ONLINE ANNEX 2.1. TECHNICAL NOTE

A. Local Stress Index for Emerging Market Economies[1]

This GFSR introduces a Local Stress Index (LSI) that measures market conditions across local government bond and FX markets in emerging market economies[2]. The index allows real-time market monitoring through a single indicator while also providing direct attribution to drivers of market stress. Unlike broader financial condition indices (FCI) that capture price of risk or cost of funding for the whole economy, the LSI focuses on stress within a specific market and therefore can be a component of a broader FCI measure. The index construction methodology is based on Hollo, Kremer and Lo Luca (2012) and Garcia-de-Andoain, Kremer (2018) can be summarized into following steps:

- **Variable selection**: The index aims to focus on variables that have low correlation in normal market conditions but can become increasingly correlated at times of stress. These measures include bid/ask spreads, intraday price movements and risk premia measures. For bond market LSI non-resident flows (scaled by the size of the bond market) and trading volumes are also included where available. This way, when large non-resident outflows or abnormal trading volumes co-occur with a jump in risk-premia or widening of bid-ask spreads, the index will pick up a signal about a potential market imbalance. While most countries will have an overlap in terms of relevant market variables, the selection is driven by country market specific considerations. For example, in countries with limited currency convertibility, the currency basis would be substituted with deliverable vs non-deliverable forward spreads. A limitation with some of these variables in the index is that structural shifts that may have occurred over the years cannot be controlled. For example, cross currency basis or risk reversals were more scarcely traded products 10-15 years and their information content from those periods might be more limited. The list of main variables included in the Local Stress Index is presented in Online Annex Figure 2.1.1, panel 1)

- **Variable transformation:** Each variable is transformed in a way that ensures a homogenous distribution and scale by applying the probability integral transform (PIT) to a cumulative distribution function (CDF). More precisely, variable X is transformed to an indicator Z, with r being the ranking number and n the total sample size, as follows:

$$Z_{n+T} = F_{n+T}(X_{n+T}) := \begin{cases} \frac{r}{n+T} \; for \;\; X_{[r]} \leq X_{[n+T]} < X_{[r+1]} \;, r = 1,2, \dots n-1, .. n+T-1 \\ 1 \; for \; X_{n+T} \;\; \geq X_{[n+T]} \end{cases}$$

[1] This section is prepared by Dimitris Drakopoulos and Dmitri Petrov.

[2] The index is calculated on 16 Countries: Brazil Chile, China Colombia, Hungary, India, Indonesia, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Thailand, Turkey.

Although this transformation generates some information loss by not maintaining the cardinal scale, it can improve them robustness over more common transformations that rely on the sample mean and standard deviation (e.g., z-score). For example, given variables such as bid-offer, or implied volatility follow highly asymmetric distributions, standardization and aggregation based on z-scores becomes problematic. Such variables are more likely to produce observations with large deviations from the mean (i.e. large z-scores) which can in turn dominate the dynamics of the aggregated index during times of stress. Additionally, the z-scores values are not comparable across variables given differences in the original distribution function of each variable. After the initial calibration period (2005–2009), the PIT uses "real time" samples and is therefore not subject to large revisions due to outliers that can change the mean and the standard deviation of the historical sample.

- **Index aggregation**: The variable aggregation relies on time-varying correlation between the transformed variables. Thus, the index increases more in a situation where stress prevails in several indicators at the same time. The index is aggregated using the following formula:

$$LSI_t = (w \; o \; Z_t) \; C_t \; (w \; o \; Z_t)'$$

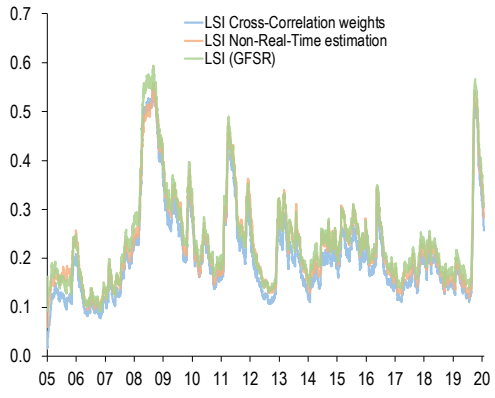
where o denotes the Hadamard-product, w is a vector of equal indicator weights, Z is a vector of transformed variables and C is a three-dimensional array of time-varying correlations. The time-varying correlation is estimated based on an exponentially weighted moving average. In order to simplify interpretation of EM wide index, equal weights are used when aggregating the country indices. The difference between equal weights and aggregation using cross country correlations is small (Online Annex Figure 2.1.1 panel 2). Alternative aggregations based on principal component analysis (PCA) yield were also tested. Under the PCA approach the first principal component tends to capture more global risk-events rather than idiosyncratic events and weighs the index more towards the exchange rate LSI. Furthermore, PCA suffers both from sub-sample robustness and is more sensitive to changes in index composition over time.

Online Annex Figure 2.1.1. LSI Methodology

1. Variables in LSI

Exchange Rate LSI	Local Bonds LSI
FX bid-ask spread	Bond bid-ask spread
Realized volatility	Realized volatility
Currency basis	Bond asset swap
Convertibility basis	Term-premium estimate
Implied Volatility	Non-resident flows
Risk-reversal ratio	Bond volume deviations

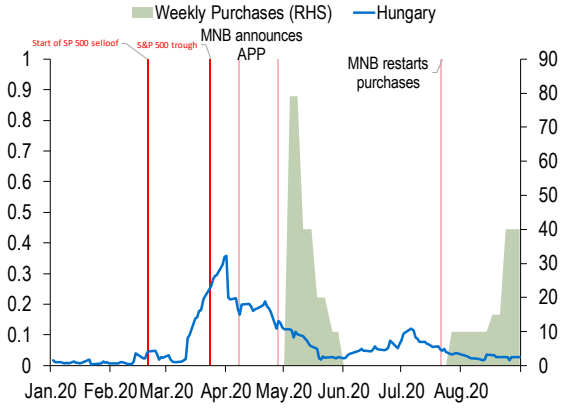
2. Alternative Aggregations of EM LSI (index)



