characterizations to analyze the heterogeneity of the impacts.

Our identification strategy builds on the idea that the growth of less-dependent home industries provides a good counterfactual for the more-dependent industries, at least in the early phases of the crisis. Based on the similarity of pre-Covid trends in 2019, this assumption seems valid. Moreover, we control for the possibility that the effects would be a result of the direct impact of the pandemic, by controlling for the cross-country variation in production, $\epsilon_{c,t}$, in each month. Arguably, Covid had a regional effect rather than a (systematic) industry-region effect, and thus this strategy should disconnect our results from the direct impacts of the disease. Moreover, we use a constrained approach in which we only focus on the early months of Covid-19 (January-April 2022) and the trade linkages between China and the EU and Americas.

Our approach allows us to provide further details of the value-chain impacts. That is, we use available information on the actual value-added changes in China to proxy for the direct shocks, which allows us, under certain assumptions, construct $\sum_{CHN} \frac{\alpha_{t,s}^{i} VA\ growth_{t,i}}{\sum_{CHN} \alpha_{t,s}^{CHN}}$ directly from the available data. We use real value-added and output growth in China to approximate value-added growth in the value chain. Assuming that the input–output relationship and structure of demand is stable during the observation period, this approximation is reasonable. This approach is similar to other attempts to isolate the growth contributions of different industries in the global value chains (Timmer, 2017; Kuusi et al., 2022).

While this approach demands more data, the shock characterization has clear merits in terms of analysing the value-chain disruptions. It allows us to measure the multiplier effect that may have resulted from the direct shock in the value chain.

There is strong anecdotal evidence that the multipliers may be large. For example, the absence of a key Chinese-produced part led to temporary automotive plant closures in Japan and Korea.[4] The disruption may also be magnified by, among other things, increased logistical problems in supplier pass-through or re-sourcing at short notice, quality problems resulting from fast delivery, and excessive resources being spent on managing a crisis. Missed sales opportunities and additional costs may also generate financial constraints and result in further operational problems.

After denoting the multiplier by β, we can rewrite the previous equation as

$$growth_{t,s} = \beta_p shock_{t,s}^{CHN} + \epsilon_{c,t} + \epsilon_p + \epsilon_s + \epsilon_{s,t}, \qquad (2)$$

where $shock_{t,s}^{CHN} = \sum_{CHN} \frac{\alpha_{t,s}^{i} VA\ growth_{t,i}}{\sum_{CHN} \alpha_{t,s}^{CHN}}$ is now constructed from the data. To isolate the Covid-19-related shock, we measure the sectoral, value-added growth in Chinese industries ($VA\ growth_{t,i}$) as relative to the growth 12 months before. Otherwise, the model has similar features as the first model (Eq. 1).

[4] This discussion of the recent practical problems in the value chains is based on reports by Baker MacKenzie (*Beyond COVID-19: Supply Chain Resilience Holds Key to Recovery*, 2020) and PwC (*Supply Chain and Third Party Resilience During COVID-19 Disruption*, 2020).

If β is estimated to equal 1, the decline in home production exactly matches the foreign direct upstream impact, as presented by theory. If β is less than 1, the impact is smaller than the direct impact. The value of β can even be negative if the foreign contraction increased domestic production, for example, due to the reallocation of production in the value chain. On the other hand, β can also be larger than 1. That may be because a decline in the foreign value added is associated with additional disturbances in the value chains for the above-mentioned reasons.

It is notable that the multiplier may also reflect unmeasured elements of the production shock that may result in over- or underestimating the multiplier effect. To analyze the role of data quality, we resort to different data sources that are discussed later.

Finally, we take a more structural view on the value-chain response and consider a two-stage IV approach. We use the initial value chain dependence as an instrument for the latter value-chain shocks, thus making it possible to make further causal observations. We divide the response periods to the initial shock phase in 1-4/2020 and the later adjustment phase 2021 onwards.

Formally, the IV estimation includes statistical inference on (1) the relationship between the Covid-19 shock and foreign, upstream production, and (2) the multiplier impact of the foreign production shock on the domestic production. As usually, the first stage equation provides an estimation equation for the average shock that value chains with different China reliance faced:

$$shock_{t,s}^{CHN} = \beta^{1st} I_{post}[dependence_s] + \epsilon_{c,t} + \epsilon_p + \epsilon_s + \epsilon_{s,t} \quad (3a)$$

I_{post} is an indicator variable that receives value 1 if the observation belongs to the 2020- period. In the second stage, the first stage prediction of the foreign shock, $\widehat{shock_{t,s}^{CHN}}$, is then used as an explanatory variable for the home changes in production:

$$growth_{t,s} = \beta^{iv} \widehat{shock_{t,s}^{CHN}} + \epsilon_{c,t} + \epsilon_p + \epsilon_s + \epsilon_{s,t} \quad (3b)$$

The approach allows us to also address the potential measurement problems of the shock. When the shock variable is subjected to measurement error, the IV approach allows us to potentially correct the attenuation bias. However, we acknowledge that this approach is not without problems. It may be prone to a failure of the exclusion restriction. That is, there may be other factors that contaminate the relationship between our instrumental variable and the Covid responses of production.

Moreover, the instrument may be weak or under identify the relationship. Under-identification of the instruments means that some or all of the instruments are irrelevant as they are not sufficient to identify the relationship between the endogenous regressors and the explained variable. Weak identification arises when the excluded instruments are correlated with the endogenous regressors, but only weakly. Estimators can perform poorly when instruments are weak (see the work of Stock and Yogo (2005) for further discussion).

