Covid-19 Supply Chain Disruptions*

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October 13, 2021

Abstract

We study the effects of international supply chain disruptions on real economic activity and prices during the Covid-19 recession and early recovery. We show that US sectors with a high exposure to intermediate goods imports from China contracted significantly and robustly more than other sectors. In particular, highly exposed sectors suffered larger declines in production, employment, imports, and exports. In addition, input and output prices moved up relative to other sectors, suggesting that the larger output declines in sectors with a high China exposure were not demand driven. Quantitatively, sectors with a one standard deviation higher China exposure experienced 3.0 and 8.3 percentage points larger output declines in March and April 2020, respectively. The estimated effects are short-lived and dissipated by June 2020.

Keywords: Supply chain disruptions, Covid-19, industrial production.
JEL Codes: E23, F14, F62.

*We thank Harald Fadinger, Efi Adamopoulou, and participants in various seminars and conferences for useful comments. Matthias Meier gratefully acknowledges funding by the German Research Foundation (DFG) through CRC TR 224 (Project C02), and financial support from the UniCredit & Universities Foundation. The analysis and conclusions are those of the authors and do not indicate concurrence by the Board of Governors of the Federal Reserve System or other members of its research staff. We thank Lukas Hack, Sarah Siegel, and Paul Tran for excellent research assistance.

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1 Introduction

Over the past decades, the world economy has become increasingly interconnected through global value chains. While global value chains raise efficiency, they may simultaneously raise the economic costs of disruptions in international supply chains.

In this paper, we study the effects of international supply chain disruptions on the US industrial sector during the Covid-19 recession and early recovery. The contraction in economic activity during the Covid-19 crisis was exceptionally rapid and deep, with industrial production plunging about as much as it did during the Great Recession in only two months (Figure 1). Another exceptional element of the Covid-19 crisis were government-mandated lockdowns of manufacturing and other facilities in response to the public health crisis. China, in particular, imposed widespread lockdowns of entire regions and sectors during February and early March 2020. These lockdowns caused sharp contractions in production and exports, and eventually spilled over to the US. Imports from China declined, especially for intermediate goods, which disrupted the supply chains of US producers.

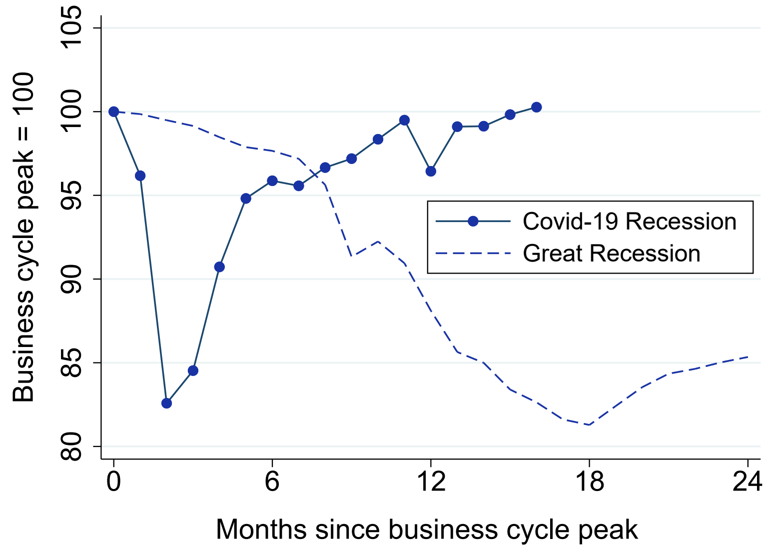
Understanding the role of international supply chain disruptions during the Covid-19 recession is important for an effective policy response.[1] For example, if lockdowns disrupt supply chains and constrain production, direct stimulus payments to households may raise inflation and have only a diminished impact on production. Potentially more effective policy interventions would aim to preserve installed productive capacity and firm-specific human capital. In the absence of such interventions, short-lived supply chain disruptions can have large and long-lasting effects. Policy interventions adopted in this spirit include the Paycheck Protection Program and the Main Street Lending Program. Evaluating the effectiveness of these programs requires empirical evidence of the impact and persistence of international supply chain disruptions during the Covid-19 crisis.

We study the effects of disruptions to supply chains connected to China on US real economic activity and prices during the Covid-19 crisis on a monthly basis.[2] Our empirical strategy exploits variation in the share of imported intermediate goods across sectors before Covid-19. The idea is that sectors that are more dependent on inputs imported from China should also be more affected by supply chain disruptions stemming from the initial Covid-19 crisis in China.

[1] An extensive literature studies the policy implications of Covid-19, e.g., lockdown policy in Alvarez et al. (forthcoming), Eichenbaum et al. (2021), Krueger et al. (2020), and Glover et al. (2020), fiscal policy in Bigio et al. (2020), Mitman and Rabinovich (2021), Auerbach et al. (2021), and Bayer et al. (2020), and monetary policy in Caballero and Simsek (2021), Woodford (2020), and Fornaro and Wolf (2020).

[2] An important advantage of using sectoral data in our analysis is its availability at monthly frequency. This is key to uncover the sharp, but short-lived, effects of Covid-19 supply chain disruptions. To the best of our knowledge, no firm-level data at monthly frequency are available to replicate our empirical approach.

Figure 1: US industrial production during the last two recessions



Notes: This figure shows aggregate industrial production after the business cycle peaks preceding the Covid-19 Recession (solid line) in February 2020, and the Great Recession (dashed line) in December 2007, based on the seasonally adjusted industrial production index from the Federal Reserve G.17 release.

We show that US sectors with high exposure to Chinese imports contracted significantly and robustly more than other sectors. In particular during March and April 2020, highly exposed sectors suffered larger declines in production, employment, imports, and exports.[3] Quantitatively, sectors with a one standard deviation higher China exposure experienced larger declines in production by 3.0 percentage points (p.p.) in March and 8.3 p.p. in April. Differences in China exposures account for about 13% of the cross-sectoral variance of industrial production growth during March and April. These differential effects appear to be relatively short-lived and become insignificant by June.

A critical question is whether our exposure measure captures the strength of supply-chain shocks across US sectors. Instead, our exposure measure might be high for industries that were also more affected through other channels during the Covid-19 recession, such as a slump in domestic demand, weaker external demand (namely from China), or tighter financing conditions. We address this concern in two ways. First, we estimate how higher China exposure relates to sectoral prices. We find that both input import prices and output prices increase by significantly more for sectors with higher China exposure. This result makes it unlikely that changes in real activity in sectors with higher China exposure mostly

[3]The time delay between lockdowns in China starting in February and China-related performance differences across US sectors starting in March likely reflects transit time and, possibly, inventory holdings.

reflect lower domestic or external demand. Second, we control for export exposure to China, non-China import exposure, external finance dependence, and sector-specific business cycle sensitivity, all computed before Covid-19. Including these controls, we still find a significant relation between a higher China exposure and a larger contraction in industrial production. In addition, our estimated effects do not significantly change when controlling for sector-specific exposures to the US-China trade war.

We further examine differences in a broader non-China import exposure. Sectors with a high non-China exposure to imported inputs also suffer larger output declines, but the responses of employment, imports, and export are insignificant. In addition, industries with a larger share of the non-China imported intermediates experienced smaller input import and output price changes relative to other industries. This last finding suggests that the broader non-China exposure mostly captures the effects of demand differences across sectors.

To construct sector-specific exposure measures, we combine detailed 6-digit NAICS import data for 2019 from the US Census with benchmark 6-digit input-output (IO) tables for 2012 from the US Bureau of Economic Analysis (BEA). We aggregate these data to compute exposure measures for 88 manufacturing and related industries (approximately 4-digit NAICS level), which we can match to the monthly sectoral industrial output and other data. For the China exposure, we construct the sector-specific value of intermediate goods imports from China and divide by the value of all intermediate goods used by that sector. For the broad non-China import exposure, we replace the numerator by intermediate goods imports excluding Chinese imports. Our empirical approach studies the extent to which sector-specific ex-ante exposures account for ex-post outcomes during the Covid-19 crisis. This approach can be justified by a simple model in which the share of establishments that use inputs imported from a specific country differs exogenously across sectors. We show that this model explains a monotonic relation between higher ex-ante exposures and larger ex-post output responses.

While there is a literature studying supply chain disruptions prior to Covid-19, it is hard to apply the lessons learned from these prior events to the Covid-19 crisis.[4] Much of the prior evidence could be influenced by its own particular circumstances, or prone to change as trade linkages evolve. Further, the disruption of US-China trade during the Covid-19 crisis differs from most prior events, as it did not originate from the destruction of infrastructure or physical capital and few supply chains were reorganized following the transitory lockdowns. At the same time, the policy implications may depend crucially on

[4]For example, Barrot and Sauvagnat (2016) and Meier (2020) study regional natural disasters in the US, Carvalho et al. (2021) and Boehm et al. (2019) the Fukushima disaster, Glick and Taylor (2010) trade disruptions caused by war, and Huang et al. (2018), Flaaen and Pierce (2019), and Amiti et al. (2020) the US-China Trade War.

the nature of the disruption and the persistence of its effects. Hence, prior evidence from natural disasters may be misleading.[5]

Despite the quickly growing empirical literature on the Covid-19 crisis, our paper is the first to provide evidence on the effects of international supply chain disruptions caused by Covid-19. Our empirical results suggest significant, albeit relatively short-lived, effects of Covid-19 supply chain disruptions. The evidence is not only important for the design of effective macroeconomic stabilization policy, it also relates to questions on the nature of the business cycle. For example, the Great Moderation is often associated with lower volatility in inventory investment (McConnell and Perez-Quiros, 2000), which can be linked to innovations in just-in-time inventory management (Kahn et al., 2002). While lean supply chains reduce inventory holding costs and raise productivity in normal times, they can also lead to more severe effects of supply chain disruptions (Ortiz, 2020). Indeed, the impact of the Covid-19 crisis on supply chains and how to make them more resilient have received a lot of attention since March 2020. These include the management literature, business consultancies, but also the media reporting on supply chain issues related to widespread lockdowns in China (see, for example, Choi et al., 2020, Schmalz, 2020, and Donnan et al., 2020). The Covid-19 crisis might even be a turning point for de-globalization (Antràs, 2020).

A number of related papers analyze the propagation of Covid-19 associated shocks through input and output linkages. For example, Barrot et al. (2021) study the effects of social distancing on GDP, Baqaee and Farhi (2020) study the role of demand and supply shocks during the Covid-19 crisis, Bonadio et al. (2020) and Eppinger et al. (2020) study the international propagation of labor supply shocks, and Acharya et al. (2020) study the policy implications of Covid-19 spreading via international trade. Closely related to our findings, Gerschel et al. (2020) simulate the effect of a productivity decrease in China and conclude that GDP in Japan and Korea responds much more than GDP in the US, France, or Germany, reflecting the higher exposure of those economies to inputs imported from China. Our empirical findings also align well with the evidence in Hassan et al. (2020). Analyzing earnings calls by public listed firms in the first quarter of 2020, the authors document that firms' primary concerns are the collapse of demand, increased uncertainty, and disruption in supply chains.

