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Covid-19 Supply Chain Disruptions

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Abstract

We study the effects of international supply chain disruptions on real economic activity and prices during the Covid-19 pandemic. 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. Moreover, input and output prices moved up relative to other sectors, suggesting that real activity declines in sectors with a high China exposure were not particularly driven by a slump in demand. Quantitatively, sectors at the third quartile of China exposures experienced larger monthly production declines of 2.5 p.p. in March and 9.4 p.p. in April 2020 than sectors at the first quartile. Differences in China exposures account for about 10% of the cross-sectoral variance of industrial production growth during March and April. The estimated effects are short-lived and dissipate by July 2020.

Keywords: Supply chain disruptions, Covid-19, industrial production.

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1 Introduction

Over the past decades, economies around the globe have become increasingly interconnected through trade and global value chains. In this environment, disruptions to the flow of goods across borders can have large economic effects. In recent years, such disruptions have been occurring at an increasing frequency, as the US-China trade war, Brexit, and policy interventions related to the Covid-19 pandemic suggest. In this paper, we study the effects of supply chain disruptions on the US industrial sector during the Covid-19 crisis.

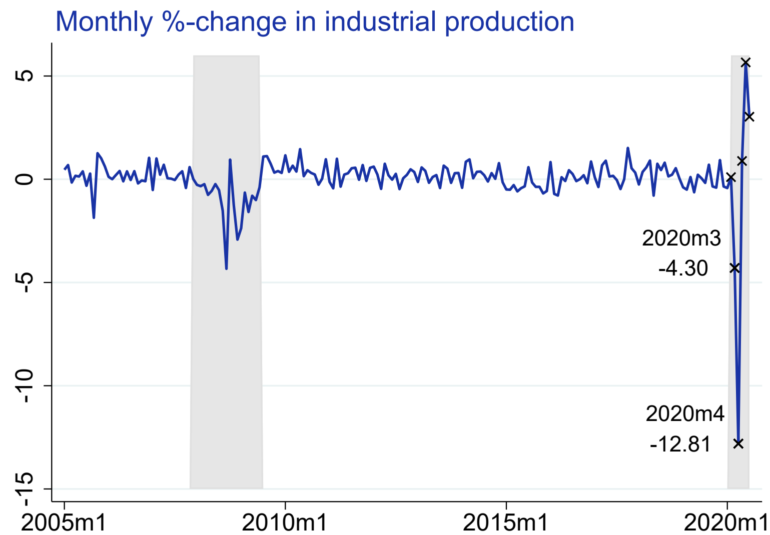
The Covid-19 crisis caused sharp contractions in economic activity across most sectors and economies. For US industrial production, the rapid decline during March and April 2020 dwarfs even the Great Recession (Figure 1). The Covid-19 crisis affected the economy through a number of different channels. These include direct channels operating through the health of the population, mandated lockdowns, and disruptions to trade, as well as other more standard channels, such as downbeat consumer and business sentiment, high uncertainty, and financial stress. Understanding the role of these channels is important for an effective policy response. For example, lockdowns can disrupt supply chains across countries and sectors. If production is suppressed because of disrupted supply chains, a fiscal intervention to stimulate demand may be ineffective. Conversely, providing liquidity or flexible furlough arrangements may be a more effective policy response to facilitate a quick recovery when the supply chain disruption dissipates.[1]

When the US-China trade deal was signed in January 2020, this was positive news for US sectors highly dependent on imports from China. Not long after, however, China responded to the emerging Covid-19 pandemic by imposing widespread lockdowns of entire regions and sectors during February and part of March 2020. In China, the lockdowns caused sharp contractions in production and exports, which eventually spilled over to the US. In fact, US imports from China declined, but mostly in March rather than in February (after accounting for seasonality and calendar effects including the Chinese New Year). The slight delay between the February lockdowns in China and the observed decline in US imports from China likely reflects transit time. Moreover, the decline in imports from China was especially large for intermediate goods, resulting in major supply chain disruptions for US producers.

We study the effects of disruptions to supply chains connected to China on US real

[1] An early discussion of the implications for policy of the Covid-19 crisis is provided by Baldwin and di Mauro (2020). By now, an extensive literature studies the policy implications of Covid-19: On optimal lockdown policy, see, e.g., Alvarez et al. (2020), Eichenbaum et al. (2020), Krueger et al. (2020), and Glover et al. (2020); on the effects of fiscal policy, see, e.g., Bigio et al. (2020), Mitman and Rabinovich (2020), Auerbach et al. (2020), and Bayer et al. (2020); and on monetary policy, see, e.g., Caballero and Simsek (2020), Woodford (2020), and Fornaro and Wolf (2020).

Figure 1: Aggregate US industrial production



Notes: The time series is the monthly percentage change in industrial production (seasonally adjusted), based on the Federal Reserve G.17 release. Recent months starting from February 2020 are highlighted by an 'x'. The growth rates for March and April are printed into the plot. Gray-shaded areas indicate NBER recession periods.

economic activity and prices during the Covid-19 crisis on a monthly basis. Our empirical strategy exploits variation in the share of imported intermediate goods across sectors before Covid-19.[2] The simple 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.

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. Quantitatively, sectors at the third quartile of China exposures experienced larger monthly production declines of 2.5 percentage points (p.p.) in March and 9.4 p.p. in April compared to sectors at the first quartile. Differences in China exposures account for about 10% 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 July. While our analysis focuses on Covid-19 disruptions of US-China trade, we also consider a broader and complementary exposure to intermediate good imports, which includes all imports except from China, and, thus, is referred to as ex-China exposure. Sectors with a high ex-China exposure to imported inputs also suffer larger output declines, but the response of employ-

[2]Using sectoral data in our analysis has some important advantages compared to using firm-level data. In particular, we can use monthly data that are publicly and quickly available in real time. For example, monthly sectoral industrial production is released two weeks after the end of the month.

ment and export is insignificant.

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 control for sector-specific cyclicality, for exports to China, and for external finance dependence, all before Covid-19. Including these controls, we still find a significant relation between a higher China exposure and a larger contraction in industrial production. Second, 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 industries with high China exposure were mostly affected by lower domestic or external demand. In contrast, industries with a larger share of the ex-China imported intermediates experienced smaller input import and output price changes relative to other industries. This finding suggests that the broader ex-China exposure captures mostly the effects of lower demand 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 level of sector detail available in the monthly 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 ex-China import exposure measure, we replace the numerator by intermediate goods imports excluding Chinese imports. Our empirical approach studies to what extent sector-specific ex-ante exposures can 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.

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.[3] Our empirical results suggest significant albeit relatively short-lived effects

[3] Chetty et al. (2020) document that lower spending of high-income individuals led to job losses for low-income individuals. Bachas et al. (2020) document a large increase in liquid asset savings across the income distribution. Balleer et al. (2020) use firm-level price data to disentangle demand and supply effects, whereas Brinca et al. (2020) disentangle labor supply and demand effects of the Covid-19 crisis.

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 from downturns featuring disruptions to supply chains. Indeed, the impact of the Covid-19 crisis on supply chains and how to make them more resilient have received a lot of attention starting from 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).

