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JEL Classification: F30, G11, G15

Keywords: Portfolio rebalancing, Equity Flows, Exchange Rates, financial stress, structural VAR, sign restrictions, regime switching

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1 Introduction

According to theoretical models of portfolio rebalancing, global investors allocate their portfolio by balancing the expected risk and return of assets across international markets. When price shocks cause the portfolio weights to deviate from their optimal risk-return maximizing values, investors rebalance their portfolios. This portfolio rebalancing – also labeled negative feedback trading or contrarian investment – induces stabilizing dynamics. As an example, consider a random shock associated with an exchange rate appreciation in some foreign country. Assuming global investors' exchange rate exposure is not perfectly hedged, this shock increases the portfolio share of that country's equities above its desired level.[1] To restore the optimal risk-return tradeoff, investors sell equities from the respective foreign equity market. These asset sales trigger equity outflows, which mitigate the initial currency appreciation.

A large empirical literature establishes that portfolio rebalancing is important in practice.[2] Curcuru et al. (2011) find that international U.S. equity investment exhibits partial rebalancing, as investors sell stocks that have recently performed well. Hau and Rey (2004) impose the sign restrictions implied by portfolio rebalancing in a structural VAR of equity flows, equity returns, and exchange rate returns, and find that the dynamics of equity flows between the United States and four advanced economies are consistent with rebalancing. Hau and Rey (2006) develop an equilibrium model of rebalancing and find that the model's predictions are supported by the data.

Portfolio managers rebalance either periodically (i.e., monthly or quarterly) or in response to major events such as currency crises or stock market crashes in which pre-established parameter thresholds are breached. These two strategies in re-assessing the risk-return tradeoff for portfolios suggest that the aggregate response of capital flows to price shocks may differ strongly between periods of high and low financial stress. Although the international finance literature on portfolio rebalancing typically assumes that the response of portfolio equity flows to asset price shocks is time invariant and exhibits stabilizing behavior, there is considerable evidence that short-term oriented equity outflows, including portfolio equity flows, are subject to sudden reversals, with foreign investments repatriated during periods of high financial stress. The dynamics of equity flows in response to financial crises are frequently viewed to be destabilizing. The extreme case

[1] International risk sharing requires a portfolio share in line with the world market portfolio. However, for home investors, foreign currency investments are associated with exchange rate risk. If markets are incomplete, so that exchange rate risk cannot be fully eliminated, this induces home bias in portfolios and rebalancing in response to exchange rate shocks.

[2] Large institutional investors, such as the Norwegian oil fund (see Ang et al. 2014), rebalance their portfolio following valuation changes towards pre-decided weights. Rauh (2009) finds evidence of partial rebalancing among small- and medium-sized defined benefit pension plans. Blake et al. (1999) document that the portfolio weights of UK pension funds exhibit slow mean reversion towards the strategic asset allocation, while Bikker et al. (2010) and De Haan and Kakes (2011) find that Dutch pension funds and insurance companies tend to be contrarian traders. Evidence against rebalancing is provided by Raddatz and Schmukler (2012). They find that investors pull out of mutual funds in times of stress and in turn fund managers move out of stressed countries. Thus, mutual funds act in a destabilizing way and transmit shocks.

of sudden stops, a sharp slowdown in private capital inflows into emerging market economies, frequently threatens a country's financial system and results in a deterioration in output and an exchange rate depreciation.[3]

In this paper we ask whether the dynamics of international equity flows induced by portfolio rebalancing are state-varying. We extend the structural VAR framework used in Hau and Rey (2004), identified using sign restrictions, by allowing for state-varying dynamics. To do this, we embed a Markov regime-switching model into the structural VAR. Allowing for time-varying behavior in this way introduces greater realism to a shock process driven by events such as global financial crises. The model is estimated using monthly data from 1995 to 2018 on equity returns, exchange rate returns, and equity flows between the U.S. and a set of advanced economies and emerging market economies (EMEs). Our results give insights to the following questions that are highly relevant for policymakers considering financial stability issues linked to international capital flows in different environments of uncertainty. Do the stabilizing dynamics of portfolio rebalancing differ between high and low levels of financial stress? How does the response of equity flows to asset price shocks differ for EMEs and advanced countries? To the best of our knowledge, this paper is the first to consider how equity flows respond to price shocks in a regime-switching setting.

We compare regime-switching models with one, two, and three states, and with both joint and independent switching of coefficients and reduced-form shock covariance matrices. A two-state model with joint switching has the largest marginal likelihood. For the VAR estimated for flows between the U.S. and EMEs, we find that one state is highly persistent, while the other state is short-lived and characterized by elevated volatility of the reduced-form shocks. The timing of switches between the two states matches periods of low and high financial stress, with periods of high stress corresponding to the Markov state with low persistence. Our main empirical result is that for equity flows between the U.S. and EMEs, the dynamics induced by rebalancing differ between episodes of high and low financial stress. A switch from the low to the high-stress regime is associated with capital outflows from EMEs. Once in the high-stress regime, the response of capital flows to exchange rate and stock price shocks is smaller than in normal, low-stress periods. For the VAR estimated on flows between the U.S. and advanced economies, by contrast, we find a single regime switch occurring in the years following the introduction of the euro. This switch likely reflects structural changes that have little to do with the state-based rebalancing that we are after in this paper. The differences in the impulse responses between the two states are also less pronounced than in the VAR estimated for flows between the U.S. and EMEs. Our estimates suggest that flow responses to price shocks are smaller in advanced economies than in EMEs. One potential explanation is that equity investments in advanced economies are better hedged, so that price movements lead to less rebalancing flows.

The empirical results contribute to several strands of the international finance literature. First,

[3]The sudden stop crisis literature is vast. See Calvo (1998), Calvo and Reinhart (2000), Calvo et al. (2004), Dornbusch and Werner (1994), Dornbusch et al. (1995), and Reinhart and Reinhart (2009).

the empirical finding that the dynamics induced by portfolio rebalancing are interrupted by switches between high and low-stress regimes for EMEs fits the stylized facts reported in the literature on capital flow reversals. Forbes and Warnock (2012), Reinhart and Reinhart (2009), Hutchison and Noy (2006) and others argue that capital inflows to EMEs are subject to sudden stops during financial crises. Second, our empirical finding that the dynamics of portfolio rebalancing is muted during periods of high financial stress is also consistent with the liquidity pull-back hypothesis by Fecht and Gruber (2012) and Nyborg and Ostberg (2014). These studies emphasize the view that investors seek to reduce their exposure to equity in times of stress. Investors have a clear preference for liquid and safe assets during periods of high financial uncertainty. Third, the empirical patterns of international equity returns, equity portfolio flows, and exchange rate returns shown in Hau and Rey (2004) have motivated other studies to consider the dynamics of alternative assets and capital flows. For example, Gyntelberg et al. (2014) use daily data on FX transactions and equity flows for Thailand to provide evidence that portfolio rebalancing is an important determinant of exchange rates. Using the same empirical approach as Hau and Rey (2004) and data on equity portfolio flows into emerging market-dedicated mutual funds, Ehlers and Takáts (2013) similarly find that evidence in favor of portfolio rebalancing for equity investment in EMEs. Breedon and Vitale (2010) find that order flow is correlated with exchange rate movements, and that this effect is mainly due to portfolio balance rather than information effects. However, these studies do not consider the possibility that the dynamics of these financial variables may change when financial uncertainty is high.

Our regime-switching approach could be used by policymakers to monitor time variation in capital flow dynamics, and thereby help to better prepare for episodes of volatile capital flows. While capital controls can limit the sharp outflows from EMEs at the onset of the "high stress" regime, our results suggest that they may have the cost of foregoing the stabilizing effects of portfolio rebalancing. Our results are also relevant for investors in international equity markets and related to the literature on asset allocation under regime switches.

The remainder of this paper is organized as follows. Section 2 motivates why portfolio rebalancing dynamics may vary in periods of low and high financial stress. Section 3 presents the structural VAR model with Markov switching and discusses model selection and the identification strategy. Section 4 discusses the data and reports their statistical properties. Section 5 presents the main results in the form of impulse responses. Section 6 discusses several robustness checks. Section 7 concludes.

2 Theoretical motivation

In this section, we argue that the dynamics of capital flows and exchange rate and equity returns are likely to change in periods of high financial stress. First, standard asset pricing models suggest that the response of capital flows to returns induced by portfolio rebalancing is smaller in periods of financial stress. Second, the impact of a given capital flow on returns is likely to increase in times of stress.

2.1 Time variation in the response of capital flows to price shocks

We begin by using a standard mean-variance model of portfolio choice, as considered for example in Bohn and Tesar (1996), to motivate time variation in portfolio rebalancing. A representative investor chooses a portfolio of risky assets to maximize

$$\max_{\mathbf{x}_t} E_t\left(R^p_{t+1}\right) - \frac{1}{2}\alpha Var_t\left(R^p_{t+1}\right),$$

where $\mathbf{x}_t$ is the vector of portfolio shares of risky assets and α is the coefficient of relative risk aversion. The portfolio return R^p_{t+1} is

$$R^p_{t+1} = \mathbf{x}'_t \mathbf{R}_{t+1} + R^f_{t+1},$$

where R^f_{t+1} is the return on a risk-free asset and $\mathbf{R}_{t+1}$ is a vector whose kth entry is the excess return on risky asset k, R_{kt}. The mean and variance of the portfolio return (conditional on the investor's information set) are

$$\begin{aligned} E_t\left(R^p_{t+1}\right) &= \mathbf{x}'_t \bar{\mu}_t + R^f_{t+1}, \\ Var_t\left(R^p_{t+1}\right) &= \mathbf{x}'_t \mathbf{\Sigma}_t \mathbf{x}_t, \end{aligned}$$

where $\bar{\mu}_t \equiv E_t\left(\mathbf{R}_{t+1}\right)$ and $\mathbf{\Sigma}_t \equiv Var_t\left(\mathbf{R}_{t+1}\right)$. The first-order condition of the maximization problem gives

$$\mathbf{x}_t = \frac{1}{\alpha}\mathbf{\Sigma}_t^{-1}\bar{\mu}_t.$$

The share of wealth invested in asset k, x_{kt}, is then given by

$$x_{kt} = \frac{1}{\alpha}\mathbf{e}'_k \mathbf{\Sigma}_t^{-1}\bar{\mu}_t, \tag{1}$$

where $\mathbf{e}_k$ is a vector containing 1 in the kth position and zeros otherwise.

The investor's wealth evolves according to

$$W_t = \left(1 + R^p_t\right) W_{t-1}.$$

If the investor chose to hold a share of x_{kt-1} of his wealth in security k at the beginning of period $t-1$, his holdings of that security before re-adjusting his portfolio in t are $\left(1 + R_{kt}\right) x_{kt-1} W_{t-1}$.

Therefore, by definition the investor's net purchases of security k, NP_{kt}, are equal to

$$\begin{aligned} NP_{kt} &= x_{kt}W_t - (1 + R_{kt})\, x_{kt-1}W_{t-1} \\ &\approx \underbrace{(R_t^p - R_{kt})\, x_{kt-1}W_{t-1}}_{\text{portfolio rebalancing}} + \underbrace{(x_{kt} - x_{kt-1})\, W_{t-1}}_{\text{change in portfolio shares}} . \end{aligned} \tag{2}$$

In the second line we have approximated $x_{kt} \approx x_{kt-1}$ in the first term on the right-hand side, following Bohn and Tesar (1996). The first term in (2) represents portfolio rebalancing: if the return of security k falls below the return of the market portfolio, the investor purchases that security to maintain constant portfolio shares. The second term represents asset purchases due to changes in the investor's desired portfolio shares.

Now consider a situation of financial stress or heightened uncertainty, captured in the model by some combination of higher risk aversion (increase in α), lower expected return on security k (fall in $\bar{\mu}_{kt}$), and higher variance of asset k's return (increase in σ_{kt}, the k,k entry in $\mathbf{\Sigma}_t$). From (1), any of these changes will lower the optimal portfolio share of security k.[4] Consequently, a regime switch from an environment of low to an environment of high financial stress is associated with net sales of security k, or in an international context with a capital flow out of region k. In the empirical results below, we will interpret the impulse responses of capital flows between the U.S. and EMEs to a regime switch as reflecting changes in investors' desired portfolio shares.

