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COVID-19 Supply Chain Disruptions[☆]

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ABSTRACT

In the early phase of the COVID-19 crisis, China imposed widespread lockdowns to contain the virus. We study the spillovers from the lockdowns to the US economy. We find that sectors with a high exposure to intermediate goods imports from China experienced significantly larger declines in production, employment, imports, and exports. In addition, relative input and output prices increased in these sectors. At the peak of the recession in April 2020, output was 16% lower in sectors with a one standard deviation higher China exposure. The estimated effects on output, input, and inflation are short-lived and dissipate by summer 2020.

1. Introduction

Over the past decades, the world economy has become increasingly interconnected through global value chains. While global value chains raise efficiency, they also raise the economic costs of disruptions in international supply chains. In this paper, we study the effects of international supply chain disruptions during the COVID-19 recession and early recovery.

In response to the COVID-19 outbreak, China imposed widespread lockdowns during February and early March 2020. These disruptions to economic activity in China were followed by a large contraction of US imports of intermediate goods from China, and a sharp decline in US industrial production in March and April 2020 (Fig. 1).

How important was the disruption in the supply of intermediate inputs from China for the decline in US real economic activity? Understanding the role of international supply chain disruptions during the COVID-19 crisis is important for an effective policy response.[1] For example, if lockdowns disrupt supply chains and constrain production, direct stimulus payments to households may have a limited impact on production and instead raise inflation. Potentially more effective are policy interventions that aim to preserve installed productive capacity and firm-specific human capital. Such interventions may prevent short-lived supply chain disruptions from leaving long-lasting scars. Policy interventions in this spirit include the Paycheck Protection Program and the Main Street Lending Program. Evaluating the effectiveness of these programs requires empirical evidence on the impact and persistence of international supply chain disruptions during the COVID-19 crisis.

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[1] An extensive literature studies the policy implications of COVID-19, e.g., lockdown policy in Alvarez et al. (2021), Eichenbaum et al. (2021), Krueger et al. (2022), and Glover et al. (2020), fiscal policy in Bigio et al. (2020), Mitman and Rabinovich (2021), Auerbach et al. (2021), and Bayer et al. (2023), and monetary policy in Caballero and Simsek (2021), Woodford (2022), and Fornaro and Wolf (2020).

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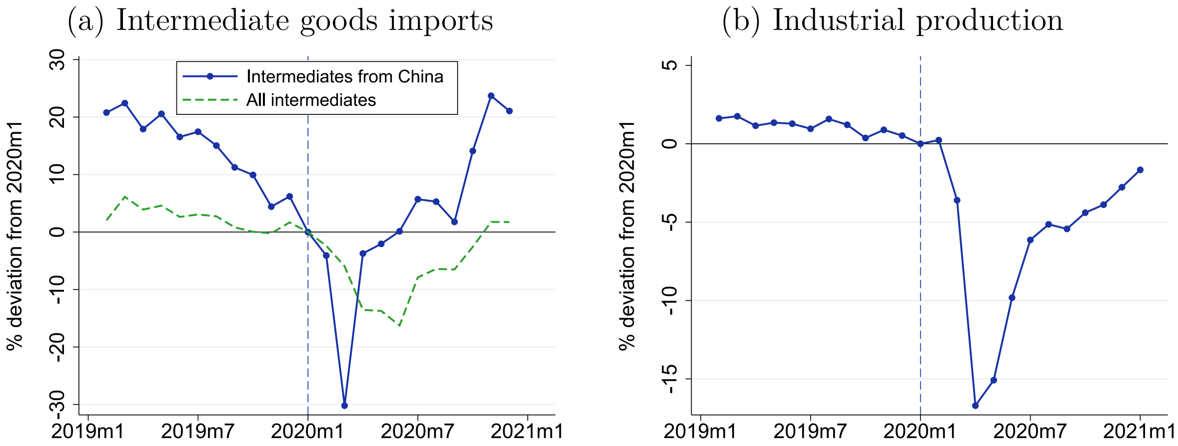

Fig. 1. COVID-19 crisis.
Notes: Panel (a) shows seasonally adjusted aggregate US imports of intermediate goods from China (solid line) and the corresponding world imports (dashed line). Covid-related goods, as identified in US International Trade Commission (2020), are excluded. The seasonal adjustment controls for trading days, calendar effects, including Easter and the Chinese New Year (following Roberts and White, 2015), and automatic outliers. Appendix B.1 provides details on the measurement of intermediate goods imports. Panel (b) shows seasonally adjusted US industrial production provided by the Federal Reserve Board.

In this paper, we provide empirical evidence on the effects of COVID-19 supply chain disruptions on real economic activity and prices in the US on a monthly basis.[2] Our empirical strategy exploits cross-sectoral differences in the share of imported intermediate goods from China prior to the COVID-19 crisis. The idea is that sectors with a higher dependence on inputs imported from China should also be more affected by supply chain disruptions stemming from the initial COVID-19 crisis in China.[3]

During February 2020, when lockdowns were first imposed in China, we find that US sectors with high exposure to Chinese imports did not significantly differ from less exposed sectors. Starting in March 2020, however, significant differences arise.[4] More exposed sectors experienced larger declines in production, employment, imports, and exports. Relative to January 2020, sectors with a one standard deviation higher China exposure experienced a 2% larger output decline in March 2020 and a 16% larger output decline in April 2020. Differences in China exposures account for 11%–14% of the cross-sectoral variance of industrial production growth during March and April. We also find that more exposed sectors experienced significantly larger declines in employment, exports, and imports. For all outcomes, the differential responses appear to be relatively short-lived and become insignificant by the summer of 2020.

An important question is whether our China import exposure predominantly captures the impact of China-related supply chain disruptions across US sectors. Potentially, sectors with high China import exposure were also more affected by the COVID-19 crisis through other channels, such as a slump in domestic demand, weaker external demand (namely from China), tighter financing conditions, or more exposure to the US–China trade war. We address the concern that our estimates are spurious in two ways. First, we show that our results are highly robust to controlling for sector-specific differences in export exposure to China, non-China import exposure, external finance dependence, business cycle sensitivity, and pre-trends, all computed before COVID-19. Second, we show that both import price inflation of intermediate inputs and output price inflation increased relatively more for sectors with higher China exposure between March 2020 and July 2020. This result makes it unlikely that changes in real activity in sectors with higher China exposure mostly reflect lower domestic or external demand. The estimated differences in producer price growth are insignificant after July. This finding may reflect a reversal to the pre-COVID trend of all industries, or it may reflect that initially less exposed industries become more affected over time which diminishes the differences across industries.

Finally, we examine differences in a broader non-China import exposure. Sectors with a high non-China import exposure also experienced larger output declines, but that finding disappears when controlling for other channels. Importantly, in sectors with high non-China import exposure, input and output prices decreased relative to other sectors, whereas we find the opposite price movement for sectors with high China import exposure. This suggests that the broader non-China exposure mostly captures the effects of demand differences across sectors.

Related literature. 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 on economic activity. Our empirical results

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

[3] Our empirical strategy to exploit heterogeneous pre-crisis exposure to intermediate goods is similar to Boehm et al. (2019), Carvalho et al. (2021), and Flaaen and Pierce (2019).

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

suggest significant, albeit relatively short-lived, differential effects of COVID-19 supply chain disruptions. Our results are not only important for the design of effective macroeconomic stabilization policy, they are also informative about 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, 2021). Indeed, the impact of the COVID-19 crisis on supply chains and the design of resilient supply chains received increased public attention since March 2020.[5] The COVID-19 crisis might even be a turning point for de-globalization (Antràs, 2021).

While there is an empirical literature studying supply chain disruptions prior to the COVID-19 shock, this literature focuses on a different set of events such as natural disasters, wars, and trade wars.[6] Natural disasters and wars involve the destruction of infrastructure and physical capital, which may generate more persistent differential effects.[7] Trade wars often result in persistently higher tariffs. In contrast, lockdowns are commonly short-lived. We therefore consider it important to provide empirical evidence on COVID-19 supply chain disruptions. Closely related empirical papers are Lafrogne-Joussier et al. (2023), which provides firm-level evidence on the sales and export response of French firms exposed to lockdowns in China, and Cerdeiro and Komaromi (2020) and Berthou and Stumpner (2022), which study the reaction of trade flows to lockdowns. Our empirical findings align well with the evidence in Hassan et al. (2020). Analyzing earnings calls by publicly listed firms in the first quarter of 2020, the authors document that firms' primary concerns were the collapse of demand, increased uncertainty, and disruption in supply chains.

A number of related papers analyze the propagation of COVID-19 associated shocks in quantitative models with input and output linkages. For example, Barrot et al. (2021) study the effects of social distancing on GDP, Baqaee and Farhi (2022) study the role of demand and supply shocks during the COVID-19 crisis, Bonadio et al. (2021) and Eppinger et al. (2020) study the international propagation of labor supply shocks, Gerschel et al. (2020) study the international propagation of a productivity decrease in China, and Acharya et al. (2021) study the policy implications of COVID-19 spreading via international trade. More broadly, we contribute to the growing theoretical literature studying the supply chain propagation of shocks, for example, Acemoglu et al. (2012), Huneeus (2018), Carvalho and Tahbaz-Salehi (2019), Meier (2020), Baqaee and Rubbo (2022), and Ferrari (2022).

The remainder of this paper is organized as follows. Section 2 presents a simple model. Section 3 describes the data and Section 4 presents our empirical findings. Section 5 provides a discussion. Section 6 concludes and an Appendix follows.

2. A model of supply chain disruptions

This section presents a simple model of supply chain disruptions. The model describes channels through which supply chain disruptions may differ in their impact across sectors. The model further guides the subsequent empirical analysis.

