Cross-border flights to safe assets in bond markets: evidence from emerging market economies

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Abstract

This paper investigates cross-border flights to safety (FTS) in sovereign bond markets from the perspective of emerging market economies (EMEs). Accurate identification of such events provides a detailed picture of sharp changes in prices of international assets and potential sources of EMEs' financial fragility. We construct new measures of the FTS occurrence and magnitude by focusing on extreme movements in long-term bond markets vis-à-vis the US for a diverse group of 21 EMEs. An adaptable time-series anomaly detection algorithm is used to recognize patterns in daily data on bond returns from 2002 to 2021. The paper shows that the FTS episodes in the entire sample of EMEs turn out to be short-lived and map well into periods of international financial and economic downturns. We demonstrate the importance of global uncertainty shocks and the US dollar exchange rate fluctuations in driving FTS, with the relative importance of the latter factor increasing after the Global Financial Crisis. The results from panel data models indicate that a range of country-specific economic, financial, and political factors matter visibly more for the FTS magnitude than their mere occurrence. This supports the notion that flights from bond markets are triggered mainly by shocks originating outside of EMEs, but the magnitude of these events may materially depend on their domestic conditions, including macroeconomic stability and policy factors. However, the role of economic fundamentals in driving FTS seems to subside post-2010 at the expense of financial factors. As a by-product, we present a database on FTS episodes in bond markets.

Keywords: emerging market economies; flight to safety; safe assets; bond markets; foreign-exchange markets; global risk

JEL Classification: E42, F32, F41, G15

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1 Introduction

The global economy has long been marked by booms and busts of financial flows among countries. This pattern is notable for emerging market economies (EMEs), where waves of sharp capital inflows and outflows often translate to crises (Forbes and Warnock, 2012; Ghosh et al., 2014; Eichengreen et al., 2018). In recent years, those economies experienced numerous instances of flight to safety (FTS) episodes, when investors re-balance their portfolios and the valuation of assets perceived as risky deteriorates. Recent examples of such episodes include the aftermath of the 2007-2009 Global Financial Crisis (GFC), the so-called taper tantrum following the Fed's decision to withdraw from quantitative easing in 2013, the 2015-2016 Chinese capital market turbulence, and the COVID-19 shock to the global economy in the first quarter of 2020 (e.g., Ferriani, 2021; Gelos et al., 2022). Arguably, the problem of cross-border FTS has intensified as a result of significant developments observed in the global economy. First, in the last two decades, emerging economies experienced rapid growth in their financial systems. International financial integration and opening up of local bond markets to foreign investors, however, created new types of risks, such as vulnerability to external financial conditions (Aizenman et al., 2021). Second, a general scarcity of safe assets in the international monetary system makes the US Treasury bonds a special asset, central to financial flows in other sovereign debt markets (Jiang et al., 2021). Consequently, when global risk levels diminish, investors typically reach for yield by acquiring riskier assets, among them sovereign bonds issued by EMEs. In times of elevated uncertainty, they deploy capital to safer assets. This, in turn, impacts the valuation of assets and market interest rates, conceivably leading to financial and macroeconomic instabilities in EMEs (Brunnermeier and Huang, 2019).

In this paper, we set out to develop new measures of cross-border FTS from sovereign bond markets in EMEs. These indicators capture both the FTS occurrence and magnitude based on extreme movements of bond returns in a diverse group of 21 EMEs. We identify the FTS episodes by applying a versatile anomaly detection algorithm on daily bond returns covering the period from 2002 to 2020. The study takes into account global macroeconomic and financial factors that potentially drive flights to safety. To this end, we construct aggregate indicators of FTS and examine their response to external shocks. Next, we investigate country-specific factors of emerging economies that influence the frequency and magnitude of such episodes in fixed-effect Poisson panel data models.

The contribution of this study is threefold. First, building on the literature on the stock-bond flight to safety (e.g., Baele et al., 2020), we construct FTS measures using the outlier detection algorithm based on an exponentially weighted moving average that has not been used in this context. Second, we add to the literature on the safety of sovereign bonds by providing an empirical investigation of high-frequency movements in sovereign bond returns. We go beyond the mere occurrence of FTS episodes and quantify their magnitude. Third, we complement studies on drivers of international financial flows by exploring determinants of precisely defined flight incidences from bond markets in EMEs, both at the aggregate and country levels. As a by-product, we present a database on FTS episodes in bond markets.

The paper shows that the FTS episodes in the entire sample of EMEs turn out to be short-lived and map well into periods of international financial and economic downturns. We demonstrate the importance of global uncertainty shocks and the US dollar exchange rate fluctuations in driving FTS, with the relative importance of the latter factor increasing after the GFC. The results from panel data models indicate that a range of country-specific economic, financial, and political factors matter visibly more for the FTS magnitude than their mere occurrence. This lends support to the notion that flights from bond markets are triggered mainly by shocks originating outside of EMEs, but the magnitude of these events may materially depend on their domestic conditions, including macroeconomic stability and policy factors. However, the role of economic fundamentals in driving FTS seems to subside post-2010 at the expense of financial factors. As a by-product, we present a database on FTS episodes in bond markets.

The rest of this paper is structured as follows. Section 2 situates the paper within the recent literature. In section 3, we lay down the identification scheme of FTS episodes and show its results. Section 4 relates FTS to global risk factors, US monetary policy, and changes in the dollar exchange rates. In section 5, we investigate country-specific drivers of FTS in a panel setting, along with a number of robustness checks. Section 6 concludes.

2 Related literature

This study lies at the intersection of three strands of the literature. First, it connects to the body of work on safe assets in the global economy, in particular their role for EMEs. The theoretical framework of this literature indicates that economic actors in the global economy need to store a fraction of their wealth in secure holdings (Caballero and Simsek, 2020). Such safe assets are relatively scarce but play a unique economic role due to their property to retain value in periods of elevated uncertainty. As shown by Krishnamurthy and Vissing-Jorgensen (2012), the low-risk properties of the US Treasury bonds make them a prominent example of a safe asset and earn them the so-called convenience yield, an additional value distinct from other sources of premiums, such as high liquidity. In the international context, the limited supply of secure assets in EMEs translates to safety-seeking cross-border financial flows and is essential for exchange rate determination (Jiang et al., 2021). On the empirical side, there are several recent attempts to determine the drivers of the safety status of various economies (Du and Schreger, 2016; Goldberg and Krogstrup, 2018; Habib et al., 2020; Dimic et al., 2021). These studies often show that determinants of safety are distinct in EMEs and advanced economies, while the cross-border dependencies of EME bond markets exhibit more instabilities, primarily due to global crisis events.

Second, our paper is linked to research on financial flow volatility and extreme capital movement episodes in EMEs, in particular portfolio-debt flows. Sudden stops in international capital flows have long been a concern for EMEs, not only subsequent output collapses but also due to little or no recovery in domestic banking systems and dynamics of credit and investment (Calvo et al., 2006). Several empirical studies investigate periods of large capital outflows or inflows to describe their changes over time and find their drivers (Forbes and Warnock, 2012; Ghosh et al., 2014; Dhar, 2021). They document that sharp capital flows experienced by EMEs stem from an interplay between global shocks and domestic vulnerabilities, with the latter often serving as 'gateways' for external factors. At the same time, the role of shocks is shown to differ substantially across capital outflow episodes (Friedrich and Guérin, 2020). Studies focused specifically on bond markets show the cross-border flows to and from EMEs to be abrupt and reverse quickly, but also that substantial contagion in those episodes across EMEs (Eichengreen et al., 2018; Li et al., 2019). Recently, however, Forbes and Warnock (2021) accentuate that the relationship between extreme capital flow episodes and global risk measures has weakened in the post-GFC period. Gelos et al. (2022), on the other hand, demonstrate that EMEs can partly shield themselves from 'capital flows at risk' stemming from adverse global shocks. They highlight the role of domestic structural factors and macroeconomic policies in shaping their response to extreme capital flows, particularly in the medium run.

