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Chinese supply chain shocks

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Non-technical summary

Research Question

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, making the trade of intermediate goods more difficult. Then, in early 2020, due to the rapid spread of Sars-CoV-2 in China, the local authorities ordered strict containment measures, which disrupted established trade routes. In late spring 2020, China reopened its production relatively fast, which likely supported the recovery in downstream industries. The question arises as to what extent and by which channels downstream manufacturing production is affected by shocks specific to Chinese supply chain trade. This is of particular interest for the US and the euro area, which have strong value chain linkages with China.

Contribution

In structural vector autoregressive models of US and euro area manufacturing, we use sign restrictions to identify shocks that alter frictions to Chinese supply chain trade. We assess the significance of such supply chain shocks for US and euro area manufacturing over the last few years. Moreover, we use more granular data sets to estimate how the identified shocks affect output and price dynamics in different branches of manufacturing.

Results

We find that in 2019, at the height of the Sino-American trade war, manufacturing production in the US was dampened by adverse Chinese supply chain shocks, which rationalizes most of the slowdown during that time. At the trough of the Covid-19 recession in spring 2020, about one-seventh of the decline in US industrial production was due to Chinese supply chain shocks; for the euro area, the corresponding fraction is slightly larger. For the recovery in 2020 and 2021, favourable Chinese supply chain shocks played a relevant role. Interestingly, the impact of China-specific supply chain shocks is not limited to manufacturing sectors that are strongly exposed to China. Moreover, negative Chinese supply chain shocks cause upward price pressure across the whole manufacturing industry.

Nichttechnische Zusammenfassung

Fragestellung

Zuletzt standen die Lieferketten aus China in wichtige Industrieregionen vor mehreren Herausforderungen. In den Jahren 2018 und 2019 verschärften sich die Handelsspannungen zwischen China und den Vereinigten Staaten. Mit der rasanten Ausbreitung von SARS-CoV-2 ordneten die Behörden in China Anfang 2020 strenge Eindämmungsmaßnahmen an, wodurch etablierte Handelsrouten unterbrochen wurden. China fuhr seine Produktion relativ schnell wieder hoch, was die Erholung in den nachgelagerten Industrien beschleunigt haben dürfte. Es stellt sich die Frage, inwieweit und über welche Kanäle die nachgelagerte Produktion von Störungen des Warenflusses in der Lieferkette aus China in wichtige Industrieregionen betroffen ist.

Beitrag

In strukturellen vektorautoregressiven Modellen der Verarbeitenden Gewerbe der USA und des Euroraums verwenden wir Vorzeichenrestriktionen, um Störungen in der chinesischen Lieferkette zu identifizieren. Die Bedeutung solcher Lieferkettenschocks für das Verarbeitende Gewerbe kann so abgeschätzt werden. Zudem verwenden wir detailliertere Datensätze, um zu analysieren, wie sich die identifizierten Schocks auf Produktion und Preise verschiedener Produktionszweige auswirken.

Ergebnisse

Auf dem Höhepunkt des chinesisch-amerikanischen Handelskonflikts im Jahr 2019 wurde die Produktion in den USA durch negative chinesische Lieferkettenschocks merklich gedämpft, was den größten Teil der Abschwächung während dieser Zeit erklären kann. Am Tiefpunkt der Corona-Rezession im Frühjahr 2020 trug der unerwartete Einbruch der chinesischen Exporte rund ein Siebtel zum Einbruch des Verarbeitenden Gewerbes bei; für den Euroraum fällt der entsprechende Anteil etwas größer aus. Für die Erholung in den Jahren 2020 und 2021 spielten vorteilhafte chinesische Lieferkettenschocks eine relevante Rolle. Interessanterweise beschränken sich die Auswirkungen China-spezifischer Lieferkettenschocks nicht nur auf Fertigungssektoren, die stark mit China integriert sind. Darüber hinaus verursachen negative Schocks in der chinesischen Lieferkette Preisauftrieb im gesamten Verarbeitenden Gewerbe.

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Abstract

In structural vector autoregressive models of United States 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 pointed towards large spillovers from the shutdown in China to manufacturing in the US and the euro area. Moreover, for the recovery in late 2020 and 2021, favourable Chinese supply chain shocks related to the shift of preferences towards goods with a large China valued-added content played a relevant role. Interestingly, the impact of Chinese supply chain 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, trade frictions, China, trade tensions, Covid-19 recession, US and euro area manufacturing.

JEL classification: E32, F41, F62.

*Makram Khalil (corresponding author): Deutsche Bundesbank, Wilhelm-Epstein Straße 14, 60431 Frankfurt am Main, Germany. Email: makram.khalil@bundesbank.de. Marc-Daniel Weber's contribution resulted from his stay at the Deutsche Bundesbank. We would like to thank Christiane Baumeister, Peter Egger, Fabian Gaus, Felix Strobel and participants at the autumn 2021 NCB G4 international economy meeting hosted by the Banque de France for useful comments and suggestions. We are also grateful for numerous useful comments from colleagues 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 supply chains with many industrial countries. Later in 2020, the focus shifted as China reopened its production relatively fast, which likely supported the recovery in industries of the trading partners. Nevertheless, until recently, transport disruptions such as port closures and shipping bottlenecks in addition to China's zero-covid strategy continue to weigh on China's supply chain trade. 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 supply 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 structural vector autoregressive (SVAR) models with monthly data on US and euro area manufacturing output as well as imports from China and the rest of the world. Adding to the study of Kilian, Nomikos, and Zhou (2021), who incorporate supply chain shocks in a recursively identified SVAR model of the US, a main contribution of our paper is the identification of trade-specific distortions specific to China as a particular and important trading partner. In our novel 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 supply 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 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 the euro area. 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 percentage point. 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-seventh of the overall decline in US manufacturing production at the trough in April 2020 (relative to February 2020); for the euro area, the corresponding fraction is slightly larger. Later in the pandemic, in 2020 and 2021, favourable Chinese supply chain shocks played an important role in supporting

[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.

the recovery in manufacturing production in both economies. This is consistent with the narrative that during the pandemic, consumer expenditure shifted towards goods that have a high Chinese value-added content (such as electronics).

Moreover, we use a more granular panel data set for US and European manufacturing industries to disentangle how the identified shocks affect different manufacturing branches.[2] 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 for US manufacturing sectors the time-varying effect of an exposure to tariffs on intermediate goods imports from China. They find an insignificant production response of relatively highly exposed sectors in 2018 and 2019, arguing that manufacturing output was not affected by the ongoing trade tensions and newly imposed import tariffs. Our results, however, indicate that the impact of increased supply chain frictions is not limited to a few sectors that have a relatively high share of imported intermediate goods from China. In fact, input-output data for the US and the European Union (EU) shows that a majority of sectors are similarly exposed to Chinese inputs.[3] Moreover, a small exposure to Chinese supplies can also be critical for production. Intuitively, in the case of very low elasticity of substitution of the input factors, supply bottlenecks in one input translate into 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 supply chain 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 slowdown in US manufacturing output during 2019 can be rationalized by increased frictions to imports from China.

Compared to earlier literature, we also take prices of imports from China into account to differentiate between supply-type and demand-type supply chain frictions. We find that the trade tensions in 2019 are consistent with shocks that lead to lower prices of imports from China.[4] In early 2020, supply-type supply chain frictions that raised prices for imports from China and the volume of imports from the rest of the world and decreased the volume of imports from China and domestic manufacturing output gained importance. Later in the pandemic, favourable demand-type Chinese supply chain shocks caused prices of imports from China and US manufacturing production to increase. We interpret this as a preference shift in favour of stronger supply chain integration with China. This is a different interpretation compared to Kilian et al. (2021), who argue that much of the US recovery after the Covid-19 recession is rationalized by easing frictions to container trade. In late 2021 and during the first half of 2022, we find that the US and the euro are were additionally hit by sizeable supply-type shocks that increased frictions in the value-chain trade with China while raising domestic import prices.

[2]Because of data availability, we use euro area time series data in the estimation of the SVAR model while the panel analysis employs European Union data.

[3]See Section 2 for more details.

[4]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.

Our approach also allows us to gauge the price adjustment 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 manufacturing industries and not only in those sectors that are highly exposed to Chinese 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 supplies face stronger price pressure in response to new trade frictions and in comparison to little exposed sectors. 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 supply 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 supply chain exposure on US industries during the sharp decline in spring 2020.[5] 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 supply chain disruptions, it is difficult to draw overall conclusions regarding the response of the aggregate manufacturing sector. Besides that many manufacturing branches are more or less similarly exposed to Chinese intermediate inputs, another issue is the difficulty in disentangling the effect of unexpected supply chain 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 supply chain exposure of US industries in early 2020. We argue instead that it is advantageous to focus on a single trading partner to identify supply 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 supply chains. Section 3 introduces SVAR models of US and euro area manufacturing that incorporate Chinese supply chain shocks based on sign restriction identification. In Section 4, we quantify the consequences of such shocks for aggregate manufacturing output. Section 5 disentangles demand-type and supply-type Chinese supply chain shocks based on the response of prices for imports from China and discusses implications for US and euro area manufacturing. In Section 6, we study the consequences of Chinese supply chain shocks with more granular US and EU data on sectoral output and producer prices. In the last section we conclude.

[5] Lafrogne-Joussier, Martin, and Mejean (2022) also study the effects of Chinese supply chain exposure during the coronavirus pandemic using French firm data.

Figure 1: **Upper panel:** Monthly seasonally and price-adjusted imports of manufacturing goods from China and the rest of world to the **US**. **Lower panel:** Monthly seasonally and price-adjusted imports of goods from China and manufacturing goods imports from the rest of world to the **euro area**. Rel to. Jan. 2018 in %. December 2017 to June 2022. Source: US Census Bureau, Eurostat, Haver Analytics and the authors' own calculations. (*) Due to lack of data, euro area real manufacturing trade flows from China are proxied by euro area nominal goods imports from China divided by Chinese producer prices converted into euros. See Appendix A.1 for details on the data sources.

2 US and European imports from China after 2018 and exposure to Chinese supplies

The upper 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, increased trade policy uncertainty, and newly imposed import tariffs. Imports from the rest of the world, however, experienced an upward tendency in 2018-2019. 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. Nevertheless, the dynamics of imports from China remained bumpy throughout 2021 and 2022 while imports from the rest of the world evolved more smoothly.