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

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

where $\sigma = 1/(1-\rho)$ is the substitution elasticity between x_t^1 and m_t^1, $\rho \in (-\infty, 1)$, $\eta \in (0,1)$, 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 for 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. Period profits of type 1 establishments are $\pi_t^1 = p(y_t^1)y_t^1 - p_t^x x_t^1 - p_t^m m_t^1$, where $p(y_t^1) = b(y_t^1)^{\gamma-1}$ is a downward-sloping isoelastic inverse demand function with $\gamma \in (0,1)$ and b_t a demand shifter. Similarly, profits of type 2 establishments are $\pi_t^2 = p_t(y_t^2)y_t^2 - p_t^x x_t^2$. Before the arrival of a supply-chain disruption, the economy is in a steady state in which type 1 establishments choose x^1 and m^1 to maximize profits, and type 2 establishments choose x^2 to maximize profits. We normalize steady state productivity a^1 such that $y^1 = y^2$. Hence, the type-specific contribution to sectoral output is solely captured by ϕ.

In period t, the economy is shocked 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 the effects of the widespread lockdown in China during February and March 2020. We consider the response of type 1 establishments under fixed input prices. The supply of m_t^1 becomes a binding constraint allowing type 1 establishments only to re-optimize x_t^1 after

[5] This includes management science, business consultancies, and the media reporting on supply chain issues related to widespread lockdowns in China (e.g., Choi et al., 2020, Schmalz, 2020, Donnan et al., 2020).

[6] 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.

[7] For 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. For the 2011 earthquake in Japan, Boehm et al. (2019) find that imports and exports of exposed US producers are depressed for up to half a year.

the disruption.[8] The first-order condition for x_t^1 after the supply chain disruption implies that the factor input ratio $z_t^1 = x_t^1/m_t^1$ is adjusted according to (see Appendix A)

$$\frac{d\log z_t^1}{d\log m_t^1} = -\frac{1-\gamma}{(1-\rho)-(\gamma-\rho)\epsilon} \le 0, \quad \text{where} \quad \epsilon = \frac{z^1 f'(z^1)}{f(z^1)} \ge 0. \tag{2.2}$$

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,

$$d\log y_t^1 = \underbrace{d\log m_t^1}_{\text{direct effect}<0} + \underbrace{\frac{-(1-\gamma)\epsilon}{(1-\rho)-(\gamma-\rho)\epsilon} d\log m_t^1}_{\text{indirect effect}\ge 0} = \Psi \cdot d\log m_t^1, \tag{2.3}$$

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., when a 1% drop in m_t^1 lowers output by 1%. The response of sectoral output is

$$d\log y_t = e^B \cdot \tilde{\Psi} \cdot d\log m_t^1, \tag{2.4}$$

where $\tilde{\Psi} = \frac{1-\eta+\eta(z^1)^\rho}{1-\eta} \cdot \Psi \ge 0$ and e^B is the import exposure to country B in steady state, see Appendix A for details of the derivations. Formally, e^B is defined as

$$e^B = \frac{p^m \phi m^1}{p^x(\phi x^1 + (1-\phi)x^2) + p^m \phi m^1}. \tag{2.5}$$

Hence, sectors with a higher import exposure to country B before the shock respond more strongly to the supply chain disruption shock.[9] Eq. (2.4) motivates our empirical analysis. Our empirical strategy is to identify cross-sectoral differences in the effects of supply chain disruptions through cross-sectoral differences in import exposures e^B.

We next discuss what shapes the effects of supply chain disruptions in the model. First, suppose the Leontieff case in which inputs cannot be substituted ($\rho \to -\infty$) and which yields $\Psi = 1$. In this special case $\tilde{\Psi} = \phi/e^B$. Hence the pass-through of $d\log m_t^1$ to sectoral output depends only on ϕ, the fraction of establishments using m^1 in production. Importantly, sectoral output will drop by more in sectors with a higher ϕ, and thus in sectors with a higher exposure e^B. Next suppose ρ is larger than in the Leontieff case, i.e., inputs are somewhat substitutable, but keep e^B unchanged (e.g., because we recalibrate η to match the same target e^B when ρ changes). As ρ increases toward perfect substitutes, Ψ falls toward zero and $\tilde{\Psi}$ falls as well. Note that rising prices of the disrupted input may amplify the output contraction. However, in the Leontieff case, higher input prices do not affect the output effects of supply chain disruptions, as long as the supply of the disrupted input is a binding constraint.

Another potential source of variation in e^B is η. As long as inputs are somewhat substitutable ($\rho > -\infty$), the sector with a lower η has a higher expenditure share e^B for m^1. At the same time, a lower η implies a lower elasticity ϵ, which results in a larger output response to the supply chain disruption. While ϕ, η, and ρ may all shape differences in the output response across sectors, our preferred view is that ϕ is the key driver. The view is motivated by the firm-level evidence in Lafrogne-Joussier et al. (2023) which shows that conditional on sourcing from China, the extent to which a firm relies on inputs from China does not predict a larger fall in output. This evidence can be rationalized by our model when the substitution elasticity is close to zero. It is further consistent with the evidence that sector differences arise because the fraction of exposed firms differs across sectors.

3. Data

Our empirical strategy exploits sectoral variation in China import exposures. In this section, we explain how these measures are constructed and describe the sectoral monthly outcomes used in our empirical analysis.

3.1. China import 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 total costs of variable inputs in sector i.

$$e_i^B = \frac{(\text{Intermediate goods imports from } B)_i}{(\text{Variable input costs})_i} \tag{3.1}$$

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 maintained by the Census. In addition, we have the value of 6-digit NAICS commodity imports (from all countries) used

[8] Modeling the supply chain shock as a binding constraint on an input is similar to Boehm et al. (2019).

[9] Given the demand function, the decline of output directly translates into higher output prices $d\log p_t^1 = -(1-\gamma)d\log y_t^1$ and similarly into higher sector-level prices. Conversely, a downward shift in the demand function through b would generate the opposite comovement between prices and output.

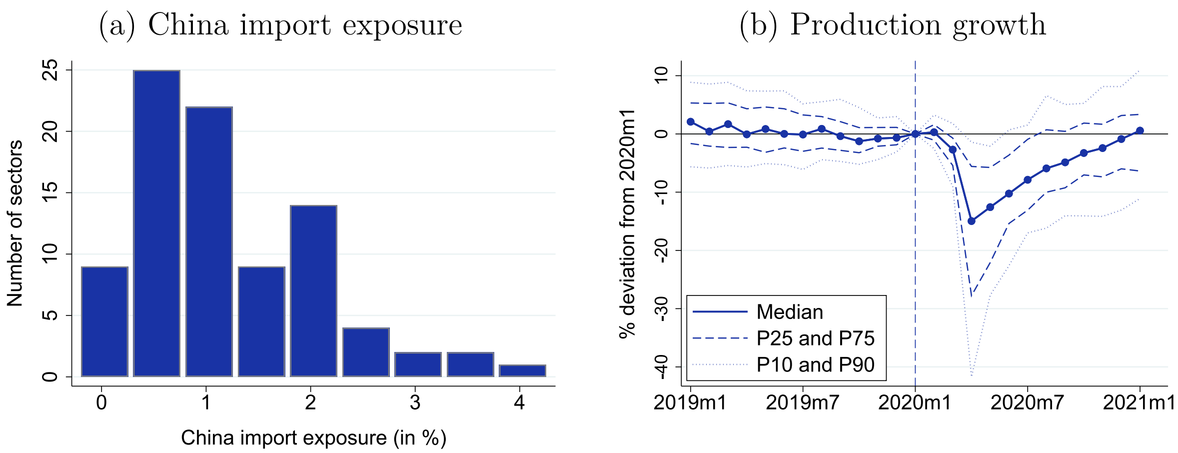

Fig. 2. Heterogeneity across industries.
Notes: Panel (a) shows the histogram of China import exposures (3.1) across US industries. Panel (b) shows percentiles of the percentage change in monthly industrial production (seasonally adjusted) across US industrial sectors, based on the Federal Reserve G.17 release.

by 6-digit NAICS sectors from the BEA's 2012 import matrix. To construct sector-specific intermediate goods imports from China, we adopt a proportionality assumption, as described in Johnson and Noguera (2012) and similarly applied to construct the World Input–Output Database (Timmer et al., 2015). We compute the denominator in (3.1) at the level of 6-digit NAICS sectors as the sum of labor compensation and the value of all intermediate inputs used in production in the BEA's use table of the 2012 input–output accounts. Finally, we aggregate the numerator and denominator to the finest level of disaggregation, roughly 4-digit NAICS sectors, for which we can match sectoral outcomes such as industrial production. For further details on the China import exposure, see Appendix B.2.

The final sample contains 88 distinct manufacturing and related industries. Panel (a) of Fig. 2 shows a histogram of China exposures across these industries.[10] We observe large differences in the input cost share of intermediates imported from China ranging from less than 0.1% to above 4%, with an average of 1.2% and a standard deviation of 0.9%. While these fractions are relatively small, our simple model in Section 2 shows that a disruption in the supply of Chinese inputs could potentially lead to as much as a complete halt of production in some US sectors. The magnitude of the effect critically depends on how easily inputs sourced from China can be substituted for inputs sourced outside of China.

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 variable input costs. The sector-specific exports to China are based on the International Trade Data.[11]

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.[12] IP is a monthly index reported 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.[13] 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 the 2020 data, which was released in May 2021.[14]

[10] Table B.1 in the Appendix lists all industries and their China exposures.

[11] The cross-sectoral correlation between the China import exposure and the non-China import exposure is 0.39, and the correlation between the China import exposure and the China export exposure is −0.06.

[12] 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.

[13] 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.

[14] We prefer to use revised data because measuring economic activity during the COVID-19 recession was challenging and some revisions are substantial. However, our main results are unaffected by the revision.

Panel (b) of Fig. 2 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 Fig. 1 during the COVID-19 recession. What stands out is the large heterogeneity across sectors. Relative to January 2020, industries at the 75th percentile of the IP growth distribution shrank by less than 5% in April 2020, while industries at the 25th percentile had shrunk by more than 25%.