Once the portfolio share has adjusted, and barring further changes in the desired portfolio share, the response of net purchases NP_{kt} to returns that is due to portfolio rebalancing declines. To see this, note that from (2) we have

$$\left.\frac{\partial NP_{kt}}{\partial R_{kt}}\right|_{x_{kt}=x_{kt-1}} = -x_{kt}W_{t-1},$$

so that the magnitude of the flow is decreasing in investors' position in security k. This is intuitive: with a lower portfolio share, a given shock has a smaller effect on the amount of wealth invested in security k and this in turn requires smaller asset sales or purchases to rebalance the portfolio. The onset of a period of financial stress initially leads to capital flows out of risky assets; and while financial stress remains elevated, the stabilizing effect of portfolio rebalancing is dampened.

2.2 Time variation in the price effects of capital flows

Consider next the effect of a capital flow shock to exchange rates and equity prices. In many models no capital flows are required to move prices, which adjust instantly to their new equilibrium level in response to news. In practice, empirical work has documented that capital flows do have an effect

[4] For example, Caporale et al. (2015) provide empirical evidence that exchange rate uncertainty typically has a negative impact on net capital flows (based on TIC data), suggesting that risk-averse investors scale back their investments in foreign-currency assets to minimize FX risk exposure.

on exchange rates (see for example Hau et al. 2010).

One model that allows us to think about this effect is Gabaix and Maggiori (2015). In that model, representative households in two countries can buy and sell foreign bonds only through financial intermediaries. These intermediaries face balance sheet constraints, which limit their risk taking. The key parameter in the model, Γ, captures the risk bearing capacity of financial intermediaries. A higher value of Γ means that intermediaries are less able or willing to take on balance sheet risks. Therefore, when Γ rises, intermediaries have to be compensated for taking on risk through a higher expected return, and hence capital flows are associated with a larger effect on prices.[5] Periods of financial stress can be thought of as periods when intermediaries' risk bearing capacity is low. It follows that a given capital flow should have a larger effect on exchange rates (and on equity prices, if equity can also be traded only via financial intermediaries) in periods of high financial stress.

A further reason why the impact of capital flows on returns is expected to be higher in times of financial stress is that risky assets are likely to become less liquid in such episodes.

3 Empirical framework

This section discusses the empirical strategy in three subsections. The first subsection presents the empirical framework and the motivation for using Markov-switching VAR (MSVAR) approach. The second subsection lays out our model selection strategy. The third subsection discusses the identification scheme used to understand the dynamics of portfolio rebalancing.

3.1 Estimating changes in parameters

To analyze the time-varying relationship between equity flows, equity returns, and exchange rate returns in periods of high and low financial stress, we estimate a Markov-switching VAR. In this empirical setup, both the coefficients and the variances are determined by an unobservable state. The objective is to identify specific periods in which the system responds differently to shocks in the variables. The MSVAR approach is preferred over models which allow for gradual changes in coefficients and variances over time (as in the time-varying parameter VARs proposed by Primiceri (2005) or Cogley and Sargent (2005)) because periods of high financial stress a priori are not expected to be persistent. Such short-lived effects related to crisis periods thus may not be detected with more complex models where parameters are allowed to change in each period.[6]

[5] See for example proposition 4 in Gabaix in Maggiori (2015), which shows that in their model, the effect of a capital flow shock f^* on the exchange rate is increasing in Γ.

[6] Our model selection procedure shows that a model with only two states fits the data better than one with more states, providing empirical support for our choice of the MSVAR approach.

Formally, the structural MSVAR with p lags can be written as:

$$A_{0,S_t} y_t = c_{S_t} + \sum_{k=1}^{p} A_{k,S_t} y_{t-k} + \epsilon_t,\ \epsilon_t \sim N(0, I), \tag{3}$$

wih I the identity matrix, y_t a 3×1 vector containing the equity excess return, the exchange rate return, and the standardized net equity flows at time t, and A_{k,S_t}, $k = 0, \ldots, p$, are 3×3 coefficient matrices. The structural shock ϵ_t and the intercepts c_{S_t} are 3×1 vectors. The state indicator $S_t \in \{1, \ldots, n\}$ determines the period-specific parameters:

$$c_{S_t} = c_s,\ A_{k,S_t} = A_{k,s} \text{ if } S_t = s,\ k = 0, \ldots, p.$$

The state of the system evolves according to a hidden Markov-switching process with an unrestricted $n \times n$ transition matrix $H = \left\{ h_{ij} = P(S_t = j | S_t = i) | i, j = 1, \ldots, n; \sum_{j=1}^{n} h_{ij} = 1\ \forall i \right\}$.

To recover the structural form, we estimate the reduced form

$$y_t = B_{S_t} X_t + A_{0,S_t}^{-1} \epsilon_t = B_{S_t} X_t + u_{S_t},\ u_{S_t} \sim N\left(0, \Sigma_{S_t}\right), \tag{4}$$

where B_{S_t} is a $3 \times (3p+1)$ matrix containing the reduced-form coefficients for each equation ordered by their lags, $X_t = (1, y_{t-1}, \ldots, y_{t-p})'$ is a $(3p+1) \times 1$ vector including the constant and stacked lagged variables, and u_{S_t} is a (3×1) vector of state-dependently distributed reduced-form shocks.

Our baseline specification includes $p = 2$ lags and $n = 2$ states.[7] For estimation we rely on Bayesian Markov chain Monte Carlo (MCMC) methods, and motivated by summary statistics displayed in Table 2, we specify the following state-independent prior distributions:[8]

– Normal for the intercepts, $B_{0,s} \sim N\left(0, \kappa_c I\right)$, $\kappa_c = .25$, with $B_{0,s}$ the first column in B_s. The prior covers (-1,1) with a 95% probability interval. According to summary statistics in Table 2, taking into account autoregressive dynamics this interval largely encompasses the empirical conditional mean of our data 0.07, 0.36 and 0.54 for, respectively, EQ and FX returns, and EQ flows).

– Minnesota type for the VAR coefficients, $B_{1,s,ij,l} \sim (b_{ij,l}, \tau_{ij,l})$, with $B_{1,s,ij,l}$ referring to the effect of variable j on variable i at lag l in state s. We set $b_{ij,1}$ equal to the coefficient estimates of a VAR(1) without intercepts and $b_{ij,l} = 0$ for $l > 1$; $\tau_{jj,1} = \kappa_b$ and $\tau_{ij,l} = 0.25 \kappa_b \sigma_i / (\sigma_j l^2)$ for $i \neq j$, $\kappa_b = 0.09$. The ratio σ_i / σ_j adjusts for the different scaling in variables, a standard in Minnesota-type prior specification (Litterman, 1986). Setting the prior mean of the first

[7] We evaluate the specification against alternative settings by marginal likelihood, see below.

[8] We specify proper, loosely informative prior distributions to be able to perform efficient model selection based on estimated marginal likelihoods, see Subsection 3.2. Proceeding in this way we avoid the fact that when overfitting a mixture model (e.g. estimating a three-state when a two-state Markov switching model is appropriate), improper or uninformative priors would lead to improper posterior distributions or highly inefficient marginal likelihood estimates, see also the discussion in Frühwirth-Schnatter (2004).

VAR lag coefficients to OLS-estimated one-state VAR(1) coefficients helps inducing a state-independent informative prior, to be able to efficiently discriminate between a one- and two-state specification by means of marginal likelihoods. The prior variance on the first variable-specific autoregressive coefficient covers a 95% probability interval of +/-0.6 around the mean, i.e., includes either 0 or 1, depending on the VAR(1) estimated persistence. Shrinking the variance of higher-order lags by l^2 and off-diagonal coefficients by a factor of 0.25 (i.e., one half in terms of standard deviation) does not induce strong shrinkage. The prior still covers 95% probability intervals of +/-0.3 and +/-0.15 around the mean of, respectively, first- and second-lag off-diagonal autoregressive coefficients.

– Inverse Wishart for covariance matrices, $\Sigma_s = IW\left(w_0, W_0\right)$, $w_0 = 12$, W_0 being diagonal to induce a variable-specific prior mean variance equal to twice the variance of variable-specific residuals from an estimated VAR(1) without intercepts. This relaxes the standard Minnesota-type prior approach of fixed residual covariance matrix (see also Kadiyala and Karlsson, 1997).

– Dirichlet for the transition matrix, $H \sim \prod_{s=1}^{n} D\left(e_{0,s1}, \ldots, e_{0,sn}\right)$, $e_{0,ss} = 2$, $e_{0,sj} = 1$, $s \neq j$.

In particular, the Dirichlet prior induces equal unconditional probability of regimes. In other words, we remain agnostic to whether different regimes in our MSVAR are driven by short-lived stress periods or by more persistent structural breaks.

When sampling from the unconstrained posterior,[9] it is a priori unknown how the draws map into the states, as label switching occurs frequently (Frühwirth-Schnatter, 2006). To account for this non-identifiability, we follow Frühwirth-Schnatter (2001) and use a random permutation sampler to obtain 20,000 draws from the posterior distribution. We discard the first 5,000 draws as burn-in and retain every 3rd draw for posterior inference. Analysis of the MCMC output reveals that for both advanced and EMEs the two states are best identified using the state-specific error covariances of equity returns. We re-order each draw to fulfil the state-identifying constraint $\Sigma_{1,11} < \Sigma_{2,11}$. Based on the ordered posterior output, we calculate impulse responses.

3.2 Model selection

Model estimation described in the previous section conditions on the number of states n. Restricting to $n = 1$, (4) reduces to a standard VAR model without hidden switching, while extending to $n = 3$ allows the system to be driven by three different states. Furthermore, the exposition so far assumes implicitly that reduced-form coefficients B_s and the covariance matrix Σ_s switch jointly between states. However, various other specifications are conceivable. For example, B_s may be fixed

[9] Estimation of MSVAR models within a Bayesian framework is standard by now (Sims, Waggoner and Zha, 2008). The interested reader finds a detailed representation of the Bayesian setup and derivation of the posterior distributions in Appendix C of e.g. Kaufmann and Valderrama (2008), with obvious extensions from two to multiple states.

across states, or coefficients and volatilities may switch independently, i.e., B_{s^1} and Σ_{s^2} depend on independently switching hidden states.

To evaluate these different specifications, we estimate marginal likelihoods $p(y|\mathcal{M})$ using the optimal bridge sampling estimator described in Frühwirth-Schnatter (2004):[10]

$$p\left(y|\mathcal{M}\right) = \frac{\int \alpha(\theta)p^*\left(\theta|y\right)q(\theta)d\theta}{\int \alpha(\theta)q(\theta)p\left(\theta|y\right)d\theta},$$

where $p^*(\cdot)$ and $p(\cdot)$ represent, respectively, the un-normalized and normalized posterior and $\alpha(\theta)$ is chosen to satisfy $\int \alpha(\theta)p\left(\theta|y\right)q(\theta)d\theta > 0$. Given a sample of length M out of the posterior $p(\cdot)$ and of length L out of the proposal $q(\cdot)$, the integrals may be evaluated numerically by simple averages

$$\hat{p}\left(y|\mathcal{M}\right) = \frac{1/L\sum_{l=1}^{L}\alpha\left(\theta^{(l)}\right)p^*\left(\theta^{(l)}|y\right)}{1/M\sum_{m=1}^{M}\alpha\left(\theta^{(m)}\right)q\left(\theta^{(m)}\right)}.$$

Given the finite-order Markov process, the density $p^*(\cdot)$ is evaluated marginally of the state indicator. To design the proposal $q(\theta)$ in an unsupervised manner, while iterating over the random permutation sampler we retain at random 2,000 moments of parameters' posterior distributions. Using 500 out of them, we construct a proposal density which closely mimics the multimodal unconstrained posterior. As weighting function $\alpha(\theta)$, we choose the optimal function minimizing the expected relative error and estimate $\hat{p}\left(y|\mathcal{M}\right)$ iterating until numerical convergence (Meng and Wong, 1996).

3.3 Identification and generalized impulse responses

The structural impact matrix $A_{0,s}^{-1}$ is identified using sign restrictions on the contemporaneous effect of structural shocks. These restrictions are shown in Table 1. The restrictions follow Hau and Rey (2004) and are based on the portfolio rebalancing theory, and thus in particular on the assumption that investors do not fully hedge their FX portfolio risk. The sign restrictions rest on three hypotheses, which correspond to the three columns in Table 1. First, because of incomplete hedging, a positive equity return differential shock leaves investors heavily exposed to foreign currency. Portfolio rebalancing then implies that investors sell their foreign equity and invest in U.S. stocks, thus generating equity flows to the U.S. and a U.S. dollar (USD) appreciation. Second, a USD appreciation leaves investors with too much exposure to the U.S. currency (again we assume incomplete hedging). Investors then rebalance their portfolio by selling U.S. equity and moving capital to the foreign market, thereby generating an equity outflow from the U.S. and lowering U.S. equity returns. Third, a positive equity flow shock, corresponding to an equity outflow from the U.S., directly affects exchange rates and equity markets. As capital is moving into foreign equity markets, the demand for foreign currency and foreign equity increases, which results in an USD

[10] θ encompasses all model parameters.

