

Lodge, David; Manu, Ana-Simona; Van Robays, Ine

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China's footprint in global financial markets

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David Lodge, Ana-Simona Manu,
Ine Van Robays

China's footprint in global financial markets

No 2861

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Abstract

Using daily data since 2017, we disentangle China-specific structural shocks driving Chinese financial markets and examine spillovers across global markets. The novelty of this paper consists of simultaneously identifying China shocks with shocks emanating from the United States and shocks to global risk sentiment – two major forces driving global financial markets – to ensure that China spillover estimates do not reflect common factors. Our results show that shocks originating in China have material impacts on global equity markets, although spillovers are much smaller than those following shocks in the United States, or those triggered by shifts in global risk sentiment. By contrast, shocks from China account for a significant proportion of variation in global commodity prices, more on a par with those of the United States. Nevertheless, spillovers from China can be significantly amplified in an environment of heightened global volatility, or when the shocks are large.

Keywords: China shocks, spillovers, global financial markets, commodities.

JEL Codes: E44, E52, G15

Non-technical Summary

What happens to global financial markets when China catches a cold? That question has long been studied for other economies, like the United States (US), where it is well documented that developments in the US economy play a dominant role in shaping global financial markets ([Miranda-Agrippino and Rey, 2020](#)). Yet spillovers from China to global markets have received much less coverage. This paper helps to plug that gap.

This paper investigates how shocks in China’s financial markets ripple through global financial markets. This is not an easy task; global financial markets are driven by a multitude of shocks which interact at high frequency. US monetary policy shocks are known to steer the global financial cycle ([Rey, 2015](#)), while shifts in global risk sentiment are shown to be a major driver of safe haven flows between countries, affecting asset pricing around the globe ([Georgiadis et al., 2021b](#)). Changes in market sentiment that relate specifically to China’s outlook are only one of many possible drivers of financial market prices.

We propose an empirical framework that jointly decomposes daily movements in Chinese and US financial asset prices into underlying drivers in the spirit of [Brandt et al. \(2021\)](#), thereby aiming to better control for possible commonalities. After years of financial liberalisation, China’s financial markets appear sufficiently reflective of economic conditions to extract information from their co-movement to identify the underlying shocks driving assets price correlations. Once identified, we use the shocks to map out the spillovers from China to financial markets in the rest of the world and to commodities using local projections à la [Jordà \(2005\)](#), similar to the approach of [Lodge and Manu \(2022\)](#).

Our empirical evidence suggests that shocks emanating from China leave a footprint on global financial markets, but the impact is smaller than those of US or global risk shocks. Global equity prices respond significantly to Chinese macro risk shocks but the impact of shocks stemming from the US or global risk shocks can be up to three times as large. By contrast, shocks in China are associated with a much more modest effect

on global bond markets. That supports the finding of the previous literature that shocks in the US, and in global risk sentiment, are key factors shaping global financial markets (Rey, 2015; Georgiadis et al., 2021b). Yet we also find that shocks originating in China play a significantly more important role in global commodity markets, in some cases even more important than shocks originating in the US. That is consistent with the role played by China in the demand for global energy and non-energy commodities – China consumes a similar amount of energy goods as the US, but a significantly higher share of global non-energy commodities – as well as with the findings of other studies (Miranda-Agrippino et al., 2020). Finally, although we find that spillovers of China shocks to global financial markets are contained, they can be strongly reinforced when they hit in a time of heightened global volatility or when the shocks are large in size. So what happens when China gets a cold? Global financial markets would sneeze as well, but we should only start worrying when symptoms of the flu appear.

Going forward, the fact that China’s policy paradigm has shifted from a tightly controlled system towards a more market-based mechanism with ongoing efforts to allow market forces to play a greater role in the functioning of credit and foreign exchange rate markets, means that global financial markets are likely to continue to catch up with China’s role in the global economy. In this context, our paper also provides a solid framework for policy makers to monitor the evolving importance of Chinese structural shocks for global financial and commodities markets.

1 Introduction

What happens to global financial markets when China catches a cold? That question has long been studied for other economies, like the United States (US), where it is well documented that developments in the US economy play a dominant role in shaping global financial markets ([Miranda-Agrippino and Rey, 2020](#)). Yet spillovers from China to global markets have received much less coverage. This paper helps to plug that gap.

Anecdotal evidence suggests that it is a gap that needs to be filled. On several occasions financial market volatility in China has spilled outwards to global markets. For example, in 2021, a slowing macro economy and rising defaults by debt-saddled property firms, including the large firm Evergrande, sent jitters across global financial markets. Similar, in the summer of 2015 and again in early 2016, sudden policy shifts – on exchange rate policy and interest-rate setting – amid concerns about China’s growth prospects had even stronger ripple effects across global financial markets. Yet, anecdotes provide a partial picture at best. A systematic understanding of the importance for global financial market of shocks stemming from China is missing.

In years gone by, neglect of spillovers from China to other financial markets may have been understandable. Before the global financial crisis, relatively underdeveloped financial markets, a largely closed capital account regime and a tightly managed exchange rate suggested limited scope for meaningful financial market spillovers from China. However, the Chinese economy has evolved rapidly since then. The policy paradigm shifted from a tightly controlled system towards one in which, according to authorities, markets should play a “decisive role” in allocating resources ([FT, 2013](#)). Monetary policy has moved from heavy reliance on quantitative targets towards using market-interest rates to steer the economy ([IMF, 2017](#); [Sun, 2015](#)). The Renminbi, although still managed, has become considerably more flexible ([McCauley and Shu, 2018](#)). Gradual capital account liberalization has greatly increased financial flows to and from China ([Lardy and Huang, 2020](#)). Moreover, China’s footprint in the global economy has grown significantly. China accounted for one-third of global GDP growth in the last decade ([Dieppe et al.,](#)

2018). It has assumed a systemic position in global trade networks and commodity markets, suggesting that shocks originating in China could entail spillovers to global asset markets.

This paper investigates how shocks in China's financial markets ripple through global markets. This is not an easy task: global financial markets are driven by a multitude of shocks which interact at high frequency. US monetary policy shocks are known to steer the global financial cycle (Rey, 2015), while shifts in global risk sentiment are shown to be a major driver of safe haven flows between countries, affecting asset pricing around the globe (Georgiadis et al., 2021b). Understanding the impact of shocks in China requires careful identification of the various drivers of global financial market sentiment. The onset of the COVID-19 pandemic, is a good example, reflecting a period when the macro outlook in China worsened quickly but also global risk sentiment plummeted and central banks resorted to unprecedented stimulus. To isolate China's role in global markets, the challenge is to purge market developments in China of key global shocks. Earlier studies have mostly analysed Chinese spillovers by examining correlations between asset prices or using event studies (N'Diaye et al., 2016), leaving room for other major forces to affect spillover estimates.

Instead, we propose an empirical framework that jointly decomposes daily movements in Chinese and US financial asset prices into underlying drivers in the spirit of Brandt et al. (2021), thereby aiming to better control for possible commonalities. Financial market data has been extensively used to extract information about the underlying drivers of markets in advanced economies such as the US (e.g. Chițu et al., 2023), but we are amongst the first to take this financial market approach to identify structural shocks in China and understand their transmission to global financial markets. By now, China-specific variables appear sufficiently reflective of market conditions to extract information from their co-movement to identify what is driving these assets. Once we have the identified shocks, we use these to map out the global spillovers from China to financial markets in the rest of the world and to commodities using local projections à la Jordà (2005), similar to the approach of Lodge and Manu (2022). The novelty of our approach, in which

we identify shocks stemming from both China and the US, also allows us to compare the relative importance of spillovers from the two countries. We also investigate whether China shocks spillovers are dependent on the state of volatility in financial markets or when shocks are particularly large.

Our work contributes to the existing literature in four ways. First, it jointly identifies a set of economically meaningful shocks that shape Chinese and US financial markets, by exploiting the cross-asset correlations in daily financial data. By doing this we are able to capture broad drivers of those financial markets rather than focus on single shocks (e.g. often US monetary policy shocks), while also purging shocks from possible common factors. Second, the paper quantifies the importance of shocks in China for changes in financial conditions in other countries. Those spillover effects are related to economically meaningful shocks rather than simply measures of connectedness, provided by a Diebold-Yilmaz type exercise in [N'Diaye et al. \(2016\)](#) for example. Third, it provides a comparison of those shocks with spillovers from the US, on which the literature is more established. Finally, we provide evidence that the spillovers from China shocks are non-linear, with responses to China's shocks amplified during periods of fragile global risk sentiment or following large China shocks.

Our empirical evidence suggests that shocks emanating from China have an effect on global financial markets, but the impact is smaller than that of US or global risk shocks. Global equity prices respond significantly to Chinese macro risk shocks but the impact of shocks stemming from the US or global risk shocks can be up to three times as large. By contrast, shocks in China are associated with a much more modest effect on global bond markets. That supports the finding of the previous literature that shocks in the US, and in global risk sentiment, are key factors shaping global financial markets ([Rey, 2015](#); [Georgiadis et al., 2021b](#)).

Yet we also find that shocks originating in China play a significantly more important role in shaping developments in global commodity markets, in some cases even larger than shocks originating in the US. That is consistent with the important role played by China in the demand for global energy and non-energy commodities – China consumes a

similar amount of energy goods as the US, but a significantly higher share of global non-energy commodities – as well as with the findings of other studies ([Miranda-Agrippino et al., 2020](#)).

The remainder of this paper is organized as follows. Section 2 discusses links to the existing literature. Section 3 presents the US-China BVAR model with financial data and discusses the identification of structural shocks. Section 4 describes the methodology for quantifying spillover to international financial markets and results. Section 5 shows a series of robustness tests while Section 6 concludes.

2 Connection with previous literature

Our paper links with two strands of the literature. First, it contributes to previous empirical work assessing spillovers from China through financial markets. [N’Diaye et al. \(2016\)](#) studied the issue with various empirical approaches: a [Diebold and Yilmaz \(2014\)](#) analysis of the interdependence of asset returns and volatility, an event study analysis, and a standard vector autoregression framework. They find that any spillovers in financial prices primarily reflect the central role China plays in goods trade and commodity markets, rather than China’s financial integration in global markets. [Fang et al. \(2021\)](#) also use the Diebold-Yilmaz approach to study spillovers and spillbacks from China to G7 economies. They find a growing role for China in financial markets, but that the magnitude of the G7 spillovers to the China remains larger than spillovers in the other direction. [Arslanalp et al. \(2016\)](#) look at how stock market returns in Asia are linked to developments in China’s equity market, finding that the role of China has increased since the global financial crisis. Compared to these studies, we focus on jointly identifying shocks in China and the US, as well as global risk shocks, to ensure that our spillover estimates are filtered from common factors.

Other papers assess spillovers from China using larger macro models. [Beirne et al. \(2021\)](#) estimate a monthly structural panel VAR model and identifying monetary policy shocks in the US and China to understand the spillovers to Asian economies. They

find that emerging Asian economies' financial markets are affected by shocks emanating from China's monetary policy. [Dieppe et al. \(2018\)](#) use various macro models to assess spillovers and present sensitivity analysis that underscores how spillovers are dependent on the strengths of the various transmission channels, as well as the policy reaction by central banks. [Miranda-Agrippino et al. \(2020\)](#) study the international transmission of the monetary policy of China and the US, using large macro BVARs. They find that while both the monetary policies of the US and China have a sizeable impact on the global economy, the channels of transmissions differ: US shocks propagate predominantly through financial markets, whereas Chinese monetary policy mainly transmits worldwide through international trade, commodity prices and global value chains. We differ from these studies by modelling spillovers at a higher frequency, as our aim is to better understand what shapes global financial markets on a daily basis.

