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.

Keywords: Supply chain disruptions, COVID-19, industrial production.
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1 Introduction

Over the past decades, the world economy has become increasingly interconnected through global value chains. While global value chains raise efficiency, they 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 (Figure 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.

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

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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. (2020), and Glover et al. (2020), fiscal policy in Bigio et al. (2020), Mitman and Rabinovich (2021), Auerbach et al. (2021), and Bayer et al. (2020), and monetary policy in Caballero and Simsek (2021), Woodford (forthcoming), and Fornaro and Wolf (2020).

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

Figure 1: Covid-19 crisis

(a) Intermediate goods imports

(b) Industrial production
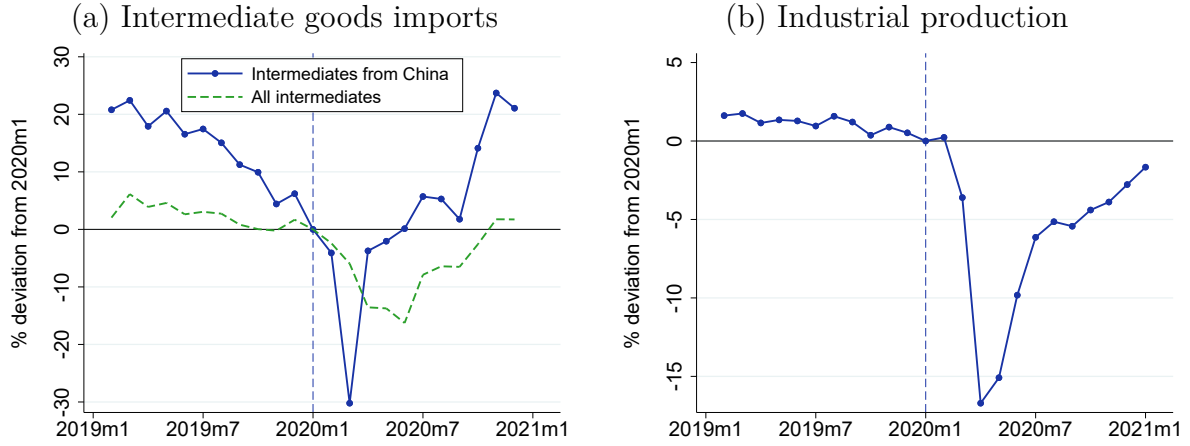
Notes: Panel (a) shows the evolution of (seasonally adjusted) aggregate US imports of intermediate goods from China (solid line) and the corresponding world imports (dashed line). Covid-related goods, as identified in US International Trade Commission (2020), are excluded. Appendix B.1 provides details on the measurement of intermediate goods imports. Panel (b) shows seasonally adjusted US industrial production.

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

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[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.

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, suggesting that international supply chain disruptions did not have persistent effects on inflation.

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 suggest significant, albeit relatively short-lived, 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 effects.[7] Trade wars often result in persistently higher tariffs. In contrast, lockdowns are commonly short-lived. We therefore

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[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 is depressed for up to half a year.

consider it important to provide empirical evidence on COVID-19 supply chain disruptions. Closely related empirical papers are Lafrogne-Joussier et al. (2021), 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 public 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 (forthcoming) 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.

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 model of supply chain disruptions

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

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

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

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

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where ϕ is the (sector-specific) share of type 1 establishments. Before the economy is shocked by a supply-chain disruption, it is in a steady state in which type 1 establishments choose x^1 and m^1 to maximize period profits $\pi^1 = p(y^1)y^1 - p^x x^1 - p^m m^1$, 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 $\pi^2 = p(y^2)y^2 - p^x x^2$. We normalize steady state productivity a^1 to ensure $y^1 = y^2$. Hence, the type-specific contribution to sectoral output is solely captured by ϕ.

In period t, the economy is 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 prices. The supply of m_t^1 becomes a binding constraint allowing type 1 establishments only to re-optimize x_t^1 after the disruption. The first-order condition for x_t^1 after the supply chain disruption implies that the factor input ratio $z_t^1 = x_t^1/m_t^1$ 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

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

where $\tilde{\Psi} = \frac{1-\eta+\eta(z^1)^\rho}{1-\eta} \cdot \Psi$ and e^B is the the import exposure to country B in steady state.[8]

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[8]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 (as results from a larger ϕ, the share of establishments that produce using imports from country B) respond more strongly to the supply chain disruption shock. The strength of this link is shaped by the substitutability of m_t^1, via the effects of ρ on $\tilde{\Psi}$. Equation (2.4) 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.

Finally, we discuss the robustness of these results. First, if we fix ϕ but let η 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 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. Second, our analysis has 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

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 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 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 Figure 2 shows a histogram of China exposures across these industries.[9] 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.[10]

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.[11] 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 indus-

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

[10]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.