Closely related are a number of papers that analyze the propagation of Covid-19 related shocks through input and output linkages. For example, Barrot et al. (2020) 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, and Bonadio et al. (2020) study the international propagation of labor supply shocks. Closely related is also Gerschel et al. (2020), who simulate the effect of a productivity decrease in China on GDP outside China. GDP in the US responds similarly to France and Germany, whereas GDP in Japan and Korea responds much more, reflecting the higher exposure of these economies to inputs imported from China.

Our paper is further related to earlier work on supply chain disruptions including Barrot and Sauvagnat (2016) and Meier (2020) on natural disasters in the US, Carvalho et al. (2020) and Boehm et al. (2019) on the Fukushima disaster, and Glick and Taylor (2010) on trade disruptions caused by war. The empirical strategy our paper uses is similar to Boehm et al. (2019), as well as Huang et al. (2018), Flaaen and Pierce (2019), and Amiti et al. (2020), who study the US-China Trade War. Our empirical findings align well with the findings 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. Interestingly, firms with prior pandemic experience (SARS or H1N1) are more resilient to the Covid-19 crisis.

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 findings. Section 5 concludes and an Appendix follows.

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 produce goods y_t^1 using imported intermediate goods from country B, denoted m_t^1, and a range of other inputs, such as capital, labor, and other imported or domestic intermediate inputs, captured by a composite factor x_t^1. The production technology is of the CES type

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

where $\sigma = 1/(1-\rho)$ is the substitution elasticity between x_t^1 and m_t^1 and z_t^1 is the ratio of the composite factor to country B intermediate inputs (factor input ratio). 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. 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 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 $\pi^2 = p(y^2)y^2 - p^x x^2$. Since only type 1 establishments use m_t, we will henceforth omit the type index of m_t^1 and z_t^1.

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: $m_t = (1-\delta)m$.[4] We consider the response of type 1 establishments before prices adjust. The supply of m_t becomes a binding constraint, which means 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 is adjusted according to (see Appendix A)

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

[4] A supply chain disruption that is common across sectors should capture the disruptions caused by the widespread lockdowns in China during February and March 2020.

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

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

The percent decline of output can vary between no response (perfect substitutes, $\rho = 1$), and a percent decline of output equal the percent decline of inputs (perfect complements, $\rho \to -\infty$). The response of sectoral output to the supply chain disruption is

$$d \log y_t = \frac{\phi y^1}{\phi y^1 + (1-\phi) y^2} \frac{(1-\rho)-(1-\rho)\epsilon}{(1-\rho)-(\gamma-\rho)\epsilon} d \log m_t. \tag{2.5}$$

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

Our empirical strategy is to identify cross-sector differences in effects of supply chain disruptions through cross-sector differences in the share of intermediate goods imported from country B. In the model, import exposure to country B is

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

and e^B monotonically increases in ϕ. Simultaneously, the sector-specific output response to a supply-chain disruption monotonically increases in ϕ, the share of establishments that produce using imports from country B. Hence, sectors with a higher import exposure also respond more to a common supply chain disruption. This provides justification to our empirical strategy.

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. 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 part of March 2020. In the aftermath of these disruptions, US imports from China plummeted in March (Figure 2), after accounting for seasonality and calendar effects (including the Chinese New Year).[5] The decline was more noticeable for intermediate goods imports from China, which rebounded well above the pre-crisis level once the effects of lockdowns in China dissipated. This suggests that US producers were subject to a major supply chain disruption. In addition, imports of intermediate goods from all other countries (ex-China) did not increase during February and March, which suggests low short-run substitutability of the disrupted supply from China. In fact, imports ex-China only start falling by April, and more severely so for final goods. This seems consistent with ex-China imports being driven by lower demand during the Covid-19 crisis in the US.

3.2 Outputs, inputs, and prices

We consider a host of sector-level outcomes including measures of output, inputs, and prices. Industrial production (IP) is our primary outcome. IP is a monthly index computed for detailed (usually 4- to 6-digit NAICS) manufacturing sectors by the Federal Reserve Board, 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) IP is based on the number of types of automobiles produced together with their list prices obtained from Ward's Communications, a publisher focused on the automotive industry, and car producers Chrysler and General Motors.[6] For the remaining 50% of industries, the Federal Reserve Board combines production-worker hours from the Bureau of Labor Statistics (BLS) and Fed data on electric power use with product prices from the BLS and spot markets to construct an industry-specific index of IP. The indexes are regularly benchmarked against the Economic Census and the Annual Survey of Manufacturers.

[5] We separately construct US imports of intermediate and final goods based on the methodology described in Section 3.3. We seasonally adjust the aggregate data using X-13ARIMA-SEATS. We account for calendar effects due to trading days and Easter and allow for automatic outlier detection. For imports from China, we also account for Chinese New Year calendar effects in a way similar to Roberts and White (2015): we follow the People's Bank of China and assume fixed sub-period lengths of 20, 7, and 20 days around the Chinese New Year (plus 3-weeks to account for transportation transit time). We use the data from 2010-2019 to estimate the seasonal and calendar effects, including the Chinese New Year, in 2020.

[6] 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

Figure 2: Aggregate US imports

(a) Imports of intermediate goods

(b) Imports of final goods

Notes: Panel (a) and (b) show the evolution of (seasonally adjusted) aggregate US imports of intermediate goods and final goods separately for imports from China and imports from elsewhere (ex-China). All series are normalized to 100 in January 2020. The gray-shaded areas indicate the NBER recession period starting in February 2020.

We aggregate the detailed IP sectors into roughly 4-digit NAICS manufacturing sectors. Panel (a) of Figure 3 shows the evolution of the median monthly IP growth together with the 25th and 75th 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%. Growth rates of IP and other variables, x_t, in this paper are 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, $h = 1$ for monthly growth rates, and $h = 12$ for yearly (12-month) growth rates. At least since Davis and Haltiwanger (1990) these growth rates have been widely used to study establishment-level employment growth. Symmetric growth rates lie in the closed interval $[-2, 2]$ and avoid extreme statistical outliers when some outcome drops close to zero. This concern is specifically prevalent during the sharp contractions of the Covid-19 recession.[7] However, our results are robust to using standard growth rates.

We further use sector-specific employment, imports, exports, import prices and output prices. 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 Bureau. 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 import matrix. Output prices are based on the sector-specific producer price indexes maintained by the BLS. In addition, we construct a number of control variables. We consider a measure of sectoral external finance dependence following the approach in Rajan and Zingales (1998), but using data between 2010 and 2019. We use sector-specific exports to China based on the International Trade Data. Finally, we consider a measure of sectoral cyclicality, which we compute as the correlation between sectoral annual IP growth and annual (aggregate) GDP growth, based on data before the Covid-19 crisis.