We further use data on sector-specific employment, imports, exports, import prices, and output prices, all aggregated to the same 88 sectors.[15] We obtain employment from the Current Employment Statistics maintained by the BLS. Sector-specific imports and exports are provided in the International Trade Data. We construct sector-specific prices for intermediate goods imports by combining product-specific price indexes from the BLS International Price Index files with the sector-specific composition of intermediate goods imports from the BEA 2012 import matrix. Output prices are based on the sector-specific producer price indexes maintained by the BLS. Throughout the paper, we use seasonally adjusted sector-level time series. Seasonally adjusted sector-level industrial production and employment series are provided by the Federal Reserve Board and the BLS, respectively. For sector-level imports, exports, import prices, and producer prices, seasonally adjusted data are not available from the data providers. We therefore apply the X-13ARIMA-SEATS to deseasonalize the data. We use data until 2019 to forecast the seasonal components in 2020.

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 the behavior of production for sectors with high China import exposure. We further discuss and address a number of potential confounders, extend the analysis to other real economic outcomes and to prices, and finally we study the role of non-China import exposures.

4.1. Empirical model

Our empirical strategy follows from the model in Section 2 and 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

$$\log(y_{it}) - \log(y_{i,2020m1}) = \alpha_t + \beta_t e_i^B + \Gamma_t Z_i + u_{it} \tag{4.1}$$

where y_{it} is a sector-time specific outcome (e.g., industrial production in the steel sector in March 2020) and Z_i is a vector of sector-specific control variables.

Our empirical analysis focuses on the exposure of US sectors to imports from China (B = China). If we assume that e_i^{China} is orthogonal to other channels that explain differential outcomes across sectors during the COVID-19 crisis, then β_t captures the effect of supply chain disruptions across sectors. 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. Effects on industrial production

We provide empirical evidence that shows how industrial production growth diverged across sectors with different China import exposure during the COVID-19 crisis.

We first estimate equation (4.1) when y_{it} is monthly industrial production, e_i^B is the China import exposure, and no control variables Z_i are included. We view this as a baseline analysis, which we extend subsequently. Fig. 3 shows the estimated β_t as markers with the shaded area indicating the 90% confidence band. The β_t are standardized to capture the differential effect on production, in percentage points (p.p.), associated with a one standard deviation higher e_i^{China}.

Three observations stand out from Fig. 3. First, from 2019 through February 2020, differences in output growth across sectors with different China import exposures are close to zero and mostly insignificant. This might be surprising against the backdrop of the US–China trade war. A potential explanation is the sectoral concentration of tariffs, which our exposure measure is unlikely to capture. In fact, our evidence is consistent with Flaaen and Pierce (2019), which shows that sectors with higher input costs due to tariff hikes do not produce significantly less than other sectors.[17] The small and positive β_t estimate in February 2020 may be surprising because the lockdowns in China started in February.[18] We think this seemingly inconsistent finding plausibly reflects the considerable period of time for cargo to travel from China to the US.[19] Indeed, aggregate US imports from China only slumped in March (Fig. 1). In addition, the immediate effect of disrupted supplies was likely dampened as US producers used their inventory of imports from China to sustain production during February.

[15] Similar to industrial production, we also use the latest data following the 2020 annual revision.

[16] A common approach in the related literature is to estimate differential treatment effects by regressing an outcome in levels on time dummies interacted with exposures as well as time and sector fixed effects. Our regression model corresponds to taking differences relative to a base period.

[17] In Section 4.3, we show that our findings are robust to controlling for trade war-related tariff changes.

[18] To be precise, the February 2020 lockdowns in China were an extension of the Chinese New Year holiday (observed from the 24th to the 30th of January, 2020) into the first weeks of February. These holiday extensions were imposed by the government to combat the epidemic. They affected many of the largest Chinese provinces and were announced in late January and further extended during February.

[19] Cargo transportation time per ship from China to the US was at least 40 days before the COVID-19 crisis: https://www.flexport.com/research/ocean-timeliness-indicator/.

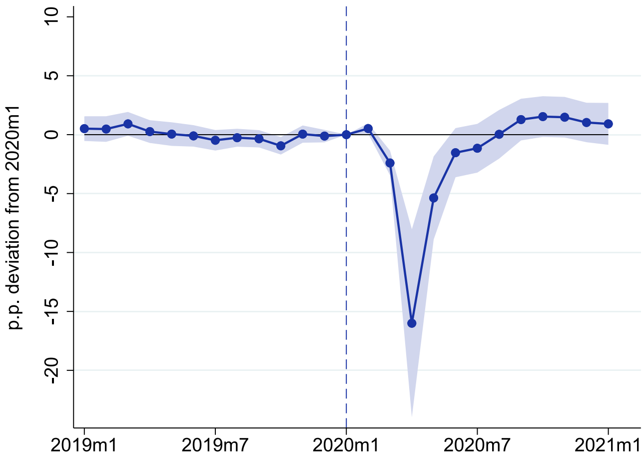

Fig. 3. Production growth and high China import exposure.
Notes: The markers show the estimated β_t coefficients based on Eq. (4.1), when y_{it} is industrial production, e_i^B is the China import exposure, and no control variables Z_{it} are included. The β_t estimates are standardized to capture the differential effect (approx. in p.p.) on industrial production associated with a one standard deviation higher e_i^{China}. The shaded area shows the 90% confidence band based on heteroskedasticity and autocorrelation robust standard errors.

Second, and this is the key finding, we find large and significant production differences in March and April 2020. Relative to January 2020, production growth was 2.4 p.p. lower in March and 15.9 p.p. lower in April for every 1 standard deviation increase in the China import exposure across sectors. The estimates suggest lockdowns in China rapidly affected US production, which is consistent with limited inventory holdings of the disrupted goods and low short-run substitutability. We further compute the fraction of the cross-sectoral variance in production growth that can be explained by different China exposures. Note that the cross-sectional standard deviations of production growth in March and April relative to January 2020 are very large, $\sigma(y_{i,2020\text{m}3}) = 6.4\%$ and $\sigma(y_{i,2020\text{m}4}) = 47.6\%$, see also Fig. 2(b). Therefore, a considerable share of the cumulative output change variance in March and April, respectively 14% and 11%, can be accounted for by different China exposures.[20]

Third, after the peak in April, differences in output growth quickly revert to zero. While more exposed sectors still experienced significantly larger cumulative production declines of 5.3 p.p. in May relative to January 2020, starting from June and through January 2021 these differences are practically zero.[21] Effectively, the stronger contraction of more exposed sectors during March and April is almost fully reversed by June. This suggests that lockdowns in China at the beginning of the COVID-19 crisis had rather transitory differential effects on US industrial production lasting for about three months.

The short-lived effects of lockdowns in China on the US economy suggested by our estimates may be relevant to the policy response. For example, to the extent that supply was constrained by the limited availability of intermediate inputs between March and May 2020, fiscal spending that stimulated aggregate demand relative to supply may have been less effective in these initial months of the COVID-19 crisis, and more effective in subsequent months. Instead, during the initial phase of the COVID-19 crisis, more effective policies would support companies to help them survive and maintain their productive capacity. Some examples of these kinds of policies would be unconventional monetary policy measures aimed at maintaining access to credit and 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-globalization, triggered by the disruptions to cross-border supply chains since early 2020 (Antràs, 2021), in the sense that the initial disruptions to domestic production, although quite large, were relatively short-lived, at least in the cross-section. 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).

We next provide a structural interpretation of our empirical estimates through the lens of our model in Section 2. Our interpretation rests on two assumptions. First, we assume the shock to intermediate goods supply from China is 30%, i.e., $d \log m_t^1 = -0.30$, in line with the peak drop in intermediate goods imports from China in Fig. 1. Second, we assume zero short-run substitutability ($\rho \to -\infty$) as supported by the estimates in Boehm et al. (2019) and Lafrogne-Joussier et al. (2023). To rationalize the differential production growth of −15 p.p. in April for a sector with an approximately 1 p.p. larger e^{China} then requires a 50 p.p. higher share of firms using m_t^1 in production in this sector versus other sectors. For example, the output is $d \log y_t = 0$ for a sector with $\phi = 0$ and $d \log y_t = 0.5 \cdot (-0.30) = -0.15$ for a sector with $\phi = 0.5$.[22] A potential explanation for the lower differential estimates for the

[20] Panel (a) of Fig. C.1 in the Appendix shows the variance decomposition across time.

[21] We further find the β_t estimates remain close to zero between January 2021 and January 2022.

[22] The range of ϕ we consider here is broadly consistent with empirical evidence on the average share of manufacturing output accounted for by firms importing from China. From Antràs et al. (2017), we conclude that the sales-weighted share of US manufacturing firms that are importers is 71% (the weighted average across M and M+ firms in Table C.1 of the Online Appendix) and that 33% of importing manufacturing firms import from China. Hence, the sales-weighted share

months following April may be a combination of diminishing supply chain shocks, $d \log m_t^1$, for those months and a higher elasticity of substitution as more substitution opportunities become available over time.

4.3. Alternative explanations

While the estimates in Fig. 3 suggest that supply chain disruptions in US–China trade early in the COVID-19 crisis had short-lived but quantitatively large differential effects on US industrial production, confounders might bias our conclusions. In this section, we show that our estimates are robust to controlling for a number of potentially alternative factors.[23]

We consider five factors: industries with higher China import exposure might also be more cyclically sensitive, be subject to different trends, rely more heavily on external finance, be more dependent on China as an export market, and be more affected by the US–China trade war and subsequent trade deal. For example, our β_t estimates in Fig. 3 could capture differences in business cycle sensitivity rather than the effects of a higher China exposure.