Table 1: Identification restrictions

	EQ return shock	FX return shock	EQ flow shock
EQ return	+	+	+
FX return	+	+	−
EQ flow	−	+	+

Notes: Identification restrictions on the contemporaneous (within the same month) effect of shocks to the variables in columns on the variables in rows. Signs are listed for positive shocks. A positive equity return differential ("EQ return") is a higher return abroad than in the U.S.; a positive FX return is a dollar appreciation; a positive equity flow is a net flow out of the U.S.. Columns 1, 2 and 3 correspond to hypotheses H1, H2 and H3 in Hau and Rey (2004).

depreciation and increasing foreign equity returns.

In thinking about shocks to flows, equity returns and exchange rate returns, we follow the analysis and shock definitions of Hau and Rey (2004). Our motivation is to revisit their analysis with up-to-date data and empirical methods, and in particular allowing for state-varying dynamics. A "flow shock" can be thought of as a shock to investors' desired asset allocations, for any given realization of asset returns. This could reflect, for example, changes in investors' risk preferences, liquidity needs, or views about the longer-term investment outlook. We think of the "equity return shock" and "FX return shock" as reflecting price movements that are not due to flows. We are agnostic about the true underlying structural source of the price movement (where several alternative interpretations would be possible), and focus on how investors following rebalancing strategies react to these price shocks.

Starting from a state s, the k-period ahead generalized impulse response function of variable i to a shock to variable j is computed as the difference in the conditional expectations with and without the structural shock:

$$IRF^{s}_{ij,t+k} = \mathbb{E}\left(y_{i,t+k}|\epsilon_{j,t}\, X_t, S_t = s\right) - \mathbb{E}\left(y_{i,t+k}|X_t, S_t = s\right), \tag{5}$$

where $\epsilon_{j,t}$ is the structural shock vector with the jth row being the only non-zero element and equal to one. Further details on the computation of generalized impulse responses are provided in Appendix A.

By using generalized impulse responses, we account for the fact that high-stress periods are likely to be short-lived. When a regime only lasts for one or two months at a time, using impulse responses conditional on staying in a given regime could be misleading (Krolzig, 2006). Because the probability of staying in a short-lived state in this case is small, the system in expectation is going to be in the persistent state within just a few periods. Fixing the system to remain within the same state thus can lead to overstated differences between the states.

Identification through sign restrictions is implemented using a procedure proposed by Rubio-Ramírez et al. (2010).[11] For our 3-variable VAR, Baumeister and Hamilton (2015) show that, conditional on a draw from the state-s posterior distribution of the covariance matrix of the reduced-form shocks, Σ_s, this algorithm implies a uniform distribution over the contemporaneous impulse responses. Let R be a diagonal matrix whose elements are normalized to be positive and Q be a rotation matrix from the QR decomposition of a 3×3 matrix drawn from the standard normal distribution. Further, let $\Sigma_s = P_s' P_s$ be the Cholesky decomposition of the covariance matrix Σ_s drawn from the marginal posterior distribution of regime s. The matrix of contemporaneous effects for regime s then is calculated as follows:

$$A_{0,s}^{-1} = P_s Q_s. \tag{6}$$

As $A_{0,s}^{-1}$ determines the contemporaneous impulse response (see Appendix A) to the structural shocks, its elements need to satisfy our sign restrictions. For a given draw of Σ_s and B_s, we generate 500 rotations Q_s and store those that satisfy our sign restrictions. This procedure is performed for 2,000 draws of the covariance matrix, which leads to a total of 1,000,000 draws of Q_s for each regime. The reported posterior distributions reflect all those rotations that satisfy the sign restrictions from all the draws.

To characterize the states, we also present how the variables respond to a regime switch. Similar to the generalized impulse responses above, we define the response of variable i to a switch from regime s to regime h in period t as:

$$IRF_{i,sh,t+k} = \mathbb{E}\left(y_{i,t+k} | S_t = h, X_t\right) - \mathbb{E}\left(y_{i,t+k} | S_t = s, X_t\right). \tag{7}$$

In a model with two states, this definition implies that the response to switching from regime s to regime h is the negative value of a switch in the other direction. The response to regime switches does not depend on the structural identification, but only on the reduced-form coefficients. As a consequence, it can be calculated directly by drawing from the posterior distribution of the reduced-form coefficients. As shown in Appendix B, the response to a regime switch depends on the variables' values in t. For a given initial state s and a draw of the reduced-form coefficients, we calculate the response of the IRF for each period identified to be in state s and then take the mean across the responses for the different periods. This procedure is repeated for 5,000 draws, which generates the distribution of responses shown in our results.

[11] As the authors note, the procedure generalizes the algorithm of Uhlig (2005).

4 Data

We use monthly country-level data for equity returns, foreign exchange rate returns, and equity flows from January 1995 to June 2018. We aggregate the data for two sets of countries: 19 advanced economies and 13 EMEs. Portfolio rebalancing in our setup constitutes portfolio adjustment between the U.S. and groups of investment assets in advanced and emerging market economies. Our choice of countries is based on the size of equity flows with a minimum 1% threshold for each country group.[12] A complete list of the countries included in the two samples is provided in Table 5 in Appendix C.

As in Hau and Rey (2004), the data on international equity flows are from the U.S. Department of the Treasury (TIC data). These data measure bilateral flows between the U.S. and various countries.[13] Net equity flows are defined as net purchases of foreign stocks by U.S. residents minus net purchases of U.S. stocks by foreign residents.[14] Positive net equity flows thus correspond to outflows from the U.S. perspective. Equity flows have increased strongly during the sample period. We therefore follow Hau and Rey (2004) and standardize monthly net equity flows with the total monthly flows after aggregating the flows within the two samples for advanced countries and EMEs.

Equity and exchange rate data are from Datastream.[15] The equity return differential is calculated as the difference between the MSCI index local currency returns of the foreign country and the U.S., where returns are calculated using log differences of the end-of-month index values.[16] Positive monthly excess equity returns imply that foreign equities outperform U.S. equities. A positive exchange rate return corresponds to a USD appreciation and is calculated as the log difference of the end-of-month nominal exchange rates expressed in USD.

To aggregate equity and exchange rate returns across countries within the same sample, we weight them by the countries' contributions to total flows in the specific month. Formally, the weight for each country i in month t for sample S is:

$$w_{i,t} = \frac{TF_{i,t}}{\sum_{i \in S} TF_{i,t}},$$

where $TF_{i,t}$ is the total equity flows between country i and the U.S. in period t. Aggregating the data has several advantages. First, the custodian and transaction biases in the TIC data mentioned by various authors (e.g., Griever et al. (2001)) are irrelevant for the advanced economies as a whole

[12] Some countries are additionally excluded due to fixed exchange rate regimes throughout most of our sample period (e.g. China). In addition, we exclude Taiwan due to issues with its flow data. In 2003, net flows in several months were larger than 20 times Taiwan's sample average, without any economic interpretation.

[13] Griever et al. (2001) provide an extensive overview on the TIC data. The data can be downloaded on the website of the U.S. Department of the Treasury.

[14] Following Hau and Rey (2004) and subsequent papers, we focus only on equity flows. Empirical work has mostly found that capital flows related to equity purchases, rather than bond purchases, are an important determinant of exchange rates (see for example Gyntelberg et al. (2018)).

[15] The respective identifiers are provided in Table 5 in Appendix C.

[16] End-of-month is defined as the last day of a month for which data is available.

Table 2: Summary Statistics

	Mean	Min.	Max.	Var.	Kurt.	Skew.	AC(1)	AC(2)
Advanced Economies								
EQ return	-0.32	-12.58	5.71	5.06	5.61	-0.52	-0.18	-0.01
FX return	0.04	-7.37	9.57	4.72	4.43	0.32	0.02	0.07
EQ flow	-0.18	-4.87	9.25	4.30	4.44	0.46	0.55	0.49
Em. Market Economies								
EQ return	0.08	-23.28	9.94	15.77	9.05	-1.44	0.08	0.07
FX return	0.37	-6.84	21.68	7.20	17.79	2.14	0.06	-0.02
EQ flow	3.16	-11.60	23.87	37.97	3.92	0.82	0.46	0.37

Notes: AC(1) refers to the autocorrelation of the first, AC(2) of the second lag.

and are likely to be less severe for EMEs. Second, international equity flows from the U.S. to these country groups are more important for the groups' overall equity market, as compared to the flows to just a single country (which will also have flows to and from many countries besides the U.S.). Equity flows within the group do not matter as they affect both countries, therefore cancelling the overall equity effect for the group.

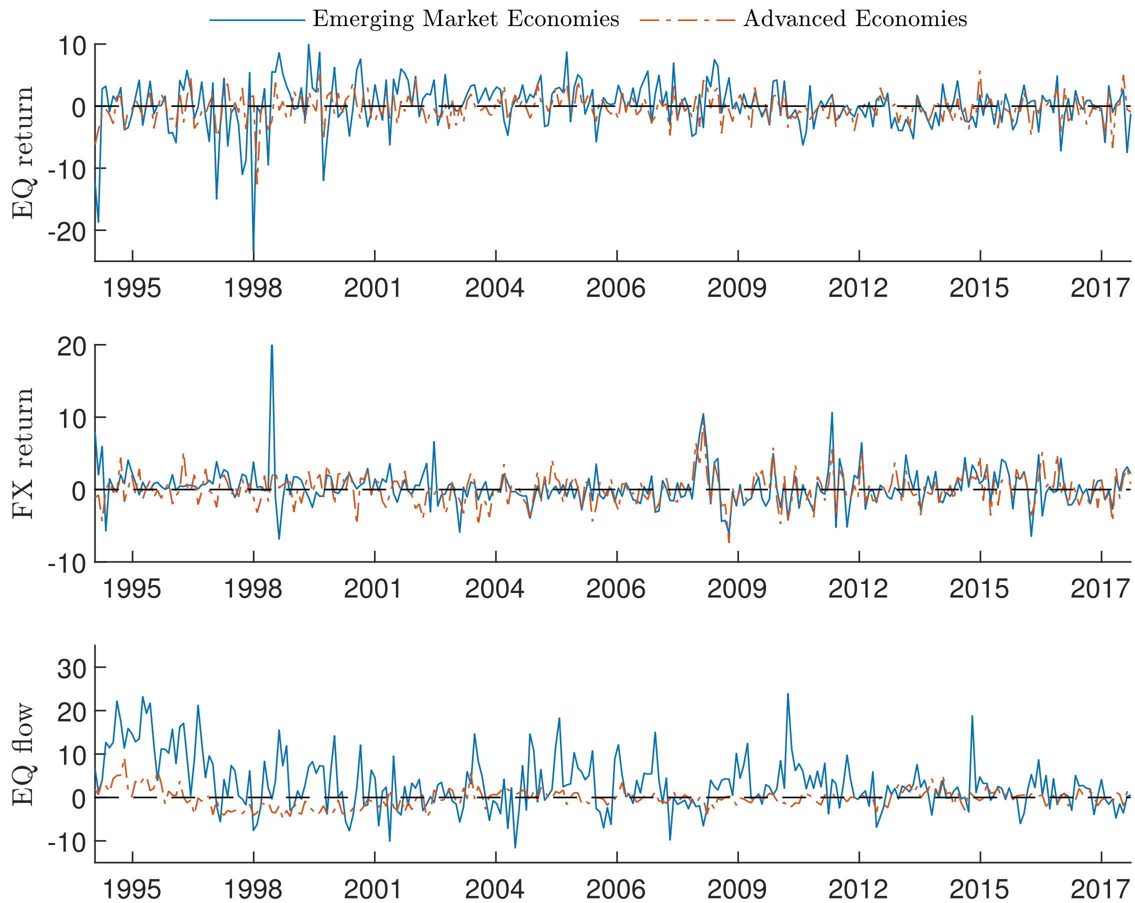
Table 2 presents summary statistics of the aggregated variables for advanced and EMEs. Three observations standout. First, most variables are centered around zero except for the positive mean for net equity flows to EMEs. A positive mean indicates that on average equity flows out of the U.S. and into EMEs. Second, the four moments of the variables for EMEs are larger than the corresponding moments for advanced economies. The variance of net equity flows for EMEs is particularly pronounced as is the kurtosis of exchange rate returns. Third, despite these differences in the moments, the level of persistence of the variables (captured by the autocorrelation coefficients) tends to be similar for advanced and emerging market economies.

