Risk Factors in International Capital Flows *

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Abstract

This paper explores the predictive relationship between financial indicators and gross capital flows – inflows and outflows – to emerging markets, with a focus on tail events. Using a dynamic factor model, I extract three indicators of commonality across a large set of financial indicators that capture global, emerging market, and country-specific conditions, respectively. I employ the factors in a quantile regression framework to explore the relationships between risk factors and capital flows to emerging economies. I report three main findings. First, I document evidences of asymmetric and nonlinear relationships between the global factor and both inflows and outflows. The asymmetric relationship is more muted for outflows. Second, the emerging market-specific factor delivers additional predictability for future inflows, while the country-specific factor has a minor role. Third, contrary to inflows, outflows show a strong correlation only with the US factor. This predictive signal is most evident during the Global Financial Crisis. These patterns hold for both in-sample and out-of-sample analyses.

Keywords: Capital flows, sudden stops, capital flight, emerging markets, downside risk.
JEL Classification: C3, E5, F32, F4, G15.

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1 Introduction

International capital flows play a central role in the globalised economy. Following a deepening of trade and financial integration since the 1990s, cross-border flows and exposure to the foreign capital have soared particularly for the emerging economies (EM). As witnessed in the Tequila crisis, Asian financial crisis, and more recent Turkish debt crisis, unexpected large fluctuations in capital flows have dire macroeconomic consequences, such as the collapse of currency, tightening of financial conditions and fire-sale of domestic assets. Such *sudden stop* crises have led to the growth of a vast literature to understand the drivers of capital flows.

This paper studies the role of financial factors in capital flows to emerging markets, with a particular emphasis on tail events. From a policymaker's perspective, the main challenge is to evaluate risks of extreme swings in capital flows, such as *sudden stops* and *capital flights*. They are rare events by nature, and it is known that non-linearity and asymmetry are the main characteristics of such crises. Extreme reversals in capital flows amplify the effect of negative shocks (nonlinearity). While a sharp drop in foreign investment leads to the recession, a sudden *surge* rarely triggers economic boom (asymmetry). Recent theoretical models of *sudden stops* such as Mendoza (2010) attempt to capture such processes via the form of *occasionally binding* constraints within the regular business cycle framework. In the empirical setting, however, it is challenging to detect such mechanisms with a standard regression strategy.

I contribute to the understanding of risk factors in capital flows in three ways. First, I evaluate the role of global, emerging market, and country-specific factors on capital flows to emerging economies, across different parts of the distribution. The central question of this literature is whether the drivers of capital flows are external 'push' factors or domestic 'pull' factors. I extend this framework further to examine their informative roles at tail events, *surges* and *sudden stops*. Unlike previous studies such as Forbes and Warnock (2012) and Ghosh et al. (2014), I avoid relying on arbitrary thresholds to define extreme episodes.[1] By constructing the entire conditional distribution of capital flows to emerging markets, I quantify the risk factors in a more agnostic, data-driven way.

[1]Most of empirical literature defined the 'sudden stop' with an arbitrary threshold, e.g. the periods when changes in inflows fall one standard deviation below its rolling historical mean, given that it also falls two standard deviation below the mean for at least one period. Such definitions follow Calvo et al. (2004) and Reinhart and Reinhart (2009).

Second, I examine the risk factors in both inflows and outflows from emerging markets. An important feature of capital flow is that it has two sides, defined by the *residency* principle. Specifically, *gross* capital flows consist of capital inflows (purchases of domestic assets by foreigners) and capital outflows (purchases of foreign assets by domestic residents).[2] Capital movements initiated by foreigners and by domestic investors are likely driven by different factors, reflecting heterogenous preferences, types, and hedging motives. Extending the works of Forbes and Warnock (2012) and Broner et al. (2013), I analyse and compare risk factors in extreme inflows (*surges* and *stops*) and outflows (*flights* and *retrenchments*).

Finally, this paper provides a potentially useful framework for motoring capital flow risk *ex ante*. Using a quantile regression approach, I estimate the entire conditional distribution of future capital flows as a function of common factors across global, EM, and local financial market indicators. I also conduct a variable selection exercise to find specific indicators of risk and returns that best forecast EM capital inflows and outflows. The timeliness of asset prices compared to official flows statistics yields practical insights even in the absence of a causal relationship: it sets the basic framework for 'nowcasting' capital flow distributions.

To evaluate risk factors in gross capital flows, I proceed in four steps. First, I extract common information across financial indicators from the 15 emerging markets and the US with the dynamic factor model. I distinguish commonalities at three different layers of aggregation: global, emerging market, and country-specific levels, in spirit of Kose et al. (2003). Such a stratification strategy is directly motived by general equilibrium models, where the dynamic factor model could be regarded as a reduced-form solution of the DSGE models. Moreover, it easily renders the interpretation within the *push* and *pull* framework on determinants of capital flows, with an extra role of the contagion across EMs. As a first step to understand the informative role of different factors on capital flows, I run standard panel regressions with country fixed effects.

Second, I employ the quantile regression framework to explore the potentially nonlinear nexus between financial conditions and capital flows in both directions: inflows and outflows. I start with the standard method of Koenker and Bassett (1978) to characterise

[2]The usual definition of *gross* inflows and outflows are based on the residency principle, not the direction of flows. For instance, the *gross* capital inflows to a country is defined as the sum of purchases of foreign assets by domestic residents plus the sales of foreign assets by domestic residents.

conditional relationships across the distribution of capital flows. Next, following Adrian et al. (2019), I estimate the in-sample predictive distribution of capital flows by fitting a flexible family of distributions to estimated quantiles. This exercise gauges the importance of higher moments and non-linearities in forecasting capital flows. Importantly, I compare the results conditional on different combinations of factors – global, EM, and country-specific – to assess the role of their information contents.

Third, as a potential risk management exercise, I analyse downside risks to the future EM capital inflows and outflows, or the predicted path upon the realisation of a *sudden stop*. Then, I turn to out-of-sample prediction exercises: I estimate near-term predictive distributions of EM inflows and outflows for the period 2006 – 2020, which comprises the Global Financial Crisis, Taper Tantrum, and COVID-19 episodes. I assess the out-of-sample predictive performance of three different models that incorporate information contents at different levels of aggregation: global, EM, and country-specific levels. This exercise evaluates practicality of this 'Capital Flow-at-Risk' framework as an *ex ante* risk management device.

Finally, to shed more light on designing policies and structural models, I employ a modern variable selection technique to identify important predictors of EM capital inflows and outflows. I conduct a case study on Turkey, which is not only one of the largest EMs but also heavily relying on capital inflows. Then, I zoom out and compare the results across 15 emerging economies.

I report three main findings. First, there are evidences of asymmetric and nonlinear relationships between the global factor and gross capital flows to EMs, but such relationships are more muted for outflows. A further scrutiny across the predictive distribution reveals that the predictability from the global factor is present across the whole sample period for inflows, but it is confined to the Global Financial Crisis (GFC) episode for outflows. In case of inflows, the inclusion of global and US factors creates a time-varying pattern in terms of variance. The predictive distribution of outflows, however, remains relatively stable over time with any extra signals from the financial market, except during the GFC.

Second, I find some evidences that the EM-wide factor renders additional predictability for future inflows, while the country-specific factor plays a marginal role at best. From a standard regression, the impact of EM factor is significant even after controlling

the global factor. Estimated moments of the predictive distribution suggest that the EM factor conveys extra predictive information on the third moment, or skewness of the predictive distribution. Such a common signal across EMs also turns out to be useful in measuring downside risks and out-of-sample forecasting, which would constitute *ex ante* monitoring of fluctuations in capital inflows.

Third, in contrast to inflows, outflows present a powerful link with the US factor. This result holds both at the standard and quantile regressions. At the lower tail of the distribution, the impact of the US factor is even steeper than that of the global factor, while it is difficult to find the role of the EM and country factors. A further investigation at predictive distribution of outflows suggests that this extra signal from the US financial indicators is contained during the Global Financial Crisis: no factor generates meaningful fluctuations in other periods. This result holds in both in-sample and out-of-sample analyses. All of these findings suggest that capital inflows and outflows are not 'two peas in a pod' in terms of their relationships to financial conditions.

The structure of the paper is the following. Section 2 provides a first look at factors and their relationship with future inflows and outflows. Section 3 introduces the quantile regression framework and explores the presence of nonlinearities and asymmetries. In Section 4, I analyse future downside risks to capital flows and the out-of-sample predictive performance of the models. Section 5 discusses the variable selection exercises and their results in both single and cross-country analyses. Section 6 concludes.

Related Literature. This paper is closely related to a recent literature on assessing the macroeconomic tail risk, or the 'Growth at Risk (GaR)' framework introduced in Adrian et al. (2019) and Giglio et al. (2016). The main appeal of this approach is that it provides a framework in which forecasting can be thought of as a risk managing exercise: in their view, the concept of GaR is defined as GDP growth at the lower fifth percentile of the predictive distribution, conditional on the index of financial stress. Adrian et al. (2018) further extended the analysis to the set of advanced economies. Building on this work, several recent papers have explored the idea on different topics: Kiley (2018) for the US unemployment and Rogers and Xu (2019) on the role of uncertainty indicators as predictors, among others.

This paper focuses on another important but less explored topic, capital flows. Two

other papers, Gelos et al. (2021) and Eguren-Martin et al. (2021), also analysed capital flows using the GaR framework. This paper is different from them in the following aspects. First, while they focused on the role of various preemptive policies through counterfactual exercises, this paper attempts to explain empirical irregularities and limitations of the GaR framework within the theoretical framework. In doing so, I scrutinise both directions of capital flows, not only inflows but also outflows, and discuss their possibly diverging behaviours. Rather than just a mere application of a new forecasting tool on another topic, this paper tests the validity of the GaR framework on capital flows by out-of-sample forecasting analyses and variable selection exercises. In this spirit, Plagborg-Møller et al. (2020) is closer to this paper, though it studies a different topic.

More broadly, the results speak to the important literature on the determinants of capital flows. The seminal papers of Calvo et al. (1993) and Fernandez-Arias (1996) pioneered the 'push and pull' framework, which decomposes the role of push (global and regional) and pull (domestic) factors. Forbes and Warnock (2012) and Broner et al. (2013) highlighted the importance of exploring both directions of capital flows, especially after 1990s. Ghosh et al. (2014) attempted to explain the determinants in the context of a simple asset-pricing model. Cerutti et al. (2017) studied the role of the global factor in capital flows, reflecting the growing focus on the global financial cycle. Avdjiev et al. (2018) investigated the determinants by the direction and components of gross capital flows and their changing roles over time.

Finally, this paper relates to a more recent strand of literature on the global financial cycle, which analyses the link between the US monetary policy, risk premia, and capital flows. Rey (2013), Bruno and Shin (2015), Miranda-Agrippino and Rey (2020) pioneered the research on this topic. Davis et al. (2021) and Degasperi, Hong and Ricco (2020) provided more in-depth study on capital flow co-movements and the effect of the US monetary policy shocks.

2 Financial Conditions and Capital Flows

Are financial conditions informative about risks to future capital flows? In order to answer the question, it is necessary to have a representative measure of financial conditions, that possibly summarises the common information across various asset prices, spreads, and

risk premia. A useful tactic in such a setting is to extract components that capture joint dynamics among a large set of indicators from the financial market.

In this section, therefore, I proceed in the following way: first, I introduce financial variables I use to extract common factors. The dataset covers global, the US, and 15 emerging economies, with a total size of more than 100,000 datapoints. Second, I briefly explain the empirical method to squeeze such a 'big data'. I employ the dynamic factor model, as in Stock and Watson (2002) and Bai and Ng (2002). In addition to the first common factor that loads to all variables in the dataset, I also explore the marginal information across 15 EMs, US, and the local economy, in spirit of Kose et al. (2003). Such a strategy is able to make implications in parallel with the standard push-and-pull framework.

2.1 Data

Throughout this paper, I focus on 15 relatively large emerging economies, including 6 Asia-pacific (India, Indonesia, Korea, Philippines, Taiwan, and Thailand), 5 Latin American countries (Argentina, Brazil, Chile, Colombia, and Mexico), and 4 others (Hungary, Russia, South Africa, and Turkey).[3] In terms of the dependent variables, I focus on gross debt Inflows and outflows, which are the largest components of capital flows (Avdjiev et al., 2018). They correspond to the sum of the portfolio debt flows and 'Other Investment' flows in the IMF's Balance of Payment Database. The scale is the percent of lagged GDP, i.e. I divide the flows by the previous quarter's GDP to achieve stationarity and avoid potential endogeneity issues with the current GDP. Capital flow data of 15 EMs are available at the quarterly frequency.