Second, our paper links to the strand of literature that aims to provide a high-frequency assessment of the drivers of financial conditions. The “gold standard” for identifying US monetary policy shocks is to use the high-frequency surprises in market data in a tight window around central bank announcements ([Jarociński and Karadi, 2020](#)). For China, that approach is hard to emulate. As [Kamber and Mohanty \(2018\)](#) note, the People's Bank of China has not, in the past, followed a pre-announced schedule for announcements. Several important decisions have been announced after markets closed on weekdays or during weekends. For that reason, we instead lean more towards the literature that has exploited daily cross-asset price correlations based on sign restrictions to understand the underlying drivers of financial asset price movements, such as [Matheson and Stavrev \(2014\)](#), [Brandt et al. \(2021\)](#) and [Chițu et al. \(2023\)](#). This continuous approach may have advantages. As [Bianchi et al. \(2022\)](#) argue, the high-frequency approach, by design, captures only the effects of the surprise component of an announcement which “at best ... represents a lower bound on the overall causal impact of monetary policy on markets”. It seems plausible that shifting expectations about monetary policy outside of the narrow window around Fed communications have notable effects on global markets. Moreover, for other shocks such as macro or risk shocks, it is

not as straightforward to identify clear “announcement” windows. Such shocks are often a result of investors continuously adjusting their views about the outlook. Our approach, which models daily developments in financial asset prices, has the advantage of tracking this process of continual adjustment in investor views.

3 A US-China BVAR model with financial data

To analyse the importance of China shocks for global financial markets, we proceed in two stages. First, we develop a Bayesian VAR model (BVAR) on daily data to identify China, US and global risk shocks using financial market data. Second, we use local projections to understand the impact of those shocks across markets in advanced and emerging economies.

3.1 BVAR model estimation and identification

We use a structural BVAR to disentangle the drivers of movements in US and Chinese financial markets, the reduced form of which can be expressed as follows:

$$Y_t = c + \sum_{l=1}^L A_l Y_{t-l} + B \varepsilon_t, \quad (3.1)$$

with vector Y_t containing the endogenous variables and c the intercepts, A_l a matrix of lagged coefficients and B a matrix that rotates the reduced form residuals into structural shocks ε_t . The vector Y_t includes six variables: yields on 1- and 10-year government Chinese bonds, China and US equity price indices, the spread between yields on Chinese and US 10-year government bonds and the bilateral exchange rate of the Renminbi against the US dollar, see Table 1.

As our shock identification rests on daily cross-asset co-movements in the US and China (as explained below), it is important to consider timing; we need to ensure that the reaction of market participants to Chinese and US shocks can be reflected in both the China and US-specific variables on the same day. We therefore use variables that

Table 1: Data description

Variable	Description	Source & Transformation
China short-term interest rate	Interest rate swap (1 year)	Bloomberg; difference
China long-term interest rate	China Government Bond Yield (10-year)	Bloomberg; difference
China equities	Shanghai ETF	Bloomberg; log difference
US equities	S&PF 500 Index	Bloomberg; log difference
China-US yield spread	Government Bond Yield (10-year) Spread between China and US	Bloomberg; difference
Renminbi-dollar exchange rate	China Renminbi Offshore Spot Currency	Bloomberg; log difference

trade round-the-clock; for Chinese equity prices we use the Shanghai ETF that aims to replicate the return in the Shanghai composite index, while for the bilateral exchange rate we rely on the offshore quotation for the Renminbi against the dollar.

The model is estimated on daily data from January 2017 to March 2023 at daily frequency, including 2 lags of the endogenous variables. The variables are specified in first (log) differences as specified in Table 1. For estimation and inference, we follow [Arias et al. \(2014\)](#) in using Bayesian techniques for identification of the structural shocks based on sign and magnitude restrictions, implemented through the BEAR toolbox by [Dieppe et al. \(2016\)](#), and assuming a normal-inverse-Wishart prior over the reduced form parameters. Narrative identification is imposed in line with [Antolín-Díaz and Rubio-Ramírez \(2018\)](#). The estimates are based on the median over 10.000 draws that satisfy the imposed restrictions.

Table 2: Identification assumptions – sign restrictions

Variable	Identified shock				
	China Monetary	China macro risk	US Monetary	US macro risk	Global risk
China short-term interest rate	–	+			
China long-term interest rate	–	+	–	+	
China equities	+	+(*)			
US equities			+(*)	+	+
China-US yield spread	–	+	+	–	–
Renminbi-dollar exchange rate	+	–	–	+	–

Note: A * denotes that additional magnitude and/or narrative restrictions are imposed. Signs denote favourable macro/global risk shocks and accommodative monetary shocks — i.e. all the shocks would boost global equity prices. A “+” for the Renminbi-dollar exchange rate denotes an depreciation of the Renminbi against the US dollar.

The identification scheme rests on using sign restrictions and has three broad building blocks. First, for both China and the US, we separate ‘monetary shocks’ from ‘macro risk shocks’ based on the reaction of domestic bond yields and equities.¹ Accommodative

¹The model does not include US bond yields directly. However, the assumptions about the relative

monetary shocks are assumed to lower government bond yields and boost equities, while favorable macro risk shocks outlook are assumed to raise yields and equities.² Second, we separate Chinese from US shocks based on assumptions about spillovers across these two economies. Consistent with the global financial cycle literature, we assume that US shocks have spillovers to China's bond markets. We also assume that shocks in both countries have a larger impact on domestic than foreign yields which is imposed via the yield spread; an accommodative US monetary policy shock, for example, will lower bond yields in the US and China, but more so in the US such that the spread between Chinese and US yields widens.³ Third, we exploit the safe-haven role of the US dollar to identify a global risk shock. Similar to [Brandt et al. \(2021\)](#), we assume that as risk sentiment improves, investors move away from safe assets such as US government bonds, which increases US yields and narrows the spread with Chinese yields (as US yields respond more to global risk shocks given the safe haven status of US assets). However, in contrast to other shocks where a narrowing yield differential would cause the US dollar to appreciate against the Renminbi, safe-haven flows out of US assets triggered by favourable risk sentiment are assumed to push the US dollar lower, in line with the literature (e.g. [Georgiadis et al., 2021a](#)).

We further strengthen the identification with magnitude and narrative restrictions.⁴ First, we employ relative magnitude restrictions to ensure domestic financial markets react most strongly to the domestic structural shocks; a monetary policy shock in China

movements of Chinese and US long-term government bond yields (captured by the spread between Chinese and US government bond yields) still allows us to identify US macro and monetary shocks, and we can use the responses of Chinese long-term yields and the China-US yield spread to proxy the response of US yields.

²Our framework relies on market interest rate to capture monetary policy shifts that are implemented via non-interest rate instruments in China. For example, since 2018 there were 18 instances in which Reserve Requirement Ratio (RRR) was reduced. In eighth of those days, China equity prices have increased. suggesting there was a standard monetary shock at play. Using the IRS rate we capture most, but not all of these shocks – the IRS rate declined on the day of the RRR cut in more than half of the instance in which RRR rate was reduced. However, we do believe that what matter most is how markets digest these policy actions, while the approach provides a consistent mapping of monetary shocks disregarding the policy instrument used.

³This logic follows the approach of [Brandt et al. \(2021\)](#) in separating shocks originating in United States and the euro area.

⁴These restrictions are not needed to uniquely identify the shocks but might help in better pinning down the (origin of the) shocks. The identified structural shocks of the model version without these restrictions are however highly correlated with those of the benchmark version.

is assumed to affect Chinese yields more strongly than a US monetary policy shock. Second, we use narrative restrictions to help tie key shocks to specific events. We assume that the Wuhan lockdown in China imposed on 23 January 2020 to contain the initial spread of COVID-19 represented an adverse shock to China macro risk sentiment, which on that day was the largest driver of the drop in Chinese equity prices. In addition, the day following the September 2021 FOMC meeting, when the Federal Reserve anticipated scaling back asset purchases after months of exceptional stimulus, is assumed to be a tightening US monetary policy shock that was the largest negative contributor to US equity prices on that day.

As we identify shocks on a daily basis using cross-asset price co-movements (rather than intra-day identification windows), it is important to underline that our approach means that each shock is likely capture a variety of factors. “US and China monetary policy” shocks include not only the explicit effects of monetary policy decisions or communication, but potentially also shifts in market expectations before and after announcements. They may also capture exogenous shocks to the term premium, inflation surprises and unanticipated changes in inflation expectations which cause expectations about the monetary policy stance to shift. Likewise, “US and China macro risk” shocks will capture a variety of influences, potentially adjustments to recent data or factors shifting the more distant outlook, while they do not distinguish between supply or demand-driven forces. China macro risk shocks can at specific times also be inflicted by unorthodox monetary policy actions such as when the PBoC guides banks to adjust the pace of lending and credit allocation.⁵ For ease of reference throughout the paper, we will apply shortened labels (i.e. “China macro risk”, “China monetary policy”, “US monetary policy”, “US macro risk” and “global risk shocks”), while acknowledging the that our identification scheme implies that each shock captures a variety of factors.

⁵That is, one element of China’s monetary policy is “window guidance” – which relies on the moral suasion to guide banks to adjust the pace of lending and credit allocation across sectors and regions in line with policy objectives. Should such a policy tool loosen lending standards (reflected also in a lowering of market interest rates) and lead to a decline in equities, for example because markets perceived such measures as reflecting a worsening of capital allocation across sectors with negative consequences on growth, that shock would be incorporated in our macro risk shock.

3.2 China-specific assumptions

While the identification assumptions are rather standard for US and global risk shocks, those for the shocks originating China might be less straightforward. Over the past decade, market forces have gained importance in determining interest rates and the exchange rate in China – although certain aspects of these mechanisms continued to be managed. As our identification strategy hinges on the assumption that the financial variables in China are sufficiently reflective of market forces, some justification of the choices for China-related variables is required.

China’s short-term interest rates: the choice of interest rates for China is motivated by the recent literature on the development of China’s monetary policy ([Gang, 2021](#)). In the past, ascertaining monetary policy shocks in China was complicated because the People’s Bank of China (PBoC) used multiple instruments, including reserve requirements and implicit credit quotas, to conduct monetary policy. Yet, as China’s financial system has liberalised, the literature suggests that financing has become more market-based ([Koivu, 2009](#); [He and Wang, 2011](#); [Sun, 2015](#)). Several studies have argued that monetary policy transmission in China was not too different from advanced economies ([Fernald et al., 2014](#); [IMF, 2017](#)). By 2017, the IMF judged that the 7-day interbank rate provided a good ‘shadow’ measure of Chinese monetary policy ([IMF, 2017](#)). That is also consistent with the PBoC’s communication that it uses short-term interest rates to signal policy changes principally through the 7-day repo rate ([PBOC \(2016\)](#); [Gang \(2021\)](#)). [Kamber and Mohanty \(2018\)](#) also use movements in one-year interest rate swap (IRS) contracts based on the interbank 7-day repo rate to measure market expectations of monetary policy, arguing that this is also the most liquid among all types of IRS contracts. We follow that choice, in selecting the short-term interest rate in our model.

China’s long-term interest rates: the motivation for using China’s government bond yields to identify shocks rests on the increasing depth and liquidity in the market. Having liberalised its bond markets in recent decades, China’s government bond market overtook Japan to become the second largest market in the world, with increased foreign

investor participation, now at 9 percent (Lardy and Huang, 2020). Indeed, Governor Yi Gang has argued that “a complete system of market-based interest rates has been formed, and the yield curve has come close to a mature pattern” as a means for transmitting monetary policy (Gang, 2021). Others have shown that monetary policy surprises, for example, move the whole term structure of yields (Kamber and Mohanty, 2018; Jones and Bowman, 2019). That suggests that longer-term government bond yields will also provide important information about China’s macro and policy developments.

China’s exchange rate: the use of the exchange rate in the identification scheme is justified by the significant increase in the flexibility of the Renminbi exchange rate that occurred prior to our sample period. IMF (2022) judged that China officially maintains a de jure managed floating exchange rate arrangement but the de facto the regime is classified as “other managed”. Yet, the evidence suggests an increasing role for market forces in driving the Renminbi exchange rate as China has taken steps towards a more flexible currency (Das, 2019). The major shift came in August 2015 when the PBoC changed the RMB/USD central parity quoting mechanism in an effort to enhance the role of market forces in determining the exchange rate. Alongside wider bands permitting greater intra-day volatility, the central parity daily exchange rate fix would make reference to the previous day close and a currency basket. Since 2015, there has been greater variation in the Renminbi exchange rate: the standard deviations of daily fluctuations of the RMB/USD rate since 2015 was three times larger than in the period before (see Appendix A for a detailed discussion on the flexibility of the Renminbi).

