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Abstract

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China Spillovers: Aggregate and Firm-Level Evidence°

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ABSTRACT

We estimate the spillovers of demand- and supply-driven shocks in China to foreign countries and firms. We combine a Structural Vector Autoregression (SVAR) framework with a broad-based measure of domestic economic activity in China and narrative evidence on domestic shocks to distinguish supply versus demand components of Chinese growth. We then assess the responses to such shocks of GDP (revenue) in other countries (firms). The results suggest that: (i) global GDP responds more to Chinese supply shocks than to Chinese demand shocks; (ii) both supply and demand slowdowns in China are followed by declines in partner country GDP and firm revenue, especially in countries and firms with stronger trade linkages to China; and (iii) Chinese supply shocks have larger impacts on countries and firms with relatively stronger input linkages to China, while Chinese demand shocks have larger impacts on countries and firms with relatively stronger output linkages to China.

JEL Classification Codes: F14; F16; F44.
Keywords: Supply-Demand Shock Decomposition; China Spillovers; Input-Output linkages.

1. Introduction

Since joining the World Trade Organization in 2001, China has played an increasingly important role in the global economy, becoming the predominant global manufacturing center and a growing source of demand, particularly for Asia. China's share of global production rose from 2 percent in 1995 to 16 percent in 2018 (Figure 1), while Chinese final demand increased from 0.3 percent to 2.2 percent of global production over the same period (Figure 2). Moreover, China's demand for manufacturing inputs, alongside its expanding final consumption, has created significant linkages with the rest of the world. These linkages are especially pronounced in Asia; for ASEAN countries, the share of output absorbed by Chinese domestic demand grew from 1 percent to 6 percent during this timeframe. Additionally, China has been a major driver of global growth, accounting for one-third of global growth from 2000 to 2014 and serving as an important counterbalance following the Global Financial Crisis (GFC), when demand elsewhere was exceptionally weak (Dizioli et al., 2016).

However, China's growth has slowed markedly in recent years, declining from an average of 7.7 percent during 2010–2019 to around 5 percent over 2020–2024. The slowdowns observed since the onset of COVID-19 have involved both supply- and demand-side factors, ranging from temporary lockdown-induced capacity constraints to a widespread decline in confidence driven by the prolonged weakness of the real estate sector. Given China's deep integration with the global economy through trade linkages, such domestic growth shocks are likely to have significant repercussions worldwide, affecting both broad macroeconomic policy and decision-making at the firm level.[1]

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[1] This paper focuses on spillovers from short-term shocks to China's GDP growth rate rather than on shocks to its trend growth. For analysis on spillovers related to a slowing of China's trend growth, see IMF (2023).

While several studies have examined the cross-country spillovers from China's GDP growth, almost none distinguish between demand and supply shocks. This distinction is important because these shocks can have different impacts on global GDP, as well as across countries and firms, as highlighted by recent theoretical literature (see, for example, Acemoglu et al., 2015; Huo et al., 2025) and discussed in the next section.

This paper seeks to fill this gap by estimating the distinct spillovers from supply- versus demand-driven shocks in China's economy for a large sample of countries and firms. The analysis proceeds in three steps. First, we identify the composition of domestic shocks driving Chinese activity—distinguishing demand from supply shocks—using a Structural Vector Autoregression (SVAR) framework. In this model, domestic negative demand shocks are identified as those associated with declines in both activity and prices, while domestic negative supply shocks correspond to falling activity paired with rising prices. To strengthen identification, we augment this approach with narrative information on (i) major supply shocks, informed by evidence on supply-side reforms in the 2000s, and (ii) significant demand shocks, derived from exogenous monetary policy changes. The results highlight important roles for both domestic supply and demand shocks in explaining overall Chinese activity, with supply shocks playing a larger role during the Global Financial Crisis (GFC) period, and demand shocks being particularly influential during the 2014–15 episode marked by currency volatility and capital outflows.

Second, we examine the responses of global GDP to these shocks. The SVAR results indicate that while global GDP reacts to both Chinese supply and demand shocks, the spillovers from supply shocks are larger and more persistent, consistent with China's relatively greater role in global production compared to global final demand (Figures 1–2). In particular, we find that a 1 percent of GDP supply

(demand) shock in China leads to a peak reduction in global GDP of approximately 0.4 percent (0.2 percent).

Third, guided by theoretical considerations that we outline in the next section, we examine how spillovers vary across countries and firms depending on the extent and type of trade exposure to Chinese demand and supply shocks. In particular, we test whether: (i) spillovers are larger for countries and firms that trade more extensively with China; and (ii) countries and firms that primarily purchase inputs from China (with relatively stronger input linkages) are more affected by Chinese supply shocks, while those that primarily sell to China (with stronger output linkages) are more impacted by Chinese demand shocks.

To test these predictions, we employ a difference-in-differences local projection method (Jordà, 2005) using both aggregate and firm-level quarterly data covering a large sample of advanced and developing countries. In this framework, we interact Chinese demand and supply shocks with newly constructed measures of trade exposure, as well as input and output dependence, at both the country and firm levels, while controlling for multiple fixed effects. This approach is key for identification for two reasons. First, local projections are better suited than SVARs for estimating interactions and heterogeneous responses, while accommodating multiple fixed effects. Second, the inclusion of multiple fixed effects—such as time fixed effects in the country-level analysis and country-time fixed effects in the firm-level analysis—allows us to control for a broad range of potential global and country-specific shocks.

The results of these analyses confirm our hypotheses. At the country level, using a panel of 50 advanced and emerging countries during the period 2002Q1–2019Q4, we find that trade linkages play a significant role in the transmission of shocks. The impact of both demand and supply shocks from China on GDP in countries with relatively high trade exposure—at the 75th percentile of the global exposure

distribution—is about 0.05 percentage point higher than in countries with relatively low trade exposure—at the 25th percentile of the distribution. The effect is sizeable as it accounts for about one-third of the unconditional effect. Moreover, the spillover effects of demand (supply) shocks are larger in countries with relatively stronger output (input) linkages with China.

The firm-level results qualitatively mirror those at the country level and are more precisely estimated, further emphasizing the importance of using firm data to capture the significant heterogeneity in how demand and supply shocks propagate through international production networks. In particular, we find that the differential effect of Chinese demand shocks on revenue growth in firms that are relatively more output dependent (at the 75th percentile of output dependence exposure) compared to those that are relatively less output dependent (at the 25th percentile of the output dependence exposure) is about 0.5 percentage point after eight quarters. Similarly, the differential revenue growth effect of supply shocks on firms with relatively higher input exposure compared to those with lower input exposure is also about 0.5 percentage point after eight quarters.

Taken together, these results demonstrate substantial spillovers from a slowdown in China at the global, country, and firm levels, with particularly large effects in countries and firms that have stronger trade linkages with China. These findings underscore China's central role in global supply chains and highlight the importance of input and output linkages in transmitting these spillovers.

Contribution to the literature: Our aggregate results are in a similar range to previous estimates in the literature, where spillovers from a 1 percentage point decline in Chinese growth have been estimated to be between 0.15 and 0.8 percentage points. Cashin and others (2016) and Dizioli and others (2016) employ GVAR models finding a 1 percent decline in Chinese GDP growth is associated with a 0.2 percentage

point decline in global growth and 0.3 percentage point decline in growth for ASEAN5 economies. Duval and others (2014) find that spillovers are proportional to China's final demand for value-added, with spillovers to Asia of 0.3 percent compared with 0.15 percent for economies with weaker value-added trade links. Furceri, Jalles, and Zdzienicka (2017) estimate an average decline of 0.4 percent in GDP after 3 years. Barcelona and others (2022) find a 0.3 percent increase in global GDP from a 1 percent of GDP expansion of credit in China. Huidrom and others (2020) study spillovers from the seven largest emerging markets, finding that spillovers from China are the largest and most broadly felt. They estimate a global spillover of 0.8 percent for China. Sznajderska and Kapuscinski (2020) estimate a both a GVAR and country-by-country Bayesian VARs finding significantly larger spillovers for the Bayesian VAR model (ranging from 0 to 1.4 percent) compared with the GVAR estimates (ranging from 0 to 0.5 percent).

There are few firm-level estimates in the literature, though Ahuja and Nabar (2012) find impacts of comparable magnitudes for industrial production and stock prices. A large literature following Autor, Dorn and Hanson (2013) focuses on the impact of China's industrial expansion on labor markets both in the US and globally (e.g., Dauth, Findeisen and Suedekum, 2017). Bloom, Draca and Van Reenen (2015) find positive spillovers from increased Chinese competition on innovation within firms, while Iacovone, Rauch and Winters (2013) and Copestake and Zhang (2023) find that an increasing role for Chinese inputs raises firm revenue.[2]

Our paper differs from previous work on China's spillovers in three main respects. First, most spillover studies have used official GDP to measure Chinese growth shocks (for example, Cashin, Mohaddes, and Raissi 2016; Dizioli and others 2011; Furceri, Jalles, and Zdzienicka 2017). Recent studies

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[2] In contemporaneous work, Ma, Rebucci and Zhou (2025) use fund-level data to uncover a nascent financial channel of spillovers from China, complementing our focus on the transmission of real shocks through production networks.

have emphasized the importance of using a broad range of indicators to accurately capture Chinese economic activity (Barcelona and others 2022; Fernald, Hsu, and Spiegel 2021). This is because the very sizable structural changes taking place over a short period of time may make accurate measurement challenging (Fernald, Hsu, and Spiegel 2021) but also due to large data revisions (Sinclair 2012) and the surprising volatility of the energy intensity of Chinese GDP (Owyang and Shell 2017).[3] Therefore, our baseline estimates measure overall Chinese activity using the Federal Reserve Bank of San Francisco's China Cyclical Activity Tracker (hereafter CCAT), developed by Fernald, Hsu, and Spiegel (2021). Second, the literature generally does not distinguish spillovers based on the type of shocks driving Chinese domestic activity. Most papers consider generic shocks to Chinese growth without using domestic data to determine whether the shock is demand or supply driven. Barcelona and others (2022) is an exception in that they both use a broad proxy for Chinese activity and measure Chinese shocks specifically driven by a credit impulse. However, they base their spillover estimate on a single aggregate for global activity where our macro estimates use a panel of 50 countries. Third, to the best of our knowledge, we are the first to estimate China's spillovers for a large sample of firms covering both advanced and emerging market economies.

Our work also relates to a growing literature on international production networks.[4] Most closely related to our work is Huo et al. (2025), who use a multi-country, multi-sector dynamic network propagation model to decompose bilateral GDP co-movement among G7 countries into components resulting from international spillovers through production networks ('shock transmission') and from

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[3] They note that between 1997 and 2000, when official GDP grew by 24.7 percent, official energy consumption declined by 12.8 percent. This implies a 30 percent reduction in energy use and a pattern not shared by any Asian economies during periods of strong growth, nor evident in earlier Chinese data.

[4] See, for instance, Chaney (2014), Bernard et al. (2018), Grossman et al. (2024), Elliott and Jackson (2024).

contemporaneous similar shocks across countries ('shock correlation'). Our paper is complementary in several ways. Conceptually, we adopt a highly flexible empirical approach—identifying shocks in an SVAR and examining spillovers in local projections—whereas Huo et al.'s structural estimation imposes substantially stronger assumptions, for instance on the functional forms of intermediate input usage and firms' production.[5] More broadly, our flexible empirical approach imposes few restrictions on the data, allowing us to test our hypotheses in up to 46 countries, whereas the data requirements for Huo et al.'s structural approach limit their sample to seven countries in the main analysis and 29 countries in extensions. Importantly, even their larger sample consists almost entirely of advanced economies and does not include China, so cannot speak to spillovers from Chinese shocks. Lastly, while Huo et al. examine country-sectors and use a sample that ends in 2007, we test our hypotheses on firm-level data through 2021, providing a more granular and up-to-date assessment of spillovers.

The remainder of the paper is organized as follows. We first provide context from the theoretical literature on how supply and demand shocks in China could propagate through production networks and why their spillovers could differ across countries and firms. We then describe our strategy for identifying Chinese demand and supply shocks. Sections 4 and 5 present our country- and firm-level analyses, respectively. Section 6 concludes.

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[5] While our hypotheses are inspired by models that use similar functional forms, as described in the Section 2, we do not *impose* these functional forms in our empirical estimations, enabling us to test our hypotheses cleanly.

2. Theoretical Context

A large and growing literature, building on the seminal work of Acemoglu et al. (2012), examines how the transmission of shocks is shaped by network structure.[6] Importantly, this literature highlights that supply and demand shocks can propagate differently through production networks. For instance, Acemoglu, Akcigit and Kerr (2015) demonstrate theoretically that demand shocks predominantly propagate upstream (i.e., to sectors selling their output to the shocked sector), while supply shocks predominantly propagate downstream (i.e., to sectors purchasing inputs from the shocked sector).[7]

To illustrate this intuitively, consider demand and supply shocks affecting a perfectly competitive industry i that uses a technology with constant returns to scale to transform inputs supplied by a second industry j into outputs used by a third industry k.

First, an exogenous negative demand shock to industry i stimulates a reduction in i's output; however, because of constant returns to scale, this does not affect the prices that i charges k. Thus, the usage of i's output by industry k is not affected, so there is no propagation downstream to i's customers.[8] In contrast, the contraction of i's production reduces its demand for inputs from industry j, so j faces its own negative demand shock and reduce its production—i.e., the demand shock propagates upstream.

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[6] For recent surveys, see Bernard and Moxnes (2018), Carvalho and Tahbaz-Salehi (2019), and Elliott and Golub (2022).

[7] In their main model with Cobb-Douglas preferences and technologies, demand shocks only travel upstream, and supply shocks only travel downstream. Generalizations of the model (e.g., Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2016) suggest limited effects in the opposing directions. Empirical results for the US—including the impact of negative demand shocks driven by Chinese exports—from Acemoglu, Akcigit and Kerr (2015) support the Cobb-Douglas version. Bernard et al. (2019) and Carvalho et al. (2021) provide further empirical evidence on such mechanisms.

[8] We abstract from general equilibrium considerations, for instance that negative shocks in one country affect wages and hence final demand from that country for products produced elsewhere. This reflects our focus on the case of China—which, as noted below, plays a relatively limited role in global final demand compared to global supply. For a full theoretical characterization of the international propagation of shocks, see Huo et al. (2025).

Second, an exogenous negative supply shock to industry i leads the industry to reduce its output but also to raise prices, as under perfect competition the productivity decline must be fully passed through to customers. In this case, industry k faces higher prices and so reduces its output—i.e., the supply shock propagates downstream. In contrast, industry j faces two opposing forces: i's lower output places downward pressure on i's demand for the input supplied by j, but i's lower efficiency also increases that demand per unit of i's output, dampening the upstream propagation of the supply shock.[9] Combining these observations, we present three hypotheses on the spillovers from shocks in China.

First, since China is relatively upstream in the global production network—playing a much larger role in global supply (Figure 1) than in global final demand (Figure 2)—supply shocks in China should have larger effects on global GDP than demand shocks in China, reflecting that industries and consumers outside China are predominantly downstream from Chinese supply rather than upstream from Chinese demand. Thus:

- o **Hypothesis 1:** *Global GDP responds more to Chinese supply shocks than to Chinese demand shocks.*

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[9] Identifying these transmission channels in the propagation of international spillovers through production networks empirically requires controlling for another channel, namely direct competition between industry i in the shocked country and the same industry in another country, which we denote i^* (see next section for details on the methodology). Consider again the exogenous negative supply shock to sector i above. When industry k (which could be located in any country) faces higher prices from industry i, it may partially substitute away from inputs produced by i and towards inputs produced by i^*. This reallocation increases demand for i^*'s output—i.e., the direct competition channel leads to *positive* spillovers from the negative shock in China. Note, however, that this positive reallocation effect cannot dominate at the global level: under constant returns to scale, a negative supply shock in China reduces overall global productivity, so while some countries or country-sectors may expand, aggregate output must fall. For details on this channel when i and i^* compete in i^*'s domestic market, see, for instance, Acemoglu, Autor, Dorn, Hanson and Price (2016). For details on this channel when i and i^* compete in third-country export markets, see, for instance, Iacovone et al. (2013) and Copestake and Zhang (2023).

Second, for a given country or country-industry pair outside China, the first-order impact of negative supply and demand shocks in China through production networks is increasing with the strength of the trade linkages:

> o **Hypothesis 2:** *Both types of shocks, on average, reduce national GDP and firm revenue in other countries, and especially so in countries with stronger trade linkages to China.*

Finally, these impacts of Chinese shocks on countries and firms should vary depending on the form of the trade linkages to China:

> o **Hypothesis 3:** *Countries and firms that predominantly purchase from China—i.e., that have relatively stronger input linkages to China—are more affected by Chinese supply shocks, while countries and firms that predominantly sell to China—i.e., that have relatively stronger output linkages to China—are more affected by Chinese demand shocks.*

In the next sections of the paper, we describe the methodology for identifying Chinese supply and demand shocks, then empirically test these hypotheses using macroeconomic and firm-level data.