[11]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.

Figure 2: Heterogeneity across industries

(a) China import exposure

(b) Production growth
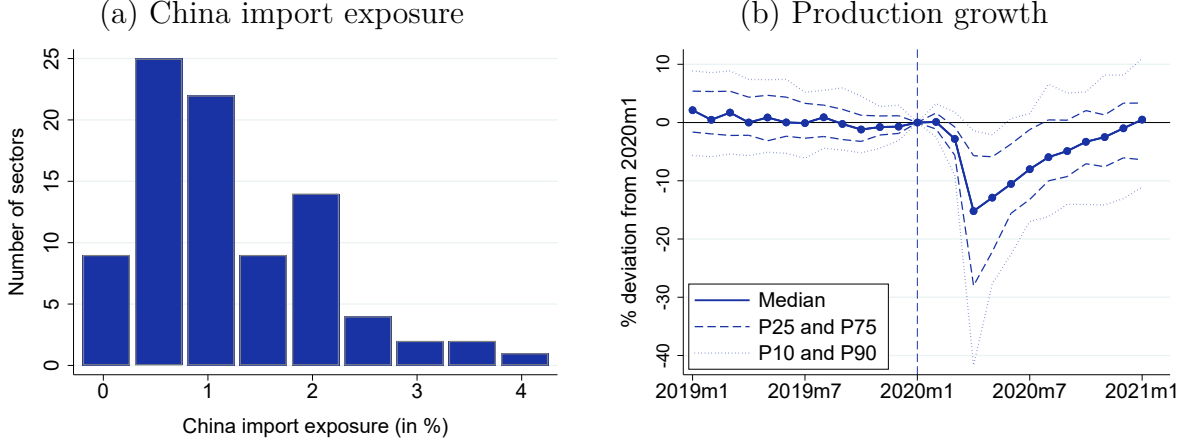
Notes: Panel (a) shows the histogram of China import exposures (3.1) across US industries. Panel (b) shows percentiles of the percentage change in monthly industrial production (seasonally adjusted) across US industrial sectors, based on the Federal Reserve G.17 release. The gray-shaded area indicates the NBER recession period March-April 2020.

tries, 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.[12] 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.[13]

Panel (b) of Figure 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 Figure 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.[14] 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 interme-

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[12]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

[13]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.

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

diate 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.

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.[15]

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[15]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.

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. Figure 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 Figure 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), who show that sectors with higher input costs due to tariff hikes do not produce significantly less than other sectors.[16] The small and positive β_t estimate in February 2020 may be surprising because the lockdowns in China started in February.[17] We think this seemingly inconsistent finding plausibly reflects the considerable period of time for cargo to travel from China to the US.[18] Indeed, aggregate US imports from China only slumped in March (Figure 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.

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 low 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

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

[17]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.

[18]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/

Figure 3: Production growth and high China import exposure
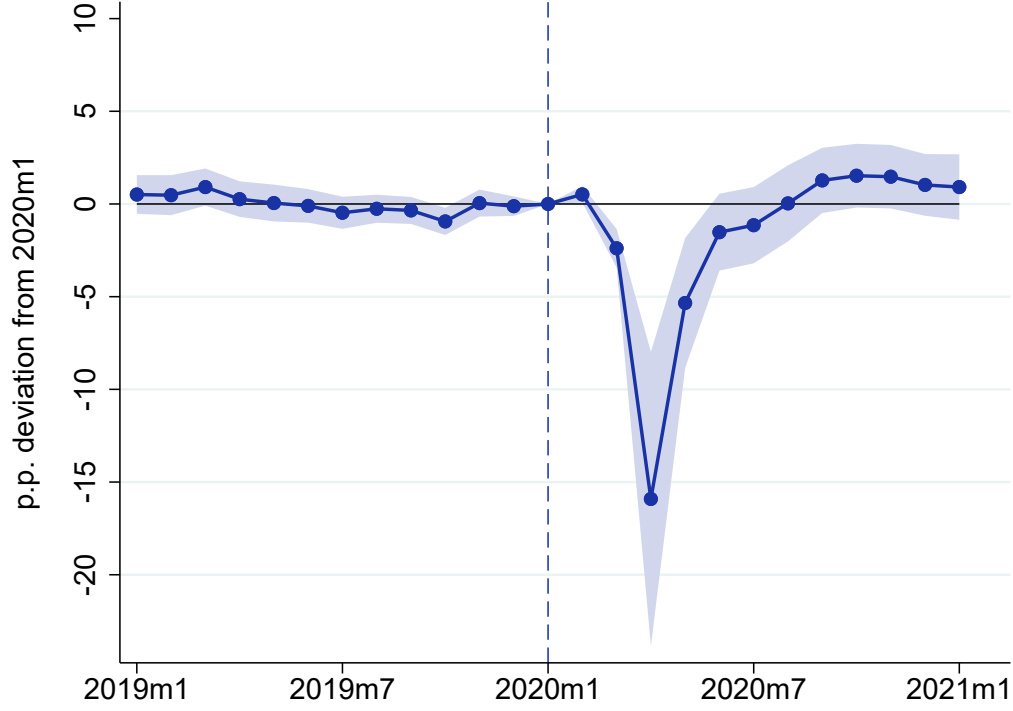
January 2020 are very large, $\sigma(y_{i,2020\text{m}3}) = 6.4\%$ and $\sigma(y_{i,2020\text{m}4}) = 47.6\%$, see also Figure 2 (b). Therefore, a considerable share of the cumulative output change variance in March and April, respectively 14% and 11%, can be accounted for by different China exposures.[19]

