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Emerging Market Bond Flows and Exchange Rate Returns*

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Abstract

We study the relationship between international bond flows and exchange rate returns for a panel of emerging market economies (EMEs). Specifically, we investigate whether international net bond flows are correlated with subsequent changes in the value of the local currency against the US dollar. Using a portfolio approach, we find evidence of a positive relationship between bond flows and future exchange rate returns of EMEs, which is not present for advanced economy currencies. EME currencies tend to depreciate following large bond outflows, while they tend to appreciate following inflows. A dollar-neutral portfolio that goes long in inflow currencies and shorts outflow currencies earns large excess returns that are not correlated with ones from known international portfolio strategies. Moreover, using an asset pricing approach, we find strong evidence that a risk factor implied by this result is priced in the cross-section of currencies. These findings are consistent with investors requiring compensation for the risk that countries experiencing large portfolio inflows today could be facing a future tightening of their aggregate financial conditions.

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1 Introduction

International portfolio flows have grown tremendously over time, in particular with regard to investments in emerging market economies (EMEs). In light of this, much attention has been focused on the role of portfolio flows for the behaviour of exchange rates in globally integrated markets. Market participants have approached this issue from the viewpoint of attempting to uncover profitable predictability patterns in exchange rates. Policy makers have been similarly interested in these dynamics as large variations in asset prices, portfolio flows and exchange rates are a potential source of concern for monetary and financial stability.

A key market in this regard is the sovereign bond market, which has seen strong growth among EMEs in recent decades, especially in the local currency segment. This has been accompanied by rapidly growing international bond portfolio flows: assets under management of global funds investing in EME bond markets increased from $11 billion in 2004 to $383 billion in 2020 (Chari et al. (2022)). Given these developments and the sheer size of this market, bond portfolio flows have the potential to play an increasingly important role not only for bond prices but also for exchange rate dynamics in EMEs.

A large and growing literature has investigated currency risk and equilibrium exchange rates from empirical and theoretical angles. From an empirical perspective, currency risk has been associated with a variety of financial and macroeconomic factors as well as country-specific characteristics, leading to some success in explaining the primitive drivers behind the forward-bias puzzle in the cross-section of currencies (e.g. Lustig et al. (2011); Lustig et al. (2014); Della Corte et al. (2016); Mueller et al. (2017) and the references therein). From a theoretical viewpoint, equilibrium models of currency risk have also incorporated macroeconomic fundamentals and policies as main ingredients (for example, output and inflation risk, as in Verdelhan (2017); Andrew et al. (2022) or fiscal policies as in Jiang (2022)), and explicitly considered the role played by international capital flows in the determination of equilibrium exchange rates (Gabaix, Xavier, and Matteo Maggiori (2015); Koijen and Yogo (2019); Lilley et al. (2020) and the references therein). Despite the growing literature suggesting potential links between bond prices and exchange rate returns, on the one hand, and portfolio flows and macroeconomic fundamentals, on the other hand, there is no clear consensus regarding the the size and the economic significance of such links in integrated international markets, and this is especially true for EMEs.

In this study, we aim at providing evidence on this question by exploring the extent to which international bond flows affect excess returns on EME currencies. We adopt an asset pricing approach and, in the spirit of the recent literature on FX carry trade strategies (e.g., among others, Lustig and Verdelhan (2007); Burnside et al. (2011); Lustig et al. (2011); Menkhoff et al. (2012a)), we sort currencies into portfolios on the size of bond flows into, or out of, the corresponding economies. We then compute the exchange rate excess returns of these flow-sorted portfolios against the US dollar over a subsequent period and examine a dollar-neutral trading strategy that goes long in the portfolio with the largest inflows and short in the one with the largest outflows.

Using a large sample of EMEs over a period spanning the past 14 years, we document a host of interesting results. First, on the one hand there is clear evidence that for EMEs that experience large bond outflows, their exchange rates subsequently depreciate significantly, generating large negative currency excess returns. On the other hand, economies that experience inflows tend to face an appreciation of their exchange rate. These effects result in an annualised excess return differential of about 9 percent that is statistically significant on average and, when cumulated over the sample period, amount to a strategy excess return of around 60 percent over the sample period as a whole. Importantly, these effects are not present in advanced economies (AEs), for which there is no statistical evidence of a cross-sectional response of exchange rate excess returns to bond flows.

The returns originating from our strategy are higher on average than any of the ones exhibited by popular FX strategies over the sample period, including FX carry, momentum and value. The strategy's annualized Sharpe ratio is also the highest at a value higher than 1. Moreover, the strategy returns exhibit a low, and often negative correlation, with the ones from other FX strategies. Using a battery of asset pricing tests, we find strong evidence that a risk factor implied by our dollar-neutral long-short portfolio strategy is priced in the cross-section of EMEs currencies. The pricing of this risk factor is very satisfactory with a high adjusted R^2, low root mean-square error and the lowest Hansen and Jagannathan (1997) distance measure.

We rationalize the results of our empirical investigation by documenting that economies whose currencies have received large bond inflows tend to experience a tightening of their financial conditions over the subsequent 1-2 years. In a simple empirical exercise, we find large bond inflows into an economy predict a deterioration of the financial conditions experienced by the same economy up to 8 quarters ahead. This deterioration is quantitatively and statistically significant in comparison with the change in financial conditions experienced by economies with large outflows. In light of this evidence, we suggest that the risk premium accruing to our portfolio strategy may be viewed as compensation for the risk of future deterioration of financial conditions.

The rest of the paper is set out as follows: Section 2 discusses the data sources and the summary statistics of the main variables used in the empirical analysis. The subsequent Section 3 lays out the details of the empirical framework and tests, while Section 4 reports the results of the baseline estimations. Section 5 discusses the potential drivers of the baseline results and, after a robustness section, a final Section 7 concludes the study.

2 Data and Statistics

In our empirical investigation, we examine currency returns of portfolios formed on the basis of bond flows into or out of EMEs. The flow data we use consists of weekly bond country flows reported by Emerging Portfolio Fund Research (EPFR). EPFR tracks flows for over 135,000 individual investment funds domiciled globally, with more than $48 trillion in total assets. EPFR also gathers data on fund manager allocations which provide country and industry weightings along with funds' equity and bond holdings. This data is all sourced directly from fund managers or administrators.

By combining the individual fund flow data and the fund allocation data, EPFR puts together country and sector flow statistics, which track the aggregate flows in and out of countries and sectors.[1] It is this country flow data that we rely on in our analysis. The data is reported each Wednesday and covers the total flows that occurred during the week prior to that. The flows are reported in millions of US dollars, starting as of January 2004. We begin our sample as of 2006 to allow us to make comparisons of observed flows with historical ones for the purpose of forming portfolios (as explained in detail below).

The absolute size of the bond flows in our dataset has tended to grow over time. This reflects actual growth in international portfolio flows, but also a gradual expansion of the EPFR data coverage across investment funds. In order to control for these effects in the data, we normalise the weekly flows for each economy by the corresponding weekly assets under management (AUM), also reported by EPFR. We observe that the weekly flows are quite volatile. In order to somewhat reduce the noise that this induces, in the subsequent empirical analysis we compute aggregate flows over the past two weeks.[2]

In total, we have 24 emerging market economies (Brazil, Chile, Colombia, Mexico, Peru, Kenya, South Africa, China, Indonesia, India, Korea, Malaysia, Philippines, Thailand, Taiwan, Czech Republic, Hungary, Poland, Romania, Russia, Turkey, Ukraine, Israel, and Morocco). In order to compare our EME-based results with advanced economies, we also utilise data for 10 developed economies (Australia, Canada, Denmark, the euro area, Japan, New Zealand, Norway, Sweden, Switzerland, and the U.K.)[3].

The exchange rate data we use consists of bilateral spot rates against the US dollar, sourced from Bloomberg, for each of the economies listed above.[4] In order to match this data with

[1]These statistics rely on both explicit allocation data and on approximations, whereby the allocations of funds that are not explicitly 100% allocated to a single country or sector are distributed into countries and sectors according to the average allocation of funds within each fund category (e.g. Global funds, Emerging Market funds, etc.)

[2]Robustness checks show that our results are not sensitive to this specific aggregation period. See Section 6 for the details of the various robustness exercises

[3]The EPFR bond flow data for developed economies is patchy in the early years, which means that we can only empirically study these economies as of 2009

[4]All spot and forward rates are expressed in terms of USD per local currency.

the portfolio flow data, we sample weekly end-of-day observations each Wednesday. We also collect forward exchange rates in order to allow us to calculate excess currency returns.

Table 1 reports summary statistics for the currency and bond flow data we use. The characteristics of currency returns do not differ too much between EMEs and AEs, although some EMEs have seen larger average depreciation rates and greater FX volatility. The portfolio bond flows are in almost all cases positive on average, as a result of growing investments into bond markets. Still, the mean flows are dwarfed by their standard deviations, reflecting the volatile nature of week-to-week portfolio flows. These flows also exhibit positive first-order serial correlations in all cases, ranging from 0.03 to 0.71 for EMEs and from 0.10 to 0.61 for AEs. The average assets under management figures typically correlate highly with the size of the respective economy.

