Chinese supply chain shocks

Khalil, Makram and Weber, Marc-Daniel

Deutsche Bundesbank, Johannes Gutenberg University Mainz

25 October 2021

Chinese supply chain shocks*

Makram Khalil[1] and Marc-Daniel Weber[2]

[1] *Deutsche Bundesbank*
[2] *Johannes Gutenberg University Mainz*

October 2021

Abstract

In structural vector autoregressive models of US and euro area manufacturing, we use sign restrictions to identify shocks that alter the frictions to Chinese supply chain trade. We find a quantitatively significant role of such shocks for the decline of US manufacturing output at the height of the Sino-American trade tensions in 2019. At the beginning of the Covid-19 pandemic in early 2020, the results point towards large spillovers from the shutdown in China to manufacturing in the US and the euro area. Moreover, during the recovery in 2020 and 2021, positive Chinese supply chain shocks related to the shift of preferences towards goods with a large China valued-added content played a role. Interestingly, the impact of China-specific trade shocks is not limited to manufacturing sectors that are highly exposed to China. Furthermore, negative Chinese supply chain shocks cause upward price pressure across the whole manufacturing industry.

Keywords: Cross-border supply-chain disruptions, China, trade tensions, Covid-19 recession, US and euro area manufacturing.

JEL classification: E32, F41, F62.

*We would like to thank Peter Egger for his useful comments. Contact: Makram Khalil (corresponding author): makram.khalil@bundesbank.de; Wilhelm-Epstein Straße 14, 60431 Frankfurt am Main. Marc-Daniel Weber's contribution resulted from his stay at the Deutsche Bundesbank. The opinions expressed in this paper are those of the authors and do not necessarily reflect the views of the Deutsche Bundesbank or the Eurosystem.

1 Introduction

In recent years, Chinese supply chains to major industrial regions have faced several challenges. In 2018 and 2019, trade tensions between China and the US exacerbated and resulted in newly imposed tariffs. With the rapid spread of Sars-CoV-2 in China in early 2020, the authorities there ordered strict containment measures, which disrupted established value chains with many industrial countries. Later in the pandemic, in 2020 and 2021, the focus shifted as China reopened its production relatively fast, which likely supported the recovery in industries of the trading partners. With regard to these developments, the questions arise as to what extent and by which channels downstream manufacturing production is affected by shocks specific to the Chinese supply chain. This is of particular interest for the US and the euro area, who have strong value chain linkages with China.

This paper tackles these questions by first identifying shocks that ease or tighten frictions in the Chinese supply chain for downstream manufacturing sectors. We employ SVAR models with monthly data on US and euro area manufacturing output as well as Chinese and rest of the world imports. Adding to the contribution of Kilian, Nomikos, and Zhou (2021), who incorporate value chain shocks in a recursively identified SVAR model of the US, a main contribution is the identification of trade-specific distortions specific to China as a particular trading partner. In our identification approach that is based on sign restrictions, we employ an important mechanism in international trade – trade diversion between goods of various trading partners. More specifically, we assume that adverse Chinese value chain shocks affect manufactured imports from China as well as domestic manufacturing production negatively, while manufactured imports from the rest of the world are affected positively. The identification is based on the idea that, in the event of unexpected disruptions in the imports from a specific trading partner, there is some trade diversion towards other trading partners, but at least in the short run the possibilities for substitution are too small to avoid bottlenecks for the downstream production industries.[1] In contrast, the other shocks in the model result in responses that imply manufactured imports from China and from the rest of the world will move in the same direction, irrespective of the sign of the response of manufacturing production in the domestic market.

We find an important role of Chinese supply chain shocks for manufacturing production in the US and in Europe. According to the estimates, in 2019, when the Sino-American trade tensions were still ongoing, manufacturing production in the US was dampened by around 1 pp. This rationalizes most of the slowdown of US manufacturing during that time. With regards to the pandemic recession in spring 2020, Chinese supply chain shocks contributed to around one-fifth of the overall decline in US manufacturing production at the trough in April 2020; for the euro area, the corresponding fraction is around one-seventh. Later in the pandemic, in 2020 and 2021, positive Chinese supply chain shocks played an import role in supporting the recovery in manufacturing production in both economies. This is consistent with the narrative that during the pandemic, consumer

[1] See Heise (2020) for supporting evidence on the consequences of the early 2020 lockdown in China for trade diversion in the US. He reports that US trade was partially diverted to other trading partners but the losses from the Chinese lockdown were by no means compensated.

expenditure shifted towards goods that have a high Chinese value added content (such as electronics).

Moreoever, we use a more granular panel data set for US and EU manufacturing industries to disentangle how the identified shocks affect different manufacturing branches. According to our results, Chinese supply chain shocks affect all manufacturing sectors significantly, regardless of whether the direct exposure to Chinese intermediate inputs is large or not. This is an important finding compared to earlier contributions. For instance, Flaaen and Pierce (2019) employ a difference-in-difference approach to estimate the time-varying effect of an exposure to tariffs on Chinese imports. They find an insignificant response of relatively highly exposed sectors during the trade tensions in 2018 and 2019, arguing that manufacturing production was likely not affected by the trade tensions. Our results, however, indicate that the impact of increased trade frictions is not limited to a few sectors with a high share of imported intermediates from China. In fact, input/output data for the US and the EU indicate that the variance regarding Chinese input exposure is not too wide.[2] Moreover, a small exposure to Chinese supplies can also be critical for production: in the case of very low elasticity of substitution of the input factors, supply bottlenecks in one input translate into large output losses regardless of how much of this input is used. More generally, sectoral shocks in the exposed sectors may translate into aggregate repercussions. This is all consistent with our finding that exposed and non-exposed sectors are both significantly affected by Chinese trade frictions. Nonetheless, and in line with intuition, the production response is stronger for sectors more heavily exposed to the Chinese supply chain. Importantly, in contrast to earlier contributions based on difference-in-differences approaches, our results suggest that most of the slow-down in US manufacturing output during 2019 can be rationalized by increased frictions to imports from China.

Compared to earlier literature, we also take prices on Chinese imports into account to differentiate between supply-type and demand-type trade frictions. We find that the trade tensions in 2019 are consistent with shocks that lead to lower Chinese import prices.[3] In early 2020, supply-type trade frictions that raised Chinese imports prices and rest of world import quantities while lowering Chinese imports and domestic manufacturing gained importance. Later in the pandemic, positive shocks to Chinese trade frictions caused Chinese import prices and US manufacturing production to increase. We interpret this as a preference shift in favour of stronger value chain integration with China. This is a different interpretation compared to Kilian et al. (2021), who argue that much of the US recovery is rationalized by easing frictions to container trade.

Our approach also allows us to gauge the price setting behaviour of domestic manufacturing producers in response to Chinese supply chain disruptions across various sectors. The results suggest that adverse Chinese supply chain shocks cause upward price pressure in domestic manufacturing. This effect is again prevalent across all industries and not only in those sectors that are highly exposed to Chinese intermediate goods supplies. Unlike in previous literature (cf. Flaaen and Pierce (2019) and Meier and Pinto (2020)), we do not find that sectors more exposed to Chinese intermediate supplies face stronger price

[2] See section 2 for more details.

[3] This is in line with the findings in Khalil and Strobel (2021), who argue that the effects of trade policy uncertainty on the US dollar led to a decline in the prices of Chinese exporters.

pressure in response to new trade frictions. We argue that this could be related to the circumstance that relatively little exposed sectors more often produce nondurable goods.