Third, on the methodological side, the paper relates to a broad literature on the flight to safety episodes in financial markets. Most empirical studies in this area focus on FTS effects between equity (stock market) and sovereign bond returns within one country or between equities and other assets, such as gold or commodities. A substantial literature related to Baur and Lucey (2010) investigates the behaviour of asset prices during market downturns, risk-return trade-offs, and their relation to various market conditions. It generally shows that safety-seeking behaviour is a prevalent phenomenon in the US financial market, even if FTS events may display nonlinearities in the degree of investors' uncertainty or the level of sovereign bond yields (Adrian et al., 2019; Boucher and Tokpavi, 2019; Soylu and Güloğlu, 2019). In one of the most comprehensive studies in this area, Baele et al. (2020) document empirical facts on FTS between bonds and stocks in the US and numerous economies. They demonstrate that FTS spells, periods when the conditional bond-stock return correlations become extremely negative, tend to be persistent and accompanied by increases in equity risk premium. It must be noted, however, that studies conducted in this area have not yet looked directly into tail events in sovereign bond markets across EMEs and their relationship to the behaviour of safe assets, such as the US Treasury bonds.

3 Identification of flight to safety episodes

This section describes the procedure used to extract FTS episodes in EME sovereign bond markets. It provides results of FTS identification and calculates aggregate, overall measures of FTS occurrence and magnitude.

3.1 FTS detection algorithm and data

The conceptual underpinnings of our FTS detection algorithm come from the distinction between safe and risky assets in the global economy. Those differences imply a certain behaviour of returns of those asses in periods of financial distress. During an FTS episode, we should observe a negative pressure on the prices of risky assets: their value decreases as international investors drop riskier assets and look for safer alternatives. The opposite is true for the US Treasury bonds, often considered a critical safe asset in the global economy.[1] Hence, during the FTS episode, the returns of EME and US bonds will temporarily change in opposite directions.

[1]Nonetheless, US Treasury bonds cannot be considered an absolutely safe asset. He et al. (2021) provide evidence of the Treasury "inconvenience yield" that may have occurred for a short period in March 2020, i.e., at the peak of the COVID-19-induced crisis. A possible explanation of this phenomenon comes from balance sheet constraints experienced by large holders of Treasuries.

The function that we use to identify FTS events makes use of asymmetric conditions imposed on 10-year bond returns in a given EME, $r_{i,t}$, and the US Treasury bond returns on the same date, $r_{us,t}$. Following our basic premise, the occurrence of FTS on the day t is defined with the following conditional function:

$$FTS^{O}_{i,t} := \begin{cases} 1 & \text{if} \quad r_{i,t} < l_{i,t} \quad \text{and} \quad r_{us,t} > l_{us,t}, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

where $l_{i,t}$ and $l_{us,t}$ are thresholds that distinguish extreme bond returns. Such a setting implies that FTS episodes happen only when changes in returns are, at the same time, extremely low for a given EME bond and extremely high for the US Treasury bond. The most common ways to identify such abnormal returns include the use of distribution-based thresholds to cut-off outliers (Baur and Lucey, 2010), possibly with structural changes in long term volatility of returns (Śmiech and Papież, 2017), or estimation of quantile regressions (Boucher and Tokpavi, 2019). Baele et al. (2020), however, provide alternative ways to extract FTS dates, such as a Markov-switching regression.

In this paper, we generally follow the threshold approach to FTS identification, but we also notice that the problem we face is similar to the outlier detection in time series when anomalies themselves are events of interest. This, in turn, opens room for numerous alternative methods for anomaly detection (see a comprehensive review by Blázquez-García et al., 2021). Given its flexibility and the fact that it may be used for a broad range of time series, we opt for the shift detection algorithm exponentially weighted moving average (EWMA), as described by Iturria et al. (2020) and Raza et al. (2015).

In the first step of the algorithm, datasets on bond returns in EMEs and the US are divided into the training and testing subsets. All stages of the procedure are then performed for each EME and the US returns. During the training phase, the z-statistics are computed for a range of λ values:

$$z_t = \lambda r_t + (1 - \lambda) z_{t-1}, \tag{2}$$

with the starting value of z_0 based on the mean of input data on bond returns. Next, a one-step-ahead prediction error is computed:

$$err_t = r_t - z_{t-1}, \tag{3}$$

and λ is estimated by minimizing the sum of the squared prediction error. This allows us to calculate the variance of model residuals, denoted as $\sigma^2_{err_0}$ which serves as the initial value of variance in the testing phase.

In the testing phase, computations in Equations (2) and (3) are iterated and the corresponding variance is estimated:

$$\hat{\sigma}^2_{err_t} = \vartheta err^2_t + (1 - \vartheta)\hat{\sigma}^2_{err_{t-1}}, \tag{4}$$

where ϑ is an error smoothing constant. This, in turn, allows us to calculate upper (l^+_t) and lower control limits (l_t^-), and detect outliers in the testing subset:

$$l_t^+ = z_{t-1} + \kappa \hat{\sigma}_{err_{t-1}}, \qquad l_t^- = z_{t-1} - \kappa \hat{\sigma}_{err_{t-1}}, \tag{5}$$

where κ is the control limit multiplier which indicates how sizeable a deviation from the threshold must be for an observation to be classified as an outlier.

In a general outlier detection scheme, a given data point is compared to both threshold limitations. In this specific case, however, we are interested only in one-side deviations for a given EME and the US bond returns. Hence, the requirement formulated in Equation (1) translates to the following set of conditions for FTS detection:

$$r_{i,t}^- < z_{i,t-1} - \kappa \hat{\sigma}_{err_{i,t-1}} \quad \text{and} \quad r_{us,t}^+ > z_{us,t-1} + \kappa \hat{\sigma}_{err_{us,t-1}}. \tag{6}$$

This implies that in the period t the return on EME sovereign bond is negative and below the lower control limit. In contrast, the return on the US bond is positive and above the threshold calculated in the EWMA algorithm.

Apart from occurrences of FTS episodes, we aim to measure their strength or magnitude. Here, we build on the idea put forward by Baele et al. (2020) in their analysis of stock-bond returns. The magnitude of FTS constructed as a product of FTS occurrence on a given date (zero or one) and the sum of the absolute value of bond returns on this date:

$$FTS_{i,t}^M = FTS_{i,t}^O \times \left(r_{us,t}^+ - r_{i,t}^- \right). \tag{7}$$

A larger wedge between the US and EME returns, $r_{us,t}^+ - r_{i,t}^-$, implies higher FTS^M values and a larger magnitude of a given FTS episode. Hence, using the $FTS_{i,t}^M$ measure, we are not only able to show whether an FTS episode happens on a particular date but also to capture its intensity.

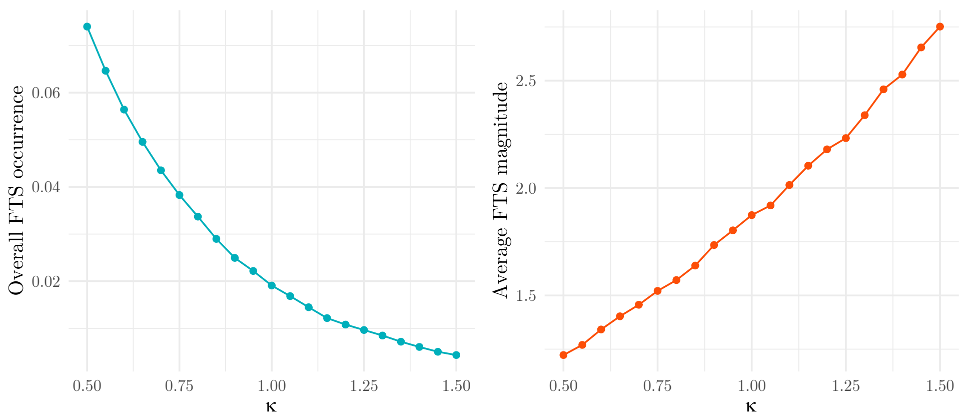
Since FTS episodes are bound to be contemporary, and sharp changes in bond returns may dissipate through various channels, we opt for high-frequency data to detect FTS episodes. The dataset we gather covers 21 major EMEs, all using their own currencies, in a maximum timespan from January 1, 2002 to March 30, 2021. Its coverage is limited by data availability. Entries for nine EMEs start later in the sample.[2] Local currency benchmark sovereign yields provided by Refinitiv Datastream are transformed into total daily returns that include both bond prices and coupon payments. Next, we convert local currency returns into dollar returns using spot dollar exchange rates sourced from the same data provider, which allows us to account for the possible impact of exchange rate fluctuations on the valuation of bonds. To simultaneously take into consideration time differences in trading hours in Latin American, European, and Asian countries, we transform the bond return series into a two-day moving average following Forbes and Rigobon (2002). Unlike many studies on bond yields in EMEs, we do not trim or winsorize bond returns in any way.

