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ABSTRACT: We estimate the impact of distinct types of slowdowns in China on countries and firms globally. First, we combine a structural vector autoregression framework with a broad-based measure of domestic economic activity in China to distinguish supply versus demand components of Chinese growth. We then use local projection models to assess the responses to such shocks of GDP growth (revenue) in other countries (firms). We find that: (i) both supply and demand slowdowns are associated with substantial declines in partner GDP and firm revenue; (ii) negative spillovers are larger in countries and firms with stronger trade links with China; and (iii) spillovers from Chinese supply shocks are stronger than spillovers from demand shocks, both at the aggregate- and firm-level.

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1. Introduction

China has played an increasingly important role in the global economy since joining the World Trade Organization in 2001, becoming the predominant global manufacturing center and a significant source of demand, especially for Asia. China's share of global production has risen from 2 percent in 1995 to 16 percent in 2018 (Figure 1). Over 2000-14 China accounted for one-third of global growth and provided an important counterbalance following the Global Financial Crisis (GFC) when demand in the rest of the world was exceptionally weak (Dizioli and others, 2016). The role of Chinese final demand has also increased, from 0.3 percent of global production in 1995 to 2.2 percent by 2018. Chinese demand for manufacturing inputs, and increasingly its own final consumption, creates important linkages with the rest of the world. These are particularly important in Asia where for ASEAN countries the share of output absorbed by Chinese domestic demand rose from 1 percent to 6 percent (Figure 2).

However, China's growth is projected to slow in the short term as we all as in the medium term: from the 7.7 percent average during 2010-2019 to a medium-term average of approximately 5 percent, according to the IMF's October 2022 World Economic Outlook (Figure 3). This decline in medium-term growth reflects slowing productivity growth and the rapidly ageing population, as well as a shift in policymakers' desired growth mix from investment towards domestic consumption (IMF, 2023). The slowdowns observed since COVID-19 have had both supply- and demand-side elements, from temporary lockdown-induced capacity constraints to a widespread decline in confidence following the persistent weakness of the real estate sector. Given China's deep integration with the global economy through trade and financial networks, such domestic growth shocks will have repercussions for the rest of the world, with implications from broad macroeconomic policy to narrow decision-making at the level of individual firms.

While several studies have examined the cross-country spillovers from China's GDP growth, almost none of these studies distinguishes between demand and supply shocks. This is important given the potential for different types of shocks to have distinct impacts. In the near term, demand-driven spillovers from the ongoing real estate crisis are likely to dominate, whereas in the medium term supply-side factors—particularly slowing productivity and a shrinking labor force—are likely to play a larger role. In this paper, we fill this gap by estimating the distinct spillovers from supply- versus demand-driven slowdowns in China's economy for a large sample of countries and firms.

We proceed in three steps. First, we identify the composition (demand vs. supply) of domestic shocks driving Chinese activity from a Structural Vector Autoregression (SVAR) model: domestic demand shocks are identified as those associated with falling activity and prices, and domestic supply shocks as those with falling activity but rising prices. The results of the SVAR model indicate that demand shocks have been dominant in the first part of our sample (up to 2014) whereas supply shocks have been more important recently, especially during lockdown periods associated with the COVID-19 pandemic (Figure 4).

Second, we gauge the aggregate cross-country spillovers from these shocks to a panel of 50 advanced and emerging countries, using Jordà's (2005) local projection framework. The results of this analysis suggest that cross-country spillovers from Chinese supply shocks are larger and more front-loaded than those of demand shocks. Rescaling our shocks to be to be equivalent to a 1 percent decline in GDP, we find that supply shocks lead to a cumulative decline in GDP of 0.6 percent in other countries after 2 years, whereas for demand shocks this figure is only 0.4 percent even after 4 years. The main channel of this difference is the larger impact on investment spending associated with supply compared to demand shocks. This reflects the pivotal role of global value chains in transmitting shocks from China; indeed, we find that supply-shock spillovers are larger in countries with stronger trade linkages to China.

Finally, we use firm-level data and estimate the impact of Chinese growth on revenues in 20,000 firms across 61 countries and 20 sectors, using quarterly balance sheet data from Capital IQ. The use of these data is novel in the literature on China's spillovers and has two main benefits. First, the breadth of the sample allows us to exploit variation across and within countries, while the high (quarterly) frequency of the data is particularly well-suited to estimating the dynamic effects of China's shocks. Second, our granular data allows us to control for unobservable country and industry factors, including any domestic policy changes that may be enacted in response to a slowdown in China.

We first run the firm-level analogues of our aggregate regressions and find that two years after a demand or supply shock equivalent to a 1 percent decline in GDP in China, average firm revenues across countries decline by 1.6 and 1.4 percent, respectively. This decline is slightly faster for supply shocks than demand shocks, as in the aggregate results. Interacting the shocks with the export share to China of each firm's industry, we again find that trade linkages can amplify negative spillovers.

We then make full use of our granular data by distinguishing between firms operating in sectors that rely more on China final's demand (output linkages) and firms operating in sectors that rely more on China's production of intermediate inputs (input linkages). We run a flexible specification that estimates the marginal impact of all four supply chain permutation shocks (demand-output, demand-input, supply-output, supply-input). Consistent with theory, we find that demand shocks have negative impacts on firms with strong output linkages to China, supply shocks have negative impacts on firms with strong input linkages to China, and the other two channels are statistically insignificant.[1] The total impact after four years of Chinese supply shocks through input linkages is roughly three times the size of the impact of Chinese demand shocks through output linkages. A firm in a sector that is one standard-deviation more dependent on Chinese inputs than average sees revenue fall by 0.6 percentage points more, in response to a negative supply shock equivalent to a 1 percent decline in GDP in China.

Taken together, our results show substantial aggregate and firm-level spillovers from a slowdown in China, and these are particularly large in countries and firms with stronger trade links to China. Spillovers from supply-driven slowdowns in China are particularly significant, with investment responding both more and more quickly at both the aggregate and firm levels, and with firms in industries more closely linked to Chinese suppliers more strongly affected. In broad terms, one can think of our results as suggesting an analogous but inverted counterpart to the 'global financial cycle' (Rey, 2013): a negative demand shock in the world's largest source of demand propagates strongly to the rest of the world through consumption and financial linkages (Miranda-Agrippino and Rey, 2020), while we find that a supply shock in the world's largest producer propagates strongly to the rest of the world through production linkages.

Related literature: Our aggregate results are in the upper range of the estimates found in the literature, where spillovers from a 1 percentage point decline in Chinese growth have been estimated to be in the range of 0.15 to 0.8 percentage points. Cashin and others (2016) and Dizoli

[1] In the context of spillovers from import competition, Acemoglu, Akcigit and Kerr (2015) show theoretically that demand shocks will predominantly propagate upstream (i.e., through output linkages), while supply shocks will predominantly propagate downstream (i.e., through input linkages). 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.

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 expansion on labor markets both in the US and globally (e.g., Dauth, Findeisen and Suedekum, 2017), while Bloom, Draca and Van Reenen (2015) find positive spillovers from increased Chinese competition on innovation within firms, and Iacavone, Rauch and Winters (2012) find that an increasing role for Chinese inputs raises firm revenue. Finally, our findings that Chinese supply shocks particularly impact downstream, customer firms align with the literature on the propagation of shocks through production networks (see, for instance, Acemoglu and others, 2012).

Our paper differs from previous work 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 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).[2] 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 other (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 global aggregate data where our estimate relies on a panel of 50 countries. Finally, 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.

[2] 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.

The remainder of the paper is organized as follows. The next section describes our strategy for identifying Chinese demand and supply shocks. Sections 3 and 4 present our macro- and firm-level analyses and results, respectively. Section 5 concludes.

1. Identification of Demand and Supply Shocks

We use the China Cyclical Activity Tracker of Fernald and others (2021) as a broad proxy of economic activity. 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.[3]

Inflation is measured using CPI. Global GDP growth and inflation, excluding China, are calculated as GDP-weighted GDP growth and CPI inflation comes from the IMF World Economic Outlook Database. The data is quarterly, and the model is estimated for the period 2001Q1-2022Q1. Our Structural Vector Autoregression (SVAR) model can be written as:

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

[3] https://www.frbsf.org/economic-research/indicators-data/china-cyclical-activity-tracker/

Where y_t contains the four variables: CCAT, China inflation, Global GDP growth, and global inflation. The global variables are computed excluding China. The coefficients b and e_t denote the intercept term and structural shocks, respectively with $E[e_t e_t{}'] = I$. p is the lag length in the model; we use 2 lags but the results are qualitatively unaffected by lags in the range 1 to 8. The matrix A_0 captures the relationship between the shocks and the endogenous variables. To recover this, the reduced form model is estimated as:

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

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 involves defining $A_0 = Qchol(\Sigma_u)$, where $chol()$ is the Cholesky decomposition and Q is an orthonormal matrix, i.e., $QQ' = Q'Q' = I$. The sign restrictions are imposed by sampling Q from a standard normal random matrix and only retaining the draws where the implied A_0 corresponds to our assumed sign restrictions. These sign restrictions are provided in Table A1. We assume that demand shocks see prices and quantities move in the same direction whereas for supply shocks they move in opposite directions. In addition, we impose that domestic shocks have no impact on global variables; this approach to separating domestic and global demand and supply is similar to that used in Forbes and others (2018). We estimate the model using the BEAR toolkit of Dieppe and others (2016).

Our SVAR estimates in Figure 4 indicate that Chinese demand and supply shocks have a broadly similar impact on domestic activity, with demand shocks being slightly larger (0.6 percent) versus supply shocks (0.45 percent) but supply shocks are marginally more persistent (6 quarters for supply shocks versus 4 quarters for demand shocks). The opposite is true for inflation, where demand shocks have a more prolonged impact, but on impact they are similar in size. By construction, negative demand shocks lead to a short-term decline in inflation while negative supply shocks are associated with a short-term increase in inflation.

Following Forbes and others (2018), we impose that domestic shocks do not affect global variables on impact to help separate the measurement of domestic and global shocks in the second stage spillover analysis. However, the SVAR also accords with our findings there, in that it indicates a more significant and persistent response of global growth to Chinese supply shocks (peak effect of 0.45 percent) relative to Chinese demand shocks (0.34 percent).

The historical decomposition of the CCAT in Figure 5 provides a more nuanced picture. Demand shocks have been the primary driver of activity until recently. For example, the large decline and rebound during the Global Financial Crisis (GFC) was primarily explained by domestic demand (with a secondary role for weaker global demand). Starting in 2015 supply shocks played a more prominent role in driving activity and during the COVID-19 period explained the majority of lockdown and reopening movements. Weak demand has weighed on activity from 2021Q2-2022Q1, owing to subdued consumption, COVID-19 related uncertainty and a weak urban labor market (see the IMF China Article IV Staff Reports in 2021 and 2022).

We use the structural shocks from the SVAR model (Figure 6) as exogenous shocks in a panel local projection framework to estimate the growth spillovers to other countries. The development of the shocks themselves closely mirrors the pattern seen in the historical decomposition of the CCAT indicator.

2. Macro Spillovers

In this section, we assess aggregate spillovers from demand and supply shocks in China using the shocks estimated in our SVAR model. We first describe the data and our local projection methodology before estimating the size and persistence of the spillovers to real GDP and aggregate investment and how these vary with a country's trade links to China.

2.1. Data and Specification

We use a panel local projection model to estimate spillovers from Chinese economic activity. In particular, we estimate the following equation for each quarter $h = 0 \ldots 16$:

$$y_{i,t+h} - y_{i,t-1} = \alpha_i + \rho t + \beta^h e_t^k + \Sigma_{n=1}^4 \gamma_n e_{t-n}^k + \Sigma_{n=t+1}^h \theta_n e_{t+n}^k + \Sigma_{n=1}^4 \kappa_n \Delta y_{i,t-n} + \Gamma' X_{i,t} + \varepsilon_{i,t+h} \quad (3)$$

where $y_{i,t+h}$ is the log of GDP in country i, α_i are country fixed effects, *t* captures a linear time trend, and X_t is a set of control variables. GDP data is from the IMF WEO. e_t^k is the structural shocks identified from the SVAR and will also be used to represent the headline activity measure, the CCAT, when it is treated as the shock for the purpose of comparison, i.e. $e_t^k, k = \{Supply\ shock,\ Demand\ shock, CCAT\}$. Controls include financial conditions indices for advanced and emerging economies (excluding China) from the IMF Global Financial Stability Report (GFSR) and the Chicago Board Options Exchange Volatility Index (VIX), as well as three lags of world export-weighted GDP growth (where the weighting excludes China). We also control for the impact of shocks in the preceding year, captured in γ_n and future shocks up to the horizon of the impulse response, h, as in Teulings and Zubanov (2014) captured in θ_n.[4]

To investigate the channels through which these shocks operate on GDP and examine how they vary across countries, we augment equation (3) as follows:

$$y_{i,t+h} - y_{i,t-1} = \mu_i + \lambda_t + \tilde{\beta}^h e_t^k * m_{i,t} + \omega m_{i,t} + \Sigma_{n=1}^{4} \kappa_n \Delta y_{i,t-n} + \Gamma' X_{i,t} + v_{i,t+h} \quad (4)$$

where λ_t and μ_i are time and country fixed effects. As an initial measure of trade linkages, we define m as exports to China from country i as a share of that country's GDP. Since the inclusion of time fixed effect allows us to control for global shocks affecting all countries (including the direct impact of the China shock e_t^k), $\tilde{\beta}^h$ captures the additional contribution from export exposure, over and above the estimate β^h.