This paper contributes in a more broader sense to a growing number of studies on the effects of disruptions in global value chains. Earlier work focuses on the consequences of supply chain disruptions caused by natural disasters (e.g., Barrot and Sauvagnat (2016), Carvalho, Nirei, Saito, and Tahbaz-Salehi (2020) and Boehm, Flaaen, and Pandalai-Nayar (2019)). Recently, the topic regained attention in the empirical literature when it comes to studying the effects of increased trade tensions and the coronavirus pandemic. Building on Flaaen and Pierce (2019), Meier and Pinto (2020) assess the time-varying effect of Chinese value chain exposure on US industries during the sharp decline in spring 2020. In the appendix, we provide a similar analysis for the US and the EU and argue that, while this approach is appealing as a first attempt to assess the importance of value chain disruptions, it is difficult to draw overall conclusions regarding the response of the manufacturing sector. Besides the problem of many sectors being more or less similarly exposed to Chinese intermediate inputs, one issue is disentangling the effect of trade frictions from other disruptions, such as those arising from local lockdowns in 2020. Santacreu, Leibovici, and LaBelle (2021) study the impact of the overall global value chain exposure of US industries in early 2020. We argue instead that it is advantageous to focus on a single trading partner to identify value chain disruptions. For example, overall intermediate imports in the US or the euro area in 2020 did not necessarily fall solely due to supply chain frictions but also because of the domestic local lockdowns leading to lower demand. We find that indeed a sizable fraction of the decline in bilateral imports from China in February and March 2020 is exogenous with respect to US and EU conditions. Nevertheless, it is not clear whether this is true for other trading partners or total imports as well.

The remainder of the paper is organized as follows. In Section 2, we briefly discuss the evolution of the imports from China and the rest of the world into the US and the euro area and the exposure of the industries to Chinese intermediates. Section 3 introduces SVAR models of US and euro area manufacturing that incorporate Chinese value chain shocks based on sign restriction identification. In this section, we also quantify the consequences of such shocks for aggregate manufacturing output. In Section 4, we study the consequence of Chinese supply chain shocks with more granular US and EU data on sectoral output and producer prices. In the last section we conclude.

2 Descriptive analysis: Chinese imports after 2018 and value chain exposure

In accordance with our identification strategy, Chinese manufacturing imports exhibit idiosyncratic growth rates compared to rest of world imports at least after 2018. The left panel of Figure 1 shows that the flow of imports from China to the US slowed markedly at the beginning of 2019, likely related to ongoing trade tensions and additional import tariffs between the US and China. With the outbreak of Sars-Cov-2 and the subsequent imposition of containment measures by the Chinese authorities in early 2020, imports plunged radically, reaching their trough in March 2020. As of April, imports recovered rapidly to pre-pandemic levels due to quick relaxations of the restrictions and plant re-openings in China. Rest of world imports, however, were not that affected by trade tensions prior to 2020.

In Europe (right panel of Figure 1), the difference in the development of Chinese and rest of world imports are not that significant as there have not been strong trade tensions between China and the euro area countries in recent years. What is salient, however, is the earlier drop in imports from China compared to rest of world imports, which can also be observed in the US data and which is due to the earlier shutdowns of Chinese production. By December 2020 at the latest, both imports from China and other countries had recovered from the pandemic-induced recession, while Chinese imports clearly exceed pre-pandemic levels.

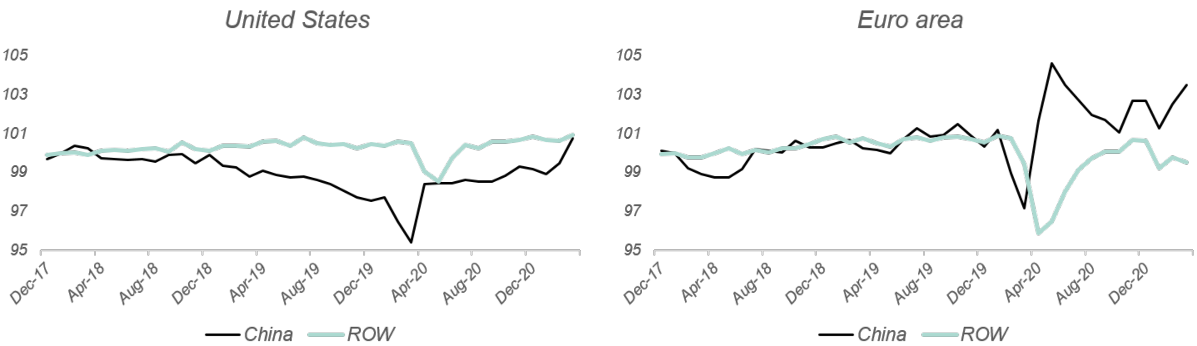

Figure 1: **Left panel:** Monthly seasonally and price-adjusted imports of manufacturing goods from China and the rest of world to the **US**. **Right panel:** Monthly seasonally and price-adjusted imports of goods from China and manufacturing goods from the rest of world to the **euro area**. Euro area real trade flows from China and the rest of world are expressed in terms of total manufacturing import prices. Index (Jan. 2018 = 100). Source: U.S. Census Bureau, Eurostat, Haver Analytics and the author's own calculations.

The degree to which Chinese trade shocks are transmitted to domestic production in the US and the EU hinges on the dependency of the industries on foreign inputs. To quantify this dependency, we construct an exposure measure to Chinese intermediate imports based on the cost share of Chinese intermediate inputs in production (cf. appendix A.3). On average, Chinese intermediate inputs account for approximately 1% of US and EU production costs. The share is highest in industries belonging to the information and communication technology (ICT) sector. Two observations are particularly important for our further analysis: (1) almost all sectors are (at least indirectly) exposed to Chinese intermediates and (2) there is heterogeneity between industries, but it is not that large. Most sectors range in their exposure between 1% and 2%.[4] This indicates that many manufacturing sectors are dependent on Chinese supplies to a similar extent.

[4]Figure 6 in the appendix A.3 shows the exposure of US (left panel) and EU (right panel) industries to Chinese inputs.

3 Chinese supply chain shocks and their consequences for US and euro area manufacturing

We employ monthly SVAR models for the US and the euro area with data on manufacturing production, Chinese and rest of the world real manufacturing imports, as well as prices for Chinese manufacturing imports, as an additional specification for the US, for the periods January 2002 to March 2021.[5] To identify Chinese supply chain shocks, we impose sign restrictions (see Table 1). We assume that adverse Chinese value chain shocks affect manufactured imports from China as well as domestic manufacturing production negatively, while manufactured imports from the rest of the world are affected positively. The basic idea is that, in the event of unexpected disruptions to the imports from China, there is trade diversion towards other trading partners. At least in the short run, however, bottlenecks for the downstream industries cannot be avoided as the possibilities to substitute goods of various trading partners are limited. We follow Kilian et al. (2021) in arguing that domestic production is affected by trade friction shocks only with a delay of one month. We think this is reasonable given delays between importing and production, as well as storage buffers. We therefore restrict the Chinese supply shock to affect manufacturing production one period after the shock. All the other signs are imposed only upon impact of the shocks.

	Domestic demand	Domestic supply	Chinese trade friction
Production	+	+	-
ROW imports	+	-	+
CHN Imports	+	-	-

Table 1: Identification of Chinese supply chain shocks.