The set of predictors consists of two parts: global/US and country-specific variables. First, the dataset contains 12 US indicators of market risk, uncertainty and spreads, representing the aggregate/global risk (Table 1). The upper panel of the Table 1 includes four well-known indicators of the aggregate market risk, such as VIX, the global risk factor from Miranda-Agrippino and Rey (2020), which is the common factor across returns of hundreds of asset classes in the world, the US risk aversion risk index from Bekaert et al. (2021), and the US macroeconomic uncertainty index from Jurado et al. (2015). In the

[3]Despite its economic importance, I drop China from the sample due to its data availability. Data on China's capital inflows and outflows start only after 1998 (People's Bank of China) or 2004 (IMF).

Table 1: Financial Indicators, the US and global economy

Variables	Transformation
VIX	log
Global risk factor (Miranda-Agrippino & Rey 2019)	level
US Macro uncertainty index (Jurado et al. 2015)	log
US Risk aversion index (Bekaert et al. 2020)	log
Gilchrist-Zakrajsek Excess Bond Premium	level
US Term spread (10Y-3M)	level
US TED spread (3M Libor- Tbill)	level
BAA - 10Y US bond Spread	level
NFCI Index (Chicago Fed)	level
NFCI Index: Leverage (Chicago Fed)	level
Global Economic Policy Uncertainty (Baker et al. 2016)	log
Global Geopolitical Risk Index (Caldara & Iacoviello 2017)	log

Sources: authors' websites and the FRED.

middle panel, there are 4 widely used spreads (excess bond premium from Gilchrist and Zakrajšek (2012), US term spread, the TED spread or the spread between the 3-month LIBOR rate and the Treasury bill rate of the same maturity, and the spread between BAA bonds and the 10-year Treasury Bond), which indicate the financial condition in the US.[4] Finally, I also include 4 other global indicators that could possibly affect capital flows in EMs in the bottom panel, namely the NFCI index constructed by the Chicago Fed, its leverage sub-component, Economic Policy Uncertainty index from Baker et al. (2016), and the geopolitical risk index from Caldara and Iacoviello (2018). Unlike other indicators, the last two variables are text-based measures.[5]

The other half of the dataset includes 12 country-specific variables, shown in the Table 2: indicators in the upper block are short and long term spreads relative to the US (10-year sovereign bonds, policy differential, and the EMBI spread) and the EMBI total return index. They have been used as measures of the country risk premium in previous studies. The middle block represents more traditional indicators of financial and credit conditions: stock price returns and volatility, the exchange rate against the US dollar, lending/borrowing spreads and the spread between the long and short sovereign bond.

[4] I use the difference between 10-year Treasury Bond and 3-month Treasury Bill yield rate for the US term spread.

[5] The NFCI index and its leverage sub-component have been used as main predictors of the vulnerability in US GDP growth: see Adrian et al. (2019) and Hasenzagl et al. (2020). The forecasting power of text-based measures has been tested in Rogers and Xu (2019).

Table 2: Financial Indicators, domestic economy

Variables	N	Transformation
Sovereign bond spread v. US (10Y)	8	level
Policy rate differential v. US	15	level
J.P. Morgan EMBI Total return index	7	log
J.P. Morgan EMBI+ bond spread	5	log
Stock price index	15	Δlog
Realised stock price volatility	15	level
USD Exchange rate (per USD)	15	Δlog
Lending spread (v. policy rate)	13	level
Deposit spread (v. policy rate)	12	level
Term spread (10Y-3M bond)	8	level
Economic Policy Uncertainty (Baker et al. 2016)	8	log
Geopolitical Risk Index (Caldara and Iacoviello 2017)	13	log

Sources: FRED, IMF, the Global Financial Database, and own calculations. The Economic Policy Uncertainty and Geopolitical Risk Index are from the original authors' websites.

The bottom panel introduces two text-based measures of uncertainty and the geopolitical risk. Finally, I collect the end-of-quarter values of all variables, in order to sync the data frequency with the dependent variable.

2.2 Methodology: Dynamic Factor Model

A natural tool to extract common information across a large set of indicators would be the dynamic factor model, as in Stock and Watson (2002) and Bai and Ng (2002). It assumes that each financial indicator can be described as the sum of two orthogonal components: a small number of latent factors that capture the joint dynamics and the residuals that represent idiosyncratic variations. Given a high degree of co-movement across the predictors, a handful of common factors can capture the majority of dynamics. In other words, each variable y_{it} in Table 1 and 2 features the following factor structure:

$$y_{it} = \mu_i + \Lambda_i F_t + \epsilon_{it}, \quad F_t = \Phi_1 F_{t-1} + \cdots + \Phi_p F_{t-p} + u_t$$

where μ is the vector of N intercepts, and F_t is a vector of r common factors that capture the common information across predictors. The factors are loaded via coefficients Λ, which represent the response of each indicator to a common shock. ϵ_{it} is an idiosyn-

cratic component that captures variable-specific movements or measurement errors. Both F_t and ϵ_t are assumed to be stationary processes with mean zero. The factors follow a VAR(p) process, where I set the leg length to be 1 for simplicity. To allow for some degree of autocorrelation, I assume that ϵ_{it} follows an AR(1) process. The error term u_t is a normal, mean zero process. To deal with missing observations, I use the Expectation Maximisation (EM) algorithm of Doz et al. (2012).[6]

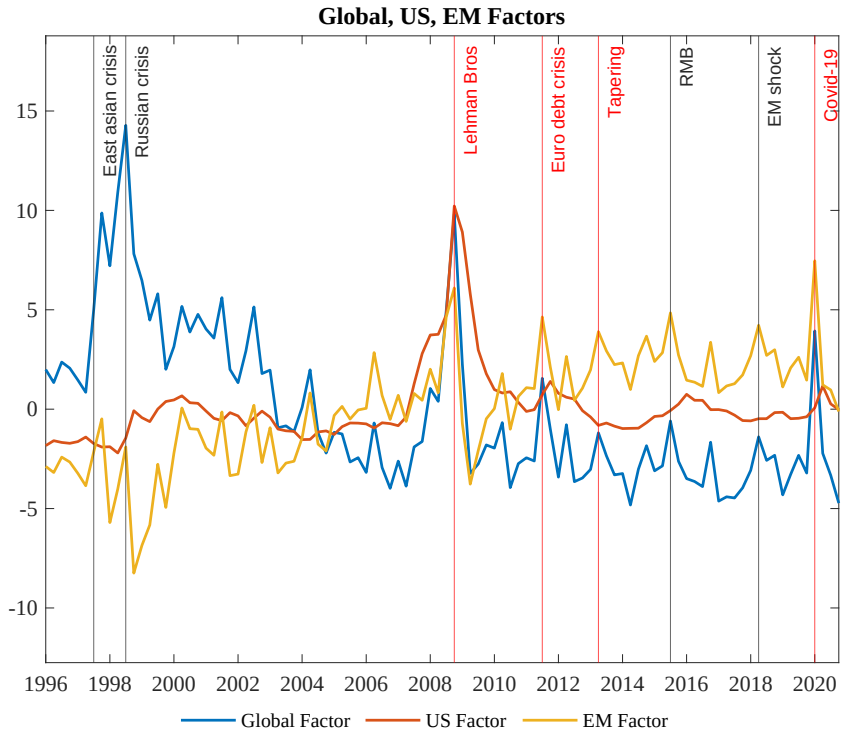
In addition to this standard formulation, I further distinguish commonalities at three different layers of aggregation: global, emerging market, and country-specific levels. Specifically, I first extract the *global factor*, which is common to the entire panel, that consists of the global and US indicators in Table 1 and variables in Table 2 for all of 15 EMs in the sample. Then I take the *EM factor* that is only common to financial indicators of 15 EMs, excluding the US and global predictors in Table 1. Finally, the last two set of factors load onto only variables from the US and each of the 15 countries, respectively. This is equivalent to the following structure:

$$y_{it} = \mu_i + \lambda_{i,g} f_t^g + \lambda_{i,EM} f_t^{EM} + \lambda_{i,c} f_t^c + \epsilon_{it} \tag{1}$$

where f_t^g is the global factor common to all variables in the dataset, f_t^{EM} captures commonalities to all except the US and global ones, and the f_t^c is the set of country-specific, or *local* factors. Such a stratification strategy, in spirit of Kose et al. (2003), is useful in at least two aspects. First, this structure is directly motived by general equilibrium models of Sargent (1989), where the dynamic factor model could be seen as a reduced-form solution of the open economy DSGE models. Second, constructing the global and local components separately allows us to evaluate the role of *push* (external) and *pull* (domestic) factors, which is a widely known framework on determinants of capital flows. With presence of the EM factor, moreover, it is possible to explore not only the global crisis and country-specific episodes but also the contagion across EMs, another important aspect of the sudden stop crises. Hence, this strategy alleviates possible mischaracterisation of commonality, which may occur if one studies only a subset of these factors.

[6]The EM algorithm first describes the likelihood in terms of both observed and unobserved (state) variables and computes the expectation of log-likelihood conditional on the data. Then, it re-estimates the parameters through maximisation of the expected log-likelihood. These two steps are iterated until convergence, to correct for the estimation uncertainty.

Figure 1: A First Look at Factors



Note: This plot shows three common factors from a large set of financial indicators from the global, US, and 15 emerging economies: the global factor (in blue), US factor (in red), and EM factor (in yellow). The red vertical bars represent global crises, while the black bars are more regional and country-specific episodes. Sample 1996Q1 – 2020Q4.

2.3 A First Look at Factors

Figure 1 plots three common factors estimated from the model in Eq (7), namely the global, US, and EM specific factors. Three results stand out across different layers of factors. First, factors well reflect major historical events, so it speaks to the validity of the empirical strategy. The global factor (in blue) successfully picks up crisis episodes, such as the fall of Lehman Brothers and the Global Financial Crisis, the European Debt crisis, and the recent breakout of COVID-19. It also spikes up around the Russian crisis of 1998, possibly due to its impact on the global financial market represented by the fall of LTCM.[7] Second, the global and EM factor show a clear pattern of divergence and convergence: the EM factor (in yellow) roughly mirrors the movement of global factor with some idiosyncratic dynamics in the early part of the sample. Two factors steadily converge and coincide around 2004, and then they move strongly in sync afterwards. Such a pattern is consistent with the growing financial integration and opening up of capital

[7]In fact, the infamous fall of Long-Term Capital Management after the Russian crisis induced a sudden 'flight to quality' amongst global investors. The Federal Reserve, in the end, has to step in by lowering interest rates to ease access to liquidity in the US capital market.

Table 3: The Role of Factors: Simple Regression Results

	Dependent variable: Gross debt flows (% of last period GDP)					
	Inflows			Outflows		
Global factor	-0.176^{***}	-0.210^{***}	-0.212^{***}	-0.093^{*}	-0.099^{**}	-0.099^{**}
	(0.051)	(0.051)	(0.052)	(0.049)	(0.042)	(0.042)
US factor		0.030	0.021		-0.150^{*}	-0.147^{*}
		(0.051)	(0.050)		(0.070)	(0.068)
EM factor		-0.119^{*}	-0.118^{*}		-0.028	-0.028
		(0.063)	(0.063)		(0.066)	(0.066)
Local factor			-0.205			0.053
			(0.143)			(0.104)
R^2	0.206	0.210	0.211	0.042	0.049	0.049

Notes: Results fixed-effect regressions with common factors (in rows) on debt inflows (left panel) and outflows (right panel). Sample: 1996Q1 – 2020Q4. Dependent variables are scaled as the percent of last quarter GDP, and factors are standardised to have a zero mean and unit variance. Clustered standard errors in parentheses. *** is significant at the 1% level, ** at the 5% level, and * at the 10% level.

markets amongst emerging economies. Finally, the role of US factor (in red) is mostly visible around the Global Financial Crisis. It shows a quite stable movement except for a sudden hike around 2007-2008, reflecting the unprecedented severity of the GFC. Overall, the extracted factors are roughly in line with major events and developments in the emerging markets.