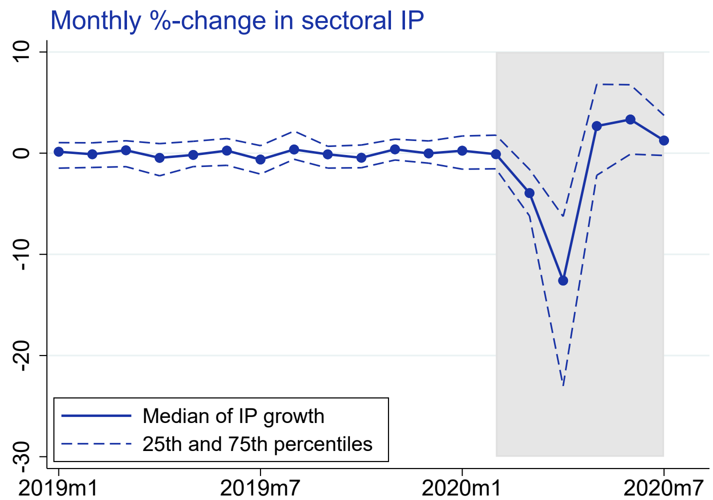
3.3 China exposure

We compute the sector-specific China exposure as the value of imported intermediate goods from China relative to the value of all intermediate goods used in production. However, sector-specific intermediate good imports from China are not directly measured by trade statistics. Instead, we observe 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 the

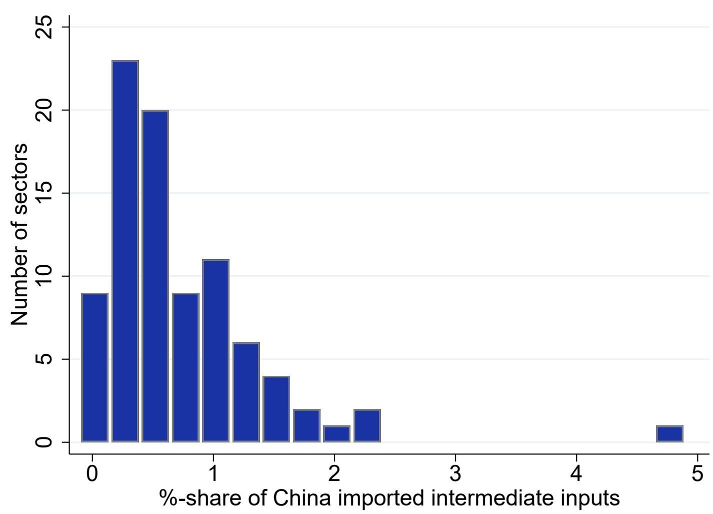
[7]For example, the (ordinary) monthly growth rate of IP in sector 3361 (Motor Vehicle Manufacturing) is below -97% in April 2020 compared to March, and above +1,000% between April and May. For comparison, the symmetric growth rates in sector 3361 for April and May are -190% and +170%, respectively.

Figure 3: Heterogeneity across sectors

(a) Distribution of industrial production growth across sectors



(b) Distribution of Chinese exposure across US sectors



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

import matrix of the Bureau of Economic Analysis (BEA) 2012 Input-Output tables. 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 sector-specific intermediate good imports from China. First, we compute the share of 6-digit NAICS commodities that is imported from China relative to all imports of the same commodity. Second, we multiply the value of a 6-digit sector's 6-digit commodity imports (from all countries) with the China import share of the 6-digit commodity. This yields an estimate of the value of imports from China of 6-digit commodities in 6-digit sectors, 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. We obtain the value of all intermediate goods used in production for each 6-digit sector from the input-output table. Our (baseline) China exposure is the ratio of intermediate goods imported from China divided by all intermediate goods, where both the numerator and denominator are appropriately aggregated across the 6-digit sectors to the roughly 4-digit NAICS sectors available for IP and other outcomes.

The final sample contains 88 distinct manufacturing and related industries. In the Appendix, Table 7 lists all industries. Panel (b) of Figure 3 shows the variation in China exposures across these industries. We observe large differences in the share of intermediates imported from China ranging from less than 0.25% to more than 2%. Throughout the empirical analysis, we discard sector 3342 (Communications Equipment Manufacturing), which is the single outlier in the distribution of China exposures with a value close to 5%, see panel (b). While these fractions are relatively small, in theory 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 (as implied by the simple model in the preceding section).

4 Empirical evidence

In this section, we provide empirical evidence suggesting that supply chain disruptions are a significant economic driver of the Covid-19 crisis.

4.1 Empirical strategy

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

$$y_{it} = \alpha_t + \beta_t e_i^B + \Gamma_t Z_{it} + u_{it}, \quad u_{it} \sim (0, \sigma_t^2) \tag{4.1}$$

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. Using the notation of Section 2, we denote by e_i^{B} the import exposure to country/region B, which we compute based on pre-Covid-19 data.

Most of our empirical analysis focuses on China exposures ($B = \text{China}$). If the exposure e_i^{China} is orthogonal to channels other than supply chain disruptions that explain differential outcomes across sectors, then β_t will capture the causal effect of supply chain disruptions. Similar strategies have been employed by Boehm et al. (2019) 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.

We next study whether industrial production fell by relatively more in sectors with higher China exposure. This naturally raises endogeneity concerns, which we address in Section 4.3. In particular, we address the concern that β_t may capture differential demand effects, by studying the effects both on (output and input) quantities and on (output and input) prices.

4.2 Industrial production and China exposure

We first estimate the β_t coefficients using a regression (4.1) of IP growth (y_{it}) on China exposure (e_i^{China}) without controls (no Z_{it}). Figure 4 shows the estimated β_t coefficients over time. The coefficients for March, April, and May 2020 stand out both in significance and magnitude compared to the coefficients estimated over the preceding three years.

In fact, before the Covid-19 crisis, the β_t coefficients are consistently close to zero and statistically indistinguishable from zero. This may appear surprising against the backdrop of the US-China trade war during these years. We propose two explanations. First, the tariffs imposed during the trade war often targeted specific 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 imported inputs they do no prohibit goods from being produced and transported across borders. In the short-run, higher tariffs have plausibly weaker effects on production than lockdowns.

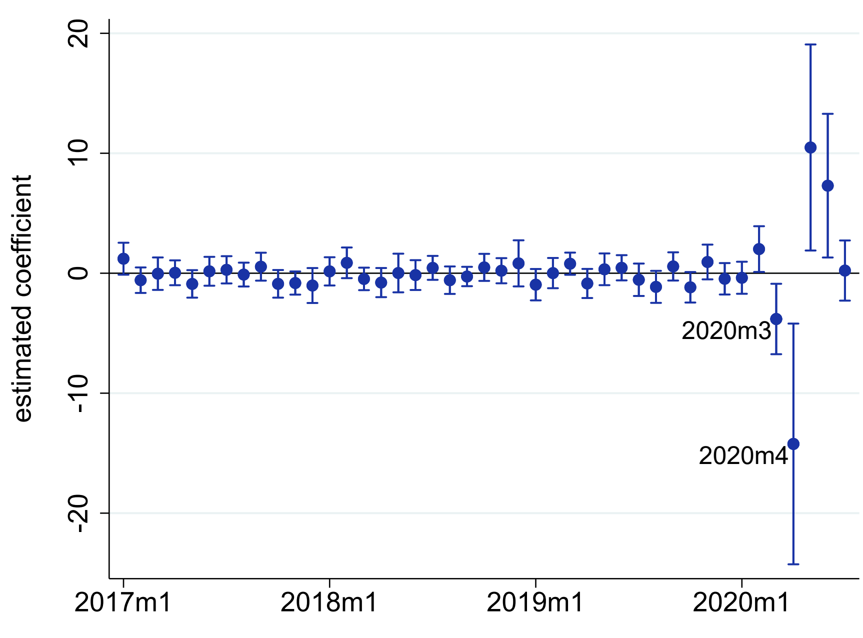
For February 2020, the positive coefficient may appear surprising at first glance. In fact, the Chinese New Year holidays were extended into the first weeks of February in many of the largest Chinese provinces, so we might expect a large negative coefficient already in February. Three explanations can plausibly account for the non-negative β_t. First, cargo transportation from a supplier in China to a US producer takes time.[8] 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

[8]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.

in April, whereas the main Chinese lockdown was in February. Apart from transportation time and inventories, this may be explained by sustained (partial) lockdowns and restrictions on production in China. A further explanation is supply chain propagation within US sectors. For example, if only some firms are directly affected by the shock, the shock may only slowly spread to other firms in the sector.