The under-identification test is an LM test of whether the rank of the matrix of reduced-form coefficients is smaller than the dimensionality of the problem. Under the null condition, the statistic is distributed as chi-squared, and a rejection of the null indicates that the matrix is of full-column rank (i.e., the model is identified, and the rejection is based on the Kleibergen-Paap (2006) rk statistic). In addition, we use the Kleibergen-Paap Wald rk F-statistic with the degrees-of-freedom adjustment for the rk statistic, following the standard small-sample adjustment for cluster–robust standard errors.

4 Data and descriptive statistics

Our dataset is a combination of three different types of data: TiVA data from OECD; monthly production (Index of Industrial Production [IIP]) data, presented by country and industry, from the United Nations Industrial Development Organization (UNIDO); and value added data. Moreover, we have combined other data sources to study robustness of our findings.

First, to analyze GVC linkages between countries and industries, we use the 2021 release of the OECD, Inter-Country Input-Output (ICIO) Tables. It covers 76 economies (including all OECD, EU, G20 and ASEAN countries) as well as region aggregates. Indicators are available for 45 industries within a hierarchy based on ISIC Rev. 4.

Second, we have gathered production and value-added data. The production data is from UNIDO and it is at the monthly level. The used Index, the IIP, measures the growth of the volume of industrial production in real terms, free from price fluctuations. The monthly indices reflect the growth of gross output, and we use it to quantify changes in home production.

We use National Bureau of Statistics of China (NBSC) data to measure Chinese industrial production value added by industry sector. We use monthly data on the year-to-year changes and deflate them by using the manufacturing producer price index. The data is collected from the Macrobond database.

As the NBSC data has limited connectivity with the TiVA data[5], we also consider a hybrid shock variable in which we approximate missing value-added growth in the NBSC data with UNIDO data. Given the temporal nature of estimates, output growth provides the best approximation of value-added growth,

[5] We were not able to link Chemicals and chemical products manufacturing; basic metals manufacturing; Fabricated metal products, except machinery and equipment manufacturing; and Machinery and equipment n.e.c. manufacturing

assuming that the input-output relationship is relatively stable during the observation period, as it explicitly stated by the data development team[6].

In the appendix, Table A1 and A2, we report the available industries and countries for the 1-4/2020 period at the industry and country level. The descriptive analysis shows that there have been marked differences in the 2018 value chain dependence ($\sum_{CHN} \alpha_{2018}^{CHN}$ in Eq. 1).

The descriptive analysis also indicate rather marked differences in the approximate shock variables, that is, $\sum_{CHN} \frac{\alpha_{t,s}^{i} VA\ growth_{t,i}}{\sum_{CHN} \alpha_{t,s}^{CHN}}$ in Eq. 2. Partly, it reflects the lack of connectable NBSC data, and the link between TiVA and the value-added measurements are done only for a subset of Chinese industries. Naturally then, the shock variables are considerably smaller than, when we also use the UNIDO data to fill the missing values. However, it is notable that when we discard even the available NBSC data, we find that the UNIDO data provides large shocks even in this case.

5 Results

5.1 Establishing the validity of the research design

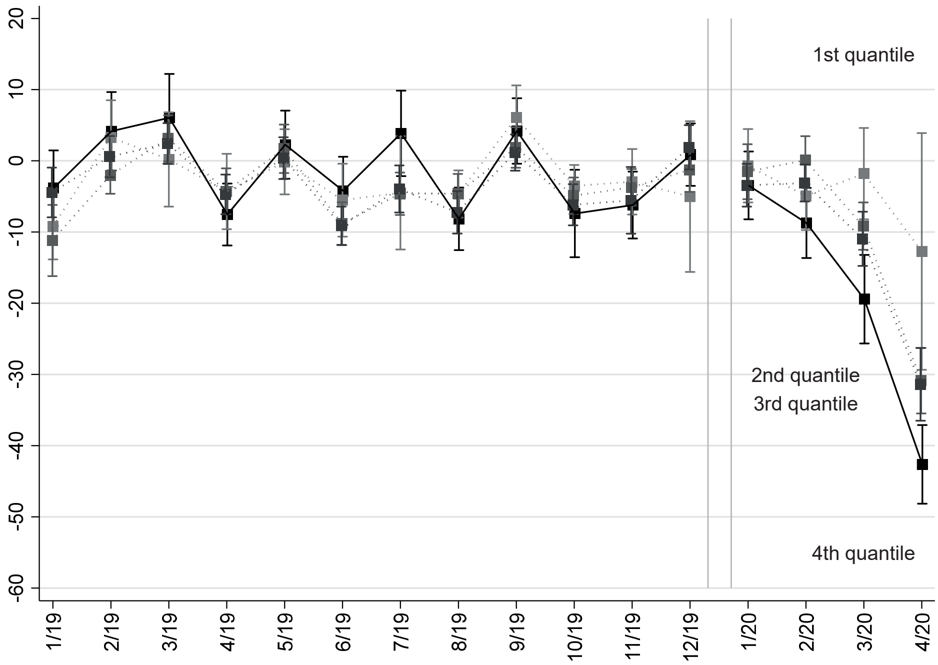
Our aim is to estimate the causal effect of value chain linkages on the home production (the final production in the value chains).

We first assess the validity of our main identifying assumption that the output growth of industries with weak connections to China provide a good counterfactual for industries with stronger connections. To show evidence of the validity, we sort industries in quantiles based on their 2018 share of Chinese value chain component. Figure 1 provides the real output quantile means and their 95 % confidence intervals (based on the simple, monthly standard errors of the observations within the quantile) for each month of 2019 and the first four months of 2020.

Figure 1 indicates that the pre-Covid trends in the growth rates as relative to 12 months earlier were similar. However, in the early months of 2020 there was a strong divergence in the output growth as relative to 12 months earlier. Furthermore, the figure indicates visual evidence of substantial output impacts. Partly, they appear to reflect common dynamics, but the output drop is not statistically significant for the least exposed, lowest quantile industries. On the other hand, for the most-exposed industries, the drop is consistently very large.