3. Identification of China Demand and Supply Shocks and Global Spillovers

Identifying Chinese supply and demand shocks requires: (i) a measure of Chinese economic activity and (ii) a means of decomposing the fluctuations in this activity into those components resulting from supply shocks, demand shocks, and other factors. On (i), we use the China Cyclical Activity Tracker (CCAT) of Fernald et al. (2021), which provides a broad proxy for economic activity. Specifically, the CCAT is the first principal component of a panel of indicators including exports, imports, air passengers, electricity

consumption, credit extension, rail use, retail sales, industrial production, government revenue, and highway usage. The breadth of these measures avoids errors in any one indicator and is more likely to represent the true state of economic activity. All series are detrended year-over-year growth rates, measured in normalized values (mean zero, unit standard deviation). The data is publicly available from the Federal Reserve Bank of San Francisco.[10]

Turning to (ii), we use a Structural Vector Autoregression (SVAR) approach. We supplement the CCAT with the following variables: Chinese inflation measured using core CPI; and global GDP growth and inflation, excluding China, calculated as GDP-weighted GDP growth and CPI inflation from the IMF World Economic Outlook Database.[11] We then use quarterly data to estimate the following model over the period 2001Q1-2019Q4:[12]

$$A_0 y_t = b + \sum_{j=1}^{p} A_j y_{t-j} + e_t \tag{1}$$

where y_t is an nx1 vector of endogenous variables, p is the lag length, A_j is an nxn matrix of parameters, b is a nx1 vector of parameters, and e_t is an nx1 vector of structural shocks. The latter is Gaussian conditional on past information with mean zero and a covariance matrix given by $E[e_t e_t'] = I$. y_t contains the six variables: CCAT, China core inflation, global GDP growth, global inflation, and the first two leading principal components from the global dataset in Table A2.3. The principal components

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capture broader global shocks such as changes to global financial conditions and commodity prices. The global growth and inflation variables are computed excluding China. The model is estimated with three lags based on an average of Hannan-Quinn, Akaike and Bayes information criteria.

The SVAR is identified following the methodology of Antolin-Diaz and Rubio-Ramirez (2018). The nxn matrix A_0 captures the relationship between the shocks and the endogenous variables. To recover this, the reduced form model is estimated as:

$$y_t = c + \sum_{j=1}^{p} B_j y_{t-j} + u_t \tag{2}$$

where $B_j = A_0^{-1} A_j$, $u_t = A_0^{-1} e_t$, $c = A_0^{-1} b$ and $E[u_t u_t'] = A_0^{-1} A_0^{-1\prime} = \Sigma_u$. The covariance matrix of the reduced form residuals, Σ_u, can be estimated from the residuals of the reduced form model. However, as is well known in the SVAR literature, the equation $A_0^{-1} A_0^{-1\prime} = \Sigma_u$ is not sufficient to identify the parameters in A_0 as the symmetry of Σ_u entails that we have fewer equations than unknown parameters. We thus need additional restrictions to identify A_0. We use sign restrictions on the relationship between e_t and y_t to identify A_0. This is solved following the Rubio-Ramirez et al (2010) algorithm. This involves defining $A_0 = Q chol(\Sigma_u)$, where $chol()$ is the Cholesky decomposition and Q is an orthonormal matrix, i.e., $QQ' = Q'Q' = I$. Following the literature, we impose sign restrictions by sampling Q from a standard normal random matrix and only retaining the draws where the implied A_0 corresponds to those

restrictions. These sign restrictions are provided in Tables 1 and 2 and discussed below. The reduced form VAR is estimated with Bayesian methods using a flat conjugate prior.[13]

Our first set of sign restrictions (Table 1) contains structural assumptions that we impose across the entire estimation window. We assume that demand shocks cause prices and quantities to move in the same direction, whereas supply shocks cause prices and quantities to move in opposite directions. We allow that Chinese shocks may have spillovers to global activity and prices, as well as the domestic economy, on impact but impose that global shocks only affect Chinese activity with a lag. This short-run zero restriction helps separate domestic and global shocks (also see narrative sign restrictions below). We also impose a long-run restriction that Chinese demand shocks do not have long run effects on domestic activity and core inflation.[14]

To further strengthen our identification of demand and supply shocks, we also impose that the identified shocks take on a specific sign during narratively identified episodes (Table 2). For China's domestic supply shocks, we use narrative restrictions based on large supply-side structural reforms identified in Alesina et al. (2024), as detailed in Figure A1.1. China enacted several supply side reforms following its ascension to the WTO. These included reforms in May 2002 to dismantle state monopolies

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[13] This prior is implemented as Normal distribution for the autoregressive coefficients and an inverse Wishart distribution for the covariance matrix. The hyperparameters are set so that the posterior is close to the estimates that would be found using OLS, implemented using MATLAB's BVAR function. We use keep 100,000 draws in our Gibbs sampler that meet our traditional sign restrictions from 947.5 million samples of the Q matrix. Of these approximately 300 meet the additional narrative sign restrictions. While the large number of attempted relative to accepted draws may suggest that they are implausible or rejected by the data, this is not correct. As noted in Kilian and Lutkepohl (2016), Ch.13 all rotations of the A_0 matrix achieved via the Q matrix fit the data equally well since they all are a decomposition of the reduced form covariance matrix Σ_u. Instead, the low fraction of admissible models indicates that these restrictions are in fact informative and thus selecting meaningful models from the data.

[14] This is implemented as a bound restriction on the long-run response of the IRF derived from each candidate draw of A_0. If the long run effect is larger than 0.2 percent for activity or 0.3 percent for CPI inflation then the draw is discarded. Smaller thresholds, closer to 0, do not make a qualitative difference but are computationally burdensome.

in electricity and promotion of new providers to foster competition (Xu and Chen 2006). Similar reforms to foster greater competition and deregulate the telecoms sector were implemented in September 2002 (Li 2011). Financial sector reforms included restructuring of state-owned banks, enhanced corporate governance and reforms to capital markets promoting IPOs and stock trading to attract more foreign and domestic capital. These culminated at the end of 2006 with the IPO of China's largest bank, Industrial and Commercial Bank of China's in October 2006.

For China's domestic demand shocks, we use narrative restrictions based on the large monetary policy shocks identified in in Chen, Ren and Zha (2018). The latter construct a monetary policy rule for M2 growth in China, where monetary aggregates have been the target of monetary policy until recently (see Maher 2024). Specifically, we impose that demand shocks identified in the SVAR take the same sign as the monetary policy shocks that are larger than 2 standard deviations, which includes only the two largest episodes, the 2009Q1 credit stimulus after the GFC, and 2015Q1 when tight monetary policy amplified capital outflows following exchange rate reforms (Figure A1.2).

Figure 3 presents the structural Chinese demand and supply shocks, while Figure 4 their contribution to the CCAT. Large positive supply shocks take place in the 2000s coinciding with structural reforms in the electricity, telecoms and the banking sector. Large positive demand and monetary policy shocks took place during the 2008-9 period, in support of the recovery from the GFC, while tight monetary conditions in early 2015 contributed to the 2015-16 weakness in domestic activity. Our historical decomposition of the CCAT shows that global shocks have been a significant driver of the Chinese business cycle, accounting for approximately two-thirds of the variance in CCAT, with domestic

shocks explaining the remaining one-third.[15] Global shocks were particularly important in explaining the depth of the decline during the GFC and in amplifying the capital flight and activity slowdown in 2015-16. Domestic shocks explain the initial activity declines during the 2015-16 slowdown, especially demand shocks relating to monetary conditions. Domestic supply shocks have become more important in the post-2016 period although activity fluctuations have been modest.

Figure 5 presents the impulse response functions from our estimated SVAR. The first two columns show that Chinese demand and supply shocks have a broadly similar impact on domestic activity, with supply having a slightly larger impact, but Chinese supply shocks have a larger and more persistent impact on Chinese core CPI.[16] Global supply shocks are important for Chinese activity whereas we find weaker evidence for the role of global demand shocks.

The third column of Figure 5 shows the estimated responses of world GDP. In line with Hypothesis 1 above, we find substantially larger spillovers from Chinese supply shocks than from Chinese demand shocks. In particular, we find that a 1 percent of GDP supply (demand) shock in China leads to a peak reduction in global GDP of approximately 0.4 percent (0.2 percent). Figure A1.4 shows the decomposition of global GDP growth, and confirms the important role of Chinese shocks, including during the GFC.

In the next two sections, we use the estimated Chinese supply and demand shocks to assess spillovers from China at both the country and firm levels, examining how these spillovers vary with the extent and type of trade exposure.

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[15] We include within "global shocks" the unidentified shocks relating to our two principal components, since these are derived from global variables. For the historical decomposition of domestic inflation see Figure A1.3.

[16] Note that Chinese supply shocks do not have a permanent effect on the level of activity in China because we use a de-trended activity measure (i.e., the CCAT) rather than GDP.

# 4.	Country-Level Spillovers

We first consider the spillovers from Chinese supply and demand shocks at the country level. We begin by describing the data and regression specifications that we use to test Hypothesis 2 and Hypothesis 3 at the country level, then we present our country-level results and assess their robustness. The subsequent section follows the same structure but extends the analysis to the firm level.

## 4.1.	Data and Specifications

We use Jordà's (2005) local projection method to estimate the response to Chinese supply and demand shocks of national GDP in countries in the rest of the world. We estimate the following equation for each quarter $h = 0 \dots 16$:

$$y_{c,t+h} - y_{c,t-1} = \alpha_c + \beta_S^h \cdot e_t^S + \beta_D^h \cdot e_t^D + \Gamma' X_{c,t} + \varepsilon_{c,t+h} \tag{3}$$

where: $y_{c,t+h}$ is the log of real GDP in country c, with GDP data taken from the IMF World Economic Outlook database; α_c are country fixed effects, which account for differences in average growth rates across countries; and e_t^d (e_t^S) denote the demand (supply) shocks identified in the previous section. $X_{c,t}$ is a set of control variables including: the lag of country c's GDP growth rate, financial conditions indices (excluding China) from the IMF Global Financial Stability Report (GFSR), and the Chicago Board Options Exchange Volatility Index (VIX), as well as world export-weighted GDP growth (where the weighting excludes China), a dummy variable for the GFC period, demand (supply) shocks in the

preceding quarter, and future shocks up to the horizon of the impulse response, h, as in Teulings and Zubanov (2014).[17]

The coefficients β_S^h (β_D^h) reflect the average responsiveness of partner country GDP to Chinese supply (demand) shocks at horizon h. They therefore provide a test of the first part of Hypothesis 2 at the country level—i.e., that supply and demand slowdowns in China are associated with declines in partner country GDP.

To test the second part of Hypothesis 2—i.e., that these spillovers are greater in countries with stronger trade links to China—we augment equation (3) and estimate the following difference-in-differences specification:

$$y_{c,t+h} - y_{c,t-1} = \alpha_c + \alpha_t + \beta_{S,T}^h \cdot e_t^S \cdot \bar{T}_{c,China}^S + \beta_{D,T}^h \cdot e_t^D \cdot \bar{T}_{c,China}^D + \Gamma' X_{c,t}^* + \varepsilon_{c,t+h} \qquad (4)$$

where α_t are time fixed effects and $\bar{T}_{c,China}$ is a measure of country c's trade links to China that we discuss below. $X_{c,t}^*$ is a set of controls that incudes the lag of country c's GDP growth rate and two additional interaction terms, $e_{t-1}^S \cdot \bar{C}_{c,China}$ and $e_{t-1}^D \cdot \bar{C}_{c,China}$, that control for potential spillovers from

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[17] Teulings and Zubanov (2014) demonstrate that local projections can be biased because the fixed effect absorbs some of the impact of a shock that takes place in future periods, and that adding future values corrects this bias.

recent Chinese shocks that occur through the direct competition channel.[18] Our time fixed effects absorb the common effect across countries of global shocks, including Chinese shocks, implying that our coefficients of interest, $\beta^h_{S,T}$ and $\beta^h_{D,T}$, reflect the differential impact of Chinese shocks on countries with relatively stronger trade links to China.

Initially, we measure country c's trade links to China using country c's direct trade with China—its imports from, and exports to, China, as a share of GDP, $ME_{c,China,t}$. Since this variable fluctuates over time in ways that may also correlate with Chinese supply and demand shocks as well as other time varying factors, we construct a time-unvarying measure by removing their global trends. For trade exposure (exports and imports as share of GDP), we run the following regression:

$$ME_{c,China,t} = \gamma_c + \gamma_t + \epsilon_{c,t}. \tag{5}$$

where γ_c and γ_t are country and time fixed effects, respectively. We take $\overline{ME}_{c,China} = \gamma_c$ as our non-time-varying measure. Intuitively, $\overline{ME}_{c,China}$ capture the average trade exposure of country c over our sample period, after removing global trends (time fixed effects).

Setting $\overline{T}^{S,D}_{c,China} = \overline{ME}_{c,China}$ in equation (4), the coefficients $\beta^h_{S,T}$ ($\beta^h_{D,T}$) denote the differential response of country c's GDP to Chinese demand (supply) shocks that is associated higher trade linkages.

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[18] See Annex 5 for details on the construction of $\bar{C}_{c,China}$, which measures the extent to which industries in country c compete with Chinese industries in domestic and foreign markets. Intuitively, $\bar{C}_{c,China}$ estimates, across all markets to which country c sells (including its domestic market), the average share of demand that is supplied by China, weighted by the importance of each market in c's sales. Thus, we take into account that supply and demand shocks in China could impact GDP in country c not just through trade linkages but also through their impact on China's competition with country c in product markets, both domestically (as considered by, for example, Acemoglu, Autor, Dorn, Hanson and Price, 2016) and in export markets (as considered by, for example, Iacovone et al., 2013, and Copestake and Zhang, 2022).

We rescale these coefficients to quantify the differential response to Chinese shocks when moving from a country with low trade linkages (at the 25th percentile of the trade linkage distribution) to one with higher trade linkages (at the 75th percentile of the distribution).[19]

Hypothesis 3 above states that the relative impact of Chinese supply and demand shocks should depend on the nature of the trade links between country c and China—specifically, on the relative importance of input and output linkages between the two countries. To measure this, we use the Multi-Region Input-Output (MRIO) tables from the Asian Development Bank, which augment the widely used World Input-Output Tables (WIOD) database with a further 19 Asian economies, providing data on the input-output linkages between 35 sectors in 62 countries for 2000 and annually from 2007-2020.

We first calculate a measure of input linkages, specifically the share of total inputs used in country c that are supplied by China:

$$I_{c,China,t} = \frac{\sum_i \sum_j Sales_{China,j \to ci,t}}{\sum_i \sum_d \sum_j Sales_{dj \to ci,t}} \tag{6}$$

where $Sales_{dj \to ci,t}$ represents total sales from industry j in origin country c to industry i in destination country c. Intuitively, we sum all inputs used by all industries in country i—from all origin countries and all origin industries, including inputs from domestic industries—and take the share that were provided by any Chinese industry. To avoid any endogeneity resulting from fluctuations in this value with global

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[19] $\bar{T}_{c,China}^{S,D}$ is measure based on gross exports and imports, or sales (depending on the measure), despite the fact the GDP is a value-added measure, to align with our firm-level analysis, which centers on firm sales (a gross measure).

trends, we purge $I_{c,China,t}$ of temporal variation using the same procedure as described for $M_{c,China,t}$ above, giving the analogous cross-sectional variable $\bar{I}_{c,China}$.

We next calculate an analogous measure of output linkages, specifically the share of all demand for country c's output that comes from China:

$$O_{c,China,t} = \frac{\sum_i \sum_j Sales_{ci \to China,j,t} + \sum_i FinalDemand_{ci \to China,t}}{\sum_i \sum_d \sum_j Sales_{ci \to dj,t} + \sum_i \sum_d FinalDemand_{ci \to d,t}}. \tag{7}$$

Intuitively, we first sum (i) all sales by all industries in country c to all destination industries in all countries (including sales to other domestic industries) and (ii) all sales by all industries in country c to all final consumers in all countries (including sales to domestic final consumers). Then we take the share of these total sales that go to industries and final consumers in China, and again purge out temporal variation using the same procedure to produce the cross-sectional variable $\bar{O}_{c,China}$.