The remainder of this paper is organized as follows. Section 2 presents a simple model to provide intuition and to guide the empirical analysis. Section 3 describes the data and Section 4 presents our empirical analysis. Section 5 concludes and an Appendix follows.

[5]In fact, based on regional natural disasters in the US, Barrot and Sauvagnat (2016) find persistent effects of supply chain disruptions on sales up to one year after the disaster. Boehm et al. (2019), who study the transmission of the 2011 earthquake in Japan, find that imports and exports of exposed US producers is depressed up to half a year after the earthquake.

2 A simple model of supply chain disruptions

Consider a sector in country A that is populated by two types of establishments. Type 1 establishments use a CES technology that combines imported intermediate goods from country B, denoted m_t^1, and a range of other inputs, such as capital, labor, and other intermediate inputs, captured by a composite factor x_t^1, to produce goods y_t^1

$$y_t^1 = a_t^1 \left[\eta(x_t^1)^\rho + (1-\eta)(m_t^1)^\rho\right]^{\frac{1}{\rho}} = f(z_t^1)m_t^1, \quad z_t^1 = \frac{x_t^1}{m_t^1}, \quad \rho \in (-\infty, 1),$$

where $\sigma = 1/(1-\rho)$ is the substitution elasticity between x_t^1 and m_t^1, and a_t^1 is exogenous productivity. Type 2 establishments produce goods y_t^2 using a linear technology in x_t^2. Hence, they use the same inputs as type 1 establishments except imported intermediate goods from country B. Aggregate sectoral output is

$$y_t = \phi y_t^1 + (1-\phi)y_t^2, \tag{2.1}$$

where ϕ is the (sector-specific) share of type 1 establishments. Before the economy is hit by a supply-chain disruption shock, it is in a steady state and type 1 establishments choose x^1 and m^1 to maximize period profits

$$\pi^1 = p(y^1)y^1 - p^x x^1 - p^m m^1, \tag{2.2}$$

where $p(y) = y^{\gamma-1}$ with $\gamma \in (0,1)$ is a downward-sloping isoelastic inverse demand function. Similarly, type 2 establishments choose x^2 to maximize $\pi^2 = p(y^2)y^2 - p^x x^2$. In steady state, we normalize productivity a^1 to ensure $y^1 = y^2$. Hence, the type-specific contribution to sectoral output is solely captured by ϕ.

In period t, the economy is hit by a supply chain disruption that lowers the supply of country B inputs by a fraction δ for all sectors in the economy: $m_t^1 = (1-\delta)m^1$. We assume the supply chain disruption is symmetric across sectors. We think this captures well the effects of the widespread lockdown in China during February and March 2020. We consider the response of type 1 establishments before prices adjust. The supply of m_t^1 becomes a binding constraint. Thus, type 1 establishments only re-optimize x_t^1 after the disruption. The first-order condition for x_t^1 after the supply chain disruption implies that the factor input ratio z_t^1 is adjusted according to (see Appendix A)

$$\frac{d\log z_t^1}{d\log m_t^1} = -\frac{1-\gamma}{(1-\rho)-(\gamma-\rho)\epsilon} \leq 0, \quad \text{where} \quad \epsilon = \frac{z^1 f'(z^1)}{f(z^1)} \geq 0. \tag{2.3}$$

The increase in z_t^1 in response to a reduction of m_t^1 depends negatively on the elasticity of substitution between the two factor inputs. For example, in the Leontieff case ($\rho \to -\infty$), if m_t^1 drops by $\delta\%$, it is optimal to lower x_t^1 by $\delta\%$ as well, and hence z_t^1 remains unchanged. The effect on output y_t^1 depends on the direct effect of lower m_t^1 and the (partially) offsetting indirect effect of higher z_t^1,

$$d \log y_t^1 = \underbrace{d \log m_t^1}_{\text{direct effect} < 0} + \underbrace{\frac{-(1-\gamma)\epsilon}{(1-\rho)-(\gamma-\rho)\epsilon} d \log m_t^1}_{\text{indirect effect} \geq 0} = \Psi \cdot d \log m_t^1, \tag{2.4}$$

where $\Psi \in [0, 1]$. Depending on ρ, the output response $d \log y_t^1$ ranges between zero, for perfect substitutes ($\rho = 1$), and $d \log m_t^1$, for perfect complements ($\rho \to -\infty$), i.e., a one percent drop in m_t^1 lowers output by 1%.

Aggregating the two types of firms, and after some algebra (see Appendix A), the response of sectoral output to the supply chain disruption is

$$\frac{d \log y_t}{d \log m_t^1} = \tilde{\Psi} \cdot e^B, \tag{2.5}$$

where $\tilde{\Psi} = \frac{1-\alpha+\alpha z^{1\rho}}{1-\alpha} \cdot \Psi$ and e^B is the share of intermediate goods imported from country B (or shortly: the import exposure to country B) in steady state, defined as

$$e^B = \frac{p^m m^1}{p^x(x^1 + x^2) + p^m m^1}. \tag{2.6}$$

Hence, sectors with a higher import exposure to country B before the shock (as results from a larger ϕ, the share of establishments that produce using imports from country B) respond more strongly to the supply chain disruption shock. The strength of this link is shaped by the substitutability of m_t^1, via the effects of ρ on $\tilde{\Psi}$. Equation (2.5) motivates our empirical analysis. Our empirical strategy is to identify cross-sector differences in the effects of supply chain disruptions through cross-sector differences in import exposures e^B.

Finally, we discuss the robustness of these results. First, if we fix ϕ but let α vary across sectors, we obtain similar results as long as inputs in type 1 production are somewhat substitutable ($\rho > -\infty$). The sector with a lower α has a higher expenditure share e^B for m^1. At the same time, a lower α implies a lower elasticity ϵ, which results in a larger output response to the supply chain disruption. Second, our analysis has conveniently maintained fixed input prices. If prices for the same inputs are common across sectors, the specific response of prices to the shock does not qualitatively change our result that in sectors with higher exposure to imported intermediate goods output should fall by relatively more.

3 Data

3.1 Covid-19 and imports from China

In response to the Covid-19 outbreak, China imposed widespread lockdowns of entire regions and sectors during February and early March 2020. As a rough check of how disruptive these lockdowns were to the supply chains of US producers, we construct a monthly time series of US intermediate goods imports from China. We use a broad measure of the share of intermediate goods in overall imports for each 6-digit NAICS commodity, as implied by the import matrix in the Bureau of Economic Analysis (BEA) 2012 Input-Output Accounts. We then multiply this share by the monthly value of imports from China for the corresponding 6-digits NAICS commodity from the International Trade Data on goods maintained by the Census Bureau. We adjust the monthly series of intermediate and final goods imports for two confounding factors during the period of interest. First, we control for seasonality and calendar effects (including the Chinese New Year).[6] Second, we account for the direct impact of the health crisis on US imports by excluding Covid-related goods (e.g., pharmaceuticals and medical equipment and supplies).[7]

The disruptions to economic activity in China were followed by a large contraction of US imports from China by March (Figure 2). Intermediate goods imports, in particular, fell by a cumulative 27% in February and March. This suggests that US producers were subject to a major supply chain disruption. Although imports quickly returned to their pre-crisis level in April, they did not compensate for the large drop in March.[8] The fast recovery of imports from China may have reflected pent-up demand, increased (precautionary) inventory demand, as well as the Phase 1 trade agreement signed in January, which lowered tariffs on US imports from China.

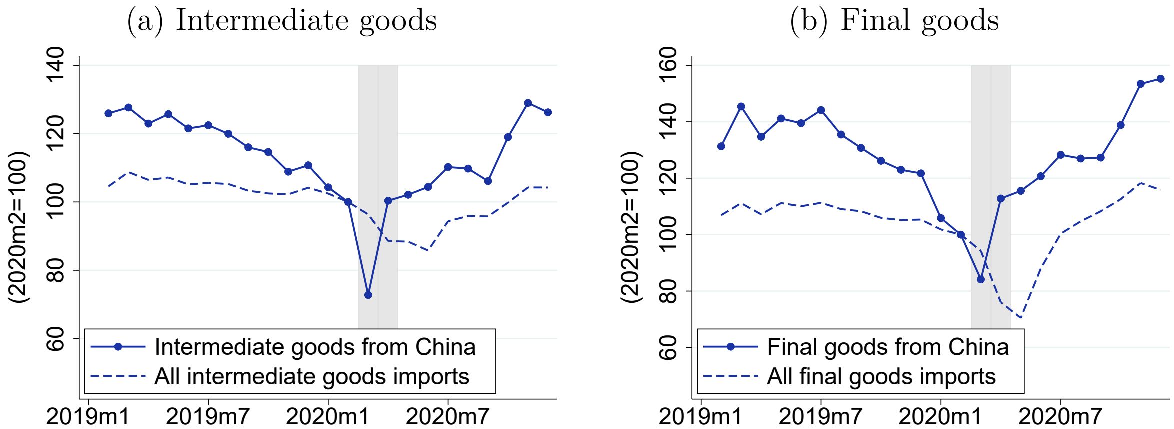
Total imports of intermediate goods (from all countries) fell 4% in March, which suggests limited short-run substitutability of the production supplies imported from China. In fact, total imports kept on falling beyond March, and they fell more severely for final goods. This is consistent with non-China imports being driven by lower demand in the US.

[6] We seasonally adjust the data using X-13ARIMA-SEATS. We allow for trading days and Easter calendar effects and for automatic outliers. For imports from China, we also account for Chinese New Year calendar effects similar to Roberts and White (2015): we follow the People's Bank of China and assume calendar effects in the 20 days leading up to, the 7 days during, and the 20 days after the New Year holiday (plus 3-weeks due to transportation time). We use the data from 2010-2019 to estimate the seasonal and calendar effects in 2020.

[7] We subtract the aggregate value of Covid-related imports, as identified by the list of 10-digit HTS codes in US International Trade Commission (2020), from the total imports from China and elsewhere.

[8] When including Covid-related goods, total intermediate goods imports from China exceeded their pre-crisis level starting in April (see Figure 6 in Appendix B).

Figure 2: Aggregate US imports



Notes: Panels (a) and (b) show the evolution of (seasonally adjusted) aggregate US imports of intermediate goods and final goods separately for imports from China and total world imports. Covid-related goods, as identified in US International Trade Commission (2020), are excluded. All series are normalized to 100 at the business cycle peak in February 2020. The gray-shaded area indicates the NBER recession period March-April 2020.