3 Empirical Framework

In order to examine the impact of bond portfolio flows on currency returns, we employ a portfolio approach, similar to numerous papers studying exchange rate predictability (e.g. Lustig and Verdelhan (2007), Burnside et al. (2011), Menkhoff et al. (2012a,b, 2016)). These studies all analyse the returns to currency portfolios formed by sorting on characteristics that may have predictive power for currency returns, such as lagged returns, carry or currency order flow.

In our case, we form currency portfolios based on lagged bond portfolio flows and examine to what extent such flows have predictive power for currency returns. In particular, we postulate that 'large' flows may be especially informative with respect to foreign exchange predictability. To operationalise the notion of 'large' flows, at each time t we compare the observed bond flow for each country with the standard deviation of country-specific flows over the past two years, and then select countries whose flows exceed (in absolute value) one standard deviation. Figure 1 displays the standardised bond flows for EMEs and highlights the 'large' flows according to our criteria.

Using this selection of EMEs, we sort currencies into four portfolios (P_1, P_2, P_3, P_4) based on the size of the bond flows. For comparative purposes, we do the same for the universe of EMEs and AEs, as well as for AEs separately. Portfolio P_1 contains the currencies with the largest bond outflows and portfolio P_4 those with the largest inflows. We then compute portfolio excess returns over the subsequent week from t to $t+1$, assuming equal investment into each of the currencies in the respective portfolios. Specifically, the excess returns for each currency are calculated as

$$rx_{t+1} = s_{t+1} - s_t + r_t^* - r_t, \tag{1}$$

where s_t denotes the log exchange rate, and r_t^* and r_t are the foreign and the US interest rates, respectively. The portfolios are rebalanced one week later, at $t+1$ based on the bond flows observed at $t+1$, and so on.

The returns of these portfolios correspond to going long in the currencies included in each portfolio, and going short the US dollar. Following the literature, we also consider a long-short portfolio where we go long the largest inflow portfolio (P_4) and go short the largest outflow portfolio (P_1). We label this portfolio, which is dollar-neutral, "$FLOW$".

4 Empirical Results

4.1 Baseline portfolio results

Table 2 reports our baseline results. The first four columns show the mean annualised excess returns on currency portfolios sorted by lagged standardised bond flows to or from the economies corresponding to the currencies in each portfolio. The last column displays the mean excess returns of the long-short $FLOW$ portfolio.

If we examine the results using all EME and all AE currencies together when forming portfolios, we find a clear monotonic pattern (first row in Table 2). Portfolio P_1 (largest outflows) displays a substantially lower mean excess return (-2.9%) than Portfolio P_4 (largest inflows) at +3.6%. In line with this, the average annualised excess return earned from going long Portfolio P_4 and short the Portfolio P_1 is positive (6.5%) and statistically significant. The top left panel of Figure 3 displays these results graphically.

However, the top right panels and bottom left panel of Figure 3, as well as Table 2 show clearly that these results are entirely driven by emerging markets currencies. The developed economy portfolios display no excess return pattern, and the mean *FLOW* portfolio excess return is slightly negative (-1.5%) and insignificant. By contrast, the mean *FLOW* excess return for EME currencies is large (8.9%) and highly statistically significant. Moreover, the EME *FLOW* portfolio generates a high annualised Sharpe ratio of 1.08.

The bottom right panel of Figure 3 displays the cumulative excess returns of the long-short *FLOW* portfolio for EME currencies. The cumulative return for this portfolio was on a general upward path throughout the sample period, earning almost 60% in the period 2006-19. By contrast, the cumulative excess return of the corresponding AE portfolio fluctuated around zero across the entire period (not displayed).

Given these results, in what follows we focus on the EME currencies in our sample. An open question is whether the excess returns generated by our bond flow sorting strategy are due to exchange rate predictability or to interest rate differentials. Figure 4 explores this issue by decomposing the EME *FLOW* portfolio excess returns into a return component due to exchange rate movements (top panels) and a component due to the difference in interest rates earned by this portfolio (lower panels). The first column of panels displays the results in terms of annualised mean returns, the second one in terms of cumulative returns. The figure shows clearly that the *FLOW* excess returns are entirely due to the exchange rate component and not to interest rate differentials. Hence, exchange rate predictability based on past bond flows are driving our results.

4.2 Bond flow predictability

Our results show that EME currency returns are predictable when conditioning on past bond flows. It is possible that this predictability could be due to the flows themselves being predictable. If past inflows predict future inflows, investors could buy the currencies of economies where inflows are predicted to take place in anticipation of appreciation pressures that would go along with such inflows, and vice versa for outflows. Lou (2012) examined flow-based explanations for return predictability among mutual funds, and showed that expected flow-induced mutual fund trading can forecast mutual fund returns.

In order to investigate this possibility within our setting, we proceed in the spirit of Lou (2012) and regress country bond flows on past flows and lagged currency returns. Based on this, we forecast future bond flows and examine excess returns on currency portfolios formed on the basis of these forecasted flows. Table 3 contains results from this exercise using combinations of flows and excess returns lagged up to four weeks. In general, both lagged bond flows and excess returns are highly significant in these predictive flow regressions and the adjusted R^2 values hover around 0.4 across the various specifications, suggesting considerable bond flow predictability.

However, the excess *FLOW* portfolio returns generated on the basis of these predicted bond flows are not very high, ranging from -0.81% to 1.75% in annualised terms, and never statistically significant. Figure 5 expands on this analysis by displaying a range of cumulative *FLOW* excess returns based on 110 different predicted bond flow series. Specifically, these were formed using all possible combinations of 1-10 lags of flows and 0-10 lags of excess returns to forecast bond flows. As the figure shows, this range of cumulative excess returns (the shaded area) is generally significantly below our benchmark returns, suggesting that bond flow predictability is not the driver of our results.

In fact, even if we were able to perfectly forecast bond flows one week ahead, the excess returns earned by forming FX portfolios based on these perfect foresight flows are unable to match our benchmark returns. The red line in Figure 5 shows the cumulative excess return on the perfect foresight-based *FLOW* portfolio. Across our sample it generates a cumulative excess return of 24%, around four tenths of the 58% generated by our benchmark specification. This reinforces our conclusion that bond flow predictability is not what is driving our results.

4.3 Commonalities with alternative FX strategies

What, then, is behind the apparent exchange rate predictability in our benchmark specification? One possibility is that it merely captures other well-known predictability patterns that the literature has uncovered. To examine this possibility, we compare the performance of our strategy to that of four popular FX strategies that have been studied in much empirical literature. These are carry, momentum (based on two different formation periods) and value strategies. The carry portfolios are based on currencies sorted by the interest rate differential at the time of portfolio formation. For the momentum portfolios, we sort currencies by past mean excess returns (1 month or 1 year prior to portfolio formation). In forming the value portfolios, we follow Asness et al. (2013) and sort currencies by the negative of the past 1-year exchange rate return minus the difference in foreign CPI inflation relative to that in the U.S. over the same period.[5]

Table 4 reports pairwise correlation coefficients for EME portfolio excess returns generated by our bond flow sorting strategy and the four alternative strategies. The table shows that for the four individual portfolios the correlations between our flow-based strategy and the alternatives tend to be relatively high, ranging from 0.62 to 0.91. However, in the case of the dollar-neutral long-short portfolio, $P_4 - P_1$, the correlations are much smaller, and in fact negative in three out of four cases. This suggests that the results for our *FLOW* portfolio do not just reflect currency predictability patterns captured by alternative well-known strategies.

To underscore this point, we compare our *FLOW* portfolio with high-minus-low excess returns

[5] Asness et al. (2013) use a 5-year lookback period, which for our sample results in a large negative mean return on the high-minus-low portfolio. A one-year lookback period, by contrast, generates a positive mean return of 2.22% annualised. When implementing the value strategy, we rely on monthly CPI and exchange rate data for the portfolio sorting.

earned from the aforementioned alternative strategies. Table 5 first reports key characteristics of these portfolios. The flow-based $FLOW$ portfolio has the highest mean excess return at 8.9% and Sharpe ratio (1.08) among all portfolios, followed by the carry portfolio with a mean excess return of 6.8% and a Sharpe ratio of 0.93. Similarly, the $FLOW$ portfolio has the highest Sortino ratio, i.e. excess return per unit of downside volatility (volatility of only negative returns). Moreover, this strategy has the lowest maximum drawdown (largest peak-to-trough loss) in the sample at −11.5%, compared with values between −16.2% and −65.5% for the other strategies.

Next, we regress the excess returns generated by our $FLOW$ portfolio on high-minus-low excess returns earned from the aforementioned alternative strategies. The results are reported in Table 6. The $FLOW$ excess returns load only weakly on the alternative returns, and the alphas are large and highly significant, ranging from 8.8% to 9.6% per annum. This suggests that there are potential diversification benefits from combining our flow-based portfolio strategy with other ones. Figure 6 confirms this conjecture: it shows that by adding the $FLOW$ portfolio to the alternative strategies (carry, momentum and value) the efficient portfolio frontier is significantly improved.