[6] https://stat.unido.org/content/dataset_description/monthly-iip

Figure 1. Industry real y-o-y output growth (%) relative to 12 months before.



Note: Quantile means and their 95 % confidence intervals (based on the simple, monthly standard errors of the observations within the quantile). Quantiles based on the 2018 share of Chinese value chain component. The sample consists of the EU and Americas industry-country pairs.

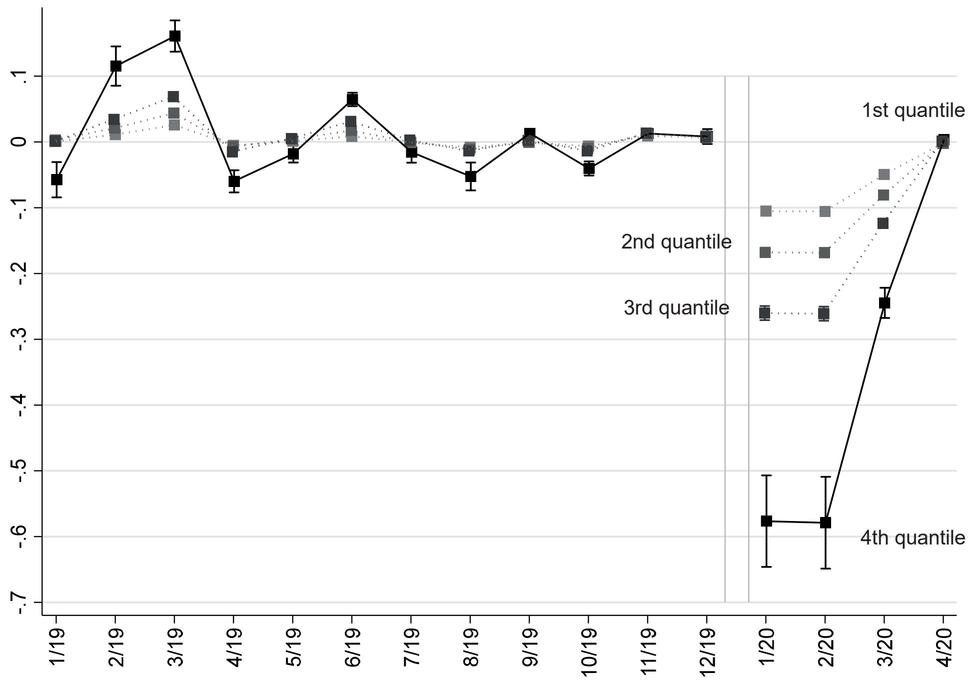
All in all, the figure indicates that our difference-in-difference setup in Eq. 1 is valid.

We then analyze data on the (direct) value chain impact of the contraction in China for the same groups ($\sum_{CHN} \frac{\alpha_{t,s}^{i} VA\ growth_{t,i}}{\sum_{CHN} \alpha_{t,s}^{CHN}}$). In Figure 2, we have used UNIDO real output data as a proxy of the value-added shock. In Figure 3, we used the NBSC data, instead.

In case of the UNIDO-data, the shock is consistently larger in the group of industries that have the largest exposure to the Chinese value chains. While the productivity shock exists in all quantiles, it is not statistically significant in the lowest dependence (1st) quantile. There are no apparent pre-Covid trends in the groups. The shock is quite small compared to the total output collapse in the value chains, as measured by the output changes. The shock mean varies between ca. -0.1% in the least affected quantile to ca. -0.6% in the most affected quantile. Already this finding suggests that the multiplier implied by the data is very large.

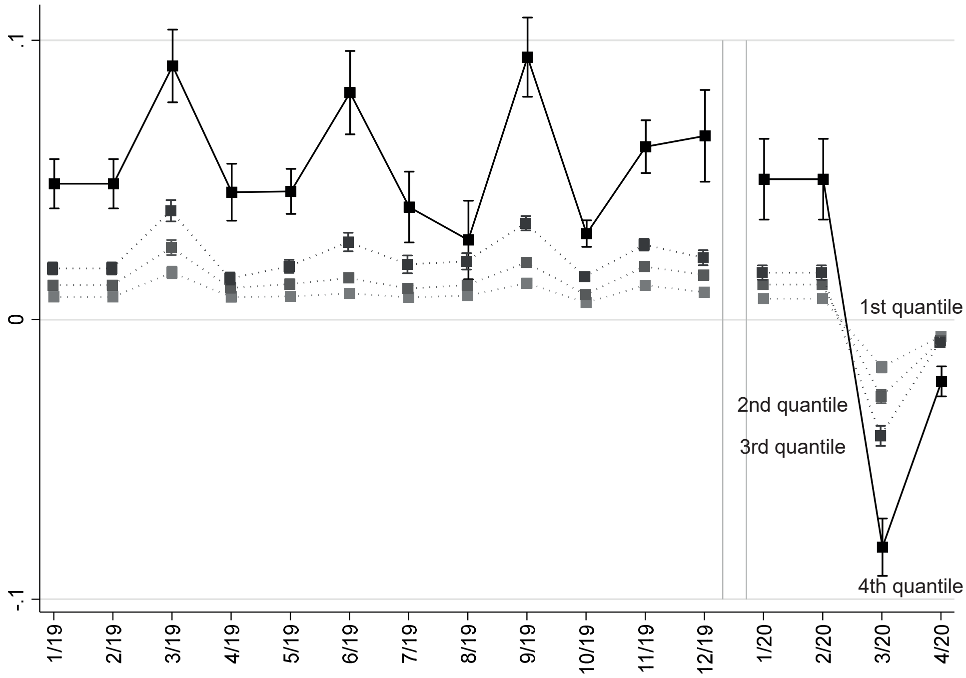
In case of the NSBC data, our possibilities to link the value-added data to the TiVA value chain data was limited, and therefore the shock is likely to be subdued (Figure 3). Nevertheless, the pattern is very similar. The figure also shows that the growth rate in the value added in the quantile with the largest China exposure was moderately larger in 2019, indicating the possibly that our use of the low-exposure industries as the counterfactual may result in underestimating the true impact of Covid. It is notable, however, that the differences are stable, indicating, that our control variables should account for their impact.