Having established the basic features of the FTS detection algorithm, we run its consecutive steps using the prepared dataset. The results of the EWMA procedure depend chiefly on the choice of the control limit multiplier parameter, κ, in Equation (6). Hence, we first investigate

[2]The dataset details and descriptive statistics are summarized in Table A.1 in the Appendix.

the algorithm outcomes for a grid of κ values, ranging from 0.5 to 1.5, each time measuring the frequency and average magnitude of FTS episodes. The error smoothing constant (ϑ) in Equation (4) is set to a recommended value 0.01 and the initial training sample is equal to 250 days.[3] The results of these simulations are depicted in Figure 1. The left-hand panel of the graph shows that there is a decreasing but non-linear relationship between κ and the share of identified episodes. For $\kappa = 0.5$, we obtain FTS occurrences on 7.400% of days. When this parameter reaches 1, the number of episodes goes down to 1.908%, and for $\kappa = 1.5$, there are only 0.434% of FTS days in the sample. The average magnitude - the mean value of FTS^M on an FTS day is increasing, as less severe FTS episodes are being discarded for higher threshold parameter values. κ value of 0.5 corresponds to 1.223 points, while the threshold parameter of 1.5 results in the average magnitude of 2.751 points.

Figure 1: FTS events under different values of the κ parameter in the EWMA algorithm



Notes: The LHS of the figure plots the overall FTS frequency, calculated as a share of FTS episodes in the total number of country-days in the sample, under subsequent values of κ threshold parameter in Equation (6), i.e., under different values of the control limit multiplier in the FTS detection. Average FTS magnitude is the mean value of FTS on event days across the sample.

When selecting the appropriate value of the multiplier parameter, we compromise between different target values for FTS frequency adopted in studies on high-frequency stock-bond FTS and choose the parameter that corresponds to the frequency of around 2% (Boucher and Tokpavi, 2019; Baele et al., 2020). In our case, $\kappa = 0.96$ leads to the identification of FTS events on 2.016% of country-days.

3.2 Identification results and the overall FTS indicator

Once FTS episodes are identified, we look into their properties, starting at the country level. Table 1 presents average changes and standard deviations of 10-year bond returns during and outside FTS episodes for all economies in the sample. Additionally, the table contains returns of the US Treasury bonds. A simple mean number of episodes varies across EMEs, but the interquartile range of 1.723%-2.390% is relatively narrow. Much more pronounced differences are related to changes in bond returns on FTS days. On average, bond returns drop by 1.316%, with

[3]For the details on the algorithm implementation in R, see Iturria et al. (2020).

the highest values for Turkey, South Africa, Russia, and Brazil, countries universally considered risky. At the same time, sizeable standard deviations of bond returns during FTS indicate high variability of the magnitude of these episodes over time. The US bond returns during FTS are comparable for all EMEs, with an average value of 0.561. Outside of the FTS episodes, mean returns on EME bonds are marginally positive but close to zero in all countries except Turkey. The mean returns on the US bonds on FTS days are similar across EMEs, with a mean value of 0.569.

Table 1: Changes in 10-year bond returns during and outside the FTS episodes

	FTS frequency	During FTS				Outside FTS	
		$\overline{r_{i,t}}$	$sd(r_{i,t})$	$\overline{r_{us,t}}$	$sd(r_{us,t})$	$\overline{r_{i,t}}$	$sd(r_{i,t})$
Brazil	2.432	-2.548	2.102	0.583	0.320	0.073	1.697
Bulgaria	2.054	-1.136	0.830	0.588	0.354	0.032	0.759
Chile	2.233	-0.800	0.689	0.561	0.280	0.011	0.604
China	2.038	-0.503	0.405	0.499	0.222	0.015	0.317
Colombia	2.399	-1.627	1.104	0.619	0.342	0.051	1.085
Czechia	1.656	-1.008	0.870	0.584	0.301	0.028	0.606
Hungary	1.782	-1.878	1.583	0.617	0.323	0.035	1.072
Indonesia	1.337	-1.116	1.617	0.593	0.386	0.014	1.109
Israel	1.723	-0.720	0.435	0.611	0.340	0.037	0.787
India	2.117	-0.756	0.572	0.548	0.301	0.008	0.501
Korea	2.159	-0.861	0.836	0.578	0.332	0.028	0.547
Mexico	1.866	-1.257	1.135	0.661	0.437	0.014	0.864
Malaysia	2.243	-0.644	0.371	0.550	0.310	0.014	0.404
Peru	2.195	-0.579	0.558	0.517	0.346	0.003	0.421
Philippines	1.342	-1.174	1.063	0.599	0.327	0.034	0.866
Poland	2.390	-1.507	1.252	0.614	0.286	0.045	0.760
Romania	2.452	-1.453	1.001	0.586	0.342	0.033	0.921
Russia	2.564	-2.535	2.999	0.618	0.336	0.049	1.519
Thailand	1.027	-0.699	0.677	0.550	0.291	0.018	0.462
Turkey	1.689	-2.802	4.320	0.614	0.410	-0.047	1.708
South Africa	2.788	-2.035	1.359	0.634	0.321	0.050	1.060
Mean	2.023	-1.316	1.228	0.587	0.329	0.026	0.860
Q(25)	1.723	-1.627	0.677	0.561	0.301	0.014	0.547
Median	2.117	-1.136	1.001	0.588	0.327	0.028	0.787
Q(75)	2.390	-0.756	1.359	0.614	0.342	0.037	1.072

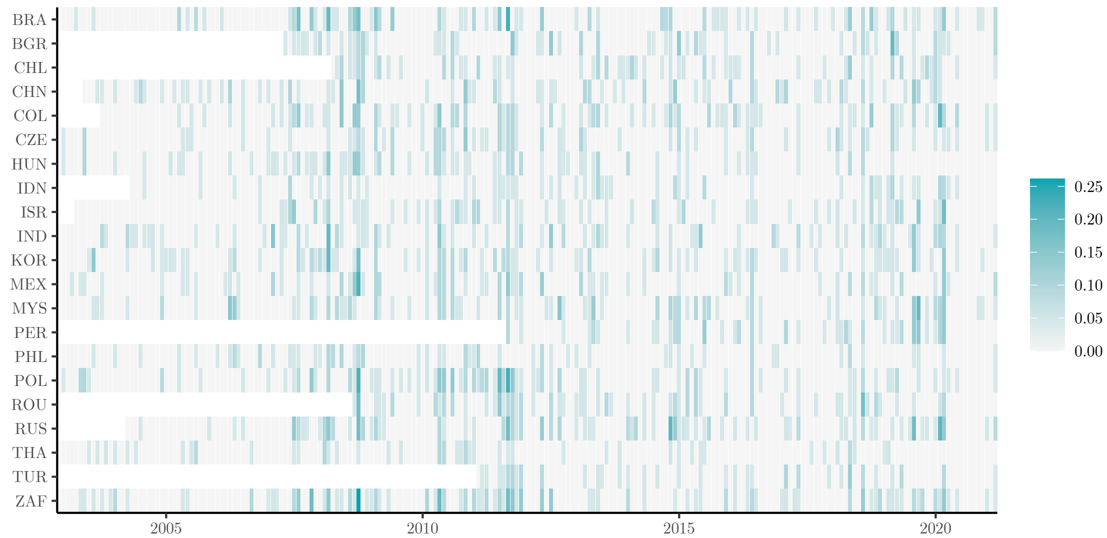
Notes: FTS frequency is calculated as a share of FTS days over the total number of days in a sample of bond returns for a given country. $\overline{r_{i,t}}$ denotes the average 10-year sovereign bond return and $\overline{r_{i,t}}$ denotes standard deviation of bond returns for a given EME. $\overline{r_{us,t}}$ and $sd(r_{us,t})$ designate analogous quantities for the US bond returns.

