Capital flows, common factors, and the global financial cycle

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- What shapes countries' exposure to the global cycle?

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- The Global Financial Cycle in risky asset prices (Rey (2013), Miranda-Agrippino and Rey (2018), Abate and Servén (2018)) and/or capital flows (Cerutti et al (2018))

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- Financial globalization and deglobalization: Forbes (2014); Rose and Wieladek (2014); Forbes, Reinhart and Wieladek (2017); Cerutti and Zhou (2017); McCauley et al (2017); Avdjiev et al (2017)

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- Determinants of exposure: Dilemma vs Trilemma (Rey (2013), Passari and Rey (2015); Obstfeld et al (2018)); investor base (Raddatz and Schmukler (2012), Cerutti et al (2017a)); banking flows (Bruno and Shin (2015b))

What we do

- Quantify the contribution of the international financial cycle to the variation of gross capital flows
  - Macro perspective: aggregate inflows and outflows
  - Factor model with global and group shocks
  - Novel estimation approach
- Investigate time patterns in the quantitative role of the international financial cycle – 'globalization'
  - Recursive model estimation over moving samples
- Assess some basic determinants of countries' vulnerability to global shocks
  - Relate factor loadings to selected policy / structural features

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- Exposure to the cycle is significantly related to financial openness, financial depth, and exchange regime flexibility
  - Trilemma redux?

Approach

- Two-level latent factor model
  - Global factors: affect flows of all countries
  - Group factors: affect flows of member countries
- M groups with N_m countries each

$$y_{m,i,t} = \left(\gamma_{m,i}\right)' G_t + \left(\lambda_{m,i}\right)' F_{m,t} + u_{m,i,t}$$

$y_{m,it}$: flows of country $i = 1, ...N_m$ in group $m = 1, ..., M$
G_t : set of r_G global factors
$F_{m,t}$: set of r_m factors specific to group m
$\gamma_{m,i}, \lambda_{m,i}$ factor loadings of country i in group m
$u_{m,i,t}$ idiosyncratic component – may be serially/cross-sectionaly (weakly) correlated and/or heteroskedastic

Approach

- Static factor model – but can encompass dynamic factors just redefining them as additional static factors
- In compact notation:

$$\mathbf{Y} = \mathbf{G}\Gamma' + \mathbf{F}\Lambda' + \mathbf{U}$$

- Λ is block-diagonal, with the m-th block containing the loadings of the N_m countries in the m-th group on their r_m group factors.
- Factors and loadings unobserved – both need to be estimated from the data

Approach: identification

- Normalization: $\frac{\mathbf{G}'\mathbf{G}}{T} = \mathbf{I}_{r_G}$ and $\frac{\mathbf{F}'_m \mathbf{F}_m}{T} = \mathbf{I}_{r_m}$ for all m
- Rotation: $\Gamma'\Gamma$ and $\Lambda'_m \Lambda_m$, $m = 1, ..., M$, are diagonal matrices
- Orthogonality across levels: $\mathbf{F}'_m \mathbf{G} = \mathbf{0}$ for all m.
  This identifies factors and loadings up to a sign change. We choose it so the largest country has a positive loading.
  No need to impose orthogonality across groups (i.e., $\mathbf{F}'_m \mathbf{F}_n = \mathbf{0}$ for $m \neq n$) as commonly done – it would be an *over*identifying restriction

Approach: estimation

- Zero restrictions in loading matrix prevent conventional PC estimation in multi-level setting
- Usual solution is to use Bayesian estimation
- Instead we use a recent extension to PC estimation (Wang (2014), Breitung and Eickmeier (2016), Choi et al (2018)). The objective is to find $\mathbf{G}, \mathbf{F}, \Gamma, \Lambda$ that solve the problem

$$\min SSR(\mathbf{G}, \mathbf{F}, \Gamma, \Lambda) = tr\left[\left(\mathbf{Y} - \mathbf{G}\Gamma' - \mathbf{F}\Lambda'\right)'\left(\mathbf{Y} - \mathbf{G}\Gamma' - \mathbf{F}\Lambda'\right)\right]$$

Approach: estimation

- Estimation done through sequential OLS regressions
  - Start from initial estimate of global factors (e.g., via CCA) and obtain estimates of group factors, then use them to reestimate the global factors at the next iteration
  - Computationally much simpler than Bayesian approach
  - Consistency (Wang 2014, Choi et al 2018), asymptotic normality (under additional conditions, Wang 2014)
  - Good small sample performance