3.2 Outcomes

We consider a host of sector-level outcomes including measures of output, inputs, and prices. Industrial production (IP) is our primary outcome.[9] IP is a monthly index computed by the Federal Reserve Board for the 'industrial sector', which comprises manufacturing, mining, and electric and gas utilities. The index is available for detailed (usually 4- to 6-digit NAICS) sub-sectors, and is constructed from an extensive range of data. For about 50% of industries, the index is based on observed physical quantities. For example, for NAICS sector 3361 (motor vehicle manufacturing) IP is based on the number of automobiles produced together with their list prices obtained from Ward's Communications and car producers Chrysler and General Motors.[10] For the remaining 50% of industries, the Federal Reserve Board uses production-worker hours from the Bureau of Labor Statistics (BLS), product prices from the BLS, and spot market data to construct industry-specific IP indexes. These indexes are regularly benchmarked against the Economic Census and the Annual Survey of Manufacturers. In the present version of the paper, we use IP data after the first annual revision of

[9]We focus on industrial production because we think it responds more quickly to supply chain disruptions. Policymakers might consider the employment response more important than the response of output. However, various labor adjustment frictions, as well as policy responses to the crisis (e.g., the Paycheck Protection Program), may substantially dampen and delay the employment response. In fact, our empirical results in Section 4 show that employment responds with a lag and less strongly compared to industrial production.

[10]More details on the data sources for the construction of the industrial production index can be found here: https://www.federalreserve.gov/releases/g17/SandDesc/sdtab1.pdf

the 2020 data, which was released in May 2021.[11]

We aggregate the detailed IP sectors into 88 sectors, which roughly correspond to 4-digit NAICS industries. We consider symmetric growth rates of the form

$$\frac{x_t - x_{t-h}}{\frac{1}{2}\left(x_t + x_{t-h}\right)}, \tag{3.1}$$

where t is a monthly time index and x_t is the IP index or another outcome of interest. We use $h = 1$ for monthly growth rates and $h = 12$ for 12-month growth rates (i.e., monthly year-over-year growth rates). As discussed in Davis and Haltiwanger (1990), these symmetric growth rates lie in the closed interval $[-2, 2]$ and avoid extreme statistical outliers when some outcome drops close to zero. This issue is especially prevalent during the sharp contractions of the Covid-19 recession.[12]

Panel (a) of Figure 3 shows the evolution of the median monthly IP growth together with the 10th, 25th, 75th, and 90th percentiles of IP growth across sectors. The median evolves similarly to aggregate IP growth in Figure 1 during the Covid-19 recession. What stands out is the large heterogeneity across sectors. While industries at the 75th percentile of the IP growth distribution shrank by around 5% in April 2020, industries at the 25th percentile shrank by more than 20%.

We further use data on sector-specific employment, imports, exports, import prices, and output prices, all aggregated to the same 88 sectors.[13] We obtain employment from the Current Employment Statistics maintained by the BLS. Sector-specific imports and exports are from the International Trade Data maintained by the Census. We construct sector-specific prices for intermediate inputs imports by combining product-specific price indexes from the BLS International Price Index files with the sector-specific composition of intermediate inputs imports from the BEA 2012 import matrix. Output prices are based on the sector-specific producer price indexes maintained by the BLS.

3.3 China exposure

We compute sector i's exposure to intermediate goods imports from country or region B as the value of sector i's imported intermediate goods from B relative to the value of all

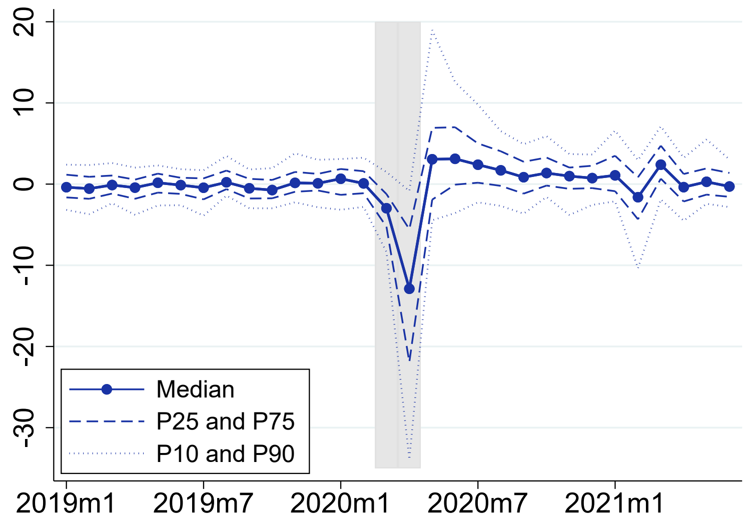
[11] We prefer to use revised data because measuring economic activity during the Covid-19 recession is particularly challenging, so data revisions may be substantial. However, none of our main conclusions changes between the earlier and latest data vintages.

[12] An extreme example is sector 3361 (motor vehicle manufacturing). The (standard) monthly IP growth rate is -98% in April 2020 and +1,509% in May. The corresponding symmetric growth rates are -192% and +177%, respectively. Our results are robust to using standard growth rates when excluding sector 3361.

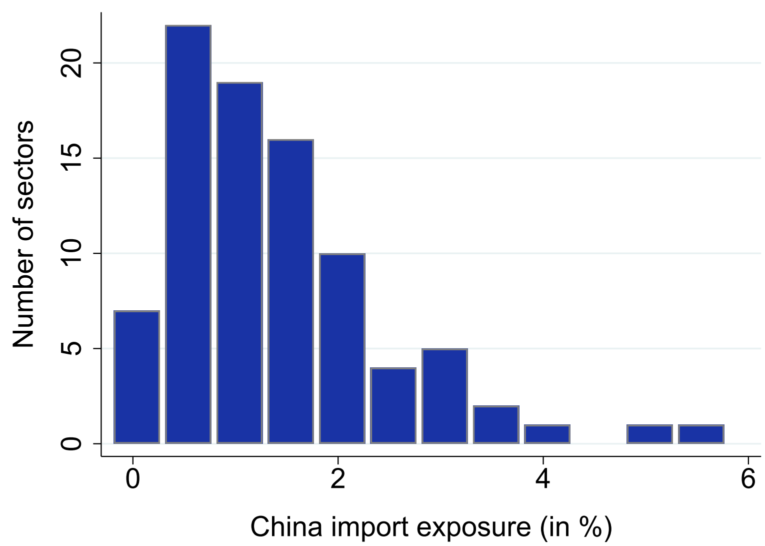
[13] For these variables, we also use the latest data including the respective annual revision of the 2020 data.

Figure 3: Heterogeneity across sectors

(a) Distribution of industrial production growth (in %)



(b) Distribution of China import exposure



Notes: Panel (a) shows percentiles of the percentage change in monthly industrial production (seasonally adjusted) across US industrial sectors, based on the Federal Reserve G.17 release. The gray-shaded area indicates the NBER recession period March-April 2020. Panel (b) shows the histogram of China import exposures (3.2) across US industrial sectors.

intermediate inputs used by sector i.

$$e_i^B = \frac{(\text{Intermediate goods imports from } B)_i}{(\text{Intermediate input costs})_i} \tag{3.2}$$

However, sector-specific intermediate goods imports from a particular country or region, say B = China, are not directly measured by trade statistics. Instead, we observe total imports from China in 2019 at the level of 6-digit NAICS commodities from the International Trade Data. In addition, we have the value of 6-digit NAICS commodity imports (from all countries) used by 6-digit NAICS sectors from BEA's 2012 import matrix. To construct sector-specific intermediate good imports from China, we adopt a proportionality assumption, as described in Johnson and Noguera (2012) and as similarly applied to construct the World Input Output Database (see Timmer et al., 2015).

In practice, we proceed in three steps to compute the numerator in our China import exposure measure (3.2). First, for each 6-digit NAICS commodity, we compute the share of imports from China relative to all imports in the 2019 trade data. Second, we multiply this 6-digit commodity China import share with the value of each 6-digit sector's intermediate goods imports (from all countries) of the same 6-digit commodity in the 2012 import matrix. This yields an estimate of the value of a 6-digit sector's (intermediate goods) imports of a 6-digit commodity from China, which is exact under the proportionality assumption. Third, we aggregate across all 6-digit commodities to obtain the total value of intermediate goods imports from China for each 6-digit sector.

The composition of intermediate and final goods for imports from China may be quite different from other countries. We therefore compute the China import share only for 6-digit NAICS commodities which primarily include intermediate goods. We use the BEA end-use classification and define intermediate goods as all industrial supplies and materials (code 1), industrial engines (code 21100), semiconductors (code 21320), and parts and engines of aircraft, vessels, and motor vehicles (codes 22010, 22020, 22220, and 302), as well as all foods, feeds, and beverages (code 0). We drop commodities from the aggregation in step three above for which we have no intermediate goods imports.[14]

The calculation of the denominator of the China import exposure measure (3.2) is more straightforward. For each 6-digit NAICS sector, we obtain the value of all intermediate inputs used in production from BEA's use table of the 2012 Input-Output Accounts. Our China exposure is the ratio of intermediate goods imported from China divided by all intermediate inputs used in production, where both the numerator and denominator are appropriately aggregated across the 6-digit sectors within the roughly 4-digit NAICS sectors available for IP and other outcomes. For further details on these steps see Appendix C.

The final sample contains 88 distinct manufacturing and related industries. In Appendix B,

[14]This procedure is conservative. Only 40% of imports are identified as intermediate inputs versus 56% in BEA's 2012 import matrix. Our results are robust to using the China import share of all imports, i.e., when not discarding commodities according to their end-use classification, see Section 4.6.

Table 6 lists all industries and their China exposures. Panel (b) of Figure 3 shows a histogram of China exposures across these industries. We observe large differences in the input cost share of intermediates imported from China ranging from less than 0.1% to above 5%, with an average of 1.4%. While these fractions are relatively small, our simple model in Section 2 shows that a disruption in the supply of Chinese inputs can lead to as much as a complete halt of production in the US. The magnitude of the effect critically depends on how easily inputs can be substituted. We further construct sector i's non-China import exposure and a China export exposure. Both exposures are constructed similarly to the China import exposure and divide the import or export flows by the total costs of intermediate inputs. The sector-specific exports to China are based on the International Trade Data.[15]

4 Empirical evidence

In this section, we provide empirical evidence suggesting that supply chain disruptions are a significant economic driver during the Covid-19 recession and early recovery. We first present our empirical strategy and then study whether industrial production fell more in sectors with higher China exposure in Subsection 4.2. In Subsection 4.3, we study the effects of higher China exposure on prices and other outcomes. We investigate how persistent the effects are in 4.4 and the role of non-China exposures in 4.5. Subsection 4.6 provides a battery of robustness checks.