Figure 2. Industry real value chain shock based on the UNIDO real output data, % of home production output.



Note: Quantile means and their 95 % confidence intervals (based on the simple, monthly standard errors of the observations within the quantile). Quantiles based on the 2018 share of Chinese value chain component. The sample consists of the EU and Americas industry-country pairs.

Figure 3. Industry real value chain shock based on the NBSC real output data, % of home production output.



Note: Quantile means and their 95 % confidence intervals (based on the simple, monthly standard errors of the observations within the quantile). Quantiles based on the 2018 share of Chinese value chain component. The sample consists of the EU and Americas industry-country pairs.

5.2 Home production contraction and the VC dependence

Let us then discuss our main estimates. In Table 1, we report how the dependence on the Chinese component of the value chain affected output in the foreign, upstream value chain. The estimated variable (Dependence) measures the impact of the pre-Covid China dependence (γ) in a given year (see, Eq. 1)

We first focus on the findings that uses data from January 2019 to April 2020 (column 1 in Table 1). We report a significant and large effect for the dependence in 2020. The point estimate of gamma for the first 4 months of 2020 (row Dependence 2020) is -1.336 and statistically significantly below 0. The multiplier indicates that for each percentage point of dependence on the Chinese value chain, there was a 1.336 percent larger contraction in the home production.

The effect is very similar independent of whether the dataset is limited to the EU and Americas, or all countries (excluding China) are included (columns 1 vs. 3).

To provide a more comprehensive analysis of this result, let us note that the average nominal value-added share of the Chinese value chain component in 2018 was recorded at 2.6% (as detailed in the Appendix). Taking into consideration the multiplier in Column 1, the monthly impact on output growth is estimated to be approximately -3.4 pps. When we examine the cumulative impact over the period spanning from January to April, the resulting total effect is -14.4 pps as relative to counterfactual without the shock. In comparison to the observed output contractions illustrated in Figure 1, the effect appears to fall within a plausible range.

Moreover, a one-standard deviation increase in exposure (2.1 pps. higher share of Chinese value added) yields a contraction of -2.8 pps., culminating in a cumulative decline of -11.7 percentage points. It is noteworthy that this effect aligns reasonably well with the overall variability observed in the output outcomes.

In each estimation, we control for the industry-country specific fixed effects as well as the month-country fixed effects to deal with the potential effect of Covid-19 and other country-level shocks. In column (4), we also study further the potential Covid-19 contamination effects by letting the effect to vary for all countries according to geographical distance, ethnicity of the home country and its contingency with China[7]. These controls only increase the value chain effects, indicating that the multiplier effects were not likely caused by Covid-19.

In column 2, we change our viewpoint to take a first look on the impacts that the dependence has had after the year 2020. We extend the data to include the latest data until the early 2023, and control for annual country-level shocks as well as the average growth of the individual industries, as before.

The findings suggest that there has been a marked change in the relationship between the dependence and home output growth. Overall, the model does not show (Dependence 2020) statistically significantly lower growth in 2020 for those industries that had stronger pre-Covid dependence to China. It indicates that the initial shock in the early months was stronger, or there has been adjustments in the value chains to accommodate the later shocks.

[7] We use the GeoDist database (Mayer and Zignago, 2011). We introduce as additional explanatory variables the cross-products of the dependency and the corresponding variables distwces, comlang_ethno, colony, and contig. It is notable that geographical distance decreases the effect that the dependence has on the economic contraction at 10 % confidence level.

From 2021 onwards the multiplier is *positive* at the 95-% confidence level. This interesting result indicates that growth in previously dependent industries have become stronger than in those that were less dependent. In the next section, we will discuss this adjustment and the underlying patterns in more detail.

Table 1. Effects of the dependence on the Chinese component of the value chain to (home) output in the foreign, upstream value chain.

	(1) Home output EU & AM, 19- 4/20	(2) Home output EU & AM, 19- 23	(3) Home output All countries, - 4/2020	(4) Home output All countries,19 - 4/20 added controls
Dependence 2020	-1.336*	-0.389	-1.420**	-3.169*
	(0.54)	(0.50)	(0.49)	(1.07)
Dependence 2021-		0.842*		
		(0.34)		
Dummy, year 2019	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Dummy, year 2020	-0.120**	-0.016	-0.584***	-0.601***
	(0.04)	(0.02)	(0.08)	(0.07)
Dummy, year 2021-		-0.017		
		(0.02)		
Dependence 2019	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
R-squared	0.203	0.087	0.240	0.240
Observations	6415	19800	9791	9583
Industries	401	401	612	599

Note: Dependence refers to γ in Eq. 1 in different time periods. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.3 The initial shock and its multiplier effect

The point estimates in Table 1 already suggest that the contraction was very large. In fact, as the contraction in home production exceeded 1, the impact of the shock was larger than the direct impact of removing *all* Chinese value added. That is, according to the theoretical considerations in the previous section, the reduction of all value added would imply a multiplier 1.

Our data allows us to decompose the effect further into the contribution of an approximated direct shock as well as its multiplier effect (β) in the value chain (see, Eq. 2). As discussed before, we resort to different data sources. First, we use data received from the NBSC. Acknowledging that the data provides only limited information about the shock, we replace missing data with the proxy of value-added growth based on the UNIDO data. This provides us with a hybrid shock variable. We also analyze a version of the shock where the UNIDO data is solely used to construct it.