Online Annex Figure 2.1.2. Country Event Studies for Bond LSI

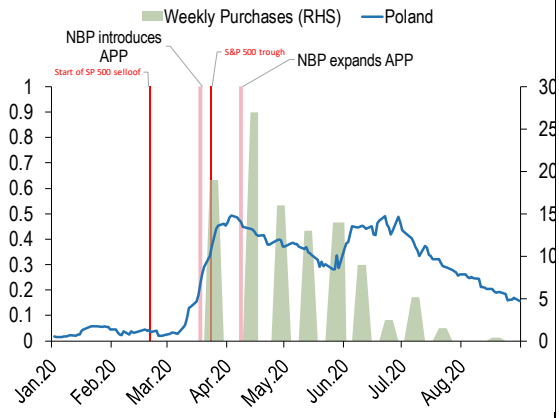
In Hungary, purchases in May seem to have had a large impact. MNB decided to step up its program in the summer as conditions deteriorated again.

1. Hungary Bond LSI and Purchases
(Index and local currency)



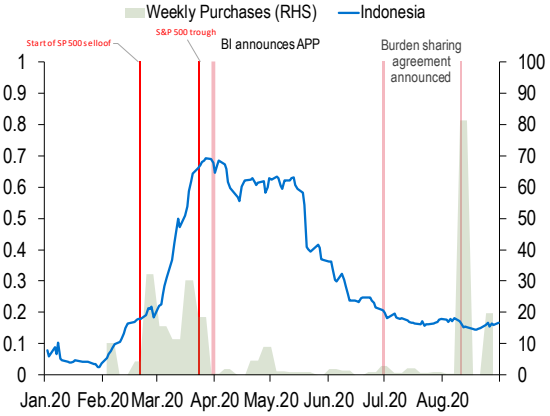
In Poland, large purchases in April were combined with a step up in issuance. Purchases tapered off as conditions improved in June, but trading volumes have remained low.

2. Poland Bond LSI and Purchases
(Index and local currency)



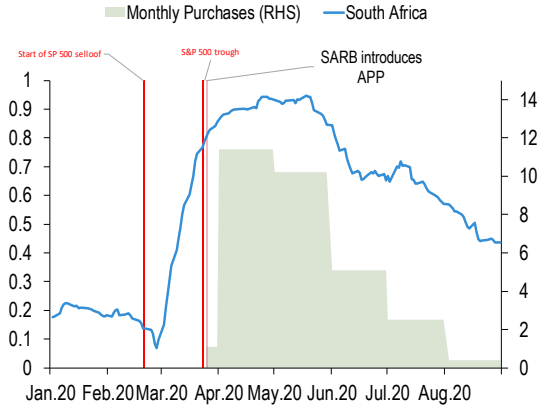
Indonesia purchases were also frontloaded and combined with large issuance. Conditions improved further following the burden sharing agreement in July.

3. Indonesia Bond LSI and Purchases
(Index and local currency)



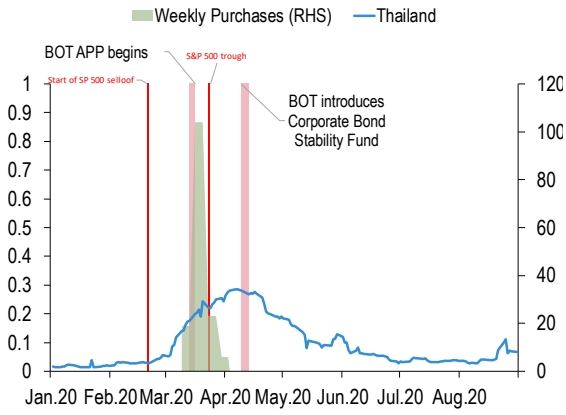
In South Africa APP has been relative limited in size and the market has remained concerned with increased issuance.

4. South Africa Bond LSI and Purchases
(Index and local currency)



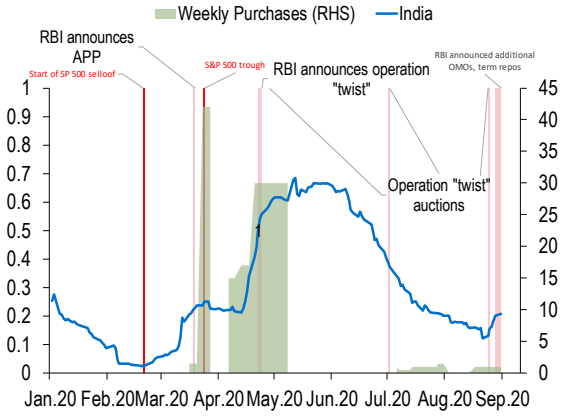
Thailand saw a swift improvement in the LSI, despite halting its APP in early April …

5. Thailand Bond LSI and Purchases
(Index and local currency)



… while in India the improvement remained limited until RBI announced its simultaneous sell/buy curve operations.

6. India Bond LSI and Purchases
(Index and local currency)



Sources: Bloomberg Finance L.P.; Country Central Banks; and IMF Calculations.

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Garcia-de-Andoain, Carlos, and Manfred Kremer. 2018. "Beyond Spreads: Measuring Sovereign Market Stress in the Euro Area." Economics Letters 159: 153–56.

Hollo , Dániel, Manfred Kremer, and Marco Lo Luca. 2012. "CISS—a Composite Indicator of Systemic Stress in the Financial System." ECB Working Paper, European Central Bank, Frankfurt.