Finally, we combine these two variables to construct a measure of the *relative* exposure of country c to China through input markets, when compared to its exposure through output markets:

$$\bar{I}_{c,China}^{rel} = \frac{\bar{I}_{c,China}}{\bar{I}_{c,China} + \bar{O}_{c,China}}. \tag{8}$$

Setting $\bar{T}_{c,China}^{S} = \bar{I}_{c,China}^{rel}$ and $\bar{T}_{c,China}^{D} = -\bar{I}_{c,China}^{rel}$ in specification (4), we can then test Hypothesis 3: $\beta_{S,T}^{h}$ ($\beta_{D,T}^{h}$) now reveals the extent to which countries that have relatively strong input (output) linkages with China see relatively stronger spillovers from Chinese supply (demand) shocks.

4.2. Results

Unconditional effects

We estimate spillovers from the demand and supply shocks derived using the SVAR, where the shocks are scaled to be equivalent to 1 percent of Chinese GDP.[20] Figure 6 presents our main results from specification (3). Negative Chinese supply shocks lead to an average decline in GDP levels of other countries by approximately 0.15 percent over two years. Interestingly, the effect of supply shocks on the average country is smaller than that on global GDP, suggesting that richer countries are more affected by these shocks. The impact of demand shocks on the average economy is of similar magnitude but occurs more rapidly and is short-lived. Declines in investment spending are an important channel, with real investment levels falling by a peak of around 0.2 percent during the same interval. Overall, these results are broadly consistent with those of Furceri, Jalles, and Zdzienicka (2017).

These findings are robust to several specifications, including: (1) a model with no control variables except the country fixed effects, (2) the full model but excluding the correction for future shocks, and (3) the full model excluding the lags of past shocks (Figure A3.1).

We also investigate the stability of the results over time, by running specification (3) using a rolling window from 2001 to 2011 to investigate how the spillover effects vary over time (Figure A3.2).[21] We find that in both cases the peak impacts of the shocks have increased in recent years, especially after the GFC. Overall, these results are consistent with China becoming a more important source of both demand and supply spillovers. In addition, we also find that China was a relatively important source of

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[20] The standard deviation of the official GDP measure over our estimation period is 2.35 percent. The CCAT measure is standardized to have a unit standard deviation, thus we scale the size of the CCAT-based shocks by 1/2.35 in order for the shock to be equivalent to a 1 percent movement in headline GDP, which is the baseline for the majority of the literature.

[21] This exercise only considers a horizon of 3 years ahead due to loss of degrees of freedom as the sample shrinks.

supply spillovers in the years immediately following its integration into the global trading system (i.e. after WTO accession in December 2001).

Finally, we examine potential differences in the magnitude of spillovers by splitting the sample between advanced economies (AEs) and emerging market economies (EMs). Consistent with the evidence on the impact of supply shocks on global and country-level GDP, we find that supply shocks generate larger spillovers in AEs (Figure A3.3). By contrast, spillover effects stemming from demand shocks are more pronounced in EMs. These findings also reflect the strong input linkages in advanced economies—such as Eastern European countries with significant manufacturing sectors (e.g., Estonia, Slovenia, Lithuania)—and the importance of raw material exports to China for many EMs (e.g., Russia, Brazil, Kazakhstan).

Heterogeneity and the role of trade exposure

Figure 7 shows the differential spillover effects associated with a country's trade exposure. We find that the difference in spillovers from a 1 percent of GDP Chinese supply (demand) shock between countries with higher trade linkages with China—those at the 75th percentile of the trade exposure distribution— and countries with relatively low linkages—at the 25th percentile—is approximately 0.05 percentage point—that is, about one-third of the average unconditional effect. These results thus confirm our Hypothesis 2.

Turning to Hypothesis 3, Figure 8 shows the results from running specification (4) with $\bar{T}^S_{c,China} = \bar{I}^{rel}_{c,China}$ and $\bar{T}^D_{c,China} = -\bar{I}^{rel}_{c,China}$. Countries with higher exposure through input linkages—specifically, moving from the 25th to the 75th percentile on $\bar{I}^{rel}_{c,China}$—see an additional 0.05 percentage point drag on GDP from negative Chinese supply shocks. Conversely, countries with higher exposure through output

linkages—specifically, moving from the 75th to the 25th percentile on $\bar{I}^{rel}_{c,China}$—see 0.2 percentage point additional drag on GDP from negative Chinese demand shocks.

While these results align with the theory and support the hypotheses, the estimated differential responses are typically imprecise, reflecting the relatively small sample size available for testing at the country level. The next section turns to firm-level data, whose larger sample size allows for a clearer examination of the role of trade linkages in transmitting shocks from China.

5. Firm-Level Spillovers

We next turn to firm-level spillovers. The impact of Chinese supply and demand shocks on firm revenue is not necessarily the same as the impact on GDP, as changes in public and private investment or import consumption could also affect GDP. Nonetheless, firm-level responses to Chinese supply and demand shocks help reveal how shocks emanating from China propagate to the rest of the world through production networks. Moreover, examining spillovers at the firm level enables us to control more granularly for potential confounders and increases our power to detect differential exposures to Chinese supply and demand shocks across countries and industries. In this section, we use an analogous methodology and structure used for the country-level spillovers in the previous section. We first describe our firm-level data and regression specifications, then we present results on the spillovers from Chinese supply and demand shocks and how they vary with supply chain linkages to China.

5.1. Data and Specifications

Our main source of data is S&P Capital IQ (CIQ), which provides detailed firm balance sheet and income statement information. Data are available at quarterly frequency, providing an advantage over other

leading corporate data providers such as Orbis or Worldscope. This higher frequency is well suited to identifying firm-level responses to high frequency shocks, such as Chinese demand and supply shocks. Our dataset covers a long timespan and a broad set of countries: 20 years of data, from 2001Q3 to 2019Q4, for 46 countries (27 AEs and 19 EMDEs). Firms in our dataset belong to a wide range of industries—20 CIQ-defined industries in total, after filtering out firms in the financial, insurance and utilities sectors.[22] After filtering, the sample consists of more than 20,000 firms.[23] Our main variable of interest is firm total revenue (IQ_TOTAL_REV), and we also use firm investment (specifically, capital expenditure, IQ_CAPEX) to cross-validate our analysis.[24] Table A2.4 displays summary statistics.

To test our hypotheses, we use a similar approach to the country-level regressions. We use local projections to estimate the average (unconditional) revenue responses to Chinese supply and demand shocks, then assess how these responses are shaped by trade linkages with China. First, we estimate the average response of firm revenue to Chinese supply and demand shocks using the following specification:

$$y_{cif,t+h} - y_{cif,t-1} = \alpha_{fq} + \beta_S^h \cdot e_t^S + \beta_D^h \cdot e_t^D + \Gamma' X_{cif,t} + \epsilon_{cif,t+h} \tag{9}$$

where the dependent variable $y_{cif,t}$ denotes the log revenue of firm f in country c and industry i; α_{fq} indicates firm-quarter fixed effects to control for unobservable time-invariant firm characteristics as well as firm seasonality in revenue, and e_t^S and e_t^D again denote the supply and demand shocks identified in

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[22] Details on the distribution of firms across countries and sectors are shown in Tables A2.5 and A2.6.

[23] We also restrict our sample to non-financial corporations and remove (i) firms that had negative values for assets or debt in any year, and (ii) observations with the incorrect sign for revenue or capital expenditure (see Arbatli-Saxegaard and others, 2022, for details).

[24] We trim all firm-level variables at the 5th and 95th percentiles to eliminate outliers.

Section 2. $\boldsymbol{X}_{cift}$ includes controls for the shocks in the preceding year, and future shocks in the next year, as well as four lags of the dependent variable, financial conditions indices for advanced and emerging economies (excluding China) from the IMF GFSR, the VIX, and three lags of world export-weighted GDP growth (as in equation (3)).

In this case, the coefficients β_S^h and β_D^h in equation (9) denote the average responsiveness of firm revenue to Chinese supply (demand) shocks after h quarters. These coefficients provide a test of the first part of Hypotheses 2 at the firm level, analogous to the coefficients in specification (3) for the country level. To test the second part of Hypothesis 2 at the firm level—i.e., to test whether spillovers from Chinese supply and demand shocks are greater for firms with stronger trade links to China—we augment equation (9) as follows:

$$y_{cif,t+h} - y_{cif,t-1} = \alpha_{fq} + \alpha_{ct} + \alpha_{it} + \beta_{S,T}^h \cdot e_t^S \cdot \overline{T}_{ci,China}^S + \beta_{D,T}^h \cdot e_t^D \cdot \overline{T}_{ci,China}^D + \Gamma' \boldsymbol{X}_{cif,t}^* + \epsilon_{cif,t+h} \qquad (10)$$

where α_{ct} are country-time fixed effects and α_{it} are industry-time fixed effects.[25] $\overline{T}_{ci,China}^S$ and $\overline{T}_{ci,China}^D$ are country-industry-level analogues of our country-level variables $\overline{T}_{c,China}^S$ and $\overline{T}_{c,China}^D$ and are described in more detail below. Analogous to $\boldsymbol{X}_{c,t}^*$, the augmented set of controls $\boldsymbol{X}_{cif,t}^*$ also includes the additional controls $e_{t-1}^D \cdot \overline{C}_{ci,China}$ and $e_{t-1}^S \cdot \overline{C}_{ci,China}$, where $\overline{C}_{ci,China}$ is an industry-level analogue of $\overline{C}_{c,China}$ and measures the extent to which country-industry ci competes with Chinese output in domestic and foreign

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[25] We do not include the country-time fixed effect in the previous equation (9) in order to gauge the full unconditional average response of revenue to supply/demand shocks and to retain comparability with the country-level regression specification (3).

markets.[26] The intuition for $\bar{C}_{ci,China}$ parallels that for $\bar{C}_{c,China}$, but at the country-industry level: $\bar{C}_{ci,China}$ estimates, across all destination markets to which country-industry ci sells, the weighted average share of demand for industry i's output that is met by Chinese producers, where the weights are the importance of each market in ci's total sales.

Specification (10) has several advantages compared to the country-level analogue (specification 4). By including both country-time and industry-time fixed effects, along with firm-quarter fixed effects, we control for country-specific macroeconomic shocks (e.g., changes in a country's monetary and fiscal policy, including in response to Chinese shocks) and for global shocks to each industry (e.g., resulting from commodity price shocks or technological innovations).

We measure exposure to China through trade linkages using the same MRIO tables as in the country-level regressions. Again, we initially measure trade linkages using import shares from and export shares to China, except now constructed at the country-industry level. Specifically, we measure imports from China relative to total output of each country-industry pair ci.

$$M_{ci,China,t} = \frac{\sum_j Sales_{China,j \to ci,t}}{Production_{ci,t}} \quad E_{ci,China,t} = \frac{\sum_j Sales_{ci \to China,j,t} + FinalDemand_{ci \to China,t}}{Production_{ci,t}} \tag{11}$$

and similarly exports to China relative to total output of each country-industry pair

$$E_{ci,China,t} = \frac{\sum_j Sales_{ci \to China,j,t} + FinalDemand_{ci \to China,t}}{Production_{ci,t}}. \tag{12}$$

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[26] See Annex 5 for details on the construction of $\bar{C}_{ci,China}$ and how it relates to the country-level measure $\bar{C}_{c,China}$.

As for the country level analysis, we define overall trade exposure $ME_{c,China,t}$ as $M_{ci,China,t} + E_{ci,China,t}$. Then, we apply an analogous procedure to control for global trends and set $\bar{T}^{S,D}_{ci,China} = \overline{ME}_{ci,China}$ in equation (10). In this case, the coefficient $\beta^h_{S,T}$ ($\beta^h_{D,T}$) in equation (10) measures the extra responsiveness to Chinese supply (demand) shocks of a firm in an industry with higher trade linkages to China.[27]

Finally, to unpack the mechanisms underlying these trade linkages, we construct country-industry-level measures of input and output linkages, building on existing industry-level measures constructed in the context of a single country's economy (e.g., Acemoglu, Akcigit and Kerr, 2015; Lane, 2025). First, we measure input linkages as the share of total inputs to country-industry ci that are supplied by China, across all Chinese industries:

$$I_{ci,China,t} = \frac{\sum_j Sales_{China,j \to ci,t}}{\sum_d \sum_j Sales_{dj \to ci,t}}.$$
(13)

Second, we measure output linkages as the share of total global demand for country-industry ci's products that comes from China, across both Chinese consumers and all Chinese industries, i.e.

$$O_{ci,China,t} = \frac{\sum_j Sales_{ci \to China,j,t} + FinalDemand_{ci \to China,t}}{\sum_d \sum_j Sales_{ci \to dj,t} + \sum_d FinalDemand_{ci \to d,t}}.$$
(14)

We then purge out temporal variation in both variables using the procedure described above for $\bar{E}_{ci,China}$, and construct our country-industry-level measure of relative input exposure:[28]

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[27] Again, we rescale the coefficients to reflect the increased responsiveness associated with moving from a country with low trade exposure (at the 25th percentile of the distribution) to one with high trade exposure (at the 75th percentile).

[28] Figures A6.1 and A6.2 respectively show the 20 country-industry pairs with the greatest input and output exposure to China. In both cases, we see that some sectors—particularly in Southeast Asia—are highly dependent on China, with a high share of production being for Chinese demand and/or a high share of all inputs being supplied by China.

$$\bar{I}_{ci,China}^{rel} = \frac{\bar{I}_{ci,China}}{\bar{I}_{ci,China} + \bar{O}_{ci,China}}. \tag{15}$$

This measure enables us to assess how the nature of each firm's exposure to China (specifically, whether its industry has relatively strong input or output linkages to China) mediates the impact of Chinese demand and supply shocks on firm revenue. Specifically, to test Hypothesis 3 at the firm level, we set $\bar{T}_{ci,China}^{S} = \bar{I}_{ci,China}^{rel}$ and $\bar{T}_{ci,China}^{D} = -\bar{I}_{ci,China}^{rel}$ and run specification (10). Similar to the country-level regressions, the coefficient $\beta_{S,T}^{h}$ ($\beta_{D,T}^{h}$) in equation (10) reveals the extent to which firms in country-industries that have relatively stronger input (output) linkages with China see relatively larger spillovers from Chinese supply (demand) shocks.

5.2. Results

Unconditional effects

Figure 9 presents the average revenue response to a negative China demand shock (left panel) or supply shock (right panel) equivalent to 1 percent of GDP. In line with the first part of Hypothesis 2—and consistent with our country-level results—both demand and supply shocks are followed by an economically and statistically significant decline in foreign firms' revenue, with a peak impact over 8 quarters of -1 percent for the supply shock and -3.5 percent for the demand shock. We find qualitatively similar results for profits.[29]

We conduct a range of robustness checks to confirm that our results are not sensitive to the inclusion of specific control variables, countries, or sectors in the sample, or to our choice of

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[29] Following a referee's suggestion, we apply the smooth local projection method of Barnichon and Brownlees (2019) to reduce volatility in the impulse response functions. Qualitatively similar results are obtained using standard local projections (Figure A4.1).

specification. In Figure A4.2, we present the impulse responses equivalent to Figure 9 by (1) dropping all the control variables from equation (9), (2) without the Teulings and Zubanov (2014) future shocks correction, and (3) without the lags of shocks. In further sensitivity analyses, we exclude countries with fewer than 250 firms (Figure A4.3-(1)) and the two largest sectors (Figure A4.3-(2)). In all cases, our findings are qualitatively robust and quantitatively similar.

Finally, we split the sample to examine firms in AEs and EMs separately (Figure A4.4) and firms in manufacturing and services separately (Figure A4.5). We find that our results remain qualitatively and quantitatively similar in all four cases.[30]

Heterogeneity and the role of trade exposure

Turning to the second part of Hypothesis 2, we estimate the differential impact of Chinese shocks on country-industry pairs with relatively high trade exposure to China, using specification (10) and setting set $\overline{T}^{S,D}_{ci,China} = \overline{ME}_{ci,China}$, as done for the country-level analysis. Figure 10 reveals that following a negative demand shock, firms operating in country-industry pairs with higher exports to China experienced larger declines in revenue, while the same is true following a negative supply shock for firms operating in country-industry pairs with higher imports. The role of exposure in relation to supply shocks is relatively smaller in magnitude than in relation to demand shocks, which is intuitive: lower Chinese demand directly impacts firm sales in country-industry pairs that export heavily to China, whereas Chinese supply shocks only have indirect impacts on firm revenue, even in industries that import extensively from China.

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[30] We do not repeat the rolling windows analysis at the firm level because many firms enter and exit the panel over time, making cross-period comparisons unreliable.

This motivates our final specification, in which we test Hypothesis 3 by distinguishing explicitly between input and output linkages.

