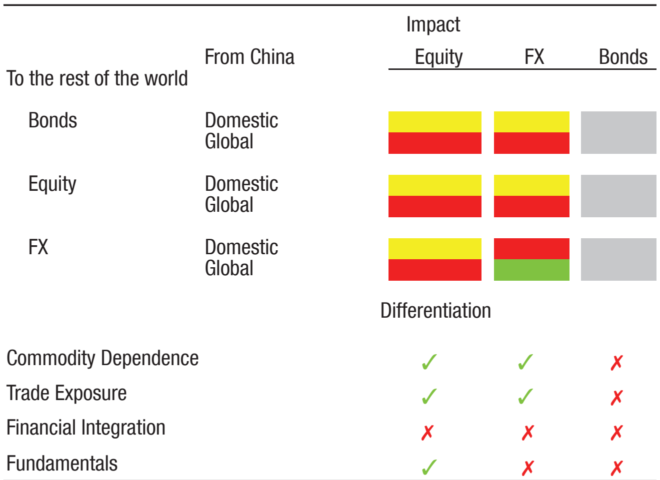
Figure 18. Financial Spillovers from China: Summary[1]



[1]The heat map summarizes the strength of financial spillovers from China. Global channels include VIX, oil prices, metal prices, U.S. S&P 500, and the U.S. 10-year yield. Color coding indicates relative strength of impact, with red highest, yellow medium, and green smallest. Gray color indicates results that are not statistically significant.

works largely through risk aversion and global commodity prices. While no asset market is immune to economic and financial developments in China, effects are felt most acutely in FX and equity markets. Countries most affected are those with deeper trade ties with China, especially Asian countries integrated in the global supply chain, commodity exporters, and EMs with weaker fundamentals (Figure 18).

This differentiation in the external effects of developments in Chinese financial markets seems to suggest that the estimated financial spillovers from China reflect primarily concerns about China's growth prospects rather than specific news about Chinese markets that would trigger a substitution of Chinese for foreign assets. Thus, improved communication of policy direction by the People's Bank of China since the beginning of 2016 may have dampened both the magnitude and frequency of these financial spillovers—as suggested by limited global market reaction to renminbi (RMB) depreciation during the second quarter of 2016.

Annex 1. Stress Test

System-Wide Analysis

The stress test envisages the following two scenarios:

- The first scenario assumes a15 percent loss rate on foreign banks' exposure to China, including total claims (ultimate risk basis), derivatives, guarantees, and credit commitments. This loss rate is similar to the one assumed in the April 2016 *Global Financial Stability Report* (GFSR) (IMF 2016a). The hurdle rate—the capital adequacy ratio (CAR) below which a banking system is considered in distress—is set at 6 percent of the Tier 1 capital ratio, consistent with the Basel III minimum capital requirements.[22]
- The second scenario considers a combined shock to foreign banks' exposure to China and Hong Kong SAR (dubbed "greater China"), given the strong economic and financial linkage between the two. Under this scenario, a 15 percent loss rate on these foreign holdings would not lower the Tier 1 CAR of BIS reporting banks below the minimum Basel III requirement of 6 percent.
- Quantifying spillovers. The global spillover effects of the two credit events above are derived using the approach developed by Espinoza-Vega and Sole (2010).
- Data. Banking systems' cross-border exposures are constructed on an ultimate risk basis using BIS data as of September 2015. The countries covered in the analysis are Australia, Austria, Belgium, Canada, Chile, France, Germany, Greece, Italy, Japan, Korea, the Netherlands, Spain, Sweden, Switzerland, Taiwan POC, the United Kingdom, and the United States. This list is not exhaustive because of limits in the number of BIS reporting banking systems, and thus there could be additional spillover effects through other banking system (such as Singapore and other Asian EMs).
- Channels. In addition to the direct credit loss from exposure to China, there are two indirect spillover channels: 1) through country A's banking system's credit exposure to another country B's banking system, which has substantial links to China's banking system, and 2, through country A's reliance on funding from country B's banking system.
- Assumptions. For loss rates between 30 and 70 percent on exposures to greater China, only the Taiwanese banking system would see its CAR fall below 6 percent. The impact on Taiwan POC's banking system would, however, be unlikely to spill over to other countries' banking systems even if they were to lose 100 percent of their holdings in and funding from Taiwanese banks, and those funding needs would be met through fire sales of assets with a 90 percent haircut on asset values.

[22]While it is ideal to use the common equity Tier 1 capital ratio (CET1 ratio), it is hard to obtain the cross-country aggregate data. Therefore, we use Tier 1 capital data at country levels as reported in the IMF's Financial Soundness Indicators database.

