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Fundamental Drivers of Financial Conditions

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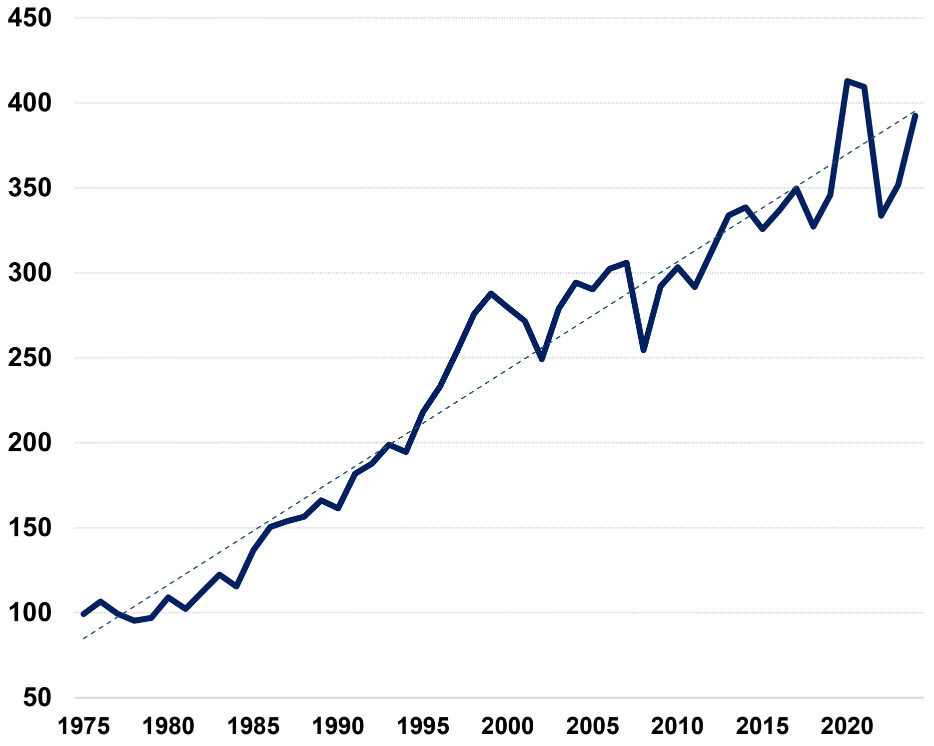
Central Bank of Chile, November, 2025.

Motivation: as asset markets grow and become integrated, understanding the drivers of financial conditions (FC) has become increasingly important

Yet the role of FC in macroeconomic outcomes, and its implications for monetary policy, is still a relatively new area of research in international finance/macroeconomics (Caballero and Simsek, this conference volume).

U.S. total debt securities plus total stock market capitalization as % GDP

(1975-2024, %GDP)



- Asset prices' movements can stem from multiple causes—e.g., investors dump bonds due to higher risk perception (e.g., fiscal deficits) → long-term yields rise (contractive). But a similar rise can come from optimism about economic growth (expansive) → looking at asset prices alone is not enough.
- This issue translates to traditional financial conditions indices, which are based on direct observation of asset prices (e.g, Hatzius et al, 2017). They are useful, but have two important limitations:
  - **Analytical:** since asset prices are a confounding, "reduced-form" manifestation of underlying shocks → developing "policy narratives" may prove difficult (e.g., are falling stocks and yields good or bad for growth?)
  - **Quantitative:** When forecasting macroeconomic outcomes, traditional FCIs are informative "on-average", but may provide misleading results for particular combinations of underlying shocks → there are relevant forecasting accuracy gains to make from considerning fundamentlal shocks.

(1) Data source: World Bank. (2) Data source: Debt securities statistics BIS. For US the line shows the sum of debt securities issued by Government, Financial corporations, and Non-Financial corporations at all original maturities as a percentage of GDP.

This paper: recover structural drivers of global and local FC, with an open-economy perspective, and use them to understand selected episodes

- **Why this is relevant:** CBs need to understand, react to, and, eventually, affect FC. Good analysis needs a disciplined approach to interpret high-frequency financial data. This discipline boils down to providing a structural, quantitative interpretation about the underlying drivers.
- **What we do:**
  1. Estimate a sign- and magnitude- restricted VAR for global asset prices—adapted and extended from Cieslak and Pang (2021). We consider 6 structural shocks as key drivers of asset prices:
     - **5 U.S. centred:** Growth, Monetary Policy, Hedging Risk Premium (typical *risk-on/off*), Common Risk Premium (preference for liquidity → depreciate all U.S. assets save the dollar), *Dollar-Hedging Risk* (shift in sentiment toward all U.S. assets, including the dollar).
     - **1 Global:** *China Growth* → key for EMEs.
  2. Then, construct FCIs based on this structural interpretation.
- **Contributions:**
  - **i. Policy:** Tool for monitoring FC in real time with a structural interpretation. Allows for scenario analysis.
  - **ii. Methodological:** Better identification of shocks, including U.S. ones. Why?
    - a) Dollar-Hedging Risk is crucial for understanding what happened in 2025.
    - b) China growth shock is key for understanding EMEs asset prices' dynamics.
    - c) Using non-U.S. assets to identify "U.S shocks" improves identification.

Methodology

Data and estimation approach

- **Daily frequency data:** sovereign 2-year and 10-year yields, stock markets, exchange rates, copper and oil prices. For **Jan 1, 2010 – Oct 22, 2025**.

- **Block of Countries:**

    - **EME:** Chile, China Colombia, Czech Republic, India, Indonesia, Malaysia, Mexico, Poland, Peru, Korea, Thailand, Brazil, Hungary, South Africa and Sri Lanka.

    - **AE:** U.S., Japan, United Kingdom, Germany, Canada, France, Italy, Norway, Spain, Sweden and Switzerland.

    - We summarize country information using a scaled PC.

- **Estimation:** Baseline model 6 variables, 6 shocks → Standard estimation methods **(Rubio-Ramirez et al, 2010)**

    - Cholesky decomposition of variance-covariance of reduced-form shocks: $\Sigma_u = BB' \quad u_t = B\epsilon_t$

    - Generate an orthonormal rotation matrix Q_i, such that $Q_i Q_i' = Q_i' Q_i = I \rightarrow u_t = BQ_i' Q_i \epsilon_t = A(Q)\ \epsilon_t(Q)$. Simulate and save matrices Q_i such that $A(Q) = BQ'_i$, meet the sign and magnitude restrictions identification.