B. Measuring the Drivers of FX Surprises during the COVID-19 Sell-Off and the Role of FX Intervention[3]

The goal of the empirical analysis is to shed light on the drivers of exchange rate movements in emerging markets and examine the role of domestic policies as well as global factors.

The specification is as follows:

$$\Delta\, Currency_{c,m} = \alpha_1 Domestic\ policies_{c,m} + \alpha_2 Global\ factors_m + \alpha_3 Domestic\ policies_{c,m}\ x\ Global\ factors_m + \alpha_4 X_{c,m} + \mu_c + e_{c,m}$$

where c and m stand for country and month, respectively. The variable details are as follows:

- **The** dependent variable $\Delta\, Currency_{c,m}$ is how much the value of domestic currency ended up higher than the forward value a month ago.[4] Specifically, it is calculated as the (negative of) percentage difference between the realized value of domestic currency (vis-a-vis the US dollar) at the end of month m and the value of one-month forward contract at the end of month $m-1$, normalized by the latter. The negative difference of the percentage value is used, hence the variable represents the percentage gain of the domestic currency above the forward one month before. Note that the analysis is also employed using simple exchange rate movements and the results are broadly consistent.
- $\boldsymbol{Domestic}\ policies_{c,m}$ include the intervention in the FX market (FXI) in a given month, and the domestic policy rate at the end of the month.
    - FXI[5] is calculated as the valuation adjusted changes in the stock of reserves for any central bank. The estimates include reserve operation in spot as well as the derivative markets. Operations in the derivative markets do not represent a drag on the reserve stock but are included in the calculations to estimate the true size of the intervention. These estimates do not adjust for FX bond sales/purchases, so may represent a partial picture in a few cases (e.g., Mexico). The variables to construct the FXI are adopted from Bloomberg, IIF, the dataset by Adler and others (forthcoming). The indicator is scaled by the actual stock of reserves.
    - The data on domestic policy rates are obtained from Bloomberg.
- $\boldsymbol{Global}\ factors_{c,m}$ consists of the effective Federal Fund rate at the end of each month, and the VIX Index averaged over the month. The data on global factors are from Bloomberg.

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[3] This section is prepared by Rohit Goel and Can Sever.

[4] This variable is expected to proxy the surprise movement in the exchange rates, given what was priced in the forward contracts. This assumes interest rate parity holds true, though the authors acknowledge that spot rates can deviate from forward rates for an extended period of time.

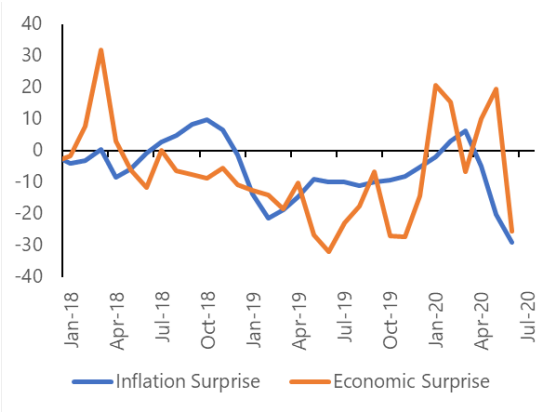
[5] Some results might be overstated due to potential endogeneity issues.

- In addition, the four interactions between these domestic policies and global factors are added to take a potential interplay between those into account.
- $X_{c,m}$ represent macroeconomic control variables, namely the surprise indices on economic activity and inflation. The indices represent the high frequency data releases vs the analyst expectations of these data releases and are meant to proxy the macroeconomic surprises. These indices are sourced from Citi and Bloomberg (see Online Annex Figure 2.1.3).
- Finally, country fixed effects (μ_c) are included to account for any time-invariant country specific factors that may potentially lead to a bias in the estimation. Standard errors are robust.

Online Annex Figure 2.1.3. Macroeconomic Surprise Indices for Emerging Markets

Economic surprises have been mixed, while inflation surprises have remained to the downside for EMs.

1. Macroeconomic Surprise Indices for EMs (Index)



Sources: Bloomberg Finance L.P.; and Citigroup.
Note: The chart shows the aggregate trend; the analysis takes country level indices into account.

Two separate regressions are employed to analyze the effect of domestic policies and global factors on domestic currencies during:

- the period of COVID-19 (GFSR Figure 2.2, panel 3); and the first column of Online Annex Table 2.1.1, and
- the 2015 China sell-off episode (GFSR Figure 2.2, panel 4); and the second column of Online Annex Table 2.1.1.

The sample consists of 14 emerging market economies in both cases: Argentina, Brazil, Chile, China, Colombia, India, Indonesia, Mexico, Malaysia, Philippines, Russia, Thailand, Turkey, and South Africa.

The period of the analysis is from January to May of 2020 in the former, whereas it is from April 2015 to February 2016 in the latter.

Note that the coefficient estimates are reported with 2 standard error confidence intervals in the panels in GFSR Figure 2.4.

As a robustness check, China is removed from the panel but the results are still consistently robust.

Online Annex Table 2.1.1. Effects of Domestic and Global Factors on FX Surprises

Variable	2020 COVID-19	2015 EM Sell-Off
FX Intervention	-0.813	2.196***
	(0.991)	(0.706)
Domestic Policy Rate	-0.376	1.788**
	(0.309)	(0.813)
VIX	-0.525***	7.928
	(0.100)	(6.748)
Federal Fund Rate	-9.659***	0.203
	(1.634)	(0.125)
FX Intervention x VIX	0.012	-0.165***
	(0.019)	(0.048)
FX Intervention x Federal Fund Rate	0.206	4.095
	(0.430)	(2.485)
Domestic Policy Rate x VIX	0.008*	-0.007
	(0.004)	(0.012)
Domestic Policy Rate x Federal Fund Rate	0.160**	-2.219**
	(0.064)	(1.011)
Controls	Yes	Yes
Country Fixed Effects	Yes	Yes
R-Squared	0.635	0.244
Countries	14	14
Observation	68	142

Source: IMF Staff Calculations.
Note: *** p<0.01, ** p<0.05, * p<0.1

Reference

Adler, Gustavo, Kyun Suk Chang, Rui C. Mano, and Yuting Shao. Forthcoming. "Foreign Exchange Intervention: A Data Set of Public Data and Proxies." International Monetary Fund, Washington, DC.