Overall, it appears that over our sample period starting in 2017, interest rates and exchange rates might sufficiently reflect market forces to use their variation to identify China-specific shocks.

3.3 Model validation: China-specific shocks and key events

To validate our model results we examine whether the identified China macro risk and monetary policy match with key macro news events and PBoC monetary policy decisions. Starting with the China macro risk shocks, the results in Table 3 confirm that on days

when important announcements were made about China’s macroeconomic outlook – both positive and negative ones – the model identifies China macro risk shocks that are larger than average. After the US-China trade war began in mid-2018, for example, markets repeatedly downgraded their view on China’s economic outlook due to escalating trade tensions, which are identified as China macro risk shocks in our model. Events related to the outbreak of the COVID-19 pandemic are also captured as shifts to macro risk sentiment, such as the denial of entry for foreign nationals who traveled to China imposed by the US administration, or the re-opening of Wuhan after a 76-day lockdown.

Table 3: China macro risk shocks and key events

Day	Event description	Shock magnitude relative to the average shock
06/07/2018	US-China trade war begins	1.1
10/05/2019	US hikes tariffs on US\$200 bil. Chinese imports	1.7
05/08/2019	US designates China as a “currency manipulator”	2.6
23/08/2019	China retaliates and hikes tariffs on US\$75 bill US imports	0.4
31/01/2020	US denies entry to foreign nationals who recently traveled in China	0.7
07/04/2020	China reopens Wuhan after a 76-day lockdown	3.0
24/07/2020	Worries about new Chinese regulation	3.9
10/11/2022	CN steps toward opening-up from zero-Covid (“20 measures”)	3.2
30/11/2022	CN official “Omicron variant is less virulent/rectification of control methods”	2.3
06/12/2022	CN officials unveiled new “10 measures” to loosen Covid policies	2.1
	Average	2.1

Also the monetary policy shocks in China are found to correspond well with PBoC announcements, either in the form of providing more liquidity to the markets or by reducing rates to combat the effects of the pandemic. Table 4 shows that in most instances when the PBoC loosened monetary policy, the model identifies larger China monetary policy shocks. Moreover, our model decomposition shows that changes in the interest rate are often explained by both monetary policy and macro risk shocks which is in line with the literature that claims that changes in policy levers can be driven by purely unanticipated shifts in monetary policy or by central bank information shocks (captured by macro risk in our case). Overall, the good correspondence between the identified shocks and important events in China over our sample confirms that our model is able to capture China-specific dynamics.

Table 4: China monetary shocks and key events

Day	Event description - monetary policy change -	Shock magnitude relative to the average shock
20/08/2019	-0.1pp reference rate cut	0.7
20/09/2019	-0.05pp reference rate cut	0.7
20/11/2019	-0.05pp reference rate cut	0.3
20/02/2020	-0.1pp reference rate cut	1.3
20/04/2020	-0.2pp reference rate cut	0.3
01/01/2018	-1.6pp RRR cut	0.0
22/01/2018	-0.3pp RRR cut	1.7
25/04/2018	-1pp RRR cut	1.9
05/07/2018	-0.5pp RRR cut	1
15/10/2018	-0.9pp RRR cut	1.6
15/01/2019	-0.5pp RRR cut	1.5
25/01/2019	-0.5pp RRR cut	0.9
15/05/2019	-0.1pp RRR cut	0.9
17/06/2019	-0.1pp RRR cut	1.8
15/07/2019	-0.1pp RRR cut	1.2
16/09/2019	-0.5pp RRR cut	0.7
06/01/2020	-0.5pp RRR cut	0.7
16/03/2020	-0.4pp RRR cut	5.8
03/04/2020	-0.1pp RRR cut	4.1
15/07/2021	-0.5pp RRR cut	0.4
Average		1.4

3.4 Model validation: historical decomposition

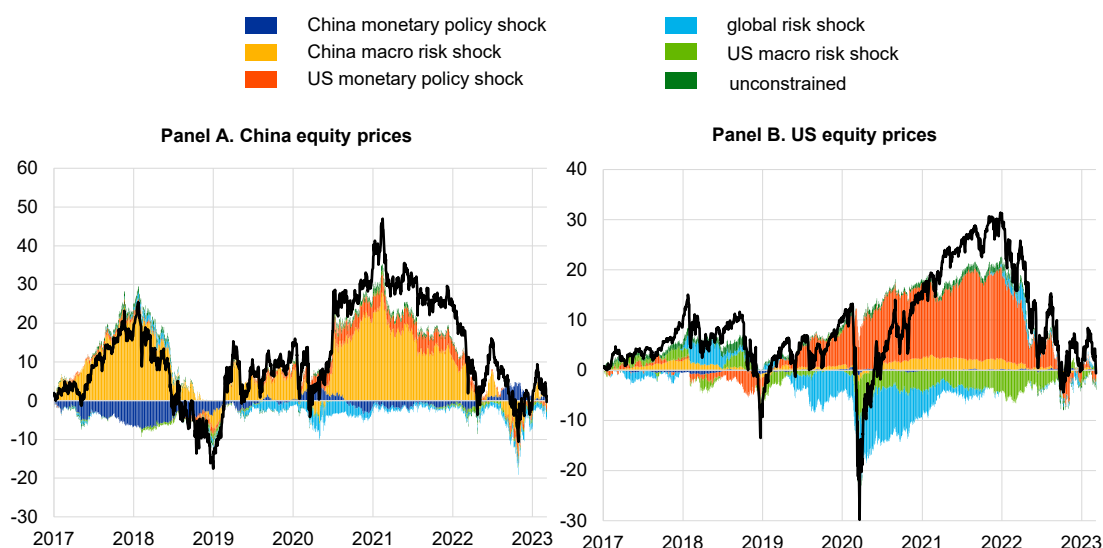
Another way of assessing model performance is to analyse whether – over time – the model is able to link shifts in financial variables to key happenings in an intuitive way. [Figure 1](#) provides the historical decomposition of equity price movements in China and US since 2017 as an example of how the model captures observed developments; an overview of the other variables is given in [Appendix B](#).

Starting with China, most of the historical changes in equity prices are accounted for by China macro risk shocks (see Panel A). During 2017, equity prices reflected offsetting effects of the market’s rising optimism about the improving Chinese macroeconomic outlook and the gradual tightening of monetary policy. However, this growth optimism receded in early 2018 with the onset of the China-US trade war, which pulled equity prices lower. Global risk shocks came into play after the outbreak of the COVID-19 pandemic as markets started to digest the potential fallout for the global economy at a time characterised by high uncertainty and, in the early phases of the pandemic, heightened risk aversion. In early 2020, markets also started pricing in a deterioration in the macroeconomic outlook in China – it being the first economy to be hit by the pandemic. Initially, adverse macro risk shocks suppressed equities but they rebounded quickly after the fast reopening of the Chinese economy and the deployment of substantial fiscal policy

support. Heightened global risk aversion weighed more persistently on the equity market in China during 2020 as the virus spread around the globe, before gradually fading in the course of 2021 in line with increased global control over the virus.

Interestingly, during the pandemic years, shifts in US monetary policy also played a role for equity price developments in China. Unprecedented monetary policy stimulus of the Federal Reserve in response to the pandemic is found to have supported equity prices in China, offsetting part of the drag imposed by a relatively tight monetary policy stance at home. Yet it is clear that, overall, Chinese equity prices are mostly determined by changes in the perceptions of the Chinese economic outlook as captured by the macro risk shocks.

Figure 1: Historical decomposition of equity prices



Note: Cumulative changes in variables since 2017. The historical decomposition shows the contribution of structural shocks to China and US equity prices. The median shocks from the posterior distribution is used, which means that the sum of shock contribution can depart from actual changes in the explained variable if the posterior distributions is skewed.

For the US, by contrast, Chinese shocks are found to not matter much, as shown in Panel B. US equity prices are dominated by US-specific shocks and global risks shocks, given the important role of the US economy in providing safe assets for the global economy in line with [Brandt et al. \(2021\)](#). Only during the onset of the pandemic, negative macro risk shocks in China trickled through minimally to weigh on US equity prices, but were overshadowed by markets reassessing the US growth outlook at the same time. After

that, the exceptional monetary policy stimulus of the Federal Reserve in response to the pandemic – and its withdrawal in late 2021 – drove US equity markets, together with shifts in global risk sentiment.

4 China’s footprint on global financial markets

4.1 Local projections setup

Having a set of identified structural shocks, we next assess how these shocks spill over to global financial and commodity markets. For this, we use the local projection method developed by Jordà (2005) in a panel setup to estimate the impact of each structural shock on a set of financial variables that link to financing conditions (equity prices, short- and long- term yields, and the exchange rate in effective terms and against the US dollar), and this in a sample of 30 advanced and emerging market economies.⁶ This approach for retrieving impulse response functions imposes fewer restrictions compared with a standard VAR approach and is more robust to misspecification. Equation 1 shows the specification:

$$\Delta Y_{i,t+h/t-1} = \alpha_{ih} + \beta_h * \varepsilon_t^s + \sum_{j=1}^3 \rho_{jh} \Delta Y_{i,t-j/t-j-1} + Controls + \epsilon_{i,t+h} \quad (1)$$

Our dependent variable $\Delta Y_{i,t+h,t-1}$ refers to the change between period t+h and t-1 in country i, ε_t^s stands for the structural shock, while the regression controls for country-fixed effects α_{ih} , lags of the dependent variable, and a series of controls (the CBOE Volatility Index (VIX) and the US and Global Citigroup Economic Surprise Index).⁷ To estimate the impact of structural shocks on commodity markets we use a similar specification, but in a time-series context rather than a panel setup, where the dependent variables refer

⁶The sample includes the following advanced economies: Australia, Canada, France, Germany, Italy, Japan, New Zealand, Norway, Spain, Sweden, Switzerland, United Kingdom. It includes the following Emerging Market Economies: Brazil, Chile, Colombia, Czech Republic, Hungary, India, Indonesia, Korea, Mexico, Malaysia, Peru, Philippines, Russia, South Africa, Thailand, Turkey, and Taiwan.

⁷Although other domestic variables could be added as controls, the local projection method provides unbiased estimates as long as the shocks are exogenous to the variables of interest (Ramey, 2016) which is the case in our estimation because it uses global shocks to assess the impact on small-open economies’ financial variables.

to oil and metal prices.

To compute the impulse response functions 20 periods ahead, we run regression (1) with h taking values from 1 to 20 and stack all β_h in an impulse response vector. Except for horizon $h = 0$, the error term is likely to be serially correlated because it is a moving average of the forecast errors from t to $t+h$. In a time series context, the standard errors need to incorporate corrections for serial correlation, such as a [Newey and West \(1987\)](#). In the panel approach, the errors may also be subject to cross-sectional dependency, thus we use [Driscoll and Kraay \(1998\)](#) corrected standard errors.⁸

To assess the importance of each of the identified shocks for financial conditions in other countries we compute the cumulative forecast error variance decomposition at horizon h . Its calculation is analogous to the computations following a VAR estimation which requires the coefficients of the structural moving average representation of the VAR model (see e.g. [Lutkepohl and Netsunajev, 2012](#)), which are provided by the local projection estimation. We follow the R-Squared estimator proposed by [Gorodnichenko and Lee \(2020\)](#) in a panel context (see also [Lodge and Manu, 2022](#)).