- **Extended model (robustness):** 7 shocks and 15 variables → Bayesian estimation **Korobilis (2022)**.

Identification

U.S 10-year > EMEs 10-year

Table 1. Baseline Identification Matrix

U.S 10-year > U.S 2-year

		(1)US Growth	(2)US Hedging	(3)US Common	(4)US MP	(5)Dollar Hedge	(6)China Growth
US	2-year	-1	-1	1	1	1	NaN
	10-year	-1	-1	1	1	1	NaN
	SPX	-1	-1	-1	-1	-1	-1
EME	10-year	NaN	NaN	1	1	NaN	-1
	H-S	NaN	-1	-1	-1	NaN	-1
	FX	NaN	1	1	1	-1	1

EMEs 10-year > U.S 10-year

U.S 10-year > EMEs 10-year

U.S 2-year > U.S 10-year

References: Matheson and Stavrev (2014), Cieslak and Schrimpf (2019), Cieslak and Pang (2021), Albagli et al (2019;2024), Manu and Lodge (2022), Gutierrez et al (2025)

Applications to individual countries: SVAR-X

Then, we estimate similar individual SVARs for several EMEs, conditioning on the estimated global shocks → results are tailored for each country.

- For each country, we estimate a Structural Bayesian VAR, using as an exogenous block the shocks identified from the global model

$$\left(1-\Phi(L)\right)y_t = c + \vartheta(L)u_t + \eta_t$$

- Where $y_t = [2y, 10y, stock, FX]$, u_t are the global structural shocks and η_t are the reduced form residual

	Local Growth	Local MP	Local Common	Local Hedging
2-year	1	1	1	1
10-year	1	1	1	1
Stock	1	-1	-1	1
FX	-1	-1	1	-1

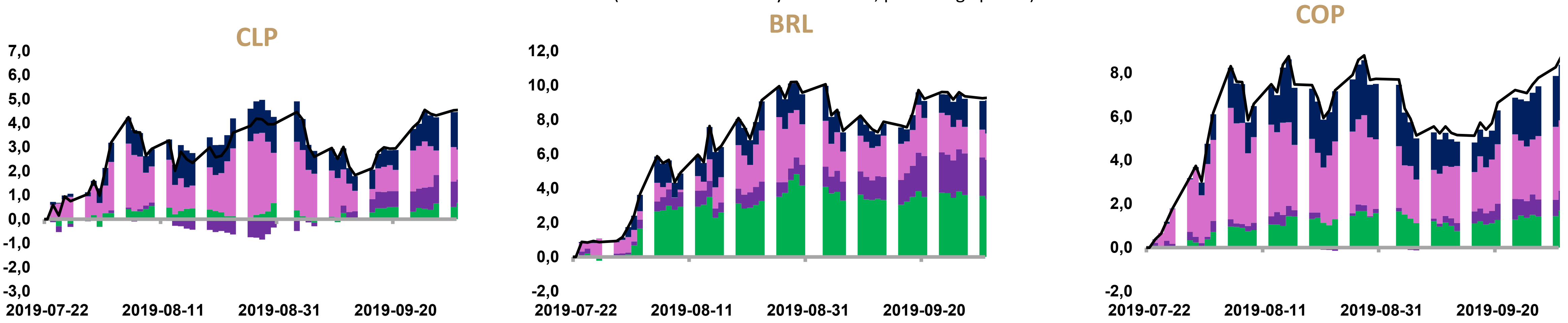
Model Results

Relevance of the China growth shock – Trade War I intensification period, 2019.

Not considering the China growth shock leads to finding large, highly correlated “idiosyncratic” shocks across EMEs.

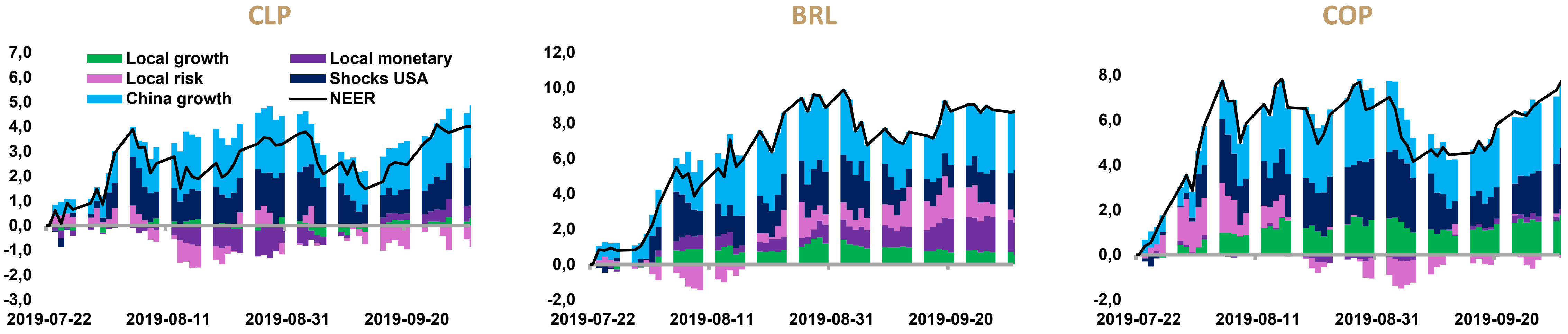
Decomposition of FX during the 2019 Trade War intensification period, with no China shock

(cumulated since July 22nd 2019, percentage points)



Decomposition of FX during the 2019 Trade War intensification period, the full model

(cumulated since July 22nd 2019, percentage points)