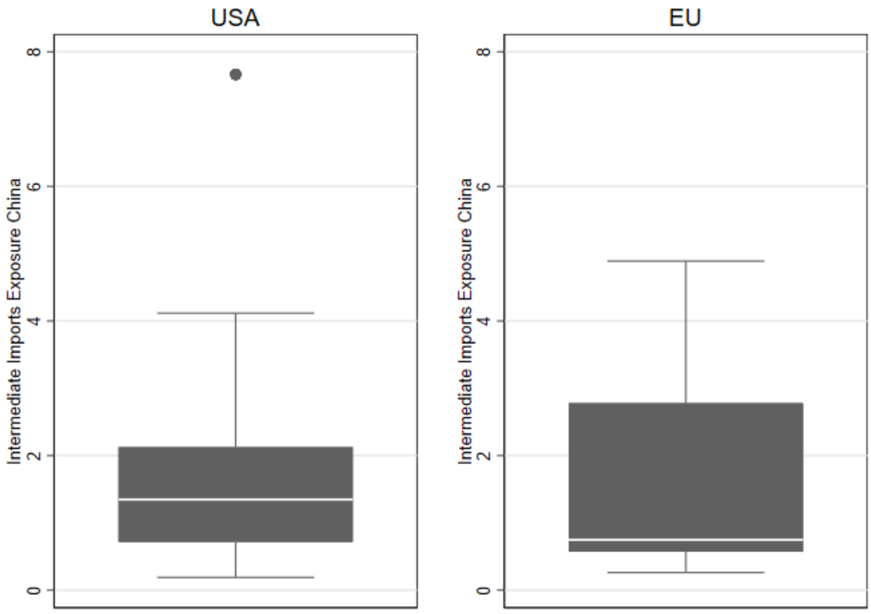


Figure 2: Box-plots characterizing the distribution of the intermediate imports exposure versus China across US and European manufacturing sectors. 'Intermediate imports exposure China' is measured as the cost share of Chinese intermediate inputs in a sector's production (in %). See A.3 for more details.

In the euro area (lower panel of Figure 1), imports from China and from the rest of the world evolve rather similarly before 2020. This changed with the pandemic. What is salient is the earlier drop in imports from China compared to imports from the rest of the world, which can also be observed for the US and which is due to the earlier shutdowns in China compared to other countries. By end of 2020, both the imports from China and from other countries had recovered, but Chinese imports exceeded pre-pandemic levels more substantially. In 2021 and early 2022 euro area imports from China increased markedly while euro area imports from rest of the world evolved relatively weakly.[6]

An important question that arises is how US and European manufacturing typically rely on imports sourced from China. To quantify the dependency of US and EU sectors on Chinese intermediate inputs, we construct an exposure measure based on input-output tables. In particular, we compute the cost share of intermediate inputs in domestic production (cf. Appendix A.3 for details). Figure 2 shows that, at the median, Chinese intermediate inputs account for 1.3% of US production costs; in the EU the corresponding number is around 0.75 %. The share is highest in industries belonging to the information and communication technology sector. Two observations are particularly important for our further analysis: (1) almost all sectors are exposed to Chinese intermediate goods and (2) there is heterogeneity between industries, but it is not that large. In the US, most sectors range in their exposure between around 0.75 % and 2%; in the EU between around 0.5% and 2.75% (see grey area in Figure 2 showing the first and third quartiles). This indicates that many manufacturing sectors are dependent on Chinese supplies to a similar extent. In Section 6 we study the role of heterogeneity across different manufacturing branches

[6]Note that for the euro area data on real manufacturing imports from China is not available. We use instead overall nominal goods imports from China divided by the Chinese producer price (converted into euros).

but first proceed with the identification of shocks to Chinese supply chain frictions and their consequences for the aggregate manufacturing sector.

3 Identifying Chinese supply chain shocks

To identify unexpected frictions in the value-chain trade with China, we propose a novel identification strategy that is based on sign restrictions. The approach builds on the idea that in case of unexpected frictions in trade from China there is trade diversion towards other trading partners. This channel is limited in the short-run as possibilities for substitution are too small to avoid bottlenecks for downstream production industries (in the US or the euro area).

We implement the sketched identification strategy within monthly Bayesian SVAR models of US and euro area manufacturing using sign restrictions (cf., inter alia, Uhlig 2005, Rubio-Ramíerz, Waggoner, and Zha 2010, and Arias, Rubio-Ramírez, and Waggoner 2018). Consider the following monthly SVAR model

$$A_0 y_t = \alpha + A_1 y_{t-1} + ... + A_k y_{t-k} + \varepsilon_t \tag{1}$$

where y_t is $n \times 1$ the vector of endogenous variables, $\varepsilon_t \sim \mathcal{N}(0, I)$ the $n \times 1$ vector of structural innovations with I denoting the $n \times n$ identify matrix, k is the lag number, and $\forall 0 \leq l \leq k$, A_l is a $n \times n$ parameter matrix. The structural matrix $A = A_0^{-1}$ is identified by imposing restrictions on the set of structural impulse response functions. For more details on the estimation algorithm and the prior specification, we refer to Appendix B.1.

In our baseline specification we include three endogenous variables: (1) domestic (US or euro area) manufacturing production, (2) domestic real manufacturing imports (excluding imports from China), (3) domestic real manufacturing imports from China. In an alternative specification in Section 5 we additionally add prices for (manufacturing) imports from China. All variables enter the model in first differences of logs.

Table 1 reports for the baseline three-variable model the imposed sign restrictions as well as the period in which the restriction is imposed on the impulse response function (IRF). We assume that adverse Chinese supply 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. Our underlying identification assumption is that, in the event of unexpected disruptions to the imports from China, there is trade diversion towards other trading partners, and thereby – at minimum – no simultaneous contraction in imports from the rest of the world (ROW). 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 assuming that domestic production is affected by unexpected trade friction shocks with a lag of only one month due to delays between import and production, as well as storage buffers. We therefore restrict the Chinese supply shock to affect manufacturing production one period after the shock. All other signs are imposed upon impact of the corresponding shocks.

	Domestic demand	Domestic supply	Chinese supply chain
Production	+ (h=0)	+ (h=0)	- (h=1)
Imports from ROW	+ (h=0)	- (h=0)	+ (h=0)
Imports from CHN	+ (h=0)	- (h=0)	- (h=0)

Table 1: Identification of Chinese supply chain shocks with sign restrictions. h denotes the period in which the restriction is imposed.

We differentiate the Chinese supply chain shock from two other structural shocks that cause imports from China and imports from the rest of the world to move in the same direction. The first shock, which we label domestic demand shock, causes domestic manufacturing production as well as imports with both trading partners to rise on impact. The second shock, which we call domestic supply shock, raises manufacturing output but with the consequence of declining imports from China and the rest of the world. The rationale behind the latter shock are shifts in domestic production towards goods with less intermediate import content or productivity gains in manufacturing that lead to lower dependency on inputs sourced from abroad. While we have no genuine interest in the transmission of other shocks than the Chinese supply chain shock, the identification of domestic supply-type and demand-type shocks serves to improve the overall capability of the model to capture manufacturing dynamics.

3.1 Data

We use – separately for the US and the euro area – monthly time series on domestic real manufacturing production, real manufacturing imports from China and the rest of the world for the period from January 2002 to June 2022. The euro area sample already begins in January 2000. Because of data availability, we use total imports of goods from China instead of manufacturing imports for the euro area. For the US, real manufacturing imports are obtained by dividing the nominal customs value (from the US Census Bureau) with the manufacturing import price index (provided by the Federal Reserve Board). For the euro area, a price index for imports from China is not available so we approximate real imports from China by dividing the nominal customs value (Eurostat) by the Chinese producer price index (provided by the National Bureau of Statistics of China) converted into euros. All series are seasonally adjusted. Appendix A.1 provides details on all the data sources.

4 Implications of Chinese supply chain shocks for US and European manufacturing

We start with the results for the US and first discuss impulse response functions. Figure 3 shows the impulse response functions for all three structural shocks in the model. It reports the posterior median together with 90% credible sets.[7] We focus on the last

[7]Baumeister and Hamilton (2018) and Baumeister and Hamilton (2020) emphasize that in the standard approach to implement sign restrictions the posterior impulse response function estimates could be

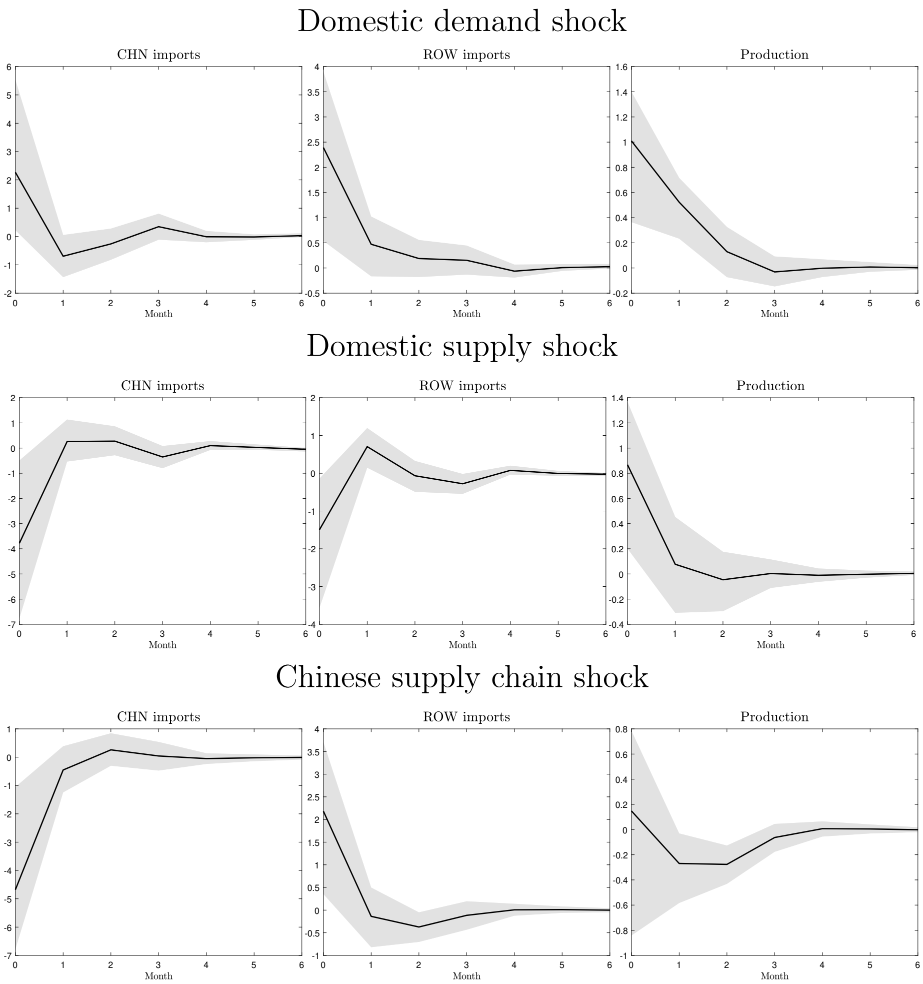
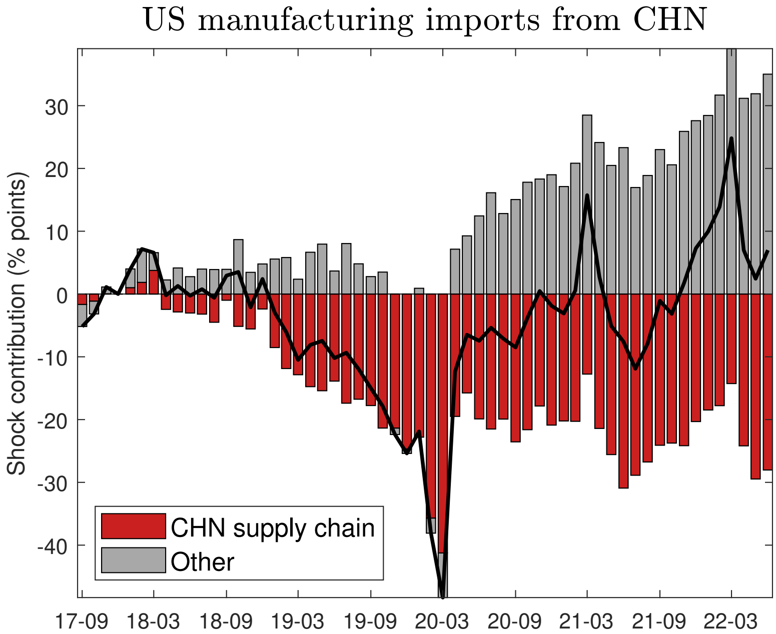