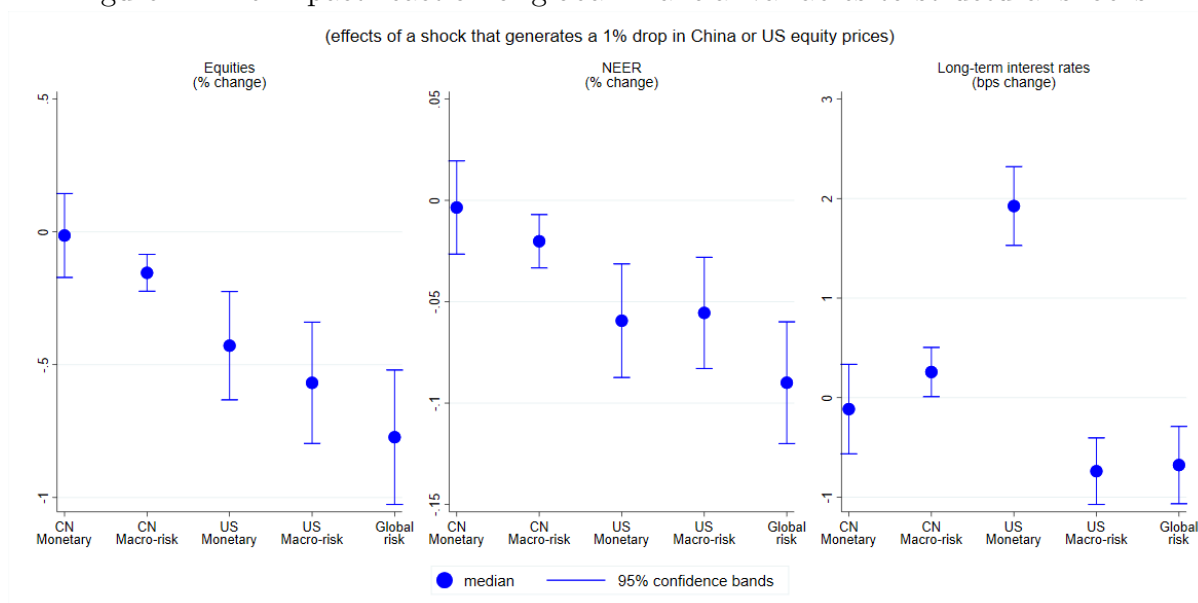
4.2 Spillovers to financial markets and commodities

[Figure 2](#) shows the impact responses of global financial market variables to the identified structural shocks; the full impulse response functions are shown in [Appendix C](#). To aid comparability, the shocks originating in China are scaled to represent a 1% drop in the Chinese stock market on impact, and the US shocks and global risk shock are re-based to generate a 1% impact drop in the US stock market.

For global equity markets, we find that China macro risk shocks matter, but much less than US shocks or global risks shocks. While global equity prices do not move when the PBoC unexpectedly changes its policy stance, significant declines are found following China macro risk shocks. This implies that a re-assessment of markets of the growth outlook in China, for example, reverberates to equity prices elsewhere. Nevertheless,

⁸[Herbst and Johannsen \(2020\)](#) flag the potential bias in local projections estimates for panel data in the presence of a lagged dependent variable and country fixed effects for short samples, but our estimation circumvents the criticism by using a daily frequency sample with a long time dimension.

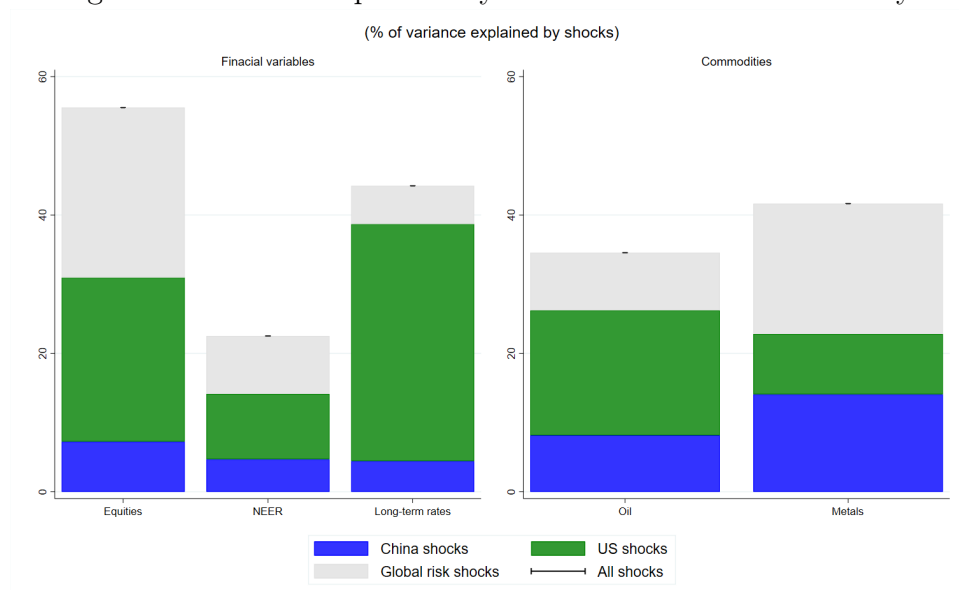
Figure 2: The impact reaction of global financial variables to structural shocks



Notes: The charts show the impact (on the same day) response of global financial market variables to structural shocks. The responses are scaled to represent the impact to China shocks (US and global shocks) that would generate a 1% drop in the China (US) equity prices. The range refers to the 95 percent confidence intervals based on Driscoll-Kraay corrected standard errors. An increase in the nominal effective exchange rate (NEER) and bilateral exchange rate against the US dollar (USD) denotes an appreciation of the currency.

the impact of US shocks (either macro risk or monetary policy shocks) or global risk shocks can easily be three to four times as large. The relatively smaller importance of shocks originating in China for global equity prices is also supported by a forecast error variance decomposition exercise which assigns only a small proportion of cross-country equity variation to China-specific shocks, see Figure 3 (left panel).

Figure 3: Variance explained by structural shocks after 20 days



For other financial market variables, spillovers from China’s macro risk shocks are significant but generally more modest when compared to equity prices. Following unfavourable macro risk shocks in China, bond yields of other countries increase while their exchange rates depreciate modestly in effective terms, see [Figure 2](#) (center and right panel). This is likely as the prospect of a more dire macro outlook in China weighs on the growth outlook of other countries, too. The forecast error variance decomposition confirms that a smaller proportion of cross-country yield and exchange rate variation reflects shocks originating in China ([Figure 3](#), left panel).

These findings contrast with a strong reaction of global yields and exchange rates to US and global risks shocks. A monetary tightening in the US is found to lift yields globally, and also global risk shocks are associated with significant bond yield spillovers. Effective exchange rates are importantly affected by global risk aversion. This is likely as safe haven flows drive a large proportion of variation in the US dollar, given the safe haven status of US dollar-denominated assets.

4.3 Isolating spillovers from China

Overall, our results are consistent with the literature illustrating that US shocks and shifts in global risk sentiment are the preeminent factors shaping global financial markets (see [Rey, 2015](#); [Georgiadis et al., 2021b](#)). In comparison, Chinese shocks matter much less. Indeed, we generally find weaker spillovers than previous studies such as [N’Diaye et al. \(2016\)](#).

Our conjecture is that the size of measured spillovers from China depends on how we clean for global shocks and other drivers. If we fail to account properly for the role of other shocks – such as global risk shocks – in shaping financial market developments in China, we could wrongly attribute spillovers to China. To properly pin down the magnitude of such spillovers, it is crucial to isolate the impact of other key global shocks; failure to do so, might result in a substantial bias. It is therefore worth illustrating the benefits of our approach which identifies China-specific shocks together with other key shocks shaping global financial markets.

To do this, we benchmark our findings on the response of global equities to China macro risk shocks to other simpler BVARs that do not separately identify US and global risk shocks within the same framework. We set up three additional BVARs: one that starts from our benchmark model but identifies only structural shocks in China and leaves the response of exchange rate to China-specific shocks unconstrained⁹, and a second and a third alternative specification which solely includes Chinese variables to identify the Chinese shocks (based on the same sign restrictions as in the benchmark model), and this with or without constraining the response to the exchange rate. [Appendix D](#) provides an overview of the identification schemes.

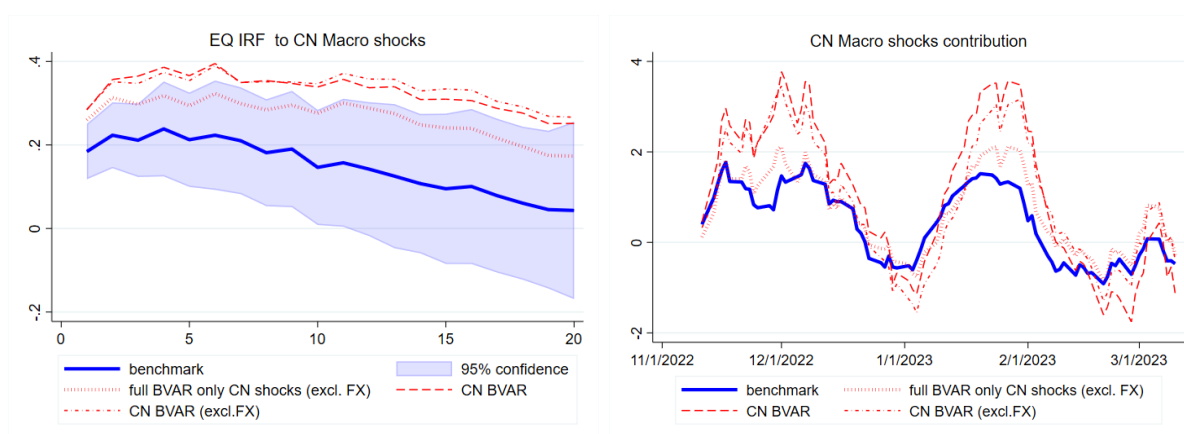
The left panel of [Figure 4](#) shows the response of global equity prices to China macro risk shocks under these alternative identification schemes for the BVAR. Results show that when China-specific structural shocks are identified from simpler models that do not properly clean for US and global risk shocks, spillovers from China are substantially stronger. Failing to account properly for global factors in China’s financial markets could therefore lead to the overestimation of China’s footprint in global markets. The right panel of [Figure 4](#) illustrates that point by showing the estimated contributions of China macro risk shocks to global equity prices for the different models around the time of China’s reopening after the COVID pandemic lockdown. All models find that during this re-opening period, a series of positive economic news shocks in China supported equities worldwide as optimism about global economic prospects grew. Yet not filtering out the influence of US and global risk shocks could have suggested that that China-specific structural shocks might have been twice as important.

4.4 China’s impact on commodity markets

Although we find moderate financial market spillovers, our results find that China does have a marked effect on commodity markets. [Figure 5](#) shows that adverse China macro risk shocks cause a significant decline in both oil and metal prices. A China macro

⁹The reasoning behind this is that the exchange rate might be particularly informative about the origin of the shock, given that we use the bilateral exchange rate against the US dollar and the latter responds strongly to both US shocks as well as shocks to global risk.

Figure 4: The importance of filtering out US and global shocks



Notes: the left panel shows the effect of China macro risk shocks identified in the benchmark model versus alternative specifications on global equity prices; the right panel displays the variation in the estimated median historical contribution to global equity prices around China’s reopening after the COVID-19 lockdown.

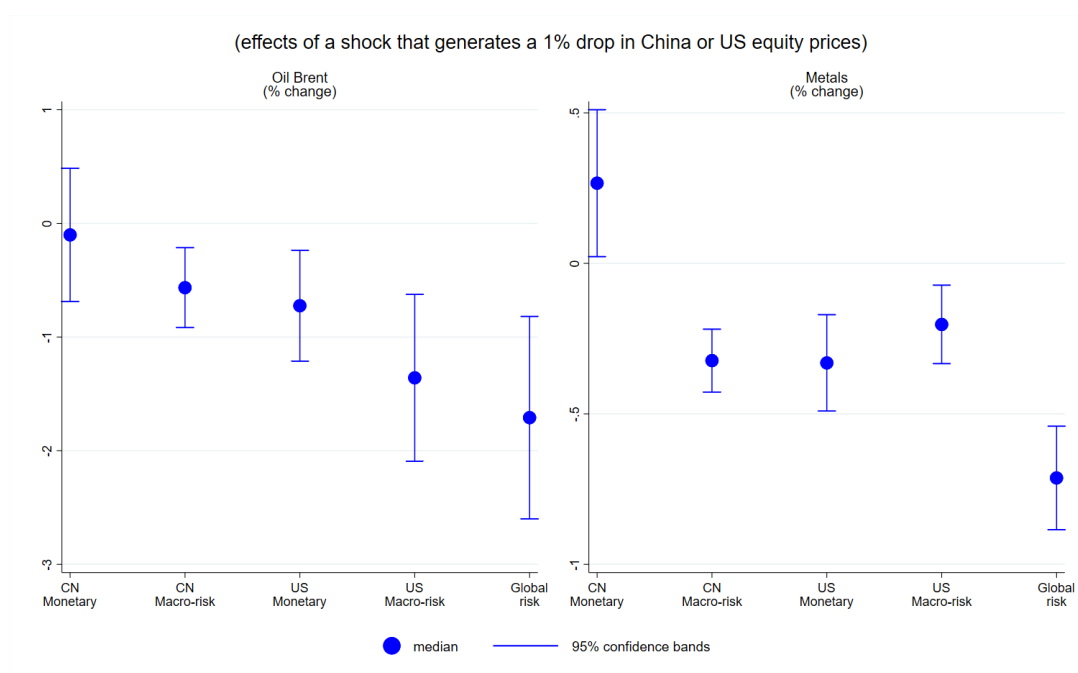
risk shock that lowers China’s equity prices by 1% translates into a decline of oil and metal prices by around 0.5%. For some commodities, particularly metals, the impact is larger than that of macro risk shocks originating in the US. This is consistent with China consuming a significantly higher share of global non-energy commodities (such as metals) than the US, while using a similar amount of energy goods (see also [Appendix E](#)). The forecast error variance decomposition confirms that China shocks account for a relatively large proportion of the variation in oil and metals prices ([Figure 3](#), right panel). Similar to the previous literature (such as [Rey, 2015](#)), these findings suggest that an important channel through which macro risk shocks in China are transmitted globally, is through commodity prices.