We address these concerns by augmenting Eq. (4.1) with five sector-specific covariates (Z_i). To control for differences in cyclical sensitivity, we compute the correlation between sectoral annual IP growth and annual (aggregate) GDP growth between 1972 and 2019. To control for pre-trends we compute the average monthly growth rate of industrial production between 2010 and 2019. Our measure of sectoral external finance dependence is based on Rajan and Zingales (1998) and uses data between 2010 and 2019. We control for China export exposure with the China share of exports in 2019. Finally, we control for exposure to the US–China trade war by using the change in effective duty rates on imports from China between August and December 2019. This time span captures the last round of tariff hikes, which were partially reversed by the Phase One trade deal.[24]

Panel (a) of Fig. 4 shows that our conclusions regarding the differential output growth of more exposed sectors are robust to controlling for the five alternative factors. In particular, panel (a) compares the baseline β_t estimates shown in Fig. 3 (blue line and markers) with the β_t estimates after adding the five covariates (green dashed line and markers). The point estimates are almost indistinguishable from each other, and the confidence bands (green dotted lines) become only marginally wider when the covariates are included. Similarly, the variance in industrial production growth in March and April, relative to January 2020, which is explained by different China import exposures hardly changes when including the covariates (panel (b) of Fig. C.2 in the Appendix).

4.4. Effects on employment, imports, and exports

We next provide evidence for employment, imports, and exports that is consistent with the evidence for industrial production. Growth in employment, imports, and exports falls by significantly more in sectors with higher China import exposure, and these differences are also short-lived.

Panel (b) of Fig. 4 shows that cumulative employment growth by April 2020 is 4.6 p.p. lower in sectors with a one standard deviation higher China import exposure. This difference is highly statistically significant and barely changes when accounting for the set of additional factors considered in Section 4.3. Our estimates mean that China import exposure accounts for 18% of the variance in employment growth across sectors (Fig. C.1). In contrast to production, the March 2020 employment growth is nearly unaffected by China import exposure. This may reflect labor adjustment frictions. Anticipating costly hiring, firms may prefer to hold on to workers until they better understand the severity and persistence of the crisis. Labor adjustment frictions may also explain why the differential employment effects are (mildly) more persistent than the production effects.

Panels (c) and (d) of Fig. 4 show that cumulative growth of both exports and imports in April 2020 contracts by more in sectors with higher China import exposure. This finding does not change when controlling for alternative factors. The persistence beyond April is similar to that for industrial production, and the estimates suggest that China import exposure accounts for similar shares of variance in import and export growth across sectors as they do for production (Fig. C.1). The export response may be a consequence of lower production. The import response is consistent with high China import exposure sectors facing larger disruptions to their input supply. In fact, the coefficient on imports becomes significantly negative in March 2020, one month before the coefficient on exports.

4.5. Effects on import and producer prices

We next show that both import and output prices increased by more in sectors with higher China import exposure. The evidence is consistent with supply chain disruptions explaining the differential effects in economic activity in sectors with higher China import exposure.

Panel (e) of Fig. 4 shows that import price inflation was significantly higher in more exposed sectors starting from February 2020. The differential effect peaks in April and some differences persist until the end of the sample. This finding does not change

of US manufacturing firms that import from China is 23%, which can be interpreted as an average of ϕ across manufacturing sectors. Reassuringly, Handley et al. (2021) show that importers account for 73% of manufacturing employment. Recent evidence in Census (2022, Table 5e) suggests that an even higher share, 54%, of US importer firms import from China, which suggests the average ϕ may be larger than 23%.

[23] Relatedly, in Section 4.5 we show evidence of differential price responses which further supports our interpretation of the production estimates.

[24] For details on the duty rate changes during the US–China trade war, see Appendix B.3. Controlling for duty changes over a longer range of time does not change our results.

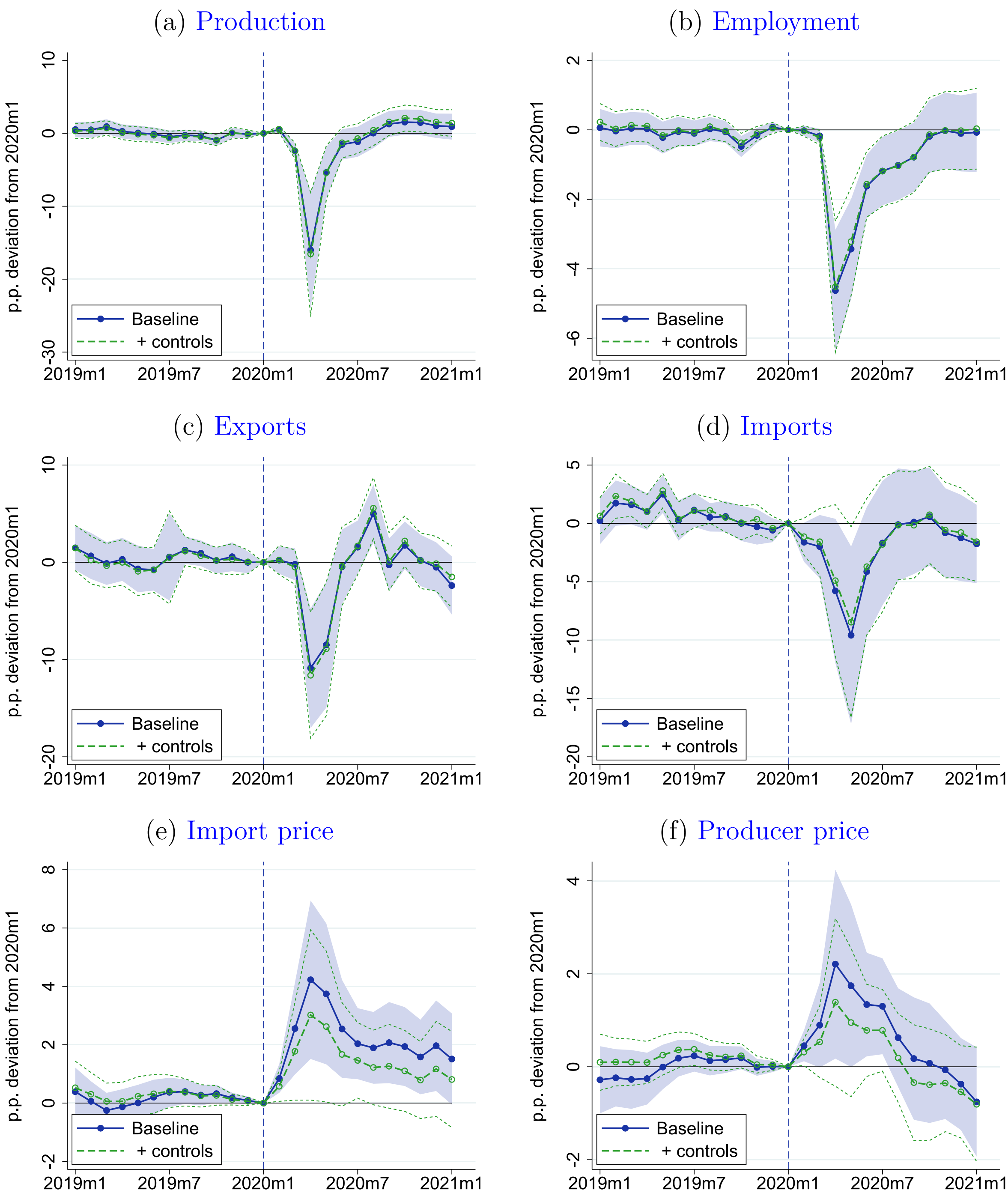

Fig. 4. Sector outcomes and high China import exposure.
Notes: The solid lines and markers ("Baseline") show the estimated β_t coefficients based on Eq. (4.1), when y_{it} is a different outcome across panels (a)–(f), e_i^B is the China import exposure and when no control variables Z_{it} are included. The dashed lines and markers ("+ controls") show the estimated β_t coefficients when we control for sector-specific pre-COVID-19 business cycle sensitivity, trends, external finance dependence, China export exposure, and duty changes during the US–China trade war and deal. The β_t estimates are all standardized to capture the differential effects (approx. in p.p.) associated with a one standard deviation higher e_i^B. The shaded area and dotted outer lines show the 90% confidence band based on heteroskedasticity and autocorrelation robust standard errors.

when controlling for potential confounders. This evidence further supports the interpretation that higher China import exposure predominantly captures the relative strength of supply shocks across sectors.

Still, it is possible that sectors with a high China import exposure were also more strongly affected by other channels of the COVID-19 recession, namely through a slump in domestic demand. If lower demand explained why industrial production fell more in sectors with higher China exposure, then we would expect prices in these sectors to fall relative to 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, which is what our results show. Panel (f) of Fig. 4 shows that relative producer price inflation increased for more exposed sectors. While the estimates are less significant than they are for import prices, they are consistent with more exposed sectors being more affected by supply chain disruptions.

4.6. Non-China import 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 from elsewhere. We consider a broad sector-specific import exposure that includes all intermediate goods imports except those originating from China.[25] Using this non-China import exposure we re-estimate regression (4.1) and present the associated β_t estimates for all outcomes in Fig. 5. Similar to China import exposures, high non-China import exposures are associated with lower production growth between March and August 2020. However, the estimates are less significant, in particular when controlling for alternative factors, and they are smaller in magnitude. Similarly, we tend to see relatively lower growth of employment, exports, and imports for sectors with higher non-China import exposure. However, the estimates are substantially smaller in magnitude and less precisely estimated. Importantly, panels (e) and (f) of Fig. 5 show that import and output prices in sectors with higher broad import exposure grow at lower rates relative to other sectors. These estimates have the opposite sign of what we find in panels (e) and (f) of Fig. 4.

The results for the non-China import exposure allow us to conclude the following. First, the China exposure effects do not seem to primarily result from broader international turmoil because, otherwise, we would expect the China exposure to have similarly small and barely significant employment effects as the non-China exposure. Second, the (weaker) relative decline in real economic activity of sectors with high non-China import exposure does not seem to reflect international supply chain disruptions, as it is associated with relatively lower price growth and no material effects on imports (in March and April). In this respect, note that the lower output price growth for sectors with high non-China import exposure is not simply a mirror image of the higher price growth for sectors with high China import exposure because, as stated in footnote , the two exposure measures are positively correlated. Instead, a potential explanation for these findings is that sectors with a high non-China import exposure were more severely hit by a decline in domestic demand due to the COVID-19 crisis, consistent with relatively lower output price growth. In support of this explanation, we find that sectors with a higher non-China import exposure tend to be more downstream than sectors with a higher China import exposure (using the downstreamness measure in Antràs and Chor, 2022).