As a first step to understand the role of factors on capital flows, I run standard panel regressions with country fixed effects:

$$y_{it} = \alpha_i + \beta(L)y_i + \gamma x^c_{i,t-1} + \delta w^g_{i,t-1} + \epsilon_{it} \tag{2}$$

where y_{it} is the dependent variable, inflows or outflows for the country i at time t. $x^c_{i,t-1}$ is a country-specific or *local* factor. $w^g_{i,t-1}$ include the global, US, and EM regional factors, which are invariant across countries. I control for the country-fixed effect, α_i and the lag of the dependent variable. Finally, I use country-by-country clustered standard errors. This simple analysis facilitates clear comparison with results from previous discussions on the determinants of capital flows, such as Forbes and Warnock (2012) and Cerutti et al. (2017). While these studies explore the relationship between capital flows and

representative measures of financial conditions, I focus on the commonality across various market indicators.

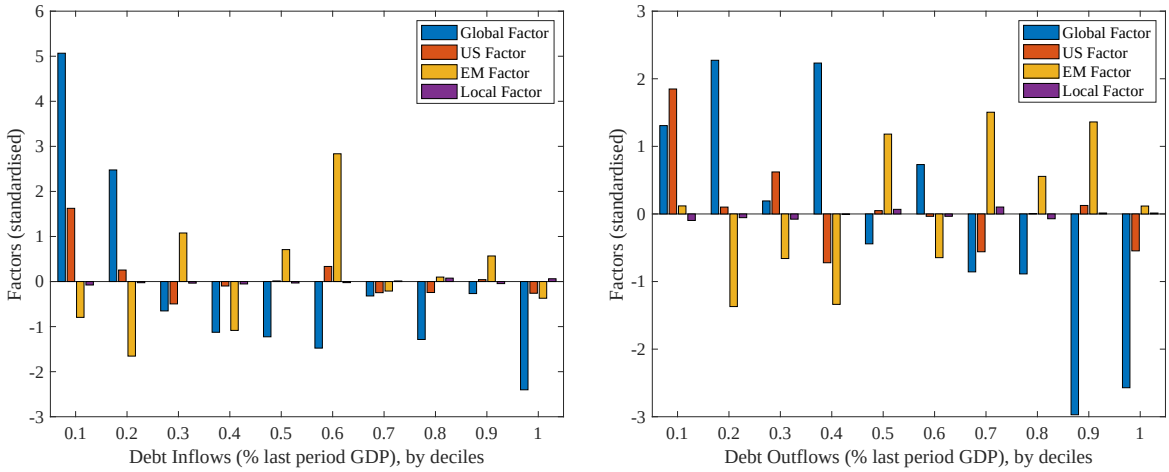
Table 3 shows the results for inflows (the left panel) and outflows of 15 EMs (right panel) as a dependent variable. The first noticeable result is that the global factor plays a significant role in all specifications: it displays a negative correlation with both inflows and outflows, and the coefficients stay roughly untouched even after other factors enter the regression. The effect of the global factor, however, is more than two times larger on inflows compared to the outflows: one standard deviation increase in the global factor shrinks inflows by 0.21 percentage point of GDP, while there is only 0.1 pp reduction for outflows.

The main difference between inflows and outflows lies on the role of US and EM regional factors. Looking at the inflows, the effect of EM factor is also significant with the same sign with the global factor. The magnitude of coefficient is slightly weaker, i.e. worsening of regional financial conditions yields inflows to fall by approximately 0.12 percentage point of GDP. The US and local factors are not significant at the 90% confidence level. This result speaks to the merit of including a regional factor: analyses based on only the subset of factors are difficult to capture the commonality across the EMs.

Interestingly, outflows tell us a different story from the inflows. While both local and EM factors become insignificant at any specification, the US factor coefficient is now negative and significant at the 90% level. Moreover, the relationship between outflows and the US factor is even more stronger than that of the global factor: one standard deviation increase in the US factor yields investors to retrench their assets by 0.14 percentage point of GDP, which is above the the effect of a global shock. In contrast to inflows, the flip side of capital flows seems to be more connected with the US financial conditions in particular.

Such a distinction between inflows and outflows motivates further analyses on the role of financial indicators. So far, the regression analysis provides the relationship on average. The main challenge to evaluate risks of extreme swings in capital flows is to explore possible non-linear and asymmetric relationships, which could capture the characteristics of rare disasters. In the next section, I formally investigate how the distribution of future capital flows varies with fluctuations in financial conditions.

Figure 2: Financial conditions by Capital Flows deciles



3 Beyond the mean: Vulnerability of Capital Flows

The exercises in the previous section are based on the standard regression framework, hence exploring the predictability on average. In practice, however, policymakers might be more concerned about higher moments: for instance, more central banks are having the financial market stability as one of the main policy objectives, beyond the traditional goals of stability in prices and output growth. This new agenda naturally leads to more attention on the volatility of capital flows. Moreover, there is a growing interest on evaluating the risk of tail events, which correspond to the famous 'sudden stop' and 'flight to quality' episodes in terms of capital inflows and outflows.

Figure 2 illustrates the relationship between median capital flows across 15 EMs and four commonly factors derived in Section 2.3 : global, US, EM regional, and the country-specific components.[8] First, the level of global factor (in blue) is markedly higher when the inflow is in the lowest decile, or the case of *sudden stops*. Moreover, the sign of global factor switches from positive to negative over the deciles: tightening in financial conditions are correlated with the drop in inflows (figure in left), and the loosening is related with the increase in inflows. A similar but less clear pattern occurs for outflows (figure in right). Second, the size of the US factor (in red) is only notable at the lowest decile for both inflows and outflows. It is modest at best in other deciles. Finally, the EM regional factor (in yellow) displays an obscure, see-saw pattern, and the size is strong

[8] I place median inflows and outflows across 15 EMs into ten bins. Specifically, first I take the median of capital flows and factors across 15 countries each period. Then I collect datapoints for any quarters with the value of flows falling into each decile. The level of factors is the average value in each bin.

in middle deciles rather than the tails. The local factor (in purple) is negligible across deciles and the direction of capital flows.

Overall, these stylised facts suggest a possible non-linear relationship between global/US financial conditions and gross capital flows. Hence, in this section, I study the predictability of financial indicators on higher moments of capital flows, above and beyond the mean. Specifically, I estimate the full conditional distribution of capital flows to a median emerging economy as a function of current financial conditions, using the method of Adrian et al. (2019) who pioneered this approach known as GDP-*at-risk*. I begin with the standard quantile regression framework of Koenker and Bassett (1978), to further scrutinise such patterns between financial conditions and future capital flows.

3.1 Quantile regressions and Nonlinearities

Since quantile regressions characterise the conditional relationship with regressors over the entire distribution of a dependent variable, it is a natural tool to explore potential nonlinearities between financial conditions and capital flows. Following Koenker and Bassett (1978), $F^{-1}(\tau) = inf\{x : F(x) \geq \tau\}$ is defined as the τth quantile of a real-valued random variable X, for any $0 < \tau < 1$. For a given quantile τ, the quantile regression estimator β_τ is chosen to minimise quantile weighted absolute value of errors:

$$\hat{\beta}_\tau = \underset{\beta_\tau \in \mathbb{R}^k}{argmin} \sum_{t=1}^{T-h} \omega_t(\tau)|y_{i,t+h} - \beta x_{it}| \tag{3}$$

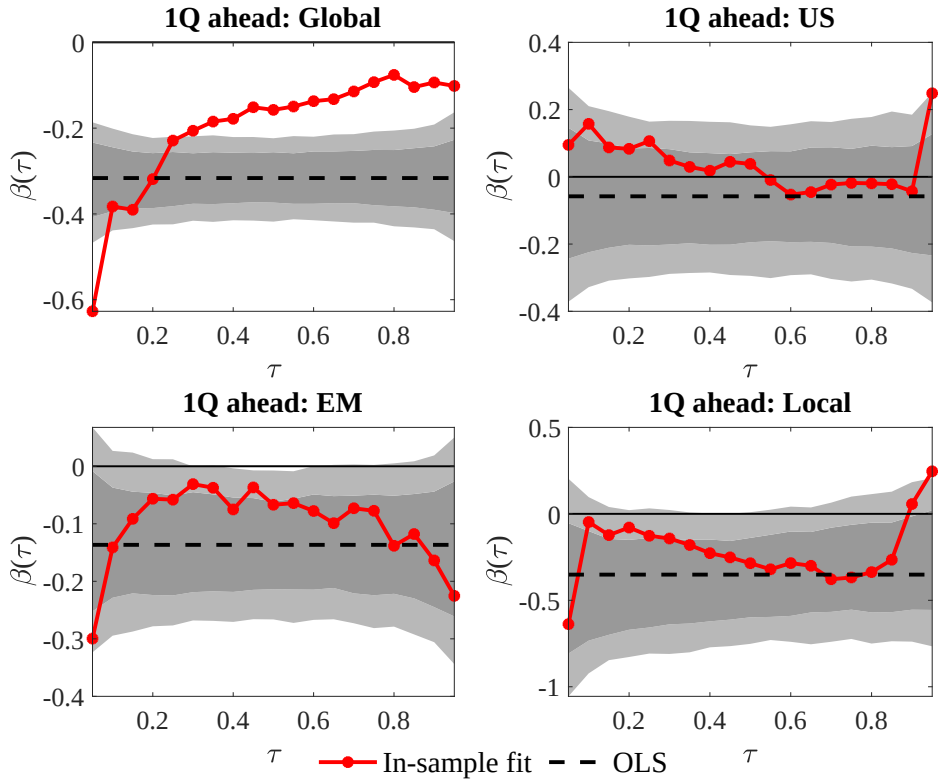
with asymmetric weights based on the sign of residuals,

$$\omega_t(\tau) = \tau \cdot \mathbf{1}_{(y_{i,t+h} \geq x_{it}\beta)} + (1-\tau) \cdot \mathbf{1}_{(y_{i,t+h} < x_{it}\beta)} \tag{4}$$

where $y_{i,t+h}$ represents either capital inflows or outflows (in terms of percent of the previous period GDP), of the country i, h quarters ahead. x_{it} is a vector of conditioning variables, including the factors obtained from the Section 2 in addition to the current inflows or outflows. 1 $(\cdot)$ denotes the indicator function. In order to take account of fixed effects in a panel data setting, I follow the two-step estimation procedure of Canay (2011).

Figure 3 presents estimated quantile regression coefficients (red dots) of one quarter ahead inflows on the four factors: global, US, EM and local. Grey areas are the 68%

Figure 3: Estimated Quantile Regression Coefficients: Inflows



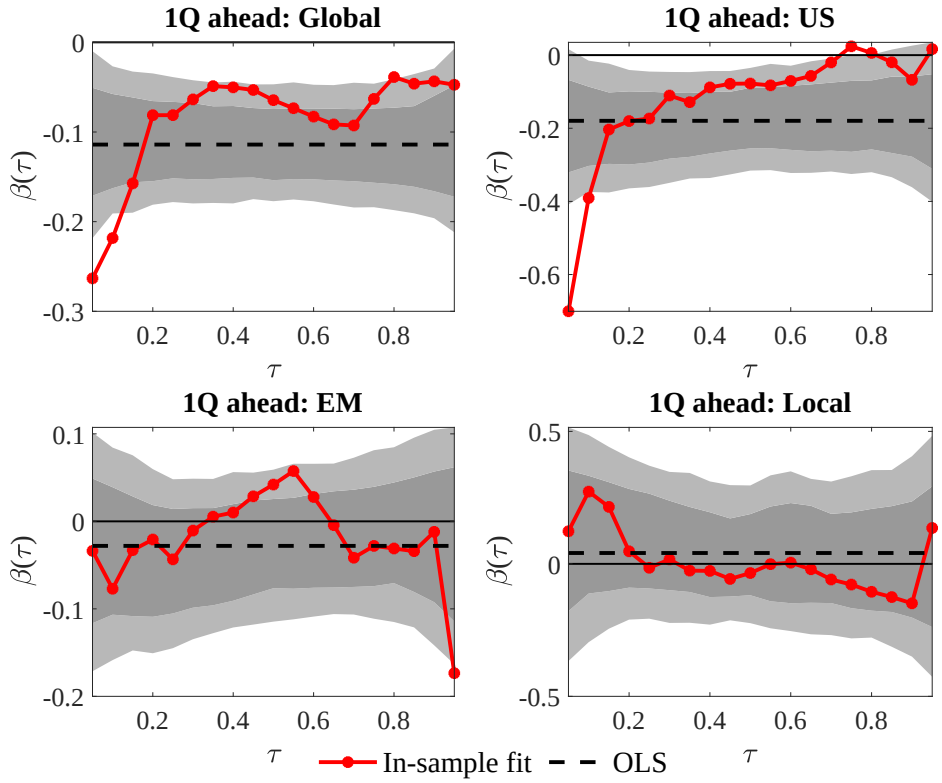
Note: This chart shows estimated quantile regression coefficients (red dots) of one quarter ahead inflows on current value of four factors: global, US, EM and local. Grey areas are 68% (dark) and 90%(light) confidence bounds for the null hypothesis that the true data-generating process is a linear model (VAR with 4 lags). Bounds are computed using 1000 bootstrapped samples. Controlled for current inflows. Sample: 1996Q2 – 2020Q4.