We differentiate the Chinese supply chain shock from two other structural shocks that cause Chinese imports and rest of the world imports to move in the same direction. The first shock, which we label US demand shock, causes US manufacturing production as well as imports with both trading partners to rise on impact. The second shock, which we call US supply shock, raises manufacturing output but with the consequences of declining Chinese and rest of world imports. The rationale behind the latter shocks are shifts in US production towards goods with less intermediate import content or productivity gains in US manufacturing that lead to lower dependency on foreign imports.

[5] The models are estimated with Bayesian techniques. The estimation imposes a Normal-Wishart prior on the parameter distribution and assumes three lags. All variables enter in first differences of logs. The euro area sample already begins in January 2000. Because of data availability, we use total imports from China instead of manufacturing imports for the euro area. Moreover, for the euro area series both Chinese and rest of world imports are expressed in terms of total manufacturing import prices. Details on the data sources can be found in the appendix. The model is estimated with the BEAR toolbox (cf. Dieppe, van Roye, and Legrand (2018)).

For brevity, we show the impulse response functions in the appendix and focus on the role of the Chinese supply chain shock for the historical pattern. Figure 2 shows the historical shock breakdown of US imports of goods from China and US manufacturing production from 2018 onwards. The decline in US imports of manufacturing goods during the trade tensions in 2018 and 2019 is mainly explained by Chinese trade frictions. In 2020, adverse Chinese supply chain shocks gained even more importance. This is in line with the consideration that the sharp and abrupt slump in intermediate imports from China in early 2020 was, from the US perspective, primarily exogenous and not related to US conditions. Notably, the shutdown in China preceded the US lockdown by several weeks. The recovery of Chinese imports after May 2020 is explained to a significant extent by the abrupt easing of Chinese supply chain shocks.

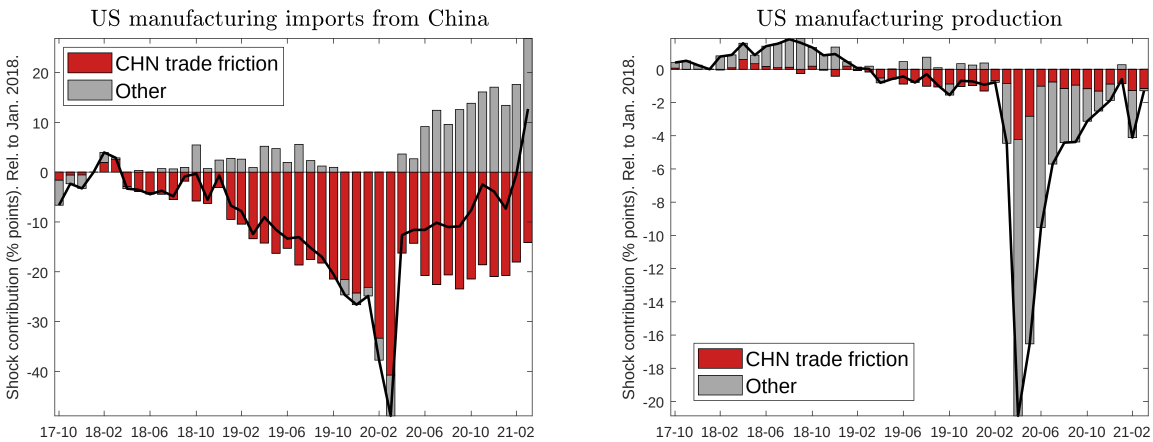

Figure 2: Monthly SVAR model for the **United states (three variables)**, February 2002 to March 2021. Historical decomposition of US manufactured imports from China and US manufacturing production for two groups of identified shocks: "CHN trade friction" are Chinese supply chain shocks. "Other" include US demand and US supply shocks and the deterministic component.

When it comes to industrial production, the results indicate important negative consequences of adverse Chinese supply chain shocks. In 2019, when trade tensions between the US and China were still ongoing, manufacturing production was dampened by around 1 pp, rationalizing most of the slowdown during that time. At the beginning of the Covid-19 recession in March 2020, additional Chinese supply chain shocks aggravated the decline of US industrial production. Compared to the overall contraction, the effect is quantitatively significant, but the direct impact of the spread of Covid-19 on domestic demand dominates.[6]

[6] As an alternative approach, one can identify China-specific trade frictions within a SVAR model based on Choleski identification. Such an approach would build more directly on Kilian et al. (2021). In a robustness check, we employ a recursive identification scheme and assume that US imports from China react instantly to shocks in private consumption and industry as well as to trade-specific shocks in third countries. Manufacturing output responds with a one-month delay to trade-specific shocks, both from China and from the rest of the world. In this model we obtain qualitatively similar results for the role of shocks to China-specific trade frictions. The results are particularly similar for the onset of Covid-19 recession. Nevertheless, in the recursively identified model, China-specific trade friction shocks

For the euro area, we find a similar important role of Chinese supply shocks at the onset of the Covid-19 recession. These shocks explain around one-seventh of the overall decline of euro area manufacturing output at its trough in April 2021 (cf. Figure 3, left panel). Before the recession, in 2018 and 2019, Chinese supply chain shocks played a rather limited role in the evolution of euro area manufacturing. This indicates that the consequences of the Sino-American trade tensions did not spillover to the euro area – at least not through the channel of disrupted value chains between China and Europe.

	Domestic dem.	Domestic sup.	CHN frict. (sup)	CHN frict. (dem)
Production	+	+	-	-
ROW imports	+	-	+	+
CHN imports	+	-	-	-
CHN import prices			+	-

Table 2: Disentangling demand-type and supply-type frictions to supply chain imports from China.

3.1 Disentangling demand-type and supply-type trade frictions

It is also of interest to understand whether identified supply chain shocks are supply-driven – for instance because they are caused by natural disasters, capacity problems in the international shipping market or other supply bottlenecks in specific goods markets – or if they are demand-driven, as it would be the case if domestic agents unexpectedly prefer to be less integrated in cross-border supply chains. A natural way to disentangle these two types of shocks is to differentiate the sign of the response of import prices. We therefore extend our SVAR model to include Chinese import prices. This enables us to distinguish between supply-type and demand-type Chinese supply chain shocks (see Table 2).

The right panel of Figure 3 shows the corresponding historical shock breakdown of US manufacturing production.[7] The figure indicates that trade tensions in 2018 and 2019 are associated with demand-type Chinese value chain shocks affecting US manufacturing. These shocks led to lower imports from China and higher rest of world imports, while US manufacturing production contracted. At the same time, Chinese manufacturing exporters lowered their prices for the US market. This is in line with findings by Khalil and Strobel (2021), who argue that Chinese exporters lowered their prices in 2018 and 2019 because of a trade-policy-uncertainty-induced response of the US dollar. Moreover, they find that actual tariffs are offset to a large degree by this channel in 2018 but in 2019 the offsetting effect declined. This can rationalize why, according to our results, imports from China responded rather late to actual tariff hikes.

In early 2020, supply-type trade frictions that raised Chinese import prices and rest-of-world imports while lowering Chinese imports and domestic manufacturing, gained importance. Interestingly, in late spring 2020 and in early 2021, decreasing Chinese trade

that impose lower imports from China are also found to result in lower imports from the rest of the world. During the trade tensions in 2019, the model therefore accounts an unreasonably large fraction of the dynamics in manufacturing to such shocks. This highlights the advantage of using sign restrictions to grasp the trade diversion channel related to supply chain disruptions.

[7] Because of lack of data, we do not conduct this exercise for the euro area.

frictions associated with increasing import prices supported manufacturing production. This aligns with the narrative that during the pandemic consumer expenditure shifted towards goods with a large Chinese value added content.