Approach: estimation

- If $u_{m,i,t}$ is not iid, more efficient estimators may be available
- Choi's (2012) GPCE: analogous to GLS. Let $\Omega = E(\mathbf{u}_t \mathbf{u}_t')$, where $\mathbf{u}_t = (u_{(1,1),t}, ..., u_{(M,N_M),t})'$. Then solve

$$\min SSR(\mathbf{G}, \mathbf{F}, \Gamma, \Lambda) = tr\left[\Omega^{-1}\left(\mathbf{Y} - \mathbf{G}\Gamma' + \mathbf{F}\Lambda'\right)'\left(\mathbf{Y} - \mathbf{G}\Gamma' + \mathbf{F}\Lambda'\right)\right]$$

- Efficiency gains arise primarily from cross-sectional heteroskedasticity
- With unknown Ω,a consistent estimator $\widehat{\Omega}$ can be used (FGPCE)
  - we employ Andrews and Monahan's HAC
- Number of factors not known ex-ante, so use information criteria to determine it.
  - IC_{p_2}, BIC, HQ (Choi and Jeung 2017)

Data

- Aggregate flows 1979-2015. IMF data
  - Gross Capital Inflows by Foreign residents (CIF)
  - Gross Capital Outflows by Domestic residents (COD)

    Both really net measures – can be positive or negative
- Core results with 47 countries – 19 advanced and 28 emerging
  - Extension adding 38 developing countries
- For estimation, flows scaled by trend GDP (as in Broner et al 2013)
  - Mitigate comovement due to correlated fluctuations in denominator

Data

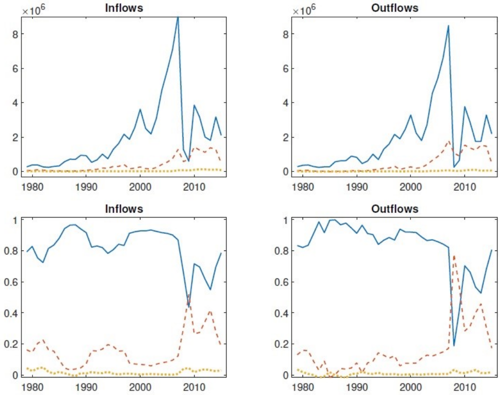
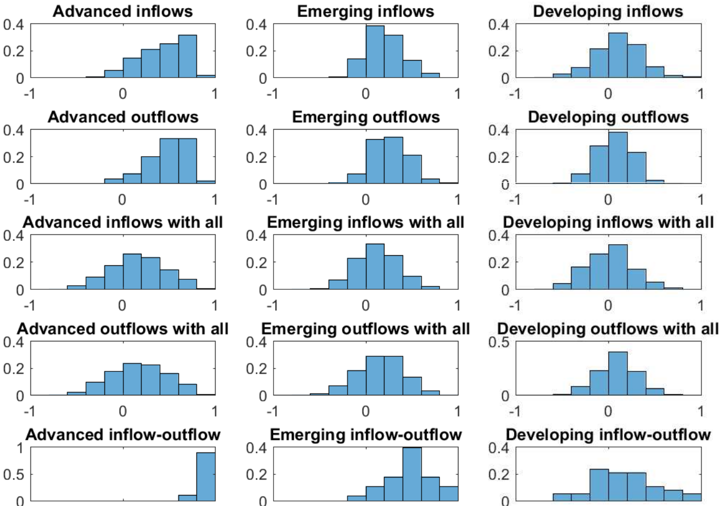


Figure 1: Gross capital flows, by country group: total flows (USD million, upper panels) and percentage shares (lower panels). Advanced (solid), emerging (dashed) and developing countries (dotted).

Data: cross-sectional dependence

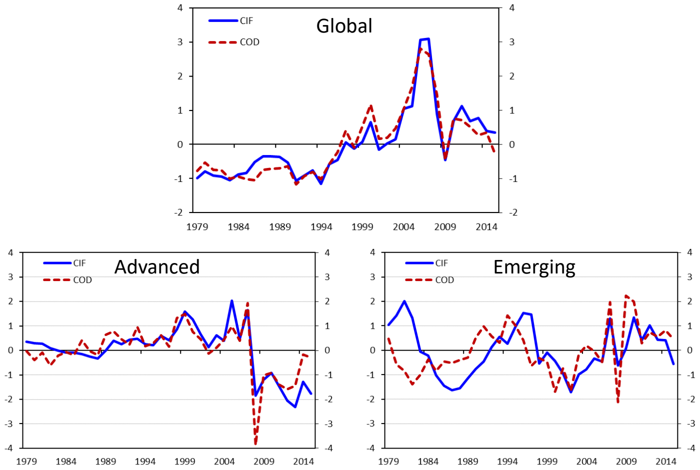
Histograms of pairwise correlation coefficients