Figure 11 shows the results from estimating equation (10) with $\bar{T}^S_{ci,China} = \bar{I}^{rel}_{ci,China}$ and $\bar{T}^D_{ci,China} = -\bar{I}^{rel}_{ci,China}$. We find that demand shocks have persistently larger negative impacts on firms with relatively strong output linkages to China, and supply shocks have persistently larger negative impacts on firms with relatively strong input linkages to China. In response to a negative supply shock equivalent to a 1 percent decline in GDP in China, firms at the 75th percentile of relative input exposure see revenue fall by 0.5 percent more over two years than do firms at the 25th percentile. Similarly, in response to a negative demand shock equivalent to a 1 percent decline in GDP in China, firms at the 75th percentile of relative output exposure also see revenue fall by 0.5 percent more than do firms at the 25th percentile. Thus, overall our firm-level results corroborate our country-level findings and provide support for Hypotheses 2 and 3.

6. Conclusion

China's spectacular growth over the last three decades has created deep trade and investment links with the rest of the world. As growth in China moderates, those linkages could in turn have adverse spillover effects. In this paper, we contribute to the literature on China spillovers in three main ways: we employ a broad measure of domestic activity in China, we distinguish spillovers based on the type of shock driving Chinese domestic growth, and we do so at both the aggregate level and in a large sample of firms covering both advanced and emerging economies.

Taken together, our results suggest that the implications of Chinese supply and demand shocks differ in important ways. At the aggregate level, Chinese supply shocks have larger spillovers to global

GDP than do Chinese demand shocks, consistent with China's central role in global production and its comparatively smaller role in global final demand. At the national and firm levels, Chinese supply shocks have relatively larger spillovers to countries and firms that source more inputs from China, while Chinese demand shocks have relatively larger spillovers to countries and firms that sell more of their output to China. These findings remain robust even when controlling for country and industry trends using firm-level data.

Our findings highlight the central role of global production networks in transmitting real shocks from China to the rest of the world. In recent years, negative demand shocks in China have been a primary concern, given the ongoing weakness in the Chinese property sector and the corresponding slowdown in investment. Over the medium term, however, negative supply shocks—for instance, related to lower Chinese TFP and labor force growth—are likely to be even more important. Our work provides guidance for policymakers in China's trading partners considering how to navigate the potential spillovers.

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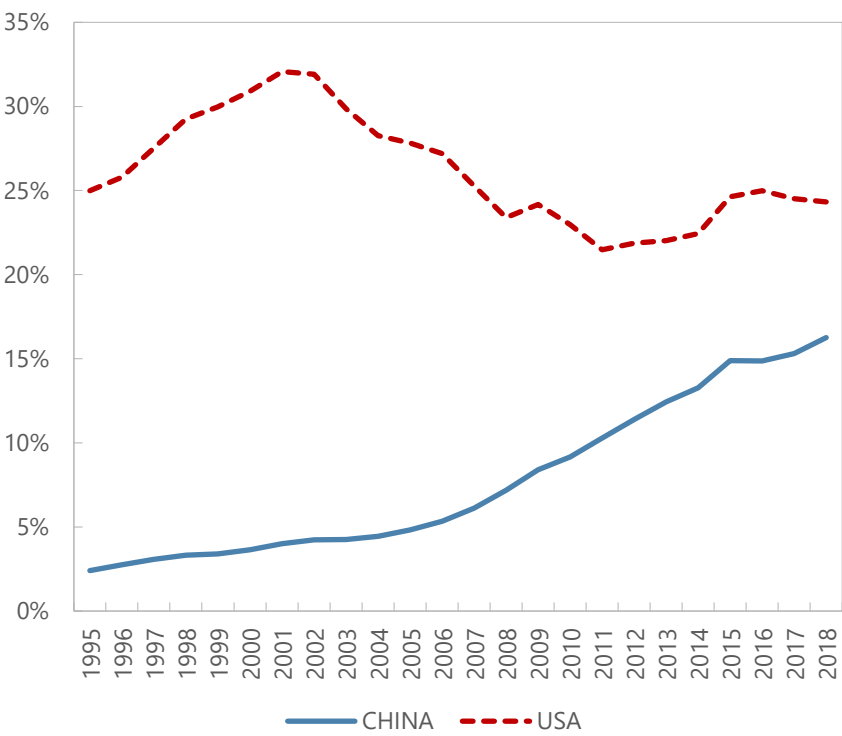
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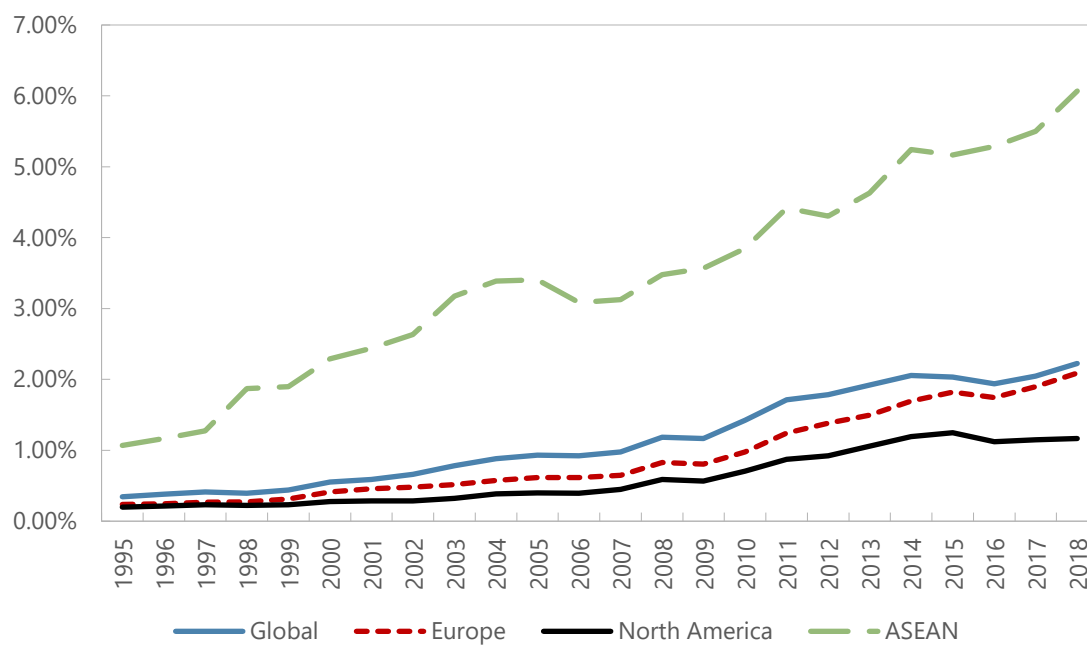
Figures

Figure 1. Share of global value added supplied by the USA and China
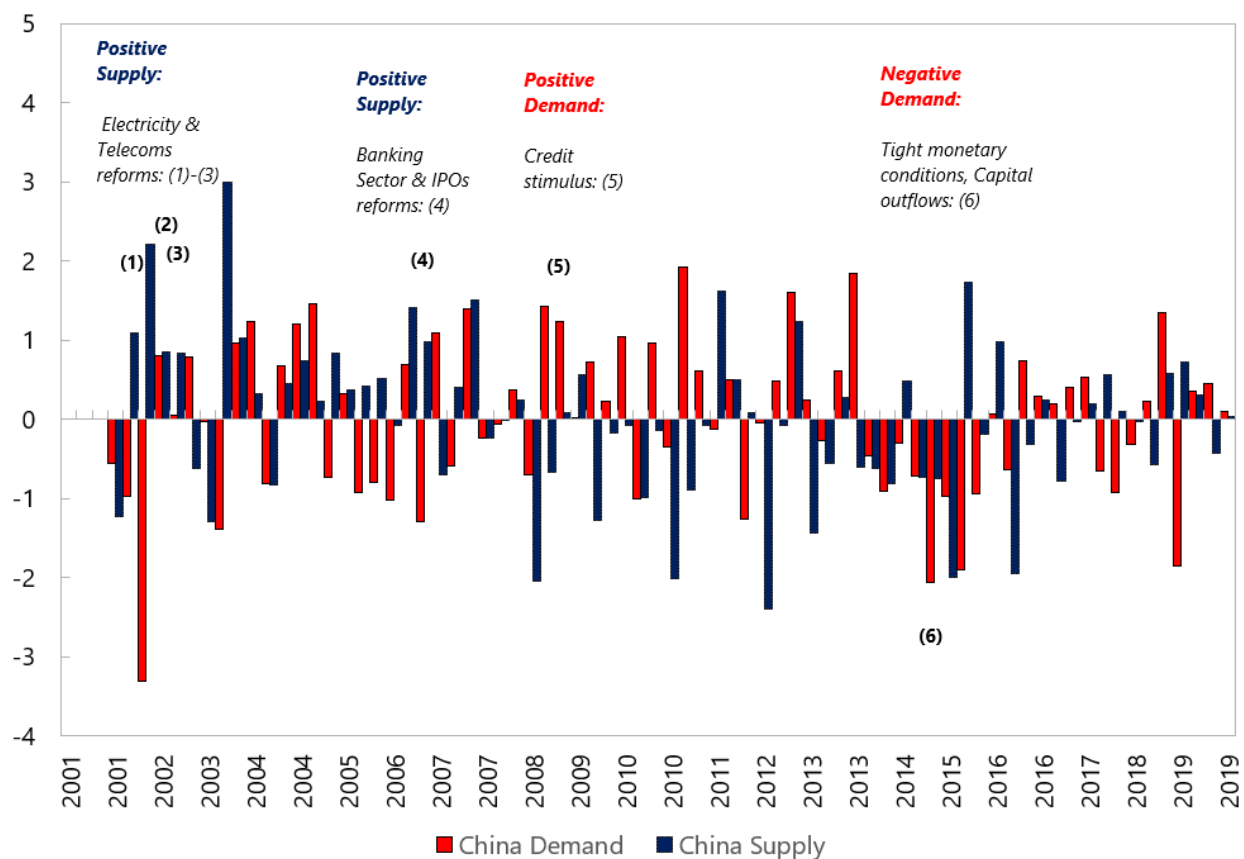

Sources: OECD TiVA, IMF staff calculations.

Figure 2. Share of value added absorbed by Chinese final demand
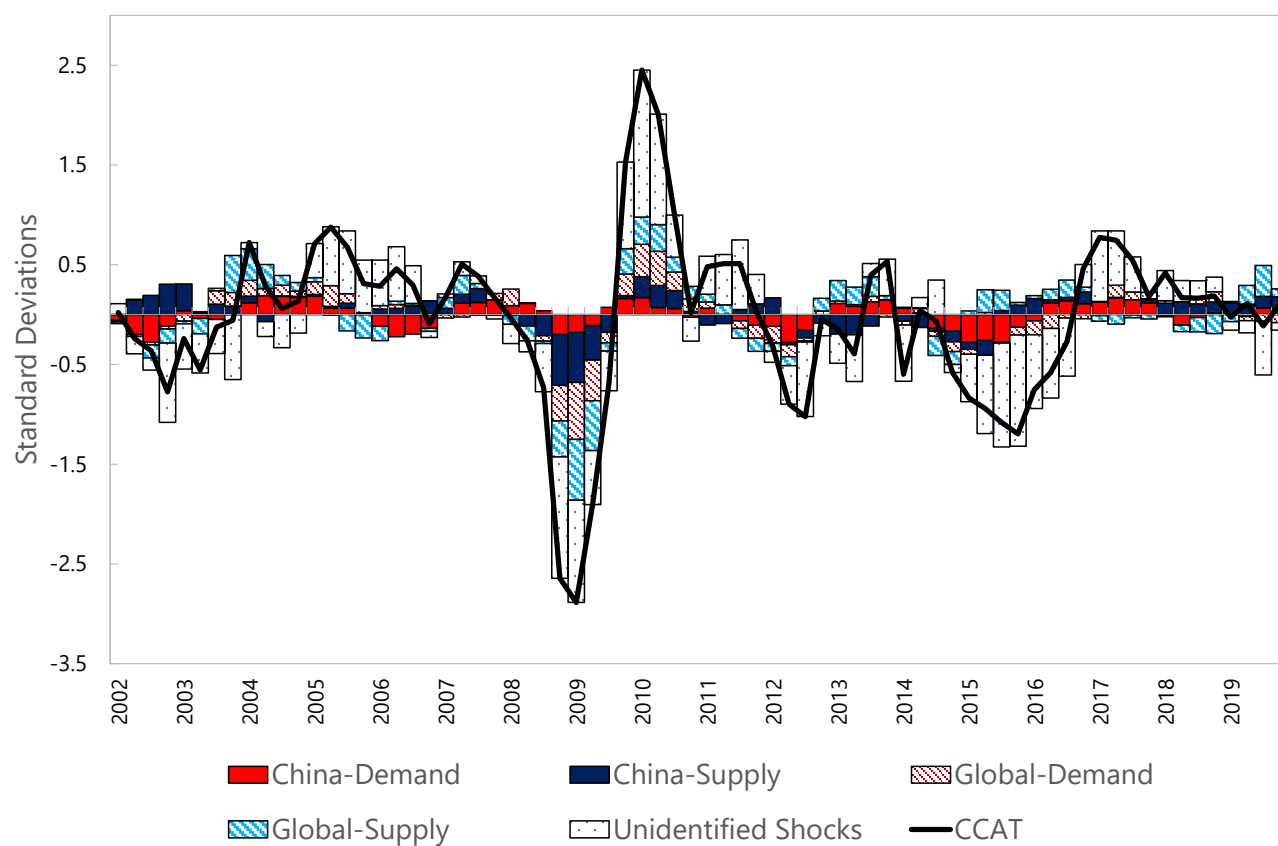

Sources: OECD TiVA, IMF staff calculations. ASEAN = average across Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Vietnam.

Figure 3. Demand and supply shocks from the narratively identified SVAR model
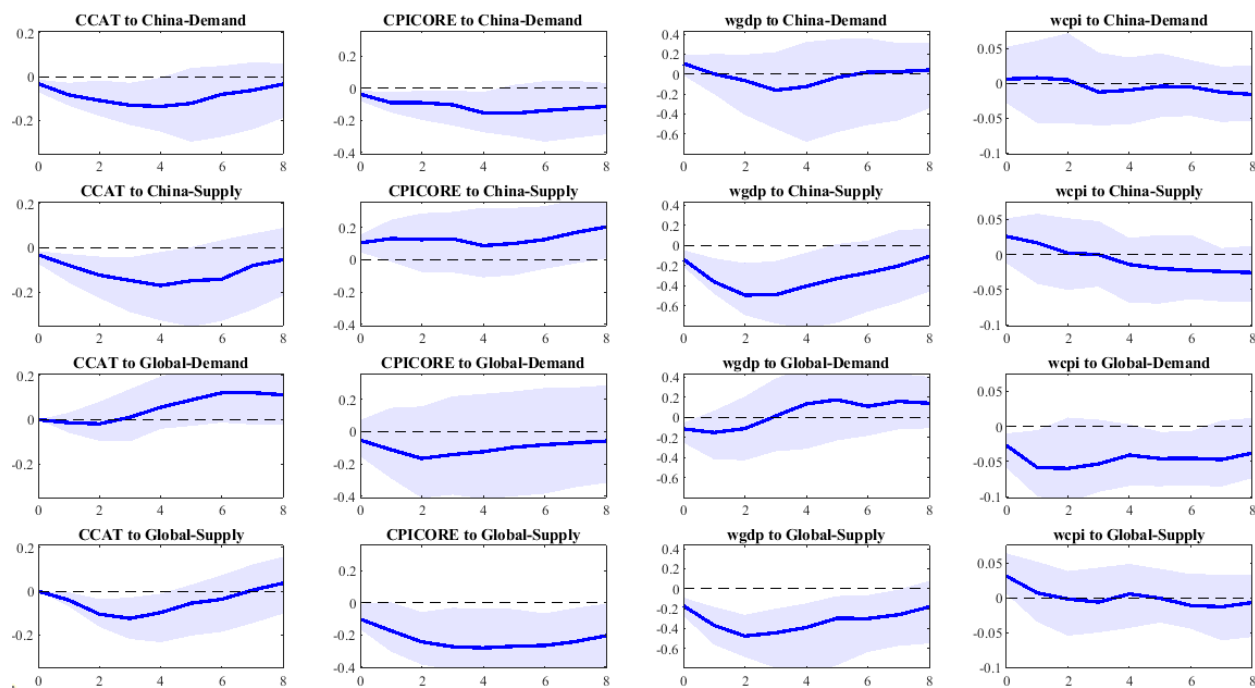

Sources: IMF WEO October 2022, Fernald, Hsu, and Spiegel (2021), IMF staff calculations. Note: Shocks are median shock series from SVAR model described in equation (1). Narrative restrictions to supply and demand shocks are noted in the chart (see Tables 1-2).