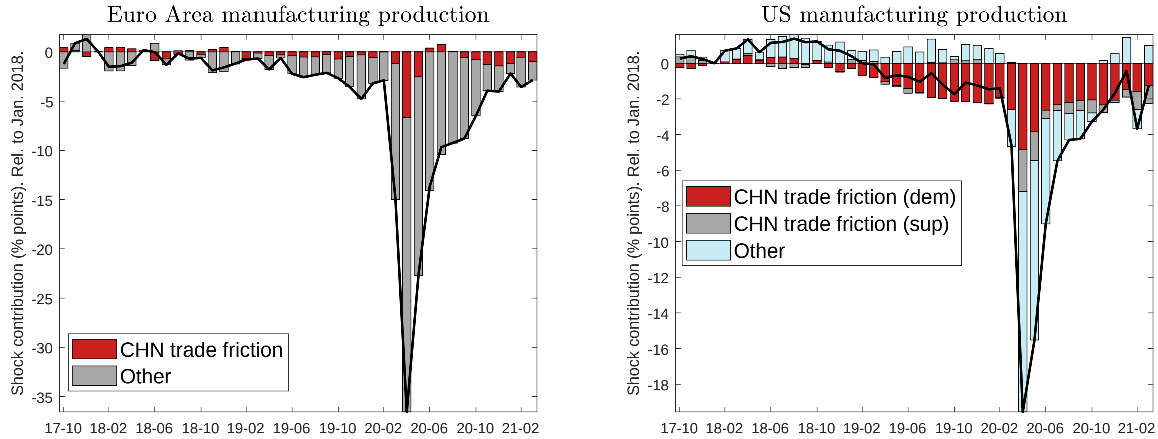

Figure 3: **Left panel:** Monthly SVAR model for the **euro area (three variables)**. February 2000 to March 2021. Two groups of identified shocks: "CHN trade friction" are Chinese supply chain shocks. "Other" include EA demand and EA supply shocks and the deterministic component. **Right panel:** Monthly SVAR model for the **United States (four variables)**. February 2002 to March 2021. Three groups of identified shocks: "CHN trade friction" are Chinese supply chain shocks. *dem* (*sup*) indicates that quantities and prices of Chinese imports move in the same (in different) direction(s). "Other" include US demand and US supply shocks and the deterministic component.

3.2 Heterogeneity in more granular sectoral data

We further trace out the channels underlying Chinese supply chain shocks by studying the effects of the identified shocks for disaggregated sectoral data. To do so, we estimate simple distributed lag models for the US and euro area manufacturing sector. In the basic specification, we estimate a panel of manufacturing industries (NAICS 4-digits for the US and NACE 3-digits in the euro area) for the period from January 2002 to March 2021 using the regression equation:

$$y_{i,t} = \beta_1 y_{i,t-1} + ... + \beta_3 y_{i,t-3} + \gamma'_{CHN,1}\chi_{CHN,t-1} + ... + \gamma'_{CHN,12}\chi_{CHN,t-12} + \\ + \gamma'_0\chi_t + ... + \gamma'_{12}\chi_{t-12} + \delta_i + \varepsilon_{i,t} \quad (1)$$

with y_t denoting the log of manufacturing real output (or in some specifications producer prices), χ_{CHN} is a vector of Chinese supply chain shocks, and χ is a vector of all other shocks identified in the SVAR.[8] Given the four-variable SVAR, χ_{CHN} is a vector that includes supply-type $\chi_{CHN,sup}$ and demand-type ($\chi_{CHN,dem}$) Chinese supply chain shocks,

[8]In the SVAR, the sign restriction imposed on the response of manufacturing output to a Chinese supply chain shock is only imposed one period after the shock. For this reason we do not include contemporaneous Chinese supply chain shocks in the regression.

and γ_{CHN} includes the corresponding coefficients $\gamma_{CHN,sup}$ and $\gamma_{CHN,dem}$. The model is estimated assuming industry fixed effects δ_i. $\varepsilon_{i,t}$ is the error term.[9]

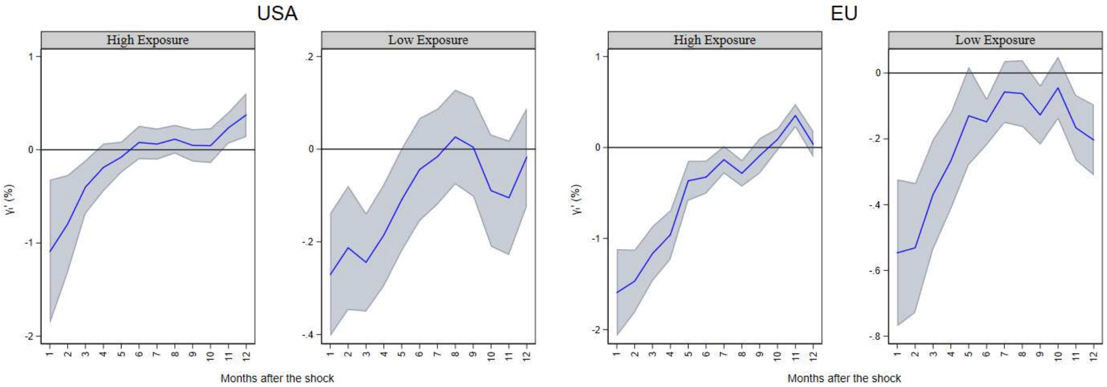

Figure 4: The effect of Chinese trade friction shocks (from the three-variable SVAR models) on **US and EU manufacturing production**. Separate regressions (see equation 1) for industries with high and low exposure to Chinese intermediate imports (sample split at the median exposure). The blue line shows the coefficient vector $\gamma_{CHN,l}$, $\forall l = 1, ..., 12$. The shaded area represents the 90% confidence interval. Period May 2002 to March 2021.

We would like to address the question of whether shocks to Chinese trade frictions only affect sectors that are highly exposed to Chinese intermediate inputs or if they also spread to relatively little exposed sectors. We start with the impact of Chinese supply shocks identified in the 3-equation SVAR models for the US and the euro area. In Figure 4 we plot the coefficients corresponding to the lags of the Chinese supply chain shock (i.e. $\gamma_{CHN,l}$, $\forall l = 1, ..., 12$) for separate regressions for high and low-exposed industries.[10] The results suggest that negative consequences of adverse China-specific trade shocks are not limited to manufacturing sectors that are highly exposed to China. Chinese supply chain shocks cause slowdowns across all manufacturing industries. This is true both in the US and the EU. Nonetheless, and in line with intuition, the effect is stronger for more heavily exposed sectors.

The findings are important in the light of earlier contributions that draw conclusions on the effects of trade disruptions based on a comparison between more and less exposed sectors with respect to intermediate input supplies. For instance, Flaaen and Pierce (2019) measure the effect of an exposure to tariffs on Chinese imports and find no statistically significant effect on manufacturing output in 2018 and 2019. Our findings suggest that their result could be linked to the circumstance that most US manufacturing sectors are to some extent exposed to Chinese intermediate supplies. Intuitively, if the opportunities to switch between inputs that are sourced domestically and inputs from several trading partners are rather limited, then a small exposure to a specific trading partner can also

[9] A detailed description of the panel data set can be found in appendix A.2. For data availability reasons, the euro area manufacturing data is proxied by data on output in the European Union (27 member aggregate).