4.5 Is the transmission of China shocks non-linear?

The empirical evidence presented so far showed that shocks originating in China have a significant, but modest, effect on global financial markets, while they entail more consequential spillovers across global commodity markets. In this section, we investigate whether these average results hide important non-linearities.

Non-linearities can arise as acute variations in financial markets might affect the transmission of shocks across countries: larger shocks may encourage investors to sell more

Figure 5: The impact reaction of commodity prices to structural shocks



Notes: The charts show the impact (on the same day) response of commodity prices to structural shocks. The responses are scaled to represent the impact to China shocks (US and global shocks) that would generate a 1% drop in the China (US) equity prices. The range refers to the 95 percent confidence intervals based on Driscoll-Kraay corrected standard errors.

aggressively risky assets to rebalance portfolios, potentially increasing spillovers. Periods of high volatility with fragile risk sentiment may generate larger price adjustments when shocks occur. Related to this, there is a large literature examining the interdependence in financial markets during periods of crisis or stress. For example, [Forbes and Rigobon \(2002\)](#) show there is a high level of equity market co-movement during well known crisis episodes (the 1997 Asian crisis, 1994 Mexican devaluation, and 1987 U.S. market crash). [Gravelle et al. \(2006\)](#) investigate why financial market crises often increase the interdependence between assets by looking at two sources: larger common shocks and changes in the structural transmission of shocks across countries (“shift-contagion”). The authors find that for many of the developed countries shocks get transmitted only during turbulent periods. More recently, building on the work of [Diebold and Yilmaz \(2014\)](#), [Iqbal et al. \(2022\)](#) examine volatility spillovers across financial and commodities markets, and show that the US stock market is at the centre of volatility spillovers when volatility is at normal levels, while the European and Chinese stock markets plus strategic commodities (e.g. crude oil and gold) become major volatility transmitters when volatility is elevated.

Differently from the above papers, we aim to understand whether the transmission of Chinese shocks is state-dependent and thus we ask two questions: (1) do we see a greater reaction of global markets when shocks from China are particularly large?; and (2) are spillovers amplified when global risk sentiment is already fragile?¹⁰

We assess these questions with two additional exercises, using local projections and focusing on China macro risk shocks. We estimate the following general regression:

$$\Delta Y_{i,t+h/t-1} = \alpha_{i,h} + \begin{pmatrix} \phi_h^L \\ \phi_h^M \\ \phi_h^H \end{pmatrix} \begin{pmatrix} I(\cdot < \gamma_1) \\ I(\gamma_1 < \cdot < \gamma_2) \\ I(\cdot > \gamma_2) \end{pmatrix}^T \varepsilon_t^s + \sum_{j=1}^3 \rho_{jh} \Delta Y_{i,t-j/t-j-1} + Controls + v_{i,t+h}, \quad (4.1)$$

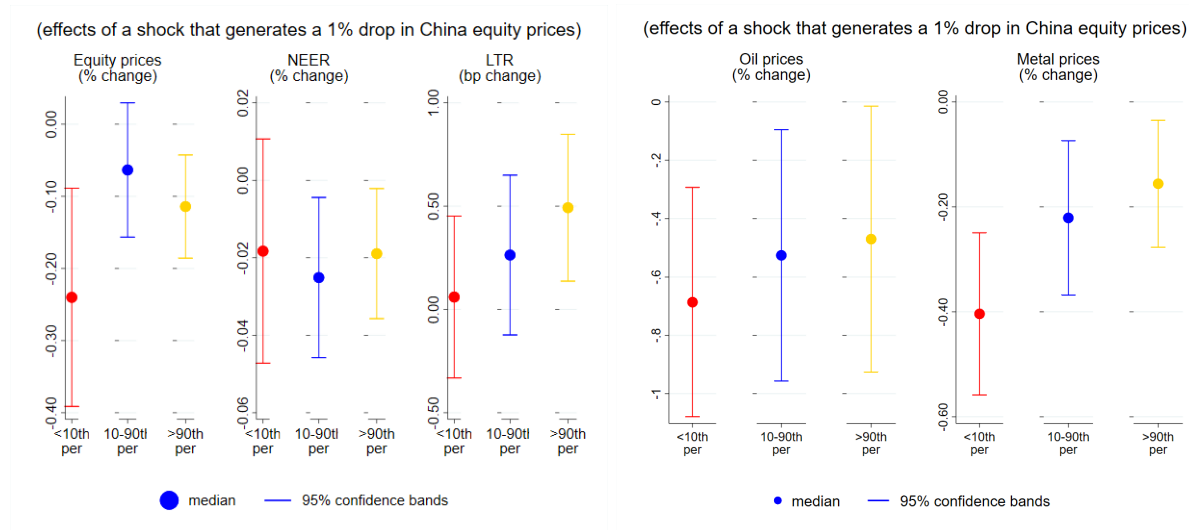
where $I(\cdot)$ is the indicator function separating the regimes depending on the threshold value γ . First, to test the effect of small versus large shocks, the indicator function reflects whether the China macro risk shock falls below, above, or between the lower and upper deciles of the shock distribution. Second, to test for difference in times of low and high volatility, the indicator function reflects whether the VIX is above or below its historical average. More details are provided in [Appendix F](#).

The impact of out-sized China macro risk shocks. We find evidence that larger China macro risk have out-sized spillover effects on global markets, as shown in the left panel of [Figure 6](#), although mostly for equity prices where the response to large downside shocks in China is estimated to be about four times as large as the response to average shocks. In other financial markets, however, there is less evidence of significant nonlinearities.

The reaction of commodity markets is also notably larger for out-sized China shocks,

¹⁰We checked to understand if there is any overlap in these two exercises. However, we find that the larger China shocks in our sample fall evenly across the two regimes of global volatility defined by the VIX. 53% of the largest negative China macro-risk shocks occur when the VIX is high; 52% of the larger positive China shocks occur in the the high volatility state.

Figure 6: Non-linearity depending on the magnitude of China macro risk shocks

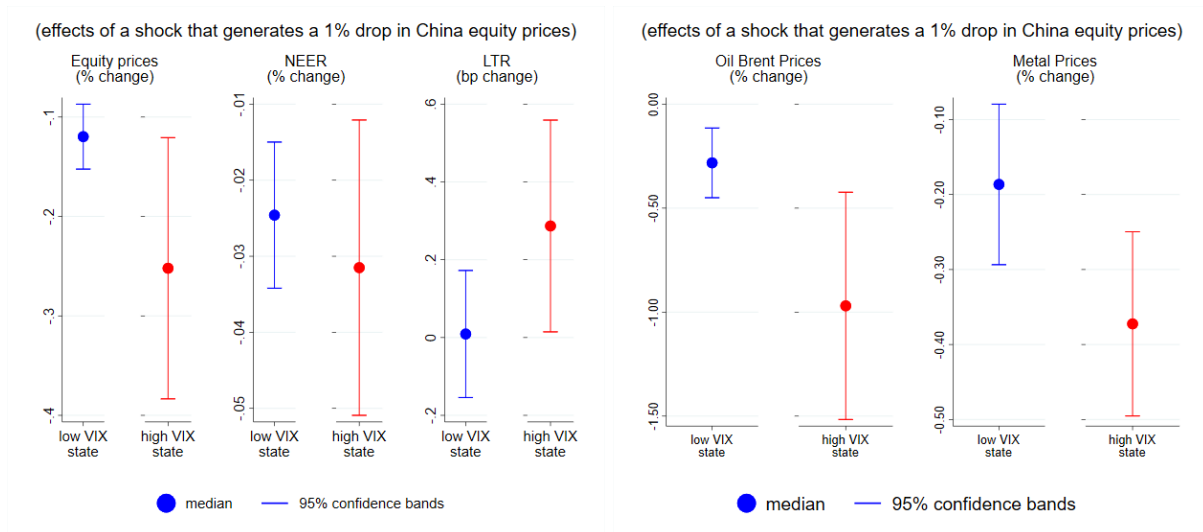


Notes: The charts show the impact (on the same day) response of global financial markets and commodity prices to structural shocks. The responses are scaled to represent the impact to China shocks (US and global shocks) that would generate a 1% drop in the China equity prices. The range refers to the 95 percent confidence intervals based on Driscoll-Kraay corrected standard errors.

as displayed in the right panel of Figure 6. Oil prices react more strongly to *negative* China macro risk shocks. Metals prices are found to also be more reactive to larger shocks, but again mostly to negative ones. This pattern might reflect China's key role in steering global growth and its heavy reliance on metals to fuel its growth.

Non-linearities during periods of high volatility. Also when global volatility is elevated, the transmission of China shocks to risky asset prices and currencies is magnified, see Figure 7. The response of global equities can be twice as large when the VIX is above average, and spillovers to nominal effective exchange rates three times as large. Commodity markets are also more susceptible for spillovers in a high volatility environment, as shown in the right panel. The impact of China macro risk shock on both oil and metals prices is significantly larger, with oil prices responding close to five times as strong. Given our sample period, which contains the COVID-19 pandemic years, this might reflect non-linearities set in place during that period.

Figure 7: Non-linearity depending on the level of volatility



Notes: The charts show the impact (on the same day) response of global market variables and commodity prices to China macro risk shocks. The responses are scaled to represent the impact to China macro risk shocks that would generate a 1% drop in China equity prices in the low and high volatility state. The range refers to the 95 percent confidence intervals based on Driscoll-Kraay corrected standard errors.

5 Robustness

To validate the robustness of our baseline results, this section looks at several sensitivity checks framed around three questions.

Can China macro risk and monetary policy shocks reasonably be separated?

Our baseline results show significant spillover effects from China macro risk shocks, but not from China monetary policy shocks. One could argue that due to the specificity of China policy set-up disentangling the two structural shocks is challenging. To check this, we set up an alternative BVAR that identifies only one China-specific shock. We assume such a shock increases interest rates more in China than in the US and leads to an appreciation of the Renminbi against the US dollar. We remain agnostic about the response of all other Chinese variables to this shock, as shown in Table 5. The results show that pooling the two shocks together does not alter the results, yet introduces more noise. The median impact response of Chinese equities to this China-specific shock is positive, suggesting that macro risk shocks are the dominant structural shock in our data (in line with how we identify macro risk shocks in our benchmark BVAR, see Table 2),

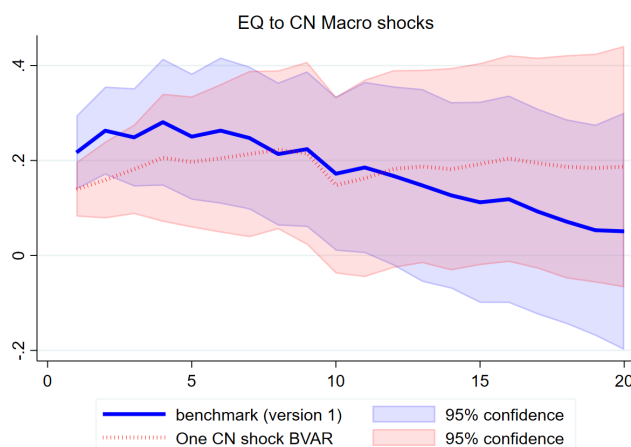
but the response is insignificant which reflects the difficulties to identify shocks in the absence of more structure.¹¹ Comparing the responses of global equities to this single China shock versus the China macro risk shocks from the benchmark model, we find only small, non-significant differences in the spillovers as shown in Figure 8.