4.7. Role of domestic supply chains

A caveat to the preceding findings is that our empirical design only accounts for sectoral differences in the direct exposure to the disruption, e_i^{China}. However, sectors may also differ in their indirect exposure through non-Chinese suppliers of intermediate inputs. A condition under which our estimates capture the direct and indirect effects is that the indirect exposure is proportional to the direct exposure. Even if this condition is not satisfied, the direct effect may still capture most of the total effect briefly after the lockdown because of transportation lags and inventories. Extending our analysis to account for *global* indirect effects is not feasible because a world input–output table is not available for sufficiently disaggregated sectors.[26]

However, extending our analysis to account for *domestic* indirect effects is feasible. Sectors may differ in their indirect exposure to the disruption in China through their domestic supply network. For example, a sector may have low direct exposure to imports from China, but it may strongly depend on inputs produced by another US sector that is in turn strongly exposed to supplies from China. We define the indirect *domestic* exposures as a weighted sum of the *direct* exposures across all the inputs that are sourced domestically. The weights are defined as the ratio of domestic inputs of commodity j used in sector i over total variable costs of sector i, similar to the direct exposure in Eq. (3.1). To compute domestic inputs we subtract imports of intermediate inputs in the import matrix from total intermediate inputs in the use matrix from the BEA 2012 Input–Output Accounts. For further details on the indirect import exposure see Appendix B.2. Table B.1 lists the indirect domestic exposures, $e^B_{i,dom}$, for all sectors. Note that this approach only accounts for first-degree indirect effects. We believe this indirect exposure is more relevant in the short run after a shock than the Leontieff inverse.

If we define the total exposure as the sum of direct and (domestic) indirect exposure, we find that they are very highly correlated with each other. Across sectors, the correlation is 0.99. The high correlation partly arises because indirect exposures tend to be smaller than direct exposures. The average for the former is 0.42 and 1.20 for the latter. In addition, sectors tend to source a sizable fraction of their inputs from firms within the same sector. When reproducing the results in Fig. 4 using total exposure, our estimates

[25] The correlation between the China import exposure and the non-China import exposure is 0.39.

[26] The World Input–Output Database includes 15 sectors in the industrial sector compared to 88 sectors in our data. Our estimates are mostly insignificant if we repeat the analysis at the level of 15 broader sectors.

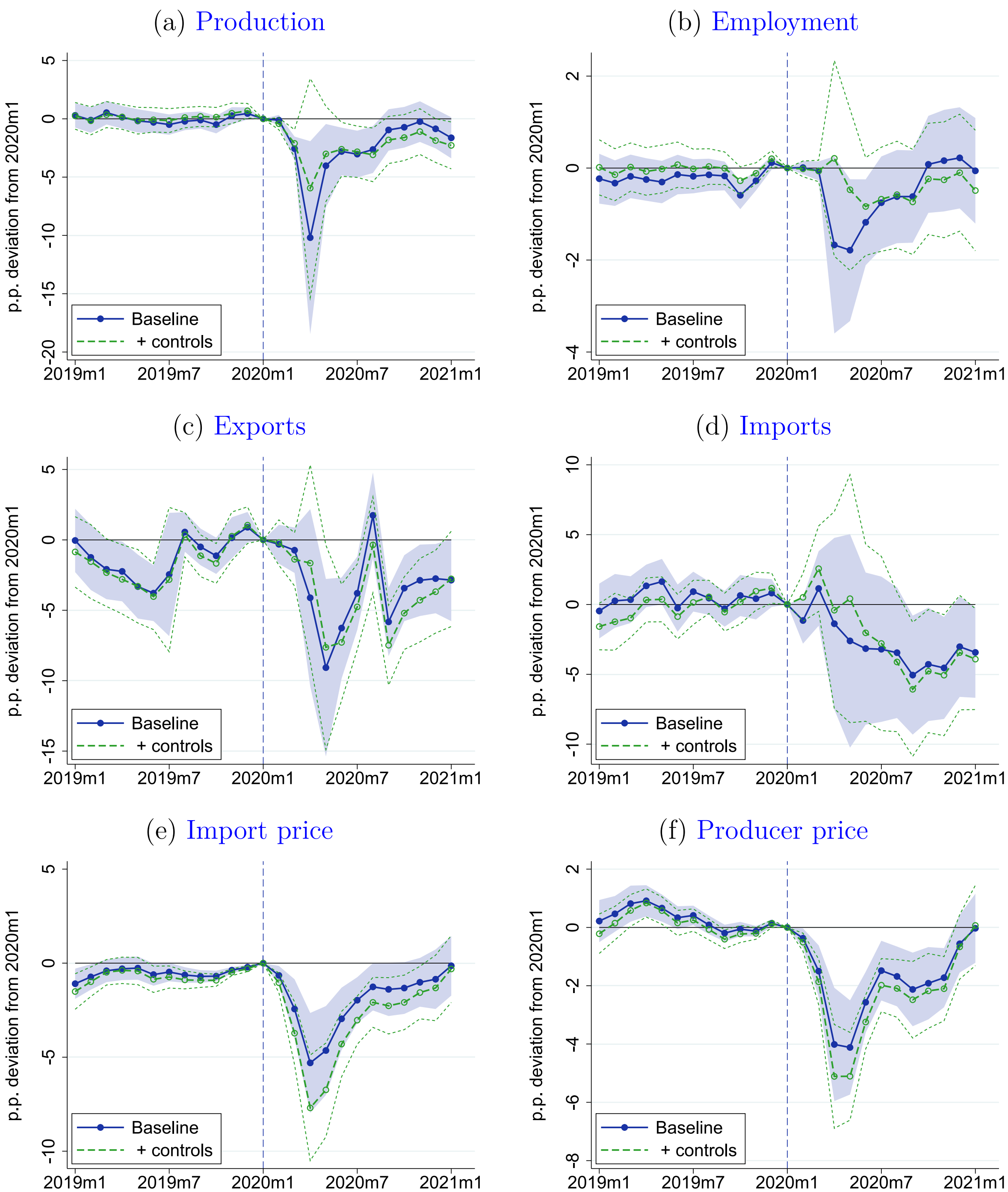

Fig. 5. Sector outcomes and high non-China import exposure.
Notes: The solid lines and markers ("Baseline") show the estimated β_t coefficients based on Eq. (4.1), when y_{it} is a different outcome across panels (a)–(f), e_i^B is the non-China import exposure and when no control variables Z_{it} are included. The dashed lines and markers ("+ controls") show the estimated β_t coefficients when we control for sector-specific pre-COVID-19 business cycle sensitivity, trends, external finance dependence, China import exposure, China export exposure, and duty changes during the US–China trade war and deal. The β_t estimates are all standardized to capture the differential effects (approx. in p.p.) associated with a one standard deviation higher e_i^B. The shaded area and dotted outer lines show the 90% confidence band based on heteroskedasticity and autocorrelation robust standard errors.

are practically identical which is not surprising given the high correlation between exposures. Because differences between the estimates are barely visible, we do not provide a figure with the estimates for total exposures.

We further study the indirect exposure only. The indirect exposure has a correlation with the direct exposure of 0.71 so we may not mechanically expect to find the same as in Fig. 4. The question is whether sectors with a higher indirect exposure through other U.S. sectors evolved differently during the COVID-19 crisis. Fig. C.3 in the Appendix shows that this is indeed the case. In fact, we find that the differential evolution of sectors with a higher indirect exposure is qualitatively and even quantitatively similar to the findings in Fig. 4. This may reflect the non-negligible positive correlation between direct and indirect exposure. Another potential explanation is that shocks to direct suppliers are well understood and lead to a swift response from downstream producers.

5. Discussion

In this section, we discuss the relation of our empirical findings to the existing literature on supply chain disruptions (e.g., Barrot and Sauvagnat, 2016; Boehm et al., 2019; Carvalho et al., 2021; Lafrogne-Joussier et al., 2023).

While the literature cited above studies firm-level data, our analysis uses sector-level data. Sectoral data offers several advantages, including the timely and public availability, its high frequency, and the possibility to jointly examine a wide range of outcomes. Interestingly, our findings that sectors with higher exposure to supply chain disruptions experience larger declines in real economic activity are qualitatively consistent with the firm-level evidence. It is not evident a priori that this relationship would hold. For example, within a sector, firms not directly affected by the supply chain shock might gain market share over disrupted competitors, leading to a relatively weaker decline or even an increase in sector-level output. Conversely, firms without direct exposure to the shock may still contract due to their connections with directly affected firms, e.g., through supply chains and trade credit. As a result, firm-level estimates of the differential effects may over- or underestimate the differential direct effects of supply chain disruptions. Moreover, the connectedness of firms within the same sectors through supply chains may amplify the contraction of sector-level real activity. In this context, our sector-level evidence complements the existing firm-level evidence, providing additional insights into the overall impact of supply chain disruptions.

One of the contributions of our analysis is to jointly examine a wide range of outcomes, including inputs, outputs, and prices. This comprehensive approach complements the findings of related studies that focus on subsets of these outcomes. Our analysis reveals differences in the timing and intensity of the contraction of the inputs and outputs we consider. Imports and production lead the contraction with exports and employment following with a one-month lag and the latter remaining subdued the longest.