[10] We split the sample at the median exposure to Chinese intermediate imports.

have large consequences in the event of increased trade frictions such as new tariffs.[11] Moreover, there are likely spillovers from highly exposed sectors to the rest of the economy because of domestic input-output linkages and other strategic complementarities. Overall, our results suggest that the effects of the trade tensions in 2018 and 2019 on US manufacturing production were significant and widespread across different manufacturing branches.

3.3 Producer price responses to adverse supply chain shocks

As a final exercise, we employ the SVAR model for the US with four variables to have a closer look at the response of US producer prices. We again use regression 1, differentiating between sectors that rely relatively strongly on Chinese intermediate imports compared to sectors that are little exposed. We focus on supply-type Chinese trade friction shocks, i.e., shocks that imply that Chinese import prices and quantities move in different directions. The results are plotted in Figure 5 (left panel). According to the estimates, Chinese supply chain shocks cause upward price pressure across all manufacturing industries. With some delay, relatively little exposed sectors also raise their prices. Interestingly, the price increase in the little exposed sectors is larger compared to more strongly exposed sectors. To inspect this seemingly puzzling result further, we group the panel into sectors that mainly produce durable goods and sectors that mainly produce nondurable goods. Many nondurable sectors have little exposure to Chinese intermediate supplies. Nevertheless, nondurable production might require a more flexible price setting as the possibility to store goods is limited. As the results in Figure 5 (right panel) indicate, sectors that produce nondurable goods react quite markedly to Chinese supply chain shocks. This can rationalize why sectors that are not heavily exposed to China, i.e., especially nondurable producers, also show a rather strong price reaction.[12]

[11] In the extreme case of a Leontief production function, a drop in imported intermediates caused by higher trade frictions would map one-to-one onto lower output regardless of the cost share of intermediate imports.

[12] These results are qualitatively similar and quantitatively even more pronounced for demand-type trade frictions or trade frictions extracted from the three-variable SVAR. In these cases, the corresponding shocks are – at least in 2018 and 2019 – likely related to US import tariff hikes that more or less directly affect producer prices. This indicates that the – per construction – corresponding decline in pre-tariff import prices is dampening producer prices of exposed sectors more strongly compared to non-exposed sectors.

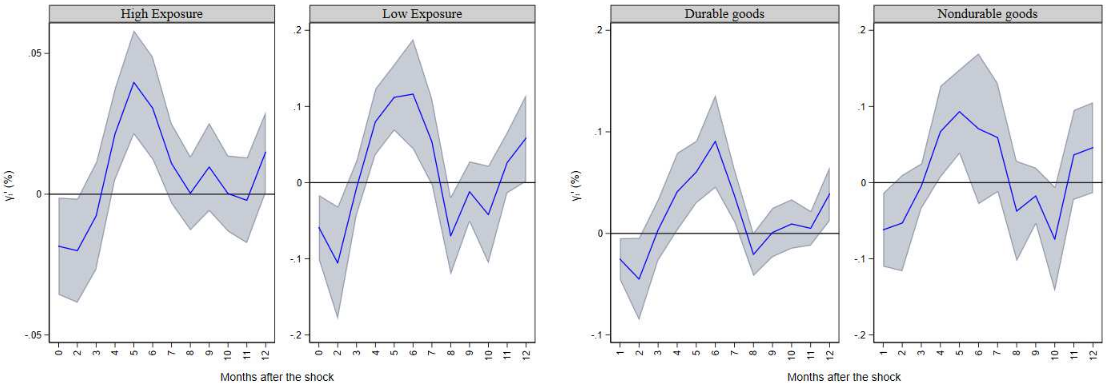

Figure 5: The effect of Chinese – supply-type – trade friction shocks (from the four-variable SVAR model) on **US manufacturing producer prices**. Separate regressions (see equation 1) for industries with high and low exposure to Chinese intermediate imports (left panel) and industries with high and low durability of the produced goods (right panel). The blue line shows the coefficient vector $\gamma_{CHN,sup,l}$, $\forall l = 1, ..., 12$. The shaded area represents the 90% confidence interval. Period May 2002 to March 2021.

4 Conclusion

In this paper, we identify shocks specific to the Chinese supply chain within SVAR models for US and euro area manufacturing employing a sign restriction approach. Our identification strategy builds on the idea that Chinese supply chain shocks result in trade diversion towards other trading partners of the US or the euro area. Trade diversion, however, cannot limit the implications of the increased bilateral trade frictions. Given adverse Chinese supply chain shocks, negative consequences for downstream manufacturing in the US or the euro area therefore cannot be avoided. In the analysis, we assess the role of unexpected frictions in the Chinese supply chain in the historical evolution of US and euro area manufacturing over the last few years. Moreover, we use granular data sets to disentangle how the identified shocks affect different branches of manufacturing. We also gauge the price setting behaviour of domestic producers.

Our results indicate that in 2019, at the height of the Sino-American trade tensions, manufacturing production in the US was dampened by Chinese supply chain shocks, which explains most of the slowdown during that time. In spring 2020, the unexpected slump in Chinese exports contributed significantly to the decline in US and EU industrial production. Compared to the overall decline at that time, the direct impact of the spread of Covid-19 on domestic demand predominated, but the effect of Chinese trade frictions was nonetheless quantitatively significant. During the recovery in 2020 and 2021, positive Chinese supply chain shocks played a relevant role, too. The latter finding is in line with a shift towards goods with a high Chinese value added content – such as electronics – during the pandemic. Importantly, we find that Chinese supply chain shocks affect production of different groups of manufacturing significantly, regardless of whether the direct exposure to Chinese intermediate inputs is large or not. Moreover, negative Chinese supply chain shocks cause upward price pressure across all the whole manufacturing industry.

The findings further show that the effects of shocks to Chinese trade frictions are not necessarily long lasting. For instance, at the beginning the Covid-19 pandemic, China resumed production and exports of intermediate inputs after a comparatively short period of time. The impact on US manufacturing was rather short lived. As a counterexample, the consequences in 2019 – at the height of the US/China trade conflict – were rather persistent.

References

Barrot, J.-N. and J. Sauvagnat (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. The Quarterly Journal of Economics (131), 1543–1592.

Boehm, C. E., A. Flaaen, and N. Pandalai-Nayar (2019). Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Thoku earthquake. The Review of Economics and Statistics (101), 60–75.

Carvalho, V. M., M. Nirei, Y. Saito, and A. Tahbaz-Salehi (2020, 12). Supply chain disruptions: evidence from the great east Japan earthquake. The Quarterly Journal of Economics 136(2), 1255–1321.

Dieppe, A., B. van Roye, and R. Legrand (2018). The Bayesian Estimation, Analysis and Regression toolbox (BEAR) – Version 4.2. European Central Bank.

Flaaen, A. and J. Pierce (2019). Disentangling the effects of the 2018-2019 tariffs on a globally connected U.S. manufacturing sector. Finance and Economics Discussion Series 2019-086. Washington. Board of Governors of the Federal Reserve System..

Heise, S. (2020). How did China's COVID-19 shutdown affect U.S. supply chains? Federal Reserve Bank of New York Liberty Street Economics, May 12, 2020, https://libertystreeteconomics.newyorkfed.org/2020/05/how-did-chinas-covid-19-shutdown-affect-us-supply-chains.html.

Khalil, M. and F. Strobel (2021). US trade policy and the US dollar. Deutsche Bundesbank Discussion Paper (forthcoming).

Kilian, L., N. Nomikos, and X. Zhou (2021). Container trade and the U.S. recovery. CEPR Discussion Paper (16277).

Meier, M. and E. Pinto (2020). Covid-19 supply chain disruptions. Discussion Paper Series Collaborative Research Center Transregio 224 (239).