The main take-away from Figure 4 are the large β_t coefficients in March and April 2020. The estimates are of economically relevant magnitudes. Industrial production growth is estimated to have been 3.8 percentage points (p.p.) and 14.2 p.p. lower in March and April, respectively, for every 1 p.p. increase in the China exposure across sectors (see first columns in Table 1). The 25th percentile of China exposure across sectors is 0.33% while the 75th percentile is 0.99%. Hence, sectors at the third quartile of China exposures experienced larger monthly production declines of about 2.5 p.p. in March and 9.4 p.p. in April than sectors at the first quartile. To understand how much variation in IP growth can be explained by variation in China exposures, note that the cross-sectional standard deviation of our China exposure measure is $\sigma(e_i^{\text{china}}) = 0.51\%$, and the standard deviations of IP growth in March and April 2020 are $\sigma(y_{i,2020\text{m}3}) = 7.20\%$ and $\sigma(y_{i,2020\text{m}4}) = 24.79\%$. Hence, in terms of R-squared, 7.4 percent of the cross-sectoral variance in March IP growth and 8.6 percent in April can be associated to different China exposures. To gauge the combined March and

Figure 4: Coefficient β_t in a regression of IP on China exposure



Notes: Markers indicate the estimated coefficients β_t in a regression of monthly IP growth in period t on China exposures according to (4.1). Vertical lines indicate 95% confidence intervals.

Table 1: Industrial Production and China exposure

(a) IP growth in March 2020

	Monthly	Monthly/Detr.	Yearly	Yearly/Detr.
China exposure	-3.816	-3.740	-4.083	-2.875
	(1.467)	(1.451)	(1.870)	(1.831)
Observations	87	87	87	87
R^2	0.074	0.072	0.053	0.028

(b) IP growth in April 2020

	Monthly	Monthly/Detr.	Yearly	Yearly/Detr.
China exposure	-14.23	-14.15	-16.25	-15.04
	(5.016)	(5.012)	(5.669)	(5.582)
Observations	87	87	87	87
R^2	0.086	0.086	0.088	0.079

Note: Based on regression (4.1). Standard errors in parentheses. The point estimates in the first column of panels (a) and (b) are identical to the March and April 2020 coefficients in Figure 4.

April effect of China exposure on industrial production, we use the year-over-year IP growth in April 2020 as outcome variable (see third column of panel (b) in Table 1). We conclude that 8.8 percent of the variance in industrial production during the Covid-19 crisis can be attributed to different China exposures.

Starting from May 2020, the β_t coefficients turns positive and significant. The growth rates of IP in May and June are substantially larger in more exposed sectors. While the reversal in May appears to be only partial compared to the large declines in March and April, by June we are closer to full reversal. In Section 4.4, we provide a more detailed discussion of the reversal starting in May. In what follows, we first focus on March and April 2020.

A potential concern is that our estimate may be biased by the presence of cross-sector differences in IP trend growth before the Covid-19 crisis. To address this concern, we consider three alternative growth rate specification. First, the month-over-month growth rate detrended by subtracting the average month-over-month growth rate in the two year until February 2020. Second, the year-over-year monthly growth rate, that is $h = 12$ in equation (3.1). Third, the year-over-year monthly growth rate detrended by its average over the two years until February 2020. Columns 2–4 of Table 1 show the estimated March and April β_t coefficients for the three alternative specifications. 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.

4.3 Demand vs. supply

A question of critical importance is whether our exposure measure indeed captures the relative strength of supply shocks. A concern is that 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, external demand (namely from China), or tighter financing conditions. We address this concern in two ways. First, we control for sector-specific cyclicality, exports to China, and external finance dependence, all computed with data before the Covid-19 crisis. Table 2 shows the March and April β_t coefficients when including these controls. We still find a significant relation between a higher China exposure and a larger contraction in industrial production. Importantly, the magnitudes of the estimated β_t change by relatively little.

Second, we estimate how higher China exposure relates to sectoral prices. If sectors with higher China exposure contracted more than other sectors mainly because they faced a larger reduction in demand, then we would expect sector-specific prices to fall. Conversely, if sectors with high China exposure are indeed more affected by international supply chain disruptions, then both their import prices and their output prices should increase relative to sectors with lower China exposure. Table 3 shows that both import (IPI) and output (PPI) prices increase by more in sectors with higher China exposure. The differences are statistically significant at the 5% level for import prices and at the 10% level for output prices. This result makes it unlikely that changes in real activity in industries with high China exposure were mostly affected by lower domestic demand. To be clear, this does not rule out that differences in China exposure capture some differential demand effects across sectors. It merely suggests that the supply chain disruption is the dominant channel picked up by differences in exposure.

Comparing observed price changes across sectors may be misleading if sectors differ in the fraction of (item-level) prices being adjusted. In fact, average price adjustment frequencies differ a lot across sectors (see, e.g., Nakamura and Steinsson, 2008 and Pasten et al., forthcoming). 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. (forthcoming). Using PPI* as outcome, we still find larger output price increases for sectors more exposed to China. The April 2020 coefficient (in column 5) remains statistically significant at the 10% level, while the March 2020 coefficient is insignificant.[9] 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

[9] In Table 3, the coefficients for PPI* are 2-3 times larger than the ones for PPI. This mainly reflects larger dispersion in PPI* and the standardized coefficients of PPI and PPI* are almost identical.

Table 2: Industrial Production with additional controls

(a) IP growth in March 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	-3.816	-3.548	-4.408	-3.389	-3.768
	(1.467)	(1.429)	(1.395)	(1.517)	(1.418)
Ext. Finance Dependence		-1.262			-1.258
		(0.512)			(0.486)
Exports to China			0.152		0.141
			(0.0447)		(0.0441)
Business cycle correlation				-3.544	-2.754
				(3.244)	(3.034)
Observations	87	87	87	87	87
R^2	0.074	0.136	0.185	0.087	0.250

(b) IP growth in April 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	-14.23	-13.96	-15.25	-11.84	-12.52
	(5.016)	(5.046)	(5.008)	(5.124)	(5.207)
Ext. Finance Dependence		-1.294			-1.528
		(1.807)			(1.784)
Exports to China			0.262		0.213
			(0.160)		(0.162)
Business cycle correlation				-19.83	-18.41
				(10.96)	(11.14)
Observations	87	87	87	87	87
R^2	0.086	0.092	0.115	0.121	0.148

Note: Based on regression (4.1). Standard errors in parentheses.

and April 2020. Given the magnitude of the disruption caused by Covid-19, this may be a strong assumption. Table 3 further shows that more exposed sectors reduce their workforce (EMP) by relatively more, especially in April, they import (IMP) less, and export (EXP) less. This draws an overall consistent picture that more exposed sectors were contracting more during the Covid-19 crisis. In the Appendix, Tables 8–13 show that the March and April β_t estimates for employment growth, import and export growth, output and input growth are broadly robust to controling for sectoral external finance dependence, exports to