2.2. Unconditional Results

We estimate spillovers from the CCAT itself as well as from the demand and supply shocks derived using the SVAR. The shocks are scaled to be equivalent to 1 percent of Chinese GDP.[5] As an initial reduced form estimate, we consider the spillovers from a shock to the headline measure of Chinese activity, i.e., the CCAT. Neither real GDP nor investment in other countries respond significantly on impact (Figure 7, first column, first and second rows respectively). The cumulative

[4] 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.

[5] 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.

impact is negative after 2 years but small, similar to the finding in the literature that the short-term spillovers from a slowdown in China is moderate (e.g., Furceri, Jalles, and Zdzienicka 2017). However, the longer-term effects are more substantial with output falling by 0.5 percent and investment by 1 percent after 4 years. The spillovers from the structural demand shocks are very similar to those estimated from the headline activity measure with a delayed impact on GDP and investment and a similar size effect after 4 years (Figure 7, second column).

The spillovers from supply shocks are both larger and their effects are felt more quickly (Figure 7, third column). The decline in GDP is significantly negative after the first year at around 0.3 percent and peaks at a 0.6 percent after 2 years. After 4 years the impact is more moderate at 0.3 percent. However, the impact on real investment is more persistent with a peak fall in investment of around 1.5 percent after 2 years moderating to 1 percent after 4 years.

Consistent with these spillovers on economic activity, we find an increase in the unemployment rate that is broadly similar across shocks and cumulates to approximately 0.15 percentage point over four years. We no significant evidence of disinflation following a demand shock (Figure A3.1, first panel). For (negative) supply shocks we see a larger price response, with a moderate increase in inflation in the first six quarters (Figure A3.1, second panel).

2.3. Conditional Results

To assess the differential spillovers from the headline activity measure and the two sets of structural shocks, we interact the shock variables with export exposure to China, as shown in equation (4). This specification estimates the additional impact of trade-related exposure to the China shocks, relative to the baseline. For the headline activity measure, we find that the response of real GDP in partner countries to a slowdown in China is around 0.15 percent larger for GDP when accounting for export exposure. The results for the supply shock are similar but slightly larger, with a peak additional impact of 0.2 percent. For the case of demand shock, we see little additional impact on the baseline and even some evidence that the medium-term effect may be slightly weaker for countries with higher export exposure to China. Given the significant role of China in manufacturing and GVCs, aggregate export exposure does not fully capture exposure as it conflates countries providing goods for final consumption in China (which may be more affected by demand shocks in China) with those providing intermediate inputs (where Chinese supply shocks may be more relevant). We consider these issues in the firm-level analysis below.

2.4. Robustness

The preceding section provided evidence that supply shocks have been driving domestic economic activity in China most recently and that the spillovers from these tend to be larger and more immediate than for demand shocks, especially in countries with stronger trade ties to China. We run 3 alternative specifications of the local projections model: (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 A3.2). The impact of the supply shock is broadly similar to the baseline model: in each case, the impact is felt within the first year and the peak effect is in region of 0.5 percent. The results for the demand shock are less stable. A simple model without controls indicates spillovers in the short-term of a similar magnitude to the long run effect in the baseline (0.3 percent v. 0.4 percent in the baseline). Controlling for past shocks but not future shocks indicate a *positive* response to a negative demand shock in the first two years before the long run impact from the base line is recovered. Specification (3) avoids this implausible result by controlling for future shocks and is broadly similar to the baseline. The robustness checks indicate that the impact of the reduced form CCAT shock may be faster than the baseline result, however given that this variable is likely to be endogenous, we consider the baseline specification more reliable as it controls for past and future changes in the CCAT which itself may be responding to various global shocks.

We check the robustness of the finding that supply shocks have been the more prominent driver of Chinese activity in the recent past (since around 2014) by estimating a larger SVAR model that includes investment and consumption spending. We assume that both spending components move the same direction as the domestic demand and supply shocks, that global shocks do not affect investment and that there is a trade-off between higher investment and consumption (i.e., that positive investment shocks imply lower consumption spending). The resulting historical decomposition preserves the result that supply shocks have dominated in the recent past, especially around lockdowns. One would expect that the addition of consumption and investment spending, both components of aggregate demand, would potentially reduce the contribution of generic demand shocks. Indeed, this is the case: the contribution of demand is smaller during the lows of the GFC and during the decline and rebound from COVID-19 lockdowns.

3. Firm-Level Spillovers

The impact of Chinese spillovers on average 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. This section therefore investigates the impact of Chinese demand and supply shocks on firms across different countries and sectors. While our sample of listed firms is not perfectly representative of all firms, it reflects the impact of Chinese shocks on relatively large and important firms and helps to uncover the key transmission channels underlying our aggregate results. We first describe our firm-level data and methodology, then present results for the spillovers from Chinese demand and supply shocks and how they vary with supply chain linkages to China.

3.1. Data

3.1.1. Firm-Level Data

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 time-span and a broad set of countries—20 years of data, from 2001Q3 to 2021Q4, for 63 countries (29 AEs and 34 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. Details on the distribution of firms across countries and sectors are shown in Tables A2.3 and A2.4. The data is restricted to non-financial corporations and cleaned to remove firms that had negative values for assets or debt in any year, and observations with the incorrect sign for revenue or capital expenditure are set to missing (see Arbatli-Saxegaard and others 2022, for details). We winsorize all firm-level variables at the 1st and 99th percentiles to eliminate outliers. After filtering, the sample consists of more than 20,000 firms. Our main variable of interest is the firm revenue. For our revenue measure, we use total revenue (IQ_TOTAL_REV); Table A2.3 displays the summary statistics for this variable. We also use the firm investment using capital expenditure (IQ_CAPEX) to cross-validate our analysis.

3.1.2. Trade Exposure to China

We use annual input-output tables to calculate country-industry-wise trade exposure to China. 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 for 2000 and annually from 2007-2020 for 35 sectors and 62 countries. We initially repeat the macro analysis at the industry level by taking the share of exports to China in total production in each country c and industry i, i.e.,

$$X_{ci,China,t} = \frac{\sum_j Sales_{ci \to China,j,t} + FinalDemand_{ci \to China,t}}{Production_{ci,t}} \tag{5}$$

We then go further by using the input-output network to calculate country-industry-wise exposures to China through global value chains (GVCs), drawing on standard measures of supply and demand linkages (see, for instance, Acemoglu, Akcigit and Kerr, 2015; Lane, forthcoming). First, we calculate the input dependence coefficients. Specifically, let $input_{ci,China,t}$ be the share of total inputs to country-industry ci that are supplied by China, across all Chinese industries, i.e.

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

Second, we calculate the output dependence coefficients. Specifically, let $output_{ci,China,t}$ be 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.

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

These input and output dependence measures provide a gauge of linkages between country-sector pairs and China. To avoid endogeneity due to the potential time-varying responses of input and output dependence—i.e., to purge trends in integration with China from the linkage measures—we replace each variable $V_{ci,China,t} \in \{input_{ci,China,t}, output_{ci,China,t}\}$ with the fixed effect $\alpha_{c,i}$ in the following regression: $V_{c,i,China,t} = \alpha_{c,i} + \alpha_t + \epsilon_{c,i,t}$. Intuitively, we take the average value of each linkage measure over time, after removing the general trend.[6] These measures allow us to assess how each firm's interlinkages with China (i.e., relatively strong upstream or downstream connections) mediate the impact of Chinese demand and supply shocks on firm revenue. We standardize the resulting coefficients $input_{ci,China}$ and $output_{ci,China}$ across our sample of firms, so that our results can be interpreted as the differential effect for a firm that is one standard deviation more exposed to China through cross-industry input or output linkages than the average. Figure A2.1 displays the top 20 country-industry pairs with the highest share of Chinese demand in total demand. Figure A2.2 displays the top 20 country-industry pairs with the highest share of total inputs supplied by 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.

[6] In robustness specifications, we do not take out the time fixed effect and instead take the simple median over time.

3.2. Empirical Specifications

We use Jordà's (2005) local projection method to estimate the revenue effects of Chinese demand and supply shocks, and how they are shaped by trade linkages with China. We proceed in three steps, the first two of which replicate our macro regressions in the firm-level setting. First, we estimate the average (unconditional) effect of Chinese demand and supply shocks on firm revenue using the following specification:

$$y_{cif,t+h} - y_{cif,t-1} = \alpha_{fq} + \beta_D^h \cdot e_t^D + \beta_S^h \cdot e_t^S + \Gamma' X_{i,t} + \epsilon_{icf,t+h} \qquad (8)$$

where the dependent variable $y_{cif,t}$ denotes the log revenue level of firm *f* in county *c* and sector *i*, e_t^S and e_t^D denote the supply and demand shocks identified in Section 2, and β_S^h and β_D^h denote the average firm revenue response to the supply and demand shocks after *h* quarters, respectively. α_{fq} indicates firm-quarter dummies to control for unobservable time-invariant firm characteristics as well as firm seasonality in revenue. $X_{i,t}$ includes controls for the shocks in the preceding year, and future shocks in the next year, 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).

Next, we extend equation (8) to estimate how the dynamic effect of China demand and supply shocks on revenues varies across firms depending on export ties to China, by estimating the following specification:

$$y_{cif,t+h} - y_{cif,t-1} = \beta_{D,X}^h \cdot e_t^D \cdot X_{ci,China} + \beta_{S,X}^h \cdot e_t^S \cdot X_{ci,China} + \alpha_{fq} + \alpha_{ct} + \Gamma' X_{i,t} + \epsilon_{cif,t+h} \qquad (9)$$

α_{ct} are country-time fixed effects to account for country specific macroeconomic shocks (such as, for example, changes in a country's monetary and fiscal policy stance or external shocks affecting the country).[7]

Finally, we move beyond the macro regressions to estimate the role of upstream and downstream GVC connections in conditioning the impact of demand and supply shocks from China. We include both the input and output linkage measures described in Section 3.1.2, interacting each with both of supply and demand shocks:

$$
\begin{aligned}
y_{cif,t+h} - y_{cif,t-1} = \beta_{D,O}^{h} \cdot e_t^{D*} \cdot output_{ci,China} + \beta_{D,I}^{h} \cdot e_t^{D*} \cdot input_{ci,China} \\
+\beta_{S,O}^{h} \cdot e_t^{S*} \cdot output_{ci,China} + \beta_{S,I}^{h} \cdot e_t^{S*} \cdot input_{ci,China} \\
+\alpha_{f,q} + \alpha_{c,t} + \alpha_{i,t} + \Gamma' X_{c,t} + \epsilon_{cif,t+h} \qquad (10)
\end{aligned}
$$

This flexible specification estimates the marginal impact of all four supply chain permutations (demand-output, demand-input, supply-output, supply-input). Crucially, we include both country-time and industry-time fixed effects ($\alpha_{i,t}$), along with firm-quarter fixed effects, allowing us to control for unobservable national policy responses as well as global industry trends. Given this demanding specification, we modify the supply/demand shock series such that in any given quarter we are only estimating two of the four main coefficients, namely the relative contributions of input and output linkages to either a demand or a supply shock (rather than to both a supply and demand

[7] We do not include the country-time fixed effect in equation (8) in order to gauge the full unconditional average response of revenue to supply/demand shocks and retain comparability with the macro regression specification (3).

shock at the same time).[8] We present our results in the next section, then discuss their robustness to alternative methodological choices in Section 3.4.

3.3. Results

Figure 9 presents the average revenue response to a negative China demand shock (blue) or supply shock (purple) equivalent to 1 percent of GDP. As expected, both demand and supply shocks are followed by an economically and statistically significant decline in foreign firms' revenue, with a peak impact after 8 quarters of -1.4 percent for the supply shock and -1.6 percent for the demand shock. These direct impacts of supply and demand shocks are not significantly different to each other in the short and medium terms and are similarly persistent. In contrast, the impact on firm investment, shown in Figure 10, does differ: while the impact of both shocks is less persistent than for firm revenue, the impact of the supply shock is substantially larger and twice as persistent, with a peak decline of almost 3 percent after 7 quarters.