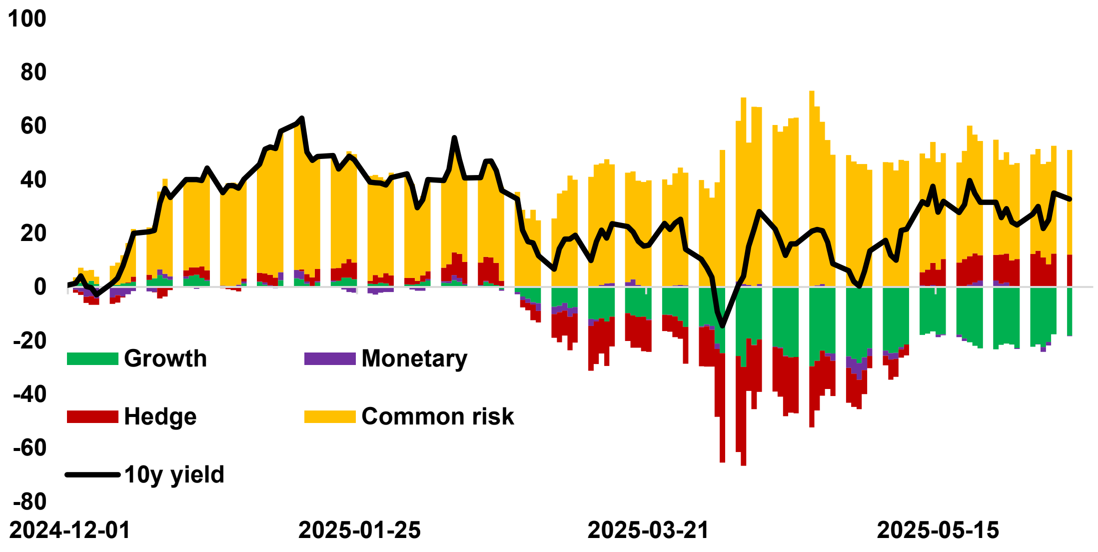


Relevance of the *Dollar-hedging shock in 2025*

Without the *dollar hedging shock* models assign the increase in U.S. 10 year yield to the *preference for liquidity shock* → The dollar should have appreciated, and EMEs assets should have suffered heavily—but the opposite happened.

Historical decomposition of U.S 10 year yield C&P (1)

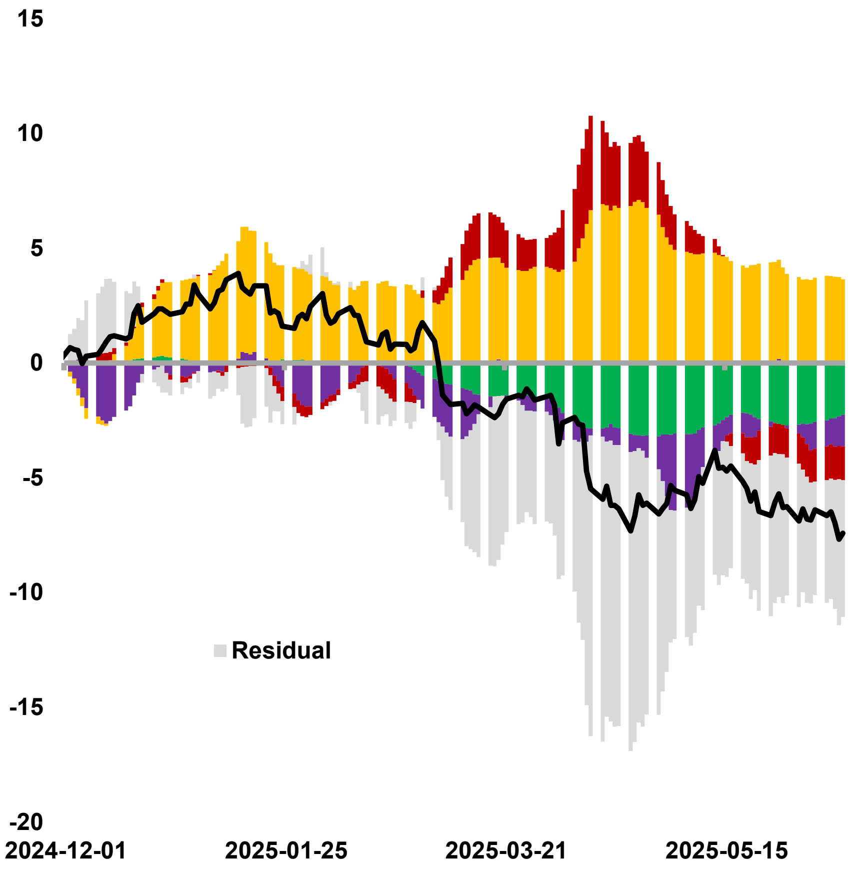
(cumulated since 01/12/24, basis points)



Variable	Change between 01/12/24 to 09/06/25
U.S 10 year yield	+30 bps
U.S 2 year yield	-15 bps
S&P 500	-0,7%
DXY	-8%

Historical decomposition of DXY C&P (1)

(cumulated since 01/12/24, basis points)



(1) Decomposition using Cieslak & Pang's (2021) shocks.

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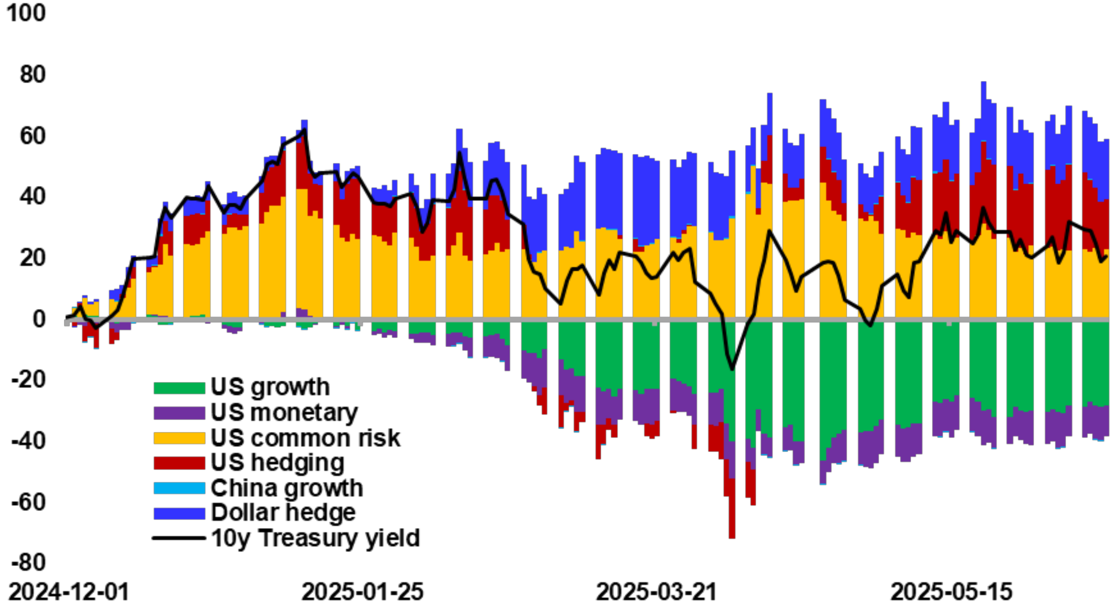