Table 2. Effects of the real value chain shock in the Chinese component of the value chain to (home) output in the foreign, upstream value chain.

	(1) Home output, EU & AM	(2) Home output, EU & AM	(3) Home output, EU & AM	(4) Home output, all countries
Shock, NBSC	63.370*			
	(24.97)			
Shock, hybrid		38.003**		23.543*
		(14.21)		(9.49)
Shock, Unido			5.428	
			(5.26)	
R-squared	0.202	0.202	0.201	0.239
Observations	6415	6415	6415	9791
Industries	401.0	401.0	401.0	612.0

Note: Shocks refers to multiplier β in 2020 (Eq. 2) and the different specifications of the shock. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 2, we show the estimates of the multiplier (β) of the value-chain shock for the months 1-4 of 2020. The multipliers turn out to be very large. As a result of a direct negative impact on home production (value-chain weighted foreign shock), the production decline in the home country has exceeded the direct shock by an order of magnitude. When we approximate missing data with Unido changes in real output, the multiplier falls but remains high (column 2). If we replace NBSC data fully with Unido data, the multiplier becomes sm aller and statistically insignificant (column 3). While production at home is strongly correlated with the UNIDO-based shock, the correspondence becomes very noisy.

Next, we deepen the analysis and take a more structural view on value chains as channels to transmit shock to other countries. We turn into a two-stage approach where the first stage analyzes the average shock that value chains have faced (Equation 3a) and the second stage uses the prediction of the foreign shock as an explanatory variable for changes in domestic production (Equation 3b). In Table 3, we again focus on the initial impact of the first Covid shock through the value chains. We use the data from the beginning of 2019 to April 2020.

Table 3. IV estimation of the effects of the real value chain shock in the Chinese component of the value chain to (home) output in the foreign, upstream value chain

	(1): Home output, EU & AM	(2): Home output, EU & AM	(3): Home output, EU & AM	(4): Home output, all countries
1st stage:				
Dependence 2020	0.003*	-0.015***	-0.071***	-0.024***
	(0.002)	(0.003)	(0.002)	(0.004)
2nd stage:				
CSBC shock 2020	-444.9			
	(338.1)			
Hybrid shock 2020		90.62***		60.55***
		(29.65)		(16.93)
Unido shock 2020			18.86***	
			(7.117)	
Observations	6,415	6,415	6,415	9,791
Industries	401	401	401	612
R-squared	-0.133	-0.002	-0.002	-0.003
P value of under-identification LM	0.127	8.97e-10	6.54e-06	7.02e-11
Kleibergen-Paap Wald rk F	3.458	23.89	1319	35.91

*Note: The 1st stage Dependence 2020 refers to β^{1st} (Eq. 3a) while the 2nd stage rows refer to β^{iv} (Eq. 3b) with different shock measures. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

The results indicate that the multipliers remain large (2nd stage results). When we use either the hybrid shock (column 2) or the UNIDO-based shock (column 3 for the EU and the Americas, column 4 for all countries excluding China), we find that the multiplier tends to be a bit higher than when reduced form OLS estimation is used. This indicates that there might be a downward attenuation bias in those findings. It is also notable that in the most reliable models the first-stage estimate of the impact of the China is negative, indicating that the shock (receiving a negative value) is larger when the dependence is larger.

The appropriateness of the instrumental variable approach is carefully analyzed. A high test statistic for the F-test of weak identification suggests that the set of instruments is strong, while the underidentification test statistic indicates that the rank of the observed model is not lower than the rank of the estimated model. As tests, we use the underidentification LM test and the Kleibergen-Paap Wald rk test for weak identification (see Schaffer, 2010; Kleibergen and Paap, 2006).

However, we notice that the shock variable based on the NBSC data column (1) proves not to be reliable. In the first-stage, the pre-covid dependence is only weakly related to the subsequent shocks and it is positive. Both the F-test and the underidentification test indicate that the measurements may not be reliable.

All in all, our results indicate a large multiplier effect, when we compare the statistics that directly aim at measuring the direct shock. While we acknowledge the problems in measuring such shocks, these findings align well with our reduced form estimates. They indicate a strong relationship between initial dependence on the Chinese value chains and the size of contraction during the early phases of the crisis.

6 Further analysis

6.1 Heterogeneity across industry types and regions

It can be argued that not all value chains are the same. For example, in some value chains it is easier to find alternative suppliers to Chinese companies than in others. For this reason, we examine the heterogeneity of our findings.

Next, we focus on different kinds of industries. We first divide industries (at the level of industry classification) in two groups based on their level of digitalization. Based on the OECD taxonomy by Calvino et al. (2018), we define high level of digitalization industries to be motor vehicles, trailers, and semi-trailers manufacturing; and other transport equipment manufacturing, while the rest are considered med-to-low-digitalization industries. Moreover, we consider another decomposition based on the R&D intensity of the industries. We define pharmaceuticals, medicinal chemical, and botanical products manufacturing, and Computer, electronic, and optical products manufacturing as the high-R&D-level industries, whereas the rest are low-to-mid-R&D industries (Galindo-Rueda and Verger 2016).

We report our findings in Table 4. We continue focusing on the early 2020s, and all variables refer to the impact in the first four months of 2020. Results of each IV estimations are presented in three columns, two for the first stage, and one for the second stage. We have used separate estimations to analyze the role of digitalization and R&D.

First, focusing on the role digitalization in the EU-Americas sample (columns a-c), we find that the effect of the dependence was primarily seen in the value chains that belong to the high-level digitalization group. In this group, the dependence has resulted to a large, negative shock (the 1st stage negative multiplier), while the shock has then resulted in a large multiplier effect in the value chain (the 2nd stage positive multiplier). For the low-digitalization industries, the relationship is not statistically significant.