(dark) and 90%(light) confidence bands representing the null hypothesis that the true data-generating process is a linear model.[9] Black dashed lines represent the ordinary least squares estimates.

There is a pronounced nonlinear relationship between the global factor and one quarter ahead capital inflows. Coefficients on the global factor are significantly different from the null of a linear model at both tails of the distribution. Regression slopes change substantially across quantiles: tightening of global financial conditions (increase in the global factor) predicts a large decline of inflows at the bottom quantile, but the negative effect is more muted at the upper quantiles. These results show a nonlinear and asymmetric relationship between the global factor and inflows. The EM regional factor may also play a role at the lower tail, but the significance is weaker. On the other hand, for the US

[9]Specifically, I estimate a vector autoregression (VAR) with four lags, Gaussian innovations and a constant using the full-sample evolution of the factors and capital flows, and bootstrap 1000 samples to compute the bounds at different confidence level for the OLS relationship. Quantile coefficient estimates that fall outside this confidence bound thus indicate that the relation between the dependent and predictive variable is non-linear.

Figure 4: Estimated Quantile Regression Coefficients: Outflows



Note: This chart shows estimated quantile regression coefficients (red dots) of one quarter ahead outflows on current value of four factors: global, US, EM and local. Grey areas are 68% (dark) and 90%(light) confidence bounds for the null hypothesis that the true data-generating process is a linear model (VAR with 4 lags). Bounds are computed using 1000 bootstrapped samples. Controlled for current outflows. Sample: 1996Q2 – 2020Q4.

and local factors, the quantile regression slopes are not statistically significantly different neither across quantiles nor from the linear model, implying that nonlinearity is less evident in those factors.

Figure 4 shows the outflows analogue. Interestingly, the relationship between the US factor and outflows is dramatic: while coefficients are flat across quantiles for inflows, it is strongly negative at the lower tail and becomes close to zero at higher quantiles for outflows. This result portrays nonlinearity between the US factor and outflows: deterioration of US financial conditions has a large negative impact at the lower tail of outflows, while the effect is negligible at higher quantiles. The slope of the US factor is even steeper than that of the global factor, in case of outflows.

Compared to inflows, the nonlinear relationship between the global factor and future outflows is more muted. Though still significant, the impact is cut by more than half at the bottom quantile. The coefficient does not surpass the 90% confidence level at the upper tail. Again, coefficients on EM and local factors are rather stable across quantiles.

Though the former displays some nonlinearity at the upper tail, it is relatively small and at the margin of the confidence bound for the null hypothesis of a linear model.

Overall, these results point to asymmetric and nonlinear relationships between the global financial conditions with the capital flows. Importantly, in contrast to inflows, there seems to be a strong link between outflow and US financial conditions, particularly at bottom quantiles. Do such features from the quantile estimates help anticipating variations in the entire distribution of inflows and outflows? I turn to answer this question in the next section.

3.2 In-Sample Predictive Distributions of Capital Flows

The quantile regression in the previous section provides a consistent estimate of the conditional quantile function, or an inverse cumulative distribution function of future capital flows, $y_{i,t+h}$ conditional on predictors x_{it} :

$$\hat{Q}_{y_{i,t+h}|x_{it}}(\tau|x_{it}) = x_{it}\hat{\beta}_\tau$$

In order to compute other features of the conditional distribution than just quantiles, I follow Adrian et al. (2019) to fit a flexible family of probability distributions to the estimated $\hat{Q}_\tau(y_{i,t+h}|x_{it})$. Specifically, I fit the skewed t-distribution of Azzalini and Capitanio (2003) to smooth the quantile function, whose PDF is given by:

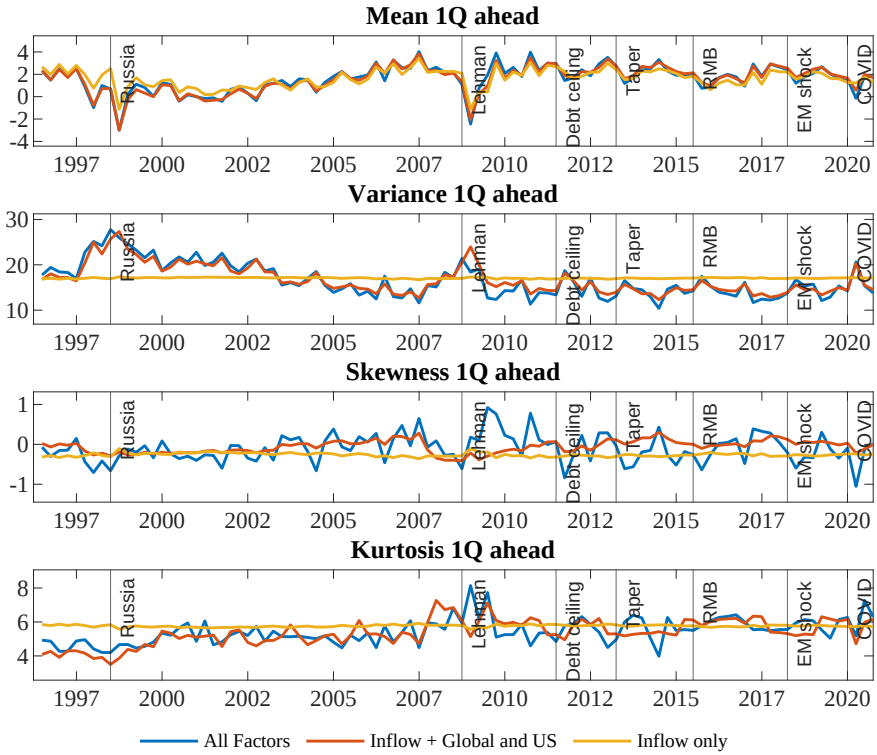
$$\hat{f}_{t+h}(y;\hat{\mu},\hat{\sigma},\hat{\alpha},\hat{\nu}) = \frac{2}{\hat{\sigma}}t\left(\frac{y-\hat{\mu}}{\hat{\sigma}};\nu\right)T\left(\hat{\alpha}\frac{y-\hat{\mu}}{\hat{\sigma}}\sqrt{\frac{\hat{\nu}+1}{\hat{\nu}+(\frac{y-\hat{\mu}}{\hat{\sigma}})^2}};\nu+1\right) \tag{5}$$

where t(·) and T(·) denote the PDF and CDF of the Student-t distribution. The parameters μ, σ, α, ν govern the location, scale, shape, and fatness of the distribution, respectively. Relative to the t-distribution, the skewed t-distribution adds the shape parameter which regulates the skewing effect of the CDF on the PDF. This is a generalised version of the usual symmetric Student-t distribution: when $\alpha = 0$, it collapses to the standard t-distribution. In the case of $\alpha = 0$ and $\nu = \infty$, the distribution reduces to a Gaussian with the mean μ and standard deviation σ.[10]

Next, the parameters $(\mu, \sigma, \alpha, \nu)$ of the skewed t-distribution are chosen to minimise the squared distance between the estimated conditional quantile function, $\hat{Q}_\tau(y_{i,t+h}|x_{it})$,

[10]For more details, see Adrian et al. (2019).

Figure 5: Moments over Time, Predictive Distribution of Inflows



Note: This chart shows time evolution of four moments of one-quarter ahead predictive distribution of inflows to a median emerging economy. Sample: 1996Q2 – 2020Q4.

and the inverse cumulative distribution function of the skewed t-distribution at 5th, 25th, 75th, and 95th quantiles:

$$\{\hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\alpha}_{t+h}, \hat{\nu}_{t+h}\} = \underset{\mu,\sigma,\alpha,\nu}{argmin} \sum_{\tau} \left(\hat{Q}_{y_{t+h}|x_{it}}(\tau|x_{it}) - F^{-1}(\tau; \mu, \sigma, \alpha, \nu) \right)^2 \tag{6}$$

for each period t = 1 ... T. In the end, this procedure generates a sequence of parameters $\{ \hat{\mu}, \hat{\sigma}, \hat{\alpha}, \hat{\nu} \}$ that match as closely as possible the conditional quantile estimates. Then it is possible to calculate the moments of fitted distribution and thus fully depict the entire conditional distribution of inflows and outflows at each point in time. Throughout this section, I focus on the one-quarter ahead predictions.

I plotted estimated moments of the one-quarter ahead predictive distribution at each period in Figure 5. Importantly, it compares results from three competing models, which have different set of conditioning variables:

M1 : current inflows (outflows)

M2 : current inflows (outflows) and the current global and US factor

M3 : current inflows (outflows) and all factors: global, US, EM, and local.

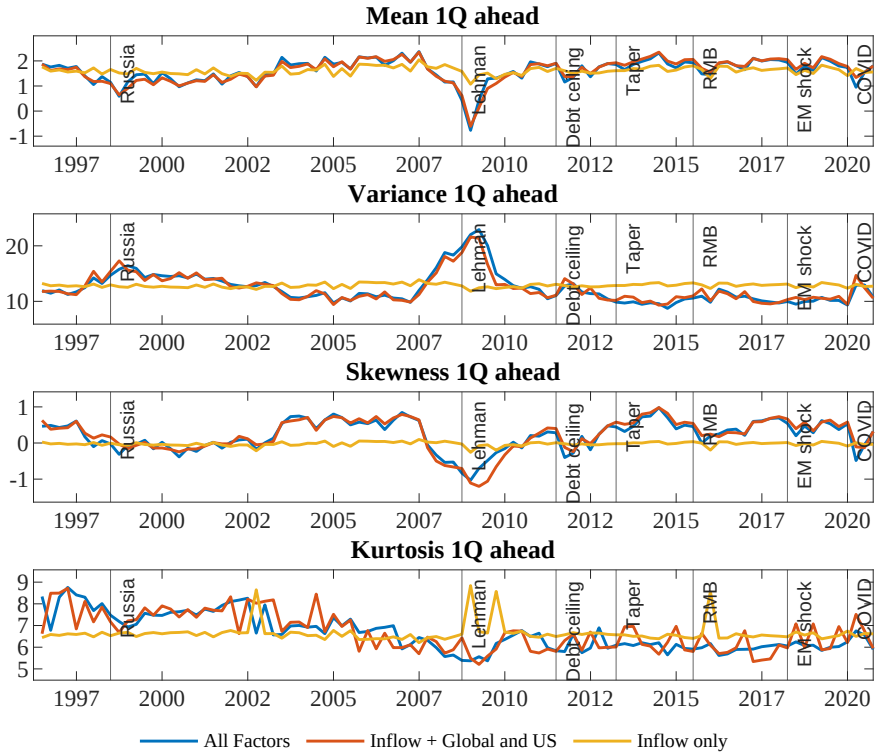
The first model corresponds to an autoregressive model, which I adopt it as a benchmark. The second model incorporates additional information from the global and US factors, in addition to realised value of capital flows. The rationale for this modelling choice came from asymmetric and nonlinear relationships between these two factors and the capital flows, portrayed in Figures 3 and 4. The last model conditions on all factors, so augmenting extra signals across financial markets in emerging economies and country-specific information. By comparing results from these three models, I can assess the marginal impact of the information content at different levels of aggregation in the conditional distribution of capital flows.