4.4 Strategy returns and compensation for risk

It is possible that the excess returns earned using our flow-based strategy could reflect compensation for exposures to various types of risks. We investigate this by regressing the excess returns generated by our $FLOW$ portfolio on a number of potential risk factors F:

$$rx_{FLOW,t} = \alpha + \beta F_t + \epsilon_t. \tag{2}$$

We follow the literature (e.g. Asness et al. (2013)) in selecting risk factors. Specifically, we include the return on the MSCI World Index in excess of the U.S. T-bill rate as a measure of the global market return, as well as the Fama and French (1993) bond market factor returns $TERM$ and DEF. The latter two are defined respectively as the difference between the 10-year U.S. Treasury note return and the T-bill rate, and as the difference between the return on a corporate bond portfolio (Barclays US IG corporate total return index) and the Treasury note return. Moreover, we include the TED spread and the Libor-OIS spread (3-month) as variables that may capture funding liquidity risk, as well as the on-the-run minus off-the-run spread on 10-year U.S. Treasuries as a measure of market liquidity risk.

We also allow for the possibility that the required compensation for exposure to market return risk factors may vary with some predetermined variables, along the lines of Ferson and Schadt (1996). In particular, following various suggestions in the literature, we consider the following conditioning variables: the VIX, the MOVE bond volatility index, the JP Morgan Global FX volatility index, and the 10-year minus 3-month slope of the U.S. term structure. We allow for such conditional effects by augmenting Equation (2) as follows:

$$rx_{FLOW,t} = \alpha + \beta F_t + \gamma Z_{t-1} F_t \epsilon_t, \tag{3}$$

where Z_{t-1} is a conditioning variable. In our case, Z_{t-1} would be the lagged first difference in one of the aforementioned variables.

Table 7 reports the results. Of the three market risk factors, only two are statistically significant: the MSCI excess return and the DEF factor (columns 1 and 3), with negative loadings. Among the liquidity factors, the funding liquidity ones appear to matter more than market liquidity. Both the TED spread and the Libor-OIS spread are significant at the 5% level, whereas the on-the-run minus off-the-run spread is significant only at the 10% level (columns 4-6).

With regard to the interaction terms, we tried several possible combinations of market risk factors and conditioning variables. Among these, only the VIX and, marginally, the FX volatility index seemed important. Surprisingly, the interaction term between the MSCI return and the VIX was not significant (column 7). Instead, VIX interacts significantly with DEF and $TERM$, and the interaction term between $TERM$ and FX volatility is significant at the 10% level (columns 8-10).

Nevertheless, the bottom line is that all of these risk factors explain little of the $FLOW$ portfolio excess returns: the R^2s range from 0 to 5.5%. Moreover, the estimated intercepts suggest that our bond flow based strategy is able to provide significant returns over and above those of strategies based on alternative risk factors. Only the intercepts associated with market risk factors can be interpreted in terms of return alphas, but among these, the alpha returns range from 7.4% to 8.9% and are all highly statistically significant.

4.5 A risk-return perspective

In this section, we examine whether the flow-based currency return results we have uncovered can be understood within an asset pricing framework. Specifically, we ask whether our $FLOW$ portfolio can be viewed as a priced risk factor in currency markets and, if so, how well it would do in pricing currency returns compared to various alternative factors considered in the literature.

In the absence of arbitrage, currency excess returns (xr) satisfy:

$$E_t[M_{t+1} rx_{t+1}] = 0, \tag{4}$$

where M_{t+1} is the stochastic discount factor (SDF). Following a large literature (e.g. Lustig and Verdelhan (2007), Lustig et al. (2011), Menkhoff et al. (2012a), Della Corte et al. (2016), Della Corte et al. (2021), and Colacito et al. (2020), among many others), we consider an SDF specification that is linear in some pricing factors f_{t+1}:

$$M_{t+1} = 1 - b'(f_{t+1} - \mu), \tag{5}$$

where b denotes a vector of factor loadings, and where μ represents the factor means. This specification implies a beta pricing model, where expected currency excess returns are given by:

$$E[xr] = \lambda' \beta \tag{6}$$

where $\lambda = \Sigma_f b$ is the market price of risk of the factors, $\Sigma_f = E[(f_t - \mu)(f_t - \mu)']$, and where the risk quantities β can be obtained as the regression coefficient of excess currency returns on f_t.

We perform two sets of tests. In the first set, we examine how well a two-factor asset pricing model is able to price currency portfolios. A standard pricing factor in the literature is the dollar factor (DOL) of Lustig et al. (2011), i.e. the average excess return across a large number of currencies vs. the US dollar. We take this to be one of the factors in our specification. We then add a second factor that is either one of a number of successful factors considered in the literature, or our own $FLOW$ factor. We consider four different factors from the literature: the carry factor (CAR, sometimes called the slope factor) of Lustig et al. (2011); the global volatility factor (VOL) of Menkhoff et al. (2012a); the global imbalance factor (IMB) of Della Corte et al. (2016); and the CDS-based sovereign risk factor (CDS) of Della Corte et al. (2021).[6]

The test portfolios in this exercise consists of our flow-based currency portfolios as well as, for each of the specifications considered, the portfolios generating the alternative pricing factors. The addition of the risk factor portfolios aims at ensuring that the factors considered price themselves, following the suggestion of Lewellen et al. (2010). We estimate the model using GMM, following the procedure described by Cochrane (2005).[7]

The results are reported in Table 8. Among the four alternative risk factors used in the literature, only the specification with the VOL factor delivers a statistically significant factor

[6]We thank Pasquale Della Corte for generously providing us with the IMB and CDS factor data.

[7]Specifically, following the literature, we only employ unconditional moments and no instruments. For inference, we compute the covariance matrix of the errors using a VARHAC procedure.

loading and market price of risk (the loading for IMB is also significant at the 10% level). However, the $FLOW$ factor has highly significant loading and risk price parameter estimates.[8] The adjusted R^2 of the VOL specification is decent at 0.41, although $FLOW$ generates an R^2 of 0.99. The latter specification also results in substantially lower root mean squared pricing errors (RMSE) compared with the other specifications. Moreover, only the VOL and the $FLOW$ specifications generate p-values for the Hansen and Jagannathan (1997) HJ distance measure below 5% (0.16 and 0.99, respectively). In summary, the two-factor pricing exercise tells us that $FLOW$ performs substantially better than the alternatives in terms of pricing the test portfolios, with VOL in second place.

In the second set of tests, we examine how well a three-factor asset pricing model does in pricing a wider set of portfolios. Specifically, we consider 16 portfolios: 4 carry, 4 momentum, 4 value, and 4 flow portfolios. In addition, we include the portfolios corresponding to the risk factors we consider, similar to the two-factor set-up. A wider set of test portfolios should alleviate concerns that the results obtained with the two-factor model were due to misleading results from a small cross-section (Lewellen et al. (2010)). The three risk factors we include consist of the dollar factor (DOL) and the carry factor (CAR), plus a third factor (f_3) that is either the global FX volatility factor (VOL), the global imbalance factor (IMB), the CDS factor (CDS), or our flow portfolio factor ($FLOW$).

Table 9 provides the results. In general, they confirm those from the two-factor estimates. The $FLOW$ factor is highly significant, both in terms of the factor loading and the market price of risk.[9] Among the other factors, only the VOL loading is marginally significant. The adjusted R^2 of the $FLOW$ specification is again much higher than for the other ones (0.89 vs between 0.01 and 0.48), and the RMSE lower (0.95 vs between 1.48 and 1.93). The HJ p-values are all above 5% this time. Overall, our results provide strong evidence that our flow-based risk factor is priced in the cross-section of currencies.

[8] The estimated risk quantities β are also highly significant for the corner $FLOW$ portfolios: $\hat{\beta}_{P1} = -0.679$ (with standard error 0.044), $\hat{\beta}_{P4} = 0.321$ (with standard error 0.044).

[9] As was the case for the two-factor model, the estimated risk quantities β are again highly significant for the corner $FLOW$ portfolios: $\hat{\beta}_{P1} = -0.679$ (with standard error 0.045), $\hat{\beta}_{P4} = 0.321$ (with standard error 0.045).

5 Strategy returns and future financial conditions

The results discussed in the previous sections document that excess returns from our proposed portfolio strategy are able to capture the salient features of the cross section of EMEs currency returns and improve upon the performance of other risk factors discussed in the literature. This begs the question as to why higher bond inflows into a country are associated with higher expected FX returns on average. One potential explanation is that higher returns may be the compensation for the risk that high-inflow countries may subsequently be more exposed to a deterioration of their financial conditions. This deterioration could be the result of overheating, excessive risk-taking, etc. To informally examine this possibility, we carry out a simple empirical exercise aiming to assess how future financial conditions change for countries seeing large inflows today, vis-a-vis countries that experience big outflows.