Figure 3: Results from the three-equation SVAR model for the **United States**: Impulse response functions (in %). Sample: February 2002 to June 2022. All variables are in first differences of logs. The grey area shows the 90% posterior probability region and the black line the posterior median. 'CHN imports' are US imports from China, 'ROW imports' are US imports from the rest of the world and 'Production' is US manufacturing production.

row, which shows how US imports from China, US imports from the rest of the world and US manufacturing production respond to an adverse shock to Chinese supply chain trade. In line with the intuition spelled out in the Introduction, after an adverse China-specific supply chain shock the decline in imports from China cannot be compensated by imports from the rest of the world. Thus, the shock leads to bottlenecks in manufacturing production. Overall, we find a marked contraction in manufacturing output in the first

unintentionally affected by the prior for the rotation matrix Q. They also caution against using the posterior median. The practical relevance of these issues for typical applications is still debated, however (cf. Inoue and Kilian 2020). Appendix B.2 demonstrates that the response of manufacturing output to adverse Chinese supply chain shocks – which is the main object of our interest – is qualitatively comparable when we use alternative identification schemes that impose no priors on the sign of this response. First, under Cholesky identification, the – tightly estimated – effects in the first and second period after the shock are negative and markedly away from zero. The magnitude of the effect is even larger compared to our benchmark sign-restricted model, making the posterior median response in the sign-restricted model a conservative estimate. Second, for models that put no sign or period restrictions on the response of production to Chinese supply chain shocks but only on the response of the import variables, we also obtain markedly negative posterior median IRFs for output in the first and second period after the shock. Overall, these robustness checks make us confident to use the posterior median obtained by the standard approach in the remainder of the analysis.



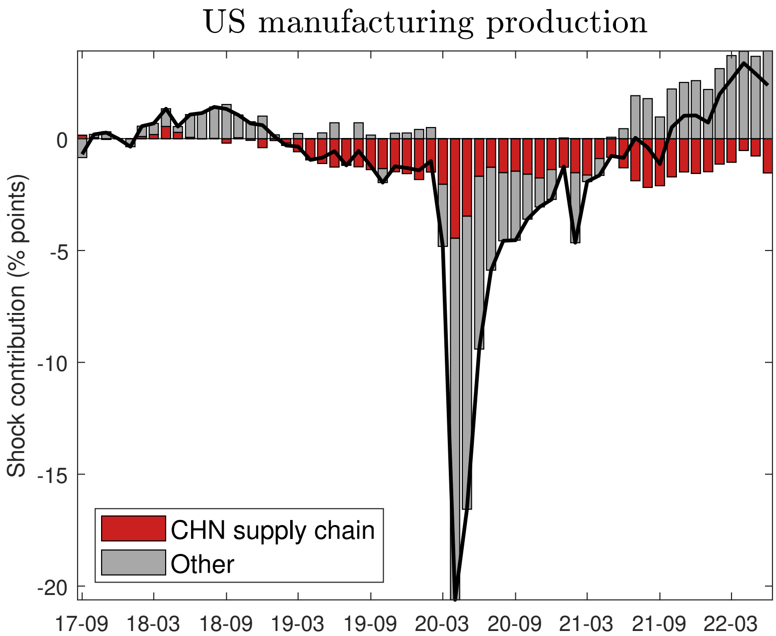


Figure 4: Three-variable SVAR model for the **United States (three variables)**. Sample: February 2002 to June 2022. Historical shocks decomposition of US manufactured imports from China and US manufacturing production for two groups of identified shocks: "CHN supply chain" are Chinese supply chain shocks, "Other" include US demand and US supply shocks and the deterministic component. September 2017 to June 2022. In %(-points) relative to December 2017.

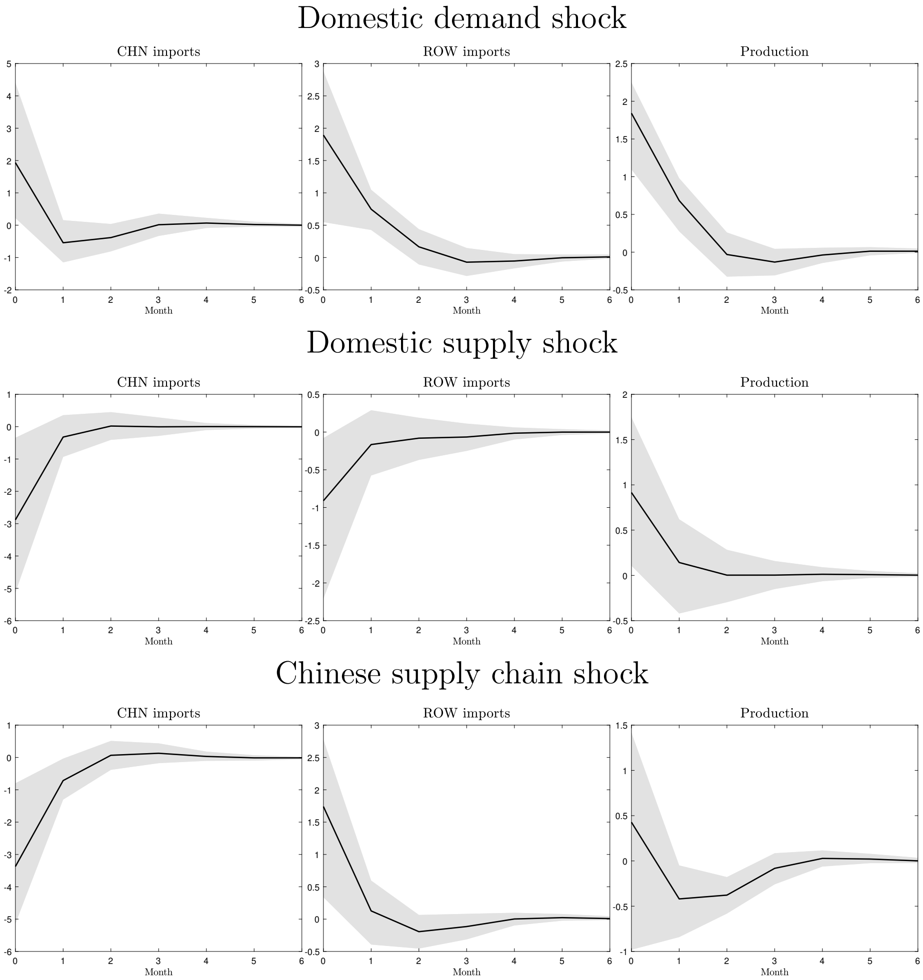


Figure 5: Results from the three-variable SVAR model for the **euro area**: Impulse response functions (in %). Sample: February 2000 to June 2022. All variables are in first differences of logs. The grey area shows the 90% posterior probability region and the black line the posterior median. 'CHN imports' are euro area imports from China, 'ROW imports' are euro area imports from the rest of the world and 'Production' is euro area manufacturing production.

and second period after the shock.

Turning to the role of Chinese supply chain shocks for the historical pattern, Figure 4 (upper panel) shows the historical contribution of the identified shocks for the evolution of US imports of goods from China from late 2017 onward. The decline in US imports of Chinese manufacturing goods during the trade tensions in 2018 and 2019 is mainly explained by unexpected frictions in the supply chain between China and the US. In February and March 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 April 2020 is explained to a significant extent by the abrupt easing of Chinese supply chain frictions.[8]

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

[8] In Section 5 we discuss in more detail the historical pattern of the cumulative effect of Chinese supply chain shocks on Chinese supply chain frictions during the pandemic.

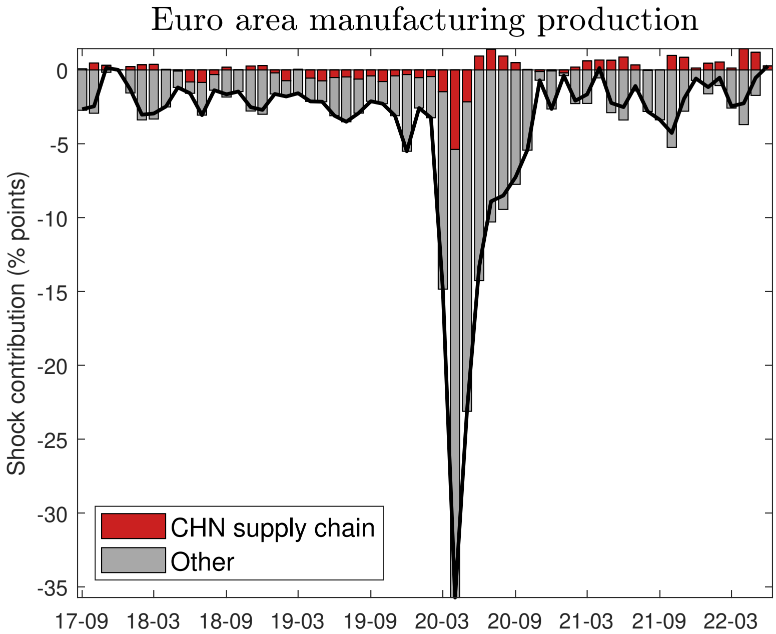


Figure 6: Three-variable SVAR model for the **euro area**. Sample: February 2000 to June 2022. Historical shock decomposition of euro area manufacturing production for two groups of identified shocks: "CHN supply chain" are Chinese supply chain shocks, "Other" include EA demand and EA supply shocks and the deterministic component. September 2017 to June 2022. In %(-points) relative to December 2017.