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.[20] Effectively, the stronger contraction of more exposed sectors during March and April are almost fully reversed by June. This suggests that lockdowns in China at the beginning of the COVID-19 crisis had rather transitory 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 for the policy response. For example, to the extent that supply was constrained by limited availability of intermediate inputs between March and May 2020,

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

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

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 kind 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-globalisation, 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. A promising avenue for future research is to understand how the COVID-19 crisis changed firms' global sourcing decisions, e.g., in the framework of Antràs et al. (2017).

4.3 Alternative explanations

While the estimates in Figure 3 suggest that supply chain disruptions in US-China trade early in the COVID-19 crisis had short-lived but quantitatively large 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.[21]

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 Figure 3 could capture differences in business cycle sensitivity rather than the effects of a higher China exposure.

We address these concerns by augmenting equation (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,

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

which were partially reversed by the Phase One trade deal.[22]

Panel (a) of Figure 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 Figure 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, that is explained by different China import exposures hardly changes when including the covariates (panel (b) of Figure C.2 in the Appendix).
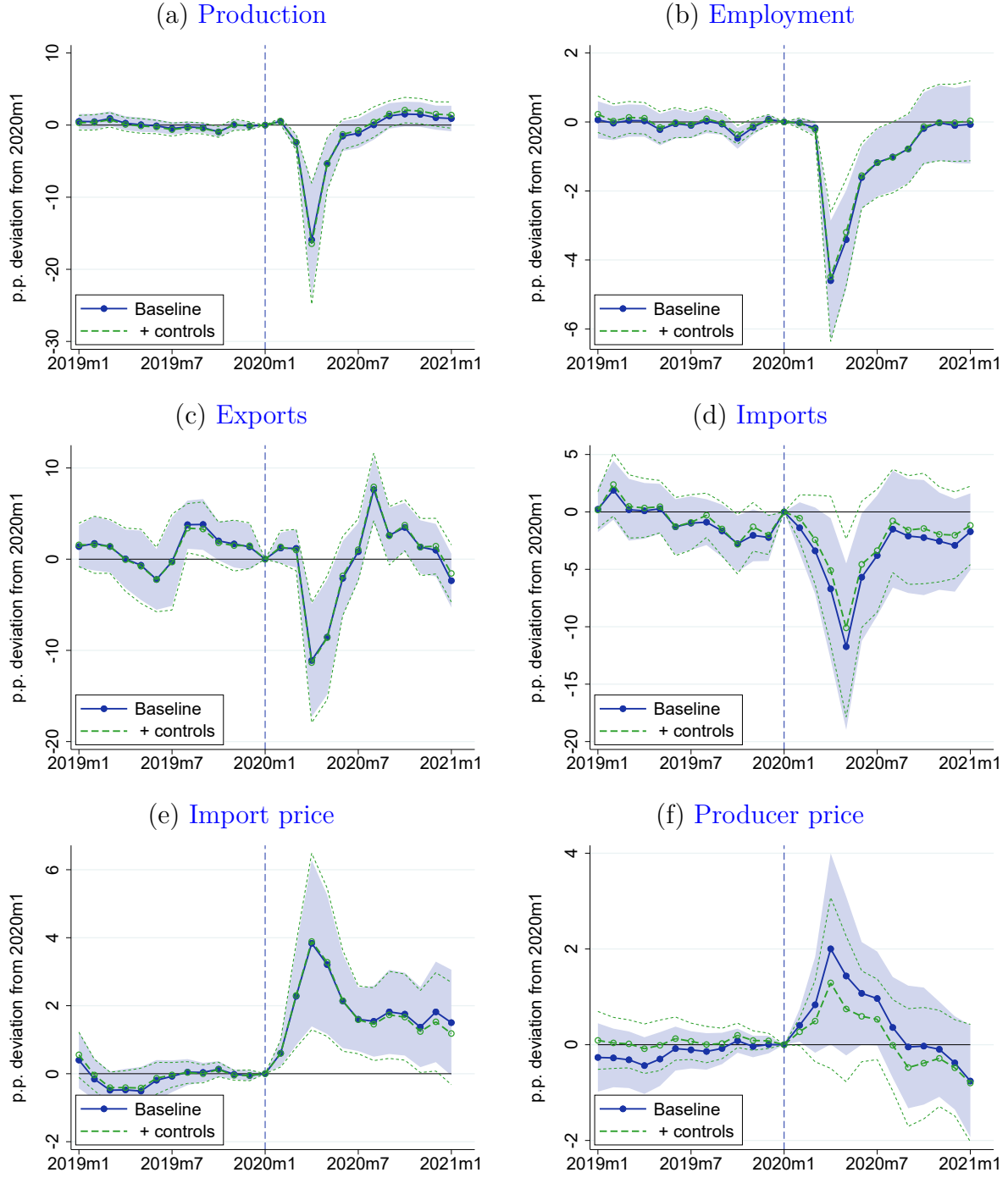
4.4 Effects on employment, imports, and exports