Pierce, J. and P. Schott (2012). A concordance between U.S. Harmonized System codes and SIC/NAICS product classes and industries. Journal of Economic and Social Measurement (37(1-2)), 61–96.

Santacreu, A., F. Leibovici, and J. LaBelle (2021). Global value chains and U.S. economic activity during COVID-19. Federal Reserve Bank of St. Louis Review (Early Edition 2021).

Appendix

A Data and descriptive statistics

A.1 SVAR analysis

The SVAR analysis is based on aggregate time series data for February 2002 through March 2021, which, for the US, includes manufacturing production data from the Federal Reserve Board, and, using Haver Analytics, seasonally adjusted U.S. goods import data from the rest of the world excluding China as well as goods import data from China from the U.S. Census Bureau. The import data were price-adjusted using the corresponding import price indexes from the Federal Reserve Board. Due to lack of data, we substitute prices for manufactured imports from China by an import price index for all Chinese goods before June 2012 and by total US import prices (excl. oil imports) before December 2005. The rest of world imports are price-adjusted using prices of total US manufacturing imports. Because of data availability, we use a price index for all commodities before December 2005.

The seasonally adjusted data for the euro area are from Eurostat and Haver Analytics. Eurostat does not report a measure of manufactured imports from China. We use instead euro area imports of overall goods imports from China. For the same reason, Chinese imports are price-adjusted with a price index for total euro area manufactured goods imports instead of a China-imports-specific measure. Rest-of-world imports are also price-adjusted using this variable.

A.2 Panel data

For the panel data regression of the lagged industrial production and producer prices on the SVAR shocks in section 3.2 and 3.3 we use monthly sectoral data for U.S. and EU manufacturing output and producer prices, respectively. The data are available at the four-digit NAICS (2012) level for the U.S. and mainly three-digit[13] NACE sectors for the EU. U.S. industrial production data are from the Federal Reserve Board's G.17 release on industrial production and capacity utilization and were obtained through Haver Analytics. For U.S. producer price indices (PPIs), we use time series from the U.S. Bureau of Labor Statistics (BLS), also provided by Haver Analytics. For the EU, data for both variables are sourced from Eurostat. Ultimately, we have data for 67 and 87 four-digit NAICS industries for industrial production and PPIs in the U.S., while 71 (IP) and 50 (PPIs) three-digit NACE sectors are available.[14]

[13] For the beverage (C11) and tobacco sector (C12), data are only available at the two-digit NACE level.

[14] The difference in respective sample sizes between the two variables arises from a lack of data for some industries over the complete time period from 2002 to 2021, which is likely due to changes in the classification systems.

A.3 Exposure to Chinese value chains

To characterize industries by their exposure to Chinese intermediate inputs in the panel analysis, we construct an exposure measure, inspired by the approach of Flaaen and Pierce (2019) and based on the cost shares of Chinese inputs. To do this, the cost of an intermediate good j in the production of industry i, use_{ij}, is related to the sum of all intermediate inputs in the production of i, M_i, plus the wages paid in industry i, $Comp_i$. Further, this share is weighted by the import share of intermediate input j in the total supply of j, i.e., the sum of domestic output Q_j and imports imp_j. This yields a measure of exposure to foreign inputs in general. To obtain an explicit measure for China, the Chinese share of imports of input j, $imp_{j \leftarrow China}$, is considered relative to total imports $imp_{j \leftarrow World}$. Finally, the result is summed over all intermediate inputs j for each industry i:[15]

$$Intermediate\ Imports\ Exposure\ China_i = \sum_j \frac{use_{ij}}{M_i + Comp_i} \frac{imp_j}{Q_j + imp_j} \frac{imp_{j \leftarrow China}}{imp_{j \leftarrow World}} \quad (2)$$

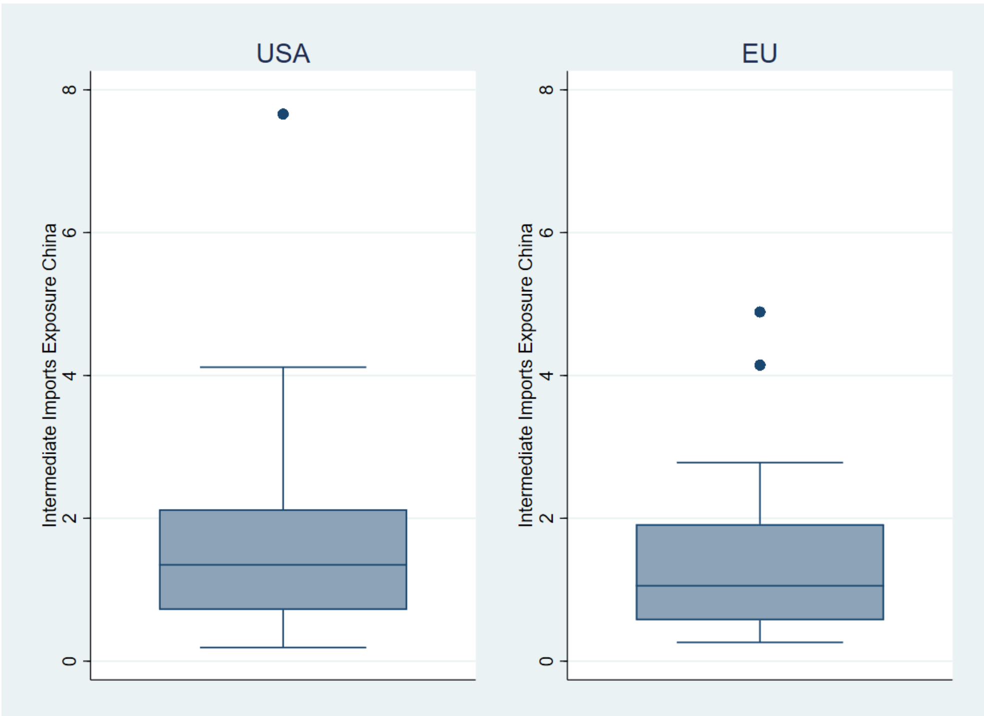

Figure 6: Distribution of Intermediate Imports Exposure China and RoW for the USA.

[15] To calculate the production cost share and the general import share, we use the SUT tables of the respective national input-output systems. We further calculate the Chinese share of imports based on 2019 annual import data. Slightly different to our approach, Meier and Pinto (2020) construct their measure of China exposure by combining the import matrix derived from the 2012 SUT tables with annual (Chinese) import data at NAICS level: $China\ exposure_i = \frac{\sum_j \frac{imp_{j \leftarrow China}}{imp_{j \leftarrow World}} imp_j}{\sum_j imp_j}$.

Thus, industries vary in terms of their dependence on Chinese inputs in three aspects: the intensity with which an input is used in production, the import share of inputs, and the share of imports from China for a given input.