We next estimate the differential impact of China shocks in country-industry pairs with relatively high export exposure to China, using specification (9). Figure 11 suggests that following a negative demand shock, firms that operate in sectors with higher exports to China experienced a larger decline in revenue. The effects are economically significant, implying that the decline in revenues is 3.4 percent larger for firms at the 90th percentile of the export exposure distribution than for firms at the 10th percentile. The role of export exposure in relation to supply shocks is

[8] We follow the literature studying the effects of tax-driven and expenditure-based austerity by distinguishing whether fiscal plans are expenditure-based or tax-based depending on whether the largest component of a fiscal correction was an increase in taxes or a decrease in expenditure. As discussed in Alesina et al. (2014), this approach reduces multi-collinearity that arises when both shocks are included, by de facto orthogonalizing them, and is more efficient than estimating responses for each shock separately. Specifically, for each quarter we set $e_t^{D*} = 0$ if $e_t^D < e_t^S$ and $e_t^{S*} = 0$ if $e_t^S < e_t^D$. In the robustness sub-section, we show that the results are qualitatively similar but less precisely estimated when including the non-orthogonalized supply and demand shocks.

relatively less significant, with the coefficient on the interaction term being significant only through the 5th quarter and of a smaller magnitude. This is intuitive given that lower Chinese demand directly impacts firm sales in country-industry pairs that export heavily to China, unlike Chinese supply shocks which would only have indirect impacts through GVCs. This motivates our final specification, which distinguishes explicitly between input and output linkages.

Figure 12 shows the results from estimating equation (10). 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. This is not the case for either of the other two channels (demand-input and supply-output), which is intuitive since one would expect the predominant direct impact of changes in Chinese supply to fall on firms sourcing inputs from China, and likewise we would expect the predominant direct impact of changes in Chinese demand to fall on firms selling to China. A firm in a sector that is one standard-deviation more dependent on Chinese demand than average sees revenue fall by 0.2 percentage point more over four years, in response to a negative supply shock equivalent to a 1 percent decline in GDP in China. In contrast, a firm in a sector that is one standard-deviation more dependent on Chinese inputs than average sees revenue fall by 0.6 percentage point more over the same period, in response to a negative supply shock of the same magnitude.

3.4. Robustness

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 specification. In Figure A4.1, we drop all the control variables from equation (8) and present the impulse responses equivalent to Figure 9. Figure A4.2 presents the average revenue responses against China shocks without the Teulings and Zubanov (2014) future correction shocks and Figure A4.3 confirm the results without the four-quarter lags of shocks. In further sensitivity analyses, we drop countries with less than 250 firms (Figure A4.5) or the two biggest sectors (Figure A4.6) from our sample and find similar results. Figures A4.7 and A4.8 show the baseline results with 2 and 6 lags respectively of the dependent variable and shocks. Figure A4.9 shows results from taking the simple median of the time-varying input/output coefficients, instead of the regression-based method described in Section 3.1.2. Finally, Figure A4.10 shows the results from including the raw supply and demand shocks in every period of specification (10).

4. 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 characterize the 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 Chinese supply shocks have particularly large repercussions around the world. We find a faster and larger aggregate response to Chinese supply shocks than demand shocks, and this remains the case even when controlling for country and industry trends using firm-level data. Demand spillovers remain substantial, particularly for firms with strong sales linkages to China—a significant consideration for policymakers in light of the ongoing weakness in the Chinese property sector and the slowdown in investment. Over the medium term, however, the even stronger supply-side spillovers that we find—coupled with projections of lower Chinese TFP and labor force growth—are likely to be even more important.

China's deeper trade links have been followed by significant financial linkages; future work could use the two-stage approach pursued here to study how different Chinese domestic shocks have spillovers via those financial links. In addition, identifying supply shocks using sectoral data would provide a useful robustness exercise to our results and allow us to gauge whether shocks in some Chinese sectors generate especially large international spillovers. Exploring heterogenous responses across firms would also shed light on vulnerabilities by characteristics such as debt levels and firms' size. This is planned future work.

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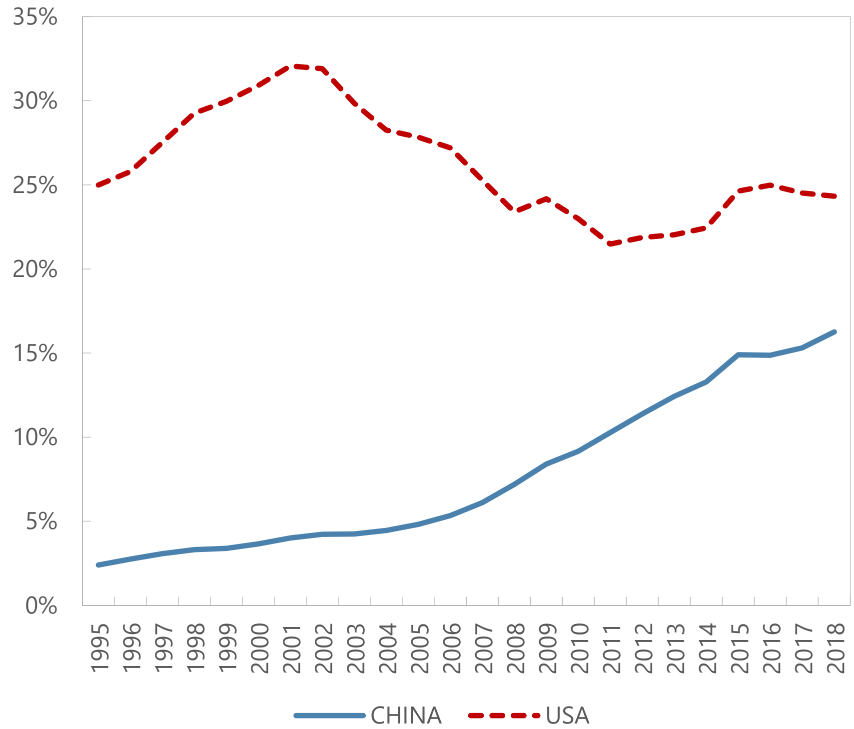
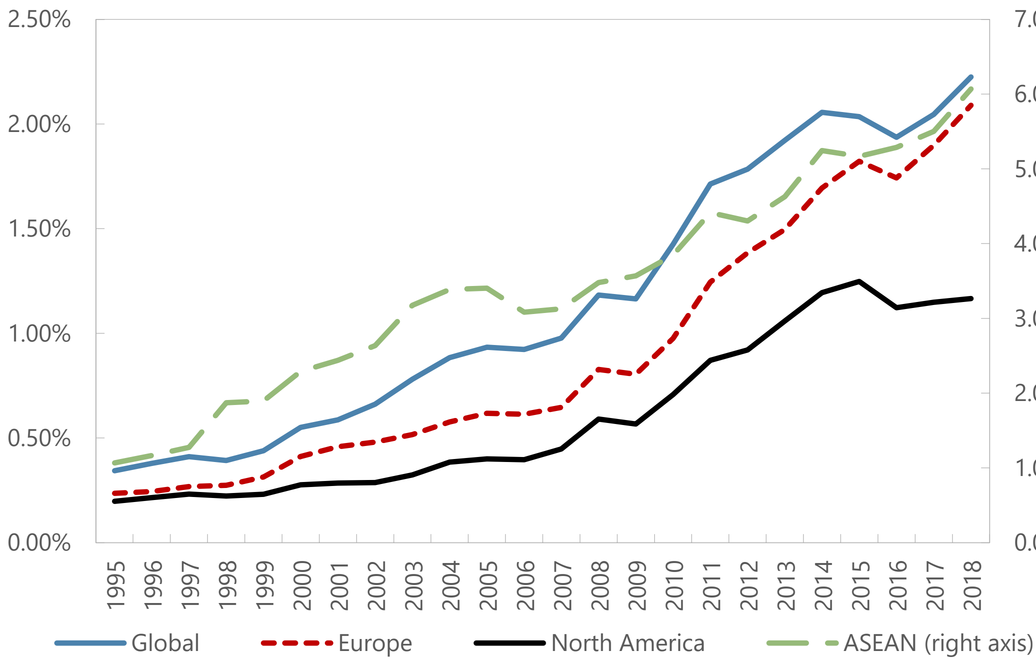
Figures

Figure 1. Share of global demand met by production in USA and China



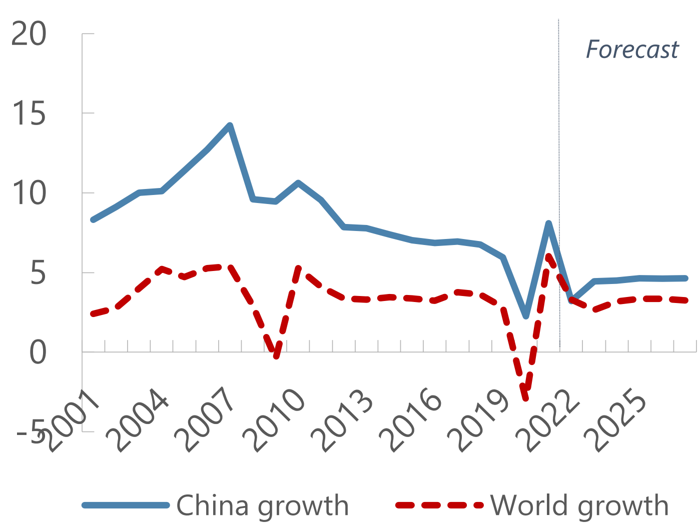
Sources: OECD TiVA, IMF staff calculations.

Figure 2. Share of output absorbed by Chinese domestic demand



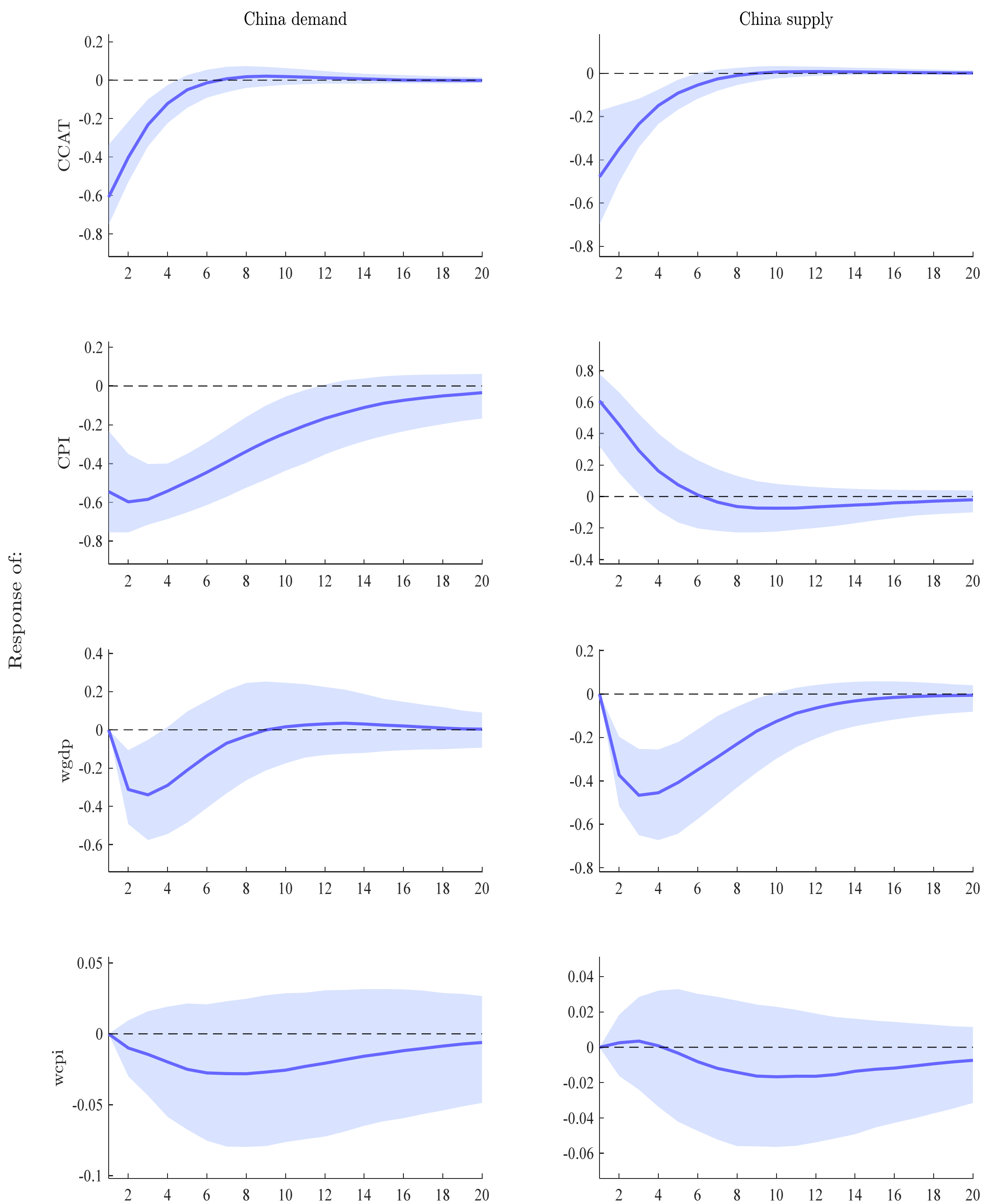
Sources: OECD TiVA, IMF staff calculations. ASEAN = average across Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Vietnam.