Table 5: BVAR with only one China specific structural shock

Variable	Identified shock			
	China shock	US Monetary	US macro risk	Global risk
China long-term interest rate	+	-	+	
China equities				
US equities		+(*)	+	+
China-US yield spread	+	+	-	-
Renminbi-dollar exchange rate	-	-	+	-

Notes: Signs denote favourable US macro/global risk shocks and US accommodative monetary shocks – i.e. all the shocks would boost global equity prices. A '+' for the Renminbi-dollar exchange rate denotes a depreciation of the Renminbi against the US dollar.

Figure 8: Global equity response to baseline China macro risk vs single China shock



Notes: The responses to one standard deviation shock. The range refers to the 95 percent confidence intervals based on Driscoll-Kraay corrected standard errors.

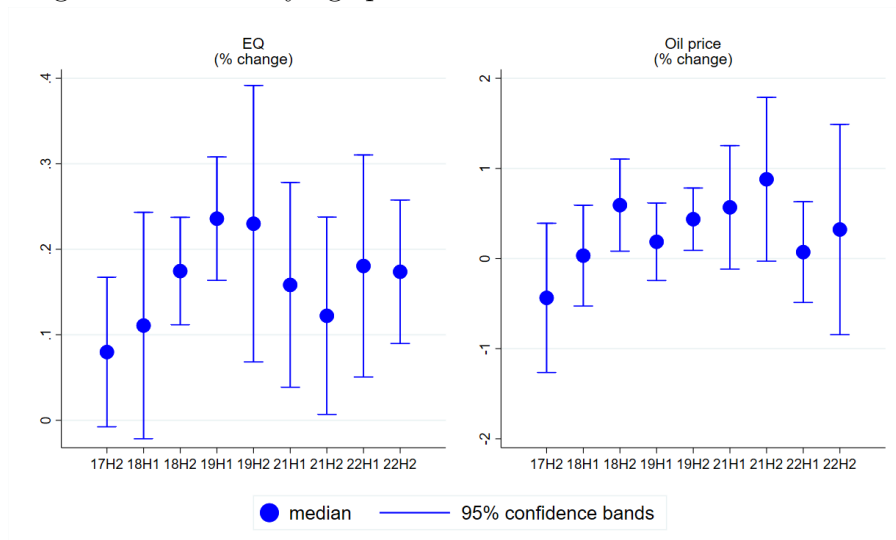
Has China’s influence on global markets increased over time? China’s evolving role in global financial markets suggest that the magnitude of the spillovers could have changed over time. To test whether that is the case over our sample we estimate the spillovers over non-overlapping six-month periods.¹² Figure 9 shows the global equity

¹¹These results are available upon request.

¹²For this exercise, we explicitly assume that the variation over time might lay in the spillovers to global financial markets and commodities, rather than in the dynamics of the BVAR model as we work with the structural shocks as estimated in our benchmark model over the full sample.

and oil price responses between 2017H2 and 2022H2, excluding 2020 due to the COVID-19 outbreak. The results suggest that spillovers from China macro risk shocks tended to increase between 2017 and 2019 both for equities and oil prices, consistent with policy ambitions in China to increase its role in the global market. The start of the pandemic has interrupted that upward move, bringing the impact of macro risk shocks again closer to the sample average for the most recent period. However, the differences between the estimated median are limited in magnitude and the confidence bounds mostly overlap for a large part, which indicates that over this (limited) period, changes in China’s footprint on global financial markets remained contained.

Figure 9: Time-varying spillovers from China macro-risk shocks



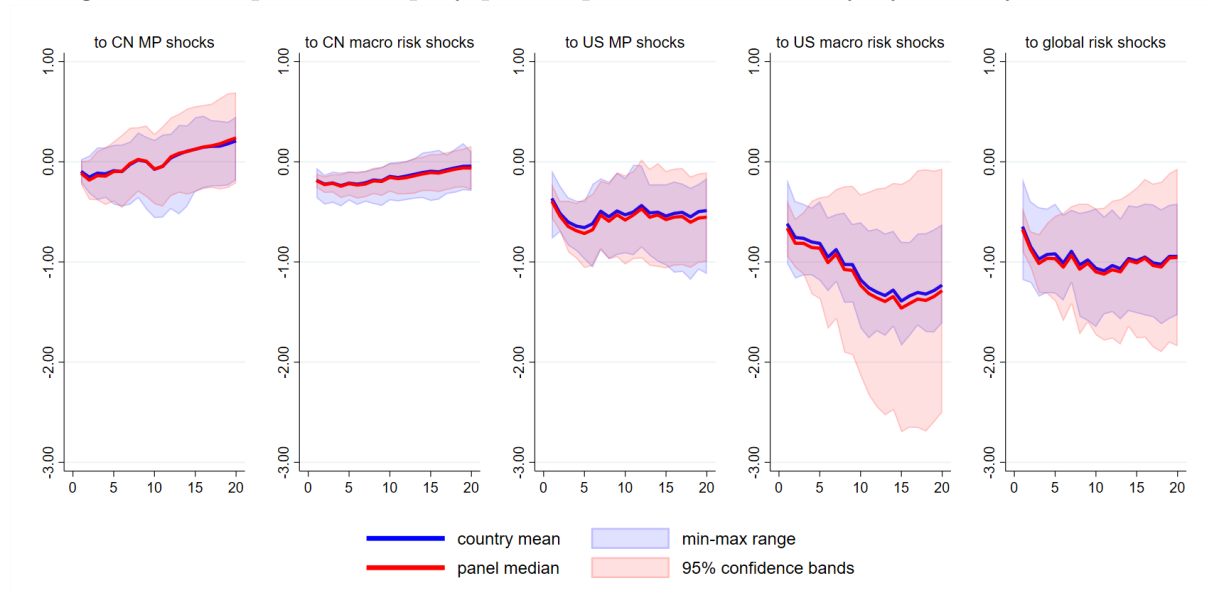
Notes: The charts show the impact (on the same day) response of global financial market variables to structural shocks. The range refers to the 95 percent confidence intervals based on Driscoll-Kraay corrected standard errors.

Are the responses heterogeneous across countries? Finally, as grouping our country sample into advanced and emerging economies might still potentially average out responses, we run local projections country by country rather than in a panel set-up.¹³ We compare the min-max range of the estimated impulse responses from the country-by-country estimates with those from the panel framework. Overall, while the min-max

¹³We apply the [Newey and West \(2014\)](#) correction to the estimated standard errors in the individual regressions to account for serial correlation in the residuals. We also use the same scaling of impulse response functions like in the panel set-up, namely impulse responses are scaled to reflect a shock that would shift (on impact) the Chinese equities by 1% for Chinese-specific structural shocks by 1% US equities for US and global risk shocks.

range is somewhat larger, the mean impulse responses of the financial variables across countries are very similar to our baseline results, as shown in Figure 10. In addition, the results remain robust to the inclusion of other domestic variables and by dropping controls or lags of the dependent variables.¹⁴

Figure 10: Responses of equity prices: panel versus country-by-country estimation



Notes: The charts show the response of equity prices to structural shocks up to 20 days based on panel and country-by-country local projections, where the range refers to the 95 percent confidence intervals based on Newey and West (in the time-series context) or Driscoll-Kraay (in a panel context) corrected standard errors.

6 Conclusion

In this paper we provide a framework to identify structural shocks originating in China (monetary and macro risk shocks) by exploring cross-correlations in Chinese and US financial markets using a daily Bayesian VAR with sign, relative and narrative restrictions. We identify shocks in China jointly with US and global risk shocks – two major forces behind daily movements in global financial markets – to better ensure that our China structural shocks are filtered for possible common factors. Building on the joint set of identified structural shocks we are able to explore the spillovers of shocks originating in China to global financial and commodities markets and compare the strength of their

¹⁴These results are available on request.

impact with US and global risk shocks.

The analysis suggests that China's macro risk shocks can have a material impact on global financial markets in specific asset classes such as equities and commodities, though spillovers to other asset classes are generally small. Shifts in US monetary policy, the US macro outlook, or in global risk sentiment are clearly more important drivers of daily dynamics in global financial markets, with the exception of certain commodities for which China seems as important as the US. Nevertheless, we do find that spillovers from China shocks are significantly reinforced when China shocks hit in a time of heightened global volatility or when Chinese shocks are large. So what happens when China gets a cold? Global equities and commodity prices would sneeze as well, but we should only start worrying when symptoms of the flu appear.

Going forward, the fact that China's policy paradigm has shifted from a tightly controlled system towards a more market-based mechanism with ongoing efforts to allow market forces to play a greater role in the functioning of credit and Forex markets, means that global financial markets are likely to continue to catch up with China's role in the global economy. In this context, our paper also provides a solid framework for policy makers to monitor the evolving importance of Chinese structural shocks for global financial and commodities markets.

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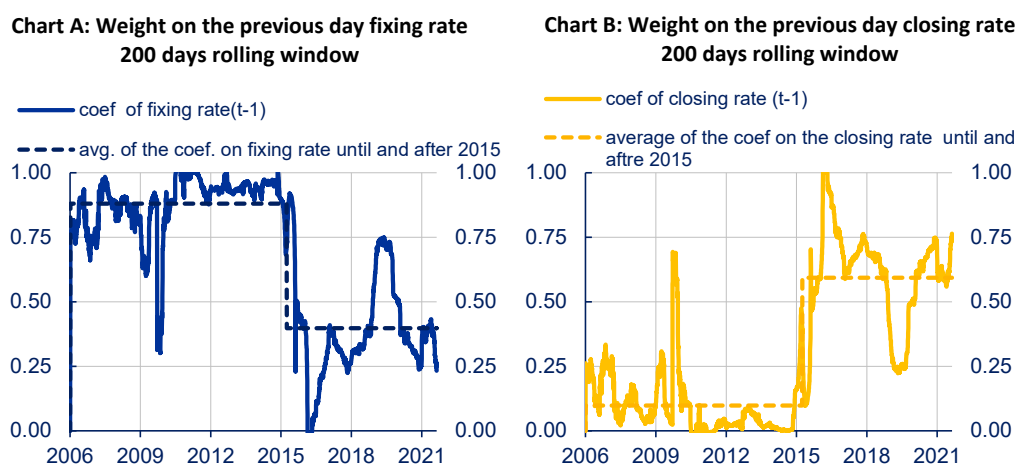
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Appendix

A Flexibility of the Renminbi exchange rate

Renminbi and market forces. Empirical evidence suggests that market forces play a greater role in determining the Renminbi exchange rate. [McCauley and Shu \(2018\)](#) show that before since August 2015, the fixing rate puts a much higher weight on the previous day's closing rate, suggesting the exchange rate has been less tightly managed by authorities. [Figure A.1](#) which updates that analysis¹⁵, shows that the weight on the previous day's closing rate remained high between 2017-22 (which is the period covered in our analysis), suggesting that market forces remain predominant in setting the daily exchange rate fix. That is bolstered by evidence that market participants are able to predict accurately the official Renminbi fixing: there are very few occasions when investors have been surprised by the actual rate chosen by authorities for the fixing (see [Figure A.2](#)).