Table 3: Other outcomes

(a) Yearly growth rates in March 2020

	IP	EMP	IPI	PPI	PPI*	IMP	EXP
China exposure	-4.083	-0.379	4.991	2.590	7.120	-9.181	-5.612
	(1.870)	(0.795)	(2.005)	(1.609)	(4.533)	(3.854)	(2.543)
Observations	87	87	87	87	87	83	83
R^2	0.053	0.003	0.068	0.030	0.028	0.065	0.057

(b) Yearly growth rates in April 2020

	IP	EMP	IPI	PPI	PPI*	IMP	EXP
China exposure	-16.25	-6.215	9.075	4.887	12.03	-12.73	-21.08
	(5.669)	(2.470)	(2.976)	(2.667)	(6.223)	(7.153)	(6.343)
Observations	87	87	87	87	87	83	83
R^2	0.088	0.069	0.099	0.038	0.042	0.038	0.120

Note: Based on regression (4.1). Standard errors in parentheses. IP: industrial production growth, EMP: employment growth, IPI: import price index growth, PPI: purchaser price index growth, PPI*: PPI growth divided by price adjustment frequency, IMP: import growth, EXP: export growth.

China, and cyclicality.

4.4 Exposure to non-Chinese inputs

We next consider a broad sector-specific import exposure that includes all intermediate goods imports except imports from China. Figure 5 in the Appendix shows the histogram of ex-China import exposures across sectors. We then re-estimate regression (4.1) using ex-China exposure and present the β_t estimates in Table 4. We find that IP contracted significantly more in sectors with higher broad import exposure. However, the responses of employment and exports is insignificant and with positive point estimates in March 2020. In contrast, in sectors with higher China exposure, employment and exports fell more (Table 3). The fact that responses are less consistent across different outcomes suggests that the ex-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 by more, but rather by less. This in turn suggests that the ex-China import exposure is high in sectors that are more severely hit by demand slumps. Overall, these results caution against interpreting the ex-China β_t coefficients in the context of supply chain disruptions.

Table 4: Outcomes for ex-China exposure

(a) Growth rates in March 2020

	IP	EMP	IPI	PPI	PPI*	IMP	EXP
Non-China exposure	-0.897	0.00554	-0.446	-0.689	-2.455	-0.430	0.163
	(0.280)	(0.0370)	(0.401)	(0.309)	(0.854)	(0.776)	(0.510)
Observations	87	87	87	87	87	83	83
R^2	0.108	0.000	0.014	0.055	0.089	0.004	0.001

(b) Growth rates in April 2020

	IP	EMP	IPI	PPI	PPI*	IMP	EXP
Non-China exposure	-2.394	-0.311	-1.175	-1.394	-4.235	-2.362	-0.830
	(0.988)	(0.442)	(0.597)	(0.507)	(1.149)	(1.397)	(1.315)
Observations	87	87	87	87	87	83	83
R^2	0.065	0.006	0.044	0.082	0.138	0.034	0.005

Note: Based on regression (4.1). Standard errors in parentheses. See notes of Table 3 for a resolution of the first row acronyms.

4.5 Persistence

We next look beyond April and March 2020 to study the persistence of China-specific supply chain disruptions on US production. Table 5 shows β_t estimates for May, June, and July 2020, and the four alternative specifications of IP growth. The first two columns of panel (a) show that industrial production increased by more for more exposed sectors relative to April 2020. However, the last two columns of Table 5 show that relative to the preceding year, industries with higher China exposure still produce relatively less. Taken together the May estimates indicate that the effects of China-specific supply chain disruptions had only partially dissipated by May. For June and July 2020, although the point estimates suggest that some negative effect persists, IP growth differences across industries associated with China exposure become statistically insignificant. A similar picture emerges when estimating the May–July 2020 β_t coefficients for other outcomes, inputs, and prices, see Table 14 in the Appendix.

Essentially, supply chain disruption occurred around February 2020 in China, attained their peak effect on US production at the end of April, and seem to have largely dissipated by July. These relatively short-lived effects of Covid-19 supply chain disruptions contrast with Barrot and Sauvagnat (2016). Using regional natural disasters in the US, the authors find that the peak effect on sales of a supplier being hit by a disaster is about one year after the disaster. Clearly, the Covid-19 recession is quite different from the severe natural disasters in their sample. For example, while a storm or a flooding may destroy productive capacity and

Table 5: Industrial Production and China exposure during May–July 2020

(a) IP growth in May 2020

	Monthly	Monthly/Detr.	Yearly	Yearly/Detr.
China exposure	10.48	10.55	-9.189	-7.991
	(4.294)	(4.293)	(4.409)	(4.344)
Observations	86	86	86	86
R^2	0.066	0.067	0.049	0.039

(b) IP growth in June 2020

	Monthly	Monthly/Detr.	Yearly	Yearly/Detr.
China exposure	7.298	7.367	-2.830	-1.631
	(2.994)	(2.999)	(3.019)	(2.956)
Observations	86	86	86	86
R^2	0.066	0.067	0.010	0.004

(b) IP growth in July 2020

	Monthly	Monthly/Detr.	Yearly	Yearly/Detr.
China exposure	0.222	0.290	-2.075	-0.876
	(1.254)	(1.248)	(2.915)	(2.844)
Observations	86	86	86	86
R^2	0.000	0.001	0.006	0.001

Note: Based on regression (4.1). Standard errors in parentheses. The point estimates in the first columns are identical to the corresponding coefficients in Figure 4. We have one observation less for May–July 2020 because the data for sector 3211 (Sawmills and wood preservation) has not been released.

infrastructure, the Covid-19 lockdowns left productive capacity and infrastructure broadly unaffected. Hence, it is at least plausible that production could resume relatively more quickly after mandated Covid-19 lockdowns ended, when compared to natural disasters.

4.6 Alternative China exposures

Our baseline China exposure builds on trade flows of 6-digit commodities and assigns them to industries using the import matrix of the input-output table and applying a proportionality assumption. A potential problem with this approach is that some 6-digit commodities are used for multiple end-uses. Some 6-digit commodities may contain a mixture of intermediate goods, capital goods, and consumption goods. This is arguably not a large problem because we start from narrowly-defined 6-digit commodities, for which the scope of mixed end-use

Table 6: Exposure to intermediate good imports

	(1)	(2)	(3)	(4)	(5)	(6)
China exposure	-3.816			-14.23		
	(1.467)			(5.016)		
– BEA intermediates		-9.588			-35.70	
		(2.282)			(7.719)	
– BEC intermediates			-5.364			-17.66
			(1.962)			(6.780)
Observations	87	87	87	87	87	87
R^2	0.074	0.172	0.081	0.086	0.201	0.074

Note: Based on regression (4.1). Standard errors in parentheses. Columns (1)–(3) are based on March 2020 IP growth, columns (4)–(6) are based on April 2020 IP growth. The first row, China exposure, is based on all sector-specific imports from China. The second (third) row is based on constructing sector-specific imports of intermediate goods from China based on BEA (UNSTATS BEC) classification of goods into end-use categories.

seems to be limited. To address the potential issue nonetheless, we categorize the 6-digit commodities using either the end-use classification from the BEA or the United Nations Broad Economic Categories (BEC) classification. We then discard 6-digit commodities not classified as intermediate inputs and proceed with the remaining commodities to construct sector-specific China exposures. It turns out that we underestimate aggregate intermediate good imports in this way. Using the BEA or BEC classification, only 37% or 45% of imports are respectively considered intermediate inputs versus 55% in the import matrix. Our empirical results, however, are robust to using the alternative exposure measures.