US and China were still ongoing, manufacturing production was dampened by around 1 percentage point, rationalizing most of the slowdown during that time (see lower panel of Figure 4). 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 relevant, but the direct impact of the spread of Covid-19 on domestic demand dominates.[9]

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 more than one-seventh of the overall decline of euro area manufacturing output at its trough in April 2020 (cf. Figure 6). 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 to a great extent – at

[9]As an alternative approach, one can identify China-specific supply chain frictions within a SVAR model based on Cholesky identification. Such an approach would build more directly on Kilian et al. (2021). In a robustness check, we employ a four-variable SVAR with a recursive identification scheme (following Kilian et al. 2021 we add as an additional variable US goods consumption expenditure but obtain similar results when we omit this variable and stick to three variables). In particular, we assume in this model 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. (see Appendix B.2 for more details on the model specification). In this model we obtain qualitatively similar results for the role of shocks to China-specific supply chain frictions, particularly for the onset of Covid-19 recession. Nevertheless, in the recursively identified model, China-specific trade friction shocks 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 for 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.

	Domstic demand	Domestic supply	CHN supply chain (sup.)	CHN supply chain (dem.)
Production	+ (h=0)	+ (h=0)	- (h=1)	- (h=1)
Imports from ROW	+ (h=0)	- (h=0)	+ (h=0)	+ (h=0)
Imports from CHN	+ (h=0)	- (h=0)	- (h=0)	- (h=0)
Prices for imports from CHN			+ (h=0)	- (h=0)

Table 2: Identification of Chinese supply chain shocks with sign restrictions. Disentangling demand-type and supply-type shocks to Chinese supply chain frictions. h denotes the period in which the restriction is imposed.

least not through the channel of disrupted value chains between China and Europe.

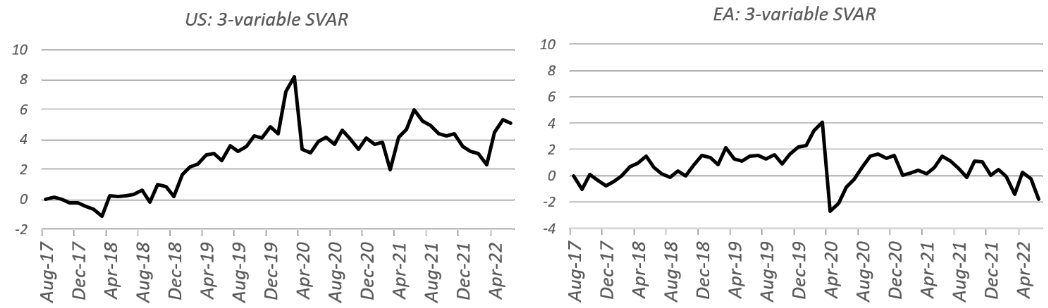
5 Disentangling demand-type and supply-type supply chain frictions

It is of interest to understand whether the identified Chinese supply chain shocks are supply-driven – for instance because they are caused by natural disasters, capacity problems on a particular shipping route 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 supply chains of a particular country. A natural way to identify these two types of shocks is to differentiate by the sign of the response of prices on imports from China. We therefore extend our SVAR model and the set of sign restrictions (see Table 2).

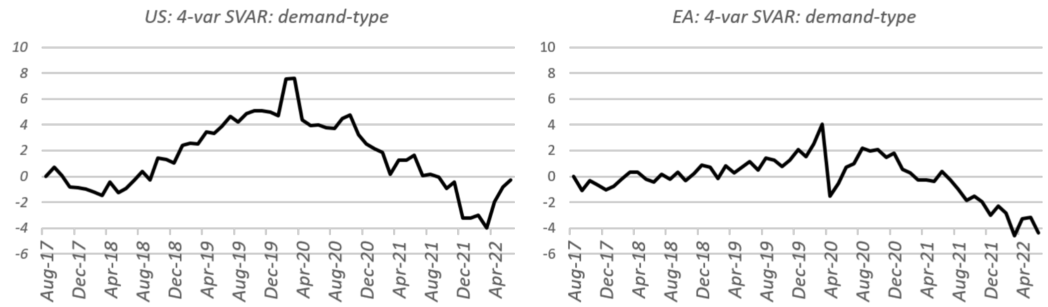
Figure 7 plots – both for the US and the euro area – the cumulative effect of Chinese supply chain shocks on frictions in the supply chain with China between August 2017 and June 2022. The upper panel shows the (single) supply chain friction identified in the benchmark three-variable model while the lower panels show the evolution of demand-type and supply-type supply chain frictions. Compared to the benchmark three-variable SVAR model, the four-variable model shows that for the US during the 2018-19 trade tensions primarily demand-type supply chain frictions increased while supply-type supply chain frictions remained comparatively stable. In February and March 2020 both in the US and the euro area demand-type and supply-type supply chain frictions increased and declined in April 2020; more so in the euro area. Interestingly, in 2021 and early 2022 demand-type supply chain frictions tended to decline both in the US and the euro area while supply-type supply chain frictions tended to increase. Notably, both developments contributed to rising imports prices in the United States and in Europe. At the end of the sample, in April and May 2022 (demand-type) supply chain frictions increased, especially in the US, which is related to the lockdowns imposed on major Chinese regions.

When it comes to the transmission of demand-type and supply-type supply chain shocks, the impulse response functions in Figure 8 show – based on the US manufacturing model – that for the same magnitude of decline of imports from China, the magnitude of the fall

Three-variable SVAR model: cumulative effect of Chinese supply chain shocks on Chinese supply chain frictions



Four-variable SVAR model: cumulative effect of **demand-type** Chinese supply chain shocks on Chinese demand-type supply chain frictions



Four-variable SVAR model: cumulative effect of **supply-type** Chinese supply chain shocks on Chinese supply-type supply chain frictions

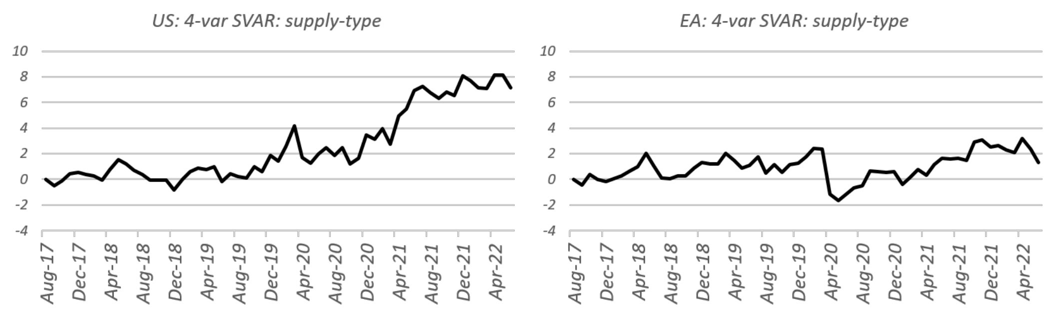


Figure 7: Cumulative effect of Chinese supply chain shocks on Chinese supply chain frictions. Results for separate models for the US and the euro area. Estimation Sample: February 2002 to June 2022 (euro area: February 2000 to June 2022). Normalized at zero in August 2017.

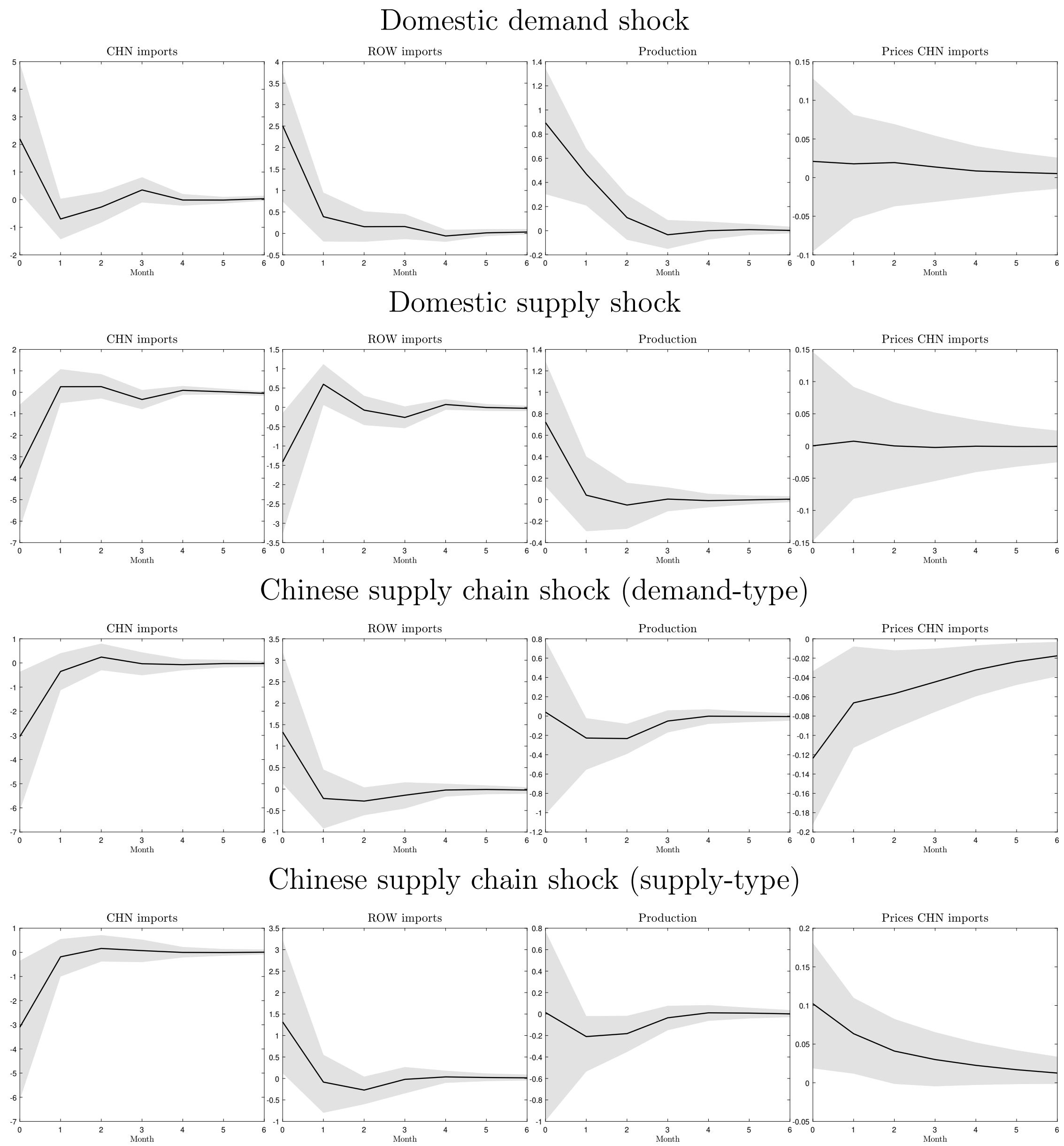


Figure 8: Results from the four-variable SVAR model for the **United States (including demand-type and supply-type CHN supply chain frictions)**. Sample: February 2002 to June 2022. Impulse response function (in %) for US manufacturing imports from China and rest of the world, and US manufacturing production, 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 90% posterior probability region. 'CHN imports' are US imports from China, 'ROW imports' are US imports from the rest of the world and 'Production' is US manufacturing production.