Interestingly, however, there is clear evidence of this only in the EU-Americas subsample, whereas when we include other countries, the difference between low- and higher-digitalization value chains becomes less prominent (columns d-f).

There are also differences in the shock effects for high- and med-to-low R&D-intensity industries. For the EU-AM sample, we find that the relationship between the shock and the initial dependence is weaker, but the multiplier effect of these (smaller) shocks are moderately larger for the high-R&D industries (columns g-i in Table 4). In this respect, the findings are relatively similar also in the full sample consisting of all other countries excluding China (columns j-l).

Table 4. Heterogeneity across industry types, IV estimations

	(1): Home output, EU & AM			(2): Home output, all countries			(3): Home output, EU & AM			(4): Home output, all countries		
	1st stage			1st stage			1st stage			1st stage		
	(a) Hybrid, highly digital industries	(b) Hybrid, med-low digital industries	(c) 2nd stage: output	(d) Hybrid, highly digital industries.	(e) Hybrid, med-low digital industries	(f) 2nd stage: output	(g) Hybrid, high R&D industries	(h) Hybrid, med-low R&D industies	(i) 2nd stage: output	(j) Hybrid, high R&D industries	(k) Hybrid, med-low R&D industies	(l) 2nd stage: output
1st stage:												
Dependence,	-0.041***	0.004*		-0.0413***	0.0142***							
highly dig.	(0.007)	(0.00225)		(0.00253)	(0.00448)							
Dependence,	-0.000	-0.012***		0.000	-0.0229***							
mid-low dig.	(0.000217)	(0.00204)		(0.000364)	(0.00410)							
2nd stage:												
Hybrid shock,			125.0*			48.25						
highly dig.			(67.49)			(30.61)						
Hybrid shock,			56.01			48.89***						
mid-low dig			(35.70)			(17.16)						
1st stage:												
Dependence,							-0.001***	0.001		-0.013***	0.003	
high R&D.							(0.000)	(0.001)		(0.002)	(0.002)	
Dependence,							0.000	-0.025***		0.002**	-0.038***	
mid-low R&D.							(0.000)	(0.007)		(0.000)	(0.006)	
2nd stage:												
Hybrid shock,									104.6*			61.56
high R&D									(55.25)			(40.95)
Hybrid shock,									83.98***			62.45***
med-low R&D.									(29.43)			(15.85)
Observations			6,415			9,791			6,415			9,791
R-squared			0.001			0.008			-0.001			-0.003
Number of id			401			612			401			612
P value of underidentification LM			0			0.000			0.000			0.000
Kleibergen-Paap Wald rk F			19.03			17.13			6.125			49.68

*Note: The 1st stage Dependence 2020 refers to β^{1st} (Eq. 3a) while the 2nd stage rows refer to β^{iv} (Eq. 3b) with different shock measures. In this specification, we have measured separately the effects for different industry groups by constructing industry-specific variables. That is, we multiply the variables with an indicator variable that assigns value 1 if observation belongs to the group and otherwise 0. Eqs. 3 are then jointly estimated under the specified distinctions. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

We have also further explored the regional dimension of our findings. We find that a focus on individual countries would overburden our estimations and our methods do not provide reliable estimates at the country level of the shock multipliers.

Rather, we can study the heterogeneity in more narrowly defined regions: the EU, the US and Canada, and the rest of the Americas. We used reduced-form modelling, and on the impact of the pre-Covid China dependence (γ) in a given year. While we again use the EU and Americas sample, we now study how the Chinese component of the value chain affected differently in these (sub)regions. We focus on the initial findings that uses data from January 2019 to April 2020.

We report a significant and large effect for the dependence in 2020 both for the EU and the northern America block consisting of Canada and the US. For the EU, the estimated multiplier indicates that for each percentage point more of dependence on the Chinese value chain, there was a 1.763 percent larger contraction (with standard error 0.688) in the home production. The corresponding number for Canada and the US is slightly larger, 2.85 percent (with standard error 1.44). Both estimates are statistically significantly different from 0 at the 5% confidence level, while their standard errors indicate a significant difference between them. For the rest of the Americas, the effect is smaller (0.738) and statistically insignificantly different from 0.[8]

6.2 Adjustments after 2020

Finally, we address more thoroughly the question regarding the adjustments of value chains after the initial shock in 2021. In Table 1, we showed that there is a positive link between later growth and initial dependence on the Chinese value chains. To provide a more comprehensive understanding of this relationship, we have conducted additional IV estimations for the later period, as presented in Table 5.

The findings suggest that value chains that were highly reliant on Chinese production have experienced slower growth in the Chinese production component after 2021 (as seen in columns a and c, where there is a negative multiplier in the first stage). However, unlike the initial response in 2020, this sluggish growth has not led to a decrease in the growth rate of home production. Instead, as a response to slow growth of the Chinese component, there has been an increase in their growth compared to less-dependent industries (as evident in columns a and c, with a negative multiplier in the second stage).

One possible interpretation is that value chains that initially suffered the most have expanded their operations outside of China. Nevertheless, the full picture is more complex than this. Indeed, the results in columns b and d (first stage) indicate that *output* growth in China has increased more in value chains that were highly reliant on the Chinese segment prior to the COVID-19 pandemic. It is plausible that Chinese production has evolved into a larger role as an organizer of upstream production, rather than solely a provider of value-added services. However, it is also important to note that these findings are affected by the limitations of our instruments, with the F-statistic falling below the usual critical levels.

[8] The authors provide estimation tables upon request.

