Capital Flows at Risk: Push, Pull and the Role of Policy

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Motivation

Macro dynamics around sudden stops in EMs (Mendoza, 2010)
Motivation

- Sudden stop episodes very costly, want to understand them
- Capital flow determinants typically studied
  - within frameworks focusing on mean outcomes, or
  - considering (arbitrary) tail episodes within logit-type frameworks
- Room for richer insight by characterising entire distribution of capital flows
Our paper

- Interested in characterising the *entire distribution* of capital flows to EMs, with a focus on tail events
- What are the underlying forces ‘shaping’ this distribution?
  - External (‘push’) vs. internal (‘pull’) factors
- What role for policy?
  - Capital flow management, macro-pru
Methodology

- Two building blocks:
  1. Use asset prices to quantify risks facing an economy
     - Split up ‘global’ and ‘local’ components
  2. Use that information to characterise the entire distribution of capital flows to a panel of countries
     (relying on quantile regression methodology)
Literature

- **Determinants of capital flows**
  
  Calvo et al. (1993), Calvo et al. (2004), Koepke (2019)
  
  ⇒ These papers typically focus on mean outcomes and/or arbitrary episodes

- **Methodology: measuring financial conditions & ‘revival’ of quantile regression**
  
  Miranda-Agrippino & Rey (2015), Arregui et al. (2018), Habib and Venditti (2018); Adrian et al (2016)
  
  ⇒ What we do differently: split financial conditions into global and domestic; use quantile regression to study entire distribution of capital flows

- **Not alone:** Gelos et al (2020) and Chari et al (2020) also look at capital flows in quantile framework
Data

- **Capital flows data**
  - Gross capital inflows (non-resident net flows)
  - Source: IMF IFS
  - Look at portfolio flows, FDI and ‘other’ (banking) flows separately
  - Also have results for resident flows

- **Financial variables used to measure financial conditions consistently across 43 countries (in the spirit of Arregui et al., 2018)**
  - Term, sovereign, interbank and corporate spreads, long-term sovereign interest rates, equity returns and volatility, and relative capitalization of financials
  - Sources: Thomson Reuters Datastream, JPM, BofAML, Barclays, S&P, MSCI

- **Policy measures**
  - Capital flow management measures (Fernandez et al, 2016)
  - Macro-prudential measures (Cerutti et al, 2017)
THE INFORMATIONAL CONTENT OF ASSET PRICES
The informational content of asset prices

- Capital flows are function of economic outlook and risk environment
- Want measure of risks facing an economy
  - Which metric to focus on?
    - Literature has identified several (growth, debt, bank health, US MP)
    - Very few degrees of freedom in quantile context
- Short-cut: rely on asset prices
  - forward looking
  - embed (risk-adjusted) expectations of outlook
  - can be thought of as information aggregation devices
- Still, similar question: which asset prices to focus on?
  - Construct summary measure of financial conditions (country-time)
The informational content of asset prices

- Want summary measure of financial conditions (proxy of ‘ease of access to finance’)

- Measure common variation in a set of asset prices (for given country)
  - Consider term, sovereign, interbank and corporate spreads, long-term sovereign interest rates, equity returns and volatility, and relative capitalization of financials
  - Extract the first principal component; that’s our **Financial Conditions Index** (simplification of Koop Korobilis 2014’s TVP-DFM with ‘macro cleaning’)

- Do this for 43 countries
Financial Conditions Indices

FCIs display a high degree of cross-country co-movement. Global average is meaningful.
The informational content of asset prices

- High degree of co-movement across FCIs
- Interesting in capital flows context:
  - Push- and pull-type components could contain differential information
- Consider a ‘global’ FCI and country-idiosyncratic FCIs
  - Global FCIs as first principal component / global average (‘push’)
  - Country-idiosyncratic FCIs as OLS residuals (‘pull’)

Capital Flows at Risk
CAPITAL FLOWS AT RISK
Does the information embedded in asset prices help us characterise the *entire distribution* of capital flows?

Explore this by:

- Relying on quantile regression methodology
- Allowing for different role of push- and pull-type factors
Standard (OLS) regression provides an estimate of the conditional mean of a variable of interest (given a set of covariates)
Capital flows at risk

Quantile regression

- Standard (OLS) regression provides an estimate of the conditional mean of a variable of interest (given a set of covariates)

- Quantile regression allows to model the entire conditional distribution (quantile by quantile)
Capital flows at risk
From OLS to QR
Capital flows at risk

From OLS to QR
Capital flows at risk

Specification

- We consider the following conditional quantile model:

\[ Q_{KF_{t,t+h}}(\tau|X_t) = \alpha_h(\tau) + \beta_{1,h}(\tau) GFCI_t + \beta_{2,h}(\tau) CFCI_{i,t} + \epsilon_i \]

where \( KF_{t,t+h} \) is the sum of capital flows into country \( i \) between quarters \( t \) and \( t + h \), \( GFCI_t \) is our measure of global financial conditions and \( CFCI_{i,t} \) is our measure of country-idiosyncratic financial conditions. \( \epsilon_i \) is a quantile-invariant, country-specific fixed effect. Function \( Q \) computes quantiles \( \tau \) of the distribution of \( KF_{t,t+h} \) given \( X_t \).