Annex 2. Diebold-Yilmaz Connectedness Index

Method

The Diebold-Yilmaz (2014) Connectedness Index defines country *j*'s spillover to or connectedness with country *i* as the fraction of the H-day-ahead forecast error variance of country *i*'s asset price that can be accounted for by innovations in the country *j*'s asset price. Based on a daily vector autoregression (VAR) and following the most recent Diebold and Yilmaz approach, an H-step generalized variance decomposition (GVD) matrix $D^{gH} = \left[d_{ij}^{gH}\right]$ is estimated with entries such as:

$$d_{ij}^{gH} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Theta_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Theta_h \Sigma \Theta_h' e_i\right)}$$

where e_j is a selection vector with *j*th element unity and zeros elsewhere, Θ_h is the coefficient matrix multiplying the *h*-lagged shock vector in the infinite moving-average representation of the non-orthogonalized VAR, Σ is the covariance matrix of the shock vector in the non-orthogonalized VAR, and σjj is the *j*th diagonal element of Σ. The entries are then normalized such that they sum to one:

$$\tilde{d}_{ij}^{gH} = \frac{d_{ij}^{gH}}{\sum_{j=1}^{N} d_{ij}^{gH}}$$

This is necessary because in the GVD setting, shocks are not necessarily orthogonal and the sums of forecast error variance contributions are not necessarily unity. The connectedness of China to a particular country is the corresponding entry of the normalized GVD matrix. The impact on a group of countries is an average of the corresponding entries.

Estimation

The model is estimated based on daily data for three asset markets (local currency stock market, bilateral exchange rate vis-à-vis the U.S. dollar, and 10-year government bond yield) of 12 advanced (Australia, Canada, France, Germany, Italy, Japan, Korea, Singapore, Spain, Taiwan POC, United Kingdom, United States) and 16 emerging markets (Argentina, Brazil, Chile, Colombia, Hungary, India, Indonesia, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Thailand, Turkey) over the period of China tensions (January 1, 2015–February 2016). Given that the co-movement is assessed through a variance decomposition, the methodology does not allow the impact of exogenous factors, such as economic news from China, to be studied.

Given that shocks can lead to both an adjustment in asset price level and a spike in the uncertainty about it, the study focuses on both the co-movements in asset returns and the co-movement in asset volatilities. Asset return is defined as the difference in the natural log of stock prices and exchange rates and the difference in the yield on government bonds. Volatility is defined as the log of the annualized daily standard deviation based on the spread between high and low prices during the day,[23] e.g., for any country *i* on day *t:*

$$volatility_{it} = ln\left\langle 100\sqrt{365\left\{0.361\left[\ln\left(P_{it}^{max}\right) - ln\left(P_{it}^{min}\right)^2\right]\right\}}\right\rangle$$

Given that volatilities tend to be distributed asymmetrically with positive skew, it is necessary to take logs to ensure approximate normality, which is one of the VAR assumptions. The VAR is estimated over a rolling 150-day window with three lags, and the forecast is done 10 days ahead. Given the large set of variables, the VAR is estimated using the elastic net shrinkage technique.

Robustness

The results discussed in the text are robust to an alternative identification that uses the Cholesky decomposition (Annex Figure 2.1).