Figure A.1: Chinese Renminbi fixing rate versus previous day fixing/closing rate

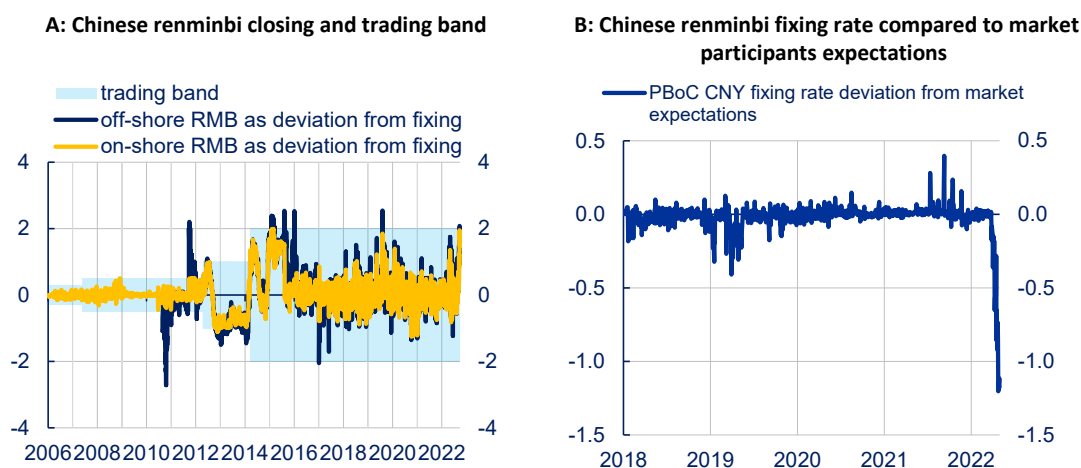


Note: Coefficients estimated from regression using 200-day rolling windows as in [McCauley and Shu \(2018\)](#).

¹⁵[McCauley and Shu \(2018\)](#) assess the factors driving the daily fixing for the Renminbi-dollar exchange rate, by regressing the daily fixing on the previous day's fixing rate and the previous day's market closing rate

$$\log(\text{fixing}(t)) = \alpha * \log(\text{fixing}(t - 1)) + \beta * \log(\text{closing}(t - 1)) + c$$

Figure A.2: Chinese Renminbi trading bands and fixing rate versus market expectations



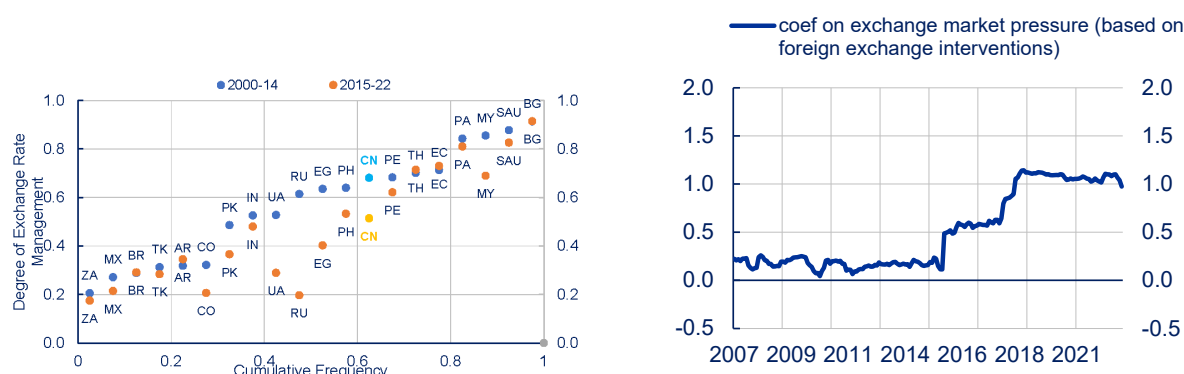
Note: On-shore RMB refers to RMB that circulates within Mainland China, while off-shore RMB refers to RMB that circulates outside Mainland China. The RMB exchange rate is allowed to fluctuate by $\pm 2\%$ band around the fixing rate. Panel B shows the official fixing rate in deviation from the fixing rate expected by market participants, where the latter is based on survey index compiled by Bloomberg since 2018.

De facto flexibility of RMB in nominal effective and SDR terms. Other measures of de facto exchange rate flexibility, following Frankel (2009) and Adler et al. (2021), suggest a substantial increase in the flexibility of China's exchange rate. First, Adler et al. (2021) assesses the change in China's degree of exchange rate management by computing the following ratio: $\rho = \frac{\sigma_{RMB}}{\sigma_{RMB} + \sigma_{FXI}}$ where σ_{RMB} refers to the daily variance of the RMB nominal effective exchange rate, while σ_{FXI} is the monthly variance of the exchange market intervention index (as % of GDP). The index takes the value 0 if the currency is floating (no intervention) and value 1 if the nominal effective exchange rate is de facto pegged. The left panel of Figure A.3 displays the index value for a range of emerging market economies (EME) calculated between 2000-14 and 2015-2022. China's exchange rate flexibility falls somewhere in the middle range, between a purely floating currency and a pegged one. The degree of exchange rate management in China since 2015 is notably lower than in the preceding 15 years.

Second, another measure of exchange rate flexibility is the approach of Frankel (2009) which examines movements of the Renminbi against a basket of foreign currencies (the US dollar, the euro the yen and the Korean won¹⁶) and a measure of exchange rate pressure,

¹⁶These currencies were the ones the PBoC's governor Zhou referred to as being the major currencies

Figure A.3: De facto flexibility of the Renminbi



Notes: Left panel: Degree of exchange rate management:2000-14 versus 2015-2021. Right panel: Rolling estimates for the coefficient on the EMP.

by estimating the following regression over monthly data: ¹⁷

$$\begin{aligned} \Delta \log(RMB_t) - \Delta \log(WON_t) = & \alpha + w_1 * (\Delta \log(USD_t) - \delta \log(WON_t)) \\ & + w_2 * (\Delta \log(YEN_t) - \Delta \log(WON_t)) \\ & + w_3 * (\Delta \log(EUR_t) - \Delta \log(WON_t)) \\ & + w_4 * (Emp - \Delta \log(WON_t)) + \epsilon_t, \end{aligned} \quad (A.1)$$

where $Emp = \Delta \log(RMB_t) + \frac{\sigma_{RMB}}{\sigma_{Res}} \Delta \log(Res_t)$ and Res stands for foreign exchange reserves.¹⁸ The equation allows to quantify the extent to which authorities allow shocks that affect demand for the currency to affect either the exchange rate movements or foreign reserves. A zero coefficient on the Emp variable would mean a completely fixed exchange rate; a high coefficient signifies a flexible exchange rate. The right panel of Figure A.3 shows the results on the exchange market pressure coefficient using a rolling-window of 24 months. The coefficient increases significantly, signalling an important degree of exchange rate flexibility.

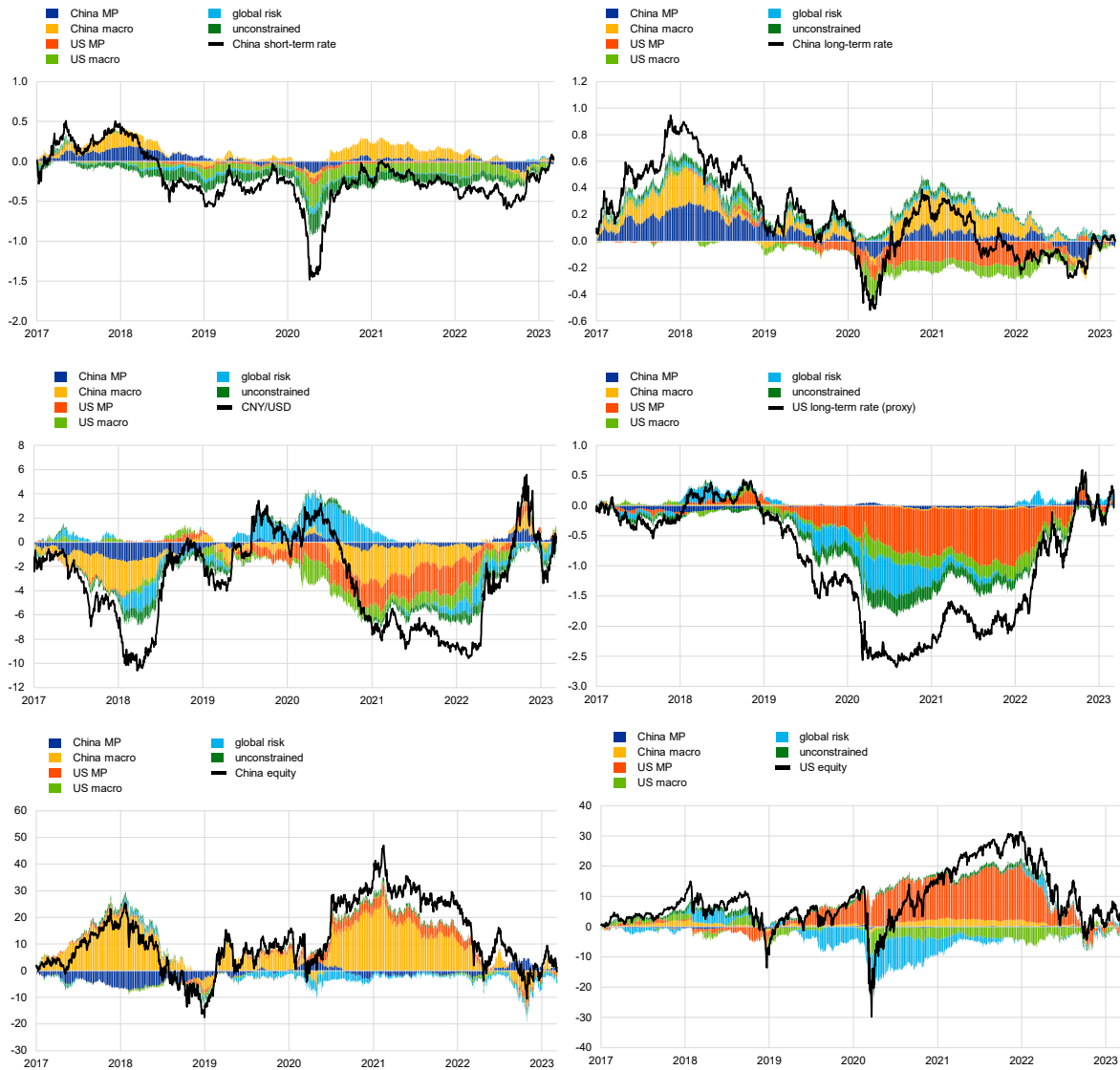
in the basket, because of their economies' importance for China current account. They represent more than 60% of the index. Prior to 2015, the PBoC did not disclose directly the composition of the basket or currency weighting.

¹⁷As in Bracke and Bunda (2011) the specification is that the coefficients on the individual anchor currencies and the coefficient on the exchange market pressure instrument sum to 1. The adding-up constraint is implemented by subtracting the changes in the log value of the Korean won on each side of the equation.