Figure 3. China and global growth 2001-2027



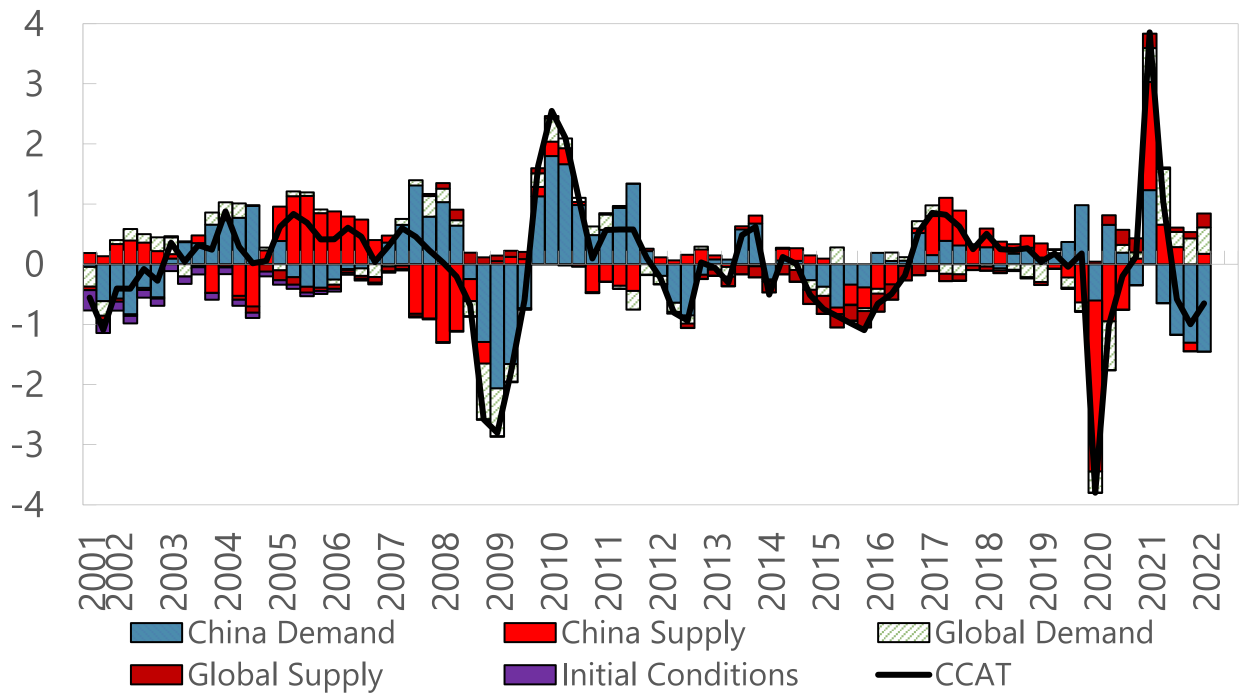
Sources:: IMF WEO October 2022, IMF staff calculations.

Figure 4. Impulse response functions for structural demand and supply shocks in SVAR model of domestic Chinese activity



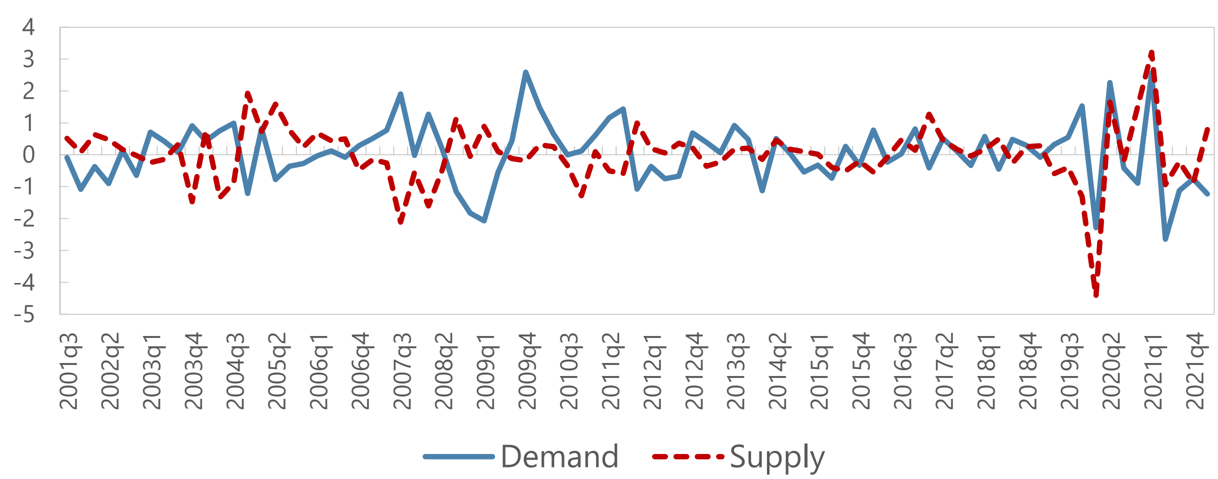
Notes: IMF WEO October 2022, Fernald, Hsu, and Spiegel (2021), IMF staff calculations.

Figure 5. Historical decomposition of the China Cyclical Activity Tracker



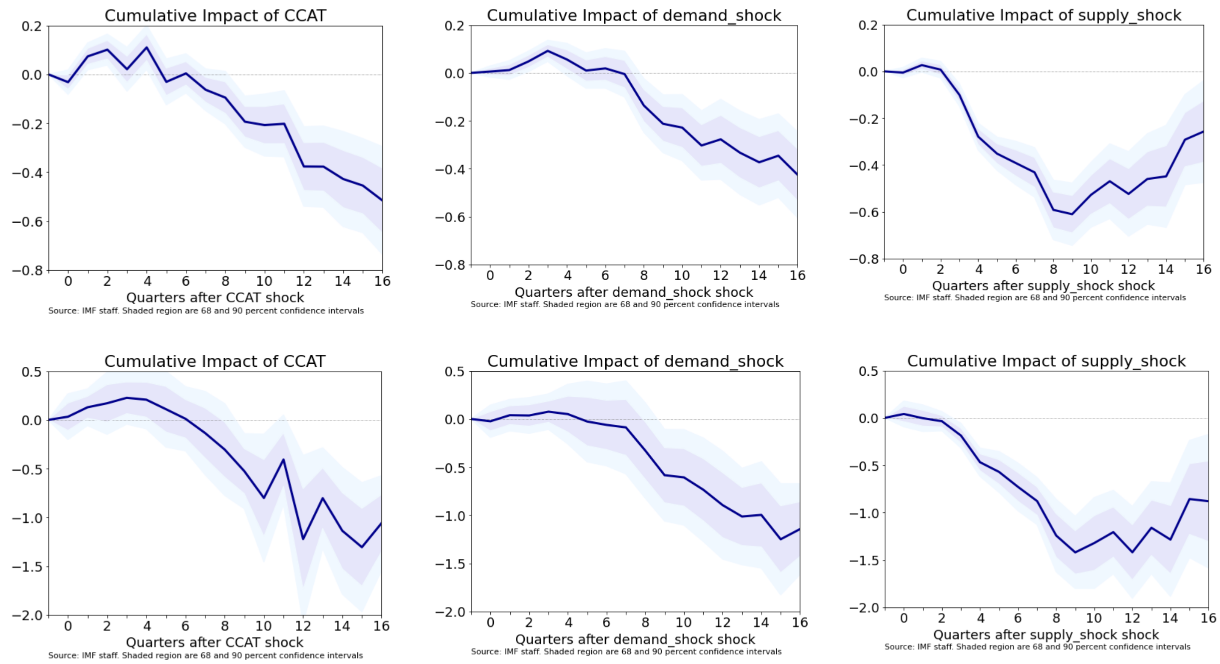
Sources: IMF WEO October 2022, Fernald, Hsu, and Spiegel (2021), IMF staff calculations.

Figure 6. Demand and supply shocks from the SVAR model



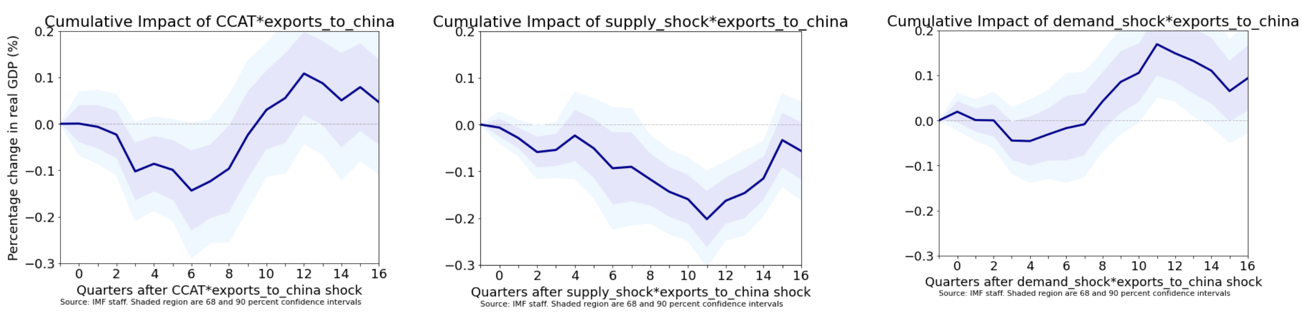
Sources: IMF WEO October 2022, Fernald, Hsu, and Spiegel (2021), IMF staff calculations.

Figure 7. Impact of negative 1 percent of GDP shock in China on the level of real GDP and investment in other countries



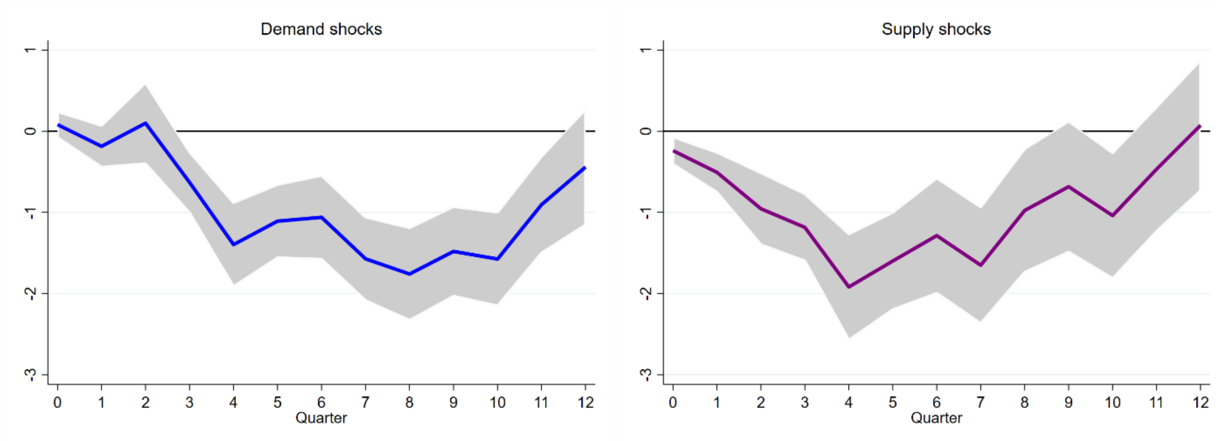
Notes: y-axis in percent. The results follow from the estimation of equation (3). The solid blue lines in the top three and bottom three panels indicate the average impact on real GDP and investment respectively of a 1 percent of GDP shock in China. Standard errors are clustered by country. The shaded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

Figure 8. Differential by export exposure for impact of a 1 percent of GDP shock in China on real GDP



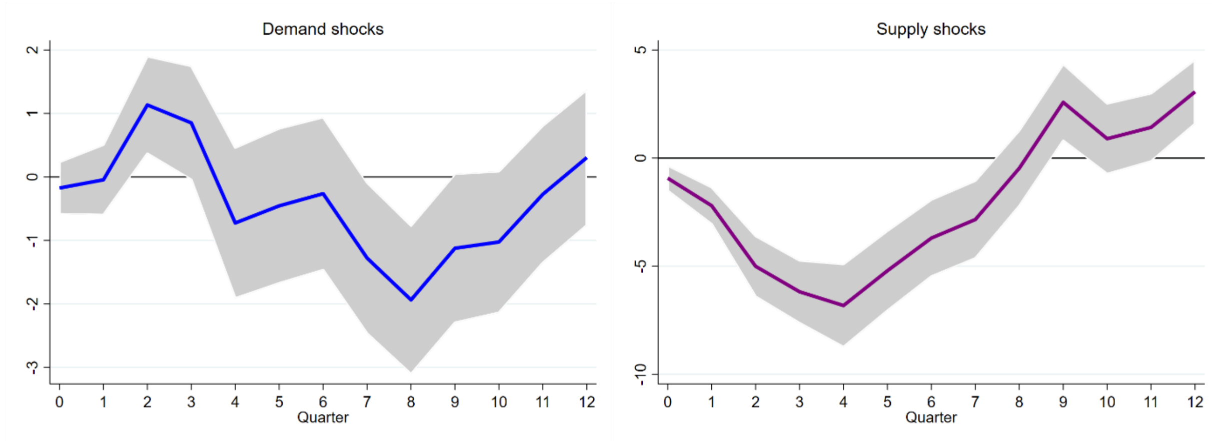
Notes: y-axis in percent. The results follow from the estimation of equation (4). The solid blue lines indicate the estimated coefficient on the interaction term with exports, for a 1 percent of GDP shock in China. Standard errors are clustered by country. The shaded areas display the 68% and 90% confidence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