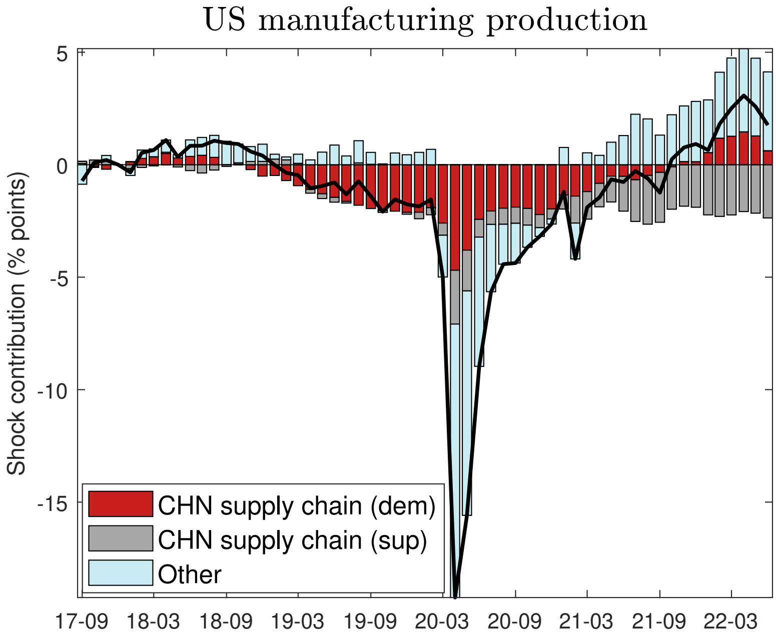


Figure 9: Four-variable SVAR model for the **United States**. Sample: February 2002 to June 2022. Historical shock decomposition for three groups of identified shocks: "CHN supply chain" are Chinese supply chain shocks. *dem* (*sup*) indicates that quantities and prices of Chinese imports move in the same (in different) direction(s), "Other" include US demand and US supply shocks and the deterministic component. September 2017 to June 2022. In %(-points) relative to December 2017.

in import prices under demand-type shocks is slightly larger compared to the magnitude of the rise in import prices under supply-type shocks. The historical shock decomposition in Figure 9 indicates that the trade tensions in late 2018 and 2019 are characterized by demand-type Chinese supply chain shocks. These shocks led to lower imports from China and higher imports from the rest of the world and depressed US manufacturing production. 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 in response to a stronger US dollar induced by trade policy uncertainty. 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, also according to our results, imports from China responded rather late to actual tariff hikes that had started already in early 2018.

In early 2020, supply-type supply chain frictions that raised prices for imports from China and the volume of imports from the rest of the world and decreased the volume of imports from China and domestic manufacturing output gained importance. In late spring 2020, decreasing demand-type and supply-type Chinese trade frictions supported the recovery of manufacturing production. Starting in in 2021, the unexpected rise in supply-type supply chain frictions, however, became a major bottleneck for US manufacturing. At the same time, increasing demand for goods with a large Chinese value-added content eased frictions in the supply chain trade with China and importantly supported US manufacturing production. This aligns with the narrative that during the pandemic consumer expenditure shifted towards goods with a large Chinese value-added content.

Appendix C reports impulse response functions and the historical shock decomposition resulting from the four-variable SVAR model of euro area manufacturing (see Figures C.1 and C.2). In a nutshell, the findings indicate that qualitatively similar as in the US demand-type and supply-type Chinese supply chain shocks both contributed to the Covid-19 recession. In 2021 and 2022 especially demand-type shocks supported the recovery of euro area manufacturing.

6 Sectoral heterogeneity in the response to Chinese supply chain shocks

To further trace out the channels underlying Chinese supply chain shocks, we study the effects of the identified shocks for disaggregated sectoral outcomes. To do so, we estimate autoregressive distributed lag models for US and EU manufacturing sectors. 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 February 2000 to June 2022 (US: February 2002 to June 2022) using the regression equation:

$$y_{i,t} = \beta_1 y_{i,t-1} + ... + \beta_3 y_{i,t-3} + \gamma'_{CHN,1}\chi_{CHN,t-1} + ... + \gamma'_{CHN,12}\chi_{CHN,t-12} + \\ + \gamma'_0\chi_t + ... + \gamma'_{12}\chi_{t-12} + \delta_i + \varepsilon_{i,t} \quad (2)$$

with $y_{i,t}$ denoting the log of manufacturing real output (or in some specifications producer prices) of industry i at time t, χ_{CHN} is a vector of Chinese supply chain shocks, and χ is a vector of all other shocks identified in the SVAR.[10] When the four-variable SVAR model is used, χ_{CHN} is a vector that includes supply-type ($\chi_{CHN,sup}$) and demand-type ($\chi_{CHN,dem}$) Chinese supply chain shocks, 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.[11]

We would like to address the question of whether Chinese supply chain shocks 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 chain shocks identified in the three-equation SVAR models for the US and the euro area. In Figure 10 (upper two panels) 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.[12] The results suggest that negative consequences of adverse China-specific supply chain shocks are not limited to manufacturing sectors that are highly exposed to China. Such shocks cause slowdowns across all manufacturing industries. This is the case both in the US and the EU. Nonetheless, and in line with intuition, the effect is stronger for more heavily exposed sectors. Notably, when for the US only the subsample May 2002 to December 2019 is considered – i.e. excluding the pandemic-induced trade

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

[11] A detailed description of the panel data set can be found in Appendix A.2. For data availability reasons, the SVAR estimates are based on euro area data while the panel analysis employs European Union data (27 member aggregate).

[12] We split the sample at the median of the exposure measure outlined in Section 2.

frictions in early 2020 – the magnitude of the effect is rather similar for exposed and non-exposed sectors (see Figure 10, lower panel). This suggests that being exposed to Chinese supply chains was a more important channel during the early Covid-19 lockdowns in China compared to earlier Chinese supply chain shocks.

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 intermediate goods sourced from China and find no statistically significant effect on manufacturing output during the trade tensions between the US and China.[13] Our findings suggest that their result could be linked to the circumstance that most US manufacturing sectors are at least to some extent exposed to Chinese intermediate supplies. Also, if the opportunities to switch between production inputs that are sourced domestically – such as materials but also labour – and imported inputs are rather limited, then a small exposure to a specific trading partner can have large consequences in the event of increased trade frictions such as new tariffs.[14] Moreover, there are likely spillovers from highly exposed sectors to the rest of the economy because of domestic input-output linkages and due to 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.

6.1 Producer price responses to Chinese 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 2, differentiating between sectors that rely relatively strongly on Chinese intermediate imports compared to sectors that are little exposed. We focus on supply-type supply chain shocks identified in the four-variable SVAR model. These shocks imply that prices and quantities for imports from China move in different directions.

The results are plotted in Figure 11 (upper panel). According to the estimates, adverse Chinese supply chain shocks cause upward price pressure across all manufacturing industries. 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 examine 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 possibly requires more flexible price setting as storage is less of an option. As the results in Figure 11 (lower panel) indicate, producer prices in sectors that produce nondurable goods react 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.

[13] In Appendix D, we conduct a similar difference-in-difference estimation exercise and arrive at the same conclusion.

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

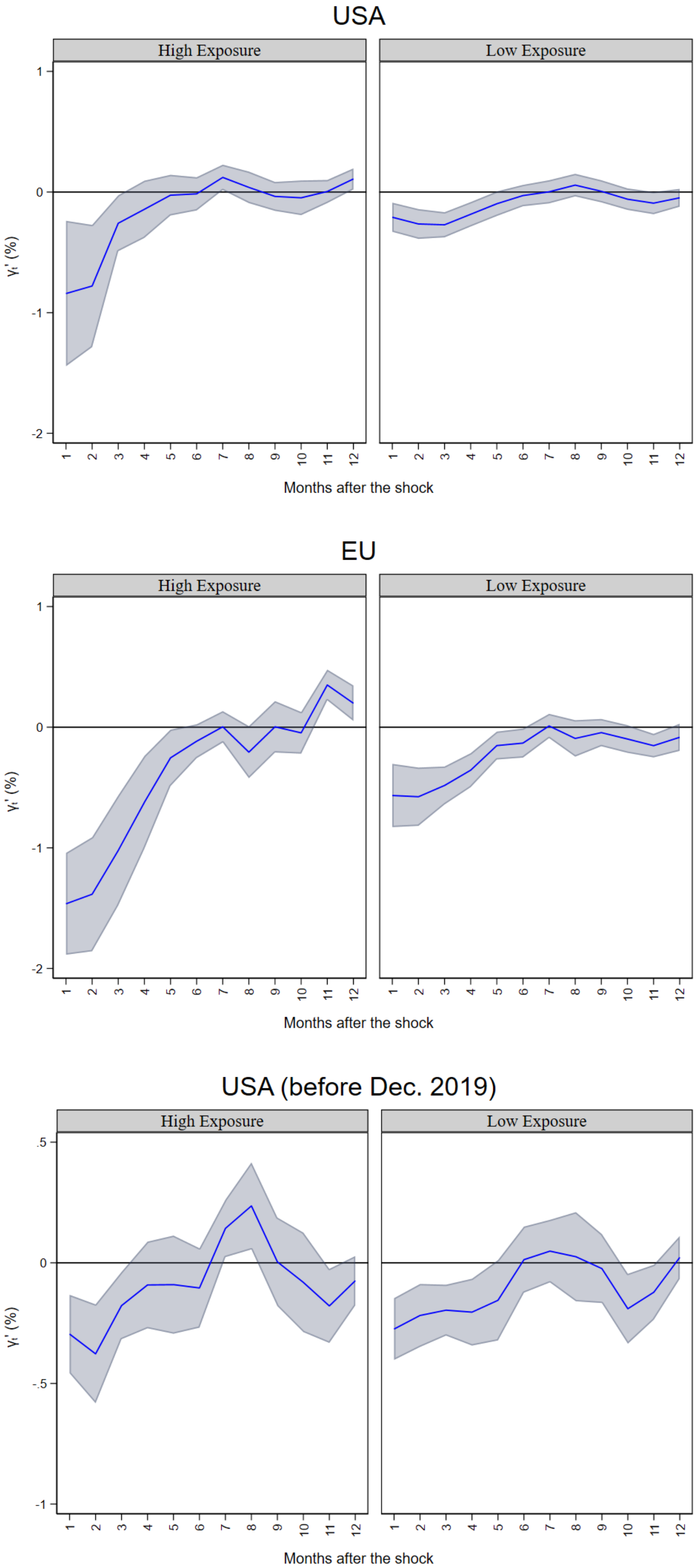


Figure 10: The effect of adverse Chinese supply chain shocks (from the three-variable SVAR models) on **US and EU manufacturing production**. Separate regressions (see equation 2) for industries with high and low exposure to Chinese intermediate imports (sample split at the median exposure). The blue line shows the coefficient vector $\gamma_{CHN,l}$, $\forall l = 1, ..., 12$. The shaded area represents the 90% confidence interval. Sample periods: Upper panels (US) May 2002 to June 2022, middle panel (EU) May 2000 to June 2022, lower panel (US) May 2002 to December 2019.