4.1 Empirical strategy

Our empirical strategy exploits differences in the sector-specific exposure to intermediate goods imported from some country or region, say B. Let i index the sectors and t the monthly time period. Our baseline regression model is

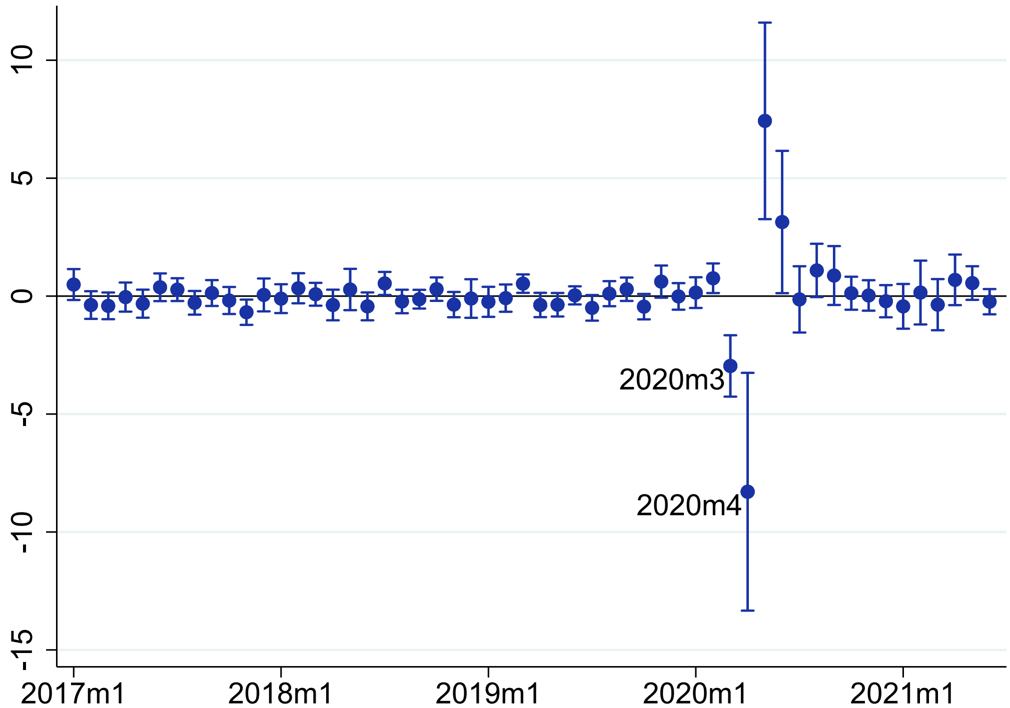
$$y_{it} = \alpha_t + \beta_t e_i^B + \Gamma_t Z_{it} + u_{it} \tag{4.1}$$

where y_{it} is a sector-time specific outcome expressed in growth rates (e.g., IP growth of steel manufacturing in March 2020) and Z_{it} is a vector of sector-time specific controls. The import exposure to country/region B, e_i^B, is standardized to have unit variance.

Most of our empirical analysis focuses on China exposures (B = China). If e_i^{China} is orthogonal to other channels, unrelated to dependence on supply chains from China, that explain differential outcomes across sectors, then β_t should capture the causal effect of supply

[15] The cross-sector correlation between the China import exposure and the non-China import exposure is 0.42, and the correlation between the China import exposure and the China export exposure is -0.15.

Figure 4: Estimated β_t coefficients for industrial production



Notes: The markers show the estimated (standardized) β_t coefficients based on equation (4.1), when y_{it} is monthly IP growth, e_i^B is the China import exposure (in %), and no control variables Z_{it} are used. The β_t estimates capture the differential IP growth (in p.p.) associated with a 1 standard deviation higher e_i^{China}. The vertical lines indicate 95% confidence intervals based on heteroskedasticity and autocorrelation robust standard errors.

chain disruptions during the early part of the Covid-19 crisis. Similar strategies have been employed by Boehm et al. (2019) and Carvalho et al. (2021) in the context of the 2011 Tohoku Earthquake, and in Huang et al. (2018), Flaaen and Pierce (2019), and Amiti et al. (2020) in the context of the US-China Trade War.[16]

4.2 Industrial production

We start with a simple empirical analysis of IP growth. In particular, we estimate the β_t coefficients based on equation (4.1), when y_{it} is monthly IP growth, e_i^B is the China import exposure (in %), and no control variables Z_{it} are used. We view this as a benchmark analysis, which we later extend into various dimensions. Figure 4 shows the estimated (standardized) β_t. These capture the differential monthly IP growth (in p.p.) associated

[16] A common approach in the related literature is to estimate differential treatment effects through a regression of some outcome in levels (instead of in differences or growth rates) on a step dummy for an event, interacted with an exposure variable. We can derive (4.1) by taking first differences of such regression model.

with a one standard deviation higher e_i^{China}.[17] The standard deviation of e_i^{China} is 1.09, which is almost identical with the interquartile range of e_i^{China} at 1.17. Notably, the coefficients from March through June 2020 stand out in significance and magnitude compared to the coefficients of the preceding three years. In what follows, we will first focus on March and April 2020 and then discuss the post-April reversal in Subsection 4.4.

A primary take-away from Figure 4 are the large negative and significant β_t coefficients in March and April 2020. The estimates are of economically relevant magnitudes. Industrial production growth is estimated to have been 3.0 percentage points (p.p.) and 8.3 p.p. lower in March and April, respectively, for every 1 standard deviation increase in the China exposure across sectors (see first columns in Table 1). To understand how much variation in IP growth can be explained by variation in China exposures, note that the cross-sectional standard deviations of IP growth in March and April 2020 are $\sigma(y_{i,2020\text{m}3}) = 6.76\%$ and $\sigma(y_{i,2020\text{m}4}) = 24.94\%$. Hence, in terms of R-squared, 19.4 percent of the cross-sectoral variance in March IP growth and 11.2 percent in April can be associated to different China exposures. To gauge the combined March and April effect of China exposure on industrial production, we use the year-over-year IP growth in April 2020 as outcome variable (see second column of panel (b) in Table 1). We conclude that 12.7 percent of the variance in industrial production growth during the Covid-19 recession can be attributed to different China exposures.

The small and non-negative coefficient for February 2020 may appear surprising at first.[18] In fact, as part of the lockdown measures to combat the epidemic, the Chinese New Year holiday (observed from the 24th to the 30th of January, 2020) was extended into the first weeks of February in many of the largest Chinese provinces. So, we might have expected a large negative coefficient already in February. Three explanations can plausibly account for the small and non-negative β_t at the onset of the crisis. First, cargo transportation from a supplier in China to a US producer takes time and, indeed, US imports from China only slumped in March.[19] Second, US producers hold some inventory of imports from China, which dampens the immediate effect. Third, the US-China trade deal signed in January 2020 may have given a small boost to sectors with higher China exposure. Relatedly, it may appear surprising that the β_t coefficient peaks only in April, whereas the main Chinese lockdown happened in February. Besides transportation time and inventory buffers, this may have reflected sustained (partial) lockdowns and restrictions on production in China,

[17] Figure 7 in Appendix D shows the estimated (standardized) β_t coefficients for year-over-year IP growth. While the March-May 2020 coefficients are significantly negative for year-over-year IP growth, base effects lead to significantly positive coefficients in April-May 2021.

[18] In February 2020 we can only attribute 1.3% of differences in IP growth to different China exposures.

[19] Cargo ships travel 12 days from China to US West Coast and 22 days to US East Coast, see https://www.langsamreisen.de/en which offers freighter travel.

Table 1: Growth rates of industrial production

(a) March 2020

	1-Month	12-Month	1-Month/Detr.	12-Month/Detr.
China import exposure	-2.960	-2.712	-2.943	-2.087
	(0.651)	(1.008)	(0.642)	(0.963)
Observations	88	88	88	88
R^2	0.194	0.078	0.196	0.052

(b) April 2020

	1-Month	12-Month	1-Month/Detr.	12-Month/Detr.
China import exposure	-8.293	-9.787	-8.276	-9.161
	(2.520)	(2.765)	(2.519)	(2.747)
Observations	88	88	88	88
R^2	0.112	0.127	0.112	0.115

(c) May 2020

	1-Month	12-Month	1-Month/Detr.	12-Month/Detr.
China import exposure	7.429	-4.311	7.446	-3.686
	(2.083)	(2.208)	(2.083)	(2.200)
Observations	88	88	88	88
R^2	0.129	0.042	0.129	0.032

(d) June 2020

	1-Month	12-Month	1-Month/Detr.	12-Month/Detr.
China import exposure	3.141	-1.483	3.158	-0.858
	(1.508)	(1.464)	(1.509)	(1.467)
Observations	88	88	88	88
R^2	0.048	0.012	0.048	0.004

Notes: The table shows the estimated (standardized) β_t coefficients in equation (4.1), when y_{it} is IP growth, e_i^B is the China import exposure, and no control variables Z_{it} are used. We consider monthly IP growth (1-Month), year-over-year IP growth (12-Month), detrended monthly IP growth (1-Month/Detr.), and detrended year-over-year IP growth (12-Month/Detr.). The β_t estimates capture the differential IP growth (in p.p.) associated with a 1 standard deviation higher e_i^B. Heteroskedasticity and autocorrelation robust standard errors are provided in parantheses.

as well as supply chain propagation within US sectors.

Before the Covid-19 crisis, the β_t coefficients in Figure 4 are consistently close to zero and mostly insignificant. This may be surprising against the backdrop of the US-China trade war during these years. Two reasons may explain this result. First, tariffs hikes during the trade war often targeted specific, narrow sectors, e.g., washing machines as analyzed in Flaaen et al. (2020). Our exposure measure is unlikely to pick up these effects. Second, while tariffs change the costs of importing inputs they do no prohibit goods from being produced and transported across borders. Especially for imported inputs lacking alternative suppliers, the costs of higher tariffs may be small compared to the costs of disrupted supply. When extending our analysis to account for tariff changes during the US-China trade war, our estimates are nearly unchanged, see Subsection 4.6.

4.3 Prices and other activity outcomes

We next analyze whether prices and other activity outcomes (besides industrial production) changed differently across sectors as a result of their exposure to imports from China. We find that both import and output prices increased, while employment, imports, and exports decreased relatively more in sectors with higher exposure.

We study the price responses to examine whether our exposure measure mostly captures the relative strength of supply shocks. It is possible that China exposure is higher mostly in industries that were affected through channels other than supply chains during the Covid-19 recession, namely through a slump in domestic demand. Lower demand could then explain why industrial production fell more in sectors with higher China exposure, in which case we would expect their specific prices to fall relative to those of other sectors. Conversely, if sectors with high exposure are indeed mostly affected by international supply chain disruptions, then both their import and output prices should increase relative to other sectors.

The three leftmost columns of Table 2 show the estimated differential year-over-year (12-month) growth rates for price outcomes, again based on equation 4.1 when no control variables are included. In March and April 2020, both import (IPI) and output (PPI) prices increased more in sectors with higher China import exposure. The differences are statistically significant at the 5% level for import prices. The differences for output prices are less significant. This result makes it unlikely that larger declines of activity in industries with high exposure mostly reflected lower domestic demand. When controlling for other variables that may correlate with the China import exposure, notably China export exposure, non-China import exposure, external finance dependence, and business cycle sensitivity, the significance levels fall toward 1% (see Subsection 4.6 and Table 7 in Appendix D).

Comparing observed price changes across sectors may be misleading if sectors differ in how quickly (item-level) prices are adjusted. In fact, average price adjustment frequencies differ a lot across sectors (see, e.g., Nakamura and Steinsson, 2008 and Pasten et al., 2020). To address this concern, we compute adjusted output price growth (PPI*) by taking the ratio of PPI growth over the average price adjustment frequency documented in Pasten et al. (2020). Using PPI* as outcome, we still find larger output price increases for sectors more exposed to China. One problem with this correction for price rigidity is that it rests on the assumption that the average price adjustment frequency is informative about the price adjustment frequency in March and April 2020. Given the magnitude of the disruption caused by Covid-19, this might be a strong assumption.