C. Impact of Asset Purchase Announcements on Local Currency Yields and Currencies[6]

The staff analysis[7] empirically explores the effect of domestic APP announcements by EM central banks on local currency sovereign bond yields and currencies[8], after controlling for domestic policy rate cuts and global factors, such as the QE announcement by the Federal Reserve or the VIX index. The estimation aims to capture both the size and the persistence of the impact. For this purpose, local projections method -proposed by Jorda (2005) with the extension introduced by Teulings and Zubanov (2014)- is used in the empirical analysis. This allows to capture the full dynamics of sovereign bond yields in the aftermath of the announcements by central banks. The specification is as follows:

$$\Delta Y_{c,t-1\to t+p} = \sum_{r=0}^{p} \alpha_1^{p,r}\, APP\ announcement_{c,t+p-r} + \sum_{r=0}^{p} \alpha_2^{p,r}\, Global\ factor_{t+p-r} + \sum_{r=0}^{p} \alpha_3^{p,r}\, \Delta Policy\ rate_{c,t+p-r} + \sum_{l=1}^{4} \Omega_1^{l}\, APP\ announcement_{c,t-l} + \sum_{l=1}^{4} \Omega_2^{l}\, Global\ factor_{t-l} + \sum_{l=1}^{4} \Omega_3^{l}\, \Delta Policy\ rate_{c,t-l} + \mu_c + e_{c,t+p} \quad (1)$$

where *c* stands for country and *t* stands for day. The dependent variable $\Delta Y_{c,t-1\to t+p}$ is the cumulative change in yield (in percentage points) from *t-1* to *t+p*. Data on yields for 10-year local currency sovereign bonds is adopted from Bloomberg.

- The variable $APP\ announcement_c$ is a dummy variable which takes 1 in the dates of APP announcements by EM central banks, and 0 otherwise.[9] Data on the dates for APP announcements are mainly based on the IMF staff research and are illustrated in Table 2 below.
- The variable $Global\ factor_t$ is either (i) a dummy variable indicating the date for QE announcement by the Federal Reserve (GFSR Figure 2.7, panels 1, 3, and 5) to capture the direct effect of that on yields, or (ii) the VIX index (GFSR Figure 2.7, panels 2, 4, and 6) as a proxy for global risk appetite. The dummy variable for the date of the QE announcement by the Federal Reserve is assigned 1 on March 23. The VIX index is adopted from the Federal Reserve Bank of St. Louis database.

[6] This section is prepared by Dimitris Drakopoulos, Rohit Goel, and Can Sever.

[7] Results in this section draw upon Drakopoulos and others (forthcoming).

[8] Drakopoulos and others (forthcoming) discusses also the effect of APPs on equity markets.

[9] This dummy variable approach comes with a caveat, since it ignores the size, duration or specific nature of each announcement – which can potentially affect the consequences of the announcement. However, it is not straightforward to apply this analysis using size or other features of APP announcements, since they have not been very clearly defined in many cases.

- The third explanatory variable is the percentage points decrease in policy rates ($\Delta Policy\ rate_c$) and adopted from Bloomberg.

Four lags of all explanatory variables are included. However, using lower/higher number of lags does not affect the results. Any bias from unobserved country-specific features are absorbed by country fixed effects (μ_c). This is important in the estimation, since those characteristics such as pre-COVID-19 market conditions, institutional capacity, policy credibility, accountability or central bank independence may yield a bias in the results by altering the impact of APP announcements.[10] Standard errors are robust.[11]

The analysis uses panel data at daily frequency from 13 emerging market economies (Online Annex Table 2.1.2). The period of the analysis is from the beginning of January 2020 to the mid-May 2020.

The coefficient estimates $\alpha_i^{p,p}$ with *i=1,2,3* are reported for 6 trading days (for *p=0,…,6*) in the aftermath of each action, and the day of the event (day 0). Thus, the estimation is able to capture the full dynamics the response of yields and hence the persistent of the effect. One standard error confidence interval is also reported. Panels 1, 3, and 5 in GFSR Figure 2.7 report results when the date for QE announcement by the Federal Reserve is used in equation (1) as the global factor, whereas panels 2,4,6 document the response with the VIX index instead.

Impact of Asset Purchase Announcements on Emerging Market Currencies

For calculating the impact of asset purchase announcements on EM currencies, the same empirical set-up as described above is used. The result is documented in GFSR Figure 2.8. The dependent variable $\Delta Y_{c,t-1\rightarrow t+p}$ in that case is the cumulative change in the exchange rate vis-à-vis the US dollar. The $Global\ factor_t$ is the QE announcement by the Federal Reserve in that analysis.

Dates for APP Announcements by EM Central Banks

As mentioned earlier, the dates for APP announcements by EM central banks are mainly based on the IMF staff research, but the staff also benefit from Arslan and others (2020) and Hartley and Rebucci (2020). Online Annex Table 2.1.2 illustrates the list of 13 EMs in the sample together with APP announcement dates.

[10] For instance, see the discussions in Arslan and others (2020), Çakmaklı and others (2020), and Hartley and Rebucci (2020).