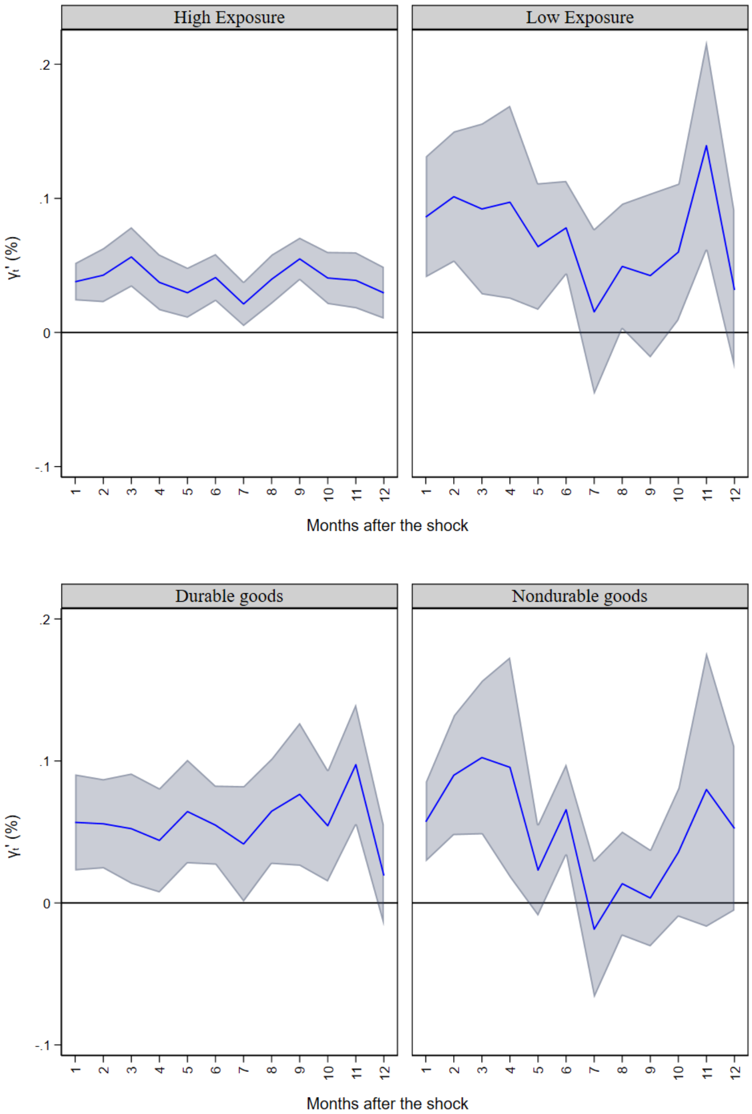


Figure 11: The effect of adverse Chinese – supply-type – supply chain shocks (from the four-variable SVAR model) on **manufacturing producer prices (US model)**. Separate regressions (see equation 2) for industries with high and low exposure to Chinese intermediate imports (upper panel) and industries with high and low durability of the produced goods (lower panel). The blue line shows the coefficient vector $\gamma_{CHN,sup,l}$, $\forall l = 1, ..., 12$. The shaded area represents the 90% confidence interval. Sample period: May 2002 to June 2022.

7 Conclusion

In structural vector autoregressive models of United States and euro area manufacturing, we use sign restrictions to identify shocks that alter the frictions to Chinese supply chain trade. 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 production over the last few years. Moreover, we use granular data sets to estimate how the identified shocks affect output and price dynamics in different branches of manufacturing.

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 early 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 supply chain shocks was nonetheless quantitatively significant. During the recovery in 2020 and 2021, favourable Chinese supply chain shocks played a relevant role. The latter finding is consistent with a demand 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 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.

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Appendix

A Data and descriptive statistics

A.1 SVAR analysis

The SVAR analysis is based on aggregate time series data for February 2000 (US: February 2002) through June 2022, which, for the US, includes manufacturing production data from the Federal Reserve Board, and, using Haver Analytics, seasonally adjusted data on US goods imports from the rest of the world excluding China as well as data on goods imports from China from the US Census Bureau. The import data were price adjusted using the corresponding import price indexes from the Federal Reserve Board.[15] 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. Imports from the rest of the world are price adjusted using the total US manufacturing import price index, adjusted by the Chinese import price component based on the average import weight over the sample. Because of data availability, we use a price index for all commodities (excl. oil) before December 2005.

The seasonally adjusted data for the euro area are obtained from Eurostat and Haver Analytics. Eurostat does not report a measure of manufactured imports from China. We use euro area imports of overall goods imports from China instead. For the same reason, imports from China are price adjusted with the Chinese producer price (Source: National Bureau of Statistics of China, Haver) converted into euros. The euro/yuan exchange rate is obtained from the International Monetary Fund's International Financial Statistics via Haver. Imports from the rest of the world are price adjusted using the price index for total euro area manufactured goods imports.

Figure A.1 plots all the time series for the United States and the euro area. As opposed to some other contributions in recent literature, we do not treat the observations during the Covid-related contraction as outliers. This has mainly two reasons. First, at least in the US, the magnitude of the contraction of manufacturing is similar compared to the Great Recession in 2009. Also real manufacturing imports in early 2020 do not appear as extreme outliers. Second, the main question of this paper is how unexpected disruptions in supply chain trade affect downstream industries. We consider the lockdowns in China in early 2020 as an exogenous event for supply chain trade. Thus, this event has the potential to improve the identification of the average estimate of Chinese supply chain shocks and should not be treated as an outlier.

A.2 Panel data

For the panel data regressions in Section 6 we use monthly sectoral data for US and EU manufacturing output and producer prices, respectively. The data are available at the

[15]The manufacturing import price indices are reported for three manufacturing subgroups. We use average import weights from 2002 to 2020 to obtain aggregate price indices.

four-digit NAICS (2012) level for the US and mainly three-digit[16] NACE sectors for the EU. US 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 US producer price indices (PPIs), we use time series from the US 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 85 four-digit NAICS industries for industrial production and PPIs in the US, while 74 (IP) and 80 (PPIs) three-digit NACE sectors are available.[17]

A.3 Exposure to Chinese supply 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:[18]

$$Intermediate\ Imports\ Exposure\ China_i = \sum_j \frac{use_{ij}}{M_i + Comp_i} \frac{imp_j}{Q_j + imp_j} \frac{imp_{j \leftarrow China}}{imp_{j \leftarrow World}} \quad (3)$$

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 US, we use the Bureau of Economic Analysis (BEA) Supply and Use tables as of 2012[19] and 2019 customs values for imports from China and the rest of the world at the ten-digit Harmonized System (HS) level by the US Census Bureau. Only goods classified as intermediate inputs and capital goods according to the

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

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

[18]To calculate the production cost share and the general import share, we use the Supply and Use (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: $China\ exposure_i = \frac{\sum_j \frac{imp_{j \leftarrow China}}{imp_{j \leftarrow World}} imp_j}{\sum_j imp_j}$.

[19]More recent tables are not yet available.

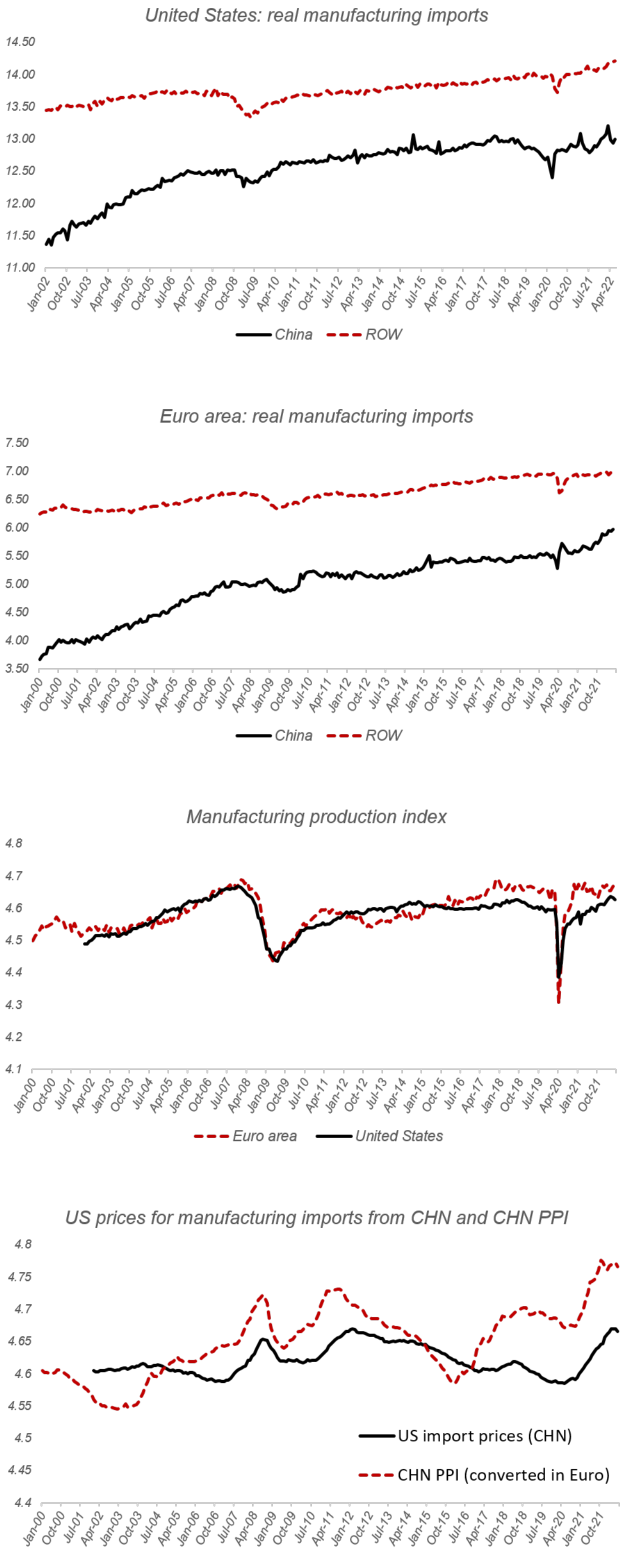

Figure A.1: US and euro area time series data. Sample: US February 2002 to June 2022; euro area February 2000 to June 2022. All variables expressed in logs.