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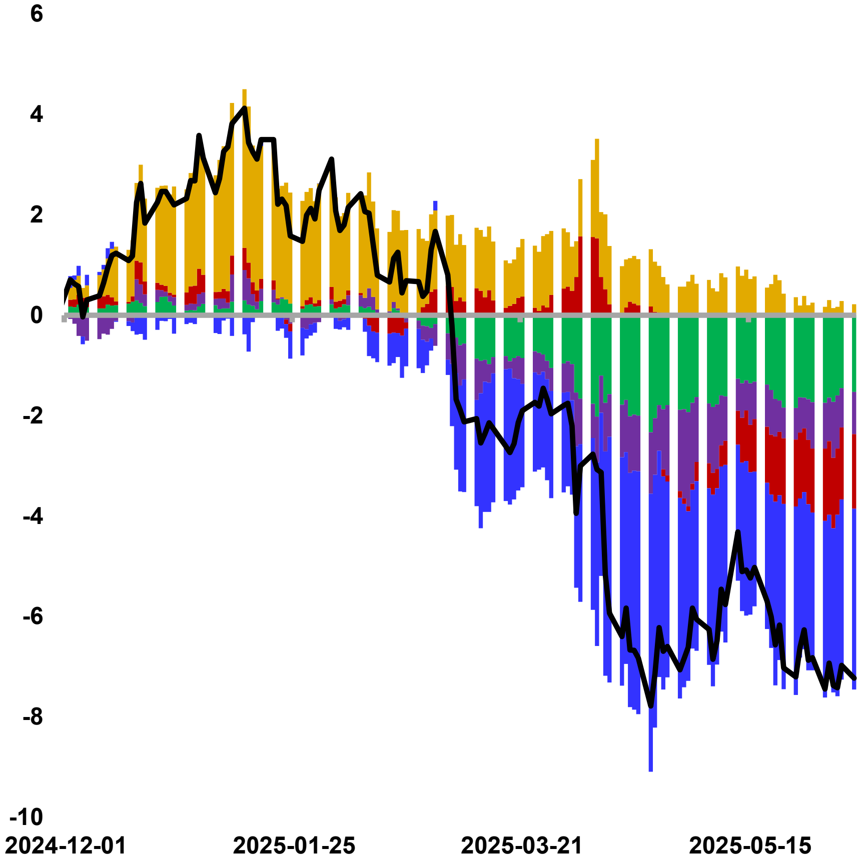


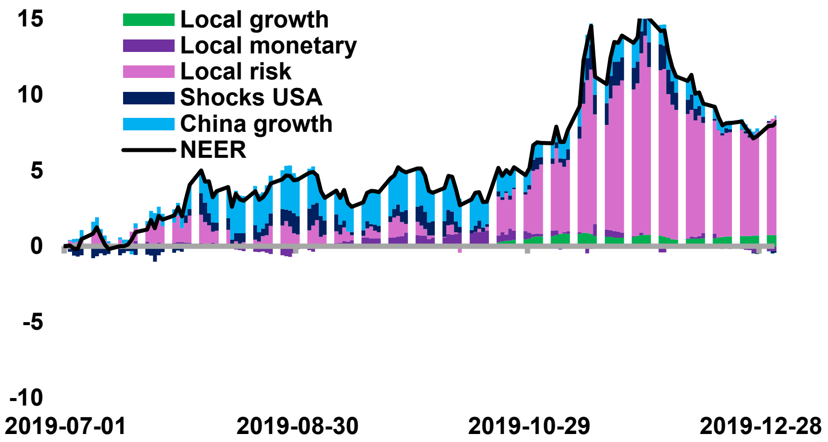
(1) Decomposition using our model's shocks.

An Application of the SVAR-X strategy for EMEs

Our historical decompositions match the commonly accepted narratives during significant past events in EMEs – adding some relevant insights

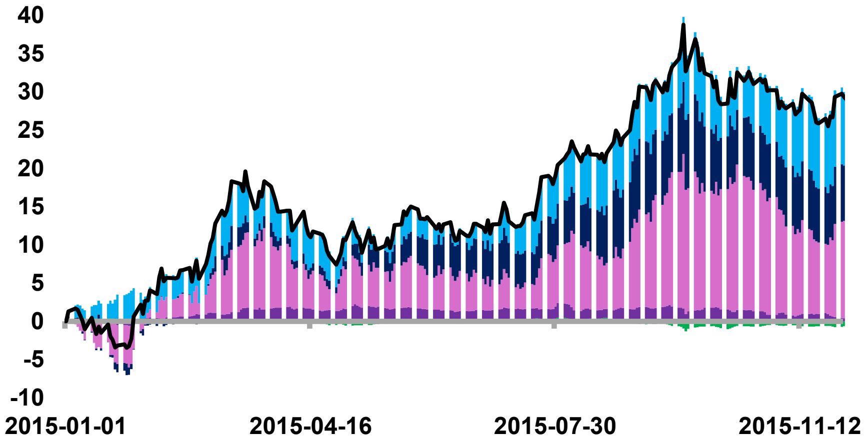
Chile FX: social unrest 2019

(cumulated since 01/01/19 to 31/12/19, percentage points)



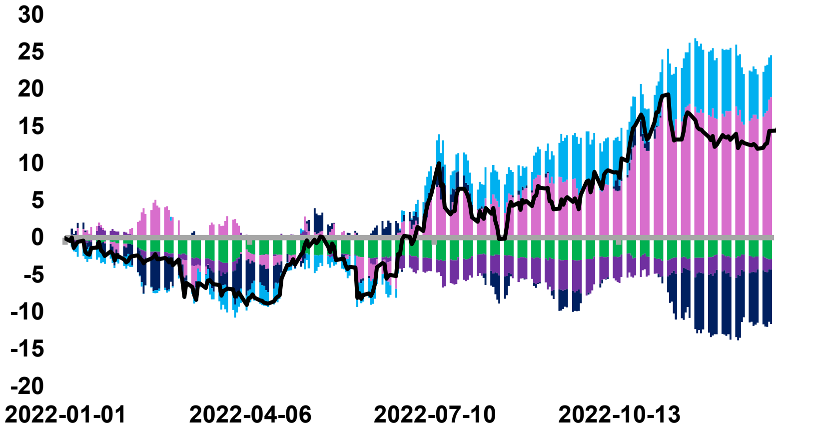
Brazil FX: impeachment 2015-2016

(cumulated since 01/01/15 to 30/11/15, percentage points)