Figure 1 plots the three variables for both advanced and emerging market economies. The plots highlight three features of the data. First, the variables appear to follow stationary processes. Second, the appreciation of the USD against EMEs during the Asian crisis, the global financial crisis, and the euro area sovereign debt crisis is visible. Third, as in Table 2, the elevated variance in equity outflows to EMEs is visible in Figure 1.

In addition, we use data for two commonly used indicators of financial stress. In particular, we use the CBOE Volatility Index (VIX) and the Emerging Bond Index Global Sovereign Spread (EMBI). The VIX is from the Chicago Board Options Exchange and measures market expectations of volatility, which are derived from the S&P 500 stock index option prices.[17] The EMBI is compiled by J.P. Morgan and tracks returns of sovereign bonds from various EMEs.[18] Presented is the spread

[17] VIX data was downloaded from Datstream with the identifier CBOEVIX.
[18] EMBI data was downloaded from Datastream with the identifier JPMGTOT(BSPRD).

Figure 1: Data series



of the sovereign bonds against benchmark U.S. Treasury bonds.

Discussion of TIC data on capital flows. In using TIC data to measure equity capital flows, we follow a number of previous empirical studies, e.g. Bohn and Tesar (1996), Brennan and Cao (1997), Hau and Rey (2004, 2006) and Caporale et al. (2017). For our purposes, TIC data have several advantages. They provide long time series at monthly frequency, which is important to estimate financial stress-related regime switches in the dynamics of capital flows. Furthermore, our paper builds on and extends Hau and Rey (2004); using the same data source therefore facilitates a comparison to their baseline without regime switching.

While popular in the literature, these data do have well-known limitations.[19] First, they only capture bilateral flows between individual countries and the United States. For example, when analyzing the influence of capital flows on equity prices in an emerging market, one would ideally want to use capital flows between that country and the rest of the world, rather than only the United States. In our empirical model, however, we include the difference in stock returns relative to the

[19] For a detailed discussion of these weaknesses, see e.g. Edison and Warnock (2008) or Bertraut and Judson (2014).

U.S. as well as the exchange rate relative to the U.S. dollar, so that using bilateral U.S. flows seems natural. Furthermore, our strategy of aggregating advanced economies and EMEs should alleviate the problem of missing third-country flows to some extent. Note also that U.S. flows represent a sizable share of overall flows (see e.g., Edison and Warnock (2008)). Second, flows between the U.S. and some other country, say Japan, reported in TIC data do not necessarily reflect flows between U.S. residents and Japanese residents. If a Japanese resident sells or purchases U.S. securities via a financial intermediary based in London, for example, TIC data would classify this transaction as a capital flow between the U.S. and the United Kingdom. The resulting financial center bias should be of little relevance, however, for our EME sample and should again be mitigated to some extent by aggregating across advanced economies. Third, equity flows related to cross-border mergers financed through stock swaps complicate the analysis. This issue should be of little importance for our EME sample.

In recent years, the empirical literature has increasingly used alternatives to TIC data. Cho et al. (2016) and Forbes and Warnock (2012), for example, use quarterly balance of payments data on net capital flows in stocks. For our purposes of identifying regime switches in capital flow dynamics, a quarterly frequency seems too low, however. A number of studies have also used inflows into equity and bond funds to measure capital flows. Such data are provided by the Emerging Portfolio Fund Research (EPFR) database, and have been studied by Fratzscher (2012), Jotikasthira et al. (2012) and Friedrich and Guerin (2020). Although EPFR data have the disadvantage of including only those flows that are intermediated by investment funds, studying the dynamics of capital flows, equity prices and exchange rates with daily or weekly EPFR data would be a promising avenue for future research.[20]

5 Results

The empirical results from the MSVAR model are presented in four subsections. The first subsection reports the results from the model selection procedure, which shows that a specification with two states and joint switching of coefficients and volatilities fits the data best. The second subsection shows that for EMEs, the two states, which are identified endogenously by the model, can be interpreted as capturing periods of low and high financial stress. In particular, it is argued that switches to and from the second state match the sharp movements in popular risk measures such as the VIX index. By contrast, for advanced economies we see only one highly persistent switch, roughly following the introduction of the euro. This single switch does not correspond to the state-based rebalancing that is the focus of this paper. In the following we therefore focus on EMEs, and report in subsection 5.3 the priors and posteriors for the variance-covariance matrix of the reduced-

[20] Some studies use proprietary data of flows at high frequency. For example, Fuertes et al. (2019) collect daily data on equity flows between 8 East Asian emerging markets and foreign residents. Such data, however, is typically available only for a limited number of countries and a limited time period.

form shocks. Equity return, exchange rate return and capital flow variances are higher in state 2, consistent with the interpretation of state 2 as a state of high volatility. The fourth subsection reports the baseline findings that the dynamics of equity returns, exchange rate returns, and equity flows, consistent with portfolio rebalancing, are state-varying for EMEs. The discussion highlights differences in these dynamics between periods of high and low financial stress using generalized impulse responses.

5.1 Model selection

In the model selection exercise, we compare models with 1, 2, and 3 states, and with both joint or independent switching of coefficients and volatilities. Table 5.1 reports the marginal likelihood for each specification, along with the standard error. The standard errors are small, indicating that the reported differences in marginal likelihoods are typically statistically significant.[21]

Table 3: Marginal likelihoods

	Advanced Economies		Em. Market Economies	
1 state	-1799.94	(0.03)	-2426.84	(0.04)
2 states, Σ only	-1777.68	(0.01)	-2271.12	(0.02)
2 states, B only	-1777.15	(0.08)	-2313.95	(0.04)
2 states, joint	**-1774.21**	**(0.02)**	**-2270.62**	**(0.02)**
2 states, independent	-1780.09	(0.05)	-2271.13	(0.08)
3 states, Σ only	-1795.45	(0.05)	-2287.79	(0.04)
3 states, B only	-1781.07	(0.22)	-2316.79	(0.14)
3 states, joint	-1796.11	(0.10)	-2286.55	(0.05)

Notes: Standard errors in parentheses.

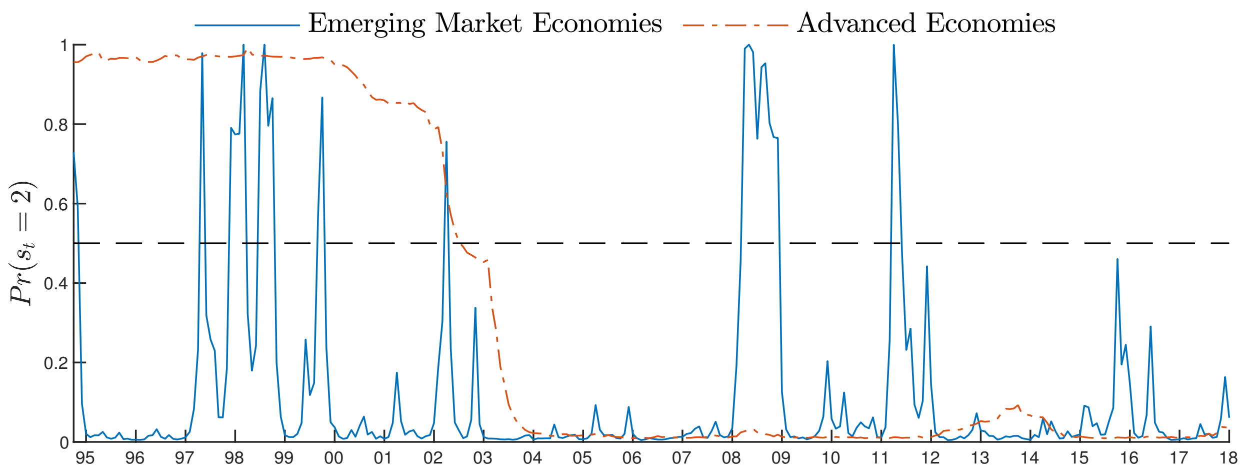
For both advanced and emerging economies, the constant parameter (single state) specification has the smallest marginal likelihood. This suggests that it is important to allow for time variation in the dynamics of stock returns, exchange rate returns and capital flows. It is also consistent with the hypothesis that portfolio rebalancing is state-based and, for example, that investors following rebalancing strategies may behave differently in crisis episodes than in normal times. Furthermore, Table 5.1 reveals that a specification with two states fits the data better than one with three states. More specifically, for both advanced and emerging market economies, the specification with the largest marginal likelihood is a two-state model where both coefficients and volatilities switch jointly. Hence, we conclude that a two-state model with joint switching fits the data best, and present results for this specification.

[21] The results reported in Frühwirth-Schnatter (2004), for example, also show small standard errors. She shows that bridge sampling typically gives smaller standard errors than importance or reciprocal importance sampling.

5.2 Identified regimes as periods of low and high financial stress

For each period, the estimation procedure provides the posterior probability of the system being in a particular state. This posterior probability is calculated as the per-period mean across draws of an indicator for whether the system is in the particular state. Figure 2 depicts this probability for both the advanced economies and the EME sample. The figure reveals that the states are well-identified, as the probability of being in the second state (with larger FX volatility) in most periods is either close to zero or close to one. More importantly, it highlights that the posterior probability of being in the second state changes over time. For EMEs, the second state exhibits little persistence and occurs infrequently. Throughout most of the EME sample, the system remains in the first state. The corresponding posterior probabilities for the sample of advanced economies – despite being estimated using the same specification and prior assumptions – look very different. Here, both states are highly persistent, and there is just one switch from state 2 to state 1. This switch occurs gradually between 2000 and 2004.

Figure 2: Posterior state probability

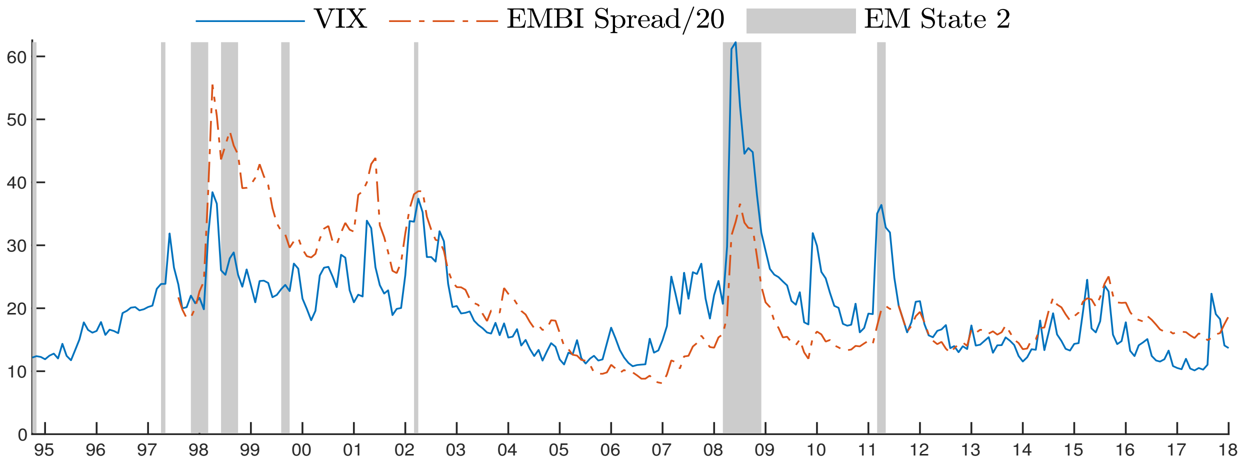


Notes: Posterior probability of being in state 2. Ticks are placed mid-year.

For advanced economies, the estimated regime switching pattern suggests a single persistent structural shift. Given its timing, one may speculate that this structural shift may be connected to the introduction of the euro and a single monetary policy for the euro area. In the following, we will focus mainly on the EME results, where the estimated regime switches are consistent with our hypothesized pattern of state-based portfolio rebalancing.

The observed pattern in Figure 2 for the EME sample is in line with what would be expected of a system with periods of high and low financial stress. Periods of low financial stress prevail throughout most of the sample and are interrupted by a few short-lived episodes of high stress. However, a priori the two states in itself do not have any economic meaning. They are endogenously determined in the Markov-switching model and only indicate that the system behaves differently in

Figure 3: Indicators of financial stress and state 2 episodes



Notes: VIX and EMBI (Global Spread) indices. Shaded areas mark periods where the estimated probability of being in the second state is larger than 0.5.

some periods. To give an interpretation to the posterior state probabilities, the behavior of the EME states is compared with movements in the VIX index (a measure of U.S. stock market volatility) and the EMBI index (a measure of the spread between bond yields in EMEs and the U.S.). These indices are commonly used measures for financial market stress, with peaks signalling periods of high financial stress.