Broad Economic Indicators (BEC) are included in the calculation.[20] For the EU, the 2017[21] 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.[22,23]

B Appendix: SVAR specification and alternative SVAR models

B.1 Details on the SVAR with sign restrictions

The Bayesian estimation of the SVAR with sign restrictions is conducted with the BEAR toolbox version 4.2 (cf. Dieppe, van Roye, and Legrand 2018). The basis workings of the algorithm are the following (for more details see, among others, Arias et al. 2018 and Dieppe et al. 2018): Starting from the reduced-form VAR underlying the structural representation in equation (1), we use a Cholesky factorization to obtain a matrix H from $HH' = \Sigma$ where Σ is the $n \times n$ variance matrix of the reduced-form VAR innovations. Defining $D = HQ$, one has to draw an orthogonal matrix Q (i.e. $I = Q'Q$) which is achieved by drawing a random matrix X from a normal distribution and employing QR decomposition such that $X = QR$ where R is an upper triangular matrix. Finally, we keep each draw $A = H'Q'$ that fulfills the imposed restrictions on the corresponding structural impulse response function. In the Bayesian estimation, we impose a Normal-Wishart prior on the distribution of the reduced-form VAR parameters.

B.2 SVAR with Cholesky identification and alternative sign restrictions

As a robustness analysis, we examine the effect of Chinese supply chain shocks on manufacturing output using alternative identification approaches. As a first alternative approach, we identify China-specific trade frictions within a SVAR model of the US based on Cholesky identification. The model adds to Kilian et al. (2021) in identifying trade-specific distortions in bilateral import flows from China. In particular we estimate the following model

$$A_0 y_t = \alpha + A_1 y_{t-1} + ... + A_k y_{t-k} + \varepsilon_t$$

where y_t is the vector of endogenous variables and ε_t is a vector of structural innovations with variance-covariance matrix Ξ. Identification is obtained by Cholesky factorisation,

[20] 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.

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

[22] 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.

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

	Domestic demand	Domestic supply	Chinese supply chain
Production	+ (h=0)	+ (h=0)	
Imports from ROW	+ (h=0)	- (h=0)	+ (h=0)
Imports from CHN	+ (h=0)	- (h=0)	- (h=0)

Table B.1: Alternative set of sign-restrictions (1). h denotes the period in which the restriction is imposed.

	Domestic demand	Domestic supply	Chinese supply chain
Production			
Imports from ROW			+ (h=0)
Imports from CHN			- (h=0)

Table B.2: Alternative set of sign-restrictions (2). h denotes the period in which the restriction is imposed.

i.e. by imposing a lower triangular matrix on $A = A_0^{-1}$ such that $\Sigma = AA'$ where Σ are the reduced-form VAR residuals. The model is estimated with a lag of $k = 3$ periods.

In a first specification we estimate a SVAR model that shares similarities with the model in Kilian et al. (2021). In particular, we include in the vector y_t (in this order and in each case as the first difference of the series in logs): (1) consumption expenditure on goods, (2) the production of the manufacturing sector, (3) goods imports from the rest of the world excluding China (seasonally and price-adjusted)[24], as well as – in addition to the three-variable model model in Kilian et al. (2021) – (4) US imports of goods from China (seasonally and price-adjusted). The identification assumes that US imports from China react on instant 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 a second specification we include the same set of variables as in the baseline sign-restricted model in Section 3: (1) manufacturing production, (2) manufactured goods imports form the rest of the world, and (3) manufactured goods imports from China. While we believe the variable order 1-2-3 being the most reasonable to identify Chinese supply chain shocks, we also experiment with ordering the Chinese supply shock second (order 1-3-2) and first (order 3-1-2).

The red bars in Figure B.1 plot the results for the four alternative models with Cholesky identification. The figure reports the first and second period response of manufacturing output to an adverse Chinese supply chain shock in period zero (all responses are normalized by the average shock standard deviation). Across all specifications, the responses are significantly negative in the first two periods. This is very similar to the pattern from the three-variable benchmark model using sign restrictions.

The point estimates from the Cholesky-identified models are larger in comparison to the posterior median effect in the baseline sign-restriction model of Section 3 Table 1 (which are plotted in blue). We discuss in footnote 9 that this likely reflects the restrictions imposed in the benchmark model on imports from the rest of the world to capture the trade diversion channel related to unexpected China-specific supply chain disruptions.

[24] Kilian et al. (2021) introduce an index capturing North American container trade and incorporate this index in their SVAR model.

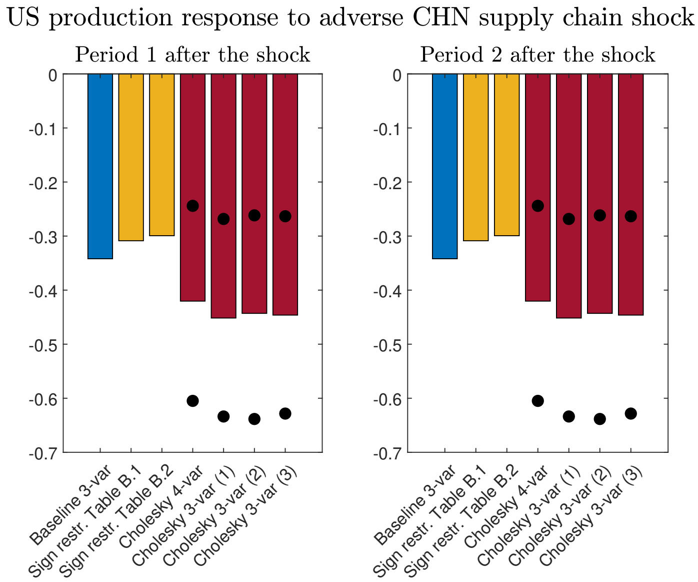

Figure B.1: Comparison of different SVAR models. First and second period impulse response function US manufacturing output to an adverse Chinese supply chain shock. Monthly SVAR for the United States (February 2002 to June 2022). First bar (blue): Benchmark three-variable sign restriction identification from Table 1. Second and third bar (yellow): alternative sign restrictions (Tables B.1 and B.2). Remaining bars (red): Estimates of Cholesky-identified SVAR models with 95% confidence intervals (black dots). Cholesky 4-var refers to four variables in the Cholesky-identified SVAR model (see text for more details). Cholesky 3-var correspondingly refers to three variables. In the three-variable Cholesky-identified SVAR model, (1), (2) and (3) refer to the ordering of Chinese imports in the VAR as first, second or third variable (see text for more details). All responses are normalized by the average shock standard deviation.

To further zero in on alternative model specifications that impose no sign restrictions on the effect of Chinese supply chain shocks on manufacturing output, we estimate two alternative SVAR models. The first specification departs from the baseline three-variable model (Section 3, Table 1) by not imposing a prior on the sign and period of the response of manufacturing output to unexpected frictions in China-specific supply chain trade (see Table B.1). The second model imposes sign restrictions only for one shock by assuming that imports from China and the rest of the world move in opposite directions upon impact (see Table B.2). Figure B.1 shows that also in these models the posterior median response in the first and second period after adverse Chinese supply shock is markedly negative. Overall, the robustness checks make us confident that the posterior median obtained in the benchmark three-variable model gives a meaningful quantitative interpretation.

C Further figures: Four-variable SVAR euro area

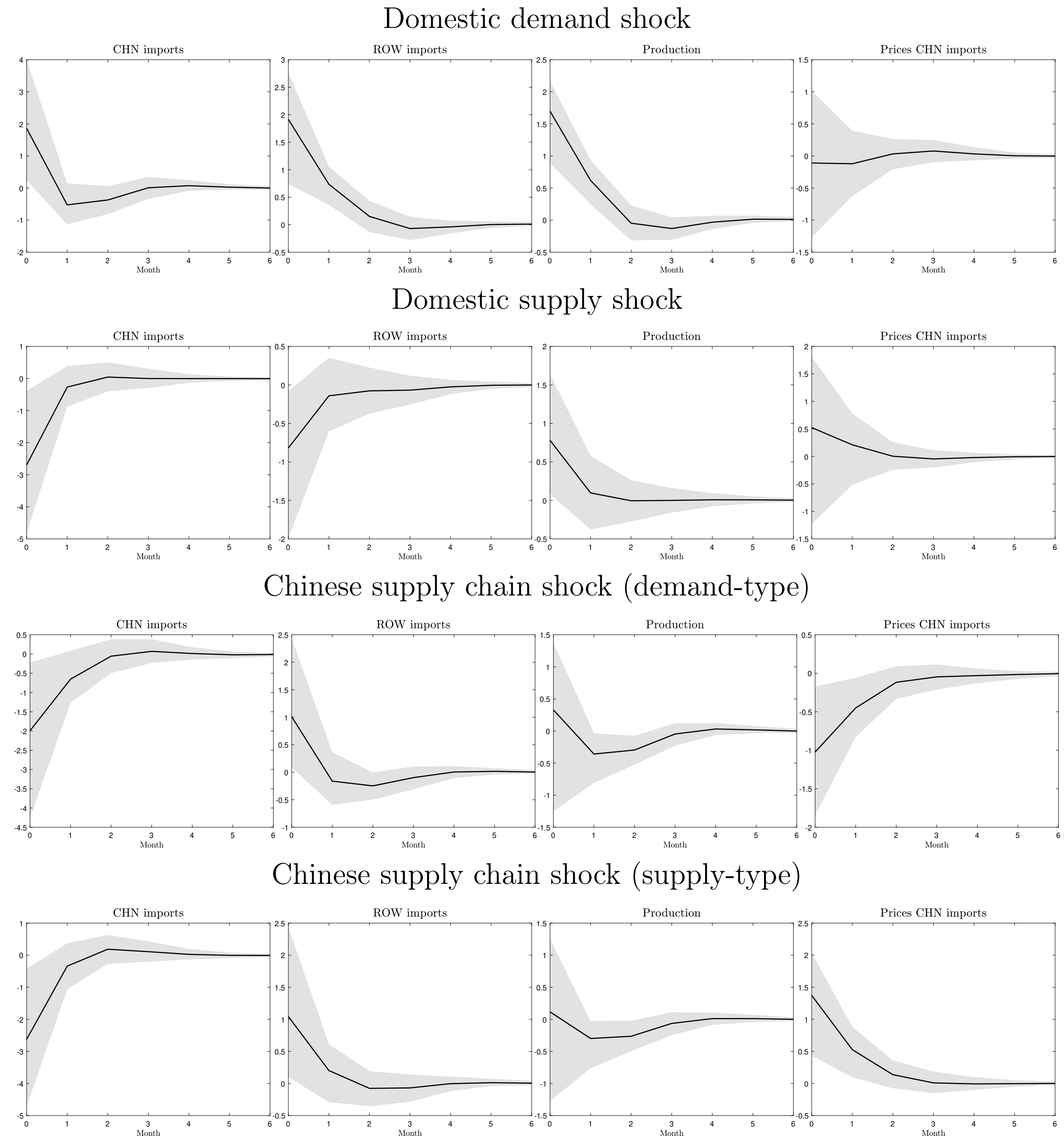

Figure C.1: Results from the monthly four-variable SVAR model for the **euro area (including demand-type and supply-type CHN trade frictions)**. Sample: February 2002 to June 2022. Impulse response function (in %) for euro area manufacturing imports from China and rest of the world, and euro area manufacturing 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 90% posterior probability region. 'CHN imports' are euro area imports from China, 'ROW imports' are euro area imports from the rest of the world and 'Production' is euro area manufacturing production.