Specifically, we summarise a broad range of financial condition indicators by using country-specific financial conditions indices (FCI) from Goldman Sachs and calculate the future change in this index for each country in portfolio 4 (P4, large inflows) and portfolio 1 (P1, large outflows).[10] We consider horizons from one to eight quarters ahead from the portfolio formation date. We then calculate the mean difference in FCIs between P4 countries and P1 countries across the various horizons. If P4 countries tend to be more risky than P1 countries, in the sense of a greater risk of future tighter financial conditions, we would expect the aforementioned FCI difference to be positive.

Figure 7 displays the results. Indeed, we do see that future changes in financial conditions tend to be tighter for big inflow (P4) countries than for big outflow (P1) countries, across all future horizons (with the exception of one quarter ahead). Moreover, the difference between P4 and P1 countries grows with the horizon, and is statistically significant at the 95% level from 4 quarters ahead onwards.

[10] The Goldman Sachs FCI data includes 17 of our 24 EMEs. The following economies are not included: Colombia, Peru, Kenya, Taiwan, Romania, Ukraine, and Morocco. We confirm that our baseline result of a high *FLOW* excess returns and Sharpe ratio hold for the subset of countries that are covered by the FCI data. The mean excess return for this subset is 11.8% (standard error 3.56) and the SR is 1.36.

This evidence suggests that that countries whose currencies receive large bond inflows tend to experience a significantly greater tightening of their financial conditions over the subsequent 1-2 years than outflow countries. Hence, the risk premium accruing to our *FLOW* portfolio strategy may be viewed as compensation for the risk of future financial tightening.

6 Robustness

Our baseline results are robust along multiple dimensions. Table 10 displays mean excess returns and Sharpe ratios of our benchmark *FLOW* portfolio (Row(1)), along with the same statistics for *FLOW* portfolios generated through a number of robustness checks. Rows (2)-(5) starts the sample at various points later than the benchmark's 2006 starting year; rows (6) and (7) uses three or five portfolios of flow-sorted currencies instead of four; rows (8)-(10) use one, three, or four weeks of lagged bond flows for portfolio formation instead of two weeks; rows(11)-(12) use two and three weeks holding periods (non-overlapping) for the FX returns instead of one week.

As the table shows, the benchmark result of a high and significant mean excess return, as well as a large Sharpe ratio holds up well across all these robustness checks. It is only for the longer return periods (rows 11-12) that the statistical significance of the mean return dips below 5%. This is because longer non-overlapping holding periods imply much fewer observations: using 2-week returns halves the number of observations, and the 3-week returns cuts observations to a third compared to the benchmark case. Qualitatively, however, the results hold up well.

7 Conclusions

What role do international bond portfolio flows play for EME exchange rates? We investigate this question by examining whether international net bond flows are correlated with subsequent changes in the value of the local currency against the US dollar. Using a portfolio approach, we find evidence of a positive, near-monotonic relationship between EME bond flows and future exchange rate returns. EME currencies tend to depreciate following large bond outflows, while they tend to appreciate following inflows. A dollar-neutral portfolio that goes long in inflow currencies and shorts outflow currencies earns large excess returns that are not correlated with ones from known international portfolio strategies. Furthermore, using an asset pricing approach, we find strong evidence that a risk factor implied by this result is priced in the cross-section of currencies. These findings are consistent with the view that investors require compensation for the risk that countries experiencing large portfolio inflows today could be facing a future tightening of their aggregate financial conditions. Indeed, we verify empirically that future changes in financial conditions tend to be significantly tighter for economies that have experienced big inflows relative to those that have seen outflows.

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Table 1. Sample statistics: FX returns, bond flows and AUMs

The table reports sample statistics for weekly log-exchange rate returns (Δs, in %), portfolio bond flows ($flow$, in millions of USD), and assets under management (AUM, in billions of USD). μ denotes mean values, σ standard deviations, and $corr$ the serial correlation coefficient. Exchange rates are expressed in terms of US dollars per local currency. Data is weekly, from January 2006 to December 2019.

	$\mu(\Delta s)$	$\sigma(\Delta s)$	$corr(\Delta s)$	$\mu(flow)$	$\sigma(flow)$	$corr(flow)$	μ(AUM)
Brazil	−0.079	2.233	−0.090	10.800	131.859	0.600	26.073
Chile	−0.052	1.518	0.044	5.434	22.983	0.647	3.767
Colombia	−0.051	1.873	−0.004	16.988	99.154	0.028	10.834
Mexico	−0.080	1.635	−0.004	27.736	102.025	0.696	24.098
Peru	0.005	0.744	−0.060	7.757	29.923	0.658	5.743
Kenya	−0.044	1.040	−0.049	0.881	3.261	0.592	0.527
South Africa	−0.114	2.431	−0.011	19.560	55.412	0.645	10.419
China	0.020	0.365	0.126	10.546	110.415	0.451	12.018
Indonesia	−0.051	1.176	0.135	26.331	87.565	0.659	15.905
India	−0.064	1.055	0.073	12.284	39.649	0.621	6.169
Korea	−0.021	1.634	−0.088	11.105	71.963	0.230	9.496
Malaysia	−0.013	0.920	0.055	12.201	41.999	0.709	7.790
Philippines	0.004	0.786	−0.006	5.783	25.091	0.654	4.989
Thailand	0.040	0.695	0.038	7.158	281.566	0.270	16.849
Taiwan	0.010	0.595	0.083	−0.000	1.037	0.462	0.181
Czech Republic	0.005	1.713	−0.005	0.112	7.663	0.432	1.498
Hungary	−0.051	2.044	0.008	5.282	29.369	0.683	6.310
Poland	−0.027	1.987	−0.047	10.665	45.820	0.679	11.782
Romania	−0.048	1.552	0.011	0.948	18.925	0.653	2.984
Russia	−0.105	1.895	0.004	19.161	79.800	0.669	16.035
Turkey	−0.205	2.083	−0.010	11.644	58.743	0.665	10.557
Ukraine	−0.321	3.711	0.033	4.282	16.311	0.635	3.328
Israel	0.039	1.130	−0.042	2.417	10.542	0.687	2.600
Morocco	−0.008	1.017	0.015	0.776	4.591	0.660	0.552
Australia	−0.010	1.722	0.030	−7.276	85.685	0.573	19.936
Canada	−0.019	1.312	−0.023	103.428	205.027	0.238	57.902
Denmark	−0.012	1.297	0.017	8.767	30.798	0.192	5.528
Japan	0.008	1.333	−0.008	24.232	96.969	0.614	39.323
New Zealand	−0.005	1.772	−0.013	2.956	10.923	0.601	2.988
Norway	−0.042	1.692	−0.076	7.189	129.692	0.100	9.848
Sweden	−0.028	1.591	−0.045	20.393	82.815	0.346	16.505
Switzerland	0.036	1.533	−0.022	10.647	129.665	0.195	30.755
UK	−0.042	1.346	−0.043	43.813	182.495	0.453	78.570
Euro area	−0.012	1.299	0.019	99.191	847.576	0.592	302.373

Table 2. Mean excess returns of portfolios sorted by bond flows

The table reports mean annualised excess returns (in percent) of currency portfolios sorted by lagged bond flows to or from the economies corresponding to the currencies in each portfolio. Bond flows are standardised by the corresponding assets under management for each economy. Portfolio P_1 contains the currencies with the largest bond outflows and portfolio P_4 those with the largest inflows. Portfolio $FLOW$ goes long portfolio P_4 and short portfolio P_1. AE denotes advanced economies and EM emerging market economies. Data is weekly, from January 2006 to December 2019. Figures in parenthesis are asymptotic standard errors. *** denotes statistical significance at the 1% level; ** at the 5% level; and * at the 10% level.

	P_1	P_2	P_3	P_4	$FLOW$
AE + EM	−2.899	1.334	2.042	3.582	6.482**
	(3.584)	(3.083)	(3.094)	(2.498)	(2.781)
AE only	4.372	4.880	7.002	2.921	−1.451
	(5.019)	(4.971)	(4.971)	(4.605)	(4.129)
EM only	−4.637	2.398	1.773	4.252	8.889***
	(3.847)	(3.847)	(4.068)	(3.794)	(3.219)