¹⁸This follows the approach of Bracke and Bunda (2011), who argue that it is preferable to that of Frankel (2009) which calculate the exchange market pressure index as the sum of unweighted change in the exchange rate and reserve variation, meaning that the results are shaped by the relative variance of the two components

B BVAR model results: historical decompositions

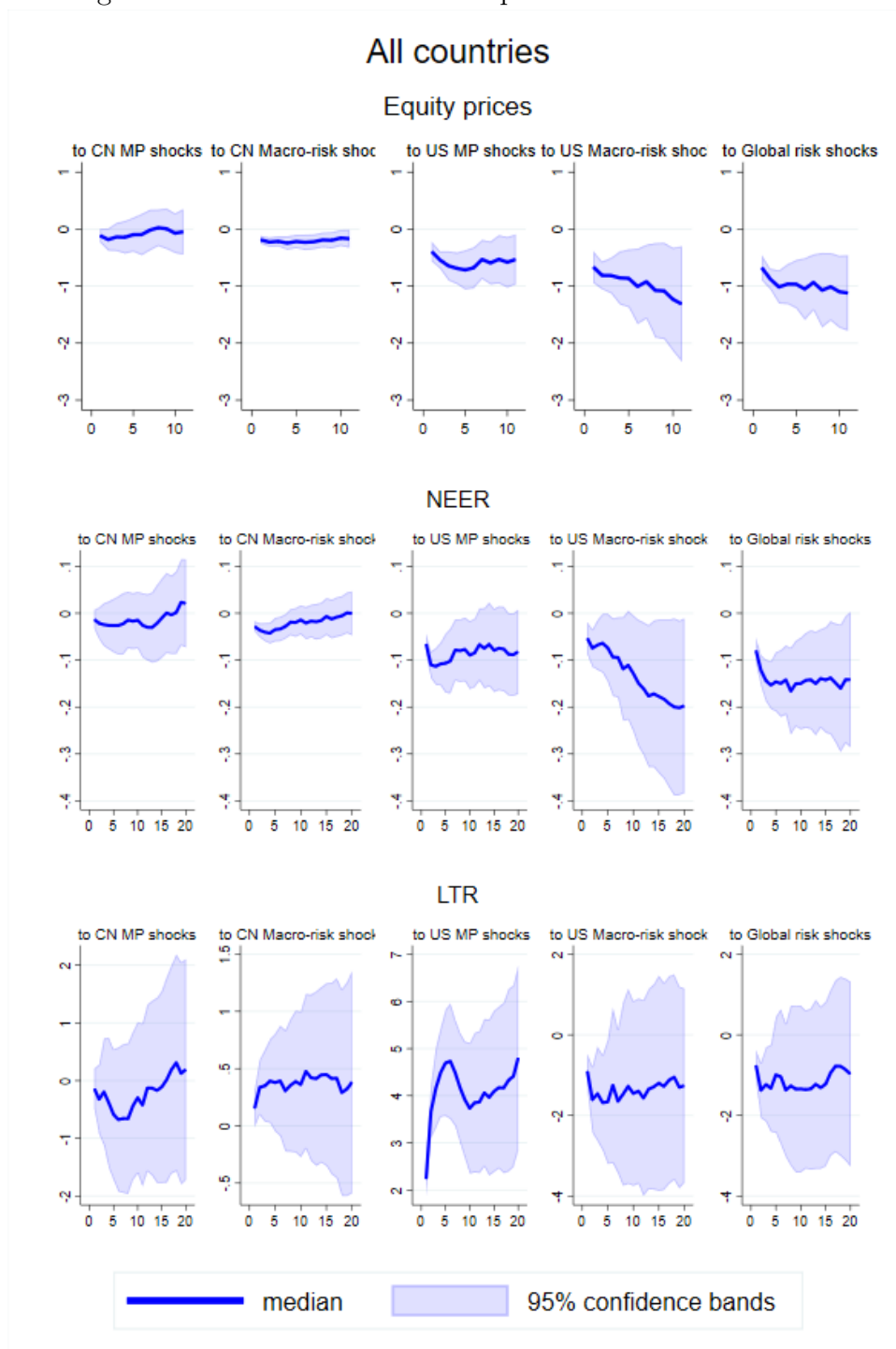
Figure B.1: Historical decompositions



Notes: Cumulative changes in variables since 2017. The median shocks from the posterior distribution is used, which means that the sum of shock contribution can depart from actual changes in the explained variable if the posterior distribution is skewed. The historical decomposition for US yields is proxied based on the estimated decomposition of Chinese long-term yields and the spread between Chinese and US long-term yields.

C Impulse responses of financial variables

Figure C.1: Financial variable responses to structural shocks



D Alternative identification schemes for China shocks

Table D.1: Full VAR to identify CN-specific shocks; no restrictions on FX

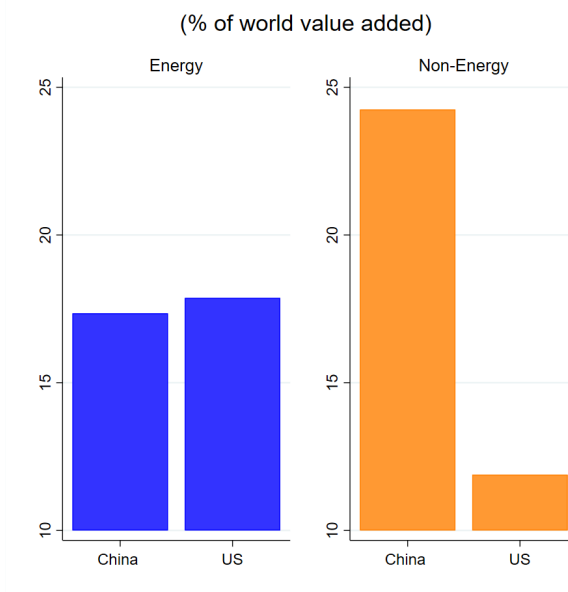
Variable	Identified shock				
	China Monetary	China macro risk	US Monetary	US macro risk	Global risk
China short-term interest rate	–	+			
China long-term interest rate	–(*)	+			
China equities	+	+(*)			
US equities					
China-US yield spread					
Renminbi-dollar exchange rate					

Table D.2: China-specific BVARs with or without restrictions on FX

Variable	Identified shock	
	China Monetary	China macro risk
China short-term interest rate	–	+
China long-term interest rate	–	+
China equities	+	+
Renminbi-dollar exchange rate	+	–

E Consumption of energy/non-energy goods

Figure E.1: Final demand of energy (non-energy) goods



Source: OECD

F Non-linear effects of China macro risk shocks

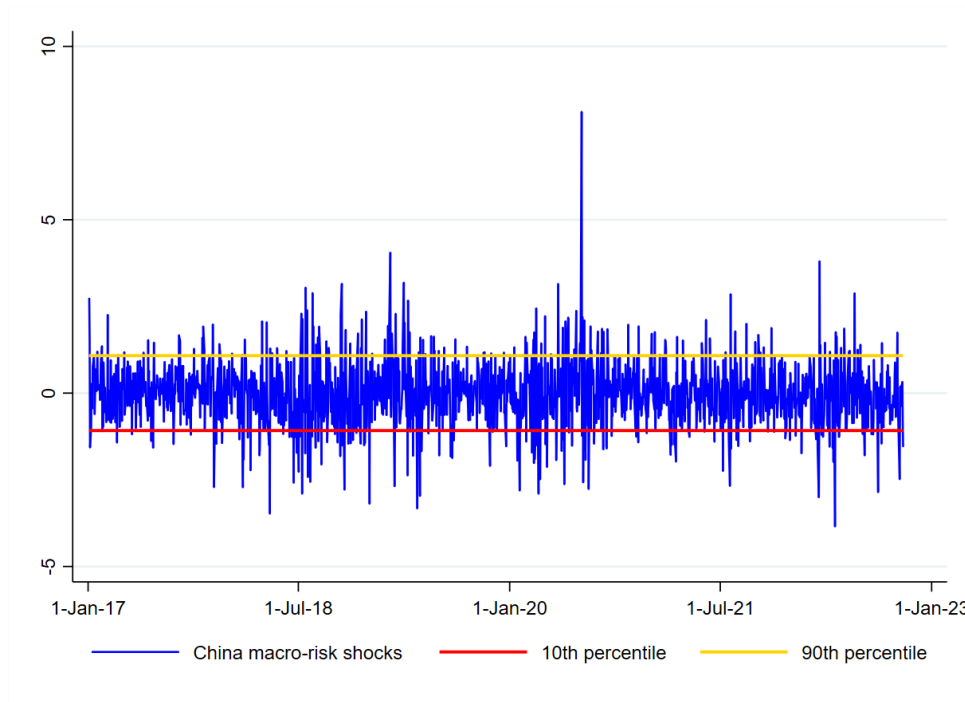
We assess the potential non-linearity of the effects of China macro risk shocks with two additional exercises using local projections. We first examine whether spillovers are affected by the magnitude of China shocks, by estimating the reaction of global financial markets to those shocks in the top and bottom deciles of our sample:

$$\Delta Y_{i,t+h/t-1} = \alpha_{i,h} + \phi_h^N \varepsilon_t^s I(\varepsilon_t^s < \gamma_1) + \phi_h^A \varepsilon_t^s I(\gamma_1 < \varepsilon_t^s \leq \gamma_2) + \phi_h^P \varepsilon_t^s I(\varepsilon_t^s \geq \gamma_2) + \sum_{j=1}^3 \rho_{jh} \Delta Y_{i,t-j/t-j-1} + Control + v_{i,t+h} \quad (\text{F.1})$$

Where $I(\cdot)$ is the indicator function, showing whether the China macro risk shock falls below, above or between the thresholds γ and δ , with the thresholds chosen to identify the lower and upper deciles of the distribution of China macro risk shocks. All

other notations are similar to baseline regression (1), with $\phi_{i,h}^N$, and $\phi_{i,h}^P$ representing the estimated response of each financial variable at horizon h to the large negative (N) and positive (P) China macro risk shocks. Figure F.1 displays China macro risk shocks with the two threshold variables that are used to define the three states.

Figure F.1: China macro-risk shocks and the 10th and 90th percentile

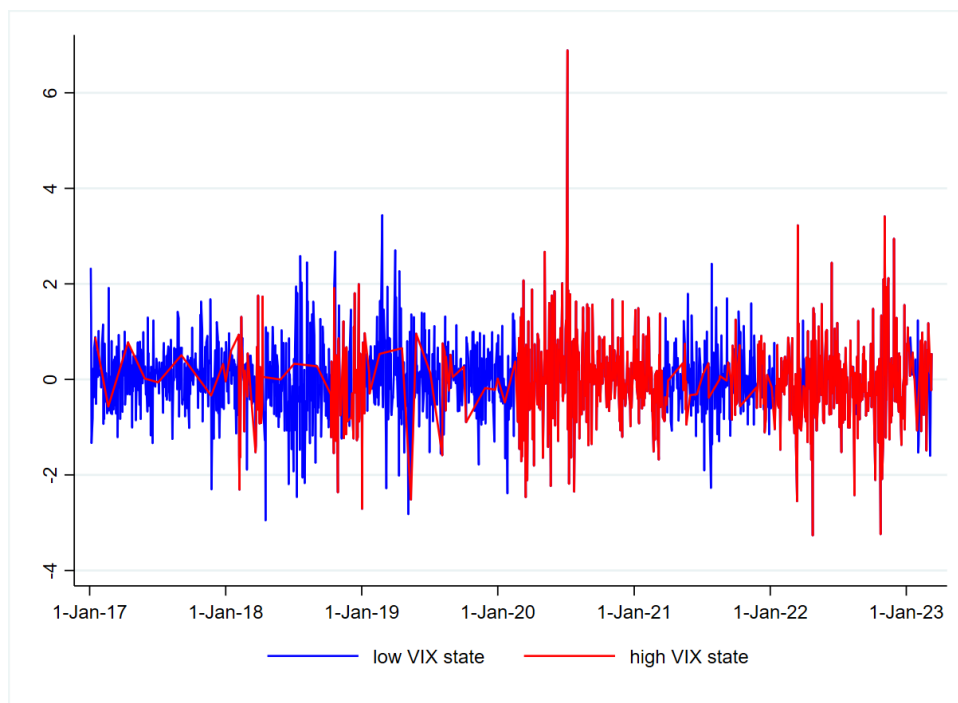


Second, we examine spillovers conditional on the global risk environment. We quantify the responses to China macro risk shocks in periods when the VIX is above and below average:

$$\begin{aligned} \Delta Y_{i,t+h/t-1} = & \alpha_{i,h} + \phi_h^L \varepsilon_t^s I(VIX_t < \gamma) + \phi_h^H \varepsilon_t^s I(VIX_t \geq \gamma) + \\ & + \sum_{j=1}^3 \rho_{jh} \Delta Y_{i,t-j/t-j-1} + Controls + v_{i,t+h} \end{aligned} \quad (F.2)$$

Where $I(\cdot)$ is the indicator function showing the regime identifier by the threshold variable, the VIX and whether it is above or below the average γ . In this case, $\phi_{i,h}^L$ representing the estimated response of each financial variable to a China macro-risk shock when the VIX is below average and $\phi_{i,h}^H$ is the response when the VIX is above average. Figure F.2 displays China macro risk shocks in the two states conditional on the VIX.

Figure F.2: China macro-risk shocks in low and high VIX states



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David Lodge

European Central Bank, Frankfurt am Main, Germany; email: David.Lodge@ecb.europa.eu

Ana-Simona Manu

European Central Bank, Frankfurt am Main; email: Ana-Simona.Manu@ecb.europa.eu

Ine Van Robays

European Central Bank, Frankfurt am Main; email: Ine.Van-Robays@ecb.europa.eu

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Postal address 60640 Frankfurt am Main, Germany

Telephone +49 69 1344 0

Website www.ecb.europa.eu

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