In the next steps, we aggregate FTS occurrence and magnitude indicators across two dimensions. First, daily measures are aggregated to lower frequencies, and we transform FTS occurrence for each EME by summing them over weeks, months and quarters. We construct both the "count" occurrence indicator, based on the number of FTS events in a given period and a "frequency" indicator, expressed as a fraction of FTS days in the total number of days. With respect to the FTS magnitude indicator, we aggregate its daily values by summing over a given period.[4] As an example, the heatmap in Figure 2 displays the country-level series in monthly frequency, measured as a fraction of FTS days in a given month. A notable feature visible in this plot is the clustering of FTS episodes at certain months, followed by a more tranquil period. Moreover, one may notice a relatively lower frequency of FTS occurrence before the GFC and a substantial increase in their frequency post-2008. Still, some country-month observations with

[4]The complete set of those series is available in the database that accompanies the paper. The database collects daily, weekly, monthly, and quarterly measures of FTS as count data, frequency, and magnitude, both for individual EMEs and in aggregates.

a higher share of FTS days seem to be more idiosyncratic. We return to the question of FTS commonality across EMEs in Section 4.1.

Figure 2: Occurrence of flight to safety episodes across countries



Notes: The heatmap displays frequency of identified FTS episodes for all EMEs included in the sample on a monthly basis. The numbers marked in the heatmap are the fraction of FTS days in a given month. Blank spaces represent unavailability of data.

Secondly, we aggregate the FTS measures across countries to obtain the overall FTS indicators, calculated for all EMEs in the sample. The overall occurrence indicator, denoted simply as FTS_t^O, shows the average frequency of FTS country-days in a given time period. By analogy, we construct the overall magnitude indicator, FTS^M, as the average value of FTS country-days. Table 2 describes the basic characteristic of the overall FTS indicators at weekly, monthly, and quarterly frequencies. It shows substantial time-variation in FTS occurrence and magnitude, as confirmed by high statistics for skewness and kurtosis. Relatively small estimates of AR(1) coefficients indicate that both overall FTS indicators show little persistence and quickly revert to the mean, although FTS^M measure displays slightly stronger autocorrelation.

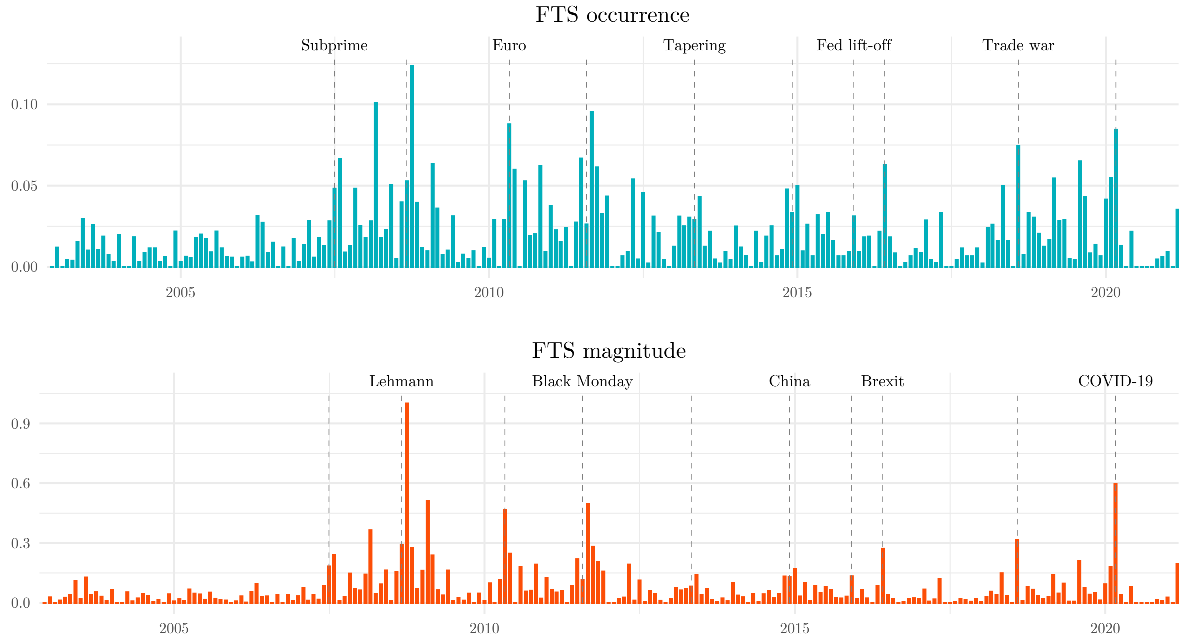
Table 2: Descriptive statistics of the overall FTS indicators

		Mean	Median	Max.	Std. dev.	Skewness	Kurtosis	AR(1)
	Weekly	0.020	0.000	0.286	0.037	2.873***	13.768***	0.112***
FTS occurrence	Monthly	0.020	0.012	0.124	0.021	1.843***	7.258***	0.238***
	Quarterly	0.020	0.016	0.062	0.015	1.201***	4.135**	0.299***
	Weekly	0.039	0.000	1.209	0.097	5.391***	43.857***	0.188***
FTS magnitude	Monthly	0.038	0.021	0.534	0.059	4.143***	27.780***	0.338***
	Quarterly	0.038	0.025	0.243	0.043	2.506***	10.091***	0.363***

Notes: The table shows summary statistic for the overall indicators of FTS occurrence and magnitude. *** and ** denote statistical significance at 0.01, 0.05 levels, respectively.

The evolution of overall FTS indicators, in monthly frequency, is plotted in Figure 3. For ease of interpretation, we normalized FTS^M for the min-max values from zero to one. The indicators turn out to map well into major international financial events, both in terms of the occurrence and magnitude. It must first be noted that the identified FTS episodes are relatively infrequent and weak before the GFC. An important jump in their intensity takes place around July-August 2007, when the financial turmoil related to the US subprime crisis began (marked as *Subprime*). After this date, the FTS incidences escalate to reach both the highest frequency (12.8% of country-days) and magnitude in October 2008, when we can narratively identify the beginning of the GFC.

Figure 3: Overall FTS measures: occurrence and magnitude



Notes: The figure displays the overall FTS measures, calculated for all EMEs in the sample, in monthly frequency. FTS occurrence indicator measures the share of FTS episodes in the total number of country-days in a given month. FTS magnitude is normalized to range from zero to one. Dashed vertical lines denote dates of events indicated in the upper parts of graphs.

Apart from the outbreak of the GFC in 2008 (*Lehmann*), the most pronounced episodes of FTS may be associated with the market crash of 2011 (*Black Monday*) and the COVID-19 financial turmoil in March 2020 (*COVID-19*). The FTS magnitude in March 2020 was around 60% of that detected at the height of the GFC. However, other global risk-off events, such as the Eurozone crisis, the Chinese capital market crash, or Brexit, may also be traced to the FTS indicators. Interestingly, some of the events marked in the graphs, such as tapering, appear to be related to an increase in the FTS occurrence but not in their magnitude.

4 Flight to safety: a global perspective

This section investigates bond-market FTS measures from a global perspective. We assess the comovement of these indicators across EMEs and relate them to major global risk factors. Next, we estimate a VAR model using the overall FTS indicator and quantify the role of global shocks in driving FTS occurrence and magnitude.