Annex 3. Event Study

Description of Events

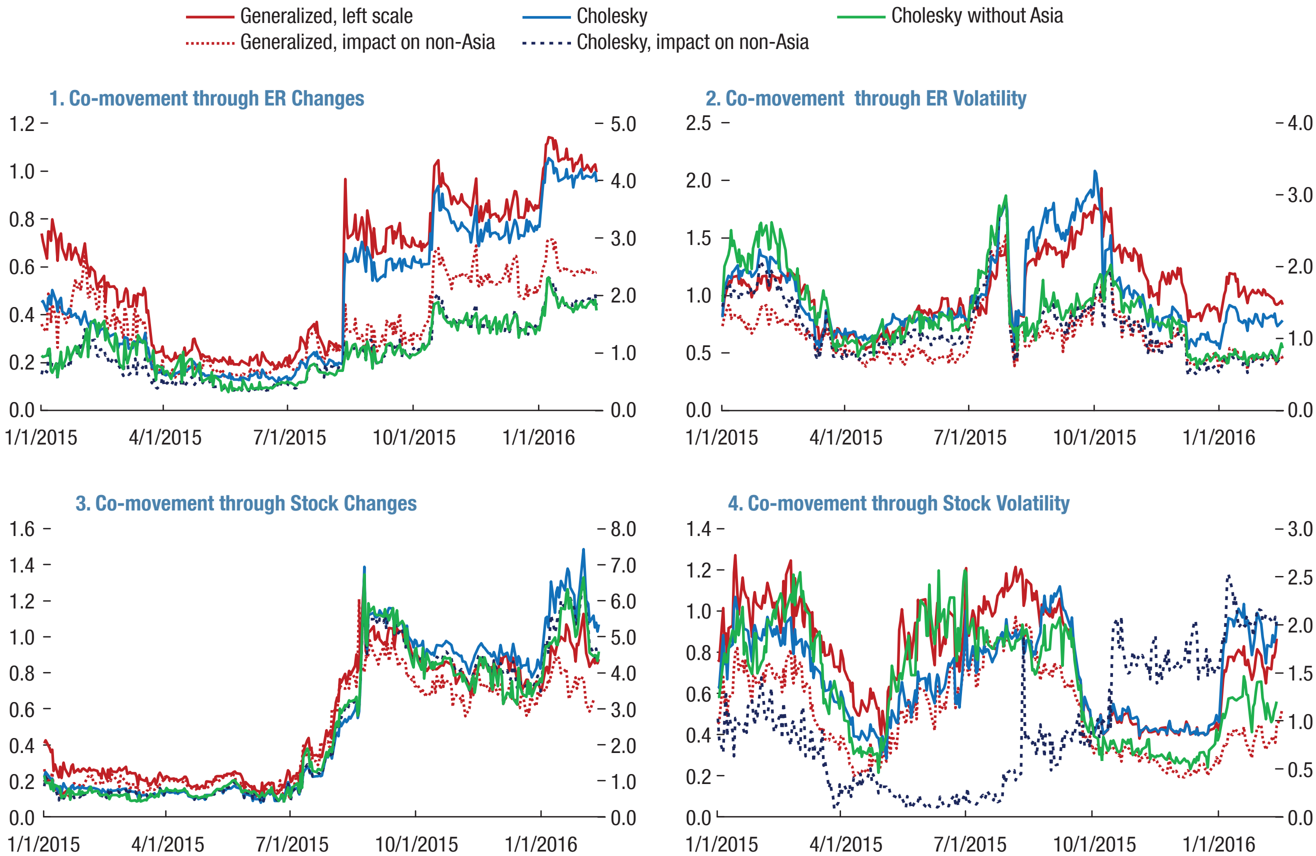
The events selected in this study contain both negative economic and financial events. These events are not necessarily related to global events, but more likely to be China specific, as shown in Annex Figure 3.1.

To identify financial shocks originating from China, we follow Arslanalp, Piao, and Seneviratne (2016) that identify exceptionally large changes in the Chinese stock market and the exchange rate related to domestic news and unrelated to global events from January 2001 to June 2016. These shocks originate from either real shocks (such as news about growth prospects) or pure financial shocks (such as news about a change in the exchange rate regime), or a mixture of both. An exceptionally large movement is defined as a daily change in the Shanghai Composite Index by more than 5 percentage points. To make sure these are unrelated to global

[23]Diebold and Yilmaz (2012), and Alizadeh, Brandt, and Diebold (2002).

Annex Figure 2.1. Robustness Checks[1]

(Share of forecast error variance due to China for an average country; within asset class co-movement)



[1]Generalized—standard specification, generalized variance decomposition Cholesky—variance decomposition with Cholesky ordering as follows: China, Asian AMs, Asian EMs, European AEs, European EMs, VIX and Western Hemisphere AEs, Western Hemisphere EMs. Choleksy on non-Asia—specification as above, but only show impact on non-Asia. Cholesky without Asia—specification excludes Asian AMs and Asian EMs in the estimation.

events, this definition excludes days when the U.S. stock market moves by more than one standard deviation just hours before the Chinese market opens (as a proxy for global events). Similarly, for the Chinese exchange rate, an exceptionally large movement is defined as a daily change in the onshore renminbi–U.S. dollar exchange rate by more than 0.5 percentage points. Similar to the approach for the stock market, to make sure these are unrelated to global events or simply movements in the U.S. dollar rather than the renminbi, days in which the U.S. Dollar Index (DXY) moves by more than one standard deviation against major Group of Ten (G10) currencies are excluded. Finally, a thorough news search is conducted to ensure that the selected China events occurred during days with major domestic news or policy announcements, as detailed in Annex 1 of Arslanalp and others (2016).

Economic news shocks are defined as the deviation of actual Purchasing Managers' Index (PMI) from consensus expectation (PMI surprise). Events are the economic news associated with a negative PMI surprise that is larger than –½ percent, which is the median of all the negative shocks in the sample. None of the events selected coincide with U.S. industrial production shocks.

Empirical Setup

Baseline Specification

$$\Delta F_{it} = \partial + \beta Event_t + \sum_{j=1}^{J} \delta_j Controls + \varepsilon_{it}$$

where F_{it} is alternatively the nominal effective exchange rates, equity returns, and long-term interest rates (domestic long-term interest rates, domestic long-term interest rates for AEs, and Emerging Markets Bond Index yields for EMs).[24]

- *Controls.* The baseline regression controls for global financial volatility (VIX), U.S. equity benchmark returns (Standard & Poor's, or S&P, 500), commodity prices, and domestic short-term interest rates. To account for the indirect impact of China shock through global financial variables, e.g., VIX, S&P 500 returns and commodity prices, these variables are regressed on dummies of China's events. Residuals of the global variables are used as control in the regressions.
- *Sample.* Daily data from January 1, 2008, to March 16, 2016. We use two-day changes to account for the time differences between countries. To test if there is any structural increase in spillovers since June 2015, the sample is divided into two sub-samples.
- *Events* are treated as dummies in the regression. There are in total 16 equity shocks, 11 FX shocks, and 20 economic news shocks in the sample.