Another contribution of our research is the estimation of how supply chain disruptions affect import and output prices. Existing firm-level studies that examine price responses tend to focus on specific types of prices. For example, Lafrogne-Joussier et al. (2023) study export prices during the COVID-19 recession and find that firms exposed to the China supply chain disruption experience lower export prices. This finding, which appears counter-intuitive in the presence of supply shocks, may reflect specific developments on export markets. Another study by Boehm et al. (2019) finds an insignificant price response for US affiliates of Japanese multinationals following the 2011 earthquake and tsunami in Japan. This result may reflect the unique pricing characteristics within multinational firms. In contrast, our sector-level evidence studies a broad set of prices. We show that supply chain disruptions are associated with higher import prices, which then propagate downstream to raise output prices. Our estimates quantify the inflationary effects of supply chain disruptions, which is relevant for quantitative research exploring the implications of supply chain shocks for monetary and fiscal stabilization policies.

Furthermore, the price responses provide additional moments that allow us to test whether our exposure measure predominantly captures differences in the intensity of supply chain disruptions across sectors. Future research could combine changes in prices and quantities to refine the identification of supply chain shocks (e.g., using sign restrictions as demonstrated by Brinca et al., 2021, for labor market shocks).

6. 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 of intermediate inputs from China contracted output by significantly and substantially more in March and April 2020 than less exposed sectors. Moreover, employment, exports, and imports fell relatively more in highly exposed sectors, while their import and output prices also increased by more than in other sectors, consistent with the expected effects of a negative supply shock. Our results suggest that differential exposure to China-specific supply chain disruptions explains 11%–14% 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 the summer of 2020.

Appendix A. Model derivation

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

$$\eta\gamma b(m^1)^{\gamma-1} f(z^1)^{\gamma-\rho}(z^1)^{\rho-1} = p^x, \quad \text{and} \qquad \eta\gamma b_t(m_t^1)^{\gamma-1} f(z_t^1)^{\gamma-\rho}(z_t^1)^{\rho-1} = p^x. \tag{A.1}$$

We combine the two first-order conditions to obtain

$$f(z_t^1)^{\gamma-\rho}(z_t^1)^{\rho-1} = (1-\delta)^{1-\gamma} f(z^1)^{\gamma-\rho}(z^1)^{\rho-1}. \tag{A.2}$$

Taking a first-order Taylor expansion w.r.t. z_t^1 and δ around $\delta = 0$, and hence $z_t^1 = z^1$, yields

$$[-(1-\rho) + (\gamma-\rho)\epsilon]\,\frac{dz_t^1}{z^1} = -(1-\gamma)d\delta, \tag{A.3}$$

where $\epsilon = \frac{z^1 f'(z^1)}{f(z^1)}$. Using $d\log z_t^1 = \frac{dz_t^1}{z^1}$ and $d\log m_t^1 \approx -d\delta$, we obtain

$$\frac{d\log z_t^1}{d\log m_t^1} = -\frac{1-\gamma}{(1-\rho)-(\gamma-\rho)\epsilon}. \tag{A.4}$$

This results in a response of type 1 production of

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

The response of sectoral output to the supply chain disruption is

$$d\log y_t = \frac{(1-\rho)-(1-\rho)\epsilon}{(1-\rho)-(\gamma-\rho)\epsilon}\;\frac{\phi y^1}{\phi y^1 + (1-\phi)y^2}\; d\log m_t^1. \tag{A.6}$$

If $\gamma \to 1$ or $\rho \to -\infty$, $d\log y_t$ only depends on the output share of type 1 establishments. We define the share of intermediate goods imported from country B in steady state as

$$e^B = \frac{p^m \phi m^1}{p^x(\phi x^1 + (1-\phi)x^2) + p^m\phi m^1} = \frac{\phi y^1}{\phi y^1 + (1-\phi)y^2}\;\frac{1-\eta}{1-\eta+\eta(z^1)^\rho}, \tag{A.7}$$

where the last equality uses $y^1 = y^2$. Then we can rewrite the response of sectoral output as

$$d\log y_t = \frac{(1-\rho)-(1-\rho)\epsilon}{(1-\rho)-(\gamma-\rho)\epsilon}\;\frac{1-\eta+\eta(z^1)^\rho}{1-\eta}\; e^B\; d\log m_t^1. \tag{A.8}$$

Appendix B. Data

B.1. Aggregate imports

We construct a monthly time series of aggregate US intermediate goods imports from China using the import matrix in the Bureau of Economic Analysis (BEA) 2012 Input–Output Accounts and the monthly value of commodity-specific imports from China from the International Trade Data maintained by the Census Bureau. From the import matrix, we compute the 6-digit NAICS commodity-specific share of intermediate goods, which allows us to compute aggregate imports of intermediate and final goods. 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).[27] 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).[28]

The disruptions to economic activity in China were followed by a large contraction of US imports from China by March (Fig. B.1, left panel). Intermediate goods imports, in particular, fell by 30% between January 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. When including Covid-related goods, total intermediate goods imports from China exceeded their pre-crisis level starting in April. The fast recovery of imports from China may have reflected the normalization in China, pent-up demand, increased (precautionary) inventory demand, as well as the Phase One trade deal signed in January, which lowered tariffs on US imports from China.

Total imports of intermediate goods from all countries (Fig. B.1, right panel) fell 6% between January and March, which suggests limited short-run substitutability of production supplies imported from China. Total imports of intermediate and final goods kept on falling beyond March, and they fell more severely for final goods (not shown). This is consistent with non-China imports being driven by lower demand in the US.

[27] 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.

[28] 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.

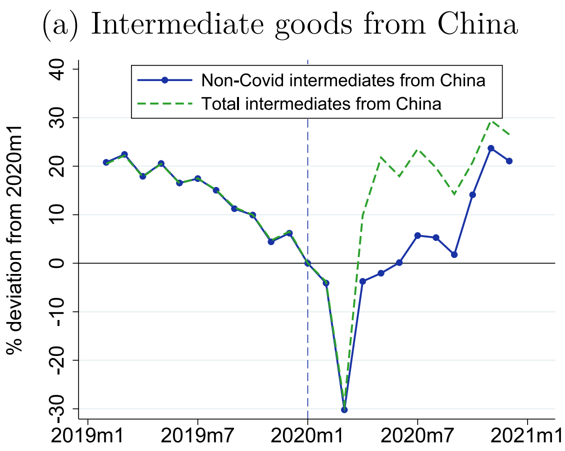

Fig. B.1. Imports.
Notes: Panel (a) shows seasonally adjusted aggregate US imports of intermediate goods from China excluding Covid-related goods (solid line) and including Covid-related goods (dashed line). Similarly, panel (b) shows seasonally adjusted aggregate global US imports of intermediate goods excluding Covid-related goods (solid line) and including Covid-related goods (dashed line). We use the definition of Covid-related goods in US International Trade Commission (2020). The seasonal adjustment controls for trading days, calendar effects, including Easter and the Chinese New Year (following Roberts and White, 2015), and automatic outliers.

B.2. Import exposures

In this section, we provide details on the construction of import exposures. We define the exposure of sector i to intermediate input imports from some country or region B as

$$e_i^B = \frac{Impii_{\cdot,i}^B}{Usevc_i} \tag{B.1}$$

where $Impii_{\cdot,i}^B$ represents sector i's imports of intermediate inputs from country or region B and $Usevc_i$ represents sector i's total variable costs, defined as the sum of total intermediate inputs used and compensation of employees. The numerator is estimated using

$$Impii_{\cdot,i}^B = \sum_j Impii_{j,i}^{2012} ImpiiSh_{j,\cdot}^{B,2019} \tag{B.2}$$

where $Impii_{j,i}^{2012}$ is sector i's 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 $ImpiiSh_{j,\cdot}^{B,2019}$ is the share of intermediate inputs of commodity j that are imported from B in 2019. The share of intermediate goods imports from country or region B is calculated as

$$ImpiiSh_{j,\cdot}^{B,2019} = \frac{Impii_{j,\cdot}^{B,2019}}{Impii_{j,\cdot}^{2019}} \tag{B.3}$$

where $Impii_{j,\cdot}^{B,2019}$ and $Impii_{j,\cdot}^{2019}$ are total intermediate goods imports of commodity j (6-digit NAICS) from country or region B and the rest of the world (including B), respectively, in 2019 (from Census). We simply define intermediate good imports as all foods, feeds, and beverages, and all industrial supplies and materials based on BEA's end-use classification (broad end-use codes 0 and 1). We then use the 10-digit HTS import data, together with the correspondence between 10-digit HTS, 5-digit end-use, and 6-digit NAICS commodity classifications to compute the value of intermediate good imports for each 6-digit NAICS commodity. Because our definition of intermediate inputs can be too restrictive in the case of some manufactured commodities, we use total imports of commodity j in computing $ImpiiSh_{j,\cdot}^{B,2019}$ when intermediate inputs accounts for more than 75 percent of total imports of commodity j according to input–output accounts import matrix, but less than 10 percent according to our measure.

The denominator of our exposure measure is simply computed as

$$Usevc_i = \sum_j Use_{j,i}^{2012} + Comp_i^{2012} \tag{B.4}$$

Table B.1
Sector-specific China import exposures.