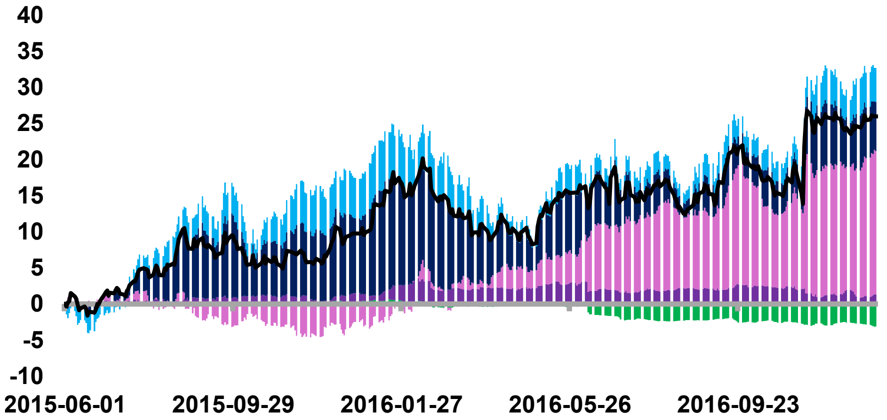
Colombia FX: political instability 2022 (1)

(cumulated since 01/01/22 to 31/12/22, percentage points)



Mexico FX: political instability 2015-2016 (2)

(cumulated since 01/06/15 to 31/12/16, percentage points)



(1) Colombia's political instability in 2002 was shaped by several domestic episodes: an unusually violent electoral cycle, a marked escalation of territorial contestation by armed group, and, later in the year, large-scale demonstration against incoming administration. (2) Mexico's 2015-2016 political instability was marked by mounting public outrage over corruption scandals, large protest driven by human-rights abuses and growing tensions over the federal government's weak institutional responses

Financial Conditions Index

Basic Idea: Estimate dynamic multipliers of the estimated shocks to macro variables →aggregate the shocks using those multipliers as weights → convert to high frequency

- For a given country, the proposed Financial Conditions Index (FCI) aggregates structural shocks using a dynamic weighting scheme.

$$\Delta y_{t+h} = c^h + \phi_1^h s_{1,t} + \Theta_1^h(L) s_{1,t} + \phi_2^h s_{2,t} + \Theta_2^h(L) s_{2,t} + \cdots + \phi_6^h s_{6,t} + \Theta_6^h(L) s_{6,t} + \epsilon_{t+h}$$

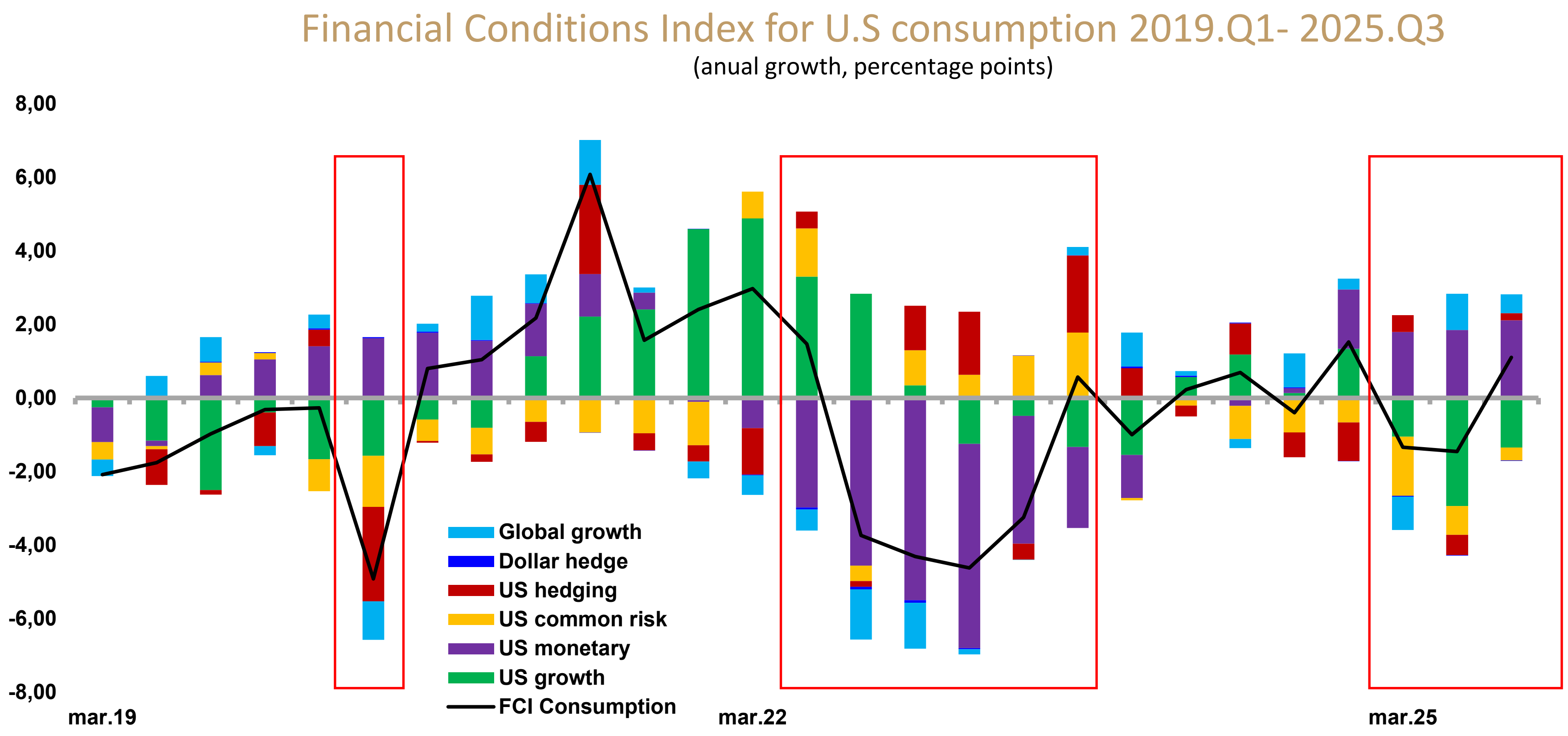
Weights are IRFs coefficients of each shocks on key macro-aggregates. The FCI for the macro-aggregate is defined as,

$$FCI_t^y = \sum_{h=1}^{P} \sum_{i=1}^{6} \phi_i^h s_{i,t}$$

- **High Frequency FCI:** since reduced form residuals are Martingale differences, with zero cross-correlation at all lags, higher frequency indicators can be constructed with mild assumptions.