[11] Results are virtually the same if standard errors are clustered at the country-level.

Further Checks

The exact dates used in our analysis are mostly consistent with those used in both Arslan and others (2020) and Hartley and Rebucci (2020). However, to alleviate any concerns, the following robustness steps are taken:

- In the case that APP announcement dates in a country in the sample may be particularly problematic, the staff re-run the test in (1) with 12 EMs dropping one EM at a time. Throughout those regressions, results in GFSR Figure 2.7 stay similar. Hence, results are not driven by any of the countries in the sample.

- There exist APP announcement dates which are close to each other, e.g., in India. This may lead to a concern on that the specification may generate biased results in such cases given the length of the analysis (i.e., 6-day period in the aftermath of each event). For instance, following an announcement at day *t*, the cumulative change in the yield at day *t+6* would reflect the impact of the announcement at day *t*, and if any, the second announcement within this period. However, by applying the extension by Teulings and Zubanov (2014), the analysis controls for the forward values of the announcements dates to isolate the effect of each day, and hence, alleviates a potentially downward bias arising from such consecutive announcements in the sample.[12] However, when the only first announcement date is adopted for each country with multiple announcement dates, results remain very similar.

- A large set of alternative combinations/identifications of domestic APP announcement dates is employed, and results are similar.

Online Annex Table 2.1.2. Dates for APP Announcements[1]

Country	Date	Country	Date
Chile	March 16, April 8	Philippines	March 24, April 10
Colombia	March 23	Poland	March 17, April 8
Hungary	March 24, April 7, April 28	Romania	March 20
India	March 18, March 20, April 23	South Africa	March 25
Indonesia	April 1	Thailand	March 19, March 23, April 7
Korea	March 19, March 25, April 9	Turkey	March 31, April 17
Mexico	April 21		

Source: IMF staff.
[1] The sample is expanded to include non-emerging markets (e.g., South Korea) as well as "operating twist" type of announcements that we don't consider as APPs in the main chapter (e.g., Mexico, April 23 date for India). The results remain robust if individual countries are removed.

[12] See Teulings and Zubanov (2014) for a detailed discussion.

References

Arslan, Yavuz, Mathias Drehmann, and Boris Hofmann. 2020. "Central Bank Bond Purchases in Emerging Market Economies." BIS Bulletin 20, Bank for International Settlements, Basel.

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Jordà, Òscar. 2005. "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review* 95 (1): 161–82.

Teulings, Coen N., and Nikolay Zubanov. 2014. "Is Economic Recovery a Myth? Robust Estimation of Impulse Responses." *Journal of Applied Econometrics* 29 (3): 497–514.

D. Central Bank Policy Responses[13]

In figure 2.1, panel 3, central bank policy options are counted only once. For example, more than one rate cut is counted as one action. Policy actions are reported by IMF country desk economists.

The emerging market sample included in Figure 2.1, panel 3 includes 50 central banks: Angola, Ghana, Kenya, Mozambique, Nigeria, South Africa, Zambia, China, India, Indonesia, Sri Lanka, Lao, PDR, Malaysia, Mongolia, Philippines, Thailand, Vietnam, Papua New Guinea, Bulgaria, Georgia, Albania, Hungary, Croatia, Poland, Romania, Russian Federation, Turkey, Ukraine, Serbia, Algeria, Egypt, Kazakhstan, Morocco, Pakistan, Tunisia, Uzbekistan, Saudi Arabia, Brazil, Chile, Colombia, Mexico, Peru, Dominican Republic, Jamaica, Guatemala, Paraguay, Serbia, Bank of Central African States (BEAC), Central Bank of West Africa States (BCEAO).

[13] This section is prepared by Patrick Schneider.

Online Annex Box 2.1. The Monetary Policy Response to the COVID-19 Crisis in China

China did not experience the financial market stress seen in other emerging markets, but authorities have still faced challenges in maintaining supportive financial conditions. After cutting policy interest rates and deploying measures to directly increase bank credit, the People's Bank of China (PBOC) scaled back expectations for further interest rate reductions in May, leading to a rebound in money and bond market yields. The policy shift came amid improving economic activity but also concerns about rising financial sector risks.

Bond yields fell in the first few months of the COVID-19 crisis as the PBOC injected liquidity and cut short-term and one-year policy rates by 30 basis points, with the latter directly reducing the reference rate for most loans. Short-term interbank rates and one-year government bond yields fell much more sharply, declining as much as 180 and 100 basis points, respectively. The improvement in funding conditions, however, largely reversed after markets adjusted expectations of further policy rate cuts in May, sending corporate and longer-maturity government bond yields above pre–COVID-19 levels.

This episode highlights some of the complexities of interest rate transmission in China.

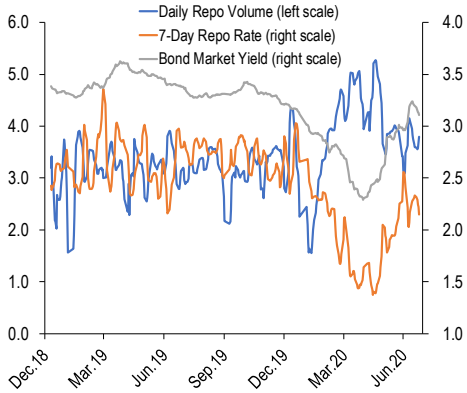
- Repo-funded bond market purchases play an important role in policy rate transmission in China's bond market but are procyclical and can create large swings in interest rates.[1] The large initial declines in short-term interbank and government bond rates this spring coincided with a sharp rise in interbank repo borrowing volumes, particularly by asset management products, suggesting that leveraged bond purchases amplified declines in interest rates (Figure 2.1.1, panel 1). When policy expectations shifted and short-term rates rose, leverage fell sharply, contributing to the subsequent sell-off in bonds.
- Short-term interbank interest rates have limited pass-through to bank funding costs. While lending rates fell, deposit costs have remained relatively sticky. This may reflect competition from deposit alternatives like wealth management products, which use leverage and other risk-taking to offer yields that are significantly higher than deposit rates, which continue to be priced relative to the benchmark deposit rate (Figure 2.1.1, panel 2). Falling interest rates led to surging flows into these deposit alternatives, limiting the benefits to bank funding costs (Figure 2.1.1, panel 3).
- Yields on long-term government bonds fell by less than half as much as on short-term bonds, steepening the yield curve to a five-year high. The smaller reduction in long-term rates reflected surging issuance of such bonds amid rising government deficits but also the limited declines in funding costs for the large state-owned banks, which absorb the majority of this issuance. Historically, long-term bond yields rarely fall below these banks' marginal (nondeposit) funding cost (Figure 2.1.1, panel 4).