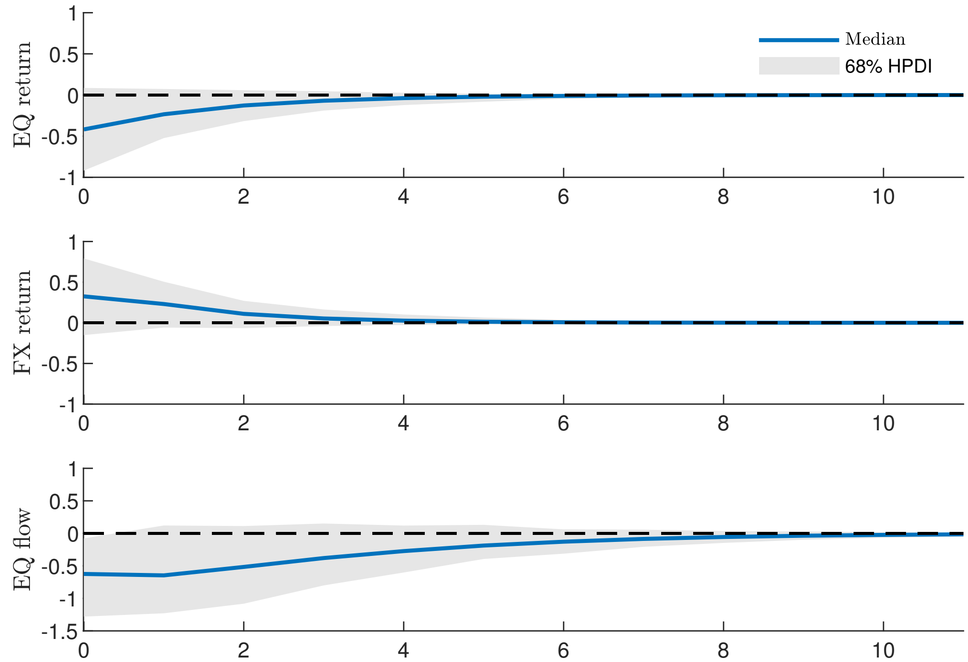
Figure 3 plots the VIX index and the EMBI index against EME state 2 episodes as identified in the Markov-switching model. The light shaded areas indicate periods when the probability of being in the second state is larger than 0.5 in the EME sample. The comparison shows that the estimated state 2 periods are well-aligned with times when financial stress indicators are elevated. The model detects stress periods for several major financial crisis episodes: (1) 1994-1995 the Mexican Peso crisis, (2) the 1997 Asian financial crisis, (3) the Russian financial crisis starting in August 1998, (4) the discontinuation of the fixed exchange rate between the Argentinean peso and the dollar in 2002,[22] (4) the global financial crisis starting in September 2008 with the Lehman Brothers' bankruptcy, and (5) the European sovereign debt crisis which peaked in 2011-2012. In addition, comparing Figures 2 and 3 shows that further peaks in the VIX are also reflected in the posterior state probability.[23]

We interpret the evidence from Figures 2 and 3 such that in the model estimated for EMEs, the second state corresponds to periods of high financial stress. It is important to note that the non-persistent pattern in the posterior state probability of state 2 does not arise from our selected priors. In general, the Dirichlet prior governs how the states are drawn and its choice can push the

[22]Note that due to the fixed exchange regime, we did not include Argentina in the EME sample.

[23]For example, financial stress related to the 9/11 attacks in 2001 or the Brexit vote in 2016 correspond to peaks in the posterior state probabilities that do not exceed the threshold of 0.5.

Figure 4: Impulse responses to a switch from state 1 to state 2



results towards more or less persistence in the states. However, the fact that the second state is considerably less persistent than the applied prior would imply that the posterior state probabilities are governed by the data. Furthermore, the comparison with the results for advanced economies shows that the prior can produce a dramatically different posterior state probability processes depending on the characteristics of the data.

The two states in the EME sample are further characterized by how the variables respond to a regime change. Figure 4 reports how the three variables respond over time following a switch from state 1 to state 2. There is a clear response when switching from state 1 to state 2. Expected emerging market excess equity returns over returns in the U.S. drop, whereas expected exchange rate returns increase by approximately 0.5% (a USD appreciation). Furthermore, equity flows react negatively (a capital flow out of EMEs) and with a 68% highest posterior density interval (HPDI) that does not include zero on impact. After a few periods, the responses are close to zero as the state probabilities converge towards their long-run mean.

The latter result is consistent with what we would expect during high-stress periods. In such periods, U.S. investors tend to move out of risky emerging market equities and repatriate capital back home. This lowers equity prices in EMEs as well as puts pressure on their exchange rates. This pattern is reflected in the estimated responses. Switching to state 2 in a month implies that for this month, foreign equities underperform U.S. equities, the USD appreciates, and capital moves away from EMEs to the United States.

5.3 Prior and posterior distribution of the reduced-form covariance matrix

The main focus of our analysis is on how the impulse response functions differ between the two states. Given the key role of the covariance matrix of the reduced-form shocks Σ_s for the estimated impulse responses,[24] Figure 5 reports the priors and posteriors for the elements of this matrix estimated for EMEs. Crucially, we use the same prior distribution for Σ_s for both states, and thus are agnostic about how impulse responses differ between the two states.

We immediately note that the posterior distributions for the elements of Σ_s in the low-stress state, $s = 1$, are sharply peaked, compared with both the prior and the (high-stress) state 2 posteriors. The posteriors for state 2 are not much narrower than the priors, indicating that they are not estimated very precisely due to the small number of observations in state 2. Nonetheless, the posterior of most elements does not coincide with the prior distribution, indicating that some information is retrieved from the data.

For the first two diagonal elements of Σ_s, the posteriors are left of the priors for state 1, but right of the priors for state 2. This indicates lower volatility in state 1 and is in line with our interpretation of the two states. In periods of financial stress, we expect the exchange rate and the equity return differential to be more volatile. In addition, the posterior covariances are always larger in absolute value in the high-stress state relative to the low-stress state.

5.4 Impulse responses for periods of low and high financial stress

The main interest of our analysis is in how the equity return differential, the exchange rate and the net flows react to shocks in each of these three variables, and how these responses differ across the two regimes. In the following, we briefly discuss the general results for both samples, before focusing on the responses that correspond to our theoretical considerations.

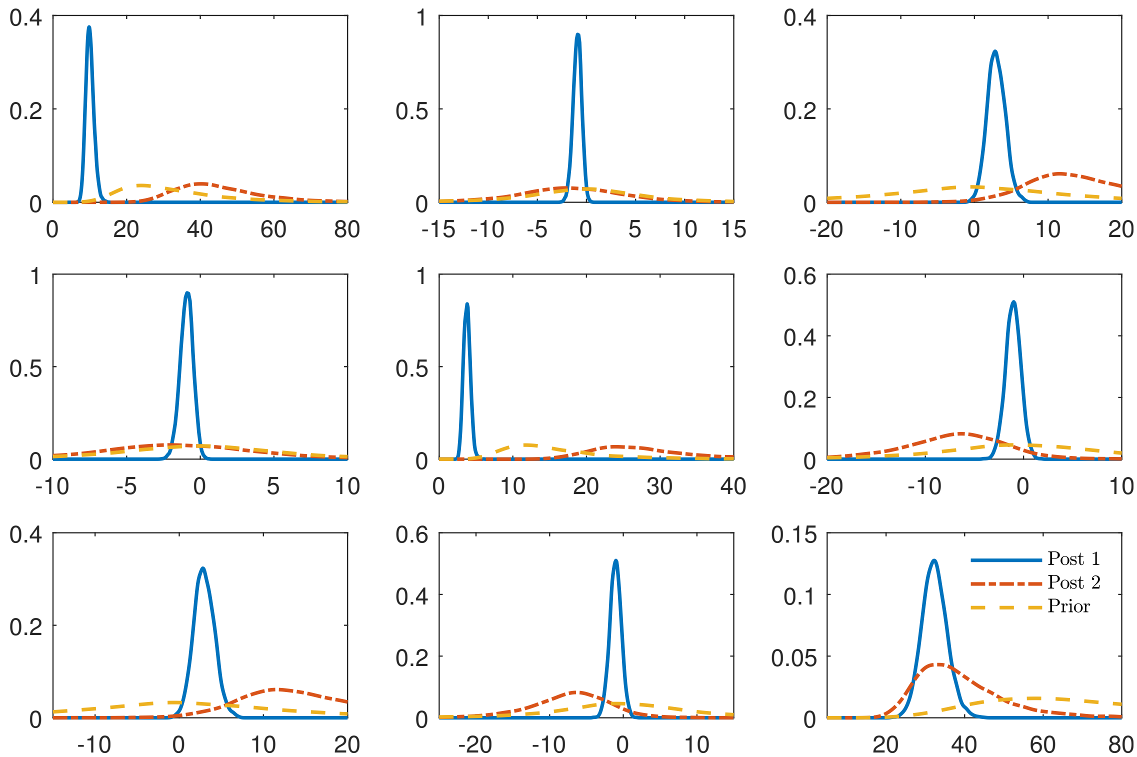
The full results for both samples are presented in Appendix C. Recall that the signs of the impulse responses on impact (within the same month) satisfy the restrictions defined in Table 1 by construction. For state 1, 4.4% (4.7%) and for state 2, 5.6% (5.3%) of draws from the posterior satisfy all sign restrictions for the EME (advanced economies) sample. Rejection rates for each restriction range from 65% to 82% (see Table 4 in the Appendix). After the contemporaneous effect of the shock, impulse responses can move in either direction. The results show that the restrictions hold beyond the initial period as the cumulative impulse responses do not revert after the initial impact.[25]

The impulses responses in Figures 8 and 9 reveal two differences between advanced and emerging market economies. First, the response of equity flows to both equity return and foreign exchange rate shocks tends to be larger in absolute terms for the EME sample. One possible explanation for this

[24] The contemporaneous impulse response is a transformation of the reduced-form covariance matrix Σ_s (see Appendix A).

[25] The exception is the impulse response of the foreign exchange rate to a equity return shock, where the lower bound of the 68% HDPI is below zero. The median though remains well above zero throughout the whole horizon.

Figure 5: EME Prior and posterior densities Σ



Notes: Posterior and prior densities of the reduced-form covariance matrix Σ_s for the EME sample.

finding is that for investments in advanced economies, there are more possibilities to hedge exposures due to their deeper financial markets, so that price shocks have less impact on investors' currency exposure and hence lead to smaller rebalancing flows. Second, the response of the exchange rate to flow shocks tends to be smaller in absolute terms in the EME sample. One possible interpretation (following the market microstructure literature, e.g., Gyntelberg et al. (2018)) is that equity flows between the U.S. and advanced economies convey more private information to the market, and thus have a larger price effect, than equity flows between the U.S. and EMEs.

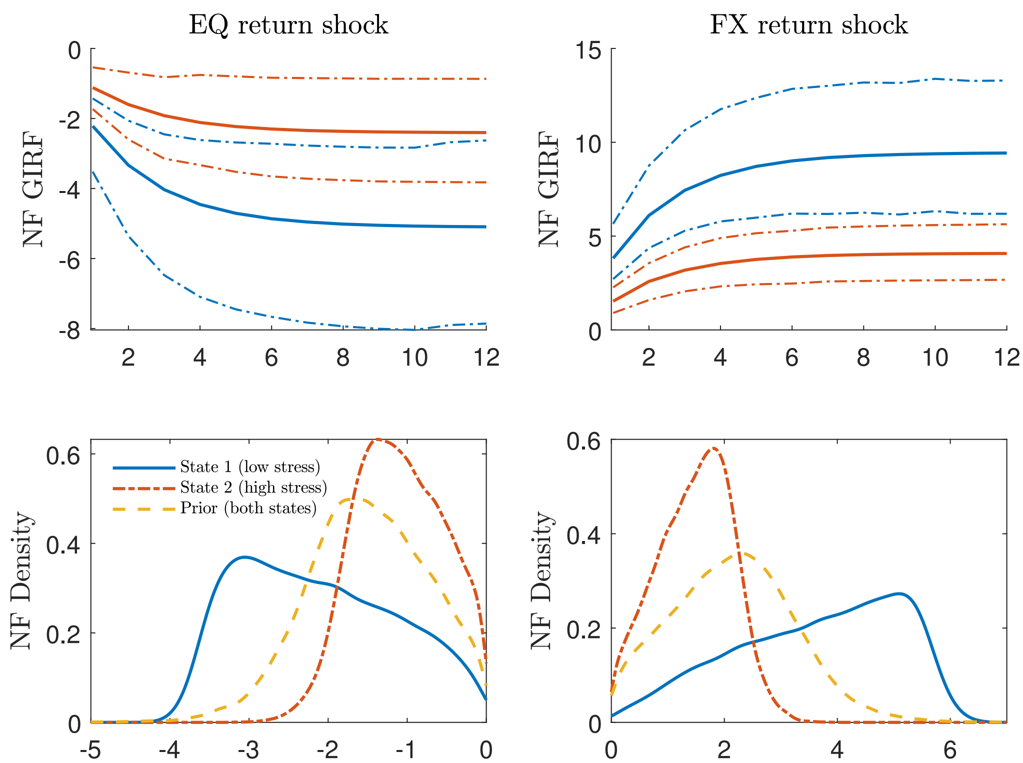
The general pattern of the impulse responses are in line with the results of Hau and Rey (2004) for the selected advanced economies. Through equity excess returns and exchange rate returns fully adjust within one to two months following the different shocks, impulse responses of net flows only converge after about a year. However, there are some differences in the magnitude of the impulse responses of the advanced country sample compared to those reported by Hau and Rey's (2004).[26] In particular, the magnitude of the flow response on impact in our sample of advanced economies tends to be smaller. On the other hand, the response of the exchange rate to a flow shock is considerably larger in our advanced country sample than in the individual countries considered in

[26] Hau and Rey (2004) show responses to a shock of one standard deviation. For comparison, their impulse responses need to be normalized to show the response to a unit shock.