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 Figure 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 (Figure 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 Figure 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 (Figure C.1). The export response may be a consequence of lower production. The import response is consistent with high China import exposure sectors

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[22]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.

Figure 4: Sector outcomes and high China import exposure

(a) Production

(b) Employment

(c) Exports

(d) Imports

(e) Import price

(f) Producer price

Notes: The solid lines and markers ("Baseline") show the estimated β_t coefficients based on equation (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.

facing larger disruptions to their input supply. In fact, the coefficient on imports becomes significantly negative already 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.
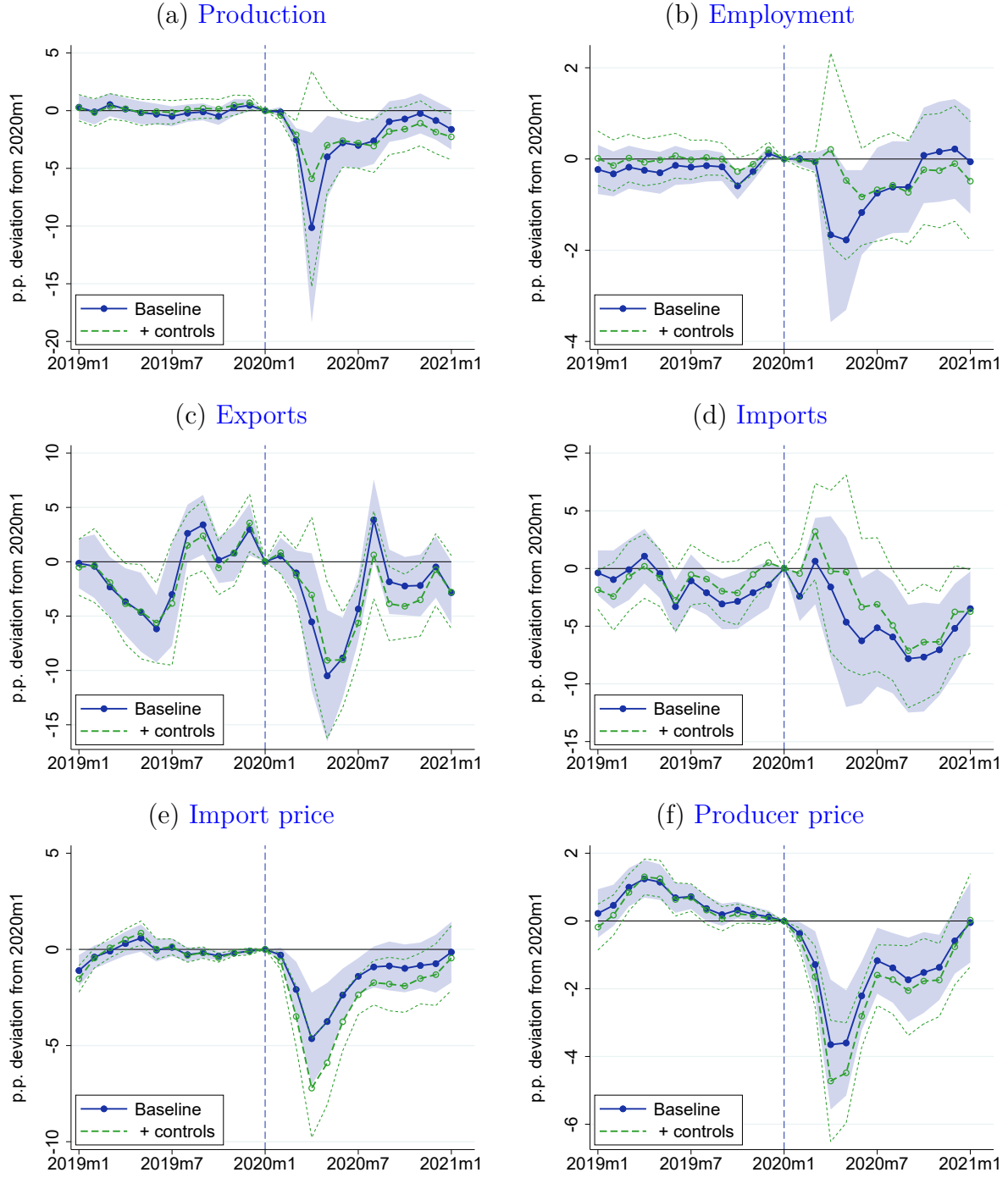
Panel (e) of Figure 4 show that import price inflation was significantly higher in more exposed sectors starting from February 2020. The differential effect peaks in April and some differences persist until the end of the sample. This finding does not change when controlling for potential confounders. This evidence further supports the interpretation that higher China import exposure predominantly capture 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 Figure 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