Figure 5 shows that financial conditions provide some extra information in terms of higher moments, or predicting vulnerability in capital inflows. Predictive distributions from all three models roughly move in tandem in terms of the mean (top panel). However, for the variance, skewness, and kurtosis, models with any extra information from financial indicators (in blue and red) generate more fluctuations, while the benchmark model (in yellow) does not display any time-varying patterns throughout the sample period.

Three observations follow from the results in Figure 5. First, the inclusion of global and US factors creates a time-varying pattern in terms of variance (the second plot). The model 2 (in red) displays a decreasing trend in variance over time: after the Russian Crisis of 1998, it steadily declines until the eve of Global Financial Crisis in 2007. The variance rises during the GFC, drops afterwards, and then stays flat until the COVID breakout in early 2020. The model predicts hikes in variance the next period during 1997 – 98 the Asian and Russian crises, fall of the Lehman brothers, and the spread of COVID in the Europe and the US – reflecting grown uncertainty in the global financial markets. Interestingly, the predicted variance from the model 3 (in blue) shows roughly the same pattern, implying that the EM and country-specific information have only marginal added values in terms of dispersion, once the global and US factors have been taken account of.

Second, the EM and country-specific factors convey extra predictive information on the third moment. As shown in the third panel of Figure 5, only the model 3 (in blue) generates variations in skewness over time, while other two models are mostly stable. Inclusion of regional and country-specific factors delivers clearly right-skewed one-quarter ahead predictive distributions during the recovery after GFC, and noticeably left-skewed

Figure 6: Moments over Time, Predictive Distribution of Outflows



Note: This chart shows time evolution of four moments of one-quarter ahead predictive distribution of outflows to a median emerging economy. Sample: 1996Q2 – 2020Q4.

ones for the Euro Area Debt Crisis and COVID shock. Estimated one-quarter ahead skewness is also negative after Tapering, Renminbi devaluation, and the EM – Argentina and Turkey in particular – shock episodes.

Finally, no model delivers meaningful variations in kurtosis over the sample. The bottom panel shows that predicted kurtosis from all of three models is quite stable over the sample, possibly except for the Global Financial Crisis period. The model 3 (in blue), which incorporates information from all four factors, displays some marginal swings during the third quarter of 2014 and 2020, but the movement is rather stable in most of the time.

Now I turn to estimated moments of the one-quarter ahead predictive distribution for outflows in Figure 6. First, in a stark contrast to the case of inflows, predicted moments show stable patterns over the sample for all models, except for the Global Financial Crisis. Fluctuations generated by models 2 and 3 (in blue and red) are muted in all other periods. The downward trend in variance before the GFC has weakened, and the movement in skewness has been more stabilised. Compared to inflows where the Russian crisis has

been characterised as the fall in the mean and rise in variance and the COVID-19 as the negative skewness, changes at any moments for those events are only marginal in the case of outflows. Any extra information from financial indicators seem to be contained solely during the GFC.

Moreover, models 2 and 3 move in tandem across all four moments throughout the sample period in Figure 6. This suggests more muted role of the regional and country-specific factors in case of the outflows. While these extra information played some role for the predictive distribution of inflows in the form of more variations in skewness, such movements mostly disappear for outflows. The evolution of kurtosis portrays some downward trends before the GFC and then is stabilised afterwards, similar to that of variance for inflows. However, it is difficult to find a discernible pattern.

I wrap up this section with a summary of results. First, using the standard quantile regression of Koenker and Bassett (1978), I presented evidences of possible asymmetric and nonlinear relationships between the global factor and capital flows. In contrast to inflows, outflows strongly display such relationships with the US factor. I further investigated such findings by estimating the full conditional distribution of capital flows to a median emerging economy as a function of current financial conditions, using the novel method of Adrian et al. (2019).

Based on the evolution of estimated moments of one-quarter ahead predictive distribution, across three models that have different information sets, I reported the specific role of information content at different levels of aggregation: global, US, EM-wide, and local. In case of inflows, the inclusion of global and US factors creates a time-varying pattern in terms of variance, while EM and local factors append extra predictive information on skewness. The predictive distribution of outflows, however, remains relatively stable over time with or without any extra signals from the financial market, except for the Global Financial Crisis period. Consistent with the previous results, the role of local and regional factors seems to be marginal in case of outflows.

4 Downside risks and Out-of-Sample Analysis

From a policymaker's perspective, it is important to monitor extreme swings in capital flows *ex ante*. To this end, I conduct out-of-sample analyses on inflows and outflows in

this section, in order to answer the following questions: Can we predict an increase in capital flow vulnerability, i.e. the probability of sudden stops and retrenchments? Can we make better predictions on capital flow movements based on signals from the financial markets? The quantile regression framework is a natural tool to answer such questions that bridge forecasting and the risk management.

4.1 Downside risks

I first investigate downside risks to the future capital inflows and outflows, or the *vulnerability* of the predicted path of flows to financial shocks. I characterise downside risks to capital flows in terms of expected shortfall, which is defined as

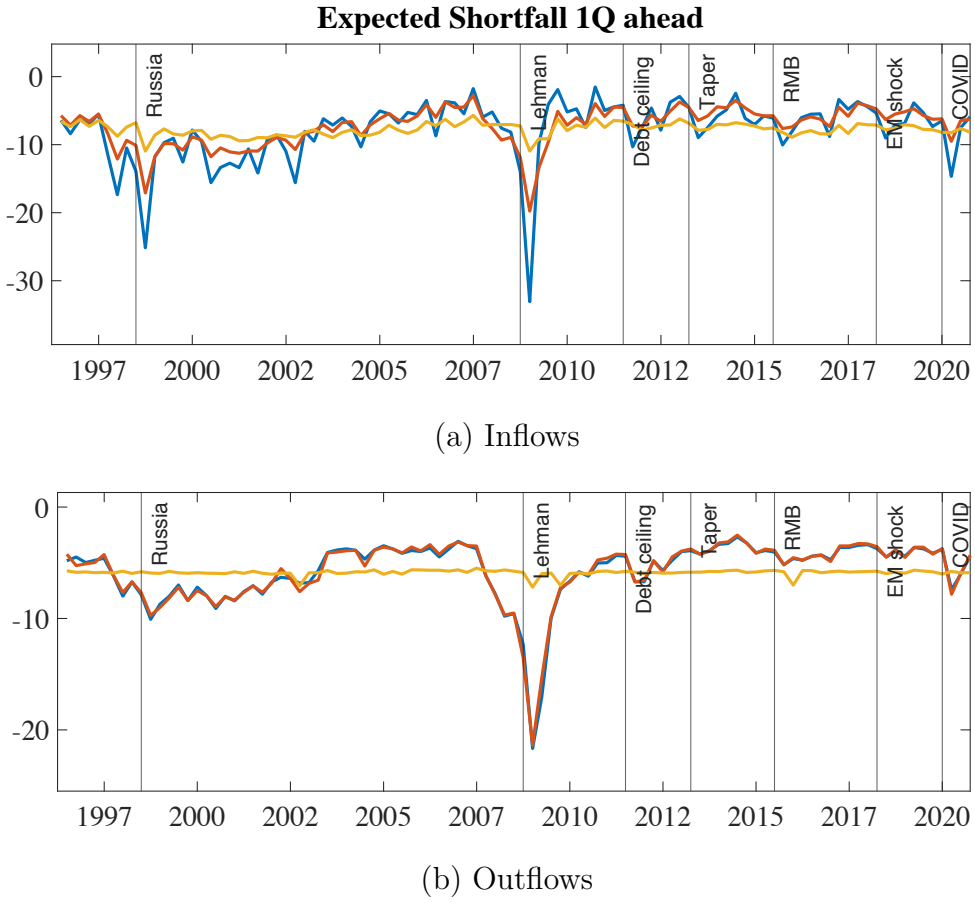
$$SF_{t+h} = \frac{1}{\pi} \int_0^{\pi} \hat{F}^{-1}_{y_{t+h}}(\tau|x_t) d\tau \tag{7}$$

for a chosen probability π. $F^{-1}_{y_{t+h}|x_t}$ is the cumulative distribution function of the estimated conditional distribution, so $F^{-1}_{y_{t+h}}(0.5|x_t)$ corresponds to the conditional median. These two measures summarise the lower and upper tail behaviours of the conditional distribution in absolute terms. I choose $\pi = 0.05$, or the 5th percentile of the distribution, which is a widely known Value-at-Risk threshold in the financial risk management literature. The 5 percent expected shortfall would measure expected inflows next period conditional on the materialisation of a *sudden stop*.

Figure 7 shows the 5 percent expected shortfall over the sample period for the three models. The top panel presents the result for inflows to the EMs. Noticeably, there are three episodes that display a pronounced fall: the Russian crisis, fall of Lehman brothers, and the COVID-19. The worst-scenario outcomes in other periods, e.g. the debt crisis and Taper Tantrum, are more muted. During these times, the model 3 (in blue) predicts more severity; in other times, predictions from models 2 (in red) and 3 are closely aligned.

On the other hand, the expected shortfall from the model 2 and 3 is almost indistinguishable for the outflows to EMs (the bottom panel). The additional role played by EM and local factors seems to be marginal, echoing the results from the section 3.2. Moreover, the Global Financial Crisis is the only period with a marked decrease in outflows, or a strong *retrenchment*. The 5 percent expected outcome at other periods remains quite stable over the sample, and the expected severity of the Russian crisis and

Figure 7: Expected Shortfall, 1Q Ahead



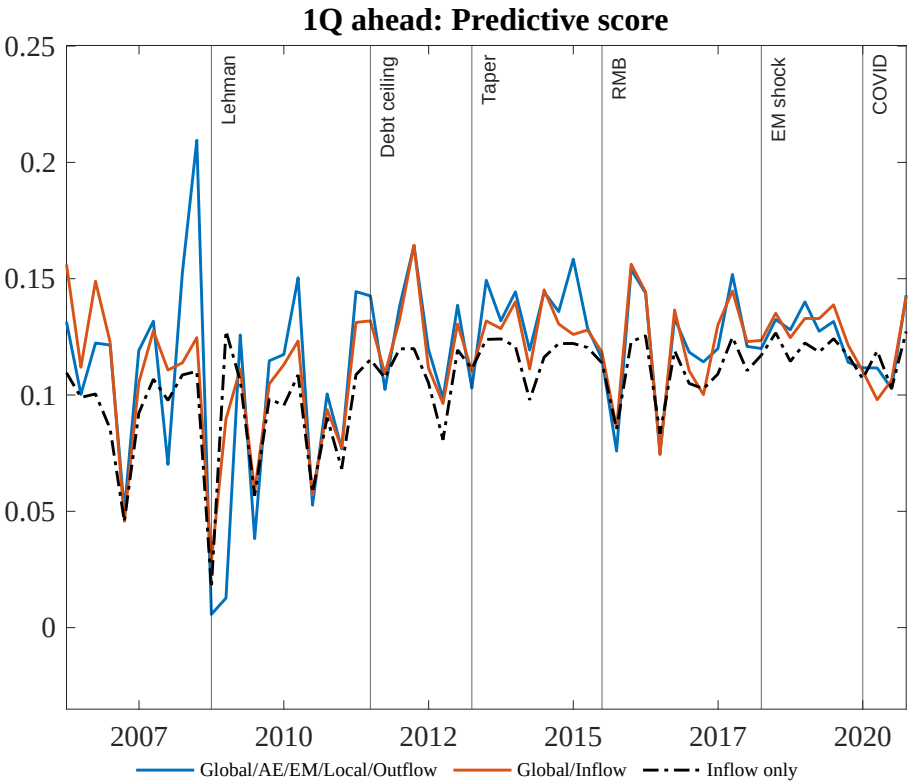
Note: This chart shows time evolution of the expected shortfall, one-quarter ahead for inflows and outflows to a median emerging economy. The first model (in yellow) conditions only on the current inflows. The second model (in red) conditions on current inflows, the current global factor and the US factor. The third model (in blue) that conditions on current inflows and all factors. The vertical bars are crisis episodes. Sample: 1996Q2 – 2020Q4.

the COVID-19 is relatively marginal. Such patterns are in line with the evolution of predictive moments for outflows, where noticeable changes in mean, variance, and skewness were mostly specific to the GFC episode.