Data: cross-sectional dependence

- Factor model approach is appropriate under strong (=pervasive) cross-sectional dependence – but potentially misleading otherwise (Onatski 2012).
    - Under weak (=localized) dependence, other approaches (e.g., spatial analysis) should be used
- Bailey et al (2015): exponent of cross-sectional dependence – should equal 1 under strong dependence.
    - For advanced and emerging countries (jointly or separately) the 95% confidence region of the ECSD includes 1, for both inflows and outflows
    - For developing countries, and for the full country sample including them, it does not, neither for inflows nor for outflows
- Focus on model with 2 groups: advanced, emerging.
    - Developing countries added later

Estimation results: factors



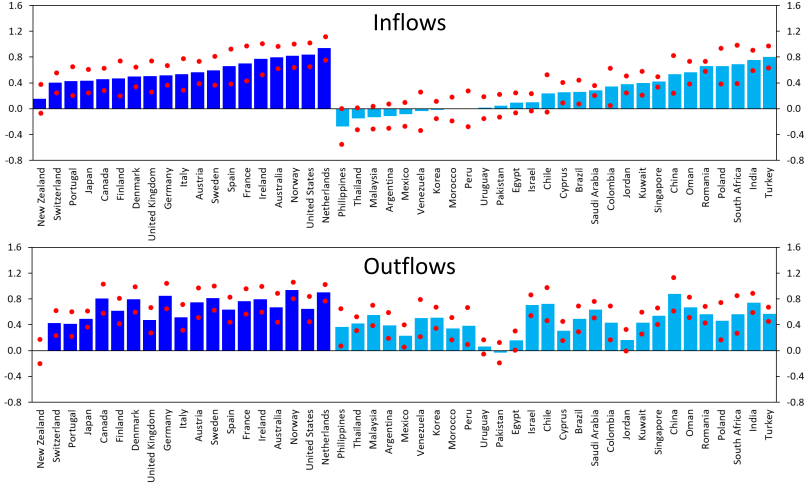
Estimation results: factors

- Global CIF and COD factors virtually identical
  - Everybody's inflows are someone else's outflows (not quite if missing countries)
- Advanced-country CIF and COD factors also highly correlated
  - A large share of their flows are intra-group
- Global factors are highly persistent – but still stationary (with break)
- Estimation residuals do not show (strong) cross-sectional or serial correlation

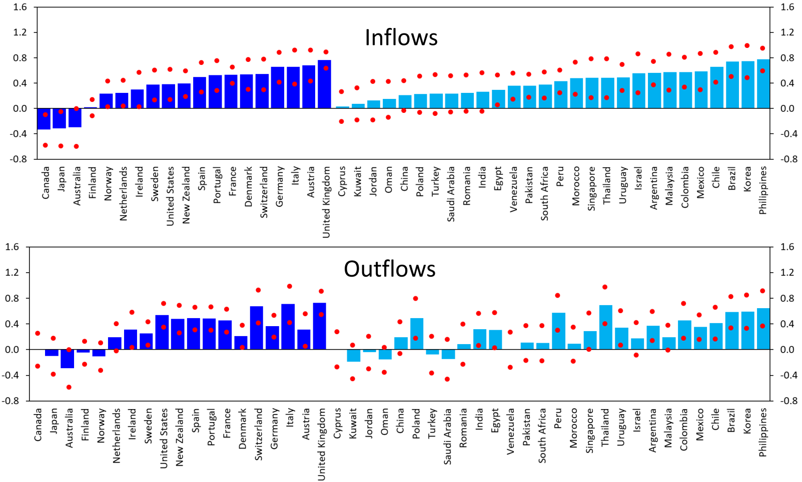
Estimation results: factor loadings

- Global shocks affect the flows of all advanced countries in the same direction
  - All significantly except New Zealand
- Similarly for emerging-country outflows – not so much for inflows
  - Inflows respond uniformly to group shocks – all loadings on CIF group factor are positive
  - Bunching of sudden stops, but not sudden flight (Rothenberg and Warnock 2011)
- Advanced-country group shocks affect differently European and non-European countries (except U.S.)

Estimation results: global factor loadings



Estimation results: group factor loadings



Variance decomposition

- Common shocks account on average for close to 50% of the variance of gross capital flows of advanced and emerging countries
  - Recall: aggregate flows, annual frequency – unlike Cerutti et al (2018). Makes a BIG difference
  - Excluding financial centers makes little difference
- Global shocks play a bigger role than group shocks – except for emerging-country inflows
- Contrast between advanced and emerging countries
  - Flows of advanced countries are dominated by common shocks
  - Flows of emerging countries are dominated by idiosyncratic shocks
- Contrast driven by the different contribution of global factors across groups
  - Twice as large among advanced countries

Variance decomposition

Gross inflows

	All countries	Advanced countries	Emerging countries
Global share	24.1	37.5	15.0
Group share	21.3	22.3	20.6
Country share	54.6	40.2	64.5