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



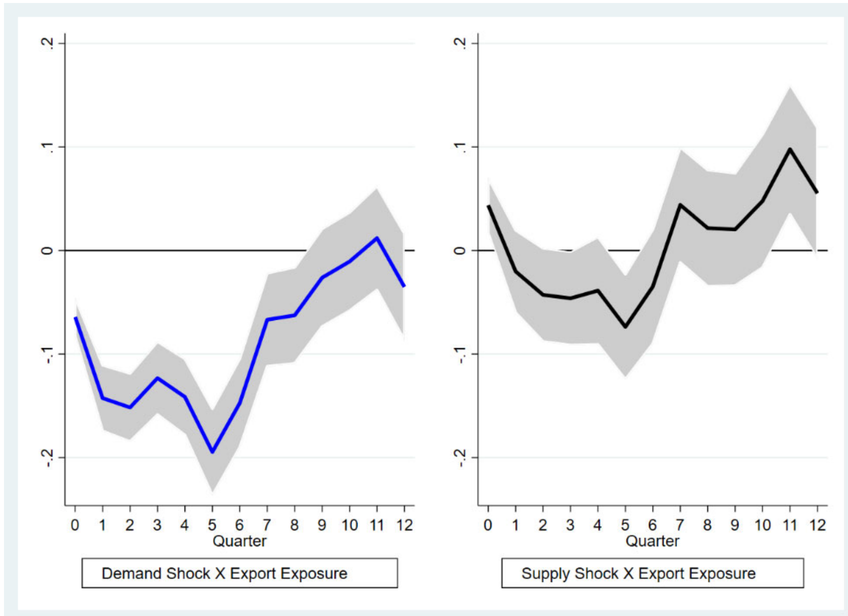
Notes: y-axis in percent. The results follow from the estimation of equation (8). The solid blue and purple lines indicate the average response of firm revenue to a 1 percent of GDP shock in China. Standard errors are two-way clustered on firms and country-time. The gray areas display the 90% confidence intervals.

Figure 10. Average effects of 1 percent of GDP shock in China on firm investment in other countries



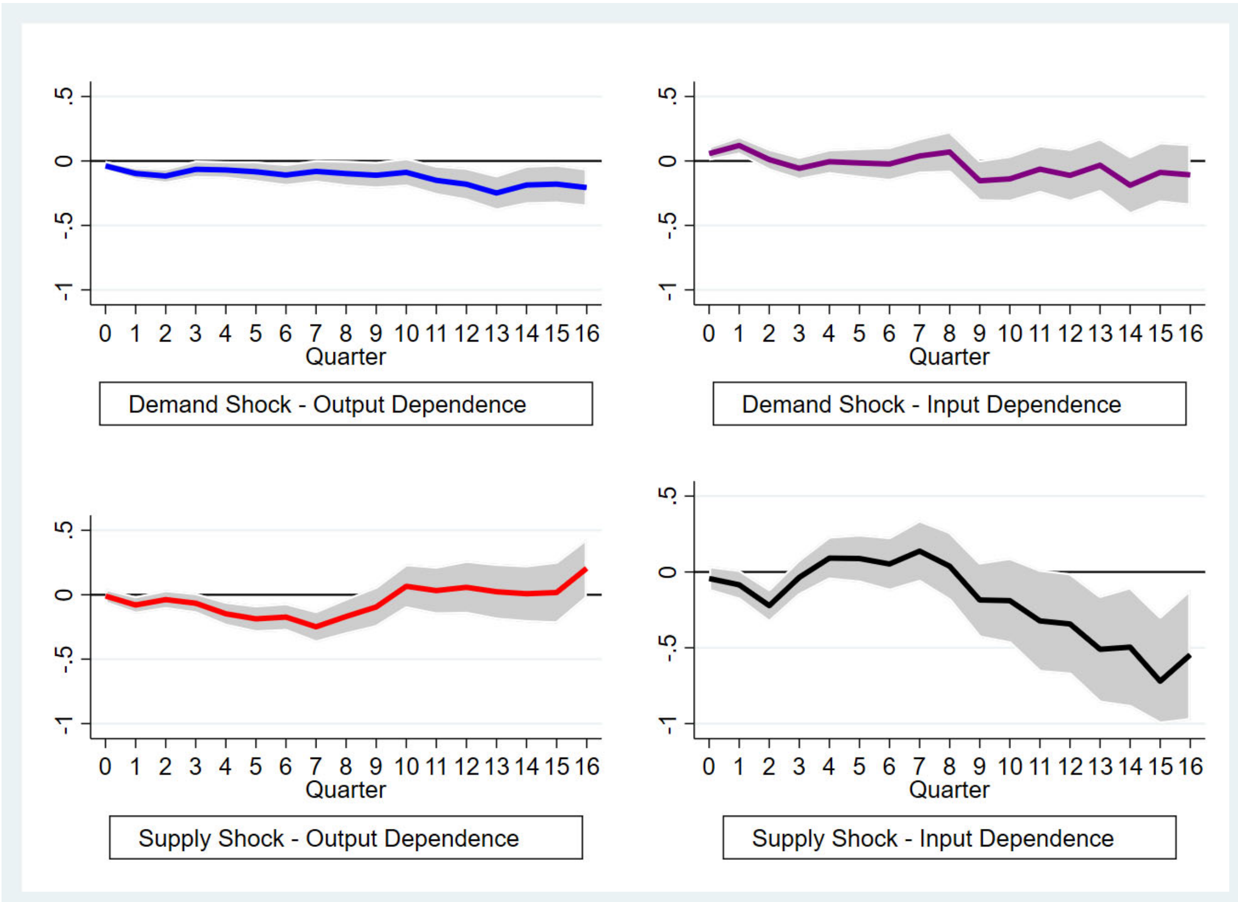
Notes: y-axis in percent. The results follow from the estimation of equation (8). The solid blue and purple lines indicate the average response of firm investment to a 1 percent of GDP shock in China. Standard errors are two-way clustered on firms and country-time. The gray areas display the 90% confidence intervals.

Figure 11. Differential by export exposure for 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 (9). The solid blue line indicates the differential response of firms operating in output vs input dependent sectors to a China demand shock. The solid purple line indicates the differential response of firms operating in input vs output dependent sectors to a China supply shock. Standard errors are clustered by firm. The gray areas display the 90% confidence intervals.

Figure 12. Differential by input and output linkages to China for 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). 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 clustered by firm. The gray areas display the 90% confidence intervals.

Annex

Annex 1: SVAR Identification

Table A1: Sign restrictions for SVAR model

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

* Short-run zero restriction that applies to the first period of the shock.

Annex 2: Data

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. Firm-Level Data Summary Statistics

	No. of Obs.	Mean	Std. Dev.	25th Pctile	Median	75th Pctile
Revenue (yoy, %)	1,528,030	6.84	41.61	-7.69	6.06	21.74
Capital Expenditure (yoy, %)	742,350	4.95	119.52	-57.98	4.44	67.11
Investment Ratio (yoy, %)	725,623	-0.49	7.86	-2.06	-0.08	1.498

Table A2.4. Number of Firms and Observations by Country

Country	Number of Firms
United States	5,076
India	3,516
Japan	2,860
Korea	2,043
Taiwan	1,822
Canada	1,522
Hong Kong	1,380
Australia	1,339
Malaysia	883
United Kingdom	873
Sweden	709
Thailand	628
Indonesia	604
Poland	541
Singapore	499
Vietnam	495
Germany	488
France	461
Israel	395
Pakistan	313
Turkey	294
Italy	274
Brazil	242
Bangladesh	212
Philippines	199
Switzerland	198
Sri Lanka	195
Norway	187
South Africa	164
Egypt	157
Greece	147
Saudi Arabia	142
Spain	140
Denmark	137
Finland	130
Russia	121
Jordan	116
Chile	109

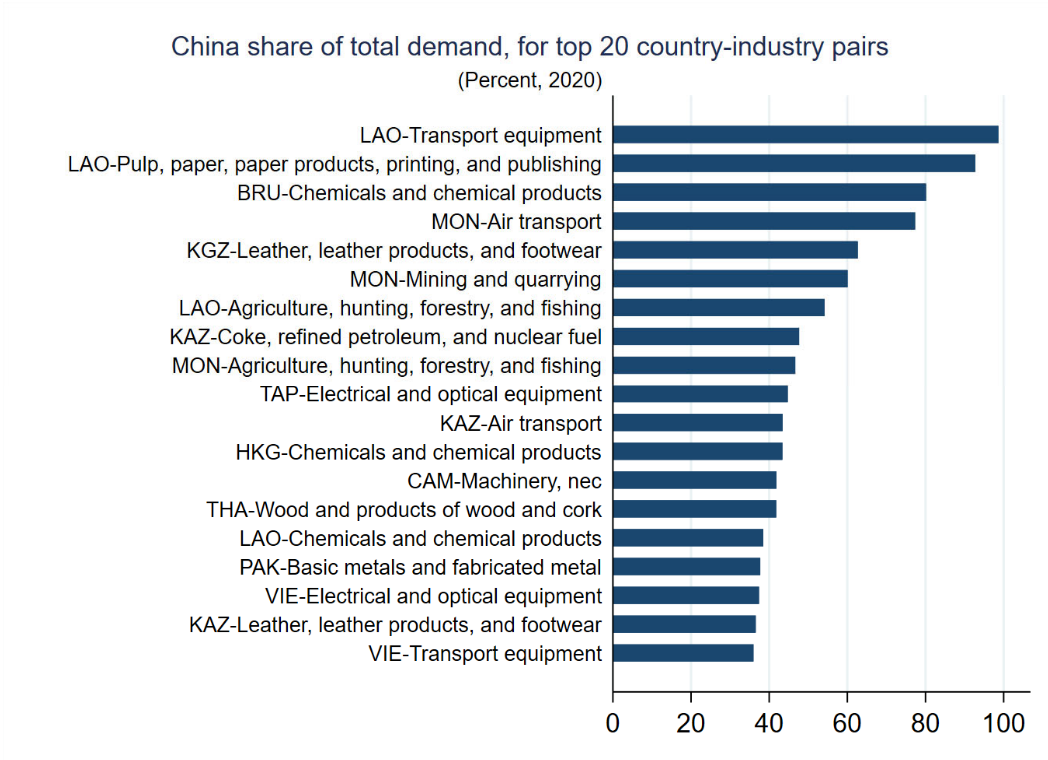
Table A2.4 (continued). Number of Firms and Observations by Country

Country	Number of Firms
Mexico	101
Netherlands	98
New Zealand	98
Nigeria	95
Kuwait	93
Belgium	86
Cayman Islands	76
Peru	75
Bulgaria	66
Ireland	62
Romania	62
Oman	61
Cyprus	60
Mauritius	54
Croatia	53
United Arab Emirates	52
Argentina	50
Austria	49
Luxembourg	48
Tunisia	45
Brunei	41
Colombia	39
Portugal	35
Malta	31
Hungary	25

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

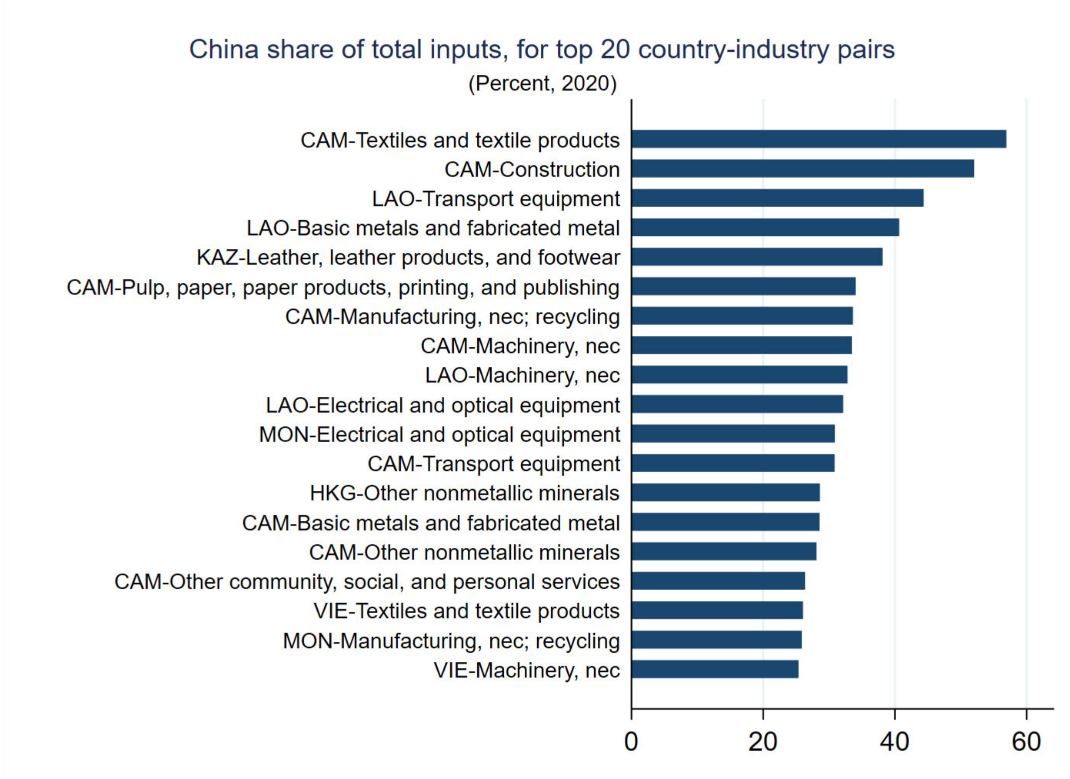
Sector	Number of Firms
Capital Goods	5,234
Materials	5,027
Software and Services	2,469
Technology Hardware and Equipment	2,363
Pharmaceuticals and Biotechnology	2,247
Consumer Durables and Apparel	2,185
Food, Beverage and Tobacco	2,027
Media and Entertainment	1,708
Health Care Equipment and Services	1,558
Energy	1,531
Consumer Services	1,460
Retailing	1,423
Professional Services	1,307
Transportation	1,010
Automobiles and Components	932
Semiconductors	836
Household and Personal Products	468
Food and Staples Retailing	412
Telecommunication Services	382

Figure A2.1. China's share in total demand



Notes: The horizontal bars represent the share of Chinese demand in total demand for a country-sector pair.