- Introduce serial correlation in residuals: block-bootstrapped standard errors

- Results unchanged if controlling for:
  - Lagged KF
  - Global and country-level GDP growth
Capital flows at risk

Data

- Take this specification to a panel dataset:
  - Argentina, Brazil, Chile, Colombia, Hungary, India, Indonesia, Mexico, Peru, Philippines, Russia, South Africa and Turkey
  - 1996Q1-2018Q4
Capital flows at risk

Push factors

Term-structure

FDI

Portfolio

Banking

Percent of GDP

Quantiles

0.05 0.25 0.5 0.75 0.95

-1.6 -1.4 -1.2 -1 -0.8 -0.6 -0.4 -0.2 0 0.2

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Capital flows at risk

Pull factors

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Percent of GDP

Quantiles

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Capital flows at risk
Fitted distributions, portfolio flows

![Graph showing fitted distributions of capital flows under average, tighter global, and tighter local financial conditions.](image)

- Average Financial Conditions
- Tighter Global Financial Conditions
- Tighter Local Financial Conditions

The graph illustrates the probability density distribution of capital flows as a percentage of GDP under different financial conditions.
Capital flows at risk

Push vs. pull factors (5th percentile)
THE ROLE OF POLICY
The role of policy

- Can policy affect the distribution of (portfolio) capital flows?
- Interested in exploring this in quantile context
- Consider effect of capital flow management measures (Fernandez et al, 2016) and macro-prudential policy (Cerutti et al, 2017)
- Use measures of policy actions, not ‘shocks’, so interpretation far from causal
The role of policy

Capital flow management

Outflow Measures

Inflow Measures

Outflow Measures & GFCI

Inflow Measures & GFCI
The role of policy

Macroprudential policy

Capital Flows at Risk
Results: taking stock

- Asset prices contain useful information for characterising the distribution of capital flows to EMs.
- Push- and pull-type factors contain differential information in terms of (i) magnitude and (ii) persistence, and effects are heterogeneous across flow types.
- There is some evidence of inflow control measures and macro-prudential policy being associated with lower likelihood of sharp outflows.
APPENDIX
The informational content of asset prices
Quantile regression

Technical details

Given a linear model for the conditional quantile function

\[ Q_y(\tau | X) = x\beta(\tau) \]  

the quantile regression estimate \( \hat{\beta}(\tau) \) is the minimiser of

\[ \hat{V}(\tau) = \min_{\beta \in \mathbb{R}^p} \sum \rho_{\tau}(y_i - x_i'\beta) \]  

where \( \rho_{\tau}(u) = u[\tau - I(u < 0)] \) is the so-called check function, which penalises residuals differently depending on whether they are positive or negative.
Quantile regression

Technical details

Difference with respect to OLS easy to see by looking at loss functions:

Figure: Quadratic and (asymmetric) absolute loss functions
Can fit skewed t-distribution distributions to fitted quantiles (conditional on different values of FCIs):

\[
f(y; \mu, \sigma, \alpha, \nu) = \frac{2}{\sigma} t\left(\frac{y - \mu}{\sigma}; \nu\right) T\left(\alpha \frac{y - \mu}{\sigma} \sqrt{\frac{\nu + 1}{\nu + \left(\frac{y - \mu}{\sigma}\right)^2}}; \nu + 1\right),
\]

where \(t(\cdot)\) and \(T(\cdot)\) respectively denote the probability density function and the cumulative density function of the Student t distribution. The distribution’s parameters determine its location \(\mu\), scale \(\sigma\), fatness \(\nu\), and shape \(\alpha\).
Capital flows at risk

Term structure dimension

- Interested in exploring the persistence of these effects
  - Does contemporaneous info help us characterise future distributions?

Focus on:
  - Portfolio flows
  - 5th percentile of the distribution (measure of ‘capital flows at risk’)
Capital flows at risk

Term structure dimension

[Graphs showing capital flows at risk for GFCI and CFCI over different horizons and percent of GDP.]
Capital flows at risk

Term structure dimension

- Information of push-type shocks for left tail very short-lived
- Information of pull-type shocks for left tail displays persistence
The role of policy
Capital flow management

- Fernandez et al (2016) compile data on capital controls by inflows and outflows for 10 asset categories
  - We use measures relevant to type of flows considered
- Data on presence of controls, not magnitude
Consider the following conditional quantile model:

\[
Q_{KF,t+h}(\tau|X_t) = \alpha_h(\tau) + \beta_{1,h}(\tau)GFCI_t + \beta_{2,h}(\tau)CFCI_{i,t} + \epsilon_i \\
+ \beta_{3,h}KAI_{i,t-4} + \beta_{4,h}KAO_{i,t-4} + \beta_{5,h}KAI_{i,t-4}GFCI_t + \beta_{6,h}KAO_{i,t-4}GFCI_t
\]

where \(KAI\) is a measure of controls on capital inflows and \(KAO\) is a measure of controls on outflows (both for portfolio flows of non-residents).
The role of policy
Macroprudential policy

- Cerutti et al (2017) compile data on the introduction of new macroprudential measures across 12 different type of instruments
- Data on number of actions, not magnitude
The role of policy

Consider the following conditional quantile model:

\[ Q_{KF_{t,t+h}}(\tau|X_t) = \alpha_h(\tau) + \beta_{1,h}(\tau)GFCI_t + \beta_{2,h}(\tau)CFCl_{i,t} + \epsilon_i \]

\[ + \beta_{3,h}MaPru_{i,t-4} + \beta_{5,h}MaPru_{i,t-4}GFCI_t \]

where \( MaPru \) is a measure of (cumulated) macroprudential policy actions.