4.2 Out-of-Sample Analysis

Next, I run the out-of-sample prediction analyses to tackle the next question: do financial indicators help improving predictions on capital flow movements? Throughout this section, I first estimate one-quarter ahead predictive distributions of inflows and outflow following the two step methodology illustrated in the previous section, with the initial estimation sample that comprises data from 1996Q2 to 2005Q4. Then, I iteratively estimate predictive distributions by expanding the estimation sample by one quarter at each iteration until 2020Q4. Importantly, I generate predictive distributions for three

Figure 8: Predictive scores, 1Q-ahead EM Inflows



Note: This chart plots the predictive score (vertical axis) of 1Q-ahead out-of-sample forecasting exercises with three different models. The first model (in black) conditions only on the current inflows, the second model (in red) conditions on current inflows and the current global factor, and the third model (in blue) that conditions on current inflows and all factors. The vertical bars are crisis episodes. In-sample 1996Q1 – 2005Q4, Out-of-sample: 2006Q1-2020Q4.

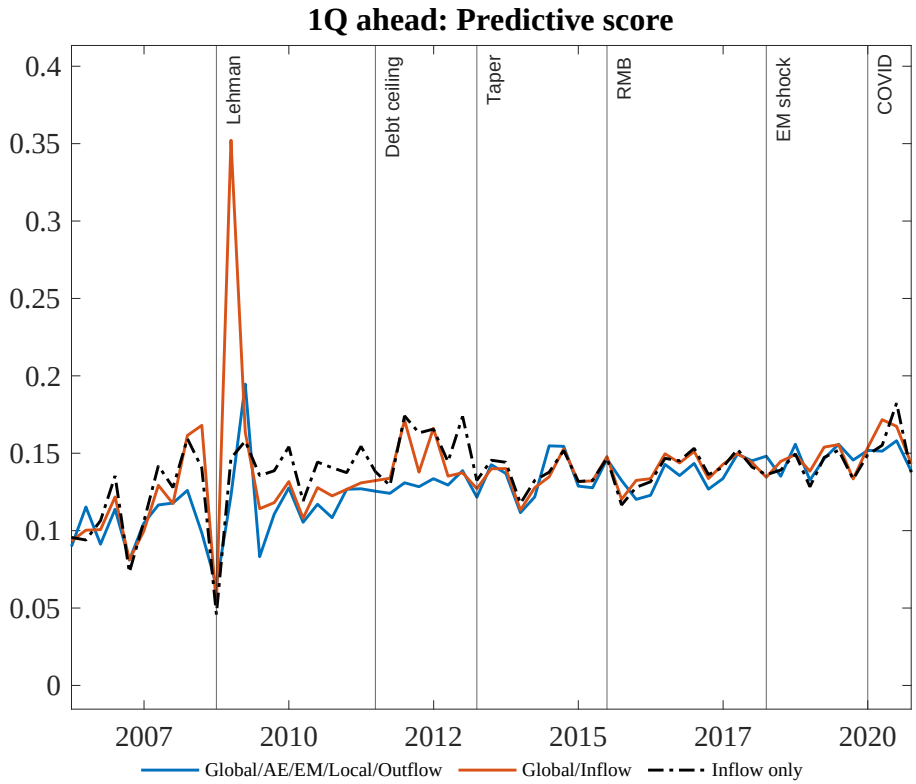
different models that incorporate information contents at different levels of aggregation: global, US, regional, and local, as defined in the section 3.2.

I employ the *predictive score* as the measure that assesses out-of-sample accuracy of predictions. It is computed by evaluating the predictive density at the outturn of future capital flows:

$$PS_{t+h} = \hat{f}_{t+h}(y_{t+h}; \hat{\mu}_{t+h}, \sigma_{t+h}, \alpha_{t+h}, \nu_{t+h}) \tag{8}$$

Higher values of the predictive scores indicate more accurate predictions, because they show that the model assigns higher likelihood to realised outcomes. I choose this measure, since the goal is to explore not only the point forecast but also the entire h-quarter ahead predictive distribution of inflows and outflows for the median emerging economy for each quarter of the interest. In order to check the accuracy across the entire distribution, it may not be sufficient to rely on the usual measure such as Root Mean Squared Errors (RMSE).

Figure 9: Predictive scores, 1Q-ahead EM Outflows



Note: This chart plots the predictive score (vertical axis) of 1Q-ahead out-of-sample forecasting exercises with three different models. The first model (in black) conditions only on the current outflows, the second model (in red) conditions on current outflows and the current global factor, and the third model (in blue) that conditions on current outflows and all factors. The vertical bars are crisis episodes. In-sample 1996Q1 – 2005Q4, Out-of-sample: 2006Q1-2020Q4.

Figure 8 plots the predictive scores of three models, from a one-quarter ahead predictive distribution of inflows to EMs. It is noticeable that any models with factors, even just global, improve forecasting performance relative to the benchmark model (in black) for most of the time. Adding EM and local factors further increases the prediction power, though overall improvement is modest and confined to just a few periods. This echoes the result from the section 3.1, where I find pronounced nonlinear relationship between the global factor and one quarter ahead capital inflows but weaker evidences on the role of regional and local factors. Though they provide extra predictive information on skewness in the section 3.2, most of them turn out to be weak signals in terms of the out-of-sample forecasting. Then, the next question would be: do global and US factors improve the predictive performance of outflows to EMs?

Again the story is little different for the outflows. From the outflows counterpart in Figure 9, signals from the financial markets only improve out-of-sample performance around the Global Financial Crisis. In other periods, it is unclear that any of the factors

provide more accurate forecasts than a simple autoregressive model (in black). After the Taper Tantrum episode in the second quarter of 2013, any models conditioning on extra factors perform only as good as the benchmark. Before this period, the forecasting accuracy of models 2 and 3 are even worse than the baseline model, except the period around the Global Financial Crisis. Interestingly, the model that conditions only on the global factor (model 2) increases the forecasting accuracy by a huge margin, right after the fall of Lehmann Brothers. Such a phenomenon echoes a strong relationship between the US factor and future outflows at tails of the distribution. Putting together the results from both directions of capital flows, the out-of-sample exercises point out to a similar story from the in-sample results.

5 Variable selection: which indicators matter?

So far, I examined the predictability of financial indicators on capital flows using the factor model. Though factor-based analyses are versatile in summarising the common information across a large set of indicators, derived factors are the combination of different structural shocks. It is difficult to interpret them in terms of one aspect, e.g. risk appetite, liquidity, or market sentiment. On a more practical side, therefore, policymakers would be interested in which specific indicators of risk and returns carry the most predictive power, since knowing a narrowly defined measures would help designing policies. For academics, it sheds more light on the theoretical model building.

To this end, I perform a variable selection exercise to find important variables that best forecast EM capital inflows and outflows. Since the main spirit of variable selection algorithms is to yield a parsimonious model among a large number of covariates by shrinking irrelevant slopes and leaving only relevant ones, it constitutes an adequate tool to search for specific financial market indicators that best predict swings in capital inflows and outflows.

Among the several choices, I resort to a Bayesian method and impose the 'horseshoe' prior of Carvalho et al. (2010), among many potential candidates of variable selection algorithms. Compared to popular frequentist methods such as LASSO, which are based on the use of penalty function, this method draws inference from the entire posterior distribution and offers a flexible hierarchical structure to collapse the entire marginal

posterior of each slope coefficient towards relevance or irrelevance, but not both. Hence, it improves the selection process by reducing both bias and parameter uncertainty.[11]

I estimate the model for each of 15 EMs on the dataset introduced in section 2.1, plus indicators that may reflect structural positions and policy regimes: the growth differential with the US, net exports, and foreign exchange (FX) reserves.[12] Hence, there is up to 27 predictors – 12 US and 15 domestic – available for each country, while the data availability varies across countries.[13] Importantly, all predictors are standardised to have a zero sample mean and unit variance, in order to make coefficients comparable across different variables.

5.1 A Case study: Turkey

I begin with a single-country analysis on Turkey. Besides being one of the largest EMs, I chose Turkey as a representative example for two reasons. First, the country experienced several major economic crises over the sample period, in 2001 and 2018. The latter was severe enough to create financial contagion to other EMs including Colombia and South Africa, by increasing the risk perception of foreign lenders. Hence it enables us to explore more tail events in addition to few global episodes, such as the Russian crisis, GFC, and the COVID. Second, Turkey has been heavily relied on capital inflows due to a chronically low savings rate. The domestic credit market features excess demands from the private sector, and the government is running one of the largest current account deficits among the EMs. Hence, identifying key predictors of future capital flow swings in Turkey is not only meaningful for its own but also for other EMs.

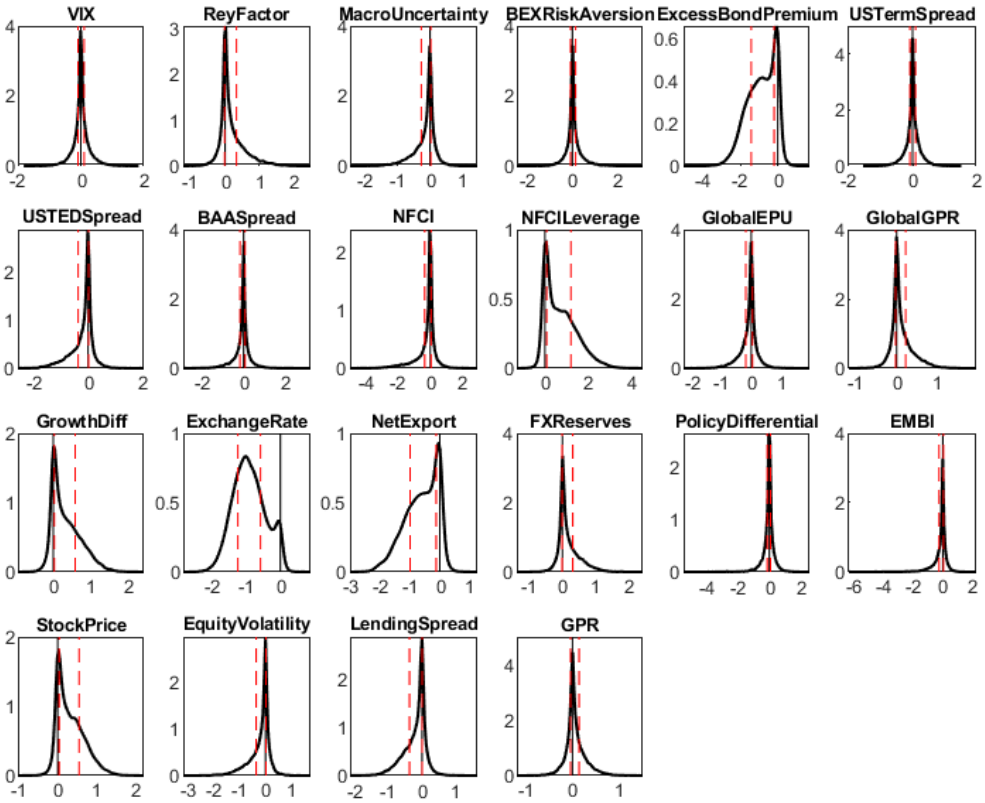
Figure 10 plots the posterior distribution of coefficients for inflows to Turkey, after applying a shrinkage method via the Horseshoe prior. The red dashed lines indicate 68% confidence bands. For a majority of indicators, the mode of the distribution is shrunken close to zero, and this is indeed the main goal of this exercise. A few predictors, such as

[11] Since the sparsity-inducing penalty function has to affect only a single point, not the entire parameter space, at a time, the L1 regularization(Lasso) introduces bias by leaving significant probability mass on irrelevant slopes while overshrinking relevant ones. See Carvalho et al. (2010) for a more technical exposition.

[12] See Blanchard et al. (2015) and Bernanke (2017) for stylised models highlighting the role of these variables, based on mercantilist motive of small open economies in particular.

[13] For example, J.P. Morgan EMBI+ bond spread, one of the popular indicators of EM domestic risk, is available for 12 countries in our sample, but the coverage is too short to cover more than 80 % of the sample period for 7 out of those 12 EMs.