Hau and Rey (2004). These differences in the magnitude can partially be attributed to the choice of the aggregated samples and the difference in the sample period. Hau and Rey (2004) analyze flows between the U.S. and individual advanced economies using data from 1990 to 2003. Hence their sample covers fewer and earlier years. Furthermore, in their setting, flows to and from other countries besides the U.S. are ignored. This then may lead to differences in the results depending on the cross-country pattern of flows within our aggregated sample. For example, if in a given month U.S. investors buy CHF equities, but at the same time euro area investors sell CHF equities, then the exchange rate effect of U.S. flows will be attenuated when using data only from Switzerland.

To evaluate the theoretical considerations from Section 2, we now turn to specific impulse responses in the EME sample. For this sample, we interpret the recovered hidden state as a persistent low- and a short-lived high-stress regime. Differences in the impulse responses thus correspond to differences in these two regimes and can be compared to our theoretical predictions.

Figure 6: EME GIRFs of equity flows to equity and exchange rate shocks



Notes: Normalized cumulative generalized impulse responses (GIRF) in EME sample. Upper row: Blue (red) solid line shows the median, the dashed line the 68% HPDI of the response over a 12 month horizon in state 1 (state 2). Lower row: Posterior and prior densities of the contemporaneous impulse responses.

Figure 6 reports how U.S. equity flows in the EME sample respond to a 1% shock to equity or foreign exchange rate returns. The first row shows the median response and 68% highest posterior density interval (HPDI) across all models that satisfy the sign restrictions. The second row shows the posterior distribution of the contemporaneous impulse response, where the prior distributions implicit in the Rubio-Ramirez et al. (2010) algorithm (and our priors about Σ_s) are shown as yellow dashed lines. Note that only one prior distribution is shown, as we use the same prior for both states.

The figure shows that equity flows to and from EMEs are less sensitive to exchange rate and equity shocks in periods of high financial stress. For both EQ return and FX return shocks, the high-stress (state 2) impulse responses of net flows are smaller in absolute value than the prior and the corresponding low-stress (state 1) responses. The difference between states is more pronounced for FX return shocks, where the 68% HPDIs of the two states do not overlap for any horizon. For EQ return shocks there is some overlap in responses between the two states, although the median low-stress response is outside the 68% HPDI of the high-stress response (and vice versa).

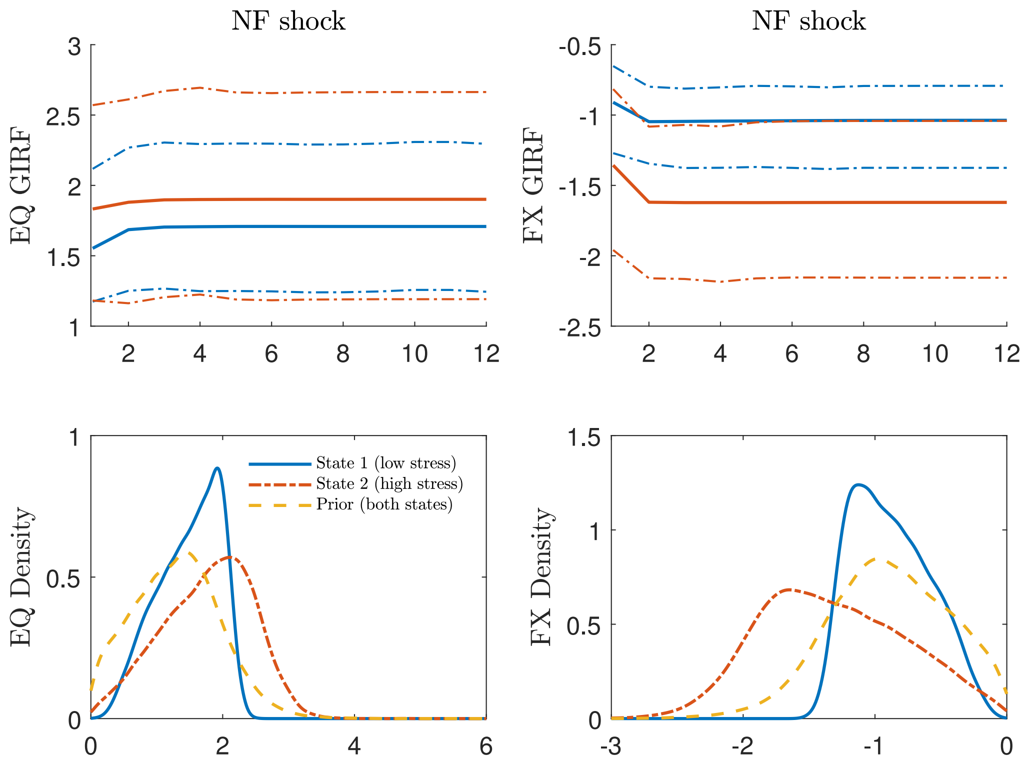
These empirical results accord with the theoretical discussion in section 2. In periods of high financial stress, investors seek to reduce their equity exposure and hold a large share of their portfolio in less risky investments. Portfolio rebalancing then requires smaller equity flows in response to equity and exchange rate shocks. The level of portfolio adjustments in terms of rebalancing across asset classes cannot be measured with our specification. However, because the data for equity flows is based on purchases and sales of equities, equity flow shocks indicate shifts to and from equities.

Portfolio rebalancing tends to dampen the effect of adverse shocks and thus could act as a stabilizing force even during crisis periods. Consider an emerging market crisis, which in our empirical setting could be captured by adverse equity or currency return shocks. Such adverse shocks would leave international investors holding too little (measured in USD) EME equity in their portfolios. This would prompt capital flows to EMEs, which mitigate the initial shocks. Because the response of equity flows is observed to be much smaller in absolute value in the second state – which corresponds closely to periods of financial turmoil in EMEs – the stabilizing force of portfolio rebalancing is weaker in periods of high financial stress.

Our second theoretical consideration relates the response of the equity return differential and the exchange rate to shocks in net flows. Figure 7 reports the corresponding impulse responses in the EME sample. For equity returns, the response is reported in the first column. The responses largely overlap for the two states and there is little difference in the contemporaneous impulse responses. Hence, we do not find any evidence for larger equity price responses during periods of financial stress, which could result from lower liquidity in the foreign stock market.

On the other hand, the response of the exchange rate to a shock in net inflows to the U.S. differs depending on the state. The second column of Figure 7 shows that the FX response tends to be larger in the high-stress state, where the median responses lie outside the 68% HDPI of the other state. This is in line with what we would expect based if foreign exchange markets are less liquid in times of financial stress. Furthermore, it is consistent with the model of Gabaix and Maggiori (2015), if financial intermediaries are less willing or able to take on balance sheet risks during times

Figure 7: EME GIRFs of equity and exchange rate returns to equity flow shocks



Notes: Normalized cumulative generalized impulse responses (GIRF) in EME sample. Upper row: Blue (red) solid line shows the median, the dashed line the 68% HPDI of the response over a 12 month horizon in state 1 (state 2). Lower row: Posterior and prior densities of the contemporaneous impulse response.

of stress.

Given the fact that few periods are identified to be in state 2, an alternative explanation for the reported differences in the responses is that the posterior distribution of impulse responses for state 2 is mainly determined by the choice of priors. However, the second rows in Figures 6 and 7 indicate that this is not the case. The posterior distributions of the contemporaneous impulse response in the two states are distinct and move in opposite directions from the prior. This results from the differences in the reduced-form covariance matrix reported in Figure 5.

5.5 Discussion

The primary focus of this paper has been to determine how the dynamics of capital flows, stock prices and exchange rates under the portfolio rebalancing prism change over time. Our approach of estimating regime switches endogenously at monthly frequency can help policymakers to monitor changes in the dynamics of capital flows. Understanding how these dynamics change in financial stress episodes allows to better prepare for such episodes. For example, the findings that financial stress episodes are associated with capital outflows from EMEs and that capital flows are less stabilizing in stress periods underscore the importance of making domestic financial markets in EMEs less dependent on foreign capital, and issuing debt in domestic rather than foreign currency.

Our paper offers some policy implications concerning the use of capital controls. Most of the literature's focus has been on capital inflow controls (Ostry et al. 2010, 2011). Some studies also suggest that controls on capital outflows in sudden stop episodes may be effective in some cases (Saborowski et al., 2014). We find that a switch towards the "high stress" regime is associated with outflows from EMEs, and it seems intuitive (although we cannot prove it in our setting) that capital controls would dampen these outflows. However, by limiting capital inflows in the "low stress" regime, one would also lose the stabilizing effects of flows that are due to portfolio rebalancing. We note, though, that our results – which concern net equity flows between the U.S. and EMEs – should not be pushed too far in drawing conclusions for capital controls. The effectiveness of capital controls likely differs depending on the type of capital flow being regulated, as well as a number of other factors (strength of fundamentals, institutional setting etc.).

Our results concerning time variation in the response of capital flows to asset prices are also relevant for international investors and related to the finance literature on the implications of regime switches for asset allocation (see e.g. Ang and Bekaert (2002), Graflund and Nilsson (2003), Bauer, Hearden amd Molenaar (2004), Guidolin and Timmermann (2008)). Compared with related papers in the finance literature, our paper estimates a structural model and investigates the dynamics of both capital flows and asset prices, rather than asset prices alone. Our findings suggest that it is important to take into account time variation and to allow the dynamics to change in stress episodes. One central theme in the literature is the "home bias puzzle" (e.g. Coerdacier and Rey (2012)), i.e., the finding that investors hold an excessive share of their portfolios in domestic equities, and thus forgo the full benefits of portfolio diversification. Our results have little to say about home bias, since we work with capital flows rather than positions. However, our finding that a switch towards the "high stress" regime is associated with a U.S. dollar appreciation and an underperformance of EME equities implies that EME investments perform poorly in high stress periods. This is consistent with the argument (e.g. Ang and Bekaert (2002)) that foreign market returns are low in stress periods, precisely when investors' marginal utility is high, which limits the diversification benefits of foreign currency investments. The finding that a switch toward the high stress regime is associated with capital outflows from EMEs to the U.S. is also consistent with Caballero and Simsek's (2013) view that simple safe assets in the U.S. have special value during economic crises.

A number of papers study time variation in capital flows, and in particular identify episodes of strong flows. While Forbes and Warnock (2012) classify strong capital flows as flows exceeding a certain threshold, Friedrich and Guerin (2020) use a regime-switching model to classify capital flow episodes. They estimate two-state regime switching models for individual EMEs, and then explore the effects of global factors (VIX, U.S. monetary policy) on the number of EMEs in the stress regime. Compared with these papers, we study the dynamics of capital flows, stock prices and exchange rates in a structural model, while they focus on the determinants of capital flows. Our paper highlights the importance of allowing for time variation in empirical models of international financial transmission. Our approach cannot answer the question whether "push" factors (global factors, such as risk sentiment or U.S. monetary policy) or "pull" factors (country-specific determinants of capital flows) drive capital flows (see e.g. Forbes and Warnock (2012) or Fratzscher (2012)). Doing so would require including candidate push and pull factors in the VAR. This is problematic given that many of these - in particular, push factors such as risk sentiment or U.S. interest rates - are potentially endogenous to U.S. dollar exchange rates and stock price returns. However, the timing of regime switches in the EME VAR – which matches increases in financial stress, including both financial crises in EMEs as well as the global financial crisis that originated in the U.S. - indicates that a combination of push and pull factors is at work.