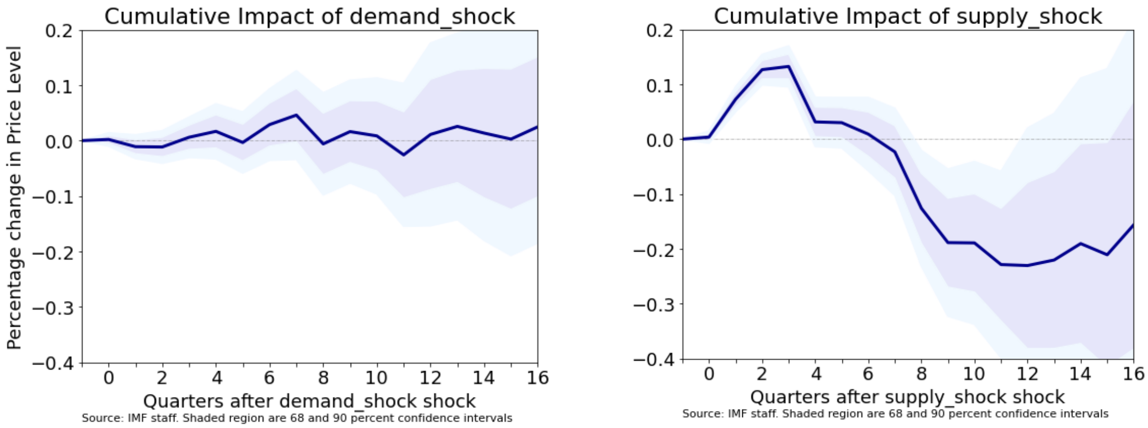
Figure A2.2. China's share in total input usage



Notes: The horizontal bars represent the share of total input usage that is supplied by China, by country-sector pair.

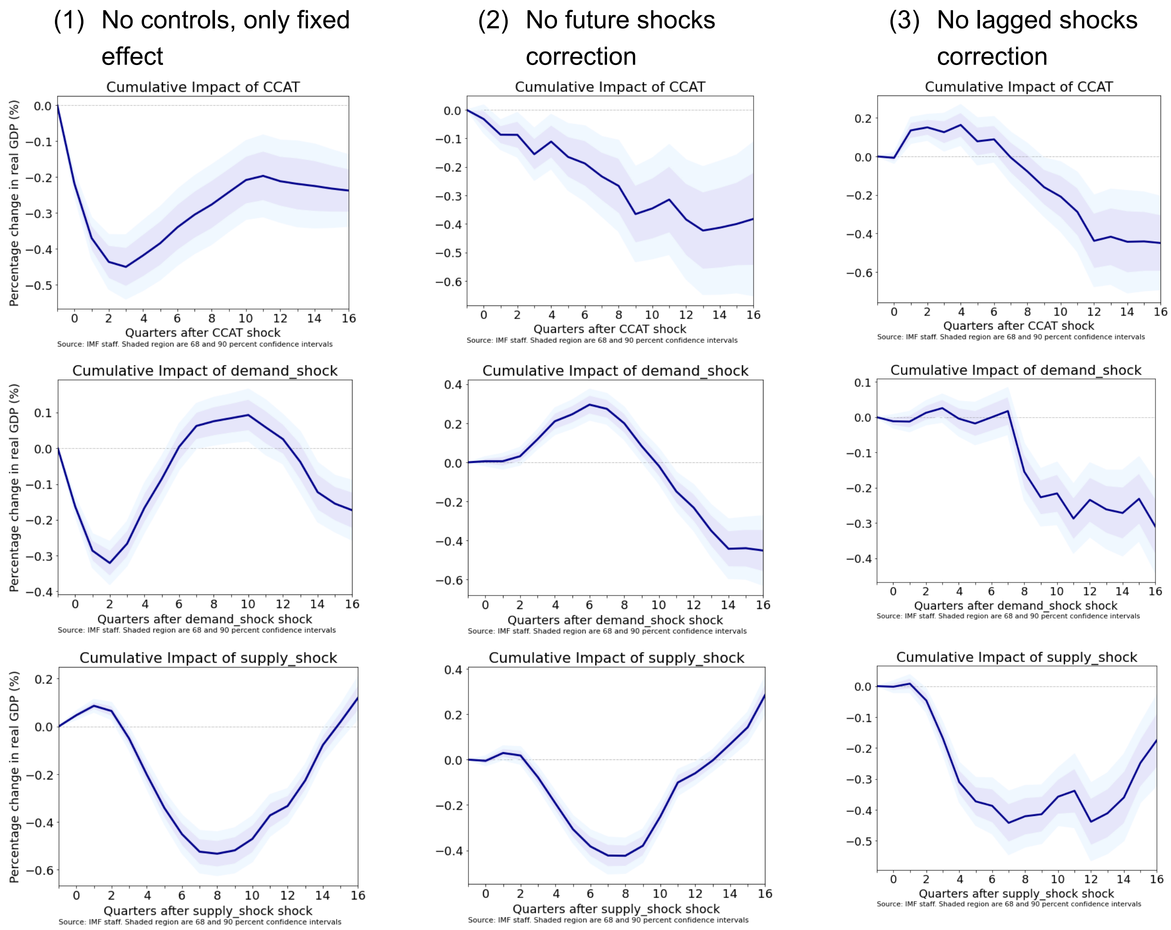
Annex 3. Robustness: Macro Analysis

Figure A3.1. Impact of negative 1 percent of GDP shock in China on the price level



Notes: y-axis in percent. The results follow from the estimation of equation (3). The solid blue lines indicate the average impact on prices 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.

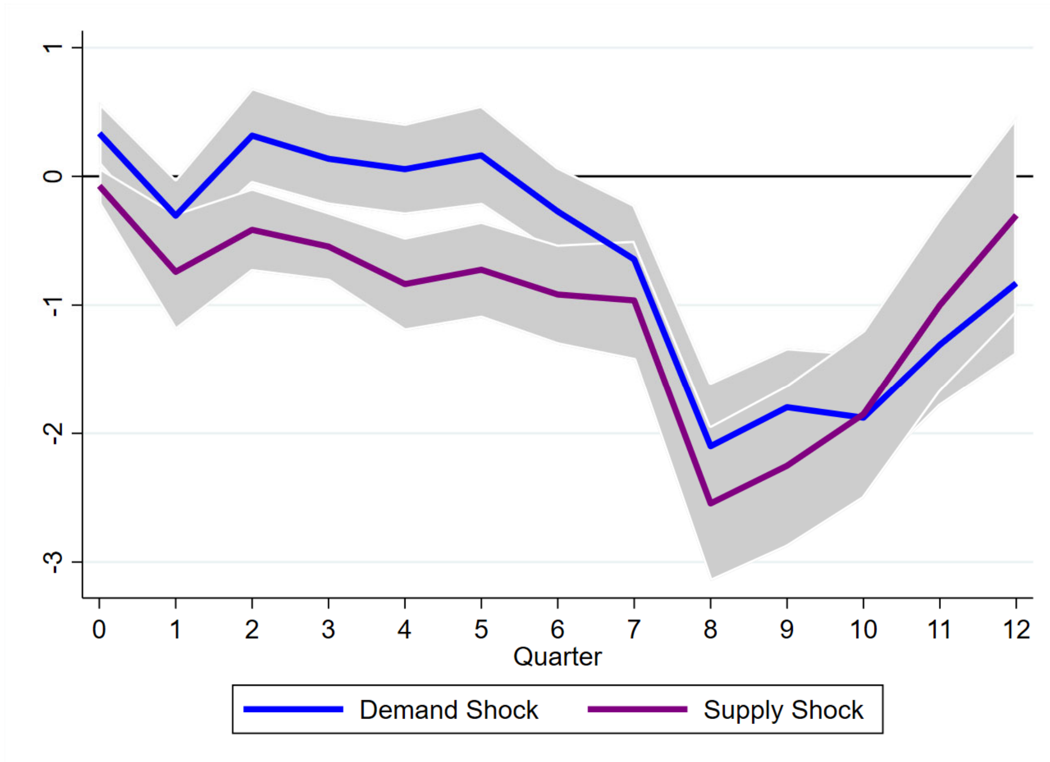
Figure A3.2. Sensitivity of spillovers to GDP to model specification



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.

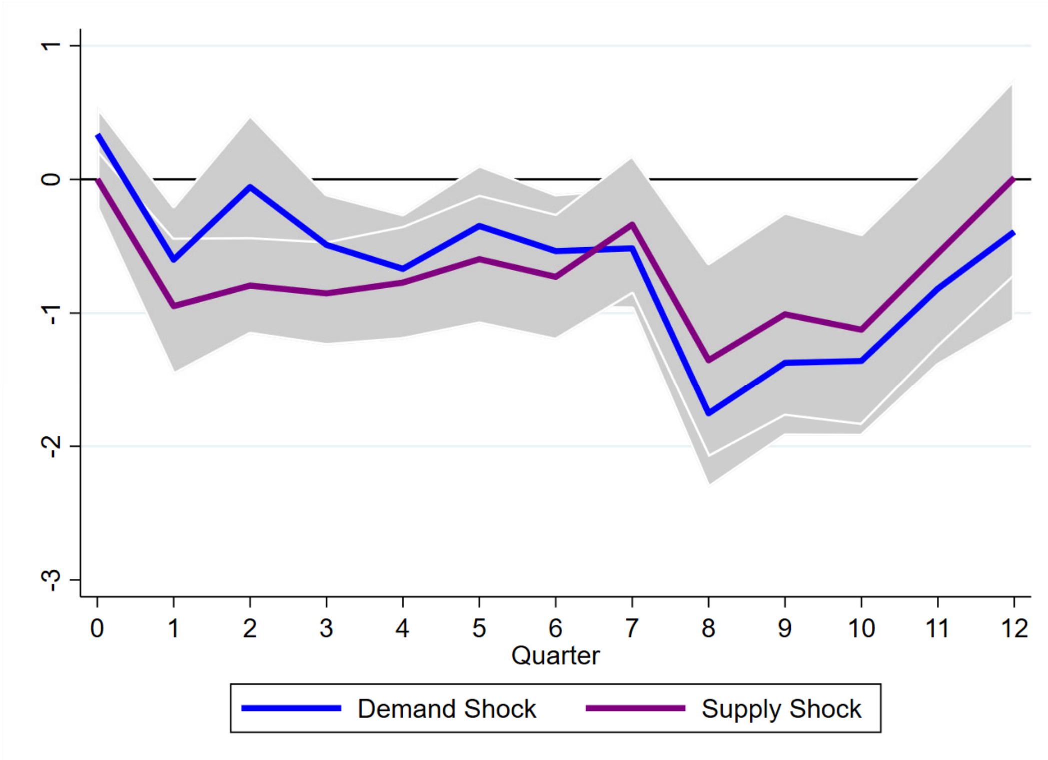
Annex 4. Robustness: Firm-Level Analysis