Figure 10: Posterior of coefficients: Turkey, Inflows

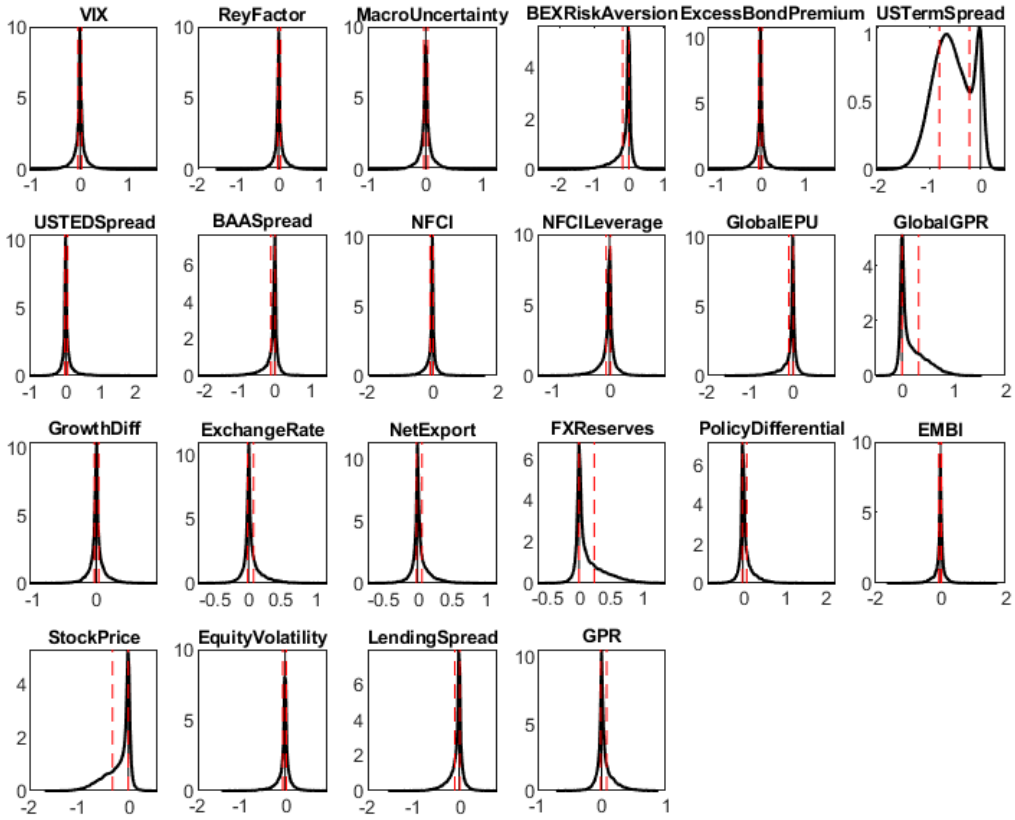


Note: Posterior densities of the coefficients on mean and predictor variables. Vertical dashed lines indicate the 68% signficance level. Sample 1996Q1 – 2020Q4. All predictors are standardised to have zero mean and a unit variance.

the FX reserves, include zero within the 68% bands. The US excess bond premium, NFCI leverage, and net exports marginally exclude zero, but the mode of the distribution is mostly indistinguishable from zero. The variable that carries the most predictive power for inflows is the exchange rate, Turkish Lira per US dollar: one standard deviation of its deprecation leads to more than 1 percentage drop in inflows.

Interestingly, the degree of shrinkage is more dramatic for outflows in Figure 11: the distribution of most indicators is closely tightened around zero. The Global Geopolitical Risk index (GPR), FX reserves, and stock prices display some mass at other values but marginally include zero within the 68% bands. The US term spread seems like the sole significant predictor for outflows: however, it has twin peaks around -1 and 0. Hence, in case of outflows, there is no clear predictor among the candidates in the dataset. Compared to previous factor-based results on the median EM, such findings appear to be echoing relatively weak out-of-sample predictive performance of the outflows. The significant role of US financial conditions for outflows in-sample analyses, however, is no longer evident. To shed more light on this issue, I turn to a cross-country analysis.

Figure 11: Posterior of coefficients: Turkey, Outflows



Note: Posterior densities of the coefficients on mean and predictor variables. Vertical dashed lines indicate the 68% signficance level. Sample 1996Q1 – 2020Q4. All predictors are standardised to have zero mean and a unit variance.

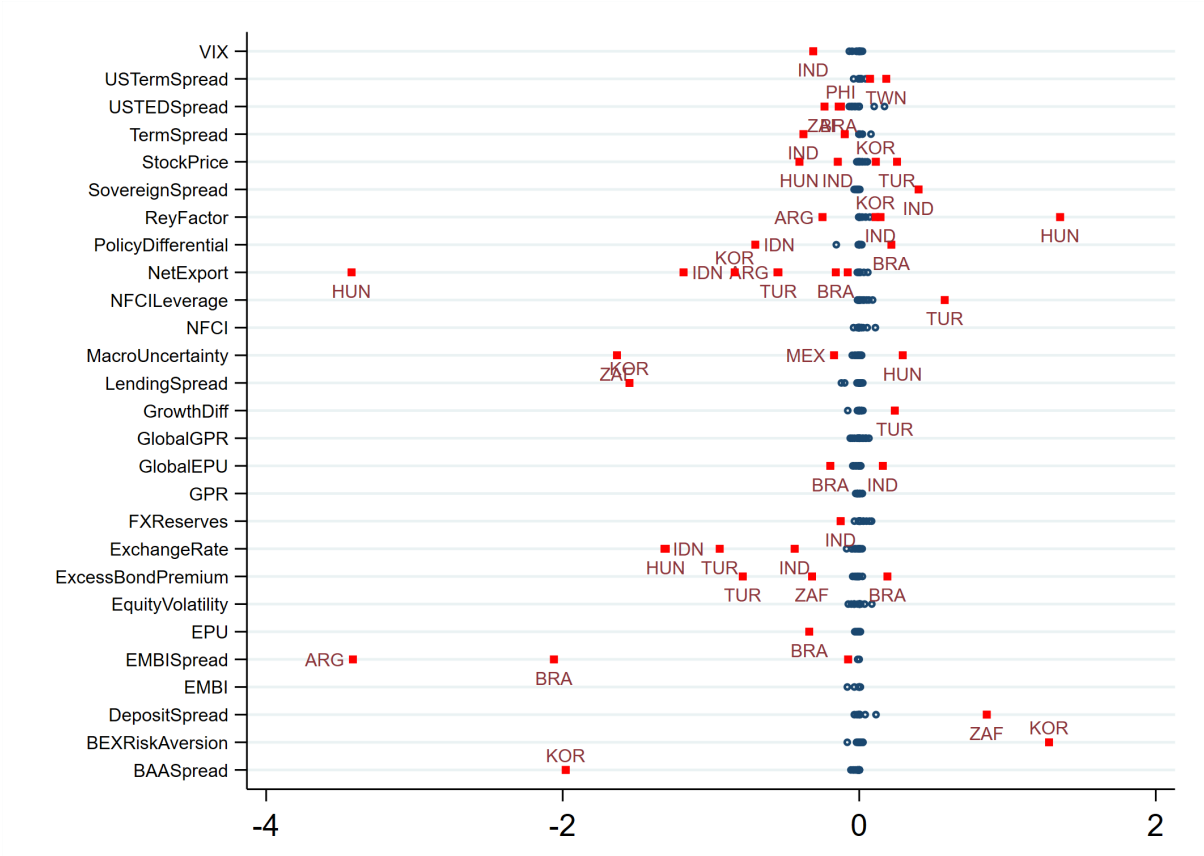
5.2 Cross-country results

Next, I zoom out and gather the results across 15 EMs on capital inflows in Figure 12. Here I plotted posterior medians of the coefficients on each of 27 predictors as dots. A dot is in red if the coefficient is significant at the 68% level, and a dot with a country label means that the size of coefficient is larger than 0.1, implying that a one standard deviation increase leads to 0.1 percentage point higher inflows to EM. I set such a small change as a minimum hurdle for a predictor to be economically meaningful.

So for instance, the red dot with a label *KOR* in the last row of Figure 12 implies that a one standard deviation increase in the BAA spread decreases inflows to Korea by 2 percentage point, and this is statistically significant at the 68% level. One can interpret the Figure 12 as a graphical representation of the common regression table in this sense.

I plotted the outflows counterpart in Figure 13 in the same spirit. Note that most of coefficients (dots) are close to zero and insignificant for many indicators. This is the main goal of the variable selection: it shows that the horseshoe prior effectively yields a

Figure 12: Relevance on Inflow



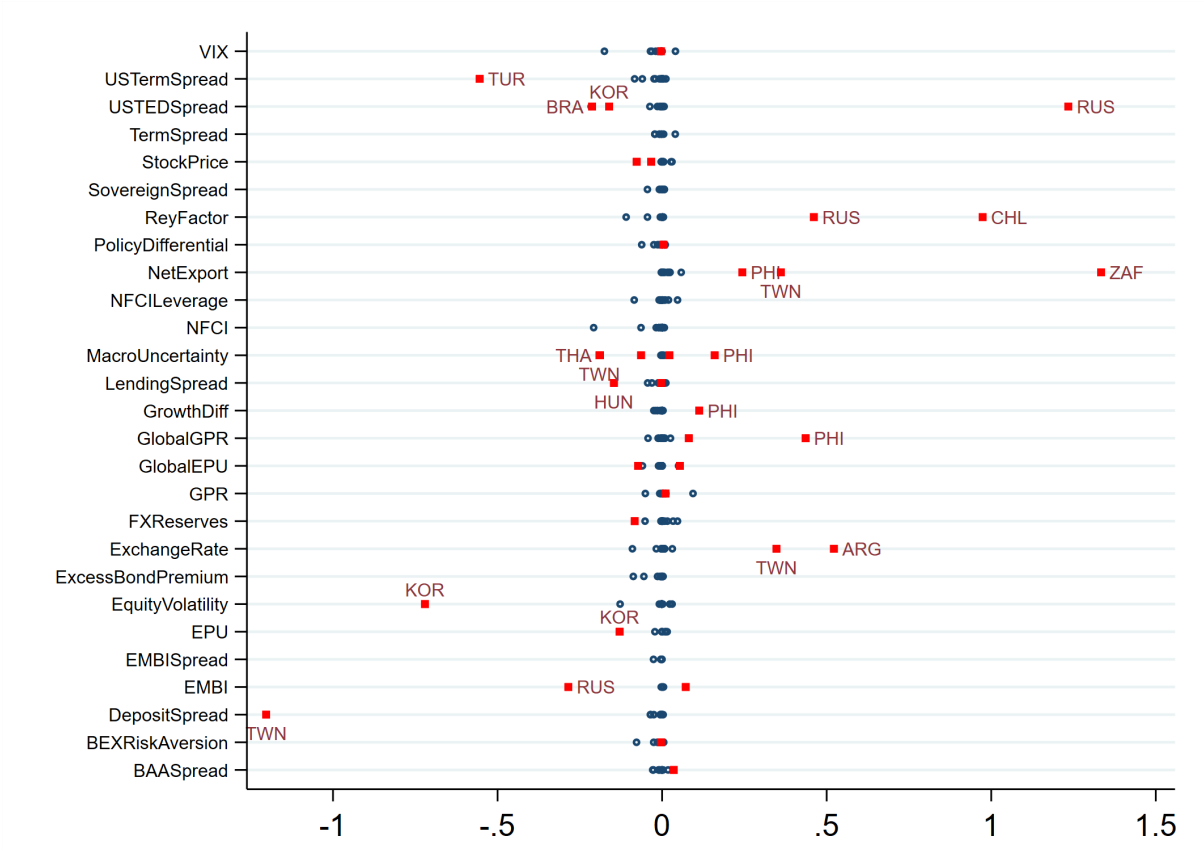
Note: Posterior medians of the coefficients on predictors (y-axis), using capital inflows as the dependent variable. Dots in each row correspond to the size of coefficients from 15 EMs. Red dots are significant at 68% level, and the size of coefficient is larger than 0.1 for dots with country labels. Sample 1996Q2 – 2020Q4. All predictors are standardised to have zero mean and a unit variance.

parsimonious model by shrinking most of coefficients to zero and leaving only few relevant ones.

Comparing figures 12 and 13, the first pronounced aspect is the difference in scales: the magnitude of coefficients is much smaller in the case of outflows. Notice that in Figure 13, there are only 3 cases (Deposit spread for Taiwan, US TED spread for Russia, and net exports for South Africa) in which a predictor affects the outflows more than 1 percentage point in absolute terms, while there are many more in case of the inflows. This confirms that the difference in effects between inflows and outflows is not just due to few outliers, but rather a pervasive phenomenon.