Gross outflows

	All countries	Advanced countries	Emerging countries
Global share	33.8	46.7	25.1
Group share	14.3	17.2	12.2
Country share	51.9	36.1	62.7

Variance decomposition: excluding financial centers

(Excluding U.S., U.K., Germany and Japan)

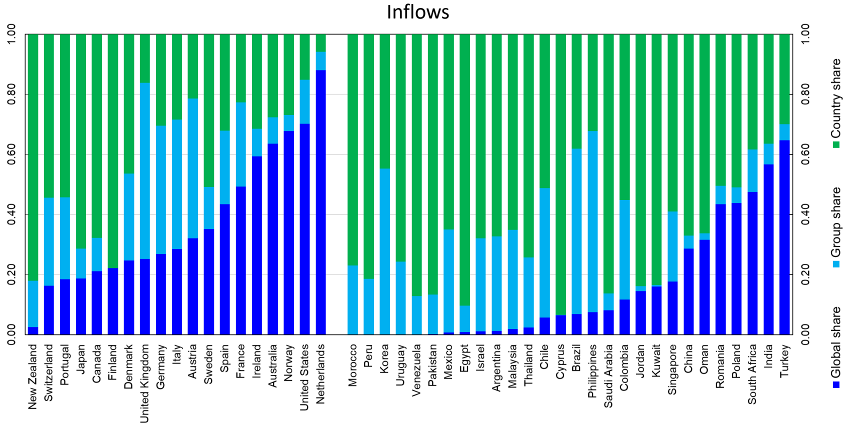
Gross inflows

	All countries	Advanced countries	Emerging countries
Global share	23.1	38.1	15.0
Group share	20.3	19.9	20.6
Country share	56.6	42.0	64.5

Gross outflows

	All countries	Advanced countries	Emerging countries
Global share	33.2	48.5	25.1
Group share	13.3	15.4	12.2
Country share	53.4	36.1	62.7

Variance decomposition



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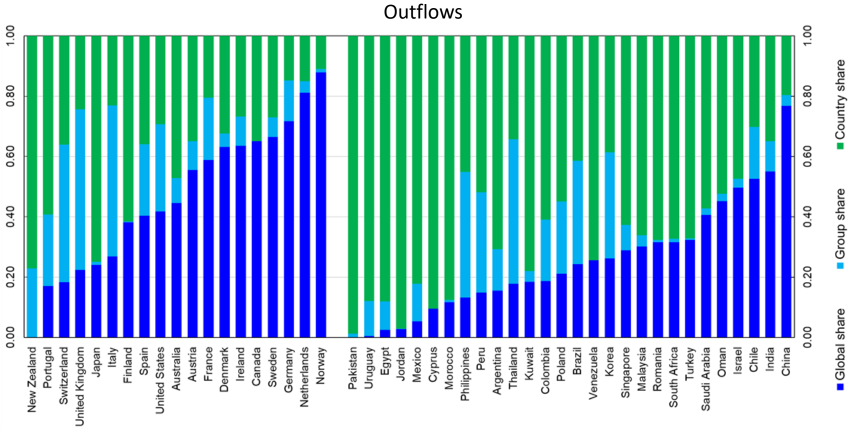


The global financial cycle

- Often summarized in the literature by
  - A handful of 'push' variables (Calvo et al (1996), Forbes and Warnock (2012), Bruno and Shin (2015b)...) reflecting conditions in global financial markets
  - Or just measures of market risk such as the VIX – negatively correlated with (in)flows (Rey (2013), Eichengreen et al (2017), Avdjiev et al (2017, 2018), Obstfeld et al (2017)...)
- Assess how the model's estimated factors relate to those variables
  - Risk measures only
  - Risk measures plus other 'push ' variables (financial and real)

Covariates of the common factors

Variables	Global CIF		Global COD		Advanced countries CIF		Advanced countries COD		Emerging countries CIF		Emerging countries COD	
A. Regressions on risk measures												
VIX (1990-2015)	-0.076	**	-0.057	***	-0.095	**	-0.154	**	-0.099	***	-0.123	***
	(0.033)		(0.021)		(0.042)		(0.068)		(0.012)		(0.027)	
R^2	0.222		0.155		0.227		0.274		0.302		0.164	
VXO (1986-2015)	-0.050	*	-0.032	*	-0.074	*	-0.134	**	-0.073	***	-0.105	*
	(0.028)		(0.019)		(0.040)		(0.066)		(0.020)		-(0.054)	
R^2	0.147		0.075		0.212		0.312		0.252		0.183	
10-year BAA spread (1979-2015)	-0.598	*	-0.509	***	-0.713	**	-1.032	*	-0.558	***	-0.812	*
	(0.311)		(0.165)		(0.352)		(0.557)		(0.226)		(0.428)	
R^2	0.266		0.237		0.245		0.229		0.155		0.131	