Figure A4.1. No Controls



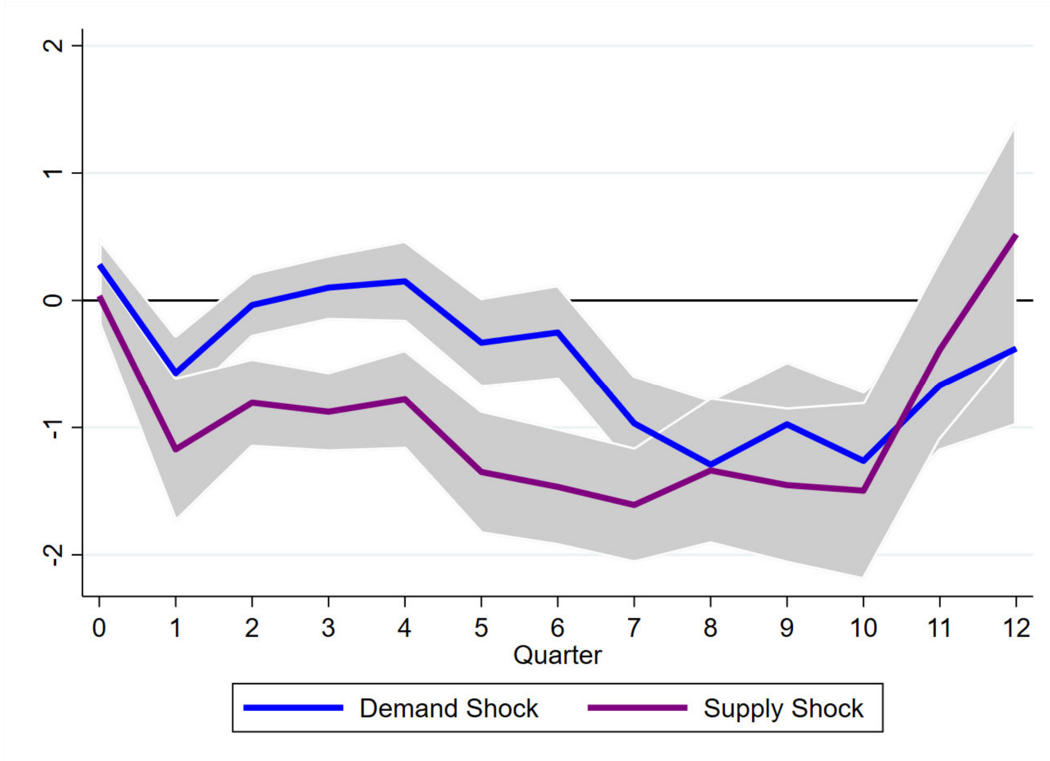
Notes: y-axis in percent. The results follow from the estimation of equation (8). The solid blue and purple lines indicate the average response of firm revenue to a 1 percent of GDP shock in China. Standard errors are two-way clustered on firms and country-time. The gray areas display the 90% confidence intervals.

Figure A4.2. With Future Shocks Correction



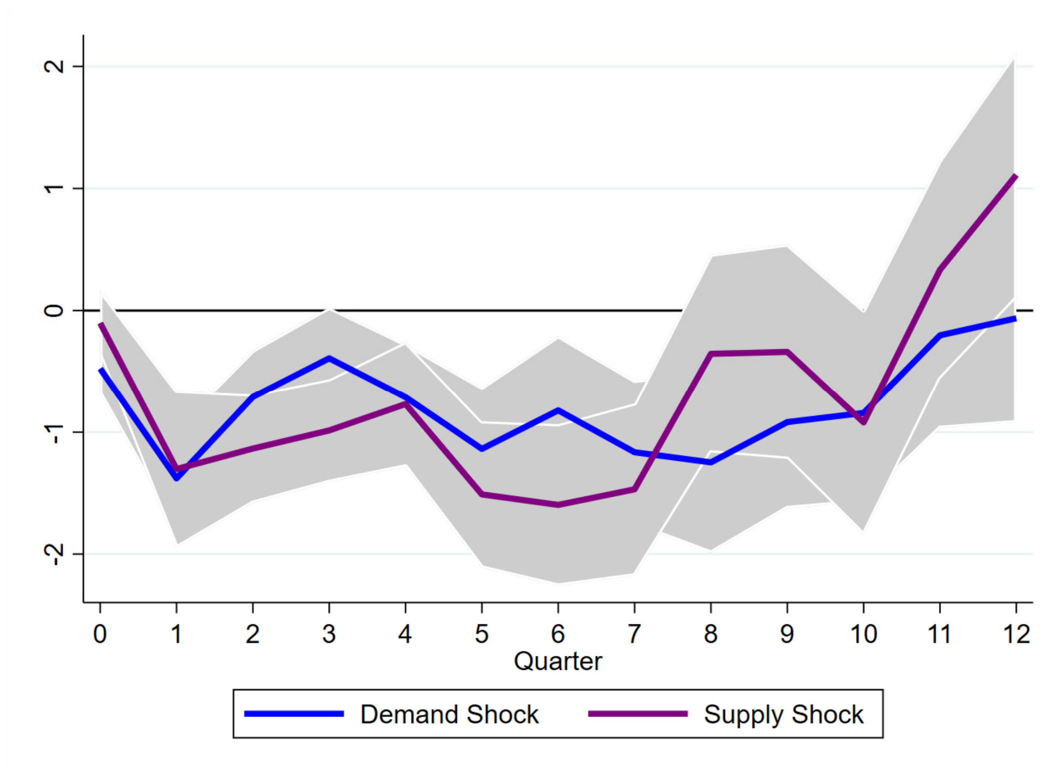
Notes: y-axis in percent. The results follow from the estimation of equation (8). The solid blue and purple lines indicate the average response of firm revenue to a 1 percent of GDP shock in China. Standard errors are two-way clustered on firms and country-time. The gray areas display the 90% confidence intervals.

Figure A4.3. No Lagged Shocks



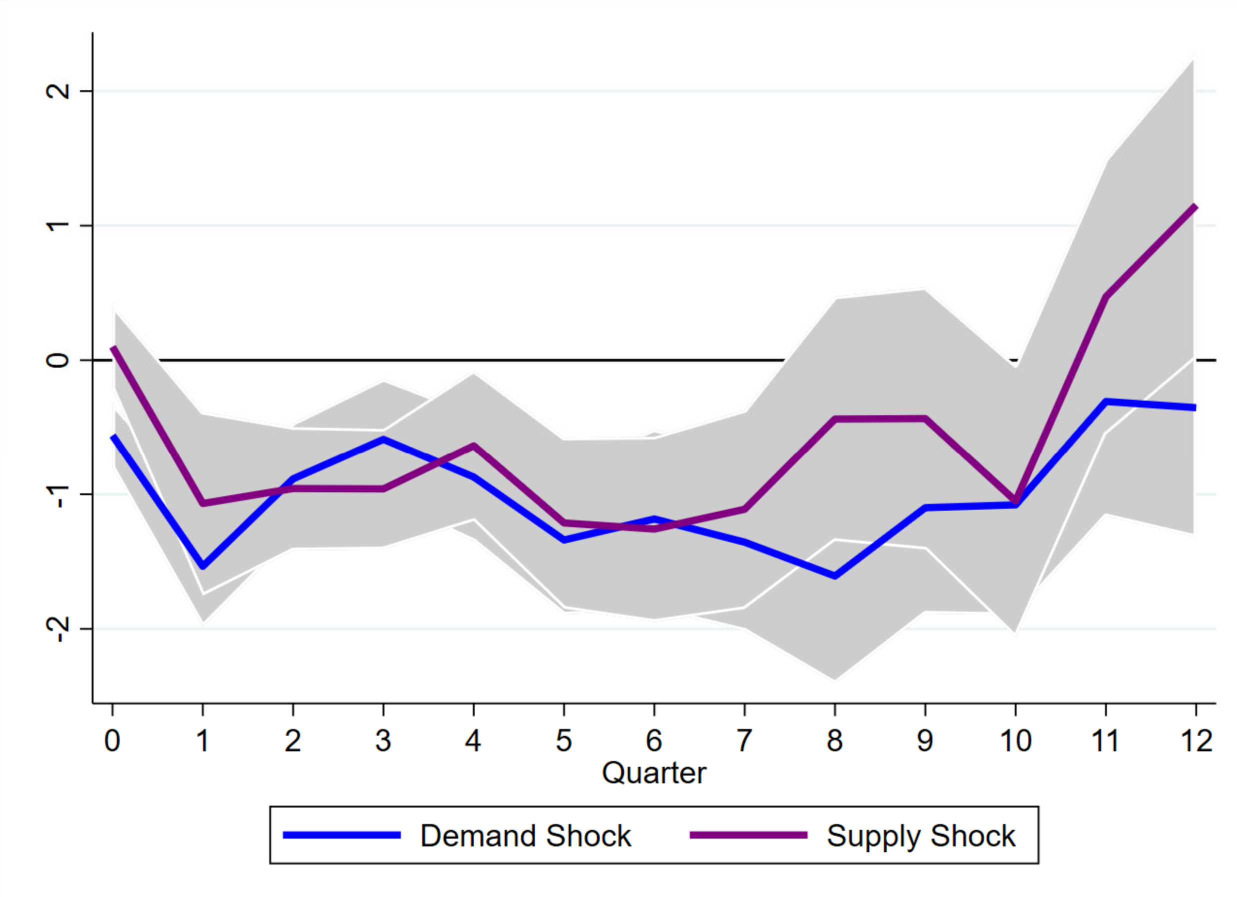
Notes: y-axis in percent. The results follow from the estimation of equation (8). The solid blue and purple lines indicate the average response of firm revenue to a 1 percent of GDP shock in China. Standard errors are two-way clustered on firms and country-time. The gray areas display the 90% confidence intervals.

Figure A4.5. Remove countries for which we have limited firms: dropping countries with less than 250 firms



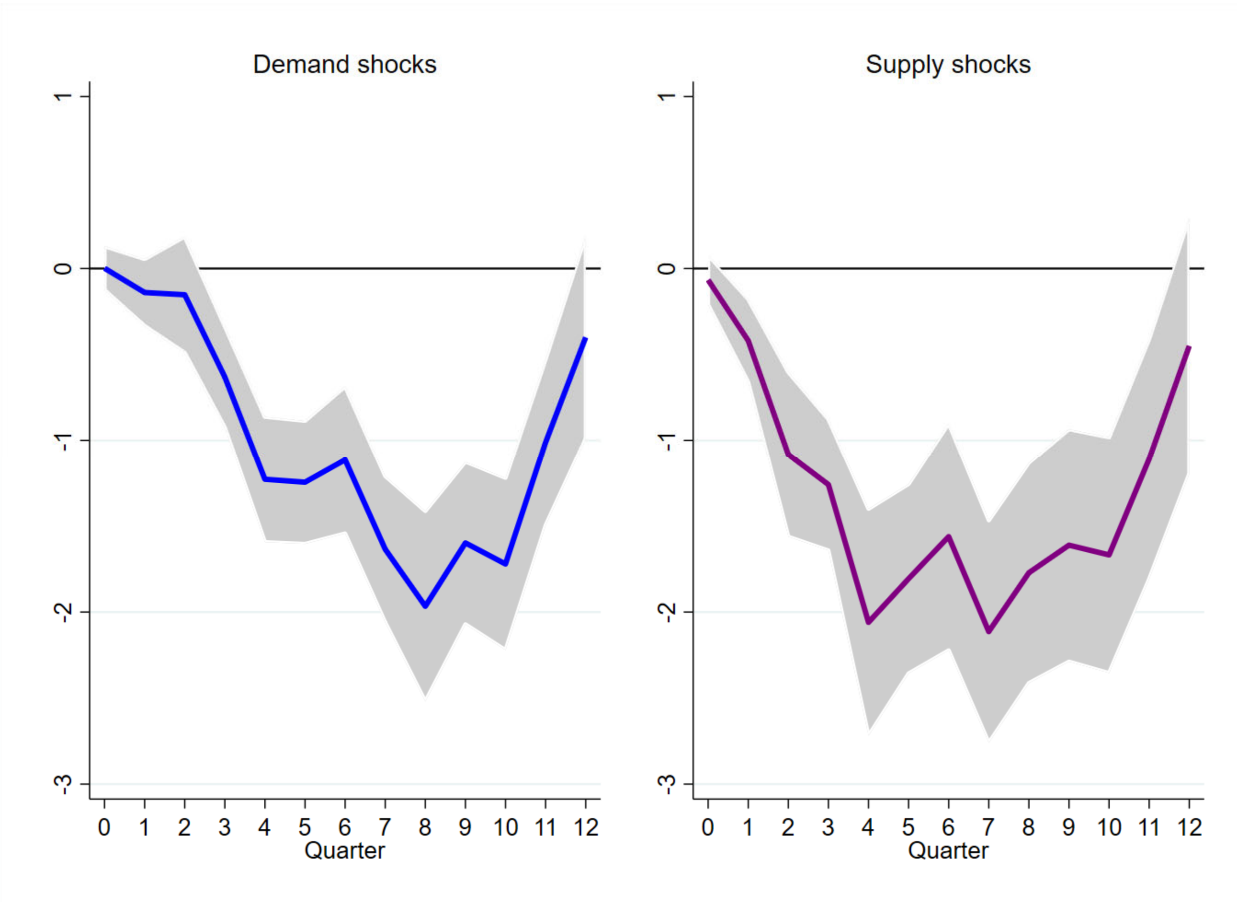
Notes: y-axis in percent. The results follow from the estimation of equation (8). The solid blue and purple lines indicate the average response of firm revenue to a 1 percent of GDP shock in China. Standard errors are two-way clustered on firms and country-time. The gray areas display the 90% confidence intervals.