The three rightmost columns of Table 2 show the differential year-over-year growth rates for outcomes other than IP. We find that more exposed sectors have relatively lower employment growth (EMP), especially in April, lower import growth (IMP), and lower export growth (EXP). This draws an overall consistent picture that more exposed sectors were contracting more during the Covid-19 recession, which makes it less likely that our results are driven by peculiar types of measurement error. The March and April β_t estimates for employment, imports, and exports are broadly robust to controlling for China export exposure, non-China import exposure, external finance dependence, and business cycle sensitivity (see Subsection 4.6).

4.4 Persistence

We next examine how persistently industries with higher China import exposure underperformed after the trough of the Covid-19 recession in April 2020. In May and June 2020, the relationship between China import exposure and monthly industrial production growth reverses sign. Sectors with higher exposure have significantly higher monthly IP growth than less exposed sectors, see Figure 4. In subsequent months, the differences are mostly small and insignificant.

The May and June reversal in the monthly rates is large and almost closes the output gap between differently exposed sectors that opened during March and April. In fact, by June the difference in the year-over-year IP growth rates between differently exposed sectors, though still negative, becomes small and statistically insignificant (see the second column of Table 1). Effectively, the larger declines of more exposed sectors during March and April were almost fully reversed in May and June, which suggests a fairly limited persistence of about four months. This finding is not exclusive to industrial production. We also find quick reversals between May and June when estimating the β_t coefficients for prices, employment, imports, and exports, (see panels (c) and (d) of Table 2).

In summary, our evidence suggests that supply chain disruption occurred around February 2020 in China, attained their peak effect on US producers in April, and seem to have largely dissipated by June. The fact that we find large effects that only lasted for few months may

Table 2: 12-month growth rates of all outcomes

(a) March 2020

	IPI	PPI	PPI*	IP	EMP	IMP	EXP
China import exposure	2.062	1.192	3.072	-2.712	-0.370	-3.805	-2.072
	(1.020)	(0.812)	(2.292)	(1.008)	(0.344)	(1.980)	(1.333)
Observations	88	88	88	88	88	83	83
R^2	0.045	0.024	0.020	0.078	0.013	0.044	0.029

(b) April 2020

	IPI	PPI	PPI*	IP	EMP	IMP	EXP
China import exposure	3.676	2.290	5.362	-9.787	-5.277	-4.718	-11.32
	(1.536)	(1.360)	(3.207)	(2.765)	(1.133)	(3.510)	(3.208)
Observations	88	88	88	88	88	83	83
R^2	0.062	0.032	0.031	0.127	0.202	0.022	0.133

(c) May 2020

	IPI	PPI	PPI*	IP	EMP	IMP	EXP
China import exposure	3.147	1.672	4.375	-4.311	-3.638	-9.650	-8.882
	(1.413)	(1.160)	(3.131)	(2.208)	(1.057)	(4.172)	(3.414)
Observations	88	88	88	88	88	83	83
R^2	0.055	0.024	0.022	0.042	0.121	0.062	0.077

(d) June 2020

	IPI	PPI	PPI*	IP	EMP	IMP	EXP
China import exposure	1.849	1.117	3.304	-1.483	-1.958	-3.381	-1.724
	(0.970)	(0.737)	(2.439)	(1.464)	(0.710)	(3.389)	(2.338)
Observations	88	88	88	88	88	83	83
R^2	0.041	0.026	0.021	0.012	0.081	0.012	0.007

Notes: The table shows the estimated (standardized) β_t coefficients in equation (4.1), when y_{it} is a year-over-year growth rate, e_i^B is the China import exposure, and no control variables Z_{it} are used. We consider growth rates of the import price index (IPI), producer price index (PPI), PPI growth adjusted by price adjustment frequency (PPI*), industrial production (IP), employment (EMP), imports (IMP), and exports (EXP). Imports and exports are missing for sectors 213, 2211, 2212, 3328, and 5111. The β_t estimates capture the differential growth rate (in p.p.) associated with a 1 standard deviation higher e_i^B. Heteroskedasticity and autocorrelation robust standard errors are provided in parantheses.

be policy relevant. For example, to the extent that supply remained constrained through June 2020, fiscal spending that stimulated aggregate demand relative to supply may have been less effective in the first few months of the Covid-19 crisis, and more effective once US production was no longer restrained by limited availability of intermediate inputs. Instead, during the initial phase of the Covid-19 crisis, more effective policies would have included supporting companies to survive and maintain productive capacity. Some notorious examples of these kind of policies would be unconventional monetary policy measures aimed at lowering credit spreads, including the Federal Reserve's main street lending program and corporate credit facilities, and programs that prevent mass layoffs, such as the Paycheck Protection Program.

Our evidence further speaks to the debate about re-sourcing or de-globalisation, triggered by the disruptions to cross-border supply chains since early 2020 (Antràs, 2020), in the sense that the initial disruptions to domestic production, although quite large, were relatively short-lived. A promising avenue for future research is to understand how the Covid-19 crisis changed firms' global sourcing decisions, e.g., in the framework of Antràs et al. (2017).

4.5 Non-China exposure

We next investigate whether our results are specific to imports from China, or whether we observe a similar pattern for sectors that depend on imports more generally. We consider a broad sector-specific import exposure that includes all intermediate goods imports except those originating from China. We re-estimate regression (4.1) using the non-China import exposure and present the β_t estimates in Table 3. We find that IP contracted significantly more in sectors with higher broad import exposure. However, the differential responses of employment, imports, and exports are insignificant, even in April. In contrast, in sectors with higher China exposure, employment and exports fell relatively more (Table 2). The fact that responses are less consistent across different outcomes suggests that the non-China import exposure does not capture the same effects as the China exposure during this particular time period. This interpretation is further supported by the evidence that import and output prices in sectors with higher broad import exposure do not increase relative to other sectors. Instead, the β_t coefficients for price growth in March and April are highly significantly negative. This in turn suggests that the non-China import exposure is high in sectors that are more severely hit by a slump in demand. Overall, these results caution against interpreting the non-China β_t coefficients as capturing the effects of supply chain disruptions.[20]

[20] In Subsection 4.6, we show that our β_t estimates for the China import exposure are broadly robust to controlling for the non-China import exposure.

Table 3: 12-month growth rates of all outcomes for non-China exposure

(a) March 2020

	IPI	PPI	PPI*	IP	EMP	IMP	EXP
Non-China import exposure	-1.293	-1.818	-6.659	-3.263	-0.0199	-1.277	-0.389
	(1.034)	(0.799)	(2.202)	(0.988)	(0.346)	(2.007)	(1.343)
Observations	88	88	88	88	88	83	83
R^2	0.018	0.057	0.096	0.112	0.000	0.005	0.001

(b) April 2020

	IPI	PPI	PPI*	IP	EMP	IMP	EXP
Non-China import exposure	-3.438	-3.781	-12.04	-6.251	-1.314	-3.500	-3.957
	(1.543)	(1.320)	(2.989)	(2.882)	(1.260)	(3.505)	(3.395)
Observations	88	88	88	88	88	83	83
R^2	0.055	0.087	0.159	0.052	0.013	0.012	0.016

(c) May 2020

	IPI	PPI	PPI*	IP	EMP	IMP	EXP
Non-China import exposure	-3.074	-3.823	-11.18	-3.826	-1.771	-5.094	-7.368
	(1.415)	(1.099)	(2.928)	(2.218)	(1.111)	(4.243)	(3.435)
Observations	88	88	88	88	88	83	83
R^2	0.052	0.123	0.145	0.033	0.029	0.017	0.054

(d) June 2020

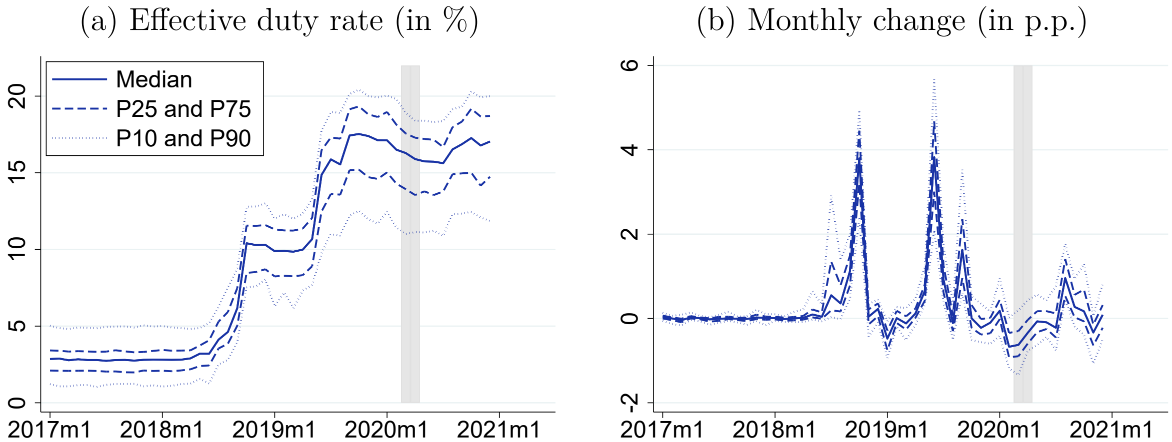
	IPI	PPI	PPI*	IP	EMP	IMP	EXP
Non-China import exposure	-1.633	-2.332	-7.000	-2.437	-1.303	-3.057	-3.749
	(0.975)	(0.703)	(2.346)	(1.449)	(0.727)	(3.371)	(2.293)
Observations	88	88	88	88	88	83	83
R^2	0.032	0.114	0.094	0.032	0.036	0.010	0.032

Notes: The table shows the estimated (standardized) β_t coefficients in equation (4.1), when y_{it} is a year-over-year growth rate, e_i^B non-China import exposure, and no control variables Z_{it} are used. We consider growth rates of the import price index (IPI), producer price index (PPI), PPI growth adjusted by price adjustment frequency (PPI*), industrial production (IP), employment (EMP), imports (IMP), and exports (EXP). Imports and exports are missing for sectors 213, 2211, 2212, 3328, and 5111. The β_t estimates capture the differential growth rate (in p.p.) associated with a 1 standard deviation higher e_i^B. Heteroskedasticity and autocorrelation robust standard errors are provided in parantheses.

4.6 Robustness

US-China trade war. The Covid-19 crisis was preceded by the US-China trade war since 2018. This included several tariff increases on imports from China and, shortly before the

Figure 5: Duty rates on US imports from China



Notes: Panel (a) shows the median and percentiles of the effective duty rate across US industrial sectors. Panel (b) shows the median and percentiles of monthly changes in the effective duty rate.