The global financial cycle

Covariates of the common factors

Variables	Global CIF	Global COD	Advanced countries CIF	Advanced countries COD	Emerging countries CIF	Emerging countries COD
			Factors			
B. Multivariate regressions						
VIX	-0.059 ***	-0.036 ***	-0.085 *	-0.159 ***	-0.084 ***	-0.133 ***
	(0.017)	(0.013)	(0.045)	(0.061)	(0.027)	(0.045)
U.S. short-term real interest rate	0.043	-0.026	0.364 *	0.606	0.243	0.583
	(0.089)	(0.077)	(0.217)	(0.380)	(0.195)	(0.399)
Log U.S. real exchange rate	5.413 ***	0.580	-10.943 *	-5.108	-11.156 **	-7.639
	(1.970)	(2.042)	(6.353)	(7.310)	(5.363)	(7.866)
U.S. real GDP growth	13.280 ***	23.275 ***	17.052 **	-3.715	-2.768	-31.188 **
	(3.464)	(3.431)	(8.464)	(12.970)	(6.936)	(12.317)
Log world commodity price index	2.610 ***	1.863 ***	-3.867 ***	-4.435 **	-1.560	-4.051 **
	(0.487)	(0.556)	(1.481)	(1.904)	(1.142)	(1.807)
R^2	0.726	0.833	0.495	0.555	0.441	0.457

Notes: All variables except U.S. real GDP growth are expressed in first differences. HAC standard errors in parentheses. All regressions include a constant. *** p<0.01, ** p<0.05, * p<0.1

The global financial cycle

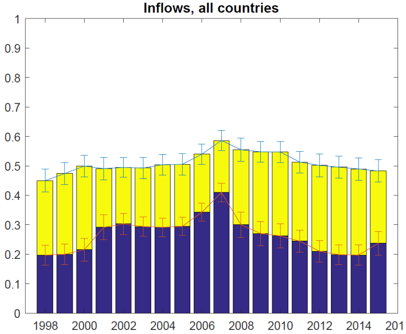
- A few 'push' variables can account for much of the variation in the model's common factors
  - Especially the global factors
  - Risk proxies consistently negative and significant
  - Significant negative effect of the U.S. RER – consistent with Bruno and Shin (2015a,b)
  - Other real variables matter too: U.S. (or world) growth, commodity prices (Reinhart et al 2018)

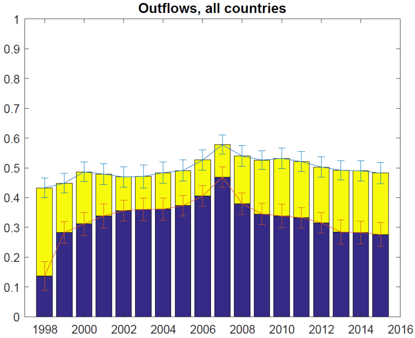
Trends in globalization

Has there been a financial globalization reversal post-crisis?

- Retreat of cross-border banking – driven by regulatory changes and/or changed risk management
  - Forbes (2014); Rose and Wieladek (2014); Forbes, Reinhart and Wieladek (2017)
  - But different measures of globalization yield different conclusions: Cerutti and Zhou 2017 (interconnectedness); McCauley et al (2017) (nationality-based banking flows)
- In our setting the variance contribution of common factors is a natural measure of "globalization" (as in Albuquerque et al 2006)
- To assess trends, reestimate factor model over 20-year windows
  - Window-wise factor estimates correlate very strongly with full-sample counterparts

Trends in globalization





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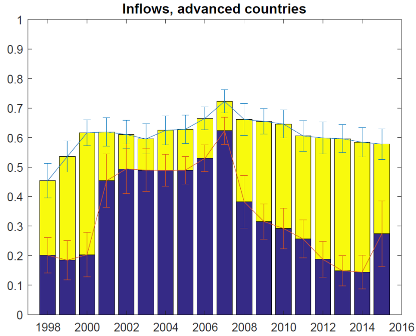

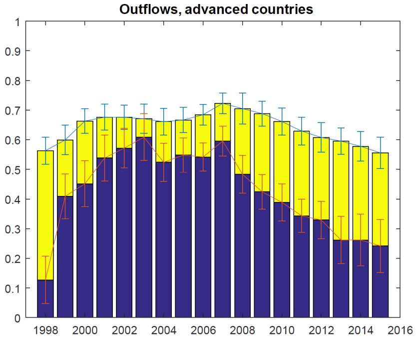

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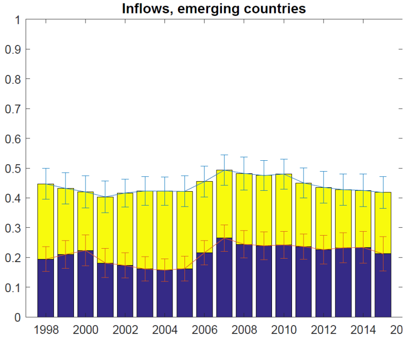