Finally, we investigate whether our results are specific to imports from China, or whether we observe a similar pattern for sectors that depend on imports more generally. We consider a broad sector-specific import exposure that includes all intermediate goods imports except those originating from China. Using this non-China import exposure we re-estimate regression (4.1) and present the associated β_t estimates for all outcomes in Figure 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

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Figure 5: Sector outcomes and high non-China import exposure

(a) Production

(b) Employment

(c) Exports

(d) Imports

(e) Import price

(f) Producer price

Notes: The solid lines and markers ("Baseline") show the estimated β_t coefficients based on equation (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.

smaller in magnitude and less precisely estimated. The fact that the responses are smaller and less significant across different outcomes suggests that the non-China import exposure does not capture the same effects as the China exposure during this particular time period.

Importantly, panels (e) and (f) of Figure 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 Figure 4. The highly significantly negative β_t coefficients for price growth in March and April suggest that sectors with a high non-China import exposure were more severely hit by a decline in demand. Overall, these results caution against interpreting the non-China β_t coefficients as capturing the effects of supply chain disruptions.

5   Conclusion

We study the role of international supply chain disruptions during the COVID-19 crisis. We show that US sectors with a high exposure to imports of intermediate inputs from China contracted output significantly and substantially more in March and April 2020 than less exposed sector. 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 explain 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.

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Appendix A   Model derivation

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 $m_t = (1 - \delta)m$,

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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

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

We combining the two first-order conditions to obtain

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

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

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

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

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

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   Imports

We construct a monthly time series of 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).[23] 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).[24]

Figure B.1: Imports

(a) Intermediate goods from China   (b) All intermediate goods
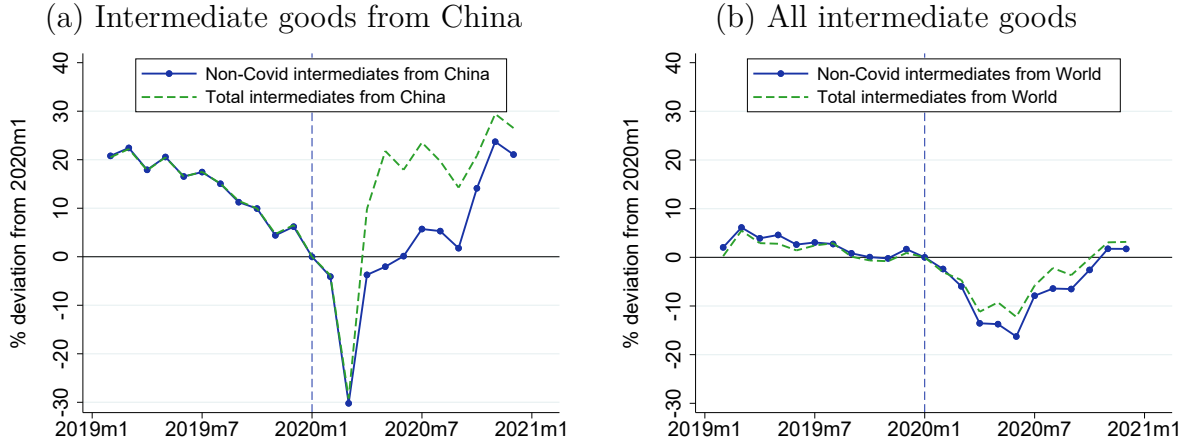
Notes: Panel (a) shows (seasonally adjusted) aggregate US imports of intermediate goods from China excluding Covid-related goods (solid line) and including Covid-related goods (dashed line). Similarly, panel (b) shows (seasonally adjusted) aggregate global US imports of intermediate goods excluding Covid-related 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 disruptions to economic activity in China were followed by a large contraction of US imports from China by March (Figure 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

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[23]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.