6 Robustness

We perform several robustness checks to verify the baseline results from the previous section. The robustness checks consider issues related to the identification through sign restrictions, the choice of weighting scheme, the sample size as well as controlling for macroeconomic data surprises. In each case, we find results that are in line with the findings from the baseline specification. Because of the similarity between the results from the baseline and the robustness checks, we discuss the outcomes of the robustness checks but do not reproduce the same graphs from the previous section.

A first concern with our results relates to recent critiques of the identification of structural VARs through sign restrictions.[27] In particular, Baumeister and Hamilton (2015) showed that inference on structural parameters identified by sign restrictions may be mainly driven by a conditional prior imposed implicitly when using the algorithm of Rubio-Ramirez et al. (2010). However, we note that Baumeister and Hamilton (2015) also showed that for our special case of a three variable VAR, the algorithm implies a uniform prior on the structural impulse responses within the identified set, conditional on the reduced form draw.

To further address such concerns, we follow the suggestion of Moon and Schorfheide (2012) and Granziera et al. (2018) and additionally report the identified set of the structural impulse responses in appendix C for the EME sample. We estimated this set by taking 1,000 rotations that satisfy the sign restrictions at the median across the reduced-form parameters.[28] The identified set is wide and looks similar to the reported posterior distribution of impulse responses in the EME sample. The main difference is that the identified set covers a larger area close to zero. Combined with the fact that Baumeister and Hamilton's (2015) results imply a uniform conditional prior within

[27] We thank two anonymous referees for pointing out such concerns.

[28] Granziera et al. (2018) suggest to report this set calculated at the mean across reduced-form draws. We use the median, as the state-dependent covariances may be skewed; the median thus better reflects the highest posterior density of reduced-form draws.

the identified set[29], this result reveals that the reported posterior distribution does not result from a conditional prior that is highly concentrated on a small subset of the identified set. Hence we conclude that our results are not driven by a highly specific conditional prior implicitly imposed through sign restrictions.

A related concern is that with the employed algorithm, reduced-form draws with a lower rejection rate contribute more often to the posterior distribution of structural impulse responses, and thus may lead to a skewed weighting of the reduced form draws. To address this concern, we make a minor adjustment to the algorithm and regenerate the structural impulse responses. In particular, instead of generating 500 rotations for each draw of reduced-form parameters, we now generate rotations until 500 of them satisfy the sign restrictions. The results obtained using this alternative algorithm are virtually the same as our baseline results and we conclude that our results are robust to this alternative algorithm.

A potential endogeneity concern arises from our weighting scheme that may put undue weight on exchange rate and equity returns in months when equity flows are especially high for a particular country. To address this concern, the model is re-estimated using constant country weights for equity returns and exchange rate returns. Such an approach reduces endogeneity issues as it no longer puts more weight on returns for some countries in specific months. The constant weighting scheme produces very similar results as our baseline results. Almost all periods that are identified to be in the second state are the same as in our baseline results, and the responses to a regime switch are qualitatively the same. In particular, for the EME sample, the response of flows to price shocks is distinct for the two states, with the flow response in the low-stress state being larger in absolute terms.

Another approach to address this endogeneity concern is to use alternative country weights that are independent of equity flows. In particular, instead of aggregating equity returns based on equity flows, we use the use the MSCI World excluding the U.S. and the MSCI Emerging markets indices. Similarly, for the exchange rate, we use the U.S. Major currency and U.S. Other important trading partner trade weighted exchange rate indices.[30]

As these indices also include several countries that are not part of our sample, some differences in the results from this alternative weighting scheme are to be expected. Nonetheless, we find the same pattern as in the baseline results. The exception is that for the EME sample, the model selection now selects the 2 state specification where only volatilities switch. However, the state identification and impulse responses yield qualitatively similar results. The periods that are assigned to be in the second (high-stress) state are mostly aligned with those in our baseline results, though fewer stress periods are detected. Though the difference is less pronounced, the response of flows to price

[29] The median being somewhat larger than the mean reveals there is some skeweness in the conditional prior. Nonetheless, the conditional prior is close to being flat within the identified set and thus not highly concentrated at the median.

[30] Though the name may suggest differently, the MSCI World excluding the U.S. index only covers equities from developed markets.

shocks has the same pattern as in our baseline results. In the high-stress state of the EME sample, flows respond less to price shocks.

A third robustness test restricts the sample to periods after January 2000. Using a sample beginning before 2000 may have influenced the findings because of the introduction of the euro in 1999 and because of changing monetary policy strategies in EMEs with respect to their national currencies after the Asian crisis between 1997 and 1998. Results from this restricted sample are in line with the baseline results presented in the previous section. This is true for the advanced country and the EME samples. In the EME sample, the second regime state again matches periods of high financial stress. Further, as in the baseline results, equity flows respond less to price shocks in periods of high financial stress. Though this separation is less pronounced, the pattern in the posterior distributions shows a result that is qualitatively the same.

A final concern is that a number of "push" and "pull" factors drive capital flows, and in addition, financial markets respond to macroeconomic data announcements (e.g., Andersen et al. (2007)). Ideally, we would want to control for these factors in our VAR by including them as exogenous variables. The challenge is that many of these factors are not available at the monthly frequency, or even more seriously, could potentially be endogenous to capital flows and (especially) asset price movements. However, we can estimate a model that includes news surprises as exogenous variables.

We use economic surprise indices compiled by Citigroup for the U.S., EMEs, and the G10 (which we use as a proxy for advanced economies).[31] They aggregate different types of news surprises with weights reflecting their estimated exchange rate impact, and with declining weights for older releases. Including these indices as exogenous variables is one way to control for the variety of economic data releases in a parsimonious way.

The inclusion of news surprises affects model selection in the EME sample (for the advanced economy sample, the results are virtually unchanged).[32] When news are included, marginal likelihood is highest for error covariance switching only. That likelihood, however, is still lower than the value reported in Table 3 for the baseline model excluding news. Estimating a SVAR with error covariance switching only implies impulse responses that are virtually identical to those implied by the baseline specification, i.e., the qualitative results are unchanged, and the results are quantitatively similar. The reason for this is that in the baseline model differences in impulse responses are mainly determined by regime-specific impact shock covariances and less so by differences in dynamic coefficients across regimes. Overall, we conclude that our results are robust to including economic news measures in the VAR.

[31] These data are available via Thomson Reuters Datastream, tickers USCESIR, EKCESIR, GXCESIR for the U.S., the euro area and the G10.

[32] Results are available upon request.

7 Conclusion

This paper studies time variation in the dynamics of equity returns, exchange rate returns, and international equity flows. We extend the analysis in Hau and Rey (2004) by introducing a Markov regime switching model into the structural VAR. The model is estimated using monthly data, 1995-2018. Rather than estimating the model for bilateral capital flows, as in Hau and Rey (2004) and most related subsequent studies, we aggregate capital flows and asset returns across advanced and emerging economies. This has the advantage of reducing the biases inherent in the TIC data on international capital flows to and from the United States.

Our results suggest that the capital flow dynamics are not stable over time, but are better described by changes in coefficients and shock covariances. For flows between the U.S. and emerging economies, we find that the estimated regimes match periods of low and high financial stress, as indicated by common risk measures. We therefore interpret the estimated regimes as reflecting low and high risk states. The stabilizing properties of portfolio rebalancing are weakened in periods of high financial stress. This finding is in line with theoretical predictions of portfolio rebalancing models, if periods of crisis are associated with increasing investor risk aversion or elevated return volatility. Also, for emerging market economies a switch towards a period of high financial stress is associated with portfolio equity outflows.

Our empirical findings have important implications for the role of equity flows in emerging market crises. Portfolio rebalancing tends to mitigate adverse shocks. For example, a negative equity return shock in emerging market economies leaves international investors holding too little emerging market equities in their portfolios, prompting equity flows into emerging market economies. These flows induce an emerging market currency appreciation and tend to dampen the equity price drop, thus mitigating the initial adverse shock. This mechanism relies on the assumptions that (1) the shock has not affected expected returns and volatility of emerging market stocks, and (2) that international investors are not completely hedged against the effects of such shocks. Our finding that portfolio rebalancing is considerably reduced in crises periods for emerging market economies implies that equity flows perform the stabilizing role that is implied by portfolio rebalancing models only to a lesser degree.

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Appendix

A Generalized impulse responses

Let $IRF^s_{j,t}$ be the stacked impulse responses of different variables i as defined in equation (5). Using the reduced form model described in equation (4), the contemporaneous impulse responses on the effect to a shock in variable j in state s can be calculated as follows:

$$\begin{aligned} IRF^s_{j,t} &= B_s X_t + A^{-1}_{0,s}\epsilon_{t,j} - B_s X_t \\ &= A^{-1}_{0,s}\epsilon_{t,j}. \end{aligned}$$

For periods after the effect, the system is allowed to switch between states. As a result, the switching probabilities need to be included when calculating the conditional expectations. The k-period ahead impulse response is calculated as:

$$IRF^s_{j,t+k} = \Sigma^n_{l=1}\mathbb{P}(S_{t+k} = l|S_t = s)B_l \begin{bmatrix} IRF^s_{j,t+k-1} \\ \vdots \\ IRF_{j,t+k-p} \\ 0 \end{bmatrix}.$$

Gathering the conditional state probabilities in Q and assuming two states ($n = 2$), we have:

$$Q = \begin{bmatrix} P(S_{t+1} = 1|S_t = 1) & P(S_{t+1} = 2|S_t = 1) \\ P(S_{t+1} = 1|S_t = 2) & P(S_{t+1} = 2|S_t = 2) \end{bmatrix},$$

allows us to get $\mathbb{P}(S_{t+k} = l|S_t = s)$ as the lth column and the sth row from the matrix Q^k, which is the kth power of matrix Q. Thus:

$$IRF^s_{j,t+k} = \Sigma^n_{l=1}\left[Q^k\right]_{sl} B_l \begin{bmatrix} IRF^s_{j,t+k-1} \\ \vdots \\ IRF^s_{j,t+k-p} \\ 0 \end{bmatrix},$$

where $[\cdot]_{sl}$ selects the element from the lth column and the sth row.

Finally, note that the contemporaneous effects $A^{-1}_{0,s}\epsilon_{t,j}$ differ for each draw and rotation. To make responses comparable, a normalization of the impulse responses is required. Specifically, we normalize the impulse responses such that a shock to variable j has a median contemporaneous effect on that variable j of 1. For example, the reported impulse responses to the EQ return shock correspond to a shock inducing a median 1pp increase in equity excess returns between EMEs and the U.S. on impact.