FCI—U.S. low frequency

A relevant advantage of this strategy for constructing FCIs is that it allows interpretation and scenario analysis.



- **2020:** COVID related risk factors and weaker growth prospects. Monetary policy partially compensated
- **2022:** Fed rate hikes, tightened conditions.
- **2025:** Initially: weaker growth and uncertainty (tariffs, institutional tensions) tightened conditions.

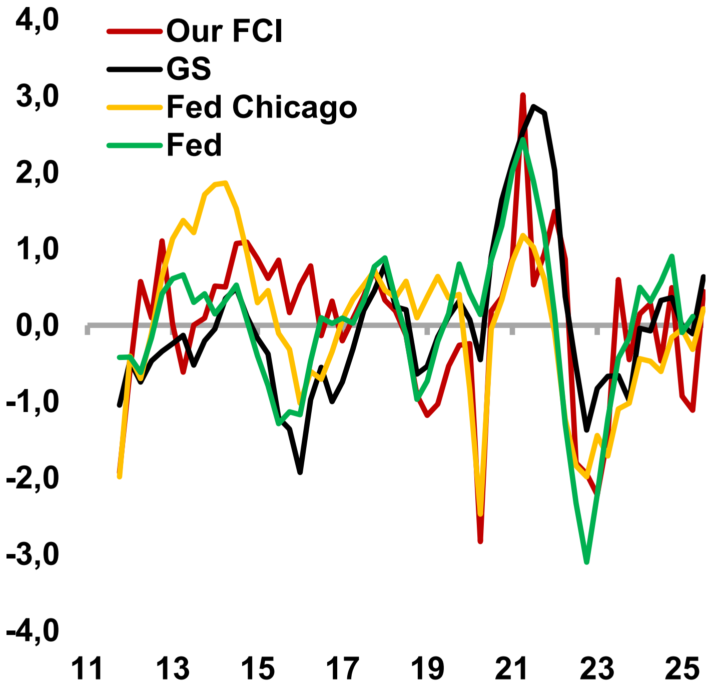
  Later: trade agreements, AI optimism, limited tariff impact, and expectations of easier monetary policy improved them.

FCI—U.S. low frequency

These advantages come at zero cost, as our FCI improves nowcasting accuracy—thanks to significant gains during periods when relying on asset prices alone, rather than their underlying drivers, could be misleading.

Financial Condition Index for U.S

(standarized)



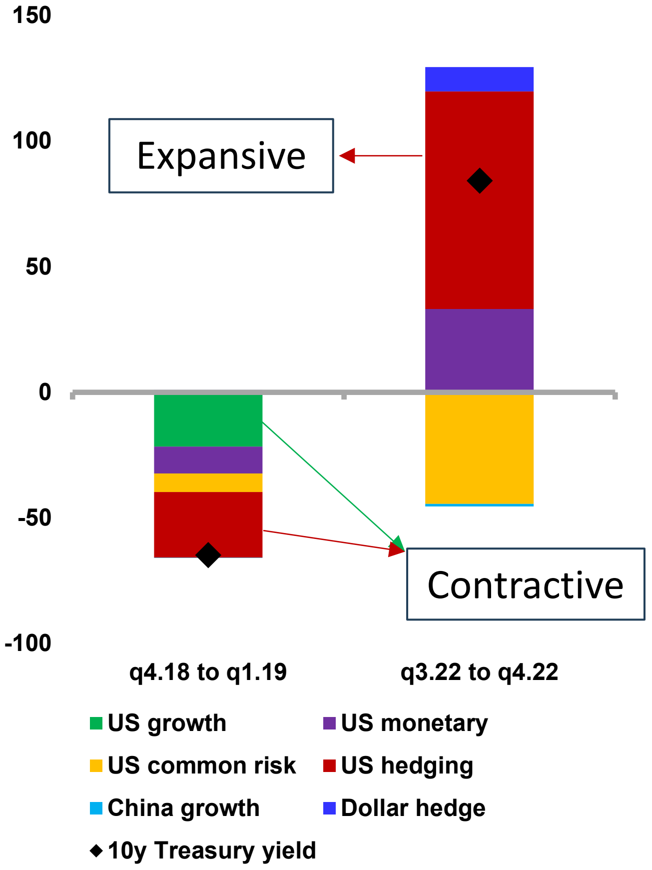
Out of sample RMSE ratios of FCI relative to the benchmark

(nowcast for internal private demand, nowcasting periods Q1.2019-Q2.2025)

FCI-GS	FCI Fed Chicago	FCI-Fed	Our FCI
0.88	0.75	0.87	0.70

U.S 10-year Treasury yield on quarters with large nowcasting gains

(basis points)