4.1 Commonality of FTS and global risk measures

In order to explore the comovement of FTS measures among EMEs, we calculate two sets of correlation coefficients, using indicators aggregated to a monthly frequency. Their distributions are summarized in Table 3. First, unconditional quantiles of correlation coefficients are calculated in a pairwise manner, based on the full correlation matrices and every possible pair of EMEs. Figure A.1 in the Appendix displays these matrices for both FTS occurrence and magnitude in the entire sample of economies. From a country perspective, China, Thailand, and Turkey are among the economies with the most idiosyncratic FTS occurrence and magnitude, while FTS measures in emerging Europe, Korea, Mexico, and South Africa are correlated with each other at high levels. Coefficients are additionally calculated for pre- and post-crisis periods to consider possible structural breaks that appear around the GFC. All three samples produce comparable median values of pairwise correlations, in each case higher for the magnitude indicators and ranging from 0.307 to 0.374.[5] The upper quantiles values, $Q(90)$, are notably larger in the pre-crisis period, suggesting a stronger comovement of FTS indicators in this period. However, pairwise correlations generally point to considerable dissociation of FTS events across EMEs.

The second set of correlation coefficients is calculated between each EME and the overall FTS indicators defined in the previous section. In this case, the coefficients are much higher than pairwise correlations, and their median values consistently exceed 0.6. The range between high and low quantiles remains sizeable and larger for the magnitude indicators. Despite this, the overall indicator reveals a strong correlation with the vast majority of economies in the sample. Similarly to pairwise correlation, it is confirmed that the comovement of FTS frequency and magnitude decreased in the post-crisis period, which is especially visible in higher quantiles of correlation coefficients.

Table 3: Correlations of the FTS measures: pairwise and with the overall indicator

Timespan	Measure	Pairwise			With FTS overall		
		Q(10)	Median	Q(90)	Q(10)	Median	Q(90)
Whole sample	FTS occurrence	0.164	0.315	0.552	0.471	0.634	0.719
	FTS magnitude	0.180	0.365	0.672	0.393	0.727	0.824
2002 – 2009	FTS occurrence	0.126	0.340	0.632	0.455	0.680	0.800
	FTS magnitude	0.123	0.398	0.784	0.356	0.765	0.887
2010 – 2021	FTS occurrence	0.140	0.307	0.512	0.414	0.618	0.706
	FTS magnitude	0.160	0.374	0.615	0.438	0.692	0.788

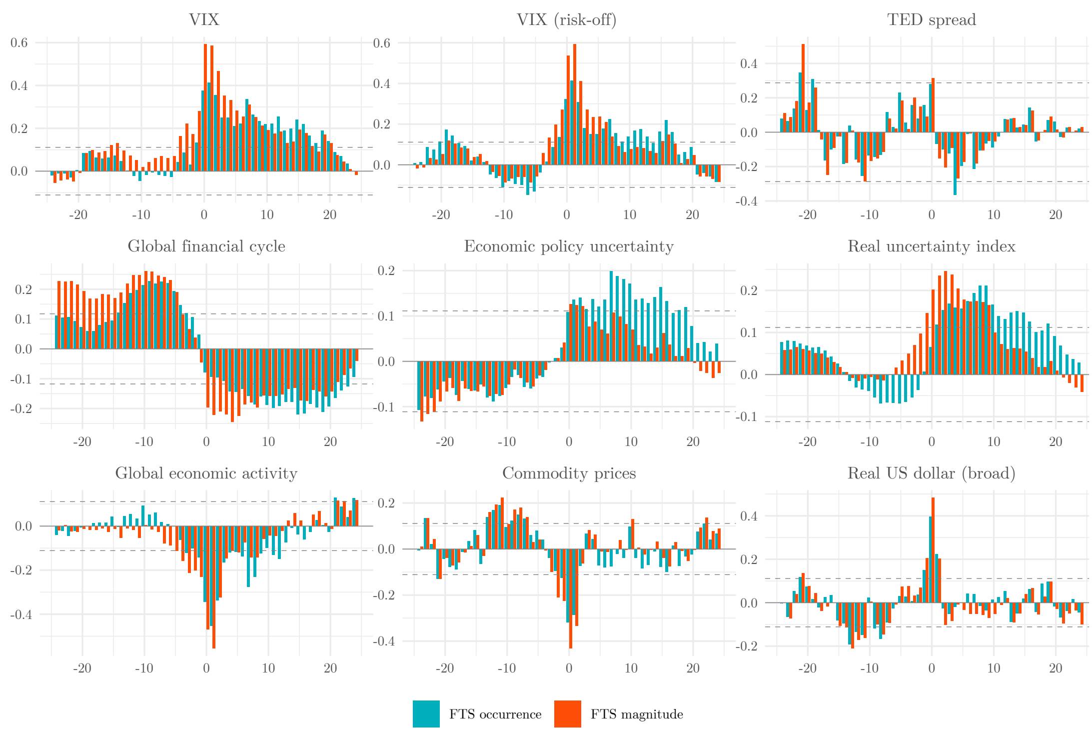
Notes: The table summarizes correlation coefficients for FTS measures across all EMEs (pairwise) and between each EME and the overall FTS indicator, in monthly frequency. $Q(10)$, Median, and $Q(90)$ denote the 10th, 50th, and 90th percentile of correlation coefficient distributions for all country pairs, respectively.

Next, we turn to the question of the relationship between FTS measures and major global risk measures. This part of the analysis aims to give an outlook on the behaviour of the overall FTS indicators vis-à-vis various cyclical financial factors, uncertainty indices, commodity prices, and the US dollar exchange rate. Figure 3 displays cross-correlation functions for leads and lags (denoted as $t + k$) of nine of such factors. The two initial graphs show correlations of FTS indicators with CBOE VIX and risk-off shocks. Risk-off shocks are defined as the 95 percentile of deviation of VIX from its trend obtained with the Hamilton (2018) filter. Hence, both of these

[5] The first principal component, based on the eigenvectors of the pairwise correlation matrix, yields similar results and explains around 28% of variability in FTS occurrence and 39% of their magnitude.

variables quantify market risk levels. Their strong, positive correlations with FTS measures at $k = 0$ lags show that FTS episodes indeed occur in periods of elevated global risk, falling asset prices, and deleveraging. The coefficients, however, are visibly stronger for FTS magnitude: they reach as high as 0.6 in period at $k = 0$ and remain significant up to $k = 20$ leads of VIX. On the other hand, cross-correlations for the TED spread, the wedge between the three-month Treasury bill and the three-month LIBOR, are hardly significant at $k = 0$ and in any of the leads or lags. This shows that constructed FTS indicators are related more to the global risk-off events than liquidity shocks.

Figure 4: Lead and lag correlations between overall FTS measures and global risk factors



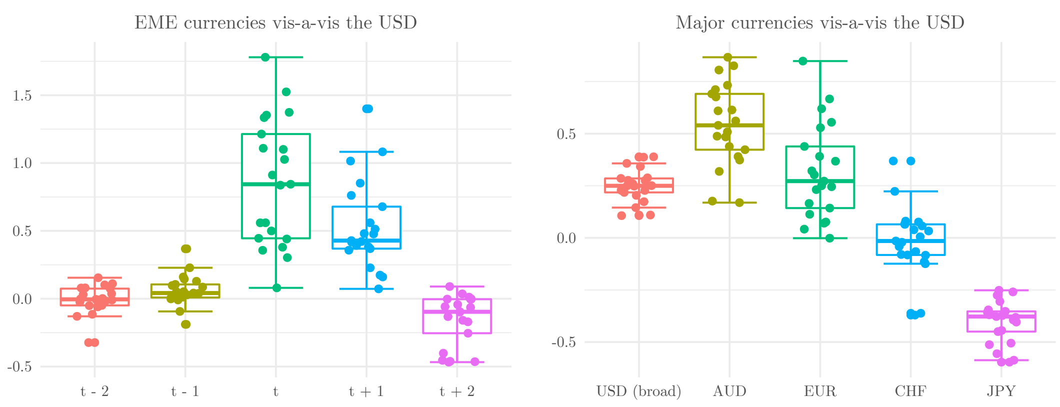
Notes: The figure plots cross correlation functions between overall FTS indicators and global risk measures. Time is given in months and bars indicate correlations between a given risk measure at period $t + k$ and the FTS measures at period t. Dashed lines indicate statistical significance at the 0.1 level.