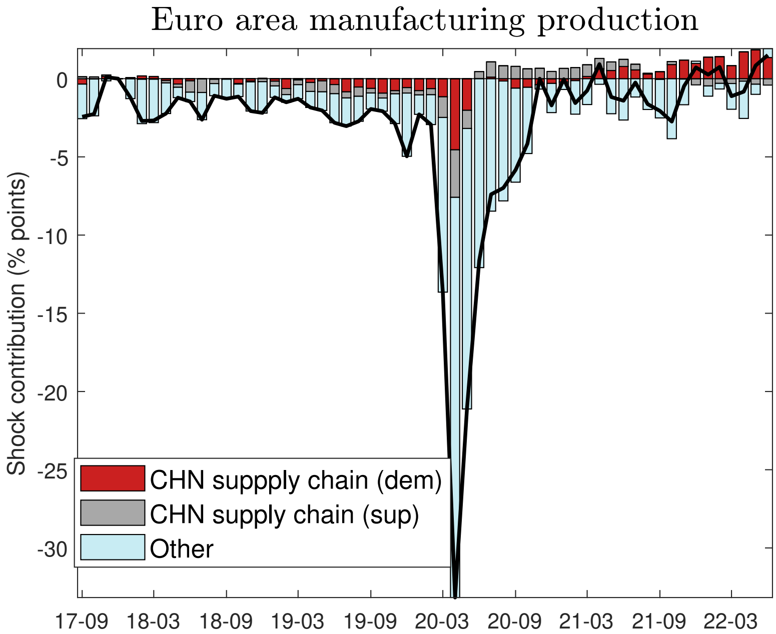

Figure C.2: Four-variable SVAR model for the **euro area**. Sample: February 2000 to June 2022. Historical shock decomposition for three groups of identified shocks: "CHN supply chain" are Chinese supply chain shocks. *dem* (*sup*) indicates that quantities and prices of Chinese imports move in the same (in different) direction(s), "Other" include US demand and US supply shocks and the deterministic component. September 2017 to June 2022. In % (points) relative to December 2017.

D Comparing the findings to estimates from a difference-in-difference approach à la Flaaen and Pierce (2019)

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.[25] 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 June 2022 – an epsiode were we find significant impacts of Chinese supply chain shocks – using the regression equation:

$$\begin{aligned} y_{it} = \alpha + \beta_t \boldsymbol{1}(M_t = t) D(\mathit{Intermediate\ Imports\ Exposure\ China}_i) \\ + \gamma_t \boldsymbol{1}(M_t = t) D(\mathit{Intermediate\ Imports\ Exposure\ RoW}_i) \\ + \rho_t \boldsymbol{1}(M_t = t) D(\mathit{Export\ Exposure\ World}_i) \\ + \theta_t \boldsymbol{1}(M_t = t) D(\mathit{Import\ Substitution}_i) + \delta_t + \delta_t + \varepsilon_{it} \end{aligned} \tag{4}$$

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-Covid-19 trend. $\mathbf{1}(M_t = t)$ is a vector of monthly dummies from January 2019 to June 2022. $\mathit{Intermediate\ Imports\ Exposure\ China}_i$ is the industry-specific exposure variable described in section A.3. We further control for a dependence on inputs from other economies (excluding China),

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

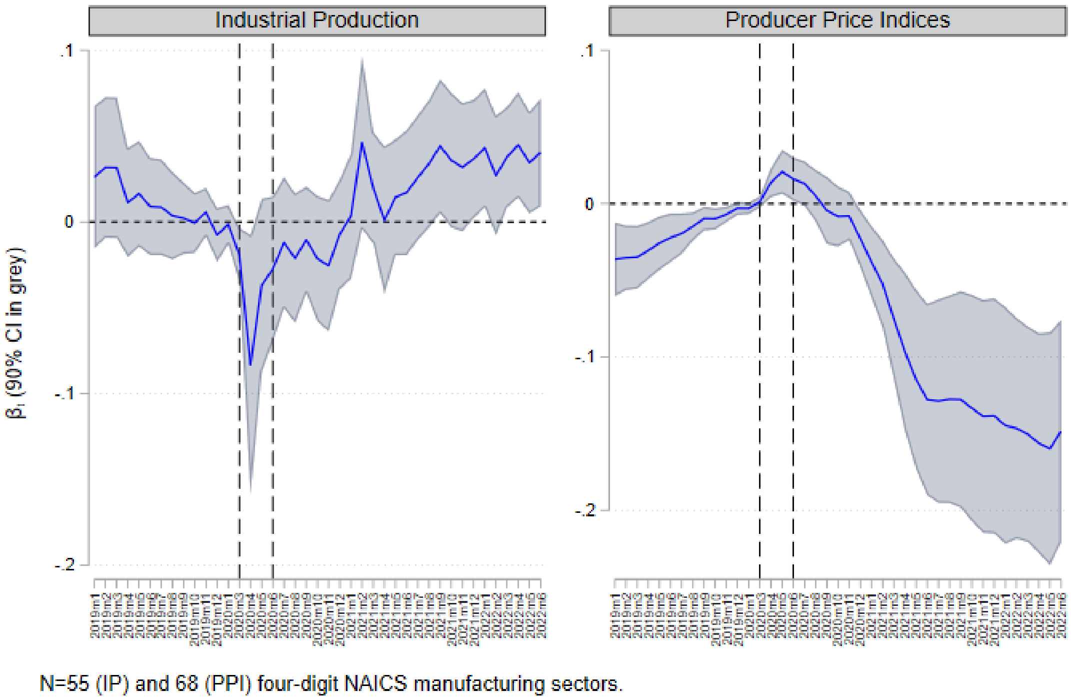

Figure D.1: Coefficient β_t in a regression of US industrial production and producer price indices on *Intermediate Imports Exposure China*$_i$ and control variables. The blue line shows the coefficients of a regression of the respective pre-crisis-adjusted dependent variable on the time trend-interacted independent variable Intermediate Imports Exposure China. The shaded area represents the 90% confidence interval. The two vertical lines mark the period of the first coronavirus wave. Sample period: January 2019 to June 2022. Base period: February 2020.

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 (3); 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 (*Export Exposure World*$_i$), which thus also controls for a general openness to exports of the respective industry. The variable *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 these 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.[26] Figures D.1 and D.2 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 US and the EU, respectively.

The estimation for the US shows that high exposure is associated with a larger decline in industrial production only during the first wave of the coronavirus pandemic 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 before late

[26] 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.

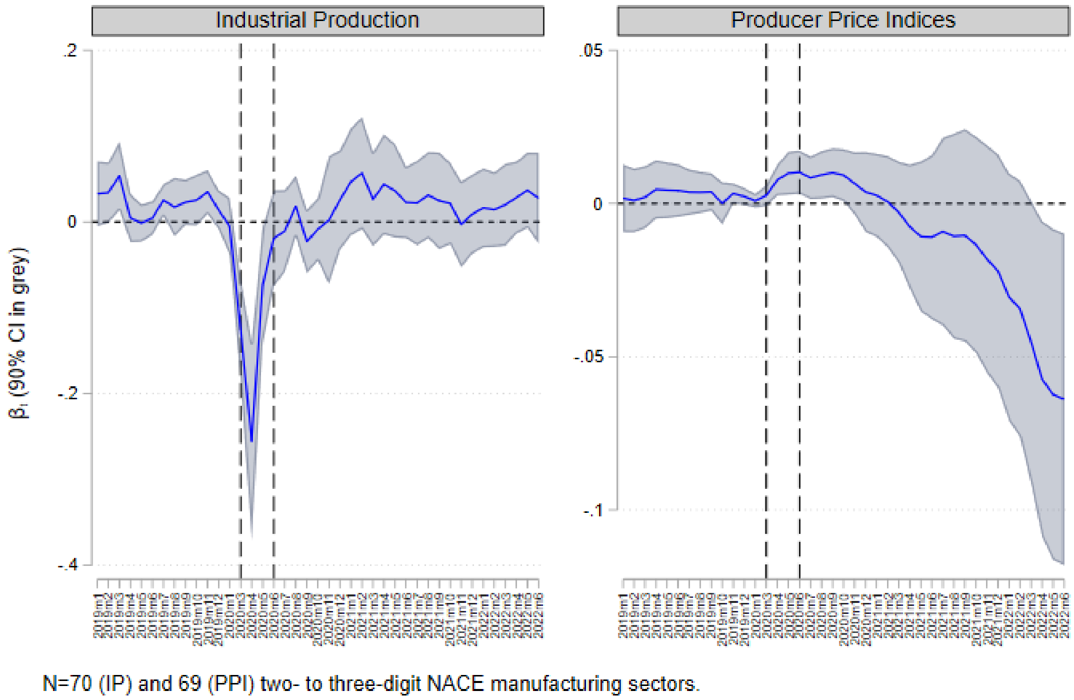

Figure D.2: Coefficient β_t in a regression of EU industrial production and producer price indices on *Intermediate Imports Exposure China*$_i$ and control variables. The blue line shows the coefficients of a regression of the respective pre-crisis-adjusted dependent variable on the time trend-interacted independent variable Intermediate Imports Exposure China. The shaded area represents the 90% confidence interval. The two vertical lines mark the period of the first coronavirus wave. Sample period: January 2019 to June 2022. Base period: February 2020.

2021 not statistically significant effect on output. Moreover, a higher dependency 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 US tariffs on imports from 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-dependent pandemic goods. Overall, the findings are similar to the results in Flaaen and Pierce (2019) and Meier and Pinto (2020). Our estimates for the EU in Figure D.2 are qualitatively similar to the US results.

Although the difference-in-difference approach seems appealing to investigate the role of disruptions in cross-border supply chains for domestic production, it is difficult to draw conclusions about the consequences for the manufacturing sector. As outlined in Section 2, most sectors in the US and in Europe are to some extent exposed to Chinese intermediate inputs, which is per construction not captured. The estimates suggest that only very large shocks – in particular the shock in early 2020 – are important, which could be related to this caveat. Moreover, it is difficult to disentangle the effect of trade frictions from other disruptions. For instance, in the EU the production decline estimate for April 2020 is rather large at around 25 percent.[27] This points towards difficulties in disentangling the effects of China-specific supply chain disruptions from local lockdowns.

[27]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. For this reason the number of sectors is smaller compared to the benchmark sample described in Appendix A.2.