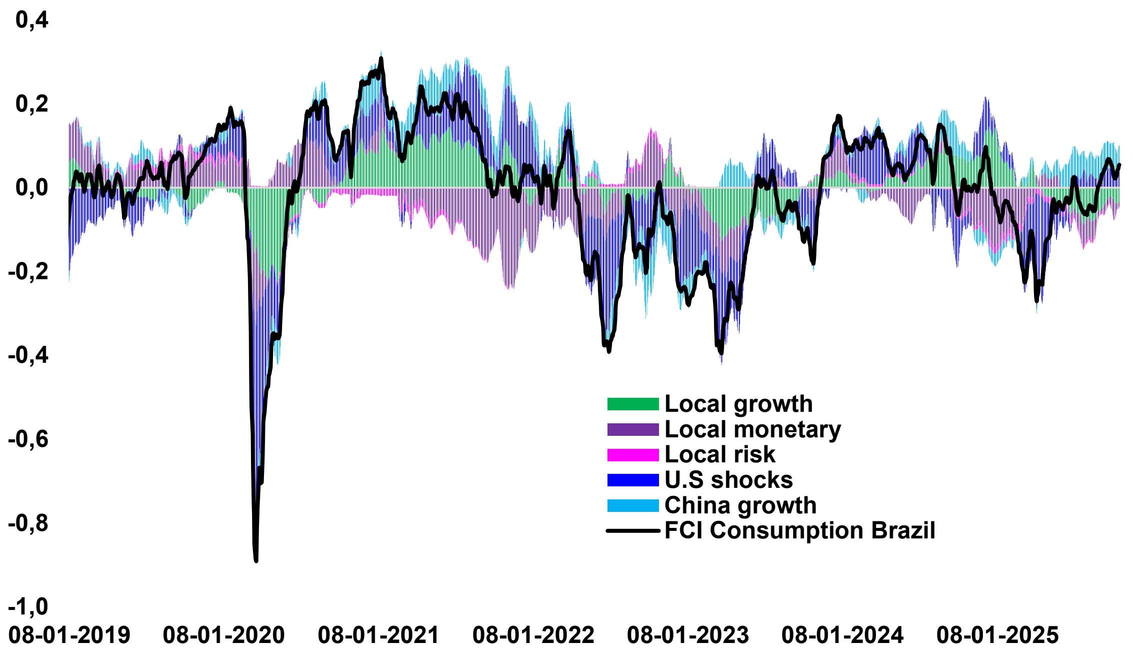


FCI—EMEs high frequency

Our FCI also has better nowcasting accuracy in EMEs.

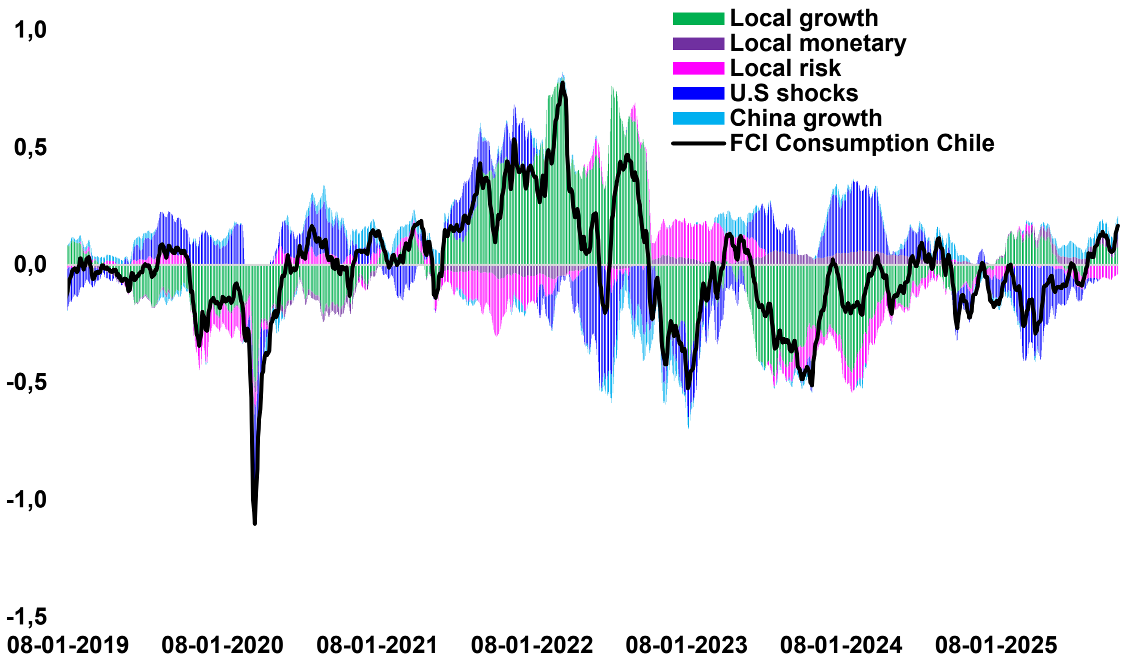
Financial Conditions Index for Brazil consumption

(quarterly growth, percentage points, 31/12/2018- 22/10/2025)



Financial Conditions Index for Chile consumption

(quarterly growth, percentage points, 31/12/2018- 22/10/2025)



Out of sample RMSE ratios of FCI relative to the benchmark

(nowcast for internal private demand)

FCI-GS	Our FCI
0.95	0.79

Out of sample RMSE ratios of FCI relative to the benchmark

(nowcast for internal private demand)

FCI-GS	Our FCI
0.97	0.66

Concluding remarks

- Understanding financial markets' dynamics is increasingly relevant for Monetary Policy.
- Yet simply observing asset prices movements (or a particular combination of them) does not tell the full story and may be quite misleading during episodes where usual correlations break down.
- Extending the analysis in Cieslak and Pang (2021), we propose a strategy to recover fundamental underlying shocks common to all asset prices. This allows a systematic and objective way of monitoring financial markets in real time.
- We also provide a shock-based Financial Conditions Index that enhances interpretability and supports scenario-based policy analysis and cross-country comparisons.
- Empirical results show that our strategy explains major financial episodes more accurately than existing approaches, especially in emerging markets.
- Overall, the framework offers a valuable tool for policymakers that need to understand, react to, and eventually affect financial conditions.
- …and one which is **already developed and applied to many EMEs**, and available upon request from interested researchers.

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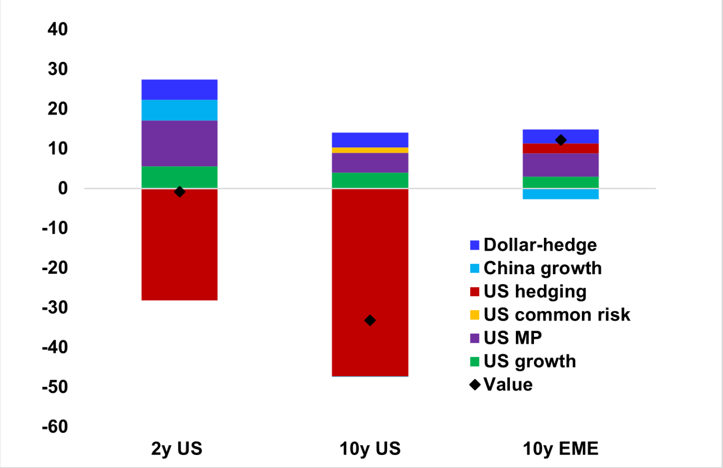
*Views included in this presentation do not necessarily represent those of the Central Bank of Chile or any of its board members.