Cross-correlations between FTS indicators and the Global Financial Cycle (GFC) measure proposed by Miranda-Agrippino and Rey (2020) reveal an interesting relationship. Correlations are positive in lags and negative in leads, which means that in the run-up to FTS events (up to $k = -5$), the GFC, constructed on the basis of various asset prices, is in expansion. However, coefficients become insignificant, close to $k = 0$, before turning negative. Altogether, it implies that the frequency and magnitude of our FTS indicators are related to boom and bust cycles in global asset prices. The next two series concern the news-based economic policy uncertainty (Baker et al., 2016) and the real uncertainty index (Jurado et al., 2015). Correlation coefficients for the former index are weaker than for the latter, especially when it comes to the FTS^M measure. Also, for the second index, correlations in leads remain significant for a number of months (up to $k = 10$). This resembles the regularity observed for correlations with VIX and indicates that FTS incidents may signify the beginning of elevated uncertainty in the global economy.

The global economic condition (GECON) index constructed by Baumeister et al. (2020) and FTS indicators displays strong negative comovement. The significance of coefficients is only transitory, and they reach their peak at $k = 1$, again with a visibly stronger correlation for the FTS^M measure. This indicates that strong FTS events happen more than often when global macroeconomic conditions deteriorate. The cross-correlation function shows an analogous pattern, although with smaller absolute values, for commodity prices (All Commodity Price Index reported by the IMF). Finally, the US dollar real effective exchange rate, calculated by the Bank of International Settlements, shows instantaneous positive correlations with FTS indicators, reaching 0.484 and 0.397 for FTS^O and FTS^M, respectively, suggesting that FTS events are linked to periods of considerable real appreciation of the dollar.

To get a more granular view of the role of exchange rate adjustments around FTS days, we calculate average returns of the nominal USD exchange rate for each EME up to two days before and two days after FTS dates. Here, we make use of the daily exchange rate data. The distributions of mean exchange rate returns are displayed using boxplots on the left-hand side of Figure 5, where a single point corresponds to one of 21 EMEs. The most discernible feature of those diagrams is that both on the day t (the FTS date) and $t + 1$, all EMEs show positive values, which indicates currency depreciation. This is consistent with the view that currencies tend to depreciate vis-à-vis the US dollar when they become riskier. Even though all EME currencies depreciated around FTS episodes, the average change of returns differs substantially across EMEs, as indicated by the wide inter-quartile range in boxplots. The mean of the entire distribution on the day t is 0.859%, with extreme values ranging from around 0.1% to 1.75%. Additionally, even though the shifts in the dollar exchange rates are sizeable, they are temporary and followed by an opposite movement of returns on $t + 2$.

Figure 5: The US dollar exchange-rate returns around FTS episodes



Notes: The LHS panel of the figure shows average changes of USD exchange rates in all EMEs from $t-2$ to $t+2$, where t is the date of the FTS. The RHS panel displays the mean returns of major currencies on FTS days. All exchange rates USD expressed as a local currency prices of the dollar, except for the USD (broad) which is the broad nominal effective exchange rate by BIS.

The right-hand side panel of Figure 5 plots distributions of mean returns of the nominal effective US dollar and four other currencies useful to investigate in this context: two currencies traditionally considered a safe haven (the Swiss franc and the Japanese yen), the euro, as well as the Australian dollar, often regarded as an example of a risky currency. Boxplots in this panel confirm that FTS days are related to a noticeable appreciation of the broad dollar (the mean of the distribution equal to 0.250%). Both the AUS and EUR depreciate on FTS days, with the mean value of their respective distributions equal to 0.543% and 0.317%. Interestingly, the direction of change in the CHF/USD exchange is unclear, with almost exactly half of the observations falling into negative territory. The JPY/USD exchange rate, in turn, reveals an unambiguous tendency to appreciate on FTS days (the mean of distribution equals -0.403%), which confirms the relative safety of this currency; for example, the fact that the JPY is often used as a low-interest funding currency for carry trades.

Preliminary statistics and observations reported in this section are consistent with the view that the occurrence and magnitude of identified FTS incidences correspond to elevated levels of risk in the global economy, or what we may call the 'bad states of the world'. They are, however, only suggestive of the specific role that different risk factors play in explaining FTS events. In the next sections, we provide a more formal examination of those determinants.

4.2 VAR analysis

When investigating the interactions between overall FTS indicators and common, global risk factors, we take into account their dynamic relationships. The analysis is performed using a standard VAR model that takes the following structural form:

$$\mathbf{A}\mathbf{y}_t = \nu + \sum_{k=1}^{p} \mathbf{B}_k \mathbf{y}_{t-k} + \mathbf{u}_t, \tag{8}$$

where $\mathbf{y}_t$ is the vector of observables, matrix $\mathbf{A}$ describes contemporaneous relationships of variables in the system, ν is the vector of constants, while $\mathbf{B}_k$ are the matrices of coefficients on lagged variables. The vector $\mathbf{u}_t$ contains zero-mean, serially uncorrelated structural disturbances.

We estimate two specifications of the VAR model, separately for the aggregate FTS occurrence and magnitude indicators. Apart from FTS^O or FTS^M series, in each case, the vector $\mathbf{y}_t$ consists of four variables. The first one is the VIX index, denoted by vix, which is calculated as a monthly average of daily values of VIX obtained from Refinitiv Datastream. High values of the index are universally considered a good proxy for overall risk in financial markets. Secondly, the system includes the real effective exchange rate index, usd, as calculated by BIS. An increase in this index implies an appreciation of the dollar against the trade-weighted basket of currencies. The third variable, $usrate$, aims to capture the monetary policy stance in the US, the leading provider of safe long-term sovereign bonds. Given the fact that for several years covered by our sample the Federal Reserve kept the federal fund rate unchanged and deployed various non-standard policies (e.g., quantitative easing), we approximate the US monetary policy with the shadow interest rate estimated by Wu and Xia (2016). This measure is intended to closely follow the effective fund rate outside the lower bound but adjust it for unconventional policies when such measures are used. Additionally, the shadow rate is deflated with the baseline CPI inflation rate in the US, provided by FRED. Lastly, $usindpro$ is obtained as deviations from the log trend of the US real industrial production index obtained with the Hamilton (2018) filter.

The reason behind the inclusion of this variable is that the US business cycle may influence global financial conditions, either directly or through the impact on other variables in the model.

Identification of the VAR system in equation (8) is achieved in the spirit Bruno and Shin (2015) and Friedrich and Guérin (2020). This identifying scheme imposes a simple recursive structure on matrix $\mathbf{A}$, using the Cholesky decomposition, with variables in vector $\mathbf{y}_t$ order from slow- to fast-moving, so that $\mathbf{y}_t = \left[usindpro, usrate, usd, vix, FTS^O\right]'$. In the second model, the last variable is replaced by FTS^M. The advantage of lining up FTS measures last in the recursive ordering is that they may respond contemporaneously to any shock in the system. Hence, the results presented in this section - e.g., impulse response function - hold as long as the partial identification of having the FTS measure last in the system is fulfilled. This also means that we can disentangle shocks that drive overall FTS while controlling for other determinants. It may be important in our case because the Fed's monetary policy, the USD exchange rate, and the VIX are strongly related, as shown in numerous recent studies.