Moreover, the number of red dots is markedly fewer for outflows. It means that most of indicators are either not statistically significant even at the 68% level, or not economically meaningful impact (less than 0.1 pp change in capital flows). Though it is interesting that many US indicators turn out to be insignificant, these results are in line

Figure 13: Relevance on Outflow



Note: Posterior medians of the coefficients on predictors (y-axis), using capital outflows as the dependent variable. Dots in each row correspond to the size of coefficients from 15 EMs. Red dots are significant at 68% level, and the size of coefficient is larger than 0.1 for dots with country labels. Sample 1996Q2 – 2020Q4. All predictors are standardised to have zero mean and a unit variance.

with distinct forecasting performances between the two flip-side of capital flows. While models with any factors improve the forecasting performance for inflows throughout the sample, there is no clear sign of improvement for outflows except for certain episodes.

Importantly, figure 12 and 13 suggest that relevant predictor variables appear to be quite heterogeneous across the 15 EMs, for both inflows and outflows. In fact, no single indicator robustly predicts either inflow or outflow, for a majority of EMs. In case of Inflows, the most widely significant variable is net export (7 out of 15 countries), followed by the exchange rate, stock price returns, and the global risk factor from Miranda-Agrippino and Rey (2020) (4 out of 15).[14] Other than US TED spread, US macro uncertainty index, and the excess bond premium, no other variable seems important for more than one-fifth of countries in the sample. It is even harder to find a universal predictor in case of the outflows: besides the US macro uncertainty index, coefficients on other indicators are

[14]The EMBI spread is significant for 60% of countries for inflows, but the sample is too small to be conclusive.

significant for only 3 countries at most.

To conclude, the variable selection exercise reinforces the result from factor-based analyses. While some indicators of financial conditions have an impact on future inflows, only few predictors have more than a modest effect on outflows. In both cases, however, it seems difficult to identify a single robust predictor across the EMs. No financial variable in the dataset plays a significant role in forecasting one-quarter ahead capital flows for more than a handful of countries, and there is often disagreement across countries about the significance and sign of effects. It is important to stress, however, that the dataset lacks measures of leverage and corporate bond spreads, which are the key variables in theoretical frameworks such as Mendoza (2010) and Bruno and Shin (2015). Therefore, the main implication of this analysis does not overturn the exsiting literature, but rather it provides a caution on making generalisations based on single-country analyses.

6 Conclusion

This paper studies potentially distinct predictability of financial indicators on the two sides of capital flows to emerging economies. As a first step, I extract common information across financial indicators from the 15 emerging markets and the US using the dynamic factor model, with three different layers of aggregation: global, regional, and country-specific levels. Then I employ the quantile regression framework to explore potentially nonlinear nexus between financial conditions and the capital flows in both directions: inflows and outflows. To evaluate the practicality of the GaR framework as an ex ante monitoring device, I analyse downside risks to future EM capital inflows and outflows and out-of-sample prediction exercises.

From the set of both traditional and state-of-the-art empirical techniques, I report three findings. First, there are evidences of asymmetric and nonlinear relationships between the global factor and both directions of capital flows to EMs, but the relationship is more muted for outflows. A scrutiny across the predictive distribution reveals that the predictability from the global factor is present across the sample period on inflows, but it is more confined to the Global Financial Crisis episode for outflows.

Second, I find some evidences that the EM regional factor renders additional predictability for future inflows, while the role of the local factor is less clear. Estimated

moments of the predictive distribution suggest that the EM factor conveys extra predictive information on the third moment, or skewness of the predictive distribution. Such a common signal across EMs also turns out to be useful in measuring downside risk and out-of-sample forecasting.

Third, in contrast to inflows, outflows display a strong link only with the US factor. Such a relationship holds in both standard and quantile regressions. A further investigation at predictive distribution of outflows suggests that this extra signal from the US financial indicators is contained during the Global Financial Crisis: no factor generates meaningful fluctuations in other periods. This result holds in both in-sample and out-of-sample analyses. All of these findings suggest that capital inflows and outflows are not 'two peas in a pod' in terms of their relationships to financial conditions.

References

Adrian, Tobias, Federico Grinberg, Nellie Liang, and Sheherya Malik, "The Term Structure of Growth-at-Risk," CEPR Discussion Papers 13349, C.E.P.R. Discussion Papers December 2018.

_ , **Nina Boyarchenko, and Domenico Giannone**, "Vulnerable Growth," *American Economic Review*, April 2019, *109* (4), 1263–1289.

Avdjiev, Stefan, Sebnem Kalemli-Ozcan, and Luis Servén, "Gross capital flows by banks, corporates and sovereigns," BIS Working Papers 760, Bank for International Settlements November 2018.

Azzalini, Adelchi and Antonella Capitanio, "Distributions generated by perturbation of symmetry with emphasis on a multivariate skew t-distribution," *Journal of the Royal Statistical Society Series B*, May 2003, *65* (2), 367–389.

Bai, Jushan and Serena Ng, "Determining the Number of Factors in Approximate Factor Models," *Econometrica*, January 2002, *70* (1), 191–221.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis, "Measuring Economic Policy Uncertainty," *The Quarterly Journal of Economics*, 2016, *131* (4), 1593–1636.

Bekaert, Geert, Eric Engstrom, and Andrey Ermolov, "Macro risks and the term structure of interest rates," *Journal of Financial Economics*, 2021, *141* (2), 479–504.

Bernanke, Ben S, "Federal Reserve Policy in an International Context," *IMF Economic Review*, April 2017, *65* (1), 1–32.

Blanchard, Olivier, "Currency wars, coordination, and capital controls," *International Journal of Central Banking*, 2017, *13* (2), 283–308.

Blanchard, Olivier J., Gustavo Adler, and Irineu de Carvalho Filho, "Can Foreign Exchange Intervention Stem Exchange Rate Pressures from Global Capital Flow Shocks?," IMF Working Papers 2015/159, International Monetary Fund July 2015.

Broner, Fernando, Tatiana Didier, Aitor Erce, and Sergio L. Schmukler, "Gross capital flows: Dynamics and crises," *Journal of Monetary Economics*, 2013, *60* (1), 113–133.

Bruno, Valentina and Hyun Song Shin, "Cross-Border Banking and Global Liquidity," *Review of Economic Studies*, 2015, *82* (2), 535–564.

Caldara, Dario and Matteo Iacoviello, "Measuring Geopolitical Risk," International Finance Discussion Papers 1222, Board of Governors of the Federal Reserve System (U.S.) February 2018.

Calvo, Guillermo A., Alejandro Izquierdo, and Luis-Fernando Mejia, "On the Empirics of Sudden Stops: The Relevance of Balance-Sheet Effects," NBER Working Papers 10520, National Bureau of Economic Research, Inc May 2004.

_ , **Leonardo Leiderman, and Carmen M. Reinhart**, "Capital Inflows and Real Exchange Rate Appreciation in Latin America: The Role of External Factors," *IMF Staff Papers*, March 1993, *40* (1), 108–151.

Canay, Ivan A., "A simple approach to quantile regression for panel data," *Econometrics Journal*, October 2011, *14* (3), 368–386.

Carvalho, Carlos M., Nicholas G. Polson, and James G. Scott, "The horseshoe estimator for sparse signals," *Biometrika*, 2010, *97* (2), 465–480.

Cerutti, Eugenio, Stijn Claessens, and Andrew K Rose, "How important is the Global Financial Cycle? Evidence from capital flows," BIS Working Papers 661, Bank for International Settlements August 2017.

Davis, J. Scott, Giorgio Valente, and Eric van Wincoop, "Global drivers of gross and net capital flows," *Journal of International Economics*, 2021, *128* (C).

Degasperi, Riccardo, Simon Hong, and Giovanni Ricco, "The Global Transmission of U.S. Monetary Policy," CEPR Discussion Papers 14533, C.E.P.R. Discussion Papers March 2020.

Doz, Catherine, Domenico Giannone, and Lucrezia Reichlin, "A Quasi–Maximum Likelihood Approach for Large, Approximate Dynamic Factor Models," *The Review of Economics and Statistics*, November 2012, *94* (4), 1014–1024.

Eguren-Martin, Fernando, Cian O'Neill, Andrej Sokol, and Lukas von dem Berge, "Capital flows-at-risk: push, pull and the role of policy," Working Paper Series 2538, European Central Bank April 2021.

Fernandez-Arias, Eduardo, "The new wave of private capital inflows: Push or pull?," *Journal of Development Economics*, March 1996, *48* (2), 389–418.

Forbes, Kristin J. and Francis E. Warnock, "Capital flow waves: Surges, stops, flight, and retrenchment," *Journal of International Economics*, 2012, *88* (2), 235–251.

Gelos, Gaston, Lucyna Gornicka, Robin Koepke, Ratna Sahay, and Silvia Sgherri, "Capital Flows at Risk: Taming the Ebbs and Flows," CEPR Discussion Papers 15842, C.E.P.R. Discussion Papers February 2021.

Ghosh, Atish R., Mahvash S. Qureshi, Jun Il Kim, and Juan Zalduendo, "Surges," *Journal of International Economics*, 2014, *92* (2), 266–285.

Giglio, Stefano, Bryan Kelly, and Seth Pruitt, "Systemic risk and the macroeconomy: An empirical evaluation," *Journal of Financial Economics*, 2016, *119* (3), 457–471.

Gilchrist, Simon and Egon Zakrajšek, "Credit Spreads and Business Cycle Fluctuations," *American Economic Review*, 2012, *102* (4), 1692–1720.

Hasenzagl, Thomas, Lucrezia Reichlin, and Giovanni Ricco, "Financial Variables as Predictors of Real Growth Vulnerability," CEPR Discussion Papers 14322, C.E.P.R. Discussion Papers January 2020.

Jurado, Kyle, Sydney C. Ludvigson, and Serena Ng, "Measuring Uncertainty," *American Economic Review*, March 2015, *105* (3), 1177–1216.

Kiley, Michael T., "Unemployment Risk," Finance and Economics Discussion Series 2018-067, Board of Governors of the Federal Reserve System (U.S.) September 2018.

Koenker, Roger W and Jr Bassett Gilbert, "Regression Quantiles," *Econometrica*, January 1978, *46* (1), 33–50.

Koepke, Robin, "What Drives Capital Flows To Emerging Markets? A Survey Of The Empirical Literature," *Journal of Economic Surveys*, April 2019, *33* (2), 516–540.

Kose, M. Ayhan, Christopher Otrok, and Charles H. Whiteman, "International Business Cycles: World, Region, and Country-Specific Factors," *American Economic Review*, September 2003, *93* (4), 1216–1239.

Mendoza, Enrique G., "Sudden Stops, Financial Crises, and Leverage," *American Economic Review*, December 2010, *100* (5), 1941–1966.

Miranda-Agrippino, Silvia and Hélène Rey, "U.S. Monetary Policy and the Global Financial Cycle," *Review of Economic Studies*, 2020, *87* (6), 2754–2776.

Plagborg-Møller, Mikkel, Lucrezia Reichlin, Giovanni Ricco, and Thomas Hasenzagl, "When Is Growth at Risk?," *Brookings Papers on Economic Activity*, 2020, pp. 167–213.

Reinhart, Carmen M. and Vincent R. Reinhart, "Capital Flow Bonanzas: An Encompassing View of the Past and Present," *NBER International Seminar on Macroeconomics*, 2009, *5* (1), 9–62.

Rey, Hélène, "Dilemma not trilemma: the global cycle and monetary policy independence," *Proceedings - Economic Policy Symposium - Jackson Hole*, 2013, pp. 1–2.

_ , "International Channels of Transmission of Monetary Policy and the Mundellian Trilemma," *IMF Economic Review*, May 2016, *64* (1), 6–35.

Rogers, John H. and Jiawen Xu, "How Well Does Economic Uncertainty Forecast Economic Activity?," Finance and Economics Discussion Series 2019-085, Board of Governors of the Federal Reserve System (U.S.) December 2019.

Sargent, Thomas J, "Two Models of Measurements and the Investment Accelerator," *Journal of Political Economy*, April 1989, *97* (2), 251–287.

Stock, James H and Mark W Watson, "Macroeconomic Forecasting Using Diffusion Indexes," *Journal of Business & Economic Statistics*, April 2002, *20* (2), 147–162.