Covid-19 crisis, the Phase 1 trade agreement. Figure 5 shows the evolution of effective duty rates on imports of intermediate inputs from China. Duty rates increased since the onset of the trade war in mid-2018 across the distribution of US industrial sectors in our sample. We observe a series of tariff hikes in 2018 and 2019, followed by a small reduction in February 2020 after the Phase 1 trade agreement, which mainly reflects a partial reversal of the last tariff hike in September 2019. Our empirical findings may potentially capture differential exposures to the trade war instead of differential exposures to the Covid-19 induced disruptions to US trade with China. To address this alternative explanation, we control for sector-specific changes in the effective duty rates on US imports from China.[21]

We regress IP growth on China import exposure when controlling for three alternative measures of the change in the sector-specific effective duty rate. First, the change between August 2019 and December 2019, including the last round of tariff hikes that were then partially undone with the Phase 1 tariff reductions. Second, the change between December 2018 and December 2019, to account for the possibly persistent effects of tariff increases earlier in 2019. Third, the change between December 2017 and December 2019, to control for the sector-specific cumulative duty changes during the trade war. Table 4 shows the results for the year-over-year IP growth rates in March and April 2020. Essentially, both

[21]Following a similar approach to Flaaen et al. (2021), we use data from the U.S. International Trade Commission to compute the effective duty rate on imports from China for each 6-digit NAICS commodity. The effective duty rate is calculated as the ratio of computed duties to the CIF value of imports for consumption (which includes freight and insurance costs). We then compute the (weighted) average duty rate across 6-digit NAICS commodities for each industrial sector in our sample, where the sector-specific weights are the value of intermediate good imports from China of each commodity, as defined in the calculation of the numerator of our exposure measure in Subsection 3.3 (see Appendix C).

point estimates and standard errors of the β_t coefficients on the China import exposure are only marginally affected when controlling for changes in effective duty rates. Similarly, we find that the May–June estimates change very little when controlling for changes in effective duty rates (see Table 9 in Appendix D).

Other channels. In Subsection 4.3, we discussed the concern that a high dependency on imports from China could correlate with a high sensitivity to other channels of the Covid-19 crisis, besides disrupted supply chains. We argued that the differential price increase for more exposed sectors suggests that the slump in domestic demand was not the most determinant factor for exposed sectors. We now want to address other possible channels that may be correlated with high China exposures, including lower external demand (namely from China), tighter financing conditions, or a higher sensitivity to business cycle fluctuations in general.

We address these concerns by enriching equation (4.1) with covariates. We construct a measure of sectoral external finance dependence following the approach in Rajan and Zingales (1998), but using data between 2010 and 2019. We also construct a measure of sensitivity to the sectoral business cycle, as the correlation between sectoral annual IP growth and annual (aggregate) GDP growth, based on data before the Covid-19 crisis. In addition, we control for China export exposure and for non-China import exposure.

Table 5 shows the March and April β_t coefficients when including these controls separately and jointly. There is still a significant relation between a higher China exposure and a larger contraction in industrial production. The magnitudes of the estimated β_t falls by 1/4 for March and 1/3 for April. Hence, high China import exposure still accounts for a substantial fraction of the cross-sector variation in IP growth. Moreover, the coefficients for the respective control variables are not consistently significant across March and April.

Finally, Table 7 in Appendix D shows the β_t estimates for all outcomes when including the full list of controls. Importantly, our results are broadly robust. The differential price response is even a lot more significant with controls. We also review the estimates for the non-China exposure in Table 3 when adding these controls (and replacing as control non-China import exposure by China import exposure). Table 8 in Appendix D shows the resulting estimates. Importantly, the differential price change remains negative and significant. The differential IP response is insignificant for April and May.

Heterogeneous sector trends. Our estimates may possibly be biased by the presence of cross-sector differences in IP trend growth before the Covid-19 crisis. To investigate whether pre-Covid trends are important, we consider detrended growth rate specifications. We detrend the monthly IP growth rate by subtracting the average monthly IP growth rate

Table 4: Growth rates of industrial production with trade-war controls

(a) March 2020

	(1)	(2)	(3)	(4)
China import exposure	-2.712	-2.908	-2.822	-2.890
	(1.008)	(1.058)	(1.064)	(1.036)
Duty change 2019m8-2019m12		0.133		
		(0.686)		
Duty change 2018m12-2019m12			-0.127	
			(0.588)	
Duty change 2017m12-2019m12				-0.283
				(0.348)
Observations	88	84	84	84
R^2	0.078	0.086	0.086	0.093

(b) April 2020

	(1)	(2)	(3)	(4)
China import exposure	-9.787	-9.939	-9.704	-10.38
	(2.765)	(2.880)	(2.888)	(2.822)
Duty change 2019m8-2019m12		-1.340		
		(1.868)		
Duty change 2018m12-2019m12			-1.602	
			(1.597)	
Duty change 2017m12-2019m12				-0.979
				(0.946)
Observations	88	84	84	84
R^2	0.127	0.146	0.151	0.151

Notes: The first row in panels (a) and (b) shows the estimated (standardized) β_t coefficients in equation (4.1), when y_{it} is year-over-year IP growth, e_i^B is the China import exposure, and we consider various combinations of control variables Z_{it}. The β_t estimates capture the differential IP growth (in p.p.) associated with a 1 standard deviation higher e_i^B. Heteroskedasticity and autocorrelation robust standard errors are provided in parantheses.

Table 5: Growth rates of industrial production with controls

(a) March 2020

	(1)	(2)	(3)	(4)	(5)	(6)
China import exposure	-2.960	-2.799	-2.201	-2.890	-2.866	-1.949
	(0.651)	(0.652)	(0.701)	(0.640)	(0.671)	(0.711)
China export exposure		1.061				0.847
		(0.652)				(0.633)
Non-China import exposure			-1.753			-1.556
			(0.701)			(0.701)
Ext. finance dependence				-1.332		-1.219
				(0.639)		(0.628)
Business cycle sensitivity					-0.419	-0.636
					(0.671)	(0.645)
Observations	88	88	88	88	88	88
R^2	0.194	0.218	0.249	0.233	0.198	0.304

(b) April 2020

	(1)	(2)	(3)	(4)	(5)	(6)
China import exposure	-8.293	-8.082	-7.968	-8.203	-7.060	-6.322
	(2.520)	(2.561)	(2.811)	(2.532)	(2.535)	(2.867)
China export exposure		1.387				0.810
		(2.561)				(2.553)
Non-China import exposure			-0.751			-1.009
			(2.811)			(2.824)
Ext. finance dependence				-1.695		-2.177
				(2.532)		(2.531)
Business cycle sensitivity					-5.450	-5.722
					(2.535)	(2.602)
Observations	88	88	88	88	88	88
R^2	0.112	0.115	0.113	0.116	0.158	0.169

Notes: The first row of panels (a) and (b) shows the estimated (standardized) β_t coefficients in equation (4.1), when y_{it} is monthly IP growth, e_i^B is the China import exposure, and we consider various combinations of control variables Z_{it}. The β_t estimates capture the differential IP growth (in p.p.) associated with a 1 standard deviation higher e_i^B. Heteroskedasticity and autocorrelation robust standard errors are provided in parantheses.

in the two-year period ending in February 2020. Similarly, we detrend the year-over-year IP growth rate, by its average over the two years ending in February 2020. Columns 3 and 4 of Table 1 show the estimated March–June β_t coefficients for detrended growth rates. Overall, the coefficients are of similar magnitude and of similar statistical significance. In addition, variation in China exposure accounts for a similar fraction of the variation in IP growth as in the baseline.

Alternative China exposures. Our baseline China exposure uses a China import share based only on intermediate goods imports, defined using BEA's end-use classification (see Appendix C). However, our narrow definition of intermediate goods implies the exclusion of some 6-digits NAICS commodities from the calculation of the numerator of our exposure measure in (3.2). To check for the robustness of this assumption, Table 10 in Appendix D considers an alternative China exposure where the China import share is based on all imports and no 6-digit NAICS commodities get excluded ('raw exposure' in the table). Both the March and April β_t are significant, but substantially smaller than the baseline. However, the raw exposures feature a statistical outlier (not present in the baseline exposures). While the exposures of 87 sectors range between 0.25% and 2%, the exposure of sector 3342 (communications equipment manufacturing) is 5%, which is six standard deviations above the mean. Excluding the outlier, the estimated magnitudes are similar between our baseline exposure and the raw exposure.

5 Conclusion

We study the role of international supply chain disruptions during the Covid-19 crisis. We show that US sectors with a high exposure to imports from China significantly and substantially contracted output relatively more during March and April 2020 compared to less exposed sectors. Moreover, employment, exports, and imports, fell relatively more in highly exposed sectors, while their import and output prices increases relatively more. Our results suggest that differential exposure to China-specific supply chain disruptions explain about 12% of the cross-sectoral differences in industrial production growth during March and April 2020. Although quite considerable upon impact, the effects appear to be relatively short-lived and become insignificant by June 2020.

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Appendix A Model

We consider the problem of type 1 establishments and drop index 1 for convenience. Before the shock, the input choices are denoted by x, m, and $z = \frac{x}{m}$. After the shock, they are denoted by x_t, m_t, and $z_t = \frac{x_t}{m_t}$. While the supply chain disruption constrains the choice of m_t to $m_t = (1-\delta)m$, the input x_t is chosen optimally before and after the shock. The first-order conditions for x/x_t expressed in terms of z/z_t and m/m_t are given by

$$\alpha\gamma m^{\gamma-1} f(z)^{\gamma-\rho} z^{\rho-1} = p^x, \tag{A.1}$$

$$\alpha\gamma m_t^{\gamma-1} f(z_t)^{\gamma-\rho} z_t^{\rho-1} = p^x. \tag{A.2}$$

We combining the two first-order conditions to obtain

$$f(z_t)^{\gamma-\rho} z_t^{\rho-1} = (1-\delta)^{1-\gamma} f(z)^{\gamma-\rho} z^{\rho-1}. \tag{A.3}$$

Taking a first-order Taylor expansion w.r.t. z_t and δ at $\delta = 0$ and hence $z_t = z$ yields

$$\left[-(1-\rho) + (\gamma-\rho)\epsilon\right] \frac{dz_t}{z} = -(1-\gamma) d\delta, \tag{A.4}$$

where $\epsilon = \frac{zf'(z)}{f(z)}$. Using $d\log z_t = \frac{dz_t}{z}$ and $d\log m_t \approx -d\delta$, we obtain

$$\frac{d\log z_t^1}{d\log m_t^1} = -\frac{1-\gamma}{(1-\rho)-(\gamma-\rho)\epsilon}. \tag{A.5}$$

This results in a response of type 1 production of

$$d\log y_t^1 = d\log m_t^1 + \frac{-(1-\gamma)\epsilon}{(1-\rho)-(\gamma-\rho)\epsilon} d\log m_t^1. \tag{A.6}$$

The response of sectoral output to the supply chain disruption is

$$d\log y_t = \frac{(1-\rho)-(1-\rho)\epsilon}{(1-\rho)-(\gamma-\rho)\epsilon} \frac{\phi y^1}{\phi y^1 + (1-\phi) y^2} \, d\log m_t^1. \tag{A.7}$$

If $\gamma \to 1$ or $\rho \to -\infty$, the response of sectoral output only depends on the output share of type 1 establishments.