[24]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.

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 (Figure 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.

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

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

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.

Table B.1: Sector-specific China import exposures

NAICS sector	e_i^{China}	NAICS sector	e_i^{China}
1133 Logging	0.052%	3273 Cement and concrete	0.776%
211 Oil and gas extraction	0.548%	3274 Lime and gypsum	0.518%
2121 Coal mining	0.555%	3279 Other nonmetallic minerals	1.271%
2122 Metal ore mining	0.983%	3311,2 Iron and Steel	0.964%
2123 Nonmetallic mineral mining	0.329%	3313 Aluminum	0.636%
213 Support activities for mining	0.471%	3314 Nonferrous metals	0.483%
2211 Electric power generation	0.029%	3315 Foundries	0.442%
2212 Natural gas distribution	0.058%	3321 Forging and stamping	0.433%
3111 Animal food	0.591%	3322 Cutlery and handtool	0.546%
3112 Grain and oilseed	0.236%	3323 Architectural metals	0.995%
3113 Sugar and confectionery	0.854%	3324 Boiler, Shipping Container	0.613%
3114 Fruit, vegetable preserving	0.670%	3325 Hardware	3.711%
3115 Dairy product	0.338%	3326 Spring and wire product	1.934%
3116 Animal processing	0.168%	3327 Machine shops	0.903%

3117	Seafood preparation	4.265%	3328	Coating, heat treating	0.429%
3118	Bakeries and tortilla	0.523%	3329	Other fabricated metals	1.117%
3119	Other food	1.174%	3331	Agriculture, construction	2.623%
3121	Beverage	1.203%	3332	Industrial machinery	1.844%
3122	Tobacco	0.920%	3333,9	Commercial, Service Industry	2.271%
3131	Fiber, yarn, and thread	1.516%	3334	Ventilation, heating	1.812%
3132	Fabric	1.179%	3335	Metalworking machinery	1.127%
3133	Textile finishing	2.545%	3336	Engine, power transmission	2.376%
3141	Textile furnishings	2.041%	3341	Computer equipment	0.705%
3149	Other textiles	1.552%	3342	Communications equipment	0.595%
315	Apparel	2.461%	3343	Audio and video equipment	0.507%
316	Leather and allied product	0.787%	3344	Semiconductor component	1.152%
3211	Sawmills, wood preservation	0.252%	3345	Navigational, measuring	0.634%
3212	Veneer, engineered wood	0.774%	3346	Magnetic and Optical Media	0.150%
3219	Other wood product	1.372%	3351	Electric lighting equipment	2.092%
3221	Pulp, paper, paperboard	0.960%	3352	Household appliance	2.074%
3222	Converted paper product	0.587%	3353	Electrical equipment	2.050%
323	Printing	0.563%	3359	Other electrical equipment	1.657%
324	Petroleum, coal products	0.045%	3361	Motor vehicle	3.238%
3251	Basic chemical	0.849%	3362	Motor vehicle body, trailer	1.929%
3252	Resin, synthetic rubber	1.456%	3363	Motor vehicle parts	2.068%
3253	Pesticide, fertilizer	1.651%	3364	Aerospace products	0.796%
3254	Pharmaceutical, medicine	0.351%	3365	Railroad rolling stock	3.556%
3255	Paint, coating, adhesive	1.804%	3366	Ship and boat building	1.078%
3256	Soap and cleaning	1.823%	3369	Other transport equipment	1.567%
3259	Other chemical product	1.313%	3371	Household furniture	2.023%
3261	Plastics product	1.147%	3372,9	Office furniture	1.572%
3262	Rubber product	2.812%	3391	Medical equipment	0.785%
3271	Clay product and refractory	0.801%	3399	Other miscellaneous mfg	0.981%
3272	Glass and glass product	1.913%	5111	Newspaper, periodical, book	0.204%

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

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

$$DutyRateAve_i^{B,t} = \sum_j DutyRate_j^{B,t} ImpiiW_{j,i}^B \qquad (B.5)$$

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

$$DutyRate_j^{B,t} = Duty_j^{B,t}/Impcif_j^{B,t} \qquad (B.6)$$

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

$$ImpiiW_{j,i}^B = \frac{Impii_{j,i}^{2012} ImpiiSh_{j,.}^{B,2019}}{\sum_j Impii_{j,i}^{2012} ImpiiSh_{j,.}^{B,2019}}. \qquad (B.7)$$