Figure 4. Historical decomposition of the China Cyclical Activity Tracker
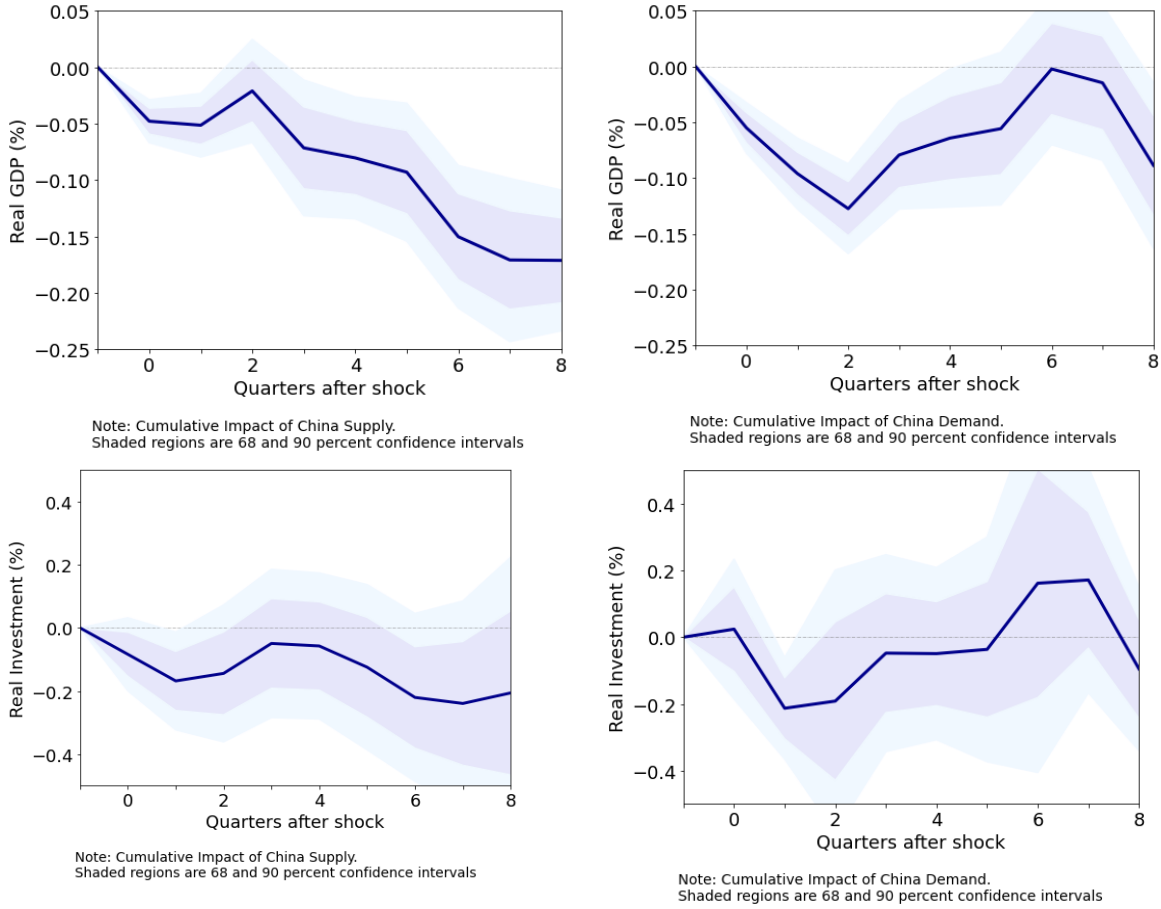

Sources: IMF WEO October 2022, Fernald, Hsu, and Spiegel (2021), IMF staff calculations. Note: The chart presents the historical decomposition of the detrended China Cyclical Activity Indicator based on the SVAR model estimated in equation (1).

Figure 5. Cumulative impulse response functions for structural demand and supply shocks in the SVAR model of domestic Chinese activity
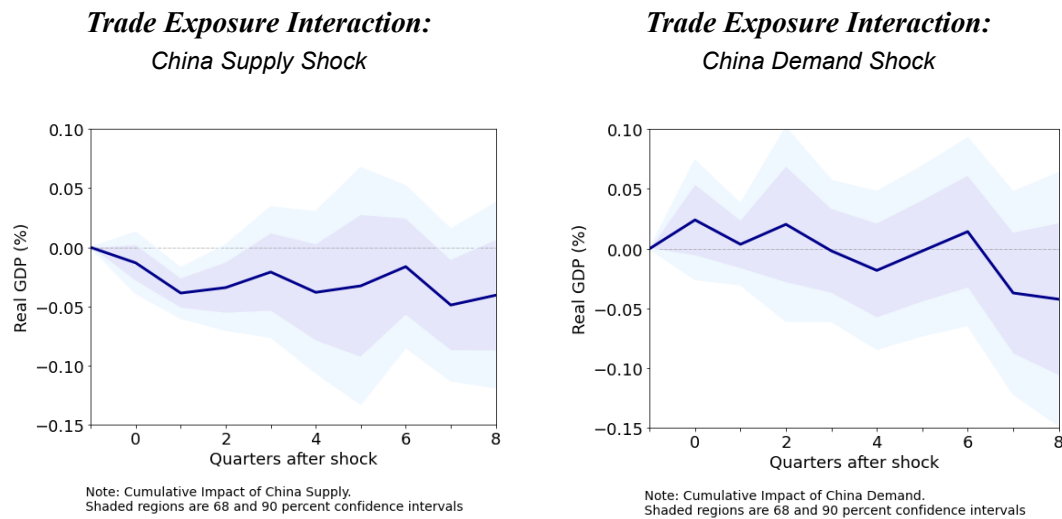

Notes: IMF WEO October 2022, Fernald, Hsu, and Spiegel (2021), IMF staff calculations. The chart plots the response of China Cyclical Activity Tracker (CCAT), Chinese Core CPI inflation (CPI), global GDP growth (ex-China) and global CPI inflation (ex-China) to the estimated China demand and supply shocks and global demand and supply shocks. Cumulative responses show deviation from level with CCAT units being in standard deviations and other variables in percent. Shaded regions are 1 standard error confidence intervals.

Figure 6. Impact of negative 1 percent of GDP shock in China on the level of real GDP and investment in other countries

Note: Cumulative Impact of China Supply.
Shaded regions are 68 and 90 percent confidence intervals

Note: Cumulative Impact of China Demand.
Shaded regions are 68 and 90 percent confidence intervals

Note: Cumulative Impact of China Supply.
Shaded regions are 68 and 90 percent confidence intervals

Note: Cumulative Impact of China Demand.
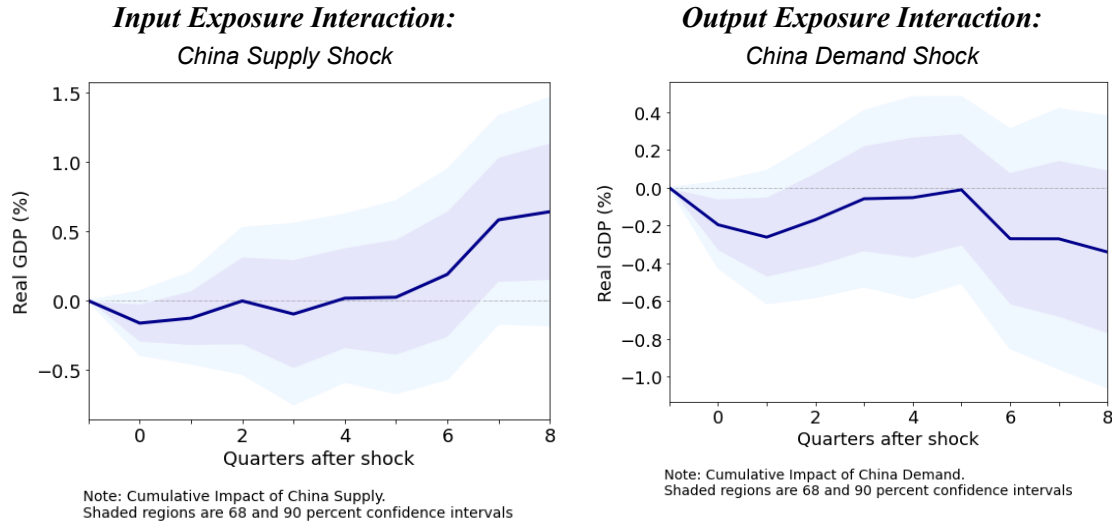Shaded regions are 68 and 90 percent confidence intervals

Notes: y-axis in percent. The results follow from the estimation of equation (3). The solid blue lines in the top two and bottom two panels indicate the average impact on real GDP and investment respectively of a 1 percent of GDP shock in China. Standard errors are clustered by country. The shaded areas display the 68% and 90% confidence intervals.

Figure 7. Differential effect of greater trade openness to the impact of a 1 percent of GDP shock in China on other countries' real GDP

Trade Exposure Interaction:
China Supply Shock

Trade Exposure Interaction:
China Demand Shock

Note: Cumulative Impact of China Supply.
Shaded regions are 68 and 90 percent confidence intervals

Note: Cumulative Impact of China Demand.
Shaded regions are 68 and 90 percent confidence intervals

Notes: y-axis in percent. The results follow from the estimation of equation (4). The solid blue lines indicate the estimated coefficient on the interaction term with trade openness (export + imports / GDP), for a 1 percent of GDP shock in China and for moving from the 25th to the 75th percentile of openness. Standard errors are clustered by country. The shaded areas display the 68% and 90% confidence intervals.
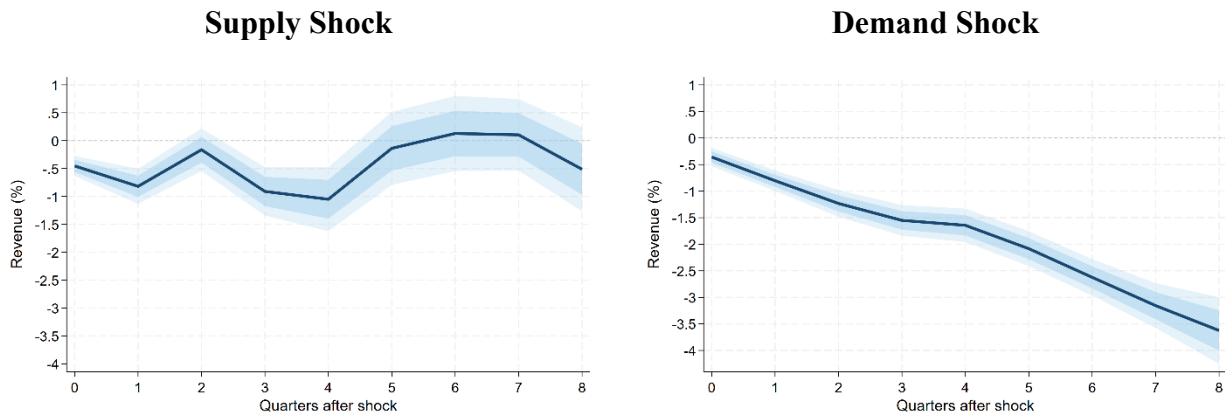
Figure 8. Differential effect of greater input or output linkages to China in the impact of a 1 percent of GDP shock in China on other countries' real GDP

Input Exposure Interaction:
China Supply Shock

Output Exposure Interaction:
China Demand Shock

Note: Cumulative Impact of China Supply.
Shaded regions are 68 and 90 percent confidence intervals

Note: Cumulative Impact of China Demand.
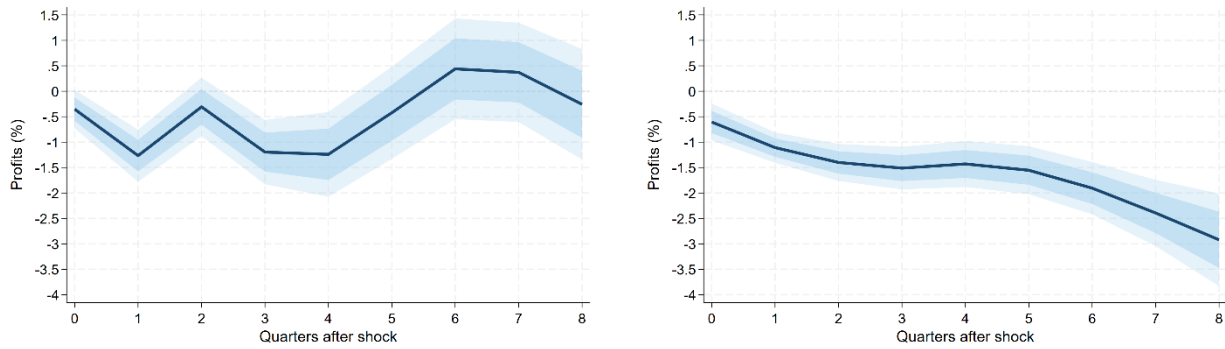Shaded regions are 68 and 90 percent confidence intervals

Notes: y-axis in percent. The results follow from the estimation of equation (4). The solid blue lines indicate the estimated coefficient on the interaction term with input or output exposure, for a 1 percent of GDP shock in China. These are computed for input (output) exposure $\bar{I}^{rel}_{c,China}$ ($-\bar{I}^{rel}_{c,China}$) moving from the 25th to the 75th percentile. Standard errors are clustered by country. The shaded areas display the 68% and 90% confidence intervals.

Figure 9. Average effects of 1 percent of GDP shock in China on firms in other countries

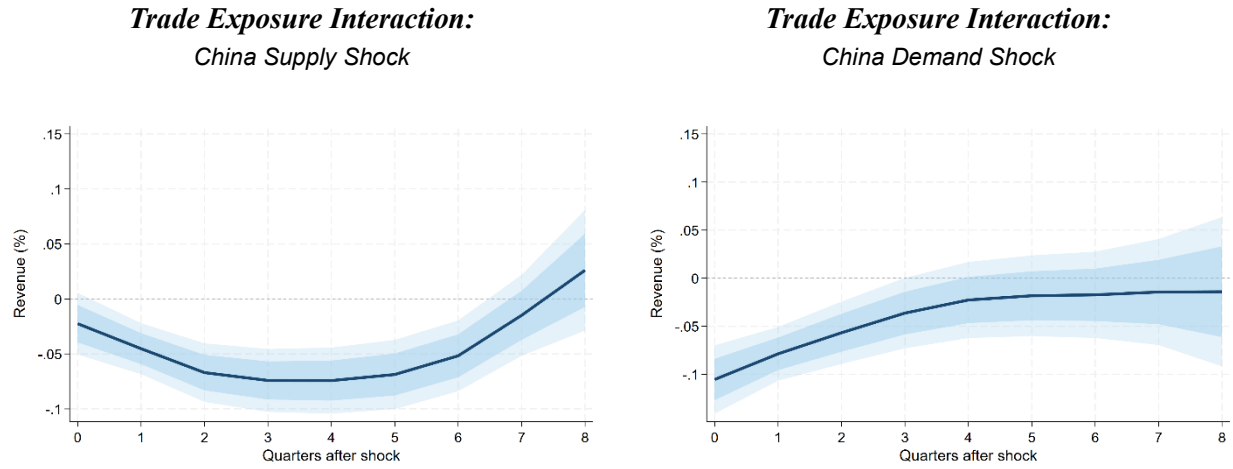## Panel (a): Firm revenue

Supply Shock

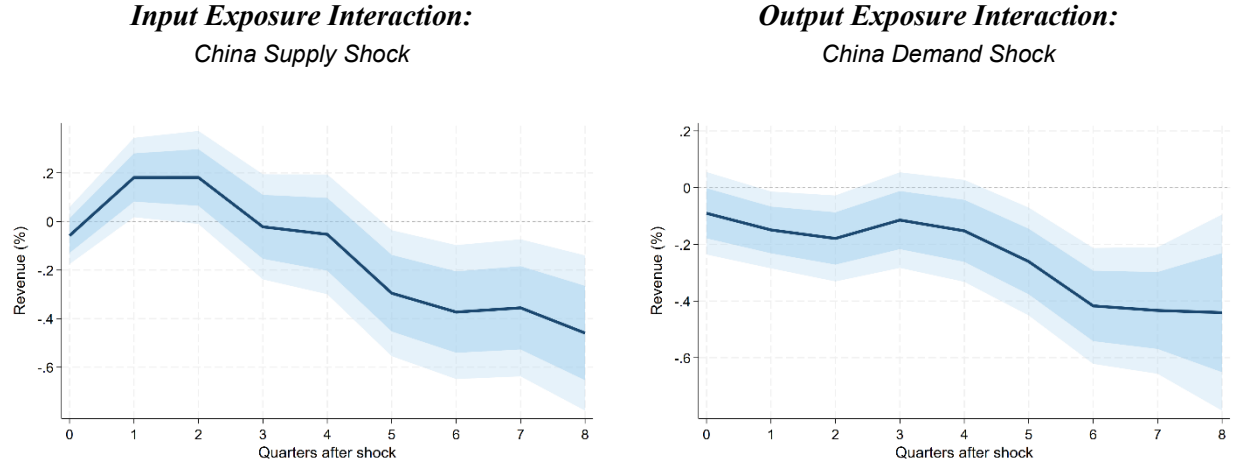**Demand Shock**

Panel (b): Firm profits

Notes: y-axis in percent. The results follow from the estimation of equation (9). Blue lines indicate the average response of firm outcomes to a 1 percent of GDP shock in China. Standard errors are two-way clustered on firms and country-time. The shaded areas display the 68% and 90% confidence intervals.