Table 3. Predicting future EME bond flows

The table reports forecasting regressions for country bond flows and associated *FLOW* portfolio FX excess returns (mean annualised values in percent) based on predicted flows. The dependent variable is the one-week ahead $(t+1)$ bond flow, standardised by the corresponding assets under management for each economy. Dependent variables are lags of these flows and lagged FX excess returns for the corresponding currencies. Coefficients are estimated using pooled OLS. Time fixed effects are included in all regression specifications. The *FLOW* portfolios are constructed by sorting countries according to predicted bond flows, forming four portfolios containing the corresponding currencies, then going long the portfolio with the largest predicted inflows and short the portfolio with the largest predicted outflows. Figures in parenthesis are asymptotic standard errors. *** denotes statistical significance at the 1% level; ** at the 5% level; and * at the 10% level.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Constant	-0.002^{*}	-0.002^{**}	-0.002^{**}	-0.002^{***}	-0.002^{**}	-0.002^{**}	-0.003^{***}	-0.002^{**}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$flow_t$	0.360^{***}	0.311^{***}	0.307^{***}	0.308^{***}	0.350^{***}	0.295^{***}	0.285^{***}	0.284^{***}
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$flow_{t-1}$		0.131^{***}	0.123^{***}	0.118^{***}		0.132^{***}	0.106^{***}	0.100^{***}
		(0.008)	(0.009)	(0.009)		(0.008)	(0.009)	(0.009)
$flow_{t-2}$			0.024^{***}	0.012			0.033^{***}	0.017^{**}
			(0.008)	(0.009)			(0.008)	(0.009)
$flow_{t-3}$				0.037^{***}				0.053^{***}
				(0.008)				(0.008)
$exret_t$					0.064^{***}	0.065^{***}	0.068^{***}	0.068^{***}
					(0.003)	(0.003)	(0.003)	(0.003)
$exret_{t-1}$						0.012^{***}	0.016^{***}	0.017^{***}
						(0.003)	(0.003)	(0.003)
$exret_{t-2}$							0.024^{***}	0.025^{***}
							(0.003)	(0.003)
$exret_{t-3}$								0.007^{***}
								(0.003)
Adj-R^2	0.398	0.408	0.408	0.408	0.420	0.431	0.436	0.436
FLOW ex.ret.	1.548	1.667	1.101	1.750	0.978	−0.810	0.346	1.269
	(2.061)	(2.144)	(2.144)	(2.135)	(2.065)	(2.352)	(2.358)	(2.442)
Sharpe ratio	0.201	0.208	0.137	0.219	0.222	−0.092	0.039	0.139

Table 4. FX portfolio excess return correlations

The table reports correlations between excess returns of EME currency portfolios sorted by lagged bond flows and excess returns of portfolios formed with alternative strategies: carry, momentum (1-month and 1-year formation periods) and value. The reported correlation coefficients correspond to portfolio-by-portfolio correlations, e.g. between bond flow portfolio P_1 and carry portfolio P_1, etc.

	P_1	P_2	P_3	P_4	$P_4 - P_1$
Carry	0.906	0.815	0.749	0.704	−0.195
Momentum (1m)	0.834	0.794	0.651	0.623	0.100
Momentum (1y)	0.775	0.868	0.703	0.730	−0.031
Value	0.822	0.740	0.776	0.781	−0.054

Table 5. High-minus-low FX portfolio characteristics

The table reports key characteristics of excess returns on high-minus-low EME currency portfolios formed using our bond flow strategy and four alternative strategies. The statistics are based on annualised returns, expressed in percent.

	Bond flow	Carry	Momentum 1m	Momentum 1y	Value
mean	8.889	6.817	4.323	−1.256	2.220
standard dev.	8.220	7.303	8.643	8.579	8.466
skewness	0.816	−0.785	−1.008	−0.652	−0.077
kurtosis	6.316	6.668	25.607	5.665	6.050
Sharpe ratio	1.081	0.933	0.500	−0.146	0.262
Sortino ratio	1.932	1.174	0.636	−0.191	0.402
Max drawdown	−11.495	−16.180	−19.492	−65.487	−21.641

Table 6. Regression of $FLOW$ returns on alternative HML returns

The table reports results from regressions of excess returns of our EME $FLOW$ currency portfolio on returns from high-minus-low (HML) portfolios based on four alternative strategies. α denotes the constant. Figures in parenthesis are asymptotic standard errors.

	Carry	Momentum 1m	Momentum 1y	Value
α	9.609***	8.852***	8.782***	9.050***
	(0.001)	(0.001)	(0.001)	(0.001)
β	−0.189***	0.073	−0.025	−0.044
	(0.056)	(0.045)	(0.047)	(0.048)
adj. R^2	0.027	0.002	−0.005	−0.004

Table 7. Regression of $FLOW$ returns on risk factors

The table reports results from regressions of excess returns of our EME $FLOW$ currency portfolio on various risk factors. α denotes the constant. Figures in parenthesis are asymptotic standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
MSCI ex.ret.	-0.095^{***}						-0.095^{***}			
	(0.023)						(0.023)			
TERM		0.067						0.068	0.044	
		(0.059)						(0.059)	(0.059)	
DEF			-0.227^{***}							-0.146^{*}
			(0.078)							(0.079)
TED spread				0.268^{**}						
				(0.118)						
on/off run					0.010^{*}					
					(0.005)					
Libor-OIS						0.339^{**}				
						(0.144)				
MSCI x VIX							-0.357			
							(0.398)			
TERM x FXvol								-8.041^{*}		
								(4.385)		
TERM x VIX									3.281^{***}	
									(1.012)	
DEF x VIX										-5.242^{***}
										(1.456)
α	8.549^{***}	8.444^{***}	8.348^{***}	2.735	4.826	3.560	8.608^{***}	8.037^{**}	8.920^{***}	7.350^{**}
	(3.139)	(3.233)	(3.180)	(4.176)	(3.921)	(3.910)	(3.136)	(3.224)	(3.187)	(3.133)
adj. R^2	0.045	0.001	0.022	0.012	0.006	0.013	0.044	0.008	0.028	0.055

Table 8. Two-factor pricing of FX portfolios

The table reports cross-sectional asset pricing results based on our flow-based currency portfolios plus the pricing factor portfolio considered in each test. The two risk factors are the dollar factor (DOL) and a second factor (f_2) that is either the carry factor (CAR), the global FX volatility factor (VOL), the global imbalance factor (IMB), the CDS factor (CDS), or our flow portfolio ($FLOW$). The parameters b are the SDF factor loadings, while the λ parameters denote the factor market prices of risk. Cross-sectional R^2 are reported, along with the root mean squared pricing errors (RMSE) and the HJ distance measure of Hansen and Jagannathan (1997). Parameters are estimated using GMM; VARHAC standard errors are reported in parentheses; values in brackets are p-values.

f_2	$b(DOL)$	$b(f_2)$	$\lambda(DOL)$	$\lambda(f_2)$	Adj.R^2	RMSE	HJ dist.
CAR	−0.031	0.124	0.192	3.281	0.041	3.089	9.471
	(0.121)	(0.120)	(3.329)	(2.990)			[0.024]
VOL	0.086	18.762**	1.017	0.055*	0.405	2.326	5.180
	(0.105)	(9.440)	(3.223)	(0.032)			[0.159]
IMB	0.028	−0.380*	0.683	−2.466	0.134	2.902	9.010
	(0.097)	(0.226)	(3.125)	(1.747)			[0.029]
CDS	−0.001	0.281	0.412	1.394	−0.173	3.289	8.169
	(0.115)	(0.322)	(3.794)	(1.615)			[0.043]
$FLOW$	0.135	0.291***	1.453	8.941***	0.991	0.403	0.134
	(0.106)	(0.095)	(3.182)	(3.235)			[0.988]

Table 9. Three-factor pricing of FX portfolios

The table reports cross-sectional asset pricing results based on 16 currency portfolios plus the pricing factor portfolios considered in each test. The 16 portfolios consist of: 4 carry, 4 momentum, 4 value, and 4 flow portfolios. The three risk factors are the dollar factor (DOL) and the carry factor (CAR), plus a third factor (f_3) that is either the global FX volatility factor (VOL), the global imbalance factor (IMB), the CDS factor (CDS), or our flow portfolio ($FLOW$). The parameters b are the SDF factor loadings, while the λ parameters denote the factor market prices of risk. Cross-sectional R^2 are reported, along with the root mean squared pricing errors (RMSE) and the HJ distance measure of Hansen and Jagannathan (1997). Parameters are estimated using GMM; VARHAC standard errors are reported in parentheses; values in brackets are p-values.