To construct the exposure measures for the U.S., we use the Bureau of Economic Analysis (BEA) Supply and Use tables (SUT) as of 2012[16] and 2019 customs values for imports from China and the rest of the world at the ten-digit Harmonized System (HS) level by the U.S. Census Bureau. Only goods classified as intermediate inputs and capital goods according to the Broad Economic Indicators (BEC) are included in the calculation.[17] For the EU, the 2017[18] supply and use tables from Eurostat's input-output accounts and 2019 customs values for imports in the CPA product classification (also from Eurostat) are used to construct the dependency measures.[19],[20]

B Additional SVAR results

B.1 Impulse response functions three-variable SVAR

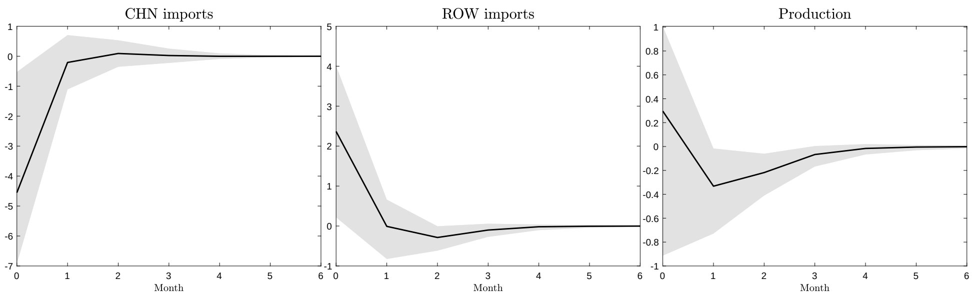

Figure 7: Results from the monthly SVAR model for the **United States**. February 2002 to March 2021. Impulse response function (in %) for US manufacturing imports from China and rest of the world, and US manufacturing production given a one-standard-deviation China import friction shock in period 1. All variables are in first differences of logs. The grey area shows the 95% confidence interval.

[16]More recent tables are not yet available.

[17]To make the trade data compatible with the industry data, the concordance of Pierce and Schott (2012) is used to match the 10-digit HS codes to the six-digit NAICS industries and the concordance of the BEA is used to match the 405 input-output codes to the six-digit NAICS codes.

[18]More recent tables in sufficient detail are not yet available.

[19]Since the trade data are in the CPA classification and the industry data are in the NACE nomenclature, and the SUT tables are also based on these classification systems, no concordance is needed to make the data compatible.

[20]Restricting import data to intermediate goods as in the U.S. study is not possible here because a concordance of the CPA classification with the Broad Economic Indicators (BEC) is not available.

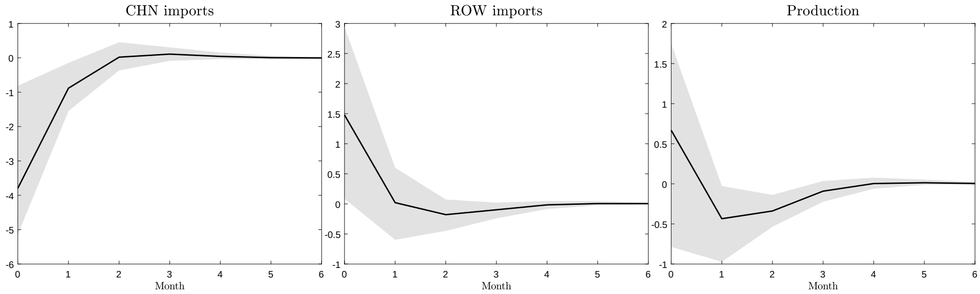

Figure 8: Results from the monthly SVAR model for the **euro area**. February 2000 to March 2021. Impulse response function (in %) for euro area manufacturing imports from China and rest of the world, and euro area manufacturing production given a one-standard-deviation China import friction shock in period 1. All variables are in first differences of logs. The grey area shows the 95% confidence interval.

B.2 Impulse response functions four-variable SVAR

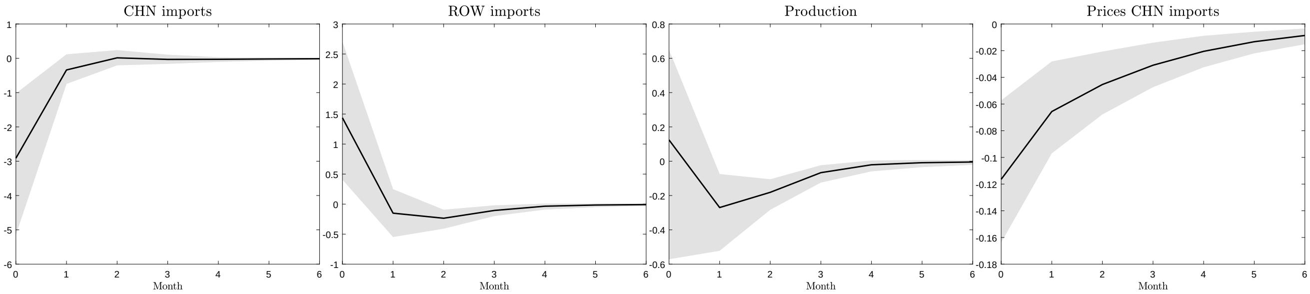

Figure 9: Results from the monthly SVAR model for the **United States (demand-type trade frictions)**. February 2002 to March 2021. Impulse response function (in %) for US manufacturing imports from China and rest of the world, and US manufacturing production, and prices for Chinese imports given a one-standard-deviation China import friction shock in period 1. All variables are in first differences of logs. The grey area shows the 68% confidence interval.

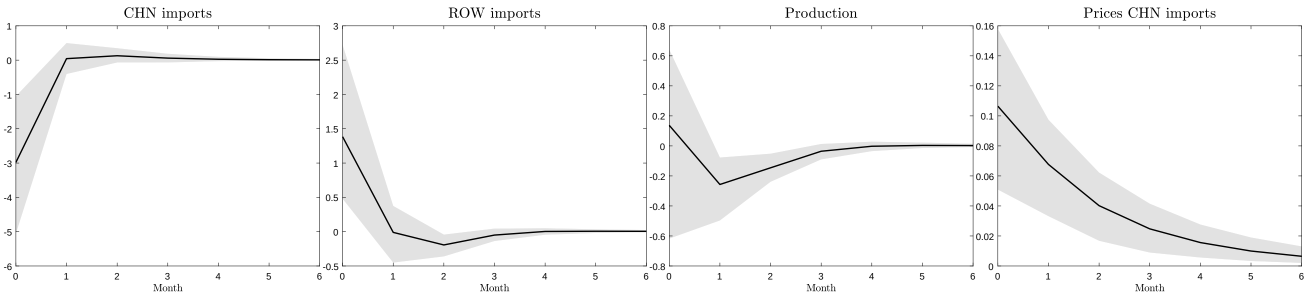

Figure 10: Results from the monthly SVAR model for the **United States (supply-type trade frictions)**. February 2002 to March 2021. Impulse response function (in %) for US manufacturing imports from China and rest of the world, and US manufacturing production, and prices for Chinese imports given a one-standard-deviation China import friction shock in period 1. All variables in first differences of logs. The grey area shows the 68% confidence interval.