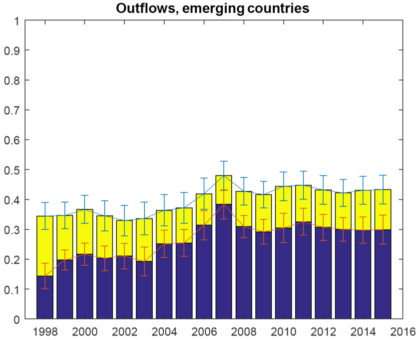

Trends in globalization

- Cycle of rise pre-crisis and fall post-crisis in the variance share of common shocks
- Driven by the changing quantitative role of global shocks
- More pronounced among advanced countries
    - Virtually absent from emerging-country inflows

Exposure to the global financial cycle

Big differences across countries / over time in quantitative role of (= vulnerability to) common shocks

- Especially global shocks
  - In the model they arise from differences in the factor loadings
- What drives those differences? Some natural candidates:
  - Openness – financial and/or real
  - Financial depth (e.g., Bruno and Shin 2015b)
  - Exchange rate regime – in more flexible regimes the exchange rate, rather than the flow volume, absorbs (part of) the impact of shocks (e.g., Goldberg and Krogstrup 2018).
    Conflicting evidence: Rey (2013), Passari and Rey (2015), Cerutti et al (2017a) vs Obstfeld et al (2018)
  - Other dimensions: commodity specialization (Reinhart el al (2018)); country / market size (Eichengreen et al (2018))

Exposure to the global financial cycle

- To answer, regress global factor loadings on candidate variables
  - To exploit time variation, pool the loadings estimates from the 20-year windows
  - Regressors measured as averages over the respective window
  - FGLS-AR(1) – crude approach to deal with persistence
  - Association rather than causation
- Results fairly similar for inflow and outflow loadings (Wald test p-value = .096)
  - Financial openness and financial depth raise vulnerability to global shocks
  - Exchange rate flexibility has the opposite effect – but significant only for inflows.

Exposure to the global financial cycle

Covariates of the global factor loadings

	CIF					COD					ALL
Variable	1	2	3	4	5	1	2	3	4	5	
Financial openness	0.251***				0.139***	0.274***				0.206***	0.166**
	[0.041]				[0.051]	[0.044]				[0.050]	[0.082]
Trade openness		0.062**			-0.046		0.0824**			0.033	-0.0447
		[0.024]			[0.031]		[0.036]			[0.037]	[0.050]
Domestic credit (% of GDP)			0.001***		0.002***			0.001***		0.001***	0.001**
			[0.000]		[0.000]			[0.000]		[0.000]	[0.000]
Exchange Rate arrangement				-0.104***	-0.115***				-0.042**	-0.042	-0.0699**
				[0.0221]	[0.0244]				[0.0197]	[0.0425]	[0.0342]
Observations	846	846	846	846	846	846	846	846	846	846	1,692
Prob > Chi2	0.000	0.010	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: Panel GLS-AR(1) regressions. The dependent variable is the global factor loadings estimates over moving 20-year windows, and a constant is included. Standard errors in brackets. The explanatory variables are averages over the respective window. Financial openness is the Chinn-Ito index, trade openness is the log of total trade over GDP, the exchange rate arrangement is measured using the De Facto aggregate classification of Ghosh, Ostry and Qureshi (2015), setting Peg = 1, Intermediate = 2, and Float = 3 . *** p<0.01, ** p<0.05, * p<0.1

Expanded sample

- Add developing countries as separate group, and re-estimate the model allowing an additional group factor
  - Global, advanced-country and emerging-country factors and loadings virtually unchanged (correlation with 2-group estimates > 0.9 for factors and >0.95 for loadings)
  - Advanced-country global (group) factor loadings and variance shares fall (rise) slightly
- Group shocks dominate global shocks in developing-country inflows (similarly to emerging countries)
  - Less than half of the loadings on the global CIF factor are positive, compared with all but 2 of the loadings on the group CIF factor
  - Developing-country inflow and outflow factors are negatively correlated – in contrast with those of the other groups
  - Developing-country inflow and outflow factors are uncorrelated with risk measures and only weakly correlated with 'push' variables
- Differing pattern of developing-country flows vis-a-vis the rest perhaps due to bigger role of official flows (Advjiev et al 2018)

Expanded sample

Gross inflows

	All countries	Advanced countries	Emerging countries	Developing countries
Global share	19.0	31.9	16.1	14.6
Group share	20.0	26.6	19.6	17.0
Country share	61.0	41.5	64.3	68.3