NAICS sector	e_i^{China}	$e_{i,\text{dom}}^{\text{China}}$	NAICS sector	e_i^{China}	$e_{i,\text{dom}}^{\text{China}}$
1133 Logging	0.05%	0.11%	3273 Cement and concrete	0.78%	0.33%
211 Oil and gas extraction	0.55%	0.32%	3274 Lime and gypsum	0.52%	0.26%
2121 Coal mining	0.56%	0.33%	3279 Other nonmetallic minerals	1.27%	0.42%
2122 Metal ore mining	0.98%	0.41%	3311,2 Iron and Steel	0.96%	0.42%
2123 Nonmetallic mineral mining	0.33%	0.27%	3313 Aluminum	0.64%	0.36%
213 Support activities for mining	0.47%	0.24%	3314 Nonferrous metals	0.48%	0.30%
2211 Electric power generation	0.03%	0.17%	3315 Foundries	0.44%	0.22%
2212 Natural gas distribution	0.06%	0.24%	3321 Forging and stamping	0.43%	0.45%
3111 Animal food	0.59%	0.38%	3322 Cutlery and handtool	0.55%	0.33%
3112 Grain and oilseed	0.24%	0.21%	3323 Architectural metals	1.00%	0.43%
3113 Sugar and confectionery	0.85%	0.39%	3324 Boiler, Shipping Container	0.61%	0.45%
3114 Fruit, vegetable preserving	0.67%	0.36%	3325 Hardware	3.71%	0.51%
3115 Dairy product	0.34%	0.30%	3326 Spring and wire product	1.93%	0.50%
3116 Animal processing	0.17%	0.22%	3327 Machine shops	0.90%	0.35%
3117 Seafood preparation	4.26%	0.55%	3328 Coating, heat treating	0.43%	0.46%
3118 Bakeries and tortilla	0.52%	0.22%	3329 Other fabricated metals	1.12%	0.40%
3119 Other food	1.17%	0.35%	3331 Agriculture, construction	2.62%	0.66%
3121 Beverage	1.20%	0.52%	3332 Industrial machinery	1.84%	0.52%
3122 Tobacco	0.92%	0.43%	3333,9 Commercial, Service Industry	2.27%	0.51%
3131 Fiber, yarn, and thread	1.52%	0.54%	3334 Ventilation, heating	1.81%	0.57%
3132 Fabric	1.18%	0.68%	3335 Metalworking machinery	1.13%	0.32%
3133 Textile finishing	2.55%	0.60%	3336 Engine, power transmission	2.38%	0.71%
3141 Textile furnishings	2.04%	0.64%	3341 Computer equipment	0.70%	0.16%
3149 Other textiles	1.55%	0.60%	3342 Communications equipment	0.59%	0.13%
315 Apparel	2.46%	0.33%	3343 Audio and video equipment	0.51%	0.23%
316 Leather and allied product	0.79%	0.27%	3344 Semiconductor component	1.15%	0.18%
3211 Sawmills, wood preservation	0.25%	0.13%	3345 Navigational, measuring	0.63%	0.17%
3212 Veneer, engineered wood	0.77%	0.36%	3346 Magnetic and Optical Media	0.15%	0.17%
3219 Other wood product	1.37%	0.43%	3351 Electric lighting equipment	2.09%	0.37%
3221 Pulp, paper, paperboard	0.96%	0.34%	3352 Household appliance	2.07%	0.57%
3222 Converted paper product	0.59%	0.56%	3353 Electrical equipment	2.05%	0.42%
323 Printing	0.56%	0.34%	3359 Other electrical equipment	1.66%	0.40%
324 Petroleum, coal products	0.04%	0.24%	3361 Motor vehicle	3.24%	1.03%
3251 Basic chemical	0.85%	0.59%	3362 Motor vehicle body, trailer	1.93%	0.91%
3252 Resin, synthetic rubber	1.46%	0.69%	3363 Motor vehicle parts	2.07%	0.61%
3253 Pesticide, fertilizer	1.65%	0.34%	3364 Aerospace products	0.80%	0.32%
3254 Pharmaceutical, medicine	0.35%	0.17%	3365 Railroad rolling stock	3.56%	1.06%
3255 Paint, coating, adhesive	1.80%	0.53%	3366 Ship and boat building	1.08%	0.43%
3256 Soap and cleaning	1.82%	0.60%	3369 Other transport equipment	1.57%	0.61%
3259 Other chemical product	1.31%	0.57%	3371 Household furniture	2.02%	0.38%
3261 Plastics product	1.15%	0.68%	3372,9 Office furniture	1.57%	0.53%
3262 Rubber product	2.81%	0.57%	3391 Medical equipment	0.78%	0.31%
3271 Clay product and refractory	0.80%	0.31%	3399 Other miscellaneous mfg	0.98%	0.38%
3272 Glass and glass product	1.91%	0.43%	5111 Newspaper, periodical, book	0.20%	0.20%

Notes: Columns 2 and 5 (e_i^{China}) show the exposure to intermediate goods imports from China (in %). Columns 3 and 6 ($e_{i,\text{dom}}^{\text{China}}$) show the indirect domestic exposure to intermediate goods imports from China (in %).

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, and $Comp_i^{2012}$ is sector i's outlays with employee compensation, both from the use table of the benchmark input–output accounts. We use the customs value of imports for consumption from Census. 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 good imports measure used in the numerator.

Finally, we aggregate the numerator and denominator to the finest level of disaggregation, roughly 4-digit NAICS sectors, for which we can match sectoral outcomes such as industrial production. Table B.1 lists all sectors together with their China import exposure. Note that the same procedure outlined above is used to construct non-China import exposures.

The indirect (domestic) exposure to country or region B, $e_{i,dom}^B$ uses the same denominator as the direct exposure, e_i^B, but the numerator is computed as

$$\sum_j Domii_{j,i}^{2012} e_j^B \tag{B.5}$$

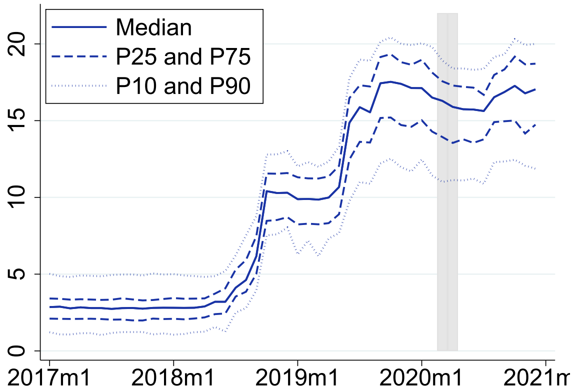

Fig. B.2. Duty rates on US imports from China.
Notes: The figure shows the median and percentiles of the effective duty rate (in %) on US imports from China across US industrial sectors.

where $Domii_{j,i}^{2012}$ is sector i's domestically sourced intermediate inputs of commodity j (6-digit NAICS) in 2012. We compute domestically sourced inputs by using the identity

$$Use_{j,i}^{2012} = Domii_{j,i}^{2012} + Impii_{j,i}^{2012}. \tag{B.6}$$

B.3. Effective duty rates on imports from China

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

$$DutyRateAve_i^{B,t} = \sum_j DutyRate_j^{B,t} ImpiiW_{j,i}^B \tag{B.7}$$

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

$$DutyRate_j^{B,t} = Duty_j^{B,t} / Impcif_j^{B,t} \tag{B.8}$$

where $Duty_j^{B,t}$ is commodity j's calculated duties on imports from 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 exposure measure as follows

$$ImpiiW_{j,i}^B = \frac{Impii_{j,i}^{2012} ImpiiSh_{j,\cdot}^{B,2019}}{\sum_j Impii_{j,i}^{2012} ImpiiSh_{j,\cdot}^{B,2019}}. \tag{B.9}$$

Fig. B.2 shows the evolution of effective duty rates across industries over time.

Appendix C. Additional empirical findings

See Figs. C.1–C.3.

Appendix D. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.euroecorev.2024.104674.

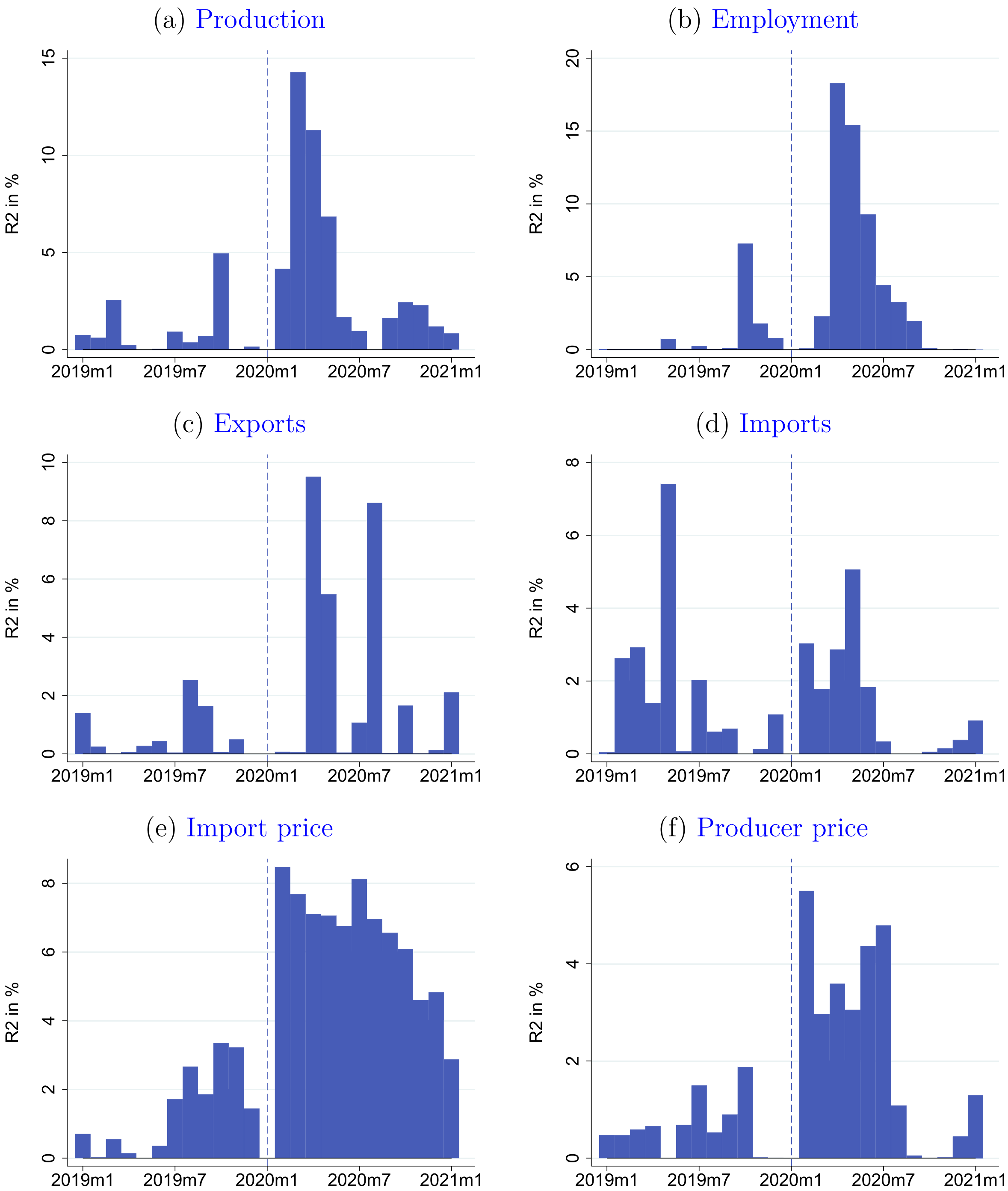

Fig. C.1. Partial R^2 for China exposure ("Baseline").
Notes: The bars show the partial R^2 based on Eq. (4.1), when y_{it} is a different outcome across panels (a)–(f), e_i^B is the China import exposure and no control variables Z_i are included.