C Comparing the findings to estimates from a difference-in-difference approach à la Flaan and Pierce (2020)

Flaaen and Pierce (2019) conducted a difference-in-difference analysis to estimate a time-varying effect of the 2018/2019 rise in bilateral tariffs between the US and China on domestic manufacturing industries.[21] Thereby, they exploit heterogeneity in US industry exposure to the tariffs. To compare our central findings from the SVAR and panel data analysis with findings in this literature, we employ a similar approach and estimate an industry panel over the period from January 2019 to March 2021 – an epsiode were we find significant impacts of Chinese supply chain shocks – using the regression equation:

$$\begin{aligned} y_{it} = \alpha + \beta_t \boldsymbol{1}(M_t = t) D((\mathit{Intermediate\ Imports\ Exposure\ China}_i) \\ + \gamma_t \boldsymbol{1}(M_t = t) D(\mathit{Intermediate\ Imports\ Exposure\ RoW}_i) \\ + \rho_t \boldsymbol{1}(M_t = t) D(\mathit{Export\ Exposure\ World}_i) \\ + \theta_t \boldsymbol{1}(M_t = t) D(\mathit{Import\ Substitution}_i) + \delta_t + \delta_t + \varepsilon_{it} \end{aligned} \tag{3}$$

where y_{it} is the logarithmized time series of industry i's production, employment or producer price indices at time t, adjusted for a linear pre-crisis trend. $\mathbf{1}(M_t = t)$ is a vector of monthly dummies from January 2019 to March 2021. $\mathit{Intermediate\ Imports\ Exposure\ China}_i$ is the industry-specific exposure variable described in section A.3. We further control for a dependence on inputs from other economies (excluding China), $\mathit{Intermediate\ Imports\ Exposure\ RoW}_i$, by weighting the cost share of imported inputs by the share of inputs imported from the rest of the world, just as in equation (2); this corresponds to overall dependence on imported inputs adjusted for the dependence on imports from China. To account for possible "forward linkages", i.e., foreign demand shocks for industry i's goods, we integrate the export share of industry i's products in total domestic supply ($\mathit{Export\ Exposure\ World}_i$), which thus also controls for a general openness to exports of the respective industry. The variable $\mathit{Import\ Substitution}_i$ controls for imports of industry i's products, imp_i, relative to the sum of domestic (Q_i) and foreign (imp_i) supply of these products. The effects of those control variables, however, are not the focus of this analysis. For all variables on the right-hand side of the equation, binary dummy variables $D(\cdot)$ are used to partition industries according to the median of the indicator.[22]

Figures 11 and 12 show the development of the coefficient β_t, i.e., the effect of higher dependence on Chinese intermediate inputs, for industrial production and producer prices for the U.S. and the EU, respectively. The estimation for the U.S. shows that high exposure is associated with a larger decline in industrial production only during the first wave of the coronavirus in March and April 2020. However, there is no statistically significant effect of above-average exposure to China during the trade tensions in 2019 and during the second half of 2020. Beginning of 2021, a higher import share from China had a slightly positive, although not statistically significant effect on output. Moreover, a higher dependence on Chinese intermediate inputs in the first half of 2020 correlates with a relative increase in producer prices in these sectors. In 2019, producer prices in exposed industries also increased at an above-average rate, possibly due to the U.S. import tariffs against China. Since the beginning of 2021, producer prices in exposed industries have been falling again, which is seemingly puzzling given the shift of demand towards China-

[21] Meier and Pinto (2020) use a similar strategy to study increased Chinese supply chain frictions at the onset of the Covid-19 recession.

[22] Standard errors are summarized at the industry level. Our estimation for the US based on continuous variable values instead of dummy variables does not yield statistically significant coefficients over the entire observation period, still the effects are of a similar magnitude.

dependent pandemic goods. Overall, the findings are similar to the results in Flaaen and Pierce (2019) and Meier and Pinto (2020). Moreover, our estimates for the EU in Figure 12 are very similar to the US results.

Although the difference-in-difference approach seems appealing to investigate the role of disruptions in global value chains for domestic production, it is, however, difficult to draw conclusions about the consequences for the manufacturing sector. First, the estimates suggest that only very large shocks – in particular the shock in early 2020 – can be captured when only differences between highly exposed and little exposed sectors are studied. Second, besides the problem of all sectors being more or less exposed to Chinese intermediate inputs, another issue is to disentangle the effect of trade frictions from other disruptions, for instance arising from local lockdowns in the US (demand-side effects) in March/April 2020. For instance, the estimates for the EU for early 2020 are rather large at close to 30 percent.[23] This points towards difficulties in disentangling the effects of supply chain disruptions from local lockdowns.

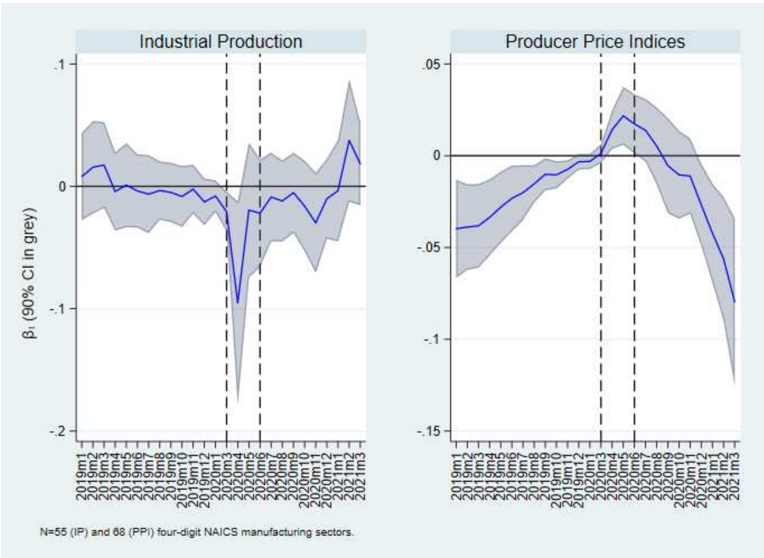

Figure 11: Coefficient β_t in a regression of US industrial production and producer price indices on $\textit{Intermediate Imports Exposure China}_i$ and control variables. The blue line shows the coefficients of a regression of the respective precrisis-adjusted dependent variable on the time trend-interacted independent variable Intermediate Imports Exposure China. The shaded area represents the 90% confidence interval. The two vertical lines mark the crisis period. Base period: February 2020.

[23] Notably, the regression exercise in this section already excludes certain sectors that were likely heavily exposed to lockdowns such as transportation equipment production or textile production. Without the exclusion of such sectors the estimated effects for industrial production would be 13% and 38% in the US and EU, respectively.

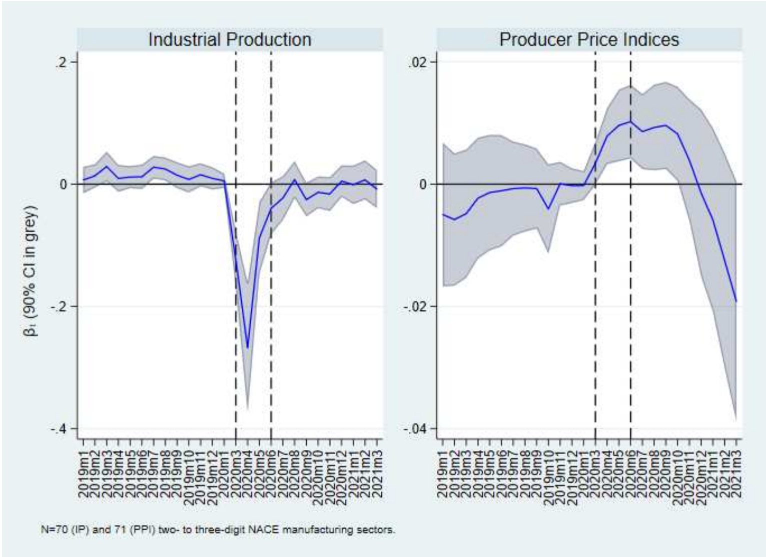

Figure 12: Coefficient β_t in a regression of EU industrial production and producer price indices on *Intermediate Imports Exposure China*$_i$ and control variables. The blue line shows the coefficients of a regression of the respective precrisis-adjusted dependent variable on the time trend-interacted independent variable Intermediate Imports Exposure China. The shaded area represents the 90% confidence interval. The two vertical lines mark the crisis period. Base period: February 2020.