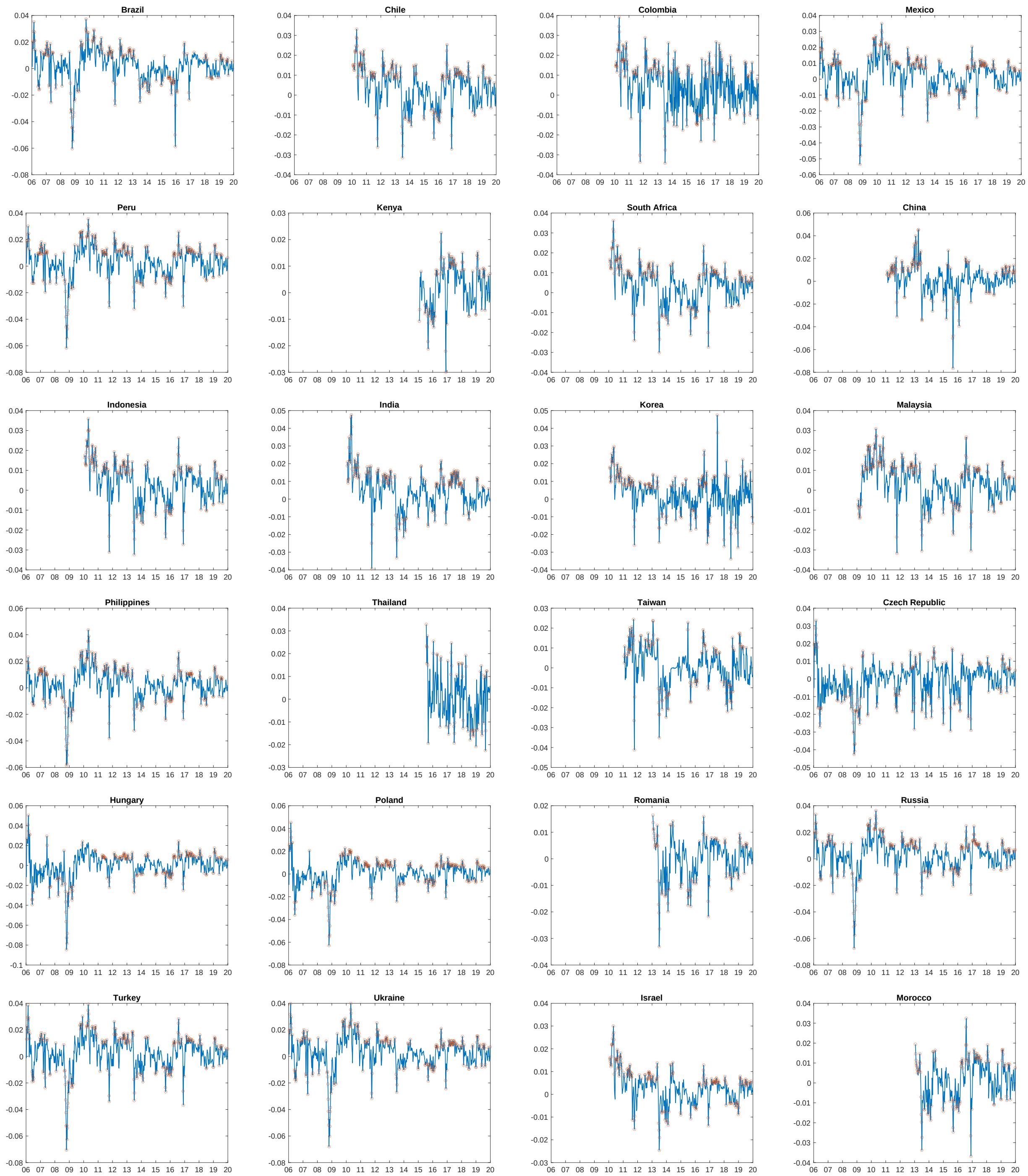
f_3	$b(DOL)$	$b(CAR)$	$b(f_3)$	$\lambda(DOL)$	$\lambda(CAR)$	$\lambda(f_3)$	Adj.R^2	RMSE	HJ dist.
VOL	−0.015	0.181	16.910*	−0.262	4.224	0.048	0.483	1.479	12.188
	(0.121)	(0.135)	(9.831)	(3.150)	(3.405)	(0.032)			[0.665]
IMB	−0.056	0.163	−0.337	−0.349	4.060	−2.160	0.325	1.717	16.853
	(0.112)	(0.134)	(0.250)	(3.066)	(3.285)	(1.756)			[0.328]
CDS	−0.028	0.065	0.148	0.001	1.866	0.747	0.003	1.948	14.809
	(0.128)	(0.149)	(0.368)	(3.629)	(3.994)	(1.816)			[0.465]
$FLOW$	0.021	0.199	0.285***	−0.161	4.231	8.594***	0.886	0.950	7.572
	(0.121)	(0.137)	(0.095)	(3.104)	(3.438)	(3.242)			[0.940]

Table 10. Robustness checks

The table reports the mean excess return, its standard error and the Sharpe ratio of the benchmark *FLOW* portfolio (row (1)), along with the same statistics for alternative *FLOW* portfolios generated through a number of robustness checks. Rows (2)-(5) starts the sample at various points later than 2006; rows (6) and (7) uses three or five portfolios of flow-sorted currencies instead of four; rows (8)-(10) use one, three, or four weeks of lagged bond flows for portfolio formation instead of two weeks; rows(11)-(12) use two and three weeks holding periods (non-overlapping) for the FX returns instead of one week. *** denotes statistical significance at the 1% level; ** at the 5% level; and * at the 10% level.

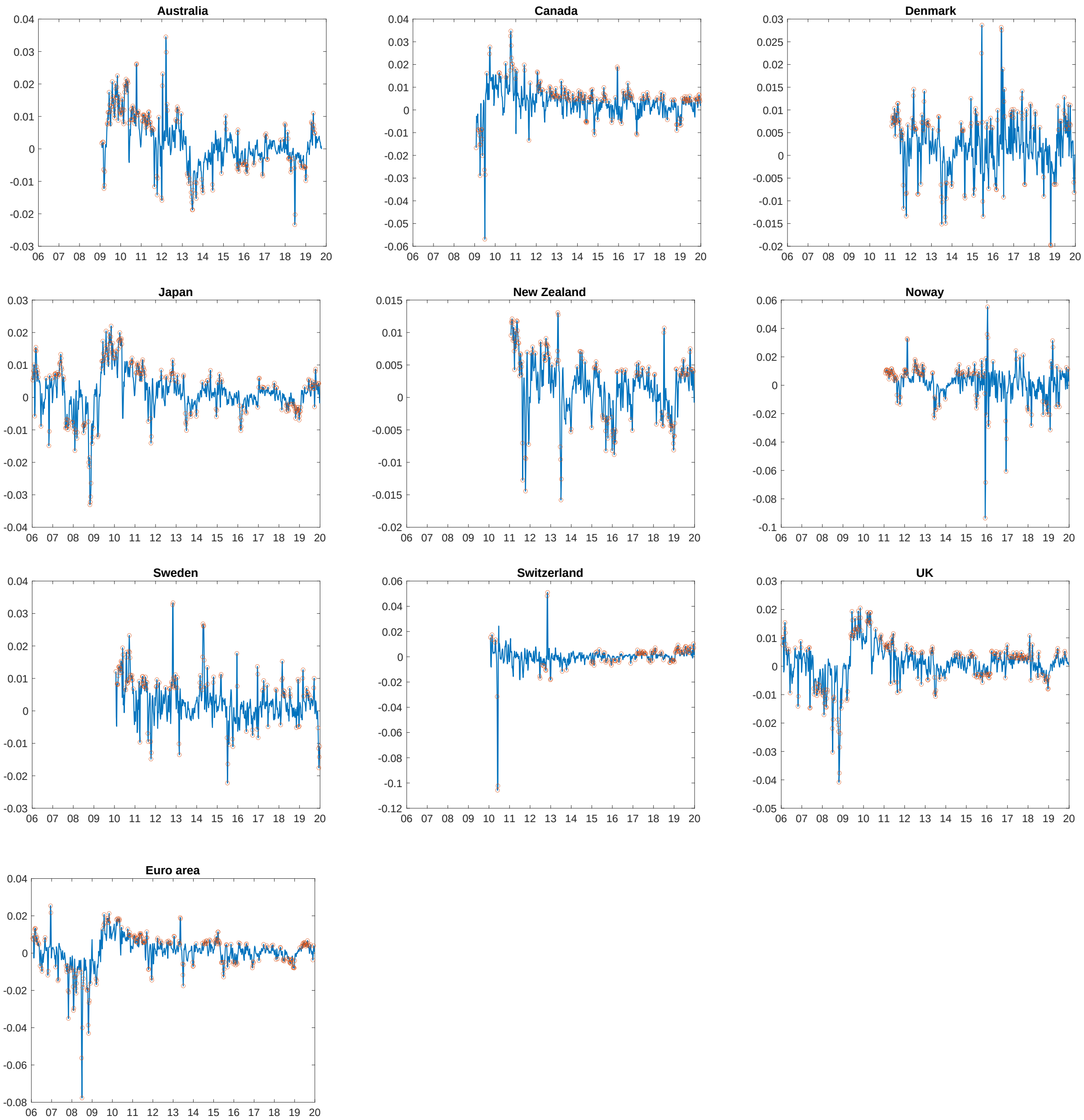
	mean return	st.error	Sharpe ratio
(1) Benchmark *FLOW*	8.889***	3.219	1.081
(2) Start sample 2007	8.719***	3.327	1.065
(3) Start sample 2008	8.564**	3.407	1.053
(4) Start sample 2009	6.749**	3.189	0.922
(5) Start sample 2010	6.376**	3.131	0.916
(6) Three FX portfolios	7.445***	2.694	1.018
(7) Five FX portfolios	10.893***	3.719	1.205
(8) 1w formation period	9.077**	3.645	1.030
(9) 3w formation period	6.435**	3.168	0.774
(10) 4w formation period	10.706***	3.345	1.210
(11) 2w return period	6.015*	3.185	0.730
(12) 3w return period	6.750*	3.547	0.739