B Responses to a regime switch

Let $IRF_{sh,t+k}$ be the stacked responses of different variables i to a switch from regime s to regime h in period t as defined in equation (7). Using the reduced form model described in equation (4), it can be calculated for period t as follows:

$$\begin{aligned} IRF_{sh,t} =& B_{1,h}y_{t-1} + \cdots + B_{p,h}y_{t-p} + c_h - B_{1,s}y_{t-1} - \cdots - B_{p,s}y_{t-p} - c_s \\ =& B_h \begin{bmatrix} y_{t-1} \\ \vdots \\ y_{t-p} \\ 1 \end{bmatrix} - B_s \begin{bmatrix} y_{t-1} \\ \vdots \\ y_{t-p} \\ 1 \end{bmatrix} = \left[B_h - B_s\right] X_t. \end{aligned}$$

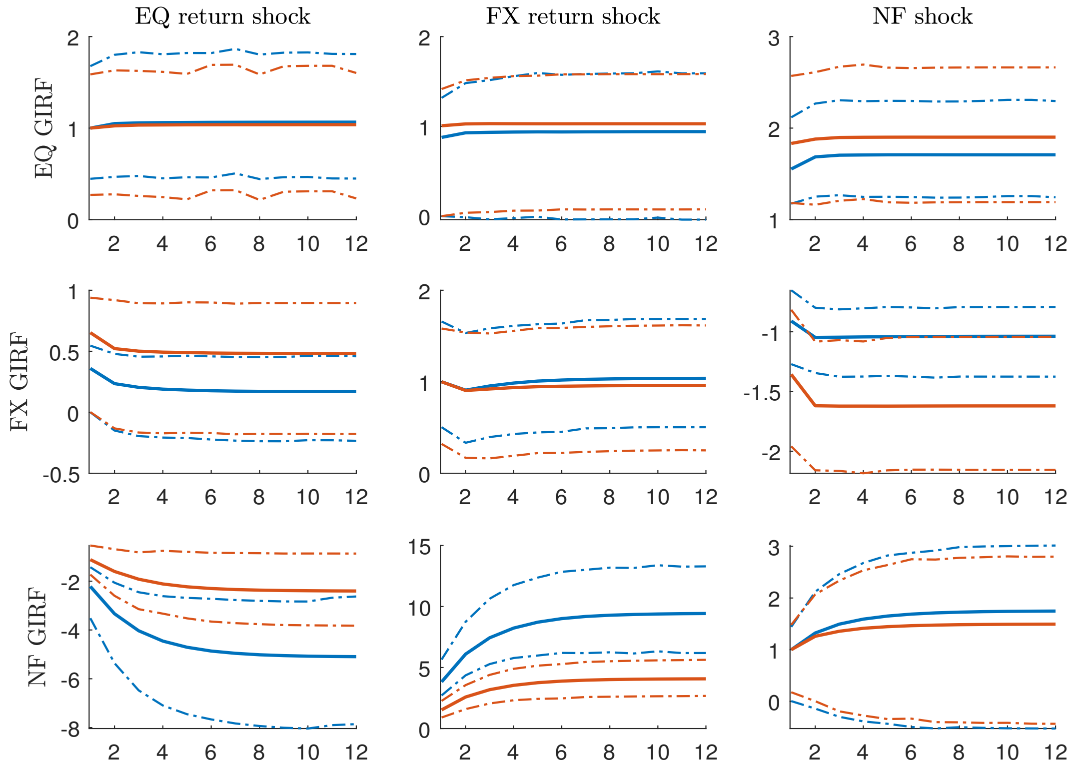
To simplify notation, let $\mathbb{E}\left[Z|s\right] \equiv \mathbb{E}\left[Z|S_t = s, X_t\right]$. Then the k-period ahead response to a switch from regime s to regime h is calculated as:

$$\begin{aligned} IRF_{sh,t+k} =& \mathbb{E}\left[y_{t+k}|S_t = h, X_t\right] - \mathbb{E}\left[y_{t+k}|S_t = s, X_t\right] \\ =& \sum_{l=1}^{2} \left(\left[Q^k\right]_{hl} B_{1,l}\right) \mathbb{E}\left[y_{t+k-1}|h\right] + \cdots + \sum_{l=1}^{2} \left(\left[Q^k\right]_{hl} B_{p,l}\right) \mathbb{E}\left[y_{t+k-p}|h\right] \\ & - \sum_{l=1}^{2} \left(\left[Q^k\right]_{sl} B_{1,l}\right) \mathbb{E}\left[y_{t+k-1}|s\right] - \cdots - \sum_{l=1}^{2} \left(\left[Q^k\right]_{sl} B_{p,l}\right) \mathbb{E}\left[y_{t+k-p}|s\right] \\ & + \sum_{l=1}^{2} \left(\left[\left[Q^k\right]_{hl} - \left[Q^k\right]_{sl}\right] C_l\right) \\ =& \sum_{l=1}^{2} \left(\left[Q^k\right]_{hl} B_l\right) \begin{bmatrix} \mathbb{E}\left[y_{t+k-1}|h\right] \\ \vdots \\ \mathbb{E}\left[y_{t+k-p}|h\right] \\ 1 \end{bmatrix} - \sum_{l=1}^{2} \left(\left[Q^k\right]_{sl} B_l\right) \begin{bmatrix} \mathbb{E}\left[y_{t+k-1}|s\right] \\ \vdots \\ \mathbb{E}\left[y_{t+k-p}|s\right] \\ 1 \end{bmatrix} \\ & + \sum_{l=1}^{2} \left(\left[\left[Q^k\right]_{hl} - \left[Q^k\right]_{sl}\right] C_l\right), \end{aligned}$$

where the state probabilities are gathered in Q as shown for the calculations of the generalized impulse responses.

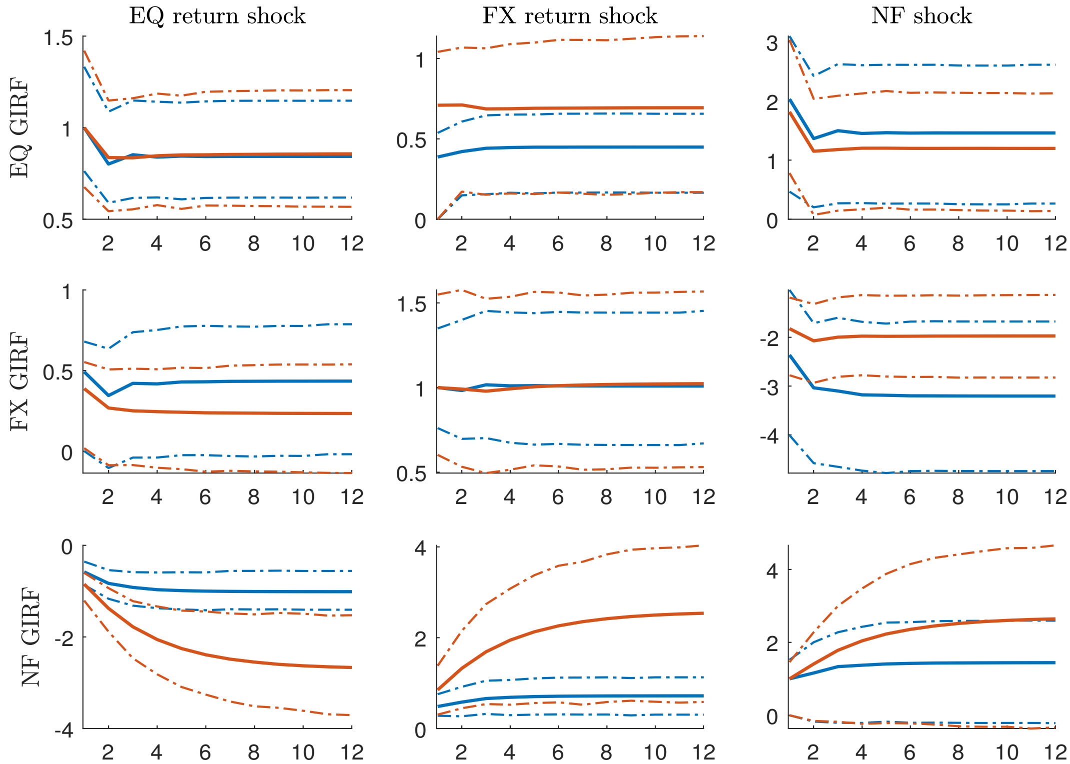
C Additional figures and tables

Figure 8: GIRFs Emerging Market Economies



Notes: Normalized cumulative generalized impulse responses (GIRF) of variables listed in rows to shocks listed the columns. Blue (red) solid line shows the median, the dashed line the 68% HPDI of the response over a 12 month horizon in state 1 (state 2). 4.44% (5.56%) of draws for state 1 (state 2) satisfy the sign restrictions.

Figure 9: GIRFs Advanced Economies



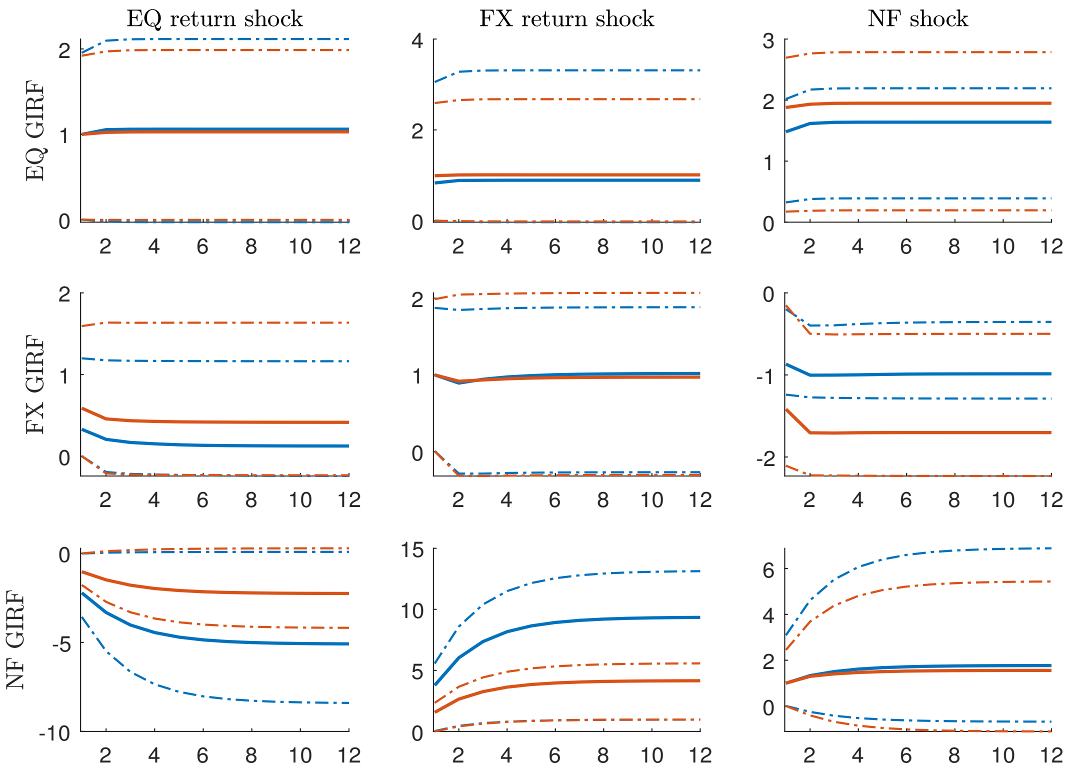
Notes: Normalized cumulative generalized impulse responses (GIRF) of variables listed in rows to shocks listed the columns. Blue (red) solid line shows the median, the dashed line the 68% HPDI of the response over a 12 month horizon in state 1 (state 2). 4.7% (5.29%) of draws for state 1 (state 2) satisfied the sign restrictions.

Table 4: Rejection rates

	Em. Market Economies		Advanced Economies	
	State 1	State 2	State 1	State 2
EQ shock	78.57 %	77.78 %	68.81 %	66.90 %
FX shock	76.20 %	73.90 %	70.36 %	76.81 %
NF shock	68.31 %	65.23 %	81.61 %	75.94 %
Any	95.56 %	94.44 %	95.30 %	94.71 %

Notes: Total number of draws: 2,000 × 500.

Figure 10: Identified Set Emerging Market Economies



Notes: Identified set for the normalized cumulative generalized impulse responses (GIRF) of variables listed in rows to shocks listed the columns. The identified set is calculated at the median of the reduced-form parameters. Blue (red) solid line shows the median response, the dashed line the upper and lower bound of the identified set.

Table 5: Countries

Country	MSCI index ticker	Currency ticker
Advanced Economies:		
Australia	MSAUSTL	MSERAUD
Austria	MSASTRL	MSEREUR
Belgium	MSBELGL	MSEREUR
Canada	MSCNDAL	MSERCAD
Denmark	MSDNMKL	MSERDKK
Finland	MSFINDL	MSEREUR
France	MSFRNCLY	MSEREUR
Germany	MSGERML	MSEREUR
Greece	MSGREEL	MSEREUR
Ireland	MSEIREL	MSEREUR
Italy	MSITALL	MSEREUR
Japan	MSJPANL	MSERJPY
Netherlands	MSNETHL	MSEREUR
Norway	MSNWAYL	MSERNOK
Portugal	MSPORDL	MSEREUR
Spain	MSSPANL	MSEREUR
Sweden	MSSWDNL	MSERSEK
Switzerland	MSSWITL	MSERCHF
United Kingdom	MSUTDKL	MSERGBP
Em. Market Economies:		
Brazil	MSBRAZL	MSERBRL
Chile	MSCHILL	MSERCLP
Colombia	MSCOLML	MSERCOP
Czech Republic	MSCZCHL	MSERCZK
Hungary	MSHUNGL	MSERHUF
India	MSINDIL	MSERINR
Indonesia	MSINDFL	MSERIDR
Israel	MSISRLL	MSERILS
Mexico	MSMEXFL	MSERMXN
Poland	MSPLNDL	MSERPLN
South Africa	MSSARFL	MSERZAR
South Korea	MSKOREL	MSERKRW
Thailand	MSTHAFL	MSERTHB

Notes: EUR series is extended back to 1995 using the series EUDOLLR from Datastream.