While lower interest rates supported the economy, they also posed risks to bank profits and added to financial vulnerabilities. For banks, limited downward flexibility in funding costs means that declines in the benchmark lending reference rate directly reduce profits and their ability to provide new financing, particularly for smaller banks. As mentioned, lower

Online Annex Figure 2.1.1. The Monetary Policy Response to the COVID-19 Crisis in China

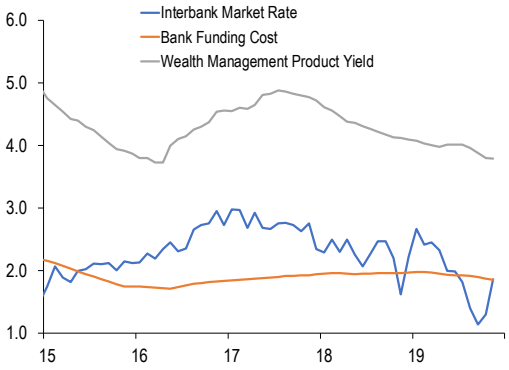
The surge in repo borrowing helped amplify initial declines in interest rates, but also contributed to the bond sell-off when investors later reduced leverage.

1. China: Daily Interbank Repo Trading Volume, Repo Rates, and Bond Prices (Trillions of renminbi, percent)



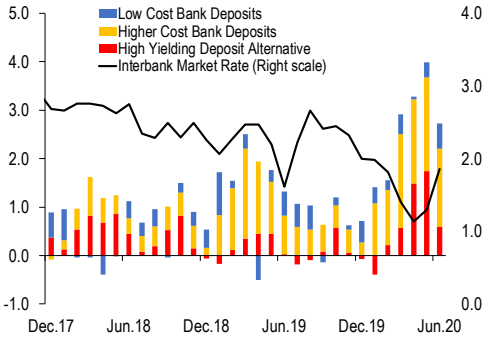
Falling interbank market rates provided relatively little pass-through to funding costs for key lenders such as banks and wealth management products.

2. China: Selected Monthly Interest Rates (Percent)



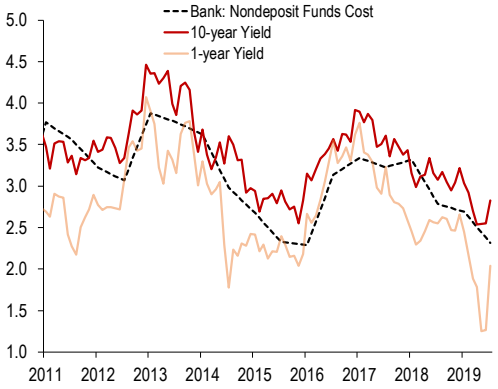
Deposit alternatives saw surging inflows as interest rates fell, suggesting that banks might see funding cost pressures from further cuts to policy rates.

3. China: Changes in Selected Financial System Liabilities and Interbank Rate (Trillions of renminbi; three-month moving averages)



Short-term rates had a limited impact on long-term yields, which remain linked to banking sector funding costs.

4. China: Government Bond Yields and Banks' Nondeposit Cost of Funding (Percent)



Sources: Bloomberg Finance L.P.; CEIC; People's Bank of China; S&P Market Intelligence; and IMF staff calculations.
Note: In panel 1, bond market yield is Bloomberg Barclays China Aggregate Index, including government, financial, and corporate bonds, and seven-day repo rate is five-day moving average of the daily weighted average rate. In panel 2, the interbank market rate is the weighted average repo rate. Bank funding cost is based on the asset-weighted average ratio of interest expense to average financial liabilities of Chinese banks with public financial statements. In panel 3, low-cost deposits include demand and overseas deposits. Higher-cost deposits include time and other deposits. Deposit alternatives include bank off-balance-sheet wealth management products, structured deposits, and money market and bond funds. In panel 4, bank funding cost data are based on financial disclosures from national state-owned-enterprise banks.

Online Annex Box 2.1 *(concluded)*

interest rates also led to a rise in asset management sector vulnerabilities. Net money market borrowing volumes by investment products surged 55 percent during the first half of 2020 to RMB 130 trillion, increasing leverage and interconnectedness with the broader financial system.

In addition to lowering policy rates, authorities have used other policy tools to accelerate credit growth and support vulnerable borrowers. The PBOC has expanded its relending facilities (which provide low-cost funding for bank lending) to nearly RMB 2.2 trillion, targeted to micro and small businesses, the agricultural sector, and privately owned and manufacturing firms. Authorities have also guided banks to increase lending and lower interest rates, particularly to these same borrower segments.

While providing additional support to the economy, credit support measures may be adding to nonfinancial sector vulnerabilities. China's corporate-debt-to-GDP rose 10 percentage points in the first quarter, against a backdrop of already very high debt servicing burdens. Household debt also continued to rise, with continued rapid growth in housing-related debt and a rebound in retail stock market leverage.