We define the share of intermediate goods imported from country B in the steady state as

$$e^B = \frac{p^m m^1}{p^x(x^1 + x^2) + p^m m^1}. \tag{A.8}$$

Using the normalization $y^1 = y^2$, we can rewrite the import exposure as

$$e^B = \frac{\phi y^1}{\phi y^1 + (1-\phi) y^2} \frac{1-\alpha}{1-\alpha+\alpha(z^1)^\rho}. \tag{A.9}$$

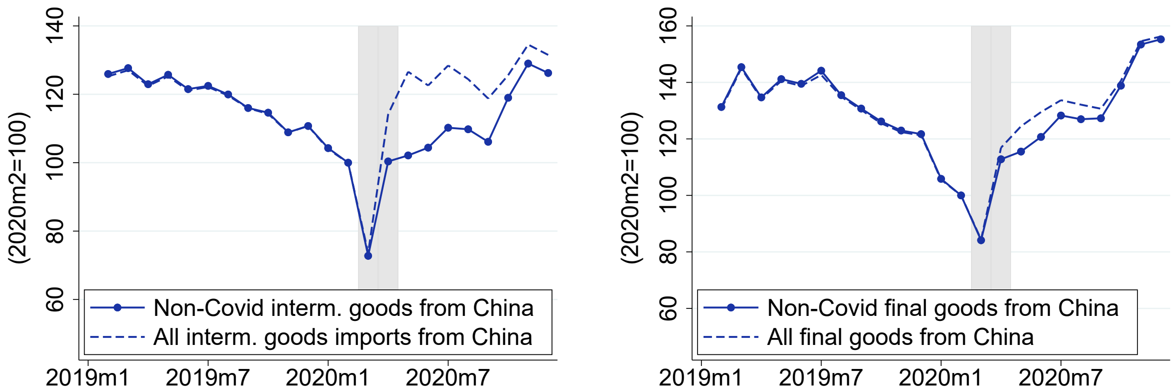
Finally, we can re-express the response of sectoral output as

$$d\log y_t = \frac{(1-\rho)-(1-\rho)\epsilon}{(1-\rho)-(\gamma-\rho)\epsilon} \frac{1-\alpha+\alpha(z^1)^\rho}{1-\alpha} \, e^B \, d\log m_t^1. \tag{A.10}$$

Appendix B Imports and import exposures

Figure 6: The role of Covid-related imports

(a) Intermediate goods (b) Final goods



Notes: Panels (a) and (b) show the evolution of (seasonally adjusted) aggregate US imports of intermediate goods and final goods separately when excluding Covid-related goods (solid line) and when considering all goods (dashed line). We use the definition of Covid-related goods proposed in US International Trade Commission (2020). All series are normalized to 100 at the business cycle peak in February 2020. The gray-shaded area indicates the NBER recession period March-April 2020.

Table 6: Sector-specific China import exposures

NAICS sector	e_i^{China}	NAICS sector	e_i^{China}
1133 Logging	0.122%	3273 Cement and concrete	1.078%
211 Oil and gas extraction	0.566%	3274 Lime and gypsum	0.715%
2121 Coal mining	0.572%	3279 Other nonmetallic minerals	1.862%
2122 Metal ore mining	0.796%	3311,2 Iron and Steel	0.995%
2123 Nonmetallic mineral mining	0.399%	3313 Aluminum	0.654%
213 Support activities for mining	0.657%	3314 Nonferrous metals	0.470%
2211 Electric power generation	0.039%	3315 Foundries	0.713%
2212 Natural gas distribution	0.080%	3321 Forging and stamping	0.528%
3111 Animal food	0.339%	3322 Cutlery and handtool	0.877%
3112 Grain and oilseed	0.230%	3323 Architectural metals	1.313%
3113 Sugar and confectionery	0.939%	3324 Boiler, Shipping Container	0.715%
3114 Fruit, vegetable preserving	0.574%	3325 Hardware	3.226%
3115 Dairy product	0.334%	3326 Spring and wire product	2.330%
3116 Animal processing	0.177%	3327 Machine shops	1.049%
3117 Seafood preparation	5.026%	3328 Coating, heat treating	0.598%
3118 Bakeries and tortilla	0.684%	3329 Other fabricated metals	1.248%

3119 Other food	1.348%	3331 Agriculture, construction	2.651%
3121 Beverage	1.351%	3332 Industrial machinery	1.330%
3122 Tobacco	0.904%	3333,9 Commercial, Service Industry	1.669%
3131 Fiber, yarn, and thread	1.840%	3334 Ventilation, heating	1.113%
3132 Fabric	1.555%	3335 Metalworking machinery	0.891%
3133 Textile finishing	3.489%	3336 Engine, power transmission	1.869%
3141 Textile furnishings	2.676%	3341 Computer equipment	0.892%
3149 Other textiles	2.412%	3342 Communications equipment	4.222%
315 Apparel	5.939%	3343 Audio and video equipment	0.560%
316 Leather and allied product	1.154%	3344 Semiconductor component	0.756%
3211 Sawmills, wood preservation	0.319%	3345 Navigational, measuring	0.688%
3212 Veneer, engineered wood	1.009%	3346 Magnetic and Optical Media	0.206%
3219 Other wood product	1.374%	3351 Electric lighting equipment	1.807%
3221 Pulp, paper, paperboard	1.136%	3352 Household appliance	1.123%
3222 Converted paper product	0.692%	3353 Electrical equipment	1.883%
323 Printing	0.823%	3359 Other electrical equipment	1.205%
324 Petroleum, coal products	0.040%	3361 Motor vehicle	3.216%
3251 Basic chemical	0.918%	3362 Motor vehicle body, trailer	2.901%
3252 Resin, synthetic rubber	1.569%	3363 Motor vehicle parts	1.702%
3253 Pesticide, fertilizer	1.833%	3364 Aerospace products	1.328%
3254 Pharmaceutical, medicine	0.531%	3365 Railroad rolling stock	2.152%
3255 Paint, coating, adhesive	2.097%	3366 Ship and boat building	1.436%
3256 Soap and cleaning	2.049%	3369 Other transport equipment	1.755%
3259 Other chemical product	1.535%	3371 Household furniture	2.902%
3261 Plastics product	1.408%	3372,9 Office furniture	1.969%
3262 Rubber product	3.651%	3391 Medical equipment	1.193%
3271 Clay product and refractory	1.308%	3399 Other miscellaneous mfg	1.297%
3272 Glass and glass product	2.854%	5111 Newspaper, periodical, book	0.351%

Notes: Sector descriptions are shortened. Columns 2 and 4 (e_i^{China}) show the exposure to intermediate goods imports from China (in %).

Appendix C Data construction

C.1 Raw exposure (based on share of total imports)

We define the exposure of sector i to intermediate input imports from country/region B as

$$e_i^B = \frac{Impii_i^B}{Use_i} \tag{C.1}$$

where $Impii_i^B$ represents sector i's imports of intermediate inputs from country/region B and Use_i represents sector i's total use of intermediate inputs. The numerator is estimated as follows,

$$Impii_i^B = \sum_j Impii_{j,i}^{2012} ImpSh_j^{B,2019} \tag{C.2}$$

where $Impii_{j,i}^{2012}$ is sector i's (nominal) intermediate input imports of commodity j (6-digit NAICS) in 2012, as given by the (j,i)-cell of the import matrix from BEA's latest benchmark Input-Output Accounts, and $ImpSh_j^{B,2019}$ is country/region's B (nominal) share of commodity j imports in 2019. Country/region's B import share is calculated as

$$ImpSh_j^{B,2019} = \frac{Imp_j^{B,2019}}{\sum_B Imp_j^{B,2019}} \tag{C.3}$$

where $Imp_j^{B,2019}$ is total (nominal) imports of commodity j (6-digit NAICS) from country/region B in 2019 (from Census). The denominator of our exposure measure is simply computed as

$$Use_i = \sum_j Use_{j,i}^{2012} \tag{C.4}$$

where $Use_{j,i}^{2012}$ is sector i's use of commodity j as an intermediate input in 2012, as given by the (j,i)-cell of the use matrix from the benchmark Input-Output Accounts.

We use the customs value of imports for consumption from Census. We use the before redefinitions version of the input-output use and import matrices. In addition, we choose the use matrix at producer prices, except for commodities codes within wholesale trade, retail trade, and transportation and warehousing services, where we use the value of such commodities at purchasers prices. This adjustment removes the value of transportation costs and trade margins, which are also absent from the intermediate goods imports measure used in the numerator.

C.2 Baseline exposure (based on share of intermediate goods imports)

In the raw exposure measure above, the China import share in equation (C.3) is computed for the set of all commodity imports. However, we prefer to calculate the baseline exposure measure based only on intermediate inputs imports, as the China import share may be quite different between intermediate and final goods. That is, instead of equations (C.2) and (C.3) we define the numerator in (C.1) as

$$Impii_i^B = \sum_j Impii_{j,i}^{2012} ImpiiSh_j^{B,2019}, \quad ImpiiSh_j^{B,2019} = \frac{Impii_j^{B,2019}}{\sum_B Impii_j^{B,2019}} \tag{C.5}$$

where $Impii_j^{B,2019}$ is the value of *intermediate goods* imports of commodity j from country/region B in 2019.

We define intermediate goods imports based on BEA's end-use classification (codes 0, 1, 21100, 21320, 22010, 22020, 22220, and 302). We then use 10-digit HTS import data, together with the correspondence between 10-digit HTS, 6-digit NAICS, and 5-digit end-use commodity classifications to compute the value of intermediate goods imports for each 6-digit NAICS commodity. We also use an alternative definition of intermediate goods imports based on the United Nations Broad Economic Categories (BEC) Rev. 4 classification (codes 111, 121, 21, 22, 31, 322, 42, and 53), together with the correspondence between 10-digit HTS, 6-digit HS, BEC Rev 4, and 6-digit NAICS commodity classifications.