Figure 10. Differential effect of greater export exposure to China in the impact of a 1 percent of GDP shock in China on firm revenue in other countries

Notes: y-axis in percent. The results follow from the estimation of equation (10) with $\bar{T}^{S,D}_{ci,China} = \overline{ME}_{ci,China}$. The solid blue line indicates the differential response of firms operating in country-industry pairs at the 75th percentile of exports to (imports from) China as a share of output, relative to firms in country-industry pairs at the 25th percentile. Standard errors are clustered by firm. The shaded areas display the 68% and 90% confidence intervals.

Figure 11. Differential effect of greater input or output linkages to China in the impact of 1 percent of GDP shock in China on firm revenue in other countries

Input Exposure Interaction:
China Supply Shock

Output Exposure Interaction:
China Demand Shock

Notes: *y-axis in percent. The results follow from the estimation of equation (10) with $\bar{T}^S_{ci,China} = \bar{I}^{rel}_{ci,China}$ and $\bar{T}^D_{ci,China} = -\bar{I}^{rel}_{ci,China}$. The solid blue lines indicate the differential response of firms operating in country-industry pairs at the 75th percentile of output exposure (input exposure), relative to firms in country-industry pairs at the 25th percentile. Standard errors are clustered by firm. The shaded areas display the 68% and 90% confidence intervals.*

Tables

Table 1: Sign restrictions imposed throughout the SVAR estimation window

Shocks: Variables:	Global Supply	Global Demand	Domestic Supply	Domestic Demand
Global GDP	+	+		
Global CPI	-	+		
China Activity	0	0	+	+,0*
China Core CPI			-	+,0*

Sign and zero restrictions apply to the first period of the shock. *We impose a long-run restriction that domestic demand shocks do not have long run effects on China activity and core CPI.
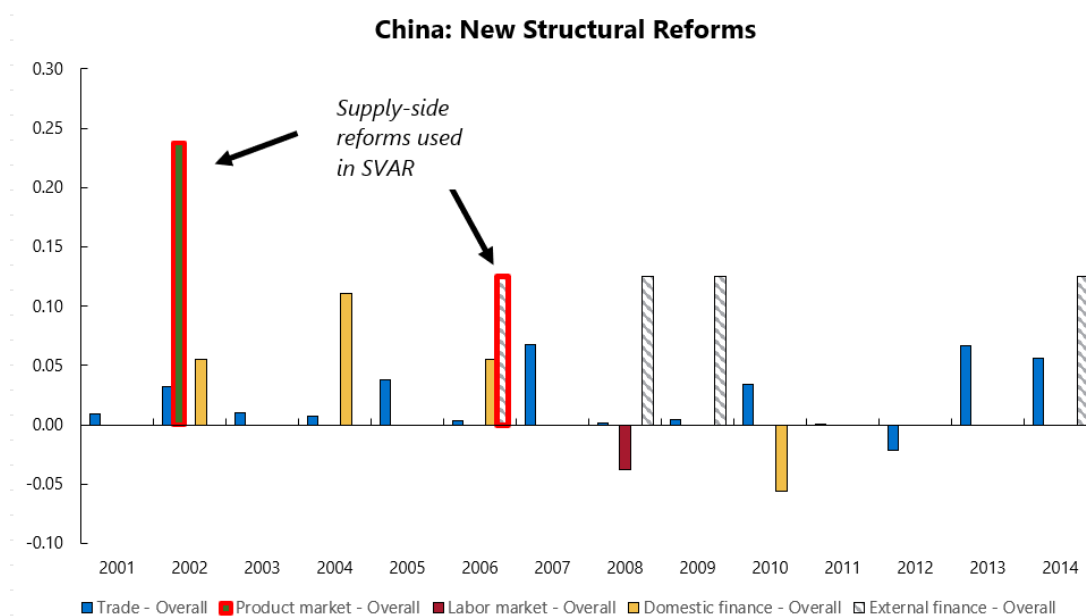
Table 2: Additional narrative sign restrictions

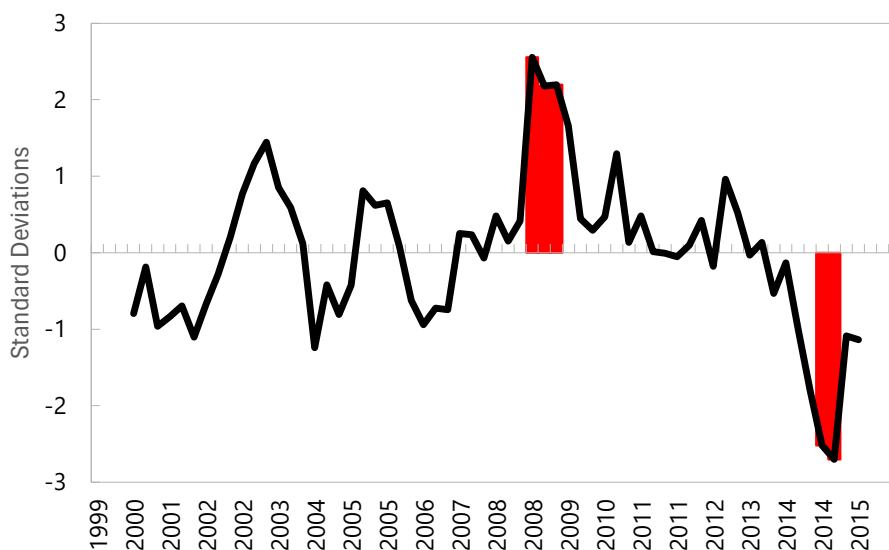| China Domestic Shock:	Date	Sign	Description
Supply	2002Q4	+	Electricity reforms enacted
Supply	2002Q3	+	Telecoms reforms enacted
Supply	2002Q1	+	Telecoms and electricity reforms announced
Supply	2006Q4	+	Banking sector reforms, IPOs
Demand	2009Q1	+	Credit stimulus after GFC
Demand	2015Q1	-	Tight credit during capital outflows and exchange rate reform

Online Annexes

Annex 1: Additional Figures

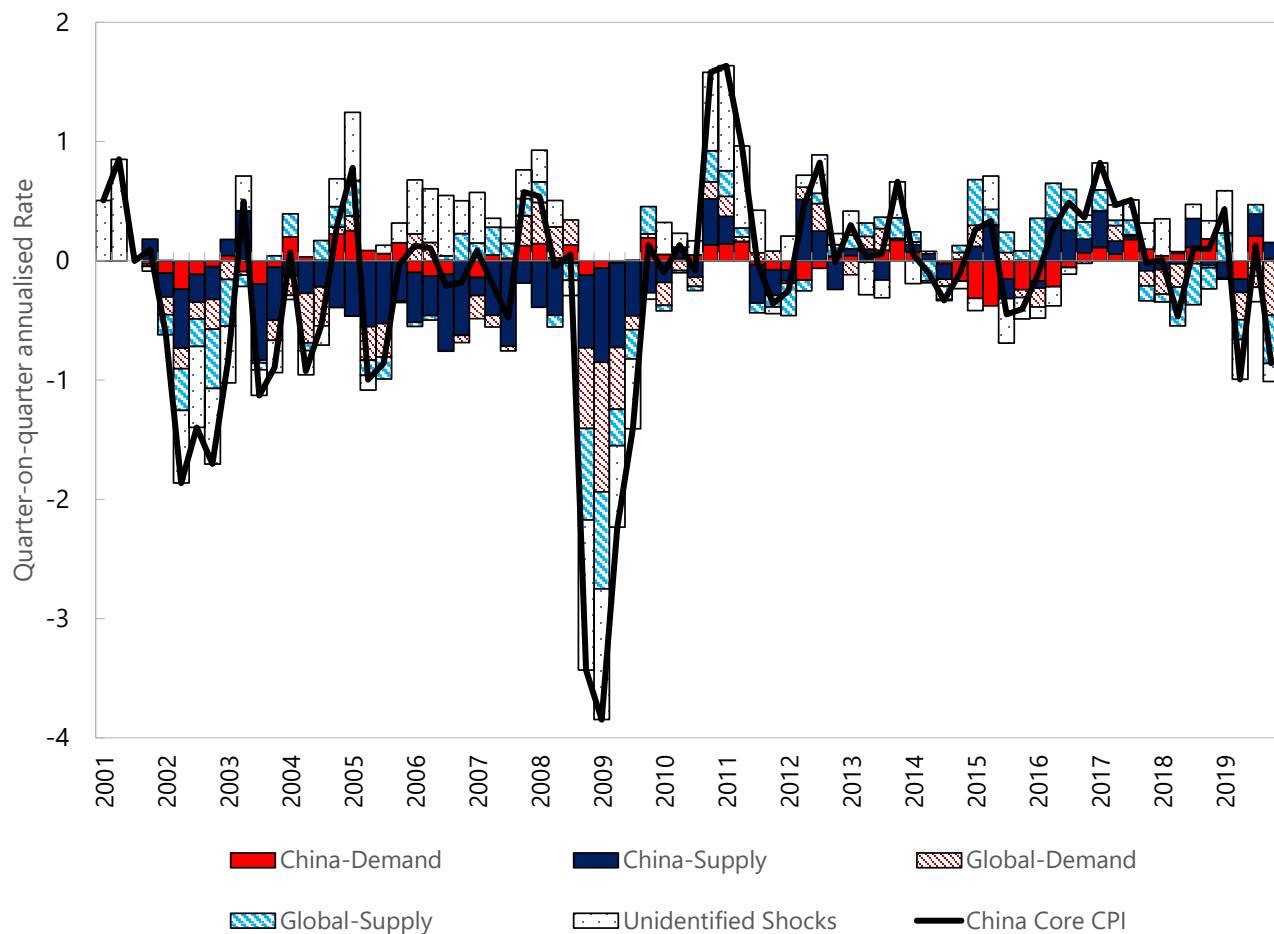### Figure A1.1. Supply-side Reforms identified in Alesina et al (2024)

Source: Alesina and others (2024). Note. Red outlines depict reforms used as narrative evidence in the SVAR.

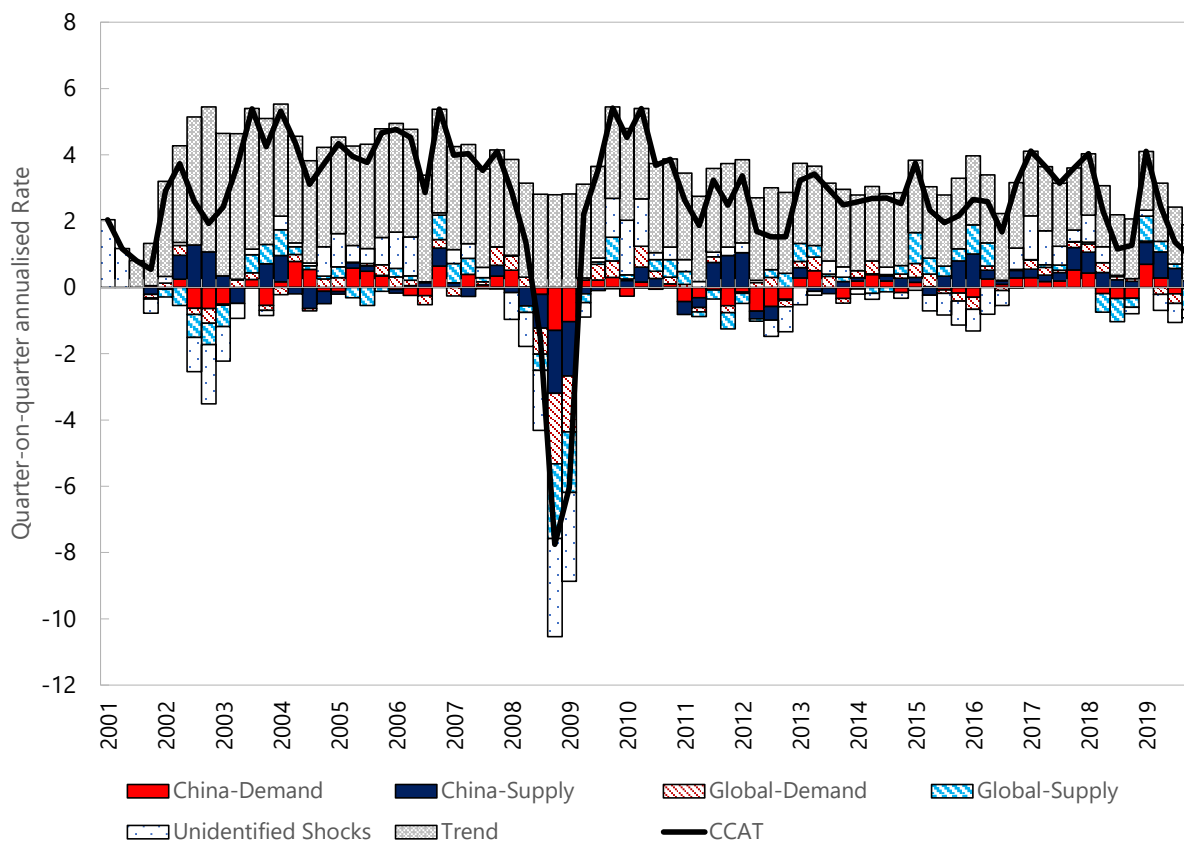### Figure A1.2. Exogenous Monetary Policy Shocks of Chen et al (2018)

Source: Chen, Ren, Zha (2018). Note. Red area denotes large (> 2 std. deviations) shocks. Narrative SVAR restriction use the first period when this shock is present. (first quarter of red bars).

Figure A1.3. Historical Decomposition of China Core CPI

Sources: IMF WEO October 2022, Fernald, Hsu, and Spiegel (2021), IMF staff calculations. Note: The chart presents the historical decomposition of de-trended China core CPI inflation based on the SVAR model estimated in equation (1).

Figure A1.4. Historical Decomposition of Global GDP Growth

Sources: IMF WEO October 2022, Fernald, Hsu, and Spiegel (2021), IMF staff calculations. Note: The chart presents the historical decomposition of the global GDP growth SVAR model estimated in equation (1). The trend is included in the decomposition due to its importance in explaining the series.

Annex 2: Additional Tables

Table A2.1. Country Sample for Macro Analysis

Advanced Economies		Emerging Market Economies	
Australia	Korea	Argentina	Thailand
Austria	Latvia	Armenia	Turkey
Belgium	Lithuania	Brazil	Ukraine
Canada	Netherlands	Bulgaria	
Cyprus	New Zealand	Chile	
Czech Republic	Portugal	China	
Denmark	Singapore	Hungary	
Estonia	Slovak Republic	India	
Finland	Slovenia	Indonesia	
France	Spain	Malaysia	
Germany	Sweden	Mexico	
Greece	Switzerland	Peru	
Ireland	United Kingdom	Philippines	
Italy		Poland	
Japan		Romania	

Table A2.2. Macro Data Sources

Definition	Source	Notes
China Cyclical Activity Tracker	Federal Reserve Bank of San Francisco (2021)	Developed by Fernald, Hsu, and Spiegel
Real GDP	Haver Analytics	
Consumer price index	Haver Analytics	
Volatility index	The Chicago Board Options Exchange	Index
World export-weighted GDP growth	Haver Analytics	Author's own calculations
Financial conditions indices	IMF GFSR	
Investment	Haver Analytics	

Table A2.3. Global Factor Data for Principal Components in SVAR Model*

Definition	Source	Transformation
S&P500 Composite Price Index	S&P	Level
Federal Funds target rate	Refinitiv	Level
US GDP	US Bureau of Economic Analysis, Dept. Of Commerce, USA	Level
US CPI all Areas	US Bureau of Labor Statistics, Dept. Of Labor, USA	Level
Baltic Dry Index	Refinitiv	Level
S&P Goldman Sachs Commodity Index Global (GSCI)	S&P	Level

All series are standardized to mean 0 and standard deviation 1 prior to extracting factors.