Table 5. Adjustments over time, IV estimations

	(a): Home output, EU & AM	(b): Home output, EU & AM	(c): Home output, all countries	(d): Home output, all countries
1st stage:				
Dependence	-0.017***	0.003***	-0.015***	0.002***
post-2020	(0.001)	(0.001)	(0.001)	(0.001)
2nd stage:				
Hybrid shock	-48.76***		-25.28	
post-2020	(18.62)		(27.63)	
Unido shock		314.3***		230.7
post-2020		(101.1)		(232.6)
Observations	19,800	19,800	30,246	30,246
Industries	401	401	612	612
R-squared	-0.020	-1.507	-0.000	-0.024
P value of underidentification LM	5.08e-05	0.00406	2.92e-07	0.0123
Kleibergen-Paap Wald rk F	626.7	12.70	181.3	5.041

*Note: The 1st stage Dependence post-2020 refers to β^{1st} (Eq. 3a) when the post period data is extended to involve years 2021-2023, while the 2nd stage rows refer to β^{iv} (Eq. 3b) with different shock measures with the corresponding data. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

7 Conclusions and discussion

This paper examines how the Covid-19 crisis was transmitted through GVCs from one country to another, with a special focus on the multiplier effects that the direct shocks may have caused. During the crisis, many factories and other branches were closed, or their operations were downsized because firms did not receive the intermediate products they needed from abroad. The analysis refines the overall understanding of the economic impact of these shocks. By utilizing information on value chain connections between countries and combining it with production disruptions in China, the shocks caused by Covid-19 on the foreign, upstream parts of the value chains and their subsequent impact on domestic production were measured.

This work provided three main results.

First, after quantifying the upstream shock and its effects with world input-output data and employing a differences-in-differences research setup, our analysis confirms that global value chains have indeed served as a channel for transmitting supply shocks between countries and industries. The magnitude of this shock was substantial, indicating that it caught entire industries by surprise. In the world of long value chains, only a few companies possess complete visibility throughout the entire chain, which often spans multiple tiers. This general lack of visibility meant that companies did not have knowledge of all the companies and locations involved in their supply chains.

Second, we discovered that disruptions within value chains have a significant multiplier effect on the downstream segments of these chains. When comparing our value chain growth accounting findings with the actual measured contractions in the value chains, our results indicate that, indeed, sourcing failures can lead to strong nonlinearities in complex supply networks, as recent literature suggests. The output in the downstream segments of the chains decreases by a factor greater than what the direct shocks alone would have implied.

Third, we demonstrated that the impact of GVC disruptions varies significantly among industries and countries. The most substantial losses resulting from this transmission occurred in highly digital industries, notably in the EU and North America. However, the effect was short-lived, and it appears that value chains that initially experienced the most significant disruptions have expanded their output after 2021.

Based on the results, it is evident that preparing for future shocks would necessitate more effective risk management of large value chains that are concurrently dependent on multiple regions. This could involve actions such as shortening value chains or developing parallel value chains. While our focus has been primarily empirical, our findings emphasize the importance of comprehending the underlying market features and institutions that shape the structure of global value chains. However, it's important to note that these findings do not suggest the abandonment of international production. It should be acknowledged that the decentralization of production and the ability to import products from other countries have also been instrumental in mitigating the impact of Covid-19 on many of the regions that were most severely affected.

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Appendix

A1. Measuring value chain linkages

Let us next formally introduce the building blocks of our value chain linkage analysis. The first element is the input coefficient matrix, $\boldsymbol{A}$, that contains the input coefficients a_{ij}, which give the global value units of intermediate goods from industry *i* that are required to produce one value unit of gross output in industry *j.* In $\boldsymbol{A}$, the numbers of rows and columns are the same and equal the numbers of total national industries (the number of countries, C, times the number of industries, I). For the final demand block, we similarly define a matrix of final demand flows, $\boldsymbol{Y}$, the row elements being the different final demand classes (in total, 5 different classes) and columns indicating flows from *i* to *j,* with the length *C*I.*

The ratios of value added to gross output in industries in country *s* are contained in a row vector $\boldsymbol{v}$. The length of this vector equals the numbers of industries, with value-added ratios for industries in *s* as the first elements ($\widetilde{\boldsymbol{v}}$) and zeros elsewhere: $\boldsymbol{v}$ = [$\widetilde{\boldsymbol{v}}$ 0]. Then, we follow Los et al. (2016) and collect the actual value-added distribution in the global value-chain matrix **(**$\boldsymbol{VA}$**)** that is

$$\boldsymbol{VA} = \boldsymbol{v}(\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{Y} * \boldsymbol{i},$$

in which $\boldsymbol{i}$ is a column vector where all elements are unity, implying that it sums the elements in each of the rows of the matrix $\boldsymbol{Y}$. The *VA* matrix has the same dimensions as *A*, including the contributions of each industry to the overall value added of other industries. The element $(\boldsymbol{I} - \boldsymbol{A})^{-1}$ is the well-known Leontief inverse, in which $\boldsymbol{I}$ is the identity matrix of appropriate dimensions. When multiplied with final demand, the Leontief inverse calculates the gross output in the industries producing the final products and also the output in industries producing the intermediate inputs required for this (Los et al., 2016). In particular, $\boldsymbol{VA}$ can be interpreted as the limiting value of the infinitely long sum of value-added contributions, with the number of stages varying from 1 to ∞.

Each column of the value chain matrix $\boldsymbol{VA}$ shows the value-added distribution of the value chains for a given final producer industry. The elements allocate the total value added into the value-added contributions of different intermediate good-producer industries globally. They provide us with the *upstream* value-added fractions of the trade partner countries in each production value chain as indexed by the final producer industry and country.