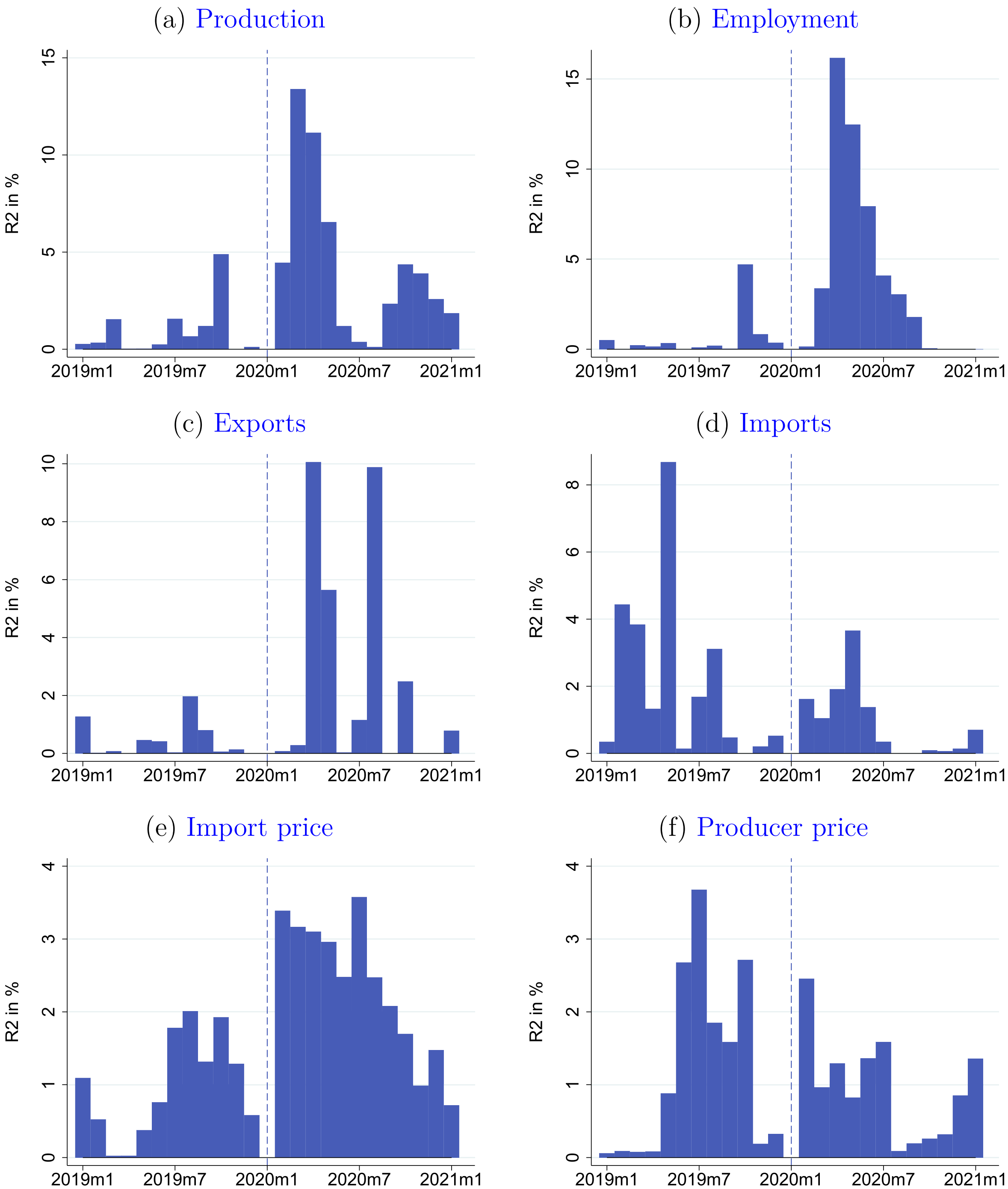

Fig. C.2. Partial R^2 for China exposure ("+ controls").
Notes: The bars show the partial R^2 based on Eq. (4.1), when y_{it} is a different outcome across panels (a)–(f), e_i^B is the China import exposure and when controlling for sector-specific pre-COVID-19 business cycle sensitivity, trends, external finance dependence, China export exposure, and duty changes during the US–China trade war and deal.

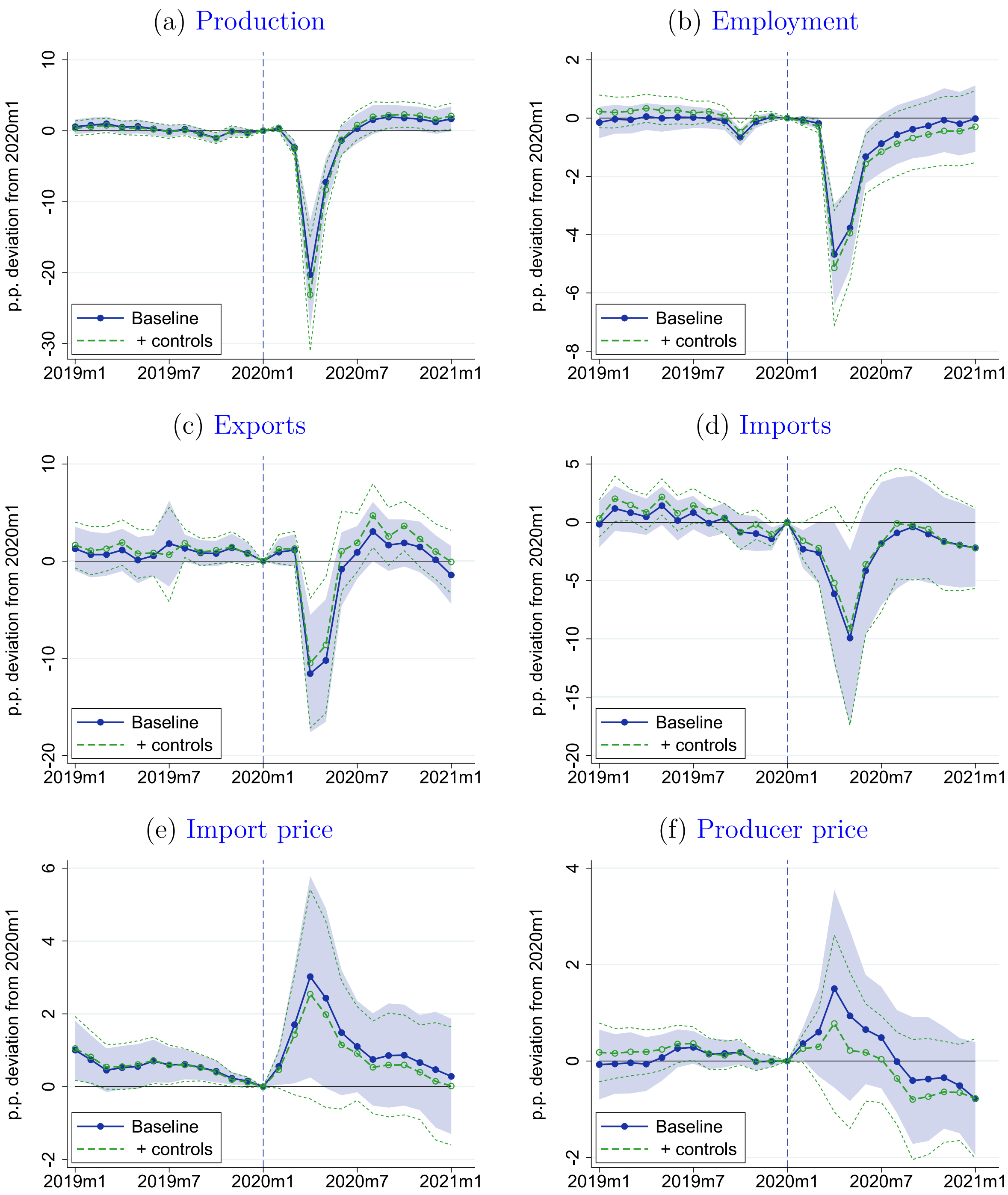

Fig. C.3. Role of domestic supply chains.
Notes: The solid lines and markers ("Baseline") show the estimated β_t coefficients based on Eq. (4.1), when y_{it} is a different outcome across panels (a)–(f), e_i^B is the China import exposure and when no control variables Z_{it} are included. The dashed lines and markers ("+ controls") show the estimated β_t coefficients when we control for sector-specific pre-COVID-19 business cycle sensitivity, trends, external finance dependence, China export exposure, and duty changes during the US–China trade war and deal. The β_t estimates are all standardized to capture the differential effects (approx. in p.p.) associated with a one standard deviation higher e_i^B. The shaded area and dotted outer lines show the 90% confidence band based on heteroskedasticity and autocorrelation robust standard errors.

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