Going forward, continuing to address interest rate transmission issues will allow authorities to increase the scope for traditional interest-rate-based monetary policy, easing debt servicing burdens and credit misallocation risks. Key policy priorities are still closing remaining prudential regulatory gaps, particularly in the asset management sector; improving market-based pricing of bank deposits; and accelerating bond market development by improving hedging mechanisms and diversifying the investor base.

This author of this box is Henry Hoyle.

[1] Adrian, Hoyle, and Natalucci (2019) provide evidence of significant procyclicality between trading and funding liquidity in China's bond market, reflecting limited hedging mechanisms and other market structure features.

Online Annex Box 2.2. Capital Controls in Times of Crisis

Large and sudden capital outflows can pose significant policy challenges for emerging market and developing economies. According to the IMF's institutional view on the liberalization and management of capital flows, in the face of an imminent crisis, temporary capital controls may help prevent a free fall of the exchange rate, preserve foreign exchange reserves, and provide breathing space until other policy adjustments, including macro-financial adjustments, take effect. This box offers insight into the characteristics and effects of capital controls in times of crisis (Bouis and others, forthcoming).

Despite exceptionally large capital outflows within a short period, the COVID-19 crisis did not trigger widespread introduction of capital controls. Given a swift recovery of capital inflows aided by ultra-loose advanced economy monetary policy, unprecedented foreign exchange interventions, access to IMF financing, a drop in gross outflows, and concerns about losing sovereign bond index membership, only a few emerging market and developing economies tightened controls to limit capital flight; some eased inflow controls. Nonetheless, in past crises, countries occasionally adjusted controls to reduce capital outflows.[1] Understanding the design of such controls and their macroeconomic effects is crucial for their effective implementation during crises.

The bulk of economies maintain at least a few capital controls (Figure 2.2.1, panel 1). Although there has been a steady move toward removing controls in the past three decades, controls have been tightened more since the global financial crisis than before the crisis (Figure 2.2.1, panel 2).

Countries responding to crises with capital controls generally tighten restrictions on outflows or ease restrictions on inflows (Figure 2.2.1, panel 3). Outflow controls implemented in crises tend to be blunt and sticky; initially they are applied to several asset classes, prohibiting or setting limits on outflows, and they are fine-tuned later as experience is gained.[2] In contrast, easing of inflows is more often targeted and price-based.[3] Outflow controls are lifted after crises have subsided and usually last longer than expected (Figure 2.2.1, panel 4).

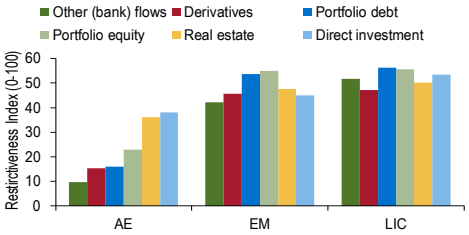
An analysis covering 27 advanced and emerging market and developing economies that experienced at least one crisis between 1995 and 2017 indicates that countries with more open capital accounts experience a significant drop in both capital inflows and outflows, unlike countries with more pervasive controls, which do not see a statistically significant effect of the crisis on capital flows (Figure 2.2.1, panel 5). However, the effectiveness of implementing capital controls to increase inflows or reduce outflows during crises cannot be firmly established because of difficulties in overcoming endogeneity issues in econometric analysis.

Online Annex Box 2.2 *(continued)*

Online Annex Figure 2.2.1. Capital Controls During Crises

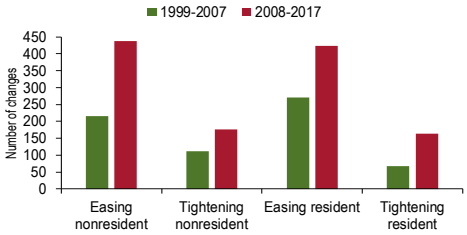
Capital controls are more prevalent in lower- and middle-income countries, but advanced economies also maintain some controls, particularly on inflows of foreign direct investment and real estate.[1]

1. Average Level of Restrictiveness, 2018



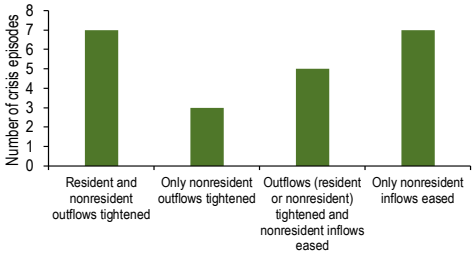
While countries continued to liberalize, more controls were tightened following the global financial crisis than earlier, in response to advanced economy unconventional monetary policy and possibly lessons learned during the crisis.

2. Number of Changes in Capital Controls (Sample of 40 countries)



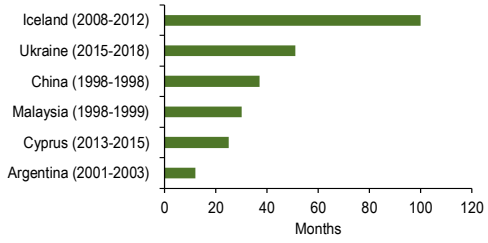
When responding with controls to crises, countries generally either tighten restrictions on outflows or ease restrictions on inflows.