Gross outflows

	All countries	Advanced countries	Emerging countries	Developing countries
Global share	23.9	39.7	27.2	13.5
Group share	12.9	23.2	11.4	8.8
Country share	63.3	37.1	61.4	77.7

Summary

- The international financial cycle, as summarized by latent common factors, accounts for a considerable part of the variation of gross capital flows of advanced and emerging countries
  - Less so for developing countries
  - Differences across country groups are mostly due to global shocks, rather than group shocks
- The cycle can be well explained by a handful of financial and real 'push' variables
- Its quantitative role rose prior to the global crisis and declined afterwards – more so among advanced countries than the rest, and driven by the changing contribution of global shocks.
- Exposure to the financial cycle is significantly related to capital account openness, financial depth, and exchange rate flexibility

End

Extra slides

Country sample

Advanced countries	Emerging countries	Developing countries	
Australia	Argentina	Albania	Paraguay
Austria	Brazil	Bangladesh	Rwanda
Canada	Chile	Benin	Sierra Leone
Denmark	China	Bolivia	Sri Lanka
Finland	Colombia	Botswana	Sudan
France	Cyprus	Bulgaria	Swaziland
Germany	Egypt	Cameroon	Tanzania
Ireland	India	Costa Rica	Trinidad and Tobago
Italy	Israel	Dominican Rep.	Tunisia
Japan	Jordan	Ecuador	Uganda
Netherlands	Korea	El Salvador	
New Zealand	Kuwait	Ethiopia	
Norway	Malaysia	Fiji	
Portugal	Mexico	Ghana	
Spain	Morocco	Guatemala	
Sweden	Oman	Haiti	
Switzerland	Pakistan	Honduras	
United Kingdom	Peru	Jamaica	
United States	Philippines	Lesotho	
	Poland	Madagascar	
	Romania	Malawi	
	Saudi Arabia	Mauritius	
	Singapore	Myanmar	
	South Africa	Nepal	
	Thailand	Nicaragua	
	Turkey	Nigeria	
	Uruguay	Panama	
	Venezuela	Papua New Guinea	

Descriptive statistics: goup averages

	CIF			COD			
	Mean	Std. Deviation	Coef. of Variation	Mean	Std. Deviation	Coef. of Variation	Correlation CIF-COD
All countries	7.39	9.65	1.09	6.21	9.41	1.86	0.44
Advanced	12.01	12.13	0.92	12.06	12.24	0.96	0.90
Emerging	6.08	7.08	1.14	6.03	8.78	1.38	0.49
Developing	6.05	10.30	1.13	3.42	8.47	2.67	0.18

Estimation results: factors

Flow / Region		CIF Global	CIF Advanced	CIF Emerging	COD Global	COD Advanced	COD Emerging
CIF	Global	1.000					
	Advanced	0.000	1.000				
	Emerging	0.000	-0.016	1.000			
COD	Global	0.952	0.137	0.063	1.000		
	Advanced	0.003	0.821	-0.068	0.000	1.000	
	Emerging	0.111	-0.140	0.343	0.000	0.157	1.000

How important is the global financial cycle?

Factors	Flow type	Freq.	Scaling GDP	Sample	All types			FDI		Portf. Eq.		Portf. Debt		Credit	
					Both	In	Out	In	Out	In	Out	In	Out	In	Out
CCR	Disaggr.	Quart.	Nom.	Small	.054	.055	.054	.104	.122	.015	.047	.041	.053	.067	.013
PC	Disaggr.	Quart.	Nom.	Small	.075	.085	.064	.093	.102	.064	.060	.083	.051	.091	.054
PC	Disaggr.	Quart.	Trend	Small	.085	.094	.075	.104	.114	.069	.063	.089	.051	.099	.053
PC	Aggr.	Quart.	Nom.	Small	.125	.159	.087								
PC	Aggr.	Quart.	Trend	Small	.133	.173	.089								
CCR	Disaggr.	Year.′	Nom.	Small	.121	.128	.113	.176	.244	.065	.084	.094	.089	.190	.065
PC	Disaggr.	Year.′	Trend	Small	.127	.138	.117	.205	.217	.096	.100	.102	.087	.178	.085
PC	Disaggr.	Year.	Trend	Small	.130	.140	.119	.210	.225	.096	.103	.109	.089	.176	.087
PC	Disaggr.	Year.	Trend	Small	.164	.178	.150	.264	.250	.111	.116	.119	.083	.187	.100
PC	Aggr.	Year.	Nom.	Small	.201	.258	.139								
PC	Aggr.	Year.	Trend	Small	.215	.279	.146								
PC	Disaggr.	Year.	Nom.	Adv	.183	.191	.175	.228	.250	.154	.115	.206	.133	.195	.246
PC	Disaggr.	Year.	Trend	Adv	.213	.211	.214	.261	.291	.176	.156	.180	.132	.211	.274
PC	Aggr.	Year.	Trend	Adv	.435	.473	.393								
PC	Aggr.	Year.	Trend	All	.281	.339	.218								