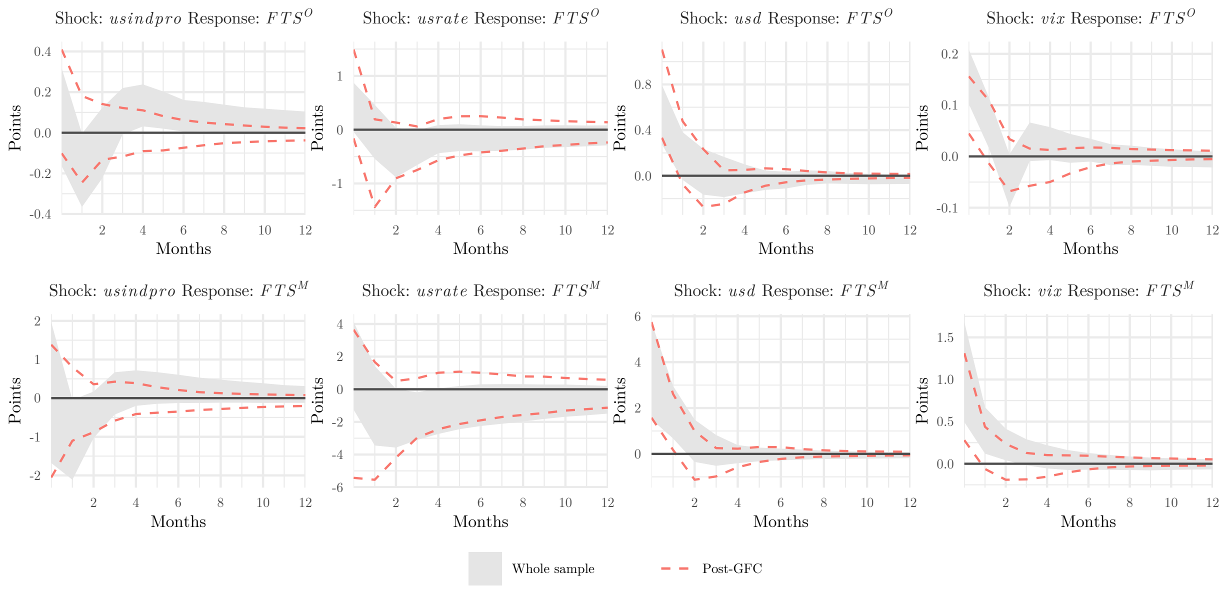
Models are estimated using data in monthly frequency for the timespan of December 2002 to March 2021, with the optimal number of autoregressive lags chosen according to the Akaike criterion. This criterion points out to three lags for the specification that contains FTS^O and two lags for the FTS^M. All estimated systems are stable, as indicated by characteristic roots, and do not reveal serial correlation in residuals. To account for possible parameter changes in the post-GFC period, we additionally estimate both models on the dataset starting in January 2010.

The structural form of the VAR models allows us to obtain impulse reaction functions (IRFs), shown in Figure 5. In all cases, we report bootstrapped 90-percent confidence intervals for the whole sample and the post-GFC subsample. Starting with the results for the FTS occurrence indicator, FTS^0, it must be noted that shocks to *usd* and *vix* have more clear-cut effects on FTS than the two remaining disturbances. In both cases, however, their immediate impact is strong, but the effects of shocks very quickly dissipate and become insignificant beyond the two-month horizon. A one percent increase in *vix* raises the frequency of FTS by around 0.1 - 0.2 percentage points. Analogous impact for *usd* is between 0.4 and 0.8 points. The post-crisis IRFs are comparable in both cases, although visibly weaker for *vix*. The confidence interval of the post-crisis IRF for *usd* appears to be more stable than the one for *vix*, especially in $t = 0$. FTS frequency positively responds to shocks to *usrate* in the initial model, while the reaction to *usindpro* shocks is visibly weaker. For the whole sample, a positive shock to output lowers FTS after one month, but this regularity disappears in the post-GFC model.

In general, the shapes of IRFs for the FTS magnitude model resemble the first set of functions. There are, however, two notable differences. First, the positive response of FTS^M to *vix* is still short-lived but more pronounced in one- and two-month horizons. Second, confidence intervals for *usindpro* and *usrate* are visibly wider, especially in the post-GFC period, which indicates more uncertainty regarding the effects of both shocks on the magnitude of FTS.

To quantify the importance of shocks for FTS indicators, we further perform a forecast error variance decomposition (FEVD) of FTS^0 and FTS^M. Table 5 displays these decompositions. Beginning with the whole sample estimates for FTS^O indicators, four shocks identified in the model explain more than 34% of its total error variance in a 12-month horizon. Shocks to *vix* are

Figure 6: Responses of FTS episodes and magnitude to shocks in the VAR



Notes: The figure displays impulse response function of FTS episodes and strength to four shocks based on VAR models described in Equation (8). Innovations are defined as follows: shock to *indpro* is given as a one-percent deviation from log trend of the US industrial production, *shadow* – a one point increase in the real shadow interest rate, *usd* – a one percent appreciation of broad dollar, *vix* – a one-point increase in the VIX. Shaded areas represent 90-percent confidence intervals estimated for the whole sample (2002:12 to 2021:03) and dashed red lines depict corresponding intervals in the model estimated for the post-GFC sample (2010:01 to 2021:03). Confidence intervals are constructed using bootstrap with 1000 replications.

responsible for the largest contribution to FTS^O, both on the impact and after 12 periods. The role of $usindpro$ and $usrate$ is negligible at first but then somewhat increases to reach around 4% and 3%, respectively. The decomposition for FTS^O changes substantially in the post-GFC model. The role of usd increases significantly, both in absolute values, from around 10% to ca. 16%, but also in relative terms, as compared to vix and remaining shocks.

FEVDs obtained for the FTS^M indicators show that four shocks explain a substantially larger fraction of forecast error variance than for FTS^0. A single variable (vix) turns out to have stronger explanatory power than all shocks in the first model. Values for usd are also higher and oscillate between around 17% and 19%. On the other hand, the contributions of $usindpro$ and $usrate$ are smaller. In the post-GFC model, we observe regularities similar to the first model: an increase in the relative role of the usd. This time the shocks to vix still have a higher contribution to FEVD but the share explained by usd slightly increases while for vix, it is more than 10 points lower. Hence, the model estimated for the post-crisis period is less successful in explaining FTS^M.

In sum, the results from the VAR analysis show that overall measures of FTS strongly respond to global financial risk shocks, as approximated by VIX. This is not surprising given the unusual predictive properties of this index highlighted, e.g., by Adrian et al. (2019). Interestingly, we find weaker evidence on the US monetary policy relevance for FTS events, which may indicate that not all EMEs are directly affected by the Fed's policy. These results hold resemblance to findings reported in Friedrich and Guérin (2020) that the impact of the US monetary policy on

Table 4: Forecast error variance decomposition of FTS occurrence and magnitude

Variable	Horizon	Whole sample					Post-GFC				
		usindpro	*usrate*	*usd*	*vix*	Total	*usindpro*	*usrate*	*usd*	*vix*	Total
FTS^O	1	0.245	0.812	10.197	15.659	26.913	0.975	1.138	16.325	6.558	24.995
	2	1.670	0.770	10.712	17.209	30.361	0.955	2.167	16.844	7.799	27.765
	3	1.709	1.650	10.344	17.567	31.271	0.930	2.544	16.360	7.596	27.431
	12	4.143	3.170	9.688	17.668	34.669	0.937	3.242	16.423	7.719	28.320
FTS^M	1	0.051	0.390	17.403	34.581	52.426	0.039	0.146	19.174	23.617	42.975
	2	1.659	0.508	19.144	33.815	55.126	0.048	0.828	21.037	23.701	45.615
	3	1.929	1.042	19.158	34.234	56.363	0.181	1.317	20.750	23.525	45.772
	12	2.104	2.966	18.588	34.146	57.803	0.333	2.051	20.677	23.355	46.416

Notes: The table shows the percent of h-step ahead forecast error variance explained by shocks identified in the VAR model. The forecast horizon is expressed in months. The whole sample runs from 2002:12 to 2021:03 and the post-GFC sample covers the period from 2010:01 to 2021:03.

international capital flows is uncertain and substantially differs over time. What needs to be highlighted, however, is the importance of the US dollar shocks, which noticeable increases, both in absolute and relative terms, in the post-GFC period. This growing impact of the dollar FTS frequency and magnitude seem to support the findings of Bruno and Shin (2015) who shows that deleveraging of global financial intermediaries and appreciation of the US dollar go hand-in-hand. Also, it corresponds to the recent body of work on the financial channel of the exchange rate, such as Avdjiev et al. (2019), that documents the role of the dollar as a major source of shocks to EMEs.

5 Country-specific drivers of flight to safety

This section investigates country-specific drivers of flight-to-safety episodes in EMEs. We first determine a panel regression that conforms with the properties of constructed FTS measures. Using a set of panel models, we provide evidence on the importance of a range of domestic factors, while taking into the global variables. Next, we put forward several modifications and sensitivity checks to the baseline model.