3. Capital Controls during Crises by Type of Flow, 1995–2017



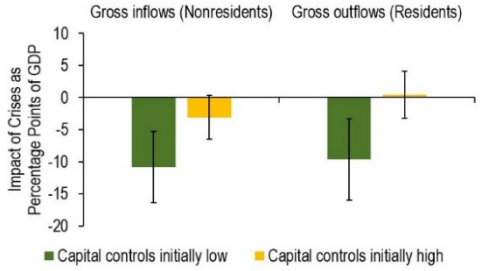
While crisis-related controls are usually intended only for a short time, they tend to remain in place for longer.[2]

4. Duration of Controls on Outflows by Nonresidents



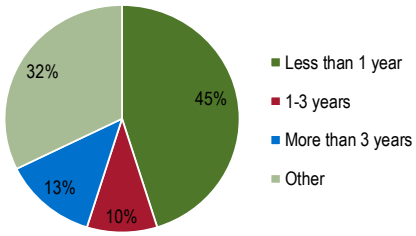
Countries with high preexisting capital controls do not suffer a statistically significant decline in capital flows during crises, unlike countries with more open capital accounts.

5. Estimated Impact of Crises on Gross Flows, According to Capital Account Openness (With 95-percent confidence interval)



Investors reallocate their investments from countries that introduce capital controls, but almost half of the surveyed investors would reinvest in the same country within a year of removal of controls.[3]

6. Period before Investors Report Resuming Investments after Removal of Controls



Sources: IMF; Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER) database; survery of 31 investors; and authors' calculations.
Note: Crisis events are identified using the database developed by Laeven and Valencia (2018). AE = advanced economy; EM = emerging market; LIC = low-income country.

[1] In panel 1, the restrictiveness of transactions corresponding to each asset is measured by the number of transactions reported as controlled in the AREAER as a percentage of all transactions related to the asset class.

[2] In panel 4, the year of the start of the crisis (when the control was enacted) and the end year of the crisis, according to Laeven and Valencia (2018), are included in parentheses. The exceptionally long period in Iceland may be partially due to the collapse of the banking system, which was one of the biggest bankruptcies in history that had to be resolved within one of the smallest monetary systems in Europe.

[3] In panel 6, the results show responses to the question "How long [after the removal of a capital control in a country from which you have exited] would you wait before resuming investing in this country/market?" based on 31 responses from a variety of investors and market participants to a survey conducted in February 2020.

Online Annex Box 2.2 *(concluded)*

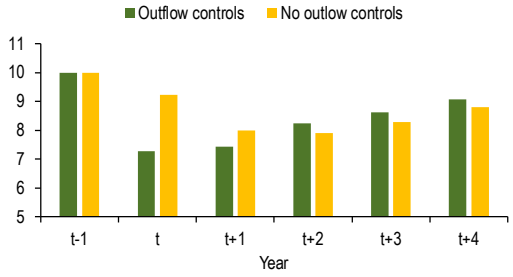
Capital controls implemented in crises do not seem to be associated with a lasting adverse effect on sovereign ratings (Figure 2.2.2, panels 1 and 2). Countries implementing controls experience a larger drop in ratings but recover them similarly to countries without controls. A survey also indicates that, although capital controls matter to investors, investors appear to be generally forgiving. The majority of those surveyed would demand higher risk premiums to invest in a country with capital controls and would reallocate their investment from a country that introduces capital controls, but almost half of them would reinvest in the same country within a year of removal of controls (Figure 2.2.1, panel 6).

Figure 2.2.2. Impact of Outflow Controls on Sovereign Ratings

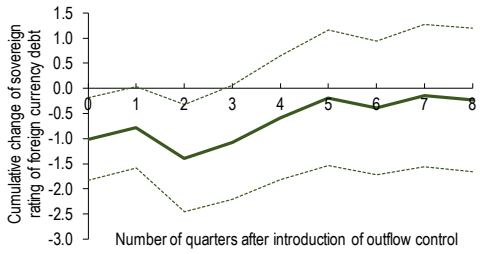
Countries tightening or introducing outflow controls experience a downgrade of their rating three times as large as the downgrade of countries not implementing controls (on average by almost 3 points) in the year the controls are implemented, but they recover their rating as fast as countries that do not use controls ...[1]

… as confirmed by econometric analysis showing the absence of a significant long-term effect of outflow controls on the rating.

1. Average Rating of Countries with and without Outflow Controls Introduced in Crisis Year *t*[2]



2. Cumulative Change of Sovereign Rating in Response to Introduction of Outflow Controls (With 90-percent confidence interval)[3]



Sources: Bloomberg Finance L.P.; IMF, FFA and Annual Report on Exchange Arrangements and Exchange Restrictions databases; and authors' calculations.
Note: Crisis events are identified using the database developed by Laeven and Valencia (2018).
[1] This could reflect a negative signal of the controls sent to the market and/or the fact that countries using these types of controls are experiencing more severe crises.
[2] Panel 1 shows the average Standard and Poor's rating of sovereign debt in foreign currency (ranging from 1 for default to 22 for AAA), rebased at value 10 the year before the crisis year *t*. For countries experiencing a crisis but not introducing outflow controls, *t* is the year the crisis starts; for countries implementing outflow controls in response to a crisis, *t* is the year the controls were introduced.
[3] Panel 2 shows the estimated dynamic effect of the introduction of controls on sovereign debt rating using the local projection approach (see Bouis and others 2020 for details).

This box was prepared by Romain Bouis, Annamaria Kokenyne, Manuel Perez, and Umang Rawat.

[1] For the purposes of this box, capital controls are capital flow management measures that discriminate based on residency. Outflow controls restrict the purchase of foreign assets by a country's residents or the liquidation and repatriation of investment of nonresidents' local assets.
[2] Based on a sample of 41 advanced economies and emerging market and developing economies that have experienced a crisis since 1995, according to Laeven and Valencia (2018).
[3] Price-based controls include taxes, levies, and unremunerated reserve requirements.

References

Bouis, Romain, Annamaria Kokenyne, Manuel Perez Archila, Umang Rawat, and Ratna Sahay. "Capital Controls in Times of Crisis—Use and Effects." Forthcoming, IMF Working Paper, International Monetary Fund, Washington, DC.