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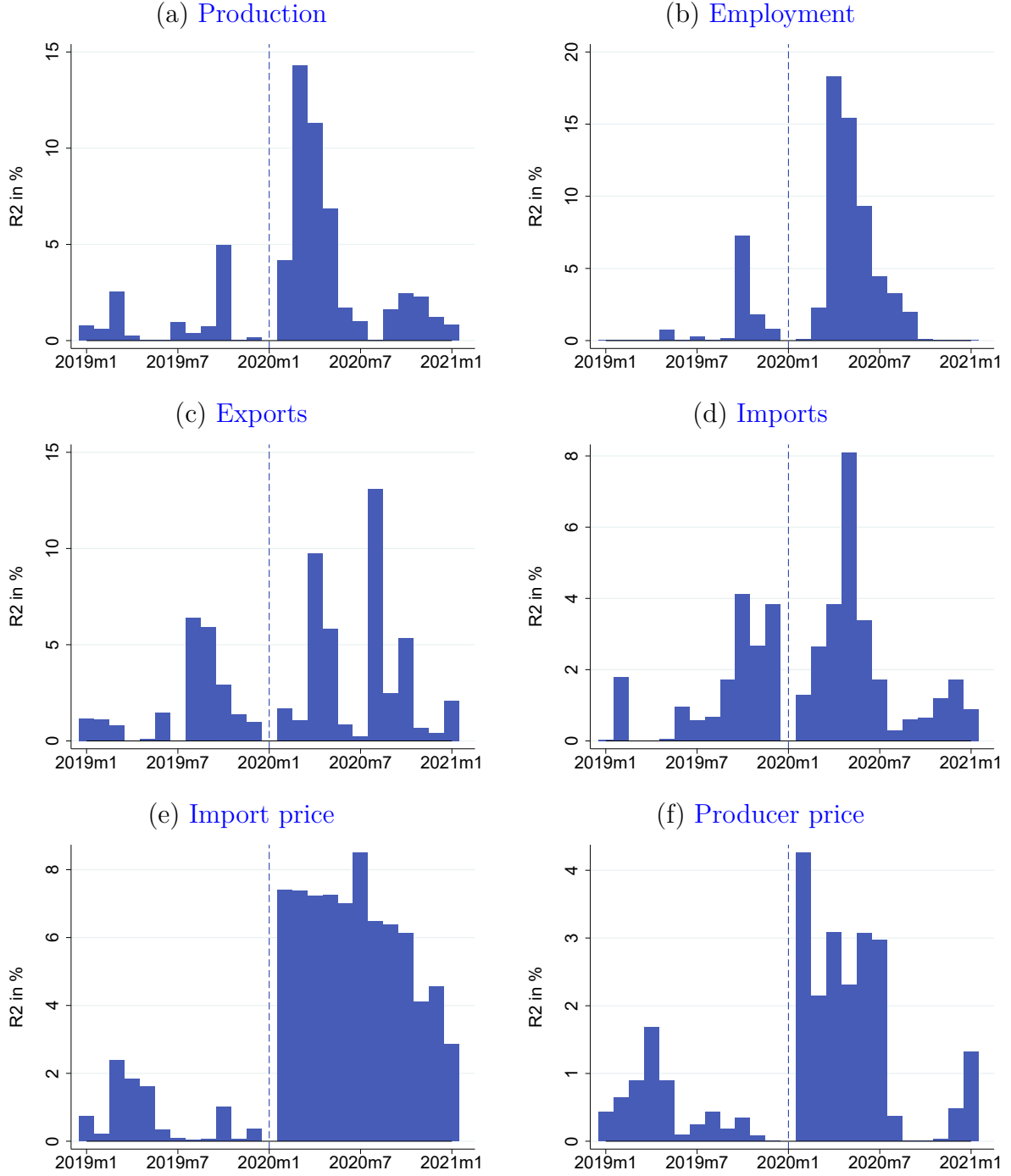
Figure B.2: Duty rates on US imports from China
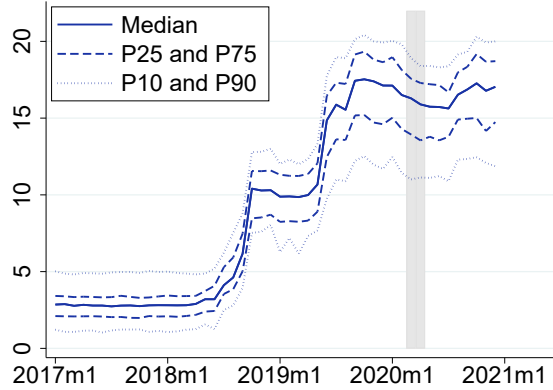
Notes: The figure shows the median and percentiles of the effective duty rate (in %) on US imports from China across US industrial sectors.