In Table 6, the first rows of panel (a) and (b) repeat the baseline April and March β_t estimates whereas the last two rows show the β_t for the alternative China exposures based on the BEA and BEC classificiations, respectively. The results are re-assuring in the sense that the results are not dramatically different. If anything, our baseline approach seems to underestimate the role of China exposure. In particular for the BEA-based classification, the R^2 is substantially larger, which suggests that China-specific supply chain disruptions explain closer to 20% of the cross-sectoral variation in IP growth during March and April 2020.

5 Conclusion

In this paper, 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 more during March and April 2020 compared to less exposed sectors. Highly exposed sectors produce less, fire more workers, export and import less, and their import and output prices increase by more. Our results suggest that differential exposure to China-specific supply chain disruptions explain about 9% of the cross-sectoral differences in industrial production growth during March and April 2020. The effects appear to be relatively short-lived and become insignificant by July 2020.

References

Alvarez, F., D. Argente, and F. Lippi (2020): "A Simple Planning Problem for COVID-19 Lockdown," CEPR Discussion Papers 14658, C.E.P.R. Discussion Papers.

Amiti, M., S. H. Kong, and D. Weinstein (2020): "The Effect of the U.S.-China Trade War on U.S. Investment," Working Paper 27114, National Bureau of Economic Research.

Antràs, P. (2020): "De-Globalisation? Global Value Chains in the Post-COVID-19 Age," *Working Paper*.

Auerbach, A. J., Y. Gorodnichenko, and D. Murphy (2020): "Fiscal Policy and COVID19 Restrictions in a Demand-Determined Economy," Working Paper 27366, National Bureau of Economic Research.

Bachas, N., P. Ganong, P. J. Noel, J. S. Vavra, A. Wong, D. Farrell, and F. E. Greig (2020): "Initial Impacts of the Pandemic on Consumer Behavior: Evidence from Linked Income, Spending, and Savings Data," Working Paper 27617, National Bureau of Economic Research.

Baldwin, R. and B. W. di Mauro (2020): *Economics in the Time of COVID-19*, VoxEU.org eBook, CEPR Press.

Balleer, A., S. Link, M. Menkhoff, and P. Zorn (2020): "Demand or Supply? Price Adjustment during the Covid-19 Pandemic," CEPR Discussion Papers 14907, C.E.P.R. Discussion Papers.

Baqaee, D. and E. Farhi (2020): "Supply and Demand in Disaggregated Keynesian Economies with an Application to the Covid-19 Crisis," NBER Working Papers 27152.

Barrot, J.-N., B. Grassi, and J. Sauvagnat (2020): "Sectoral Effects of Social Distancing," *CEPR Covid Economics*.

Barrot, J.-N. and J. Sauvagnat (2016): "Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks," *The Quarterly Journal of Economics*, 131, 1543–1592.

Bayer, C., B. Born, R. Luetticke, and G. Müller (2020): "The Coronavirus Stimulus Package: How large is the transfer multiplier? ," Cepr discussion papers, C.E.P.R. Discussion Papers.

Bigio, S., M. Zhang, and E. Zilberman (2020): "Transfers vs Credit Policy: Macroeconomic Policy Trade-offs during Covid-19," Working Paper 27118, National Bureau of Economic Research.

Boehm, C. E., A. Flaaen, and N. Pandalai-Nayar (2019): "Input Linkages and the Transmission of

Shocks: Firm-Level Evidence from the 2011 Thoku Earthquake," *The Review of Economics and Statistics*, 101, 60–75.

Bonadio, B., Z. Huo, A. A. Levchenko, and N. Pandalai-Nayar (2020): "Global Supply Chains in the Pandemic," Working Paper 27224, National Bureau of Economic Research.

Brinca, P., J. B. Duarte, and M. F. e Castro (2020): "Measuring Sectoral Supply and Demand Shocks during COVID-19," *CEPR Covid Economics*.

Caballero, R. J. and A. Simsek (2020): "Asset Prices and Aggregate Demand in a "Covid-19" Shock: A Model of Endogenous Risk Intolerance and LSAPs," Working Paper 27044, National Bureau of Economic Research.

Carvalho, V. M., M. Nirei, Y. Saito, and A. Tahbaz-Salehi (2020): "Supply chain disruptions: evidence from the great east japan earthquake," mimeo, University of Cambridge.

Chetty, R., J. N. Friedman, N. Hendren, M. Stepner, and T. O. I. Team (2020): "How Did COVID-19 and Stabilization Policies Affect Spending and Employment? A New Real-Time Economic Tracker Based on Private Sector Data," Working Paper 27431, National Bureau of Economic Research.

Choi, T. Y., D. Rogers, and B. Vakil (2020): "Coronavirus Is a Wake-Up Call for Supply Chain Management," *Harvard Business Review*.

Davis, S. J. and J. Haltiwanger (1990): "Gross Job Creation and Destruction: Microeconomic Evidence and Macroeconomic Implications," in *NBER Macroeconomics Annual 1990, Volume 5*, National Bureau of Economic Research, Inc, NBER Chapters, 123–186.

Donnan, S., C. Rauwald, J. Deaux, and I. King (2020): "A Covid-19 Supply Chain Shock Born in China Is Going Global," *Bloomberg*.

Eichenbaum, M. S., S. Rebelo, and M. Trabandt (2020): "The Macroeconomics of Epidemics," Working Paper 26882, National Bureau of Economic Research.

Flaaen, A., A. Hortaçsu, and F. Tintelnot (2020): "The Production Relocation and Price Effects of US Trade Policy: The Case of Washing Machines," *American Economic Review*, 110, 2103–27.

Flaaen, A. and J. Pierce (2019): "Disentangling the Effects of the 2018-2019 Tariffs on a Globally Connected U.S. Manufacturing Sector," *Finance and Economics Discussion Series*, 2019.

Fornaro, L. and M. Wolf (2020): "Covid-19 Coronavirus and Macroeconomic Policy," CEPR Discussion Papers 14529, C.E.P.R. Discussion Papers.

Gerschel, E., A. Martinez, and I. Mejean (2020): "Propagation of shocks in global value chains: the coronavirus case," *IPP Policy Brief*.

Glick, R. and A. M. Taylor (2010): "Collateral Damage: Trade Disruption and the Economic Impact of War," *The Review of Economics and Statistics*, 92, 102–127.

Glover, A., J. Heathcote, D. Krueger, and J.-V. Ríos-Rull (2020): "Health versus Wealth: On the Distributional Effects of Controlling a Pandemic," *CEPR Covid Economics*.

Hassan, T. A., S. Hollander, L. van Lent, and A. Tahoun (2020): "Firm-level Exposure to Epidemic Diseases: Covid-19, SARS, and H1N1," Working Paper 26971, National Bureau of Economic Research.

Huang, Y., C. Lin, S. Liu, and H. Tang (2018): "Trade Linkages and Firm Value: Evidence from the 2018 US-China "Trade War"," IHEID Working Papers 11-2018, Economics Section, The Graduate Institute of International Studies.

Johnson, R. C. and G. Noguera (2012): "Accounting for intermediates: Production sharing and trade in value added," *Journal of International Economics*, 86, 224 – 236.