Table C.2: Average, over the sample indicated in the column "Sample" ("Adv." corresponds to advanced countries -characterized by nonbig=0 or ad=1 in Cerutti et al. (2017c) data-, while "Small" correspond to 63 non-large countries -characterized by nonbig=1 in Cerutti et al. (2017c)-), of adjusted R^2 when the flows indicated are regressed over a factor estimated from 6 non-central advanced countries and another factor estimated from 12 emerging countries. CCR uses the factors provided in Cerutti et al. (2017c); PC stands for Principal components estimator; "Aggr." indicates that all flow types are summed; Yearly′ indicates that the the quarterly factors are aggregated yearly (rather than being estimated with the yearly data); "Trend" indicates that flows are normalized by trend (as opposed to nominal) GDP (HP filter with parameter 100 at yearly frequency); 2 indicates that 2 factors from advanced and 2 factors from emerging countries are used. Regressions with less than 10 degrees of freedom are excluded. Values in the first row correspond to those in figure A7 of Cerutti et al. (2017c). Following Cerutti et al. (2017c), columns "All" and "All types" with disaggregated data average the adjusted R^2 over FDI, portfolio equity, portfolio debt, bank credit and total portfolio (portfolio debt plus portfolio equity).

How important is the global financial cycle?

Factors	Flow type	Freq.	Scaling GDP	Sample	All types			FDI		Portf. Eq.		Portf. Debt		Credit	
					Both	In	Out	In	Out	In	Out	In	Out	In	Out
CCR	Disaggr.	Quart.	Nom.	Small	.122	.137	.106	.252	.166	.120	.127	.088	.097	.130	.019
PC	Disaggr.	Quart.	Nom.	Small	.148	.163	.132	.250	.187	.158	.151	.121	.120	.145	.058
PC	Disaggr.	Quart.	Trend	Small	.154	.171	.138	.259	.199	.160	.154	.130	.124	.156	.060
PC	Aggr.	Quart.	Nom.	Small	.187	.233	.138								
CCR	Disaggr.	Yearly′	Nom.	Small	.293	.307	.278	.438	0.426	.255	.350	.215	.213	.356	.171
PC	Disaggr.	Yearly′	Nom.	Small	.284	.296	.271	.429	.415	.227	.318	.211	.205	.332	.164
PC	Disaggr.	Yearly	Nom.	Small	.289	.297	.280	.423	.416	.228	.317	.220	.245	.330	.167
PC	Disaggr.	Yearly	Trend	Small	.301	.311	.289	.450	.459	.217	.330	.248	.236	.344	.171
PC	Aggr.	Yearly	Trend	Small	.453	.486	.406								
PC	Disaggr.	Yearly	Nom.	Adv.	.355	.364	.345	.384	.464	.211	.372	.404	.196	.452	.331
PC	Disaggr.	Yearly	Trend	Adv.	.359	.373	.345	.427	.516	.223	.395	.393	.207	.478	.353
PC	Aggr.	Yearly	Trend	Adv.	.610	.654	.559								
PC	Aggr.	Yearly	Trend	All	.533	.575	.480								

Table C.4: Average, over the sample indicated in the column "Sample" ("Small" correspond to 63 non-large countries -characterized by nonbig=1 in Cerutti et al. (2017c)-, "Adv." corresponds to advanced countries -characterized by nonbig=0 or ad=1 in Cerutti et al. (2017c) data-, and "Big" corresponds to US, UK, Japan and European Monetary Union members as of 2017), of adjusted R^2 when the flows indicated are regressed over a factor estimated from 6 non-central advanced countries and another factor estimated from 12 emerging countries plus 8 US variables (VIX, nominal and real funds rate, TED spread, yield curve slope, GDP growth, growth in real effective exchange rate and M2 growth). CCR uses the factors provided in Cerutti et al. (2017c); PC stands for Principal components estimator; "Aggr." indicates that all flow types are summed; Yearly′ indicates that the the quarterly factors are aggregated yearly (rather than being estimated with the yearly data); "Trend" indicates that flows are normalized by trend (as opposed to nominal) GDP (HP filter with parameter 100 at yearly frequency); 2 indicates that 2 factors from advanced and 2 factors from emerging countries are used. Regressions with less than 10 degrees of freedom are excluded. Values in the first row correspond to those in figure 5 of Cerutti et al. (2017c). Following Cerutti et al. (2017c), columns "All types" with disaggregated data average the adjusted R^2 over FDI, portfolio equity, portfolio debt, bank credit and total portfolio (portfolio debt plus portfolio equity).