Appendix C   Additional empirical findings

Figure C.1: Partial R^2 for China exposure ("Baseline")

(a) Production

(b) Employment

(c) Exports

(d) Imports

(e) Import price

(f) Producer price

Notes: The bars show the partial R^2 based on equation (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.

Figure C.2: Partial R^2 for China exposure ("+ controls")
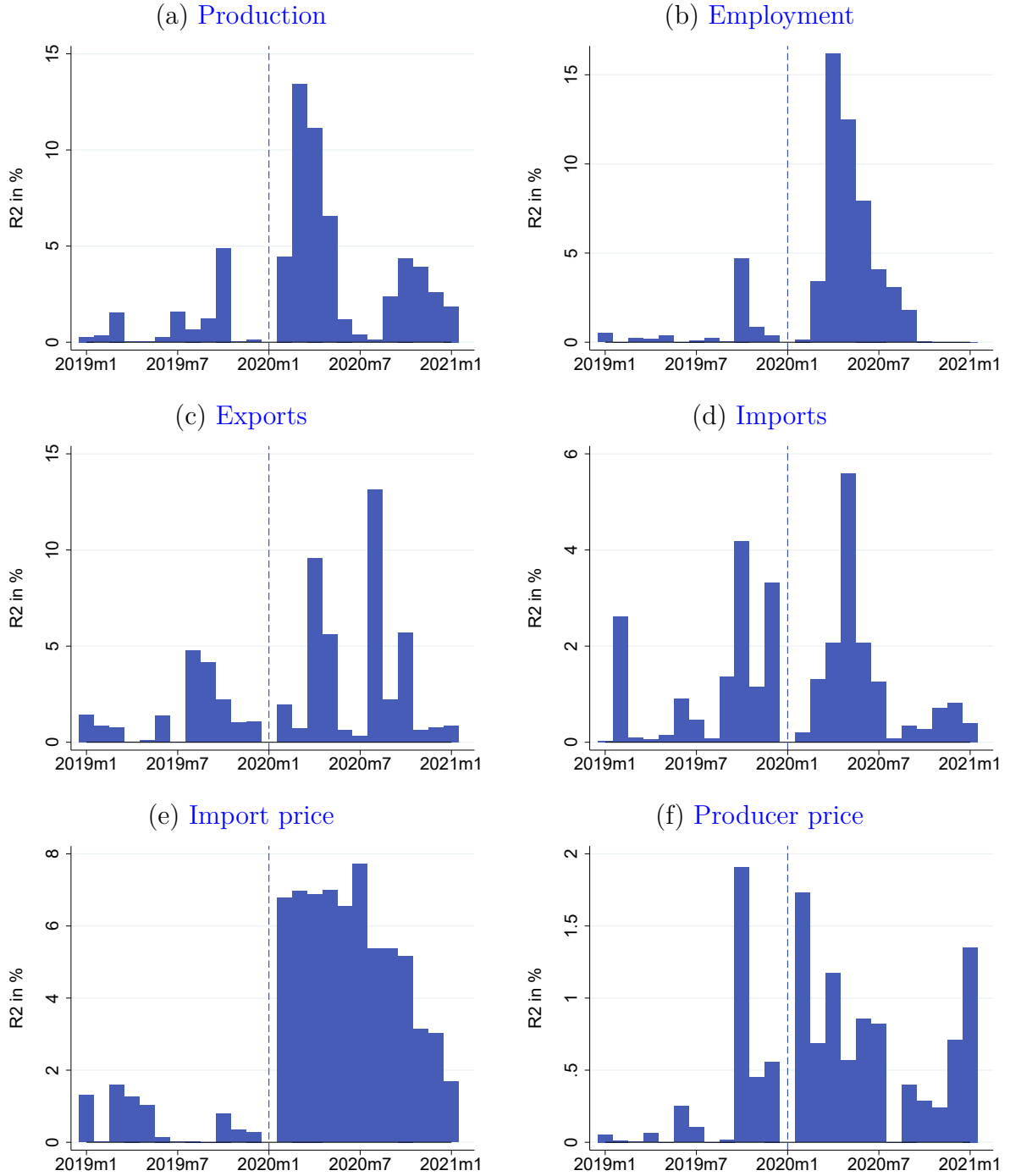
(a) Production

(b) Employment

(c) Exports

(d) Imports

(e) Import price

(f) Producer price

Notes: The bars show the partial R^2 based on equation (4.1), when y_{it} is a different outcome across panels (a)–(f), e_i^B is the China import exposure and when controling 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.