Table A2.4. Firm-Level Data Summary Statistics

	No. of Obs.	Mean	Std. Dev.	25th Pctile	Median	75th Pctile
Revenue (yoy, %)	875,664	7.29	45.31	-5.58	5.64	18.81
Capital Expenditure (yoy, %)	333,781	5.24	127.21	-50.91	5.52	61.31
Gross Profits (yoy, %)	805,121	-6.65	61.32	-11.75	5.97	24.21

Table A2.5. Number of Firms and Observations by Country

Country	Number of Firms
United States	3,838
India	3,222
Japan	2,604
Korea	1,836
Hong Kong	1,286
Australia	1,144
Canada	1,038
Malaysia	830
United Kingdom	767
Thailand	603
Sweden	578
Indonesia	514
Poland	482
Singapore	467
Germany	450
France	439
Vietnam	425
Pakistan	307
Turkey	269
Italy	236
Bangladesh	200
Brazil	195
Sri Lanka	193
Philippines	187
Switzerland	183
Greece	145
Norway	129
Spain	125
Finland	115
Russia	115
Denmark	105
Mexico	91
Netherlands	87
Belgium	78
Romania	59

Table A2.5 (continued). Number of Firms and Observations by Country

Country	Number of Firms
Bulgaria	58
Cyprus	56
Ireland	55
Austria	47
Croatia	45
Luxembourg	43
Portugal	34
Malta	29
Hungary	22
Slovenia	17
Kazakhstan	14
Total	**23,762**

Table A2.6. Number of Firms and Observations by Sector

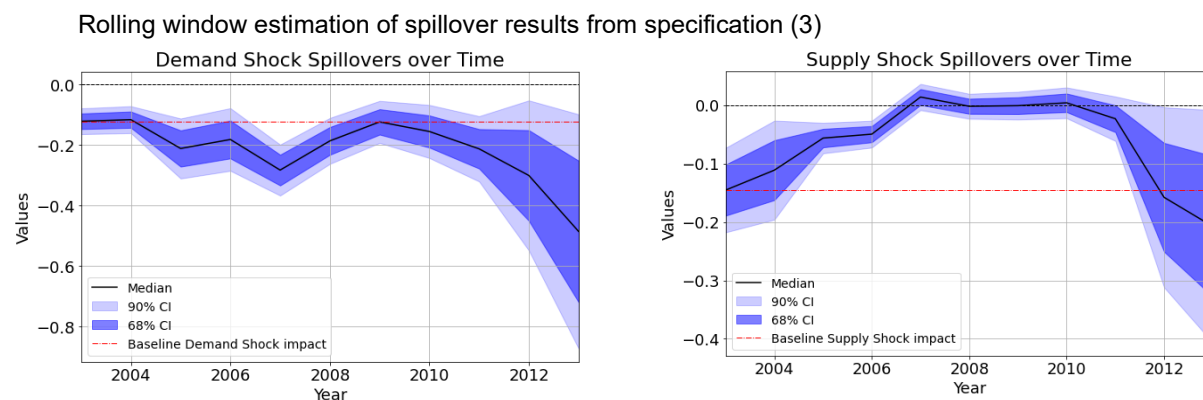| Sector	Number of Firms
Capital Goods	3,518
Materials	3,193
Software and Services	1,658
Consumer Durables and Apparel	1,566
Food, Beverage and Tobacco	1,344
Pharmaceuticals and Biotechnology	1,269
Technology Hardware and Equipment	1,206
Real Estate	1,169
Energy	1,168
Media and Entertainment	1,098
Consumer Services	1,042
Health Care Equipment and Services	1,016
Retailing	980
Professional Services	932
Transportation	701
Automobiles and Components	609
Semiconductors	408
Household and Personal Products	309
Food and Staples Retailing	297
Telecommunication Services	279

Annex 3. Country-Level Analysis: Additional Figures

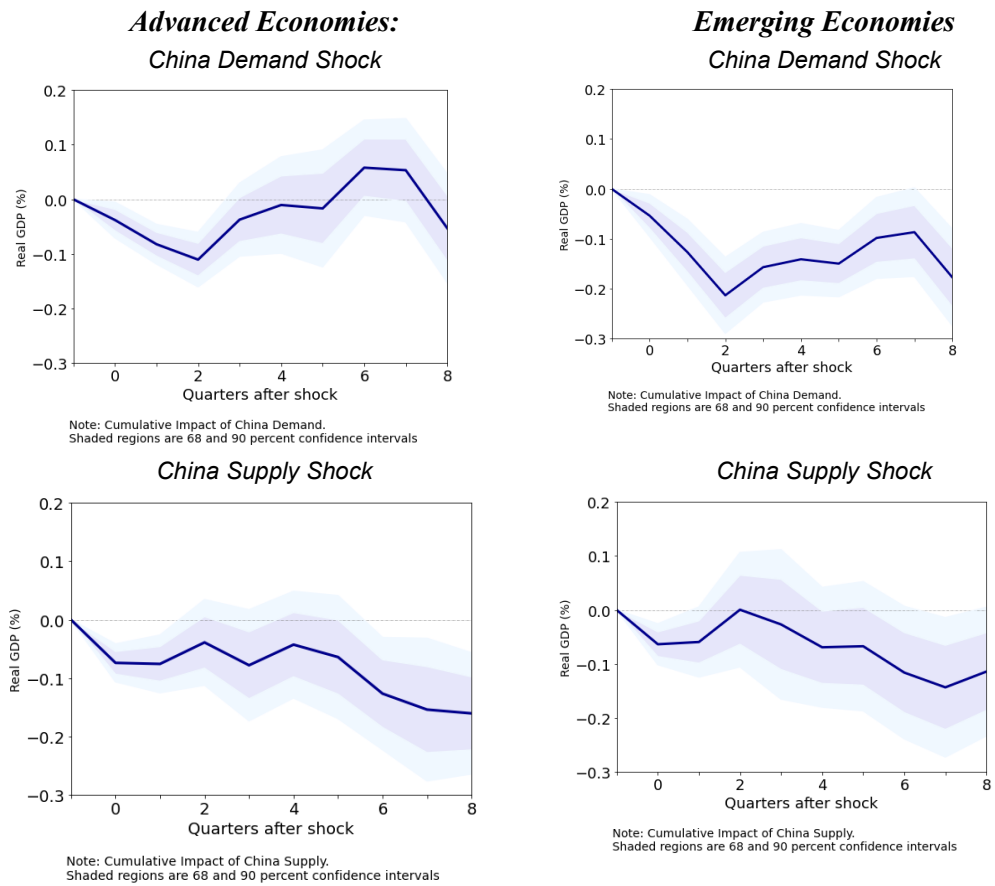### Figure A3.1. Sensitivity of spillovers to GDP to model specification

Notes: y-axis in percent. The results follow from the estimation of equation (3). The solid blue lines indicate the average impact on real GDP of a 1 percent of GDP shock in China. Standard errors are clustered by country. The shaded areas display the 68% and 90% confidence intervals.

Figure A3.2. Sensitivity of spillovers to GDP to time variation

Notes: y-axis in percent. The results follow from the estimation of equation (3) where the sample is rolled forward from 2001 to 2013 with a maximum IRF horizon of 8 quarters. The solid black lines show the peak negative effect for each subsample. Standard errors are clustered by country. The shaded areas display the 68% and 90% confidence intervals.

Figure A3.3. Spillover estimates for Emerging Markets and Advanced Economies

Advanced Economies:
China Demand Shock

Note: Cumulative Impact of China Demand.
Shaded regions are 68 and 90 percent confidence intervals

Emerging Economies
China Demand Shock

Note: Cumulative Impact of China Demand.
Shaded regions are 68 and 90 percent confidence intervals

China Supply Shock

Note: Cumulative Impact of China Supply.
Shaded regions are 68 and 90 percent confidence intervals

China Supply Shock

Note: Cumulative Impact of China Supply.
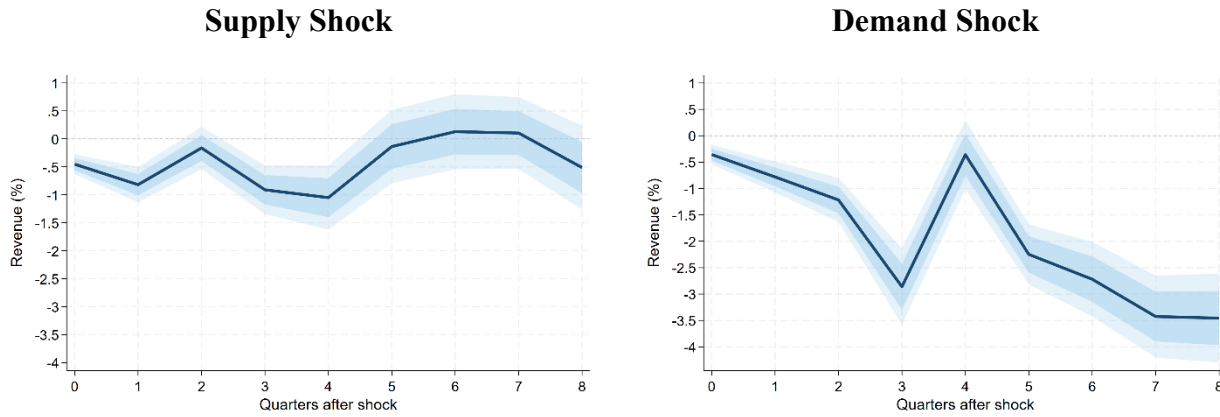Shaded regions are 68 and 90 percent confidence intervals

Notes: y-axis in percent. The results follow from the estimation of equation (4). The solid blue lines indicate the estimated coefficient on the interaction term with exports, for a 1 percent of GDP shock in China. Standard errors are clustered by country. The shaded areas display the 68% and 90% confidence intervals. The sample is restricted to only AE and EM countries, respectively.

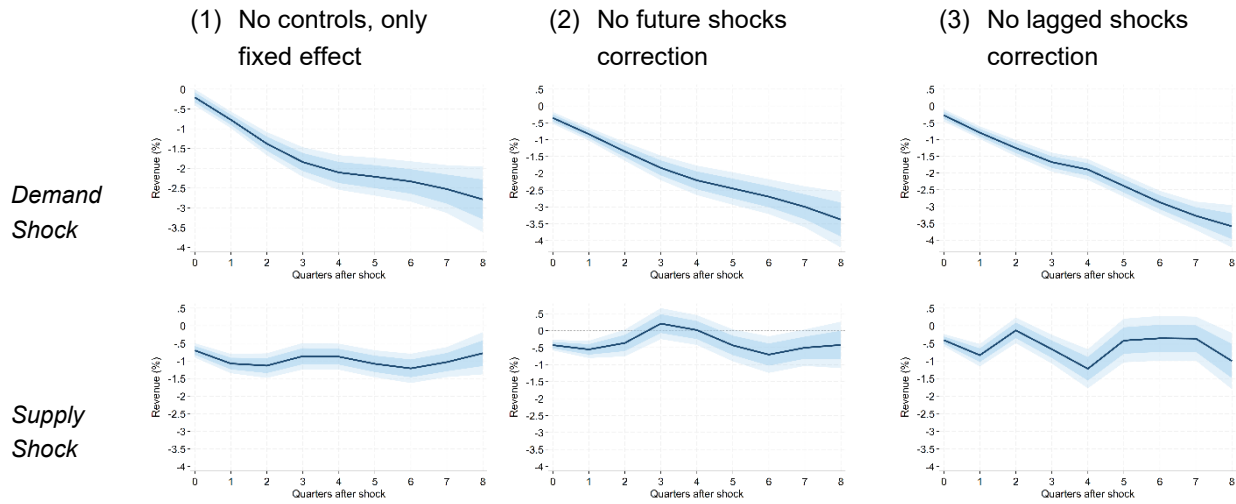**Annex 4. Firm-Level Analysis: Additional Figures**

Figure A4.1. Average effects of 1 percent of GDP shock in China on firms in other countries – non-smoothing of coefficients

Panel (a): Firm revenue

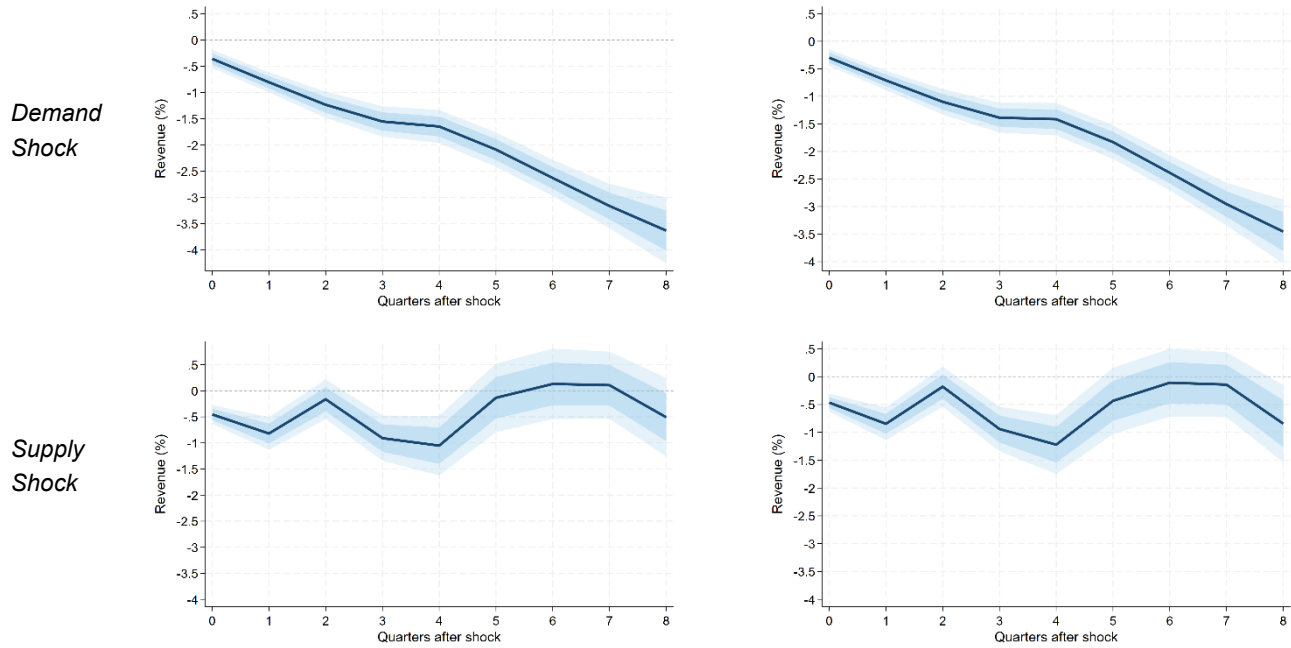**Supply Shock**   **Demand Shock**

Notes: y-axis in percent. The results follow from the estimation of equation (9). Blue lines indicate the average response of firm outcomes to a 1 percent of GDP shock in China. Standard errors are two-way clustered on firms and country-time. The shaded areas display the 68% and 90% confidence intervals.

Figure A4.2. Sensitivity of spillovers to firm revenues to model specification

(1) No controls, only fixed effect	(2) No future shocks correction	(3) No lagged shocks correction

Notes: y-axis in percent. The results follow from the estimation of equation (9). Blue lines indicate the average response of firm outcomes to a 1 percent of GDP shock in China. Standard errors are two-way clustered on firms and country-time. The shaded areas display the 68% and 90% confidence intervals.