Figure 1. Standardised bond flows, EMEs



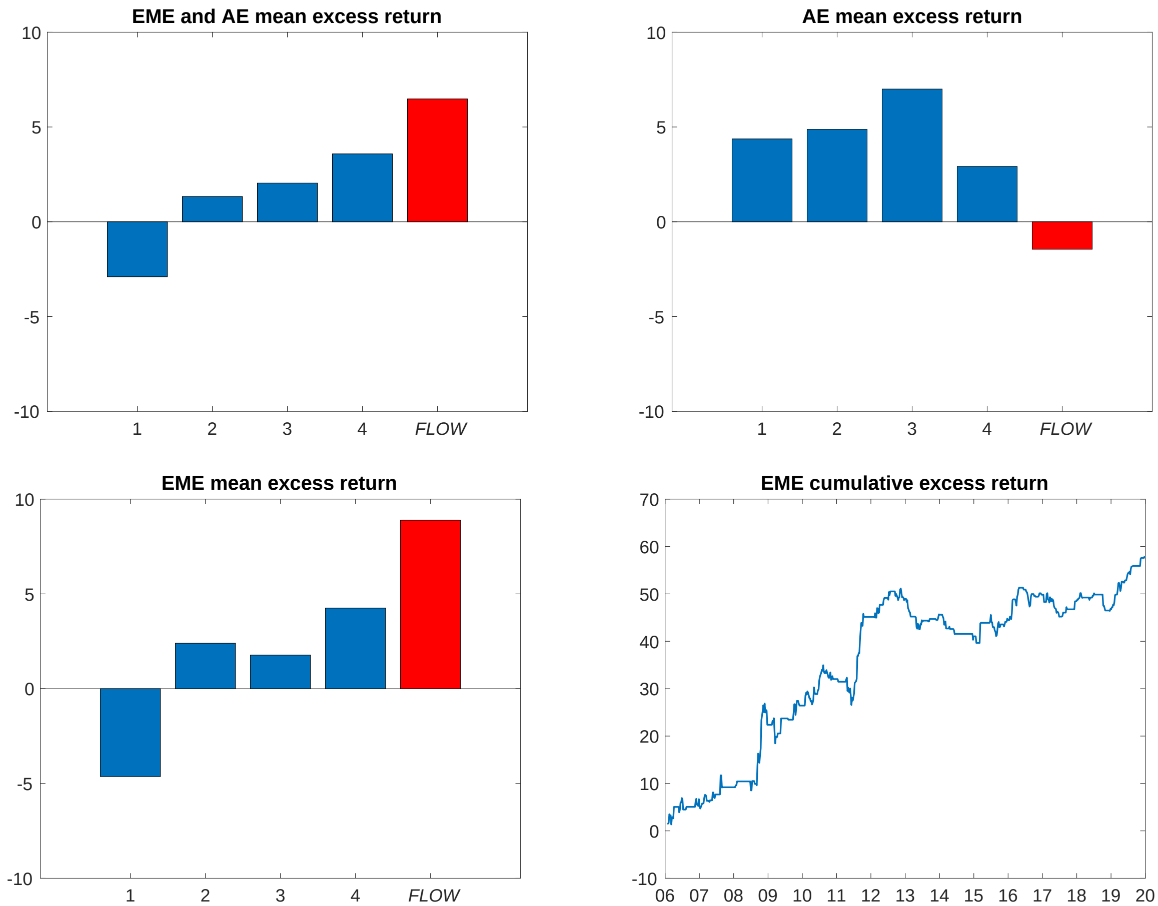
EPFR bond flows, standardised by assets under management. Orange markers denote flows that in absolute size are larger than one standard deviation, as measured over the preceding two years.

Figure 2. Standardised bond flows, AEs



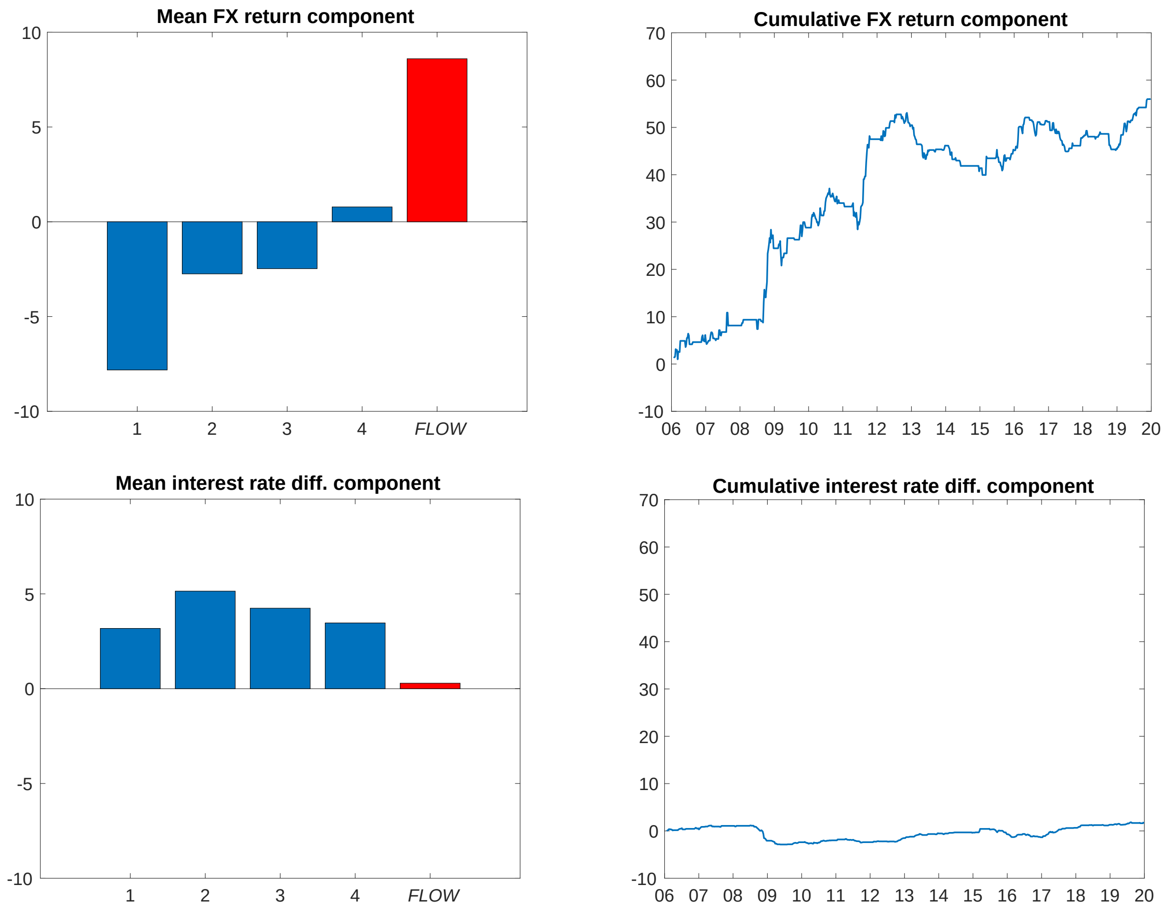
EPFR bond flows, standardised by assets under management. Orange markers denote flows that in absolute size are larger than one standard deviation, as measured over the preceding two years.

Figure 3. Portfolio excess returns



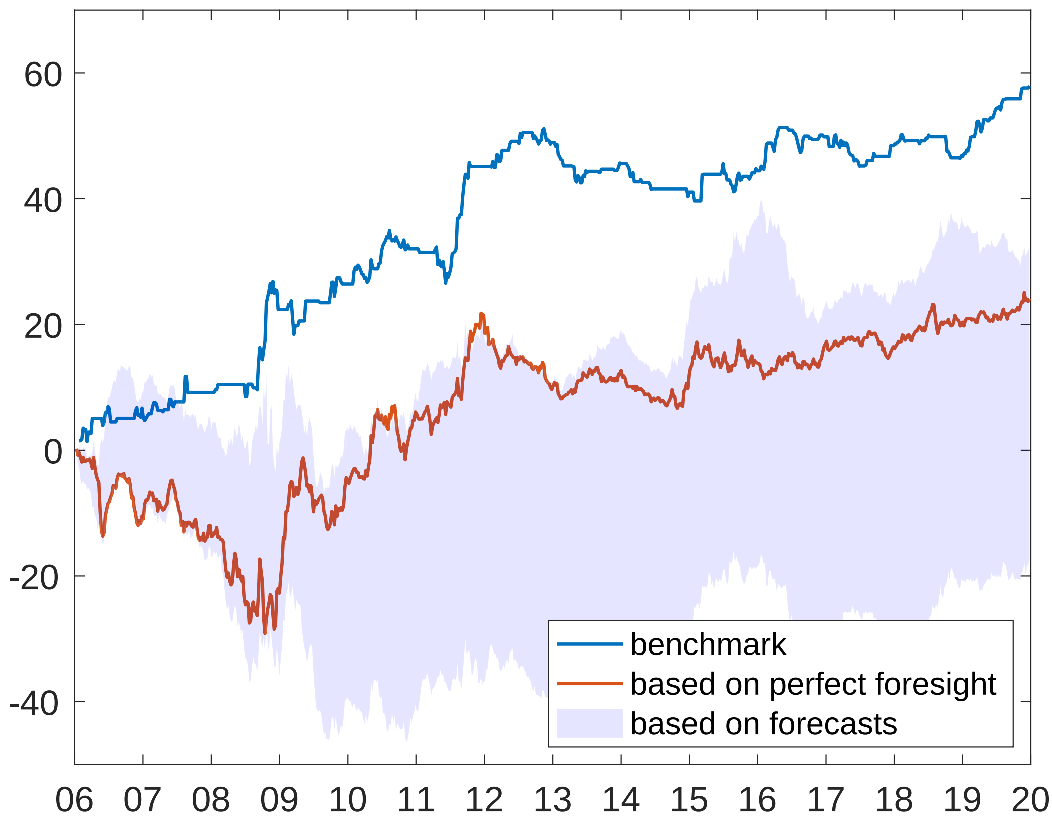
Excess returns of portfolios formed by sorting on lagged bond portfolio flows. Portfolio 1 consists of currencies with the largest outflows prior to the formation of the portfolio, and portfolio 4 the ones with the largest inflows. Portfolio $FLOW$ goes long portfolio P_4 and shorts portfolio P_1. Bar charts show mean excess returns over the entire sample (annualised); the line graph is the cumulative excess return of the EME $FLOW$ portfolio. Returns are continuously compounded and expressed in percent.