Kahn, J. A., M. M. McConnell, and G. Perez-Quiros (2002): "On the causes of the increased stability of the U.S. economy," *Economic Policy Review*, 8, 183–202.

Krueger, D., H. Uhlig, and T. Xie (2020): "Macroeconomic Dynamics and Reallocation in an Epidemic," Working Paper 27047, National Bureau of Economic Research.

McConnell, M. M. and G. Perez-Quiros (2000): "Output Fluctuations in the United States: What Has Changed since the Early 1980's?" *American Economic Review*, 90, 1464–1476.

Meier, M. (2020): "Supply Chain Disruptions, Time to Build, and the Business Cycle," *Discussion Paper Series - CRC TR 224*.

Mitman, K. and S. Rabinovich (2020): "Optimal Unemployment Benefits in the Pandemic," CEPR Discussion Papers 14915, C.E.P.R. Discussion Papers.

Nakamura, E. and J. Steinsson (2008): "Five Facts about Prices: A Reevaluation of Menu Cost Models," *The Quarterly Journal of Economics*, 123, 1415–1464.

Pasten, E., R. Schoenle, and M. Weber (forthcoming): "The Propagation of Monetary Policy Shocks in a Heterogeneous Production Economy," *Journal of Monetary Economics*.

Rajan, R. and L. Zingales (1998): "Financial Dependence and Growth," *American Economic Review*, 88, 559–86.

Roberts, I. and G. White (2015): "Seasonal Adjustment of Chinese Economic Statistics," RBA Research Discussion Papers rdp2015-13, Reserve Bank of Australia.

Schmalz, F. (2020): "The coronavirus outbreak is disrupting supply chains around the world – here's how companies can adjust and prepare," *Business Insider*.

Timmer, M., E. Dietzenbacher, B. Los, R. Stehrer, and G. de Vries (2015): "An Illustrated User Guide to the World InputOutput Database: the Case of Global Automotive Production," *Review of International Economics*, 23, 575–605.

Woodford, M. (2020): " Effective Demand Failures and the Limits of Monetary Stabilization Policy," Cepr discussion papers, C.E.P.R. Discussion Papers.

Appendix A

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

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

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

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

Appendix B

Table 7: List of all sectors

NAICS	description	NAICS	description
1133	Logging	3273	Cement and concrete product
211	Oil and gas extraction	3274	Lime and gypsum product
2121	Coal mining	3279	Other nonmetallic mineral product
2122	Metal ore mining	3311,2	Iron and Steel Manufacturing
2123	Nonmetallic mineral mining	3313	Alumina and aluminum production
213	Support activities for mining	3314	Nonferrous metal production
2211	Electric power generation	3315	Foundries
2212	Natural gas distribution	3321	Forging and stamping
3111	Animal food	3322	Cutlery and handtool

3112	Grain and oilseed milling	3323	Architectural and structural metals
3113	Sugar and confectionery product	3324	Boiler, Tank, Shipping Container
3114	Fruit and vegetable preserving	3325	Hardware
3115	Dairy product	3326	Spring and wire product
3116	Animal slaughtering and processing	3327	Machine shops; turned product; screw
3117	Seafood product preparation	3328	Coating, engraving, heat treating
3118	Bakeries and tortilla	3329	Other fabricated metal product
3119	Other food	3331	Agriculture, construction, mining
3121	Beverage	3332	Industrial machinery
3122	Tobacco	3333,9	Commercial and Service Industry
3131	Fiber, yarn, and thread mills	3334	Ventilation, heating, AC, refrigeration
3132	Fabric mills	3335	Metalworking machinery
3133	Textile, fabric finishing, fabric coating	3336	Engine, turbine, power transmission
3141	Textile furnishings mills	3341	Computer and peripheral equipment
3149	Other textile product mills	3342	Communications equipment
315	Apparel	3343	Audio and video equipment
316	Leather and allied product	3344	Semiconductor, electronic component
3211	Sawmills and wood preservation	3345	Navigational, measuring
3212	Veneer, plywood, engineered wood	3346	Magnetic and Optical Media
3219	Other wood product	3351	Electric lighting equipment
3221	Pulp, paper, and paperboard mills	3352	Household appliance
3222	Converted paper product	3353	Electrical equipment
323	Printing, related support activities	3359	Other electrical equipment
324	Petroleum and coal products	3361	Motor vehicle
3251	Basic chemical	3362	Motor vehicle body and trailer
3252	Resin, synthetic rubber and fibe	3363	Motor vehicle parts
3253	Pesticide, fertilizer	3364	Aerospace product and parts
3254	Pharmaceutical and medicine	3365	Railroad rolling stock
3255	Paint, coating, and adhesive	3366	Ship and boat building
3256	Soap, cleaning, toilet preparation	3369	Other transportation equipment
3259	Other Chemical Product	3371	Household and institutional furniture
3261	Plastics product	3372-9	Office Furniture Manufacturing
3262	Rubber product	3391	Medical equipment and supplies
3271	Clay product and refractory	3399	Other Miscellaneous Mfg
3272	Glass and glass product	5111	Newspaper, periodical, book

Note: Some sector descriptions are shortened.

Figure 5: Heterogeneity across sectors

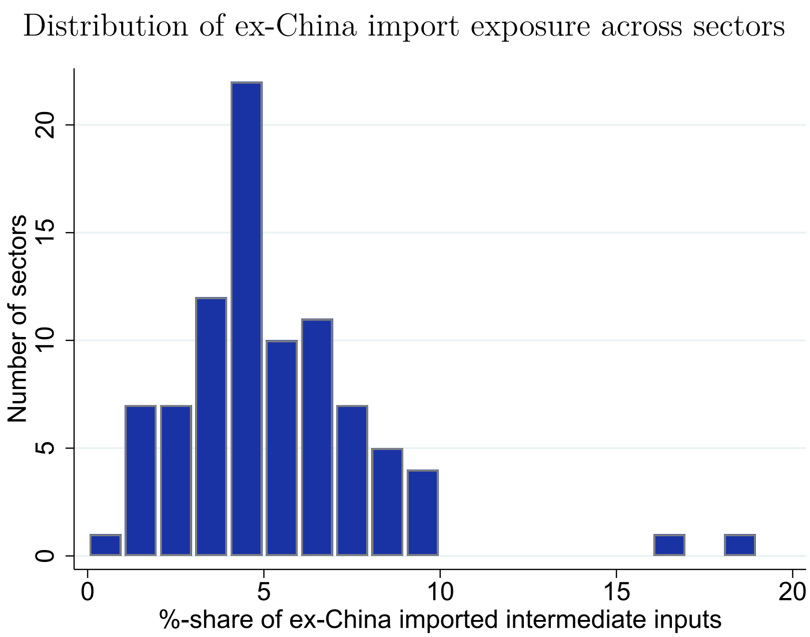


Table 8: Employment (EMP) with additional controls

(a) Employment growth in March 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	-0.227	-0.253	-0.243	-0.262	-0.328
	(0.189)	(0.187)	(0.191)	(0.196)	(0.197)
Ext. Finance Dependence		0.119			0.129
		(0.0670)			(0.0676)
Exports to China			0.00407		0.00547
			(0.00612)		(0.00613)
Business cycle correlation				0.288	0.432
				(0.419)	(0.422)
Observations	87	87	87	87	87
R^2	0.017	0.053	0.022	0.022	0.070

(b) Emploment growth in April 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	-5.732	-5.682	-6.292	-4.169	-4.653
	(2.192)	(2.211)	(2.169)	(2.185)	(2.214)
Ext. Finance Dependence		-0.236			-0.396
		(0.792)			(0.758)
Exports to China			0.143		0.114
			(0.0695)		(0.0688)
Business cycle correlation				-12.95	-11.92
				(4.673)	(4.735)
Observations	87	87	87	87	87
R^2	0.074	0.075	0.119	0.152	0.183

Note: Based on regression (4.1). Standard errors in parentheses.