Figure A4.3. Sensitivity of spillovers to firm revenues to model specification
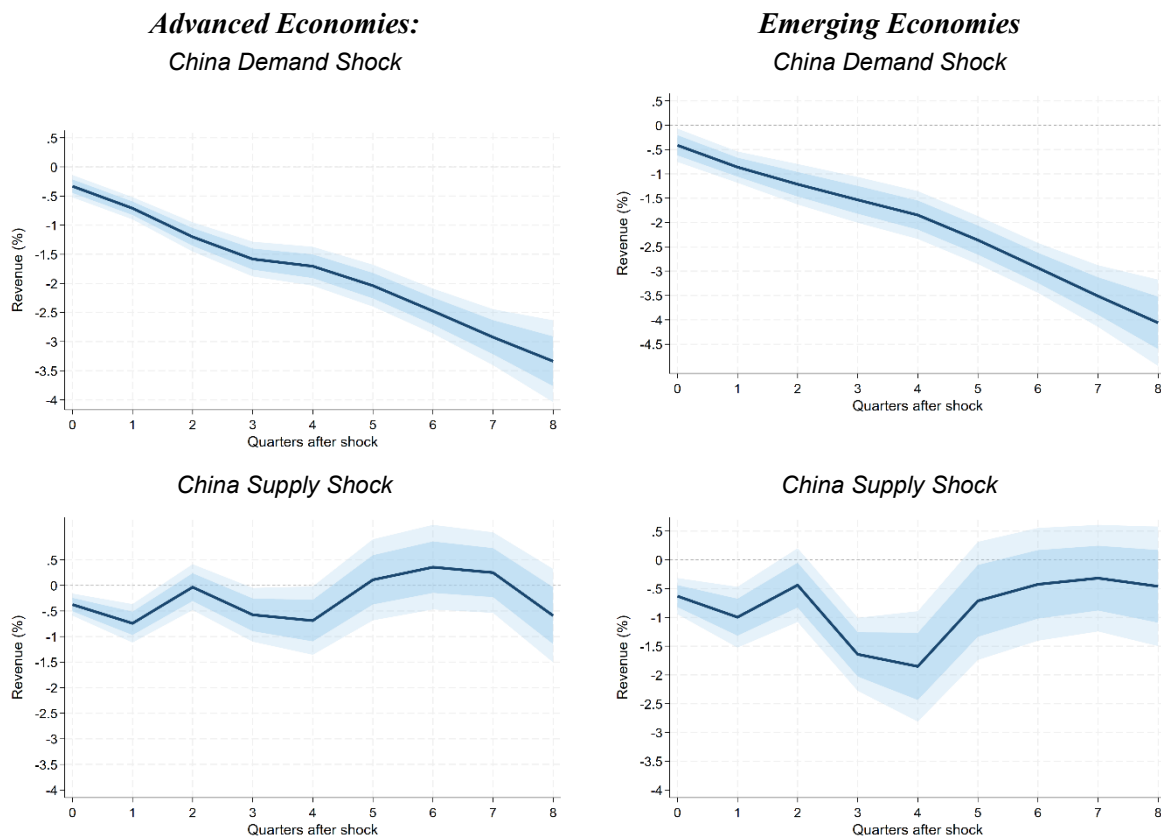
(1) Excluding countries with less than 250 firms

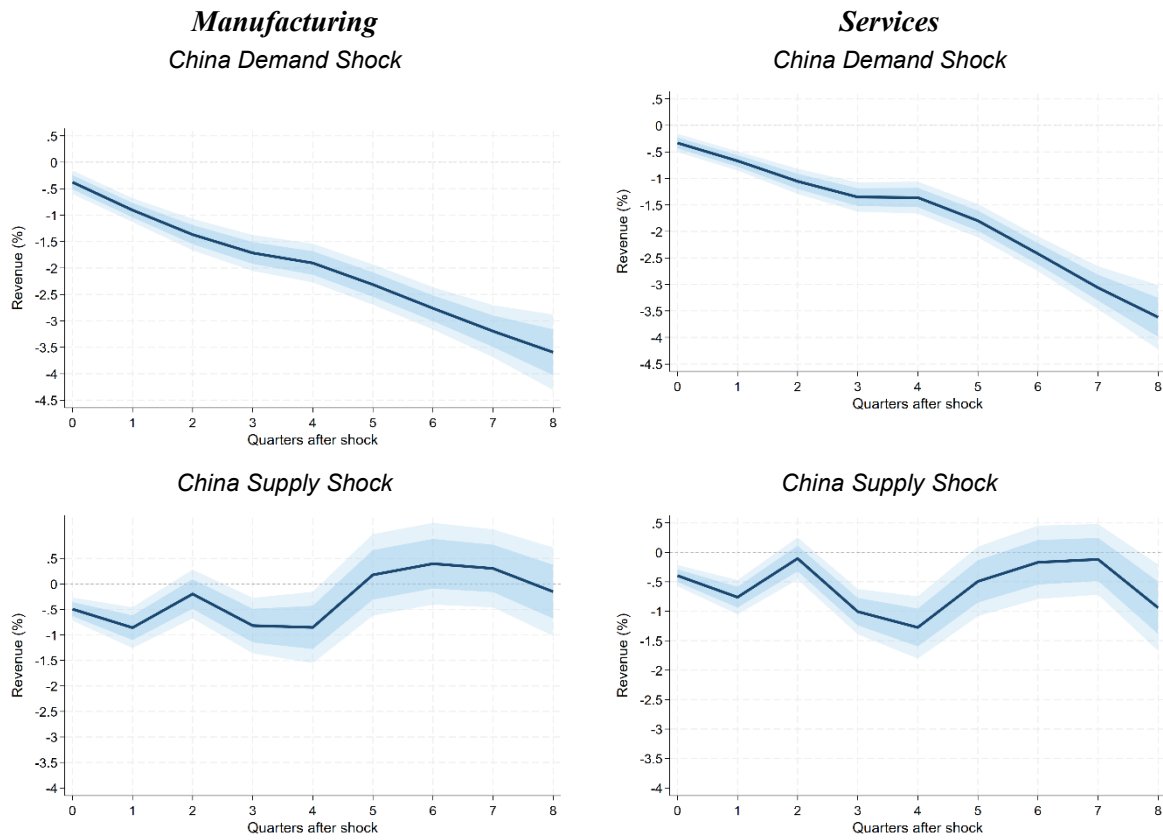(2) Excluding the Two Biggest Sectors: Materials and Capital Goods

Notes: y-axis in percent. The results follow from the estimation of equation (9). Blue lines indicate the average response of firm outcomes to a 1 percent of GDP shock in China. Standard errors are two-way clustered on firms and country-time. The shaded areas display the 68% and 90% confidence intervals.

Figure A4.4. Spillover estimates for Emerging Markets and Advanced Economies

Notes: y-axis in percent. The results follow from the estimation of equation (9). The solid blue and purple lines indicate the average response of firm revenue to a 1 percent of GDP shock in China. Standard errors are two-way clustered on firms and country-time. The shaded areas display the 68% and 90% confidence intervals.

Figure A4.5. Average effects: manufacturing vs. services

Manufacturing

China Demand Shock

Services

China Demand Shock

China Supply Shock

China Supply Shock

Notes: y-axis in percent. The results follow from the estimation of equation (9). The solid blue and purple lines indicate the average response of firm revenue to a 1 percent of GDP shock in China. Standard errors are two-way clustered on firms and country-time. The shaded areas display the 68% and 90% confidence intervals.

Annex 5. Measuring Competition with China

We aim to account for the fact that countries that have stronger trade links with China may also compete more with China, both domestically (as considered by, for example, Acemoglu et al., 2016) and in export markets (as considered by, for example, Iacovone et al., 2013, and Copestake and Zhang, 2022). Such competition can be measured as the product of two factors:

1. How important a given destination market is to country c or country-industry ci, and

2. China's market share in that destination market.

We can measure this at the country level as follows:

$$C_{c,China,t} = \sum_d \left(\underbrace{\frac{\sum_i \sum_j Sales_{ci \to dj,t} + \sum_i FinalDemand_{ci \to d,t}}{\sum_i \sum_e \sum_l Sales_{ci \to el,t} + \sum_i \sum_e FinalDemand_{ci \to e,t}}}_{Importance\ of\ destination\ market\ d} \times \underbrace{\frac{\sum_i \sum_j Sales_{China,i \to dj,t} + \sum_i FinalDemand_{China,i \to d,t}}{\sum_i \sum_e \sum_j Sales_{ei \to dj,t} + \sum_i \sum_e FinalDemand_{ei \to d,t}}}_{Chinese\ competition\ in\ destination\ market\ d} \right)$$

The first term measures how important destination country d is for exports from country c, by taking total sales by c into that country (to supply both other industries and final demand) and dividing it by the total sales by c to all countries in the world. The second term measures the strength of Chinese competition in destination country d, by taking total sales by Chinese companies to country d and dividing that by d's total purchases of products produced anywhere in the world. Intuitively, we take the average share of demand that is supplied by China, weighted across countries, where the weights are the importance of each destination country for the sales of the country c under consideration. Having constructed this term, we can apply the procedure described in the main text to purge temporal variation and produce the final variable $\bar{C}_{c,China}$, which we interact with each of e_t^S and e_t^D and include in $X_{c,t}^*$ in equation (4). Thus, we control for

spillovers of Chinese demand and supply shocks that occur through direct competition with Chinese firms in domestic and export markets.
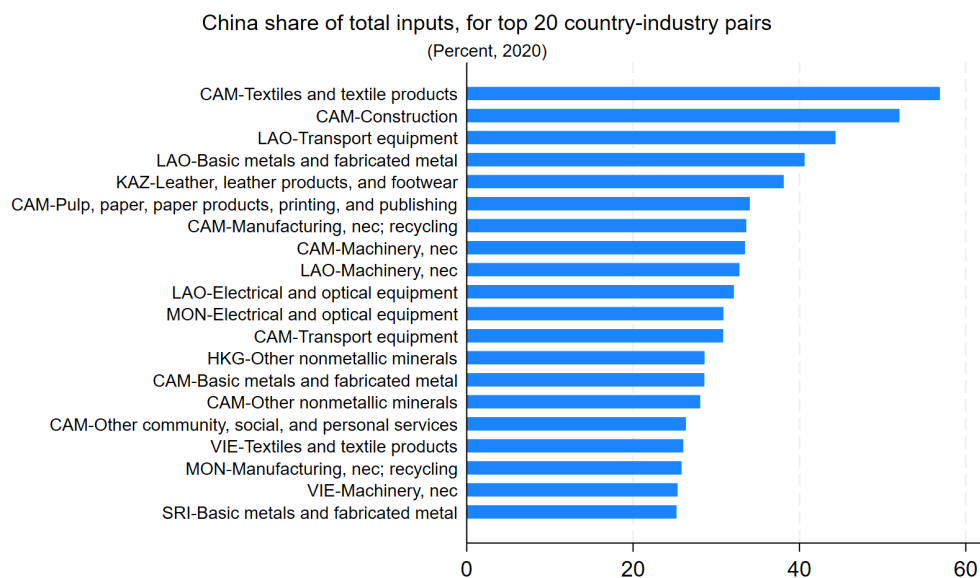
We also construct an analogous industry-level measure to use with our firm-level data:

$$C_{ci,China,t} = \sum_d \left(\underbrace{\frac{\sum_j Sales_{ci \to dj,t} + FinalDemand_{ci \to d,t}}{\sum_e \sum_l Sales_{ci \to el,t} + \sum_e FinalDemand_{ci \to e,t}}}_{Importance\ of\ destination\ market\ d} \times \underbrace{\frac{\sum_j Sales_{China,i \to dj,t} + FinalDemand_{China,i \to d,t}}{\sum_e \sum_j Sales_{ei \to dj,t} + \sum_e FinalDemand_{ei \to d,t}}}_{Chinese\ competition\ in\ destination\ market\ d} \right)$$

Here, the first term measures how important destination country d is for exports from country-industry ci, by taking total sales by ci into that country (to supply both other industries and final demand) and dividing it by the total sales by ci to all countries in the world. The second term measures the strength of Chinese competition in destination country d, by taking total sales by Chinese companies in industry i to country d and dividing that by d's total purchases of industry i products produced anywhere in the world. Intuitively, we take the average share of demand for industry i's products that is supplied by China, weighted across countries, where the weights are the importance of each country's domestic market for the country-industry ci under consideration. We then apply the industry-level procedure to purge temporal variation, as described in the main text, to produce the final variable $\bar{C}_{ci,China}$, which we interact with each of e_t^S and e_t^D and include in $X_{cif,t}^*$ in equation (10).
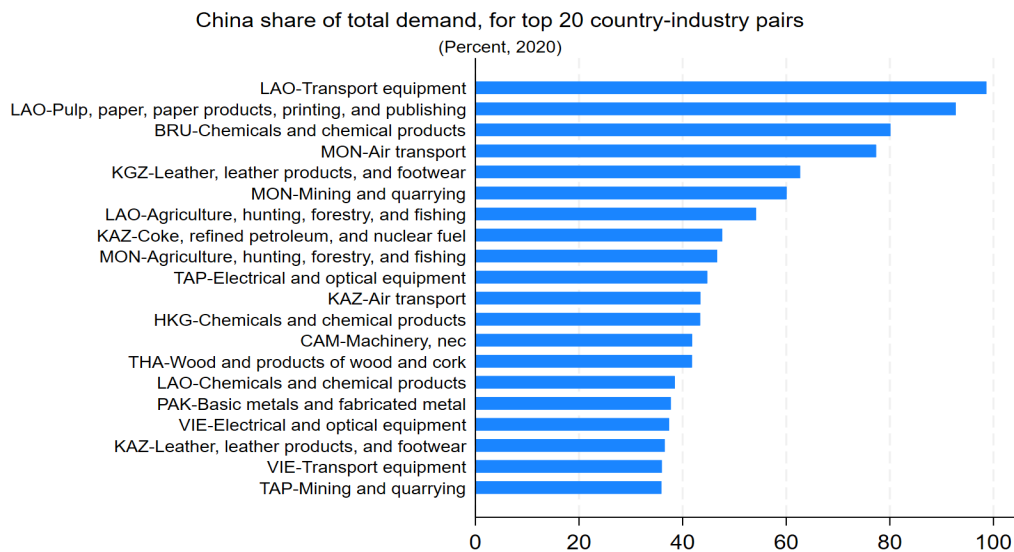
Annex 6. Input-Output Linkages

Figure A6.1. China's share in total input usage

China share of total inputs, for top 20 country-industry pairs
(Percent, 2020)

Notes: The horizontal bars represent the share of total input usage that is supplied by China, by country-sector pair, in percent. Bars are shown for the 20 country-industry pairs with the highest shares.
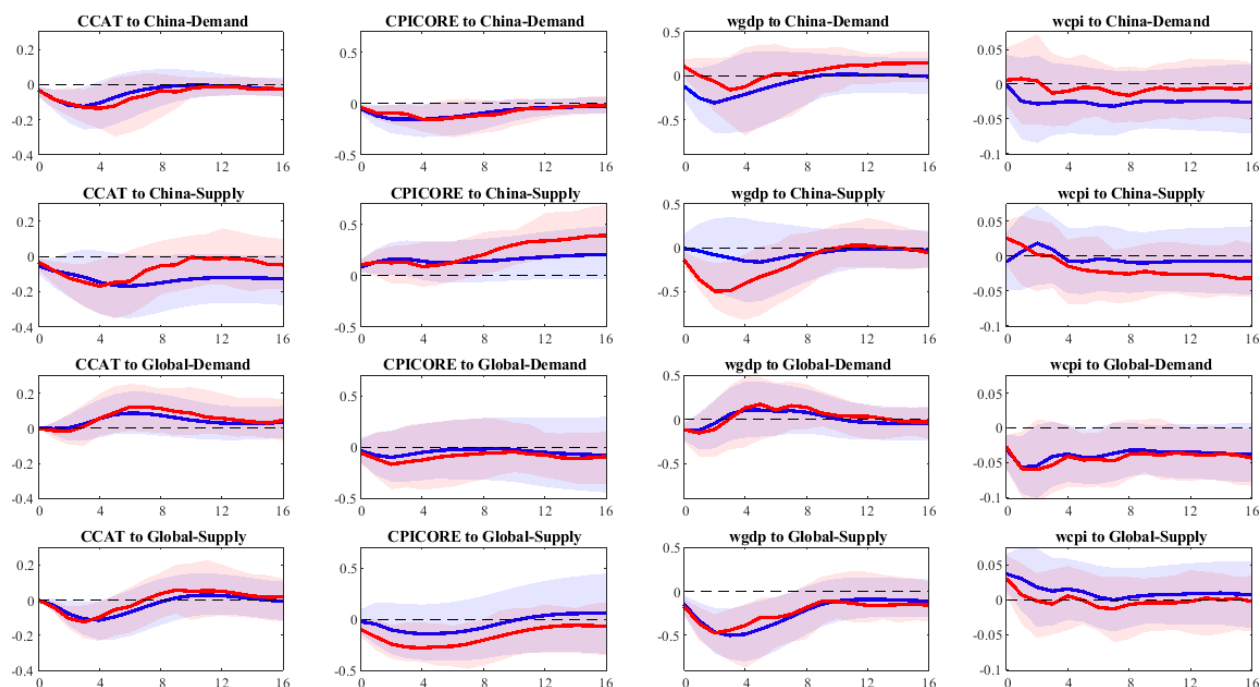
Figure A6.2. China's share in total demand

China share of total demand, for top 20 country-industry pairs
(Percent, 2020)

Notes: The horizontal bars represent the share of Chinese demand in total demand for the output of each country-sector pair, in percent. Bars are shown for the 20 country-industry pairs with the highest shares.

Annex 7. Contribution of Narrative Information to the SVAR Model

Figure A7.1. Cumulative impulse response functions for structural demand and supply shocks in the SVAR model without narrative information (blue) and with narrative information (red)

Notes: IMF WEO October 2022, Fernald, Hsu, and Spiegel (2021), IMF staff calculations. The chart plots the response of China Cyclical Activity Tracker (CCAT), Chinese Core CPI inflation (CPI), global GDP growth (ex-China) and global CPI inflation (ex-China) to the estimated China demand and supply shocks and global demand and supply shocks. Cumulative responses show deviation from level with CCAT units being in standard deviations and other variables in percent. Shaded regions are 1 standard error confidence intervals.