A2. Additional Tables and Figures

Table A1. Descriptive statistics. Observations by industry

Industry	ISIC Code	Number of Obs.		CHN VA share 2018	Direct shocks, % of output NBSC	Hybrid	UNIDO
Wood and products of wood and cork manufacturing, except furniture	16	132	mean	1.36 %	-0.003 %	-0.040 %	-0.086 %
			std	0.38 %	0.016 %	0.024 %	0.067 %
Coke and refined petroleum products manufacturing	19	96	mean	1.65 %	-0.001 %	-0.042 %	-0.069 %
			std	0.92 %	0.010 %	0.029 %	0.053 %
Chemicals and chemical products manufacturing	20	124	mean	1.94 %	-0.002 %	-0.071 %	-0.110 %
			std	0.59 %	0.016 %	0.049 %	0.085 %
Pharmaceuticals, medicinal chemical, and botanical products manufacturing	21	116	mean	1.32 %	-0.001 %	-0.033 %	-0.071 %
			std	0.63 %	0.011 %	0.021 %	0.067 %
Rubber and plastics products manufacturing	22	132	mean	2.27 %	-0.003 %	-0.079 %	-0.137 %
			std	0.75 %	0.025 %	0.056 %	0.108 %
Other non-metallic mineral products manufacturing	23	136	mean	1.55 %	-0.009 %	-0.049 %	-0.110 %
			std	0.56 %	0.031 %	0.033 %	0.088 %
Basic metals manufacturing	24	132	mean	1.89 %	-0.002 %	-0.075 %	-0.115 %
			std	0.47 %	0.016 %	0.046 %	0.083 %
Fabricated metal products, except machinery and equipment manufacturing	25	132	mean	2.26 %	-0.002 %	-0.113 %	-0.160 %
			std	1.04 %	0.019 %	0.088 %	0.138 %
Computer, electronic, and optical products manufacturing	26	107	mean	5.81 %	0.025 %	-0.077 %	-0.386 %
			std	4.41 %	0.091 %	0.058 %	0.466 %
Electrical equipment manufacturing	27	124	mean	4.46 %	0.002 %	-0.118 %	-0.329 %
			std	3.20 %	0.082 %	0.087 %	0.356 %
Machinery and equipment n.e.c. manufacturing	28	128	mean	2.99 %	0.000 %	-0.131 %	-0.223 %
			std	1.46 %	0.035 %	0.103 %	0.206 %
Motor vehicles, trailers, and semi-trailers manufacturing	29	124	mean	2.95 %	0.000 %	-0.105 %	-0.219 %
			std	1.36 %	0.052 %	0.084 %	0.201 %
Other transport equipment manufacturing	30	116	mean	3.33 %	-0.031 %	-0.136 %	-0.264 %
			std	1.77 %	0.065 %	0.126 %	0.276 %
All (unweighted)		1599	mean	2.56 %	-0.002 %	-0.083 %	-0.174 %
			std	2.10 %	0.045 %	0.077 %	0.224 %

Table A2. Descriptive statistics. Observations by country

Country	Number of Obs.	CHN VA share in 2018	Direct shocks, % of output		
			NBSC	Hybrid	UNIDO
Argentina	32	2.32 %	-0.001 %	-0.100 %	-0.154 %
Austria	52	2.06 %	-0.001 %	-0.069 %	-0.133 %
Belgium	52	1.82 %	-0.004 %	-0.056 %	-0.106 %
Bulgaria	48	2.01 %	-0.004 %	-0.068 %	-0.139 %
Brazil	52	3.24 %	-0.020 %	-0.116 %	-0.225 %
Canada	52	3.41 %	-0.001 %	-0.116 %	-0.245 %
Chile	48	4.00 %	-0.014 %	-0.164 %	-0.287 %
Colombia	48	3.19 %	-0.014 %	-0.124 %	-0.226 %
Cyprus	32	1.42 %	-0.004 %	-0.052 %	-0.093 %
Czech Republic	48	3.75 %	0.006 %	-0.093 %	-0.244 %
Germany	52	1.96 %	-0.002 %	-0.061 %	-0.128 %
Denmark	48	1.94 %	-0.003 %	-0.072 %	-0.129 %
Spain	52	2.49 %	-0.004 %	-0.090 %	-0.174 %
Estonia	52	3.74 %	0.002 %	-0.102 %	-0.261 %
Finland	20	1.69 %	-0.002 %	-0.066 %	-0.106 %
France	52	2.52 %	-0.001 %	-0.074 %	-0.159 %
Greece	52	2.12 %	-0.003 %	-0.075 %	-0.133 %
Croatia	52	1.52 %	0.000 %	-0.045 %	-0.094 %
Hungary	52	2.87 %	0.000 %	-0.086 %	-0.200 %
Ireland	32	1.90 %	-0.003 %	-0.065 %	-0.133 %
Italy	52	1.99 %	-0.002 %	-0.072 %	-0.137 %
Lithuania	52	1.46 %	-0.001 %	-0.053 %	-0.093 %
Luxembourg	48	1.94 %	0.000 %	-0.043 %	-0.094 %
Latvia	35	1.79 %	0.002 %	-0.057 %	-0.129 %
Mexico	48	4.54 %	0.007 %	-0.134 %	-0.326 %
Netherlands	52	2.76 %	0.000 %	-0.077 %	-0.182 %
Peru	48	4.91 %	-0.001 %	-0.125 %	-0.345 %
Poland	52	3.35 %	0.000 %	-0.104 %	-0.238 %
Portugal	48	1.86 %	-0.003 %	-0.066 %	-0.127 %
Romania	52	1.41 %	-0.001 %	-0.041 %	-0.089 %
Slovakia	52	2.92 %	0.002 %	-0.098 %	-0.212 %
Slovenia	44	2.95 %	0.000 %	-0.101 %	-0.199 %
Sweden	40	1.78 %	-0.007 %	-0.065 %	-0.125 %
United States of America	52	2.21 %	0.000 %	-0.069 %	-0.157 %

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