Table 9: Import prices (IPI) with additional controls

(a) Import price growth in March 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	4.991	4.943	4.645	4.208	3.522
	(2.005)	(2.021)	(2.010)	(2.061)	(2.089)
Ext. Finance Dependence		0.223			0.394
		(0.724)			(0.716)
Exports to China			0.0885		0.109
			(0.0644)		(0.0649)
Business cycle correlation				6.480	7.954
				(4.407)	(4.468)
Observations	87	87	87	87	87
R^2	0.068	0.069	0.088	0.091	0.124

(b) Import price growth in April 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	9.075	9.125	8.573	8.058	7.258
	(2.976)	(3.002)	(2.986)	(3.069)	(3.120)
Ext. Finance Dependence		-0.236			-0.0125
		(1.075)			(1.069)
Exports to China			0.128		0.153
			(0.0957)		(0.0969)
Business cycle correlation				8.421	10.13
				(6.563)	(6.675)
Observations	87	87	87	87	87
R^2	0.099	0.099	0.118	0.116	0.142

Note: Based on regression (4.1). Standard errors in parentheses.

Table 10: Output prices (PPI) with additional controls

(a) Output price growth in March 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	2.590	2.694	2.417	1.822	1.611
	(1.609)	(1.616)	(1.624)	(1.643)	(1.678)
Ext. Finance Dependence		-0.491			-0.356
		(0.579)			(0.575)
Exports to China			0.0443		0.0596
			(0.0521)		(0.0521)
Business cycle correlation				6.355	6.799
				(3.515)	(3.590)
Observations	87	87	87	87	87
R^2	0.030	0.038	0.038	0.066	0.086

(b) Output price growth in April 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	4.887	5.059	4.693	3.712	3.508
	(2.667)	(2.680)	(2.699)	(2.733)	(2.800)
Ext. Finance Dependence		-0.805			-0.610
		(0.960)			(0.959)
Exports to China			0.0498		0.0724
			(0.0865)		(0.0870)
Business cycle correlation				9.732	10.16
				(5.844)	(5.991)
Observations	87	87	87	87	87
R^2	0.038	0.046	0.042	0.069	0.082

Note: Based on regression (4.1). Standard errors in parentheses.

Table 11: Output prices adjusted by price rigidity (PPI*) with additional controls

(a) Adjusted output price growth in March 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	7.120	7.782	5.590	5.845	4.447
	(4.533)	(4.474)	(4.398)	(4.689)	(4.507)
Ext. Finance Dependence		-3.112			-2.739
		(1.602)			(1.544)
Exports to China			0.392		0.416
			(0.141)		(0.140)
Business cycle correlation				10.56	13.50
				(10.03)	(9.641)
Observations	87	87	87	87	87
R^2	0.028	0.070	0.110	0.041	0.168

(b) Adjusted output price growth in April 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	12.03	12.71	10.75	10.19	9.104
	(6.223)	(6.201)	(6.211)	(6.433)	(6.442)
Ext. Finance Dependence		-3.208			-2.789
		(2.221)			(2.207)
Exports to China			0.327		0.361
			(0.199)		(0.200)
Business cycle correlation				15.19	17.48
				(13.76)	(13.78)
Observations	87	87	87	87	87
R^2	0.042	0.065	0.072	0.056	0.111

Note: Based on regression (4.1). Standard errors in parentheses.

Table 12: Imports (IMP) with additional controls

(a) Import growth in March 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	-9.181	-9.279	-9.639	-8.137	-8.807
	(3.854)	(3.890)	(3.865)	(3.962)	(4.052)
Ext. Finance Dependence		0.407			0.343
		(1.370)			(1.376)
Exports to China			0.142		0.123
			(0.122)		(0.125)
Business cycle correlation				-9.489	-7.743
				(8.550)	(8.786)
Observations	83	83	83	83	83
R^2	0.065	0.067	0.081	0.080	0.091

(b) Import growth in April 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	-12.73	-13.01	-13.54	-12.68	-14.26
	(7.153)	(7.215)	(7.181)	(7.410)	(7.557)
Ext. Finance Dependence		1.130			1.259
		(2.542)			(2.565)
Exports to China			0.249		0.261
			(0.227)		(0.233)
Business cycle correlation				-0.536	3.461
				(15.99)	(16.39)
Observations	83	83	83	83	83
R^2	0.038	0.040	0.052	0.038	0.055

Note: Based on regression (4.1). Standard errors in parentheses.

Table 13: Exports (EXP) with additional controls

(a) Export growth in March 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	-5.612	-6.014	-5.598	-4.834	-5.226
	(2.543)	(2.513)	(2.572)	(2.608)	(2.631)
Ext. Finance Dependence		1.671			1.580
		(0.885)			(0.893)
Exports to China			-0.00426		-0.0170
			(0.0811)		(0.0812)
Business cycle correlation				-7.073	-6.463
				(5.630)	(5.706)
Observations	83	83	83	83	83
R^2	0.057	0.097	0.057	0.075	0.112

(b) Export growth in April 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	-21.08	-22.25	-21.79	-17.11	-19.16
	(6.343)	(6.213)	(6.367)	(6.299)	(6.287)
Ext. Finance Dependence		4.904			4.531
		(2.189)			(2.134)
Exports to China			0.222		0.151
			(0.201)		(0.194)
Business cycle correlation				-36.04	-31.74
				(13.60)	(13.63)
Observations	83	83	83	83	83
R^2	0.120	0.172	0.133	0.191	0.240

Note: Based on regression (4.1). Standard errors in parentheses.

Table 14: Other outcomes

(a) Yearly growth rates in May 2020

	IP	EMP	IPI	PPI	PPI*	IMP	EXP
China exposure	-9.189	-4.047	8.107	3.537	8.961	-18.59	-14.12
	(4.409)	(2.303)	(2.786)	(2.186)	(5.906)	(8.392)	(6.948)
Observations	86	86	86	86	86	82	82
R^2	0.049	0.035	0.092	0.030	0.027	0.058	0.049

(b) Yearly growth rates in June 2020

	IP	EMP	IPI	PPI	PPI*	IMP	EXP
China exposure	-2.830	-1.351	5.155	2.810	9.261	-10.07	-2.419
	(3.019)	(1.485)	(1.887)	(1.333)	(4.577)	(6.730)	(4.716)
Observations	86	86	86	86	86	82	82
R^2	0.010	0.010	0.082	0.050	0.046	0.027	0.003

Note: Based on regression (4.1). Standard errors in parentheses. IP: industrial production growth, EMP: employment growth, IPI: import price index growth, PPI: purchaser price index growth, PPI*: PPI growth divided by price adjustment frequency, IMP: import growth, EXP: export growth.