Spillover Channels

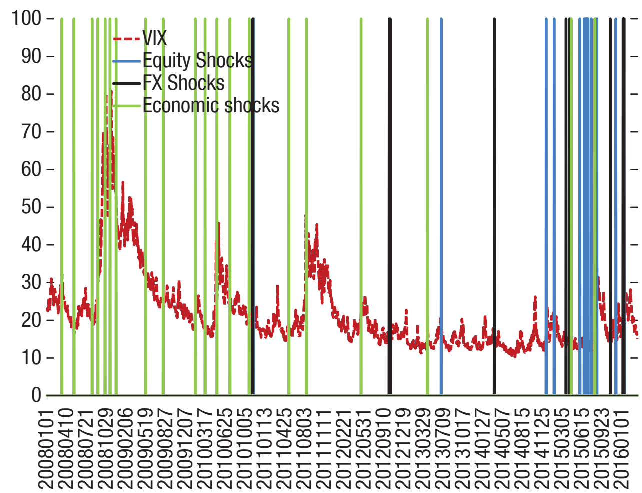
Four key potential spillover channels are tested: trade, financial, risk, and commodity-exporting channels. Countries are divided into high/low subgroups based their trade exposure, financial exposure, risk level, and commodity-exporting status.

- *Trade exposure* is measured by exports to China divided by GDP. Countries in the 75 percentile and above are considered to have a high trade exposure to China.
- *Financial exposure* is calculated as (portfolio + FDI + banks claims on China)/GDP. Countries in the 75 percentile and above are considered to have high financial exposure to China.
- *Risk level* is determined by indicators of country vulnerability.
- *Commodity exporters* are those countries with net commodity exports higher than zero.

Annex 4. Vector Autoregression Model

The impact of Chinese financial market developments and economic news on global and EM markets is analyzed in a vector autoregression (VAR) framework. The baseline VAR includes three groups

Annex Figure 3.1. Selected China Shocks



Sources: IMF staff estimates.
Note: 16 events on major equity declines and 13 events on major FX fluctuation, and 20 large negative ceonomic news shocks.

of endogenous variables: Chinese (equities, bilateral exchange rate against the U.S. dollar), global (VIX, S&P 500 stock index, U.S. 10-year yield, oil price and metals price index) and EM[25] (equities and bilateral exchange rate against the U.S. dollar). VIX and the U.S. 10-year yield enter the model as simple daily differences, whereas all the remaining variables are included as natural logarithm differences. The model also includes two exogenous variables: the surprise in Chinese industrial production (IP) data (calculated as the difference between the released value and the consensus forecast of the value at the time of release and zero on other days) and the Citi economic surprise index for the U.S. economy (which is an amalgamation of similar surprises in a variety of economic variables including GDP, IP, PMI, etc.).

The baseline model is run on daily data from January 1, 2005, through April 22, 2016, with five lags on both endogenous and exogenous variables. Variables are ordered chronologically for the Cholesky decomposition: Chinese variables followed by global variables and EM variables.[26]

All the results in the main text survive various robustness checks. Altering the number of lags in the model

[24]Using EMBI yields for EMs is due to the small country coverage of data on long-term interest rates among EMs.

[25]Argentina, Brazil, Chile, Colombia, Hungary, India, Indonesia, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Thailand, and Turkey.

[26]On any given day, Chinese markets generally close before U.S./most commodity/most EM markets open.

or replacing Chinese IP data surprises with the Citi economic surprise index does not materially affect the outcome. The baseline model specification includes the average daily returns on EM equities and exchange rates. The results do not differ substantially if the EM variable responses are instead calculated as averages of responses of individual EM country asset prices estimated in separate VAR models. Excluding Asian EM countries that do not follow the baseline chronological ordering of variables (since they are in the same or a similar time zone as China) from the EM average likewise produces similar results. Finally, placing the global variables ahead of the Chinese variables in the Cholesky decomposition ordering also qualitatively preserves the results regarding impact of China on EM asset prices.[27]

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[27]To preserve chronological ordering in this alternative setup, global variables are lagged one day when placed ahead of the Chinese variables. The resulting impact of the latter on the former is understandably different from that obtained in the baseline specification. Yet the impact of the Chinese variables on EM asset prices remains qualitatively similar.

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