Figure A4.6. Dropping the Two Biggest Sectors: Materials and Capital Goods



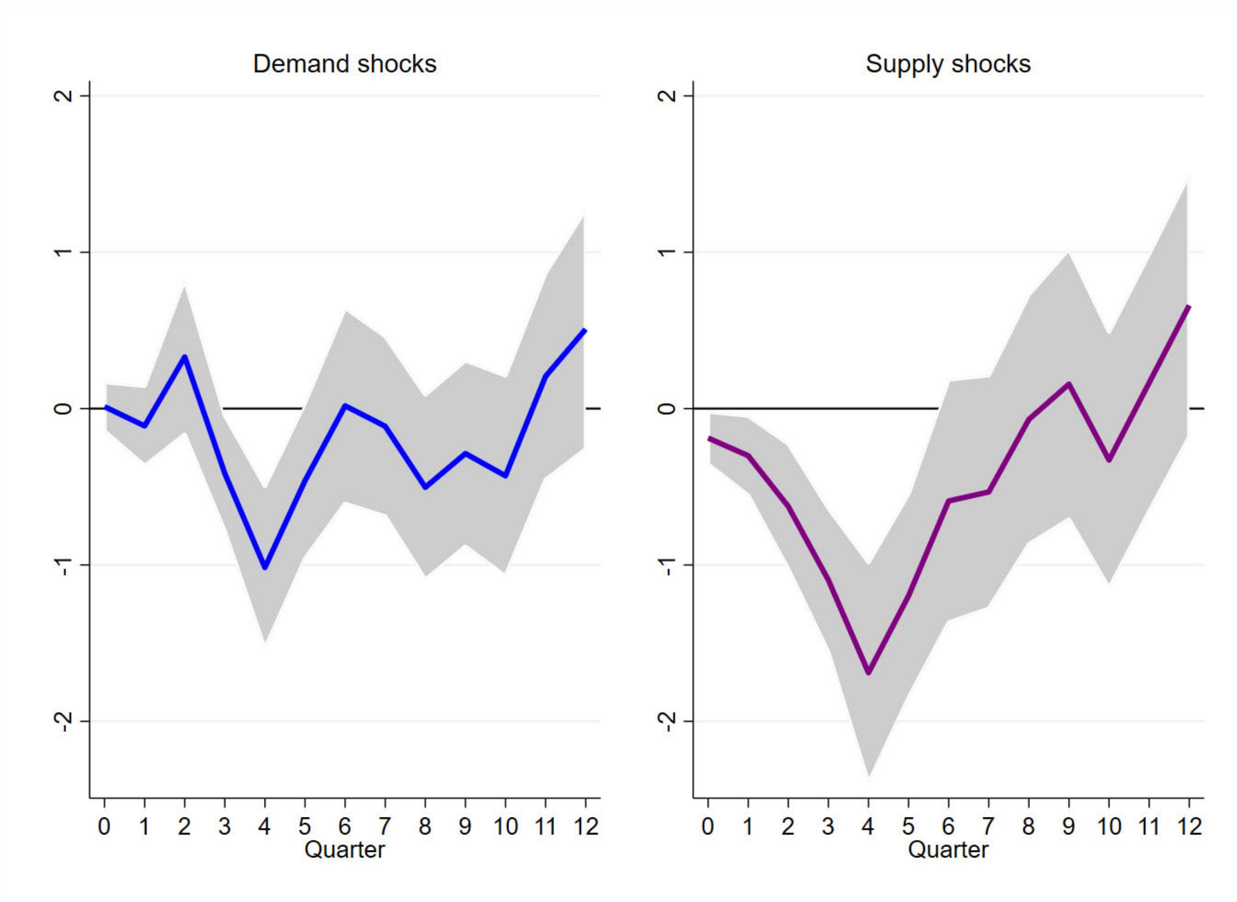
Notes: y-axis in percent. The results follow from the estimation of equation (8). The solid blue and purple lines indicate the average response of firm revenue to a 1 percent of GDP shock in China. Standard errors are two-way clustered on firms and country-time. The gray areas display the 90% confidence intervals.

Figure A4.7. Average effects of 1 percent of GDP shock in China on firm revenue in other countries, 2 lags of dependent variables



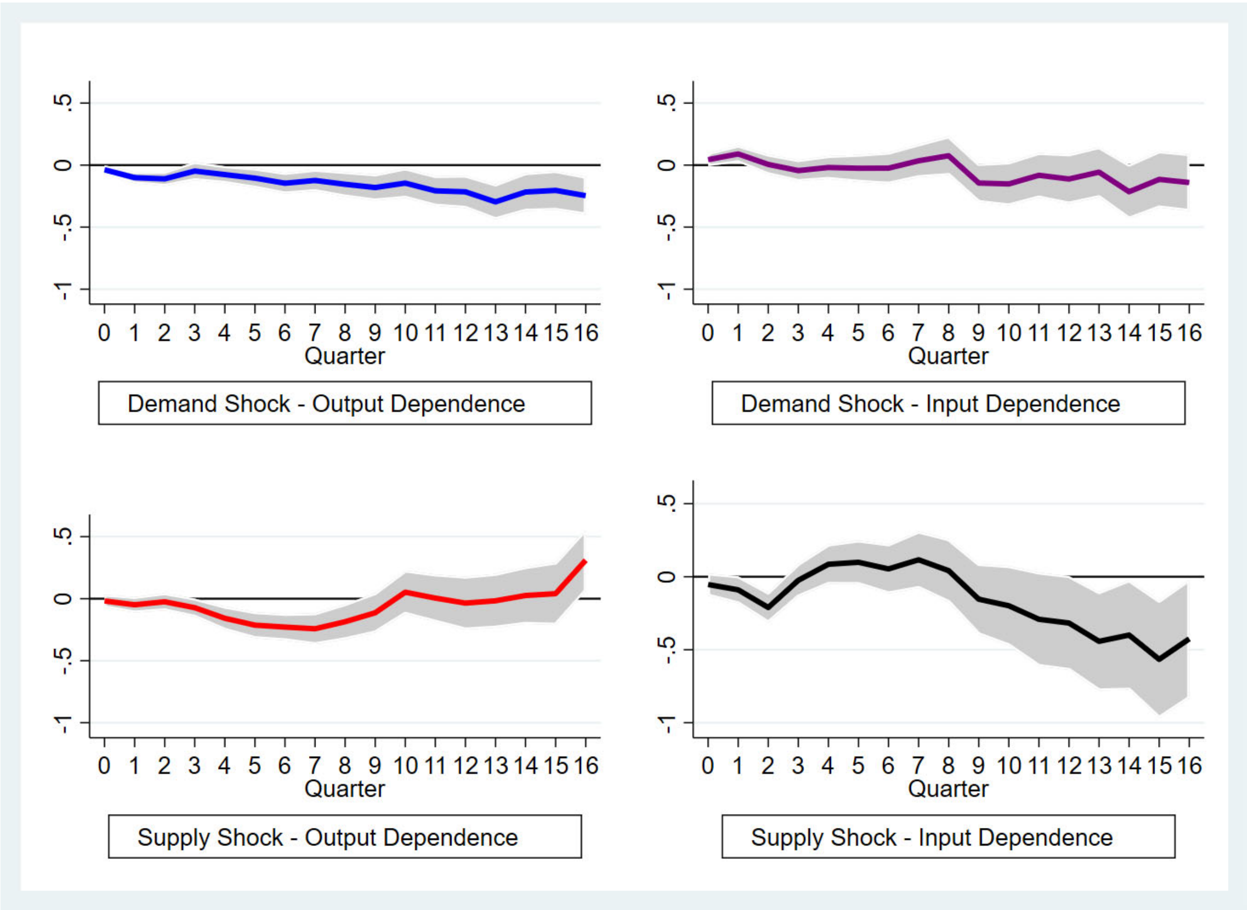
Notes: y-axis in percent. The results follow from the estimation of equation (8). The solid blue and purple lines indicate the average response of firm revenue to a 1 percent of GDP shock in China. Standard errors are two-way clustered on firms and country-time. The gray areas display the 90% confidence intervals.

Figure A4.8. Average effects of 1 percent of GDP shock in China on firm revenue in other countries, 6 lags of dependent variables



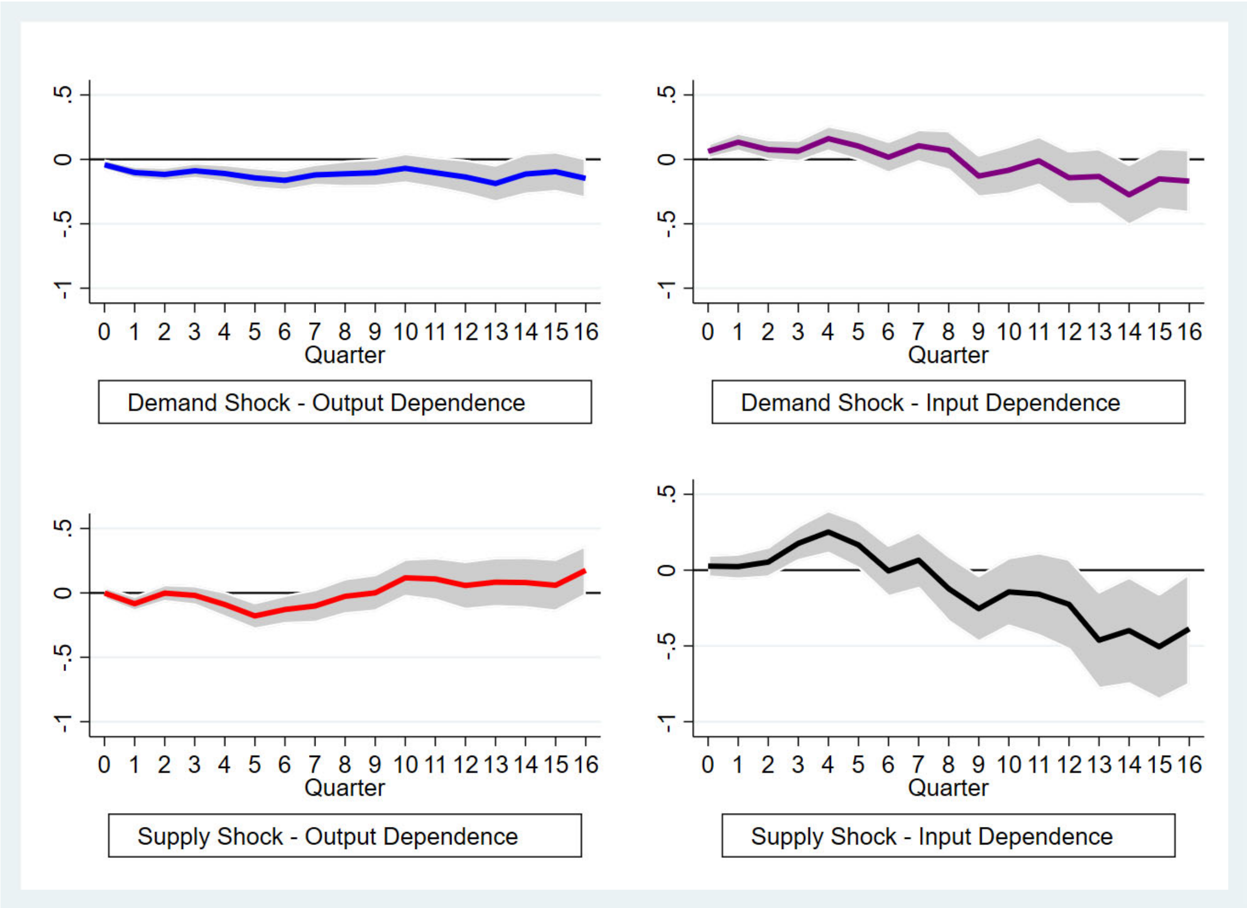
Notes: y-axis in percent. The results follow from the estimation of equation (8). The solid blue and purple lines indicate the average response of firm revenue to a 1 percent of GDP shock in China. Standard errors are two-way clustered on firms and country-time. The gray areas display the 90% confidence intervals.

Figure A4.9. Using simple median of the time-varying linkage coefficients



Notes: y-axis in percent. The results follow from the estimation of equation (10), except using the simple median of the time-varying linkage coefficients instead of the regression method described in the text. 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 clustered by firm. The gray areas display the 90% confidence intervals.

Figure A4.10. Including raw supply and demand shocks in every period



Notes: y-axis in percent. The results follow from the estimation of equation (10), except using e_t^D *and* e_t^S *instead of* e_t^{D*} *and* e_t^{S*} *as described in the text. 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 clustered by firm. The gray areas display the 90% confidence intervals.*

PUBLICATIONS

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