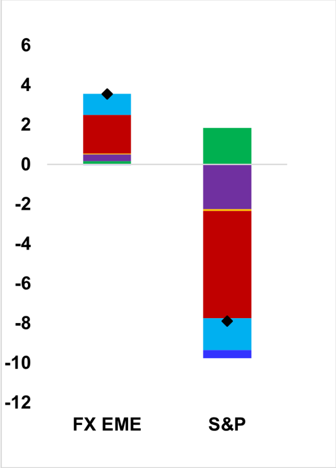
Historical decomposition

Our historical decompositions match the commonly accepted narratives during significant past events.

Historical Decomposition During the 2011 Euro Debt Crisis

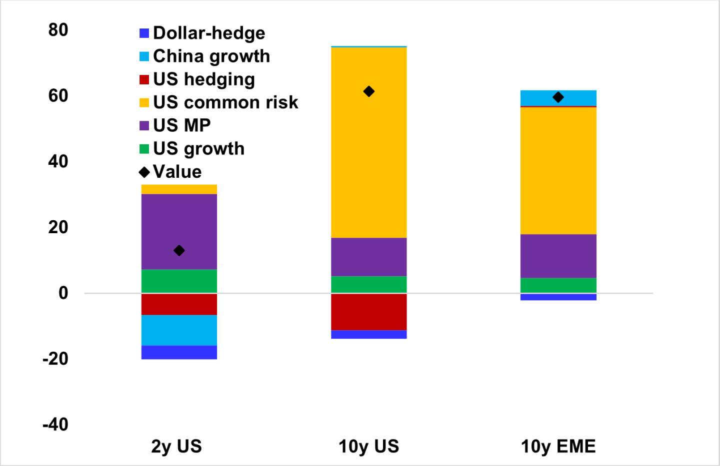
(cumulated since Oct 26th to Nov 25th 2011. Yields in bp., stock and NEER in pp.)

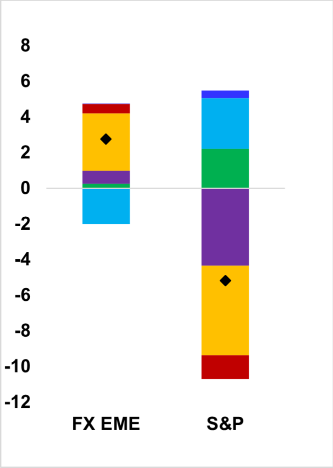




Historical Decomposition During the 2013 Taper Tantrum

(cumulated since May 22th to Jun 25th 2013. Yields in bp., stock and NEER in pp.)



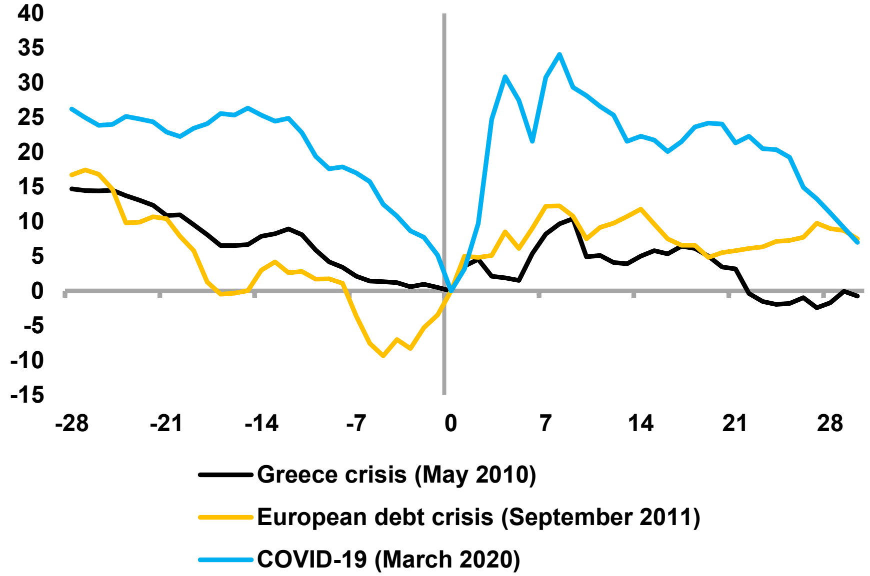


Better identification of other U.S. shocks

Example: C&P *risk-off* shocks drive EME long-term rates lower—A divergence from historical risk-off patterns.

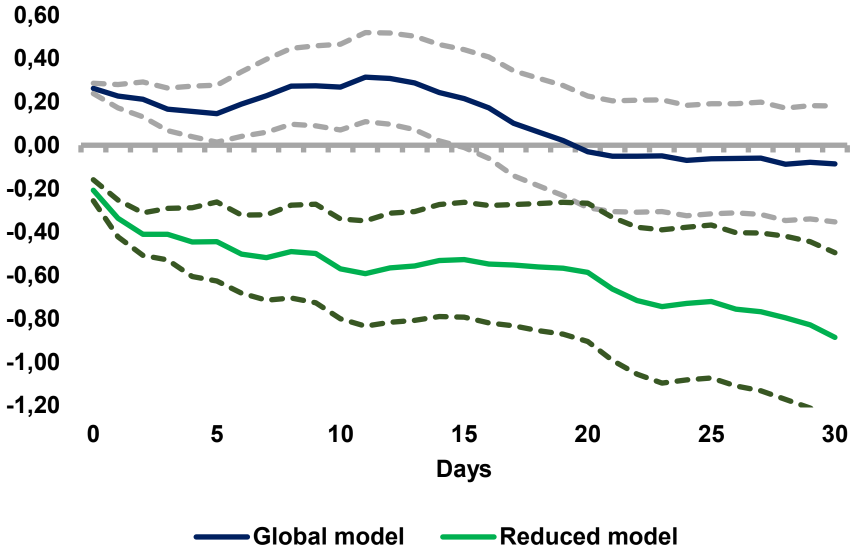
Event study: 10y EM yield response during risk-off episodes (1)

(cumulated since t=0, basis points)



IRF of EME's 10y yield to a risk-off shock (2)

(basis points)



(1) T=0 day selection: Apr 26–27, 2010: Greek bonds downgraded to junk status; contagion fears spread; September 13, 2011: On this day, global financial markets were shaken by escalating fears of a Greek default and broader contagion risks across the eurozone; Mar 9, 2020: "Black Monday I" – Dow falls 2,014 points (-7.8%). (2) Estimates are based on Jorda's (2005) local projection approach. The figure displays the impact response to a one-standard-deviation shock. Compares the Cieslak and Pang (2021) shocks ("reduced model") and the shocks that we propose in this paper ("Global model"). Dot lines represent a 80% confidence Interval.