C.3 Effective duty rates on imports from China

We define the average effective duty rate on sector i's intermediate goods imports from country/region B as follows

$$DutyRateAve_i^{B,t} = \sum_j DutyRate_j^{B,t} ImpiiW_{j,i}^B \tag{C.6}$$

where $DutyRate_j^{B,t}$ is the effective duty rate on commodity j's imports (6-digit NAICS) from country/region B and $ImpiiW_{j,i}^B$ is sector i's weights for commodity j. The effective duty rate on the left is computed as

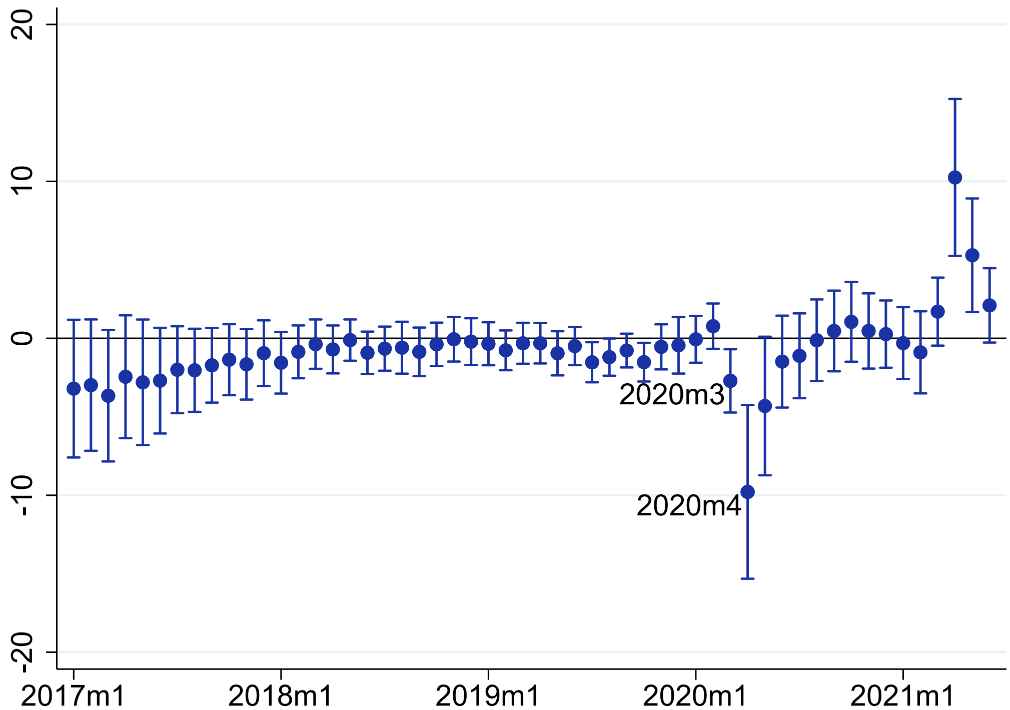
$$DutyRate_j^{B,t} = Duty_j^{B,t} / Impcif_j^{B,t} \tag{C.7}$$

where $Duty_j^{B,t}$ is commodity j's calculated duties on imports from country/region B in period t and $Impcif_j^{B,t}$ is the cost, insurance, and freight value of these imports. These variables are obtained from the dataweb maintained by the US International Trade Commission. The corresponding weights are calculated based on the numerator of our (raw) exposure measure as follows

$$ImpiiW_{j,i}^B = \frac{Impii_{j,i}^{2012} ImpSh_j^{B,2019}}{\sum_j Impii_{j,i}^{2012} ImpSh_j^{B,2019}}. \tag{C.8}$$

Appendix D Additional empirical findings

Figure 7: Estimated β_t coefficients for the year-over-year IP growth rate of IP



Notes: The markers show the estimated (standardized) β_t coefficients based on equation (4.1), when y_{it} is year-over-year IP growth, e_i^B is the China import exposure (in %), and without control variables Z_{it}. The β_t estimates capture the differential IP growth (in p.p.) associated with a 1 standard deviation higher e_i^B. The vertical lines indicate 95% confidence intervals based on heteroskedasticity and autocorrelation robust standard errors.

Table 7: 12-month growth rates of all outcomes with controls

(a) March 2020

	IPI	PPI	PPI*	IP	EMP	IMP	EXP
China import exposure	3.003	2.166	7.379	-1.402	-0.362	-3.163	-2.003
	(1.120)	(0.876)	(2.279)	(1.119)	(0.401)	(2.280)	(1.517)
Observations	88	88	88	88	88	83	83
R^2	0.166	0.179	0.299	0.177	0.028	0.066	0.073

(b) April 2020

	IPI	PPI	PPI*	IP	EMP	IMP	EXP
China import exposure	6.048	4.436	12.89	-6.929	-4.938	-3.642	-9.498
	(1.611)	(1.428)	(3.088)	(3.137)	(1.271)	(4.072)	(3.491)
Observations	88	88	88	88	88	83	83
R^2	0.254	0.228	0.351	0.187	0.272	0.030	0.244

(c) May 2020

	IPI	PPI	PPI*	IP	EMP	IMP	EXP
China import exposure	5.313	3.919	11.55	-1.773	-2.853	-7.944	-5.211
	(1.497)	(1.196)	(3.113)	(2.486)	(1.204)	(4.831)	(3.765)
Observations	88	88	88	88	88	83	83
R^2	0.233	0.249	0.301	0.122	0.175	0.074	0.173

(d) June 2020

	IPI	PPI	PPI*	IP	EMP	IMP	EXP
China import exposure	3.067	2.455	7.793	-0.0544	-1.349	-1.924	0.855
	(1.055)	(0.759)	(2.522)	(1.668)	(0.813)	(3.920)	(2.605)
Observations	88	88	88	88	88	83	83
R^2	0.179	0.252	0.243	0.072	0.128	0.027	0.092

Notes: The table shows the estimated (standardized) β_t coefficients in equation (4.1), when y_{it} is a year-over-year growth rate, e_i^B is the China import exposure, and Z_{it} includes as control variables the China export exposure, non-China import exposure, external finance dependence, and business cycle sensitvity. We consider growth rates of the import price index (IPI), producer price index (PPI), PPI growth adjusted by price adjustment frequency (PPI*), industrial production (IP), employment (EMP), imports (IMP), and exports (EXP). Imports and exports are missing for sectors 213, 2211, 2212, 3328, and 5111. The β_t estimates capture the differential growth rate (in p.p.) associated with a 1 standard deviation higher e_i^B. Heteroskedasticity and autocorrelation robust standard errors are provided in parantheses.

Table 8: 12-month growth rates of all outcomes for non-China exposure with controls

(a) March 2020

	IPI	PPI	PPI*	IP	EMP	IMP	EXP
Non-China import exposure	-2.379	-2.585	-8.416	-2.240	0.157	0.0945	-0.0292
	(1.104)	(0.863)	(2.245)	(1.102)	(0.395)	(2.251)	(1.498)
Observations	88	88	88	88	88	83	83
R^2	0.166	0.179	0.299	0.177	0.028	0.066	0.073

(b) April 2020

	IPI	PPI	PPI*	IP	EMP	IMP	EXP
Non-China import exposure	-5.715	-5.496	-16.42	-2.510	1.085	-2.122	-1.216
	(1.587)	(1.406)	(3.042)	(3.090)	(1.252)	(4.021)	(3.446)
Observations	88	88	88	88	88	83	83
R^2	0.254	0.228	0.351	0.187	0.272	0.030	0.244

(c) May 2020

	IPI	PPI	PPI*	IP	EMP	IMP	EXP
Non-China import exposure	-5.052	-5.404	-15.08	-2.338	-0.275	-1.679	-5.924
	(1.474)	(1.178)	(3.067)	(2.449)	(1.186)	(4.770)	(3.717)
Observations	88	88	88	88	88	83	83
R^2	0.233	0.249	0.301	0.122	0.175	0.074	0.173

(d) June 2020

	IPI	PPI	PPI*	IP	EMP	IMP	EXP
Non-China import exposure	-2.732	-3.325	-9.367	-1.977	-0.525	-2.029	-4.577
	(1.039)	(0.748)	(2.484)	(1.643)	(0.801)	(3.870)	(2.572)
Observations	88	88	88	88	88	83	83
R^2	0.179	0.252	0.243	0.072	0.128	0.027	0.092

Notes: The table shows the estimated (standardized) β_t coefficients in equation (4.1), when y_{it} is a year-over-year growth rate, e_i^B is the non-China import exposure, and Z_{it} includes as control variables the China export exposure, non-China import exposure, external finance dependence, and business cycle sensitvity. We consider growth rates of the import price index (IPI), producer price index (PPI), PPI growth adjusted by price adjustment frequency (PPI*), industrial production (IP), employment (EMP), imports (IMP), and exports (EXP). Imports and exports are missing for sectors 213, 2211, 2212, 3328, and 5111. The β_t estimates capture the differential growth rate (in p.p.) associated with a 1 standard deviation higher e_i^B. Heteroskedasticity and autocorrelation robust standard errors are provided in parantheses.

Table 9: Growth rates of industrial production with trade-war controls

(a) May 2020

	(1)	(2)	(3)	(4)
China import exposure	-4.311	-4.239	-4.356	-4.757
	(2.208)	(2.284)	(2.308)	(2.249)
Duty change 2019m8-2019m12		-1.652		
		(1.481)		
Duty change 2018m12-2019m12			-0.912	
			(1.276)	
Duty change 2017m12-2019m12				-0.755
				(0.754)
Observations	88	84	84	84
R^2	0.042	0.065	0.057	0.062

(b) June 2020

	(1)	(2)	(3)	(4)
China import exposure	-1.483	-1.601	-1.917	-1.840
	(1.464)	(1.504)	(1.518)	(1.481)
Duty change 2019m8-2019m12		-0.768		
		(0.976)		
Duty change 2018m12-2019m12			0.261	
			(0.839)	
Duty change 2017m12-2019m12				-0.331
				(0.497)
Observations	88	84	84	84
R^2	0.012	0.026	0.019	0.024

Notes: The first row in panels (a) and (b) shows the estimated (standardized) β_t coefficients in equation (4.1), when y_{it} is year-over-year IP growth, e_i^B is the China import exposure, and we consider various combinations of control variables Z_{it}. The β_t estimates capture the differential IP growth (in p.p.) associated with a 1 standard deviation higher e_i^B. Heteroskedasticity and autocorrelation robust standard errors are provided in parantheses.

Table 10: Growth rates of industrial production and an alternative China exposure

(a) March 2020

	Baseline (full sample)	Raw exposure (full sample)	Raw exposure (excl. 3342)	Baseline (excl. 3342)
China import exposure	-2.960	-0.975	-2.400	-3.386
	(0.651)	(0.717)	(0.932)	(0.662)
Observations	88	88	87	87
R^2	0.194	0.021	0.072	0.235

(b) April 2020

	Baseline (full sample)	Raw exposure (full sample)	Raw exposure (excl. 3342)	Baseline (excl. 3342)
China import exposure	-8.293	-3.376	-8.156	-9.559
	(2.520)	(2.649)	(3.462)	(2.595)
Observations	88	88	87	87
R^2	0.112	0.019	0.061	0.138

(c) May 2020

	Baseline (full sample)	Raw exposure (full sample)	Raw exposure (excl. 3342)	Baseline (excl. 3342)
China import exposure	7.429	3.465	6.942	8.266
	(2.083)	(2.200)	(2.892)	(2.158)
Observations	88	88	87	87
R^2	0.129	0.028	0.063	0.147

(d) June 2020

	Baseline (full sample)	Raw exposure (full sample)	Raw exposure (excl. 3342)	Baseline (excl. 3342)
China import exposure	3.141	2.155	4.612	3.612
	(1.508)	(1.528)	(2.007)	(1.570)
Observations	88	88	87	87
R^2	0.048	0.023	0.058	0.059

Notes: The table shows the estimated (standardized) β_t coefficients in equation (4.1), when y_{it} is the monthly IP growth rate, e_i^B is the alternative China import exposure, and no control variables Z_{it} are used. The alternative China import exposure does not discard 6-digit commodities based on their end-use classification (raw exposure). The last two columns exclude sector 3342, which is a statistical outlier in the raw exposure distribution. The β_t estimates capture the differential growth rate (in p.p.) associated with a 1 standard deviation higher e_i^B. Heteroskedasticity and autocorrelation robust standard errors are provided in parantheses.