Figure 4. EME portfolio excess return decompositions



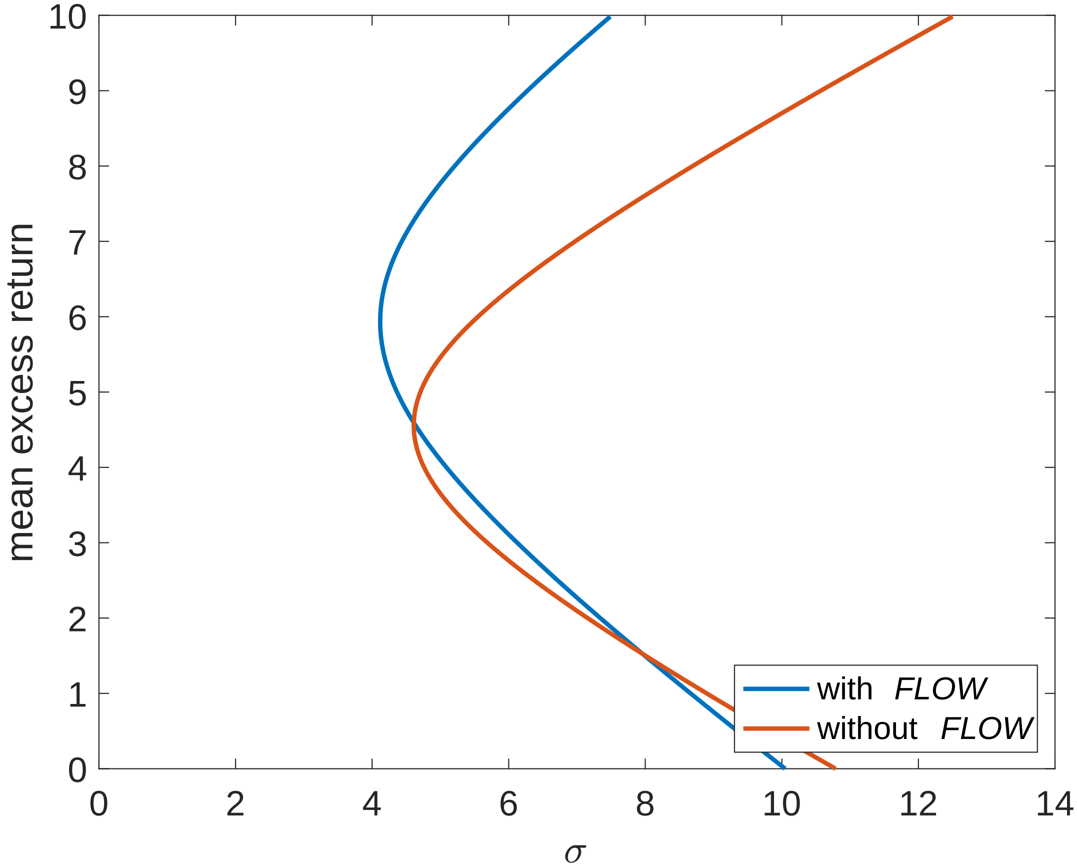
Mean and cumulative excess portfolio return components due to FX returns and to interest rate differentials. P_1 consists of currencies with the largest bond outflows and P_4 the ones with the largest inflows. Portfolio $FLOW$ goes long P_4 and shorts P_1. Returns are in percent; mean returns are annualised.

Figure 5. Forecast-based cumulative portfolio excess returns



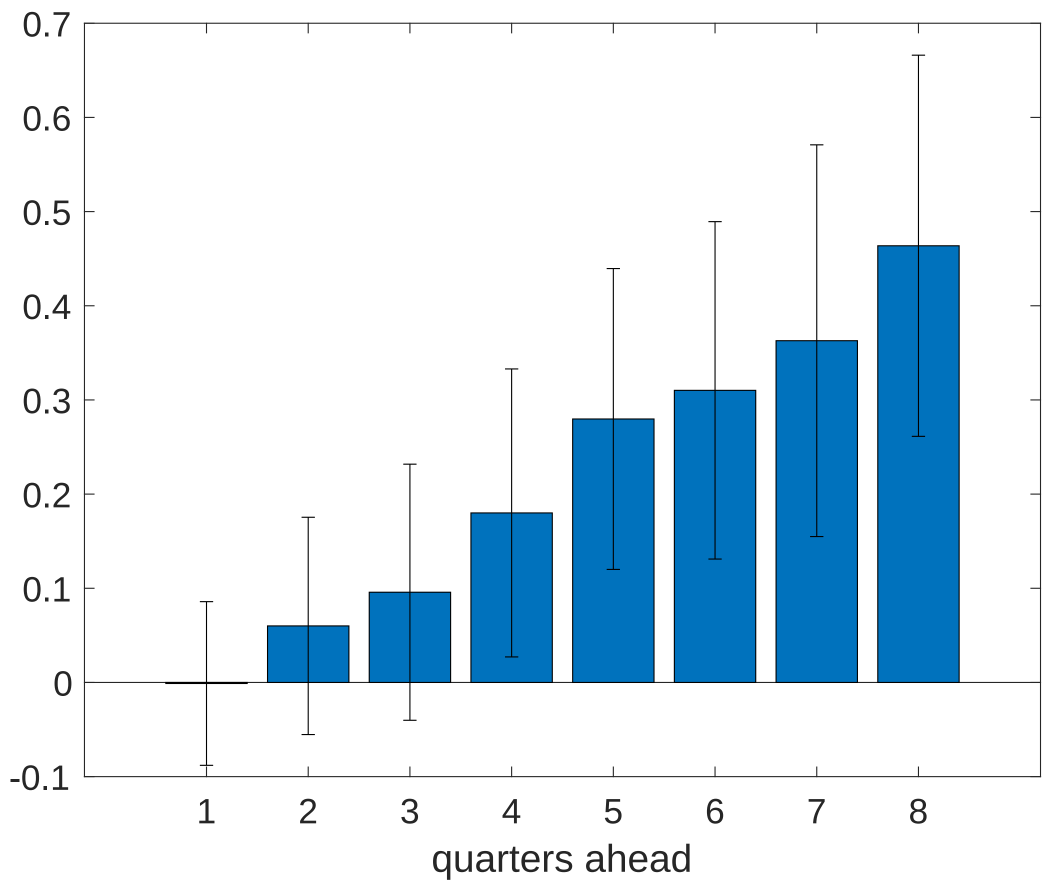
Cumulative excess returns of long-short *FLOW* portfolios formed by going long the portfolio of EME currencies with the largest bond inflows and going short the portfolio with the largest outflows. The blue line corresponds to the *FLOW* portfolio based on our benchmark methodology, where FX portfolios are formed by sorting on lagged bond portfolio flows. The shaded area displays the range of cumulative *FLOW* excess returns where FX portfolios are formed on the basis of 110 different forecasted flow series (using different combinations of lagged flows and FX excess returns to forecast flows). The red line corresponds to the *FLOW* portfolio formed using perfectly forecasted future bond flows. Returns are expressed in percent and are continuously compounded.

Figure 6. Efficient portfolio frontiers



Minimum variance portfolios constructed by combining the portfolios listed in Table 5 (blue line) and the same portfolios but excluding the *FLOW* portfolio (orange line). The mean portfolio returns and standard deviations are based on annualised returns, expressed in percent.

Figure 7. Future FCI changes: P4 minus P1 economies



Changes in future financial conditions indices (FCI): difference in mean value for EME economies whose currencies are in Portfolio 4 minus that of economies in Portfolio 1. A higher FCI value indicates tighter financial conditions. Changes are calculated up to 8 quarters ahead from each portfolio formation date. Portfolio 1 consists of currencies with the largest bond portfolio outflows prior to the formation of the portfolio, and Portfolio 4 the ones with the largest inflows. Error bars are 95% confidence intervals. The FCI data is from Goldman Sachs.

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