5.1 Panel regression setup

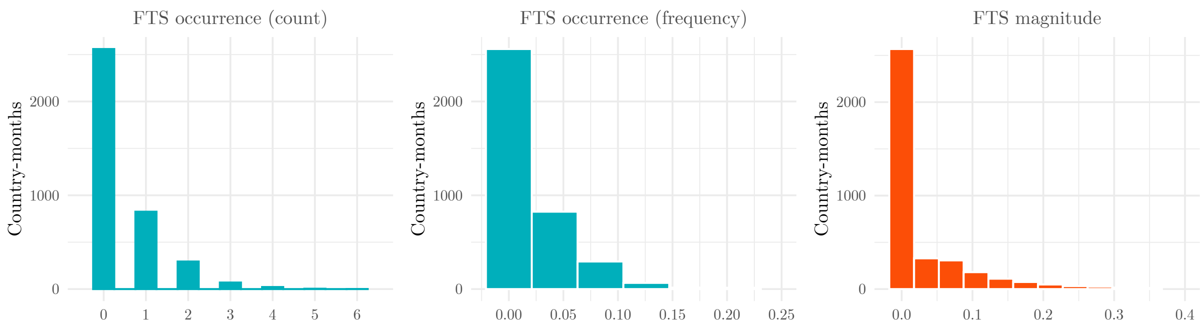
The starting point of our analysis consists of a panel regression specification in which the FTS occurrence ($FTS^O_{i,t}$) and magnitude ($FTS^M_{i,t}$) measures are introduced as dependent variables. This model should allow us to quantify the role of domestic economic and financial variables for FTS, while controlling for a set of global factors, which – as we have already seen – are essential for the FTS determination. It should provide an answer to what makes EMEs more prone to experience FTS. The linear form of a suitable panel regression is given as:

$$FTS_{i,t} = \mu_i + \sum_{r=1}^{R} \beta_m v_{t,r} + \sum_{s=1}^{S} \delta_s X_{i,t-1,s} + \varepsilon_{i,t}, \tag{9}$$

where $i \in \{1, ..., N\}$ is the number of countries in the sample and $t \in \{1, ..., T\}$, the number of months, while μ_i denotes country-level fixed effects that account for possibly omitted, time-invariant country characteristics. Global explanatory variables are given by $v_{t,r}$, and they enter the regression equation in time t, since we may plausibly assume that – from the EMEs' perspective – they are determined exogenously. The set of domestic variables, $X_{i,t-1,s}$, however, is lagged in order to alleviate potential endogeneity between FTS measures and country-specific conditions. A mean-zero serially independent error is given as $\varepsilon_{i,t}$.

However, the FTS identification procedure adopted in Section 3 leaves us with a specific type of dependent variables. Figure 7 plots histograms for three FTS measures pooled across all EMEs and periods. By construction, all dependent variables are highly skewed, non-negative time series. As the FTS events are bound to be rare, they also contain a large fraction of zeroes: 2559 out of 3775, or ca. 68% of country-month observations, are found at the corner solution. The FTS occurrence distribution on the left-hand side of Figure 7 is a typical example of zero-truncated count data. Note, however, that the distribution of FTS episodes is not zero-inflated since there are no excess zeros, i.e., there is no additional process that generates zeros in this distribution, and any date in the sample could possibly be an FTS date. According to our definition of FTS frequency and magnitude, the FTS^0 is the basis for the remaining two FTS indicators. Under these circumstances, the regular, linear panel techniques may produce biased parameter estimates.

Figure 7: Distribution of dependent variables in panel models



Notes: The figure displays the empirical distributions of the number of country-months for FTS occurrence indicators as count data (number of country-months) or a fraction of total country months.

Hence, a natural way is to go beyond the linear form of the panel regression in Equation (9). Taking into consideration the properties of dependent variables, we opt for the fixed-effect Poisson model in the baseline specification of our panel model. Developed to work with count data, this estimator is particularly well-suited to deal with the FTS^0 indicators. Moreover, due to its strong robustness properties, it may be employed for any type of continuous, non-negative outcome variable, as long as standard errors are corrected to account for the conditional mean assumption of this model (see, Wooldridge, 1999). FE-Poisson estimates are obtained via maximum likelihood, and we calculate robust standard errors with clusters on units–countries.

As mentioned, there are two broad groups of explanatory variables in the panel regression, which we summarize in Table 5. Global variables consist of major international risk factors, discussed in Section 4. Next to the month-to-month changes in the VIX index (*dvix*), the broad real US dollar returns (*dusd*), and changes in the Federal Reserves shadow rate (*dustrate*), global variables include the composite global economic activity indicator (*gecon*). Additionally, to account for the likely co-occurrence of FTS episodes in more than one EME at the time, we construct the dummy variable, *contagion*, that takes the value of one when at least 25% of EMEs in the sample experience FTS in a given period.

Table 5: List of explanatory variables used in panel models

Variable	Description	Raw data source
Global variables		
dvix	CBOE VIX implied volatility based on S&P 500 options; monthly average of daily data; first differences	Refinitiv Datastream
usd	Real effective (trade-weighted) exchange rate of the US dollar; monthly log rate of return	BIS Statistics
dusrate	Shadow interest rate of the Federal Reserve; deflated by the consumer price index; first differences	Wu and Xia (2016) and FRED
gecon	Global economic activity indicator based on real quantities, prices, transportation costs, etc.	Baumeister et al. (2020)
contagion	Dummy variable: takes the value of one when at least 25% of countries in the sample experience FTS in a given month	Own FTS measure
Domestic variables		
indprod	Industrial production in constant USD; log deviation from the Hamilton filter trend	WB Global Economic Monitor
current	Current account balance as a percent of GDP; interpolated from annual to monthly data with cubic spline	IMF World Economic Outlook
reerov	Real effective exchange rate index; log deviation from the Hamilton filter trend	BIS Statistics
yield	Nominal 10-year benchmark yield on sovereign bonds; monthly averages of daily data	Refinitiv Datastream
inflation	Consumer price index; annual changes	WB Global Economic Monitor
govtdebt	General government debt to GDP ratio; first differences; interpolated from annual to monthly data	IMF Global Debt Database
usdrv	Realized variance of the domestic currency exchange rate vis-à-vis the US dollar; calculated using daily log returns	Refinitiv Datastream
polstab	"Political Stability and Absence of Violence" index; relative to the US and first differenced; interpolated from annual to monthly data	WB Worldwide Governance Indicators

When selecting the group of domestic variables included in panel regressions, we combine insights coming from the literature on extreme financial flows and country-specific risks in EMEs. We aim to pin down a tractable but comprehensive set of economic, financial, and policy-related measures that reflect EMEs' vulnerability or resilience to FTS, serving as "pull" factors for FTS occurrence and magnitude (e.g., Forbes and Warnock, 2012). Additionally, these variables should indicate EMEs' ability to alleviate financial flow pressures (Goldberg and Krogstrup, 2018), or – in our case – the FTS events.

In the first place, we introduce three "usual suspects" among country-specific factors that drive financial flows to and from EMEs (Forbes and Warnock, 2012; Ghosh et al., 2014; Li et al., 2019). The *indprod* variable, based on the industrial production index, reflects business cycle conditions in EMEs. Negative output gaps are expected to indicate weaker macroeconomic fundamentals and increase the risk of experiencing FTS. The current account balance to GDP (*current*) is included as one of the most common external sustainability measures of an economy. Deterioration in a country's current account may translate to mismatches in its balance of payment and worsen its position vis-à-vis foreign lenders. The next variable, *reerov*, approximates the overvaluation of a country's real effective exchange rate. It is defined as the REER deviation from its trend implied by the Hamilton (2018) filter, with higher values indicating larger overvaluation of the exchange rate and expected depreciation of the domestic currency, which may, in turn, relate to a greater susceptibility to FTS.

Second, we take into account the 10-year nominal sovereign bond yield. The *yields* variable serves an essential purpose because information on a country's relative safety characteristics responsible for the intensity of FTS episodes may already be embedded in its long-term bond level yield, at least partially (Habib et al., 2020; Janus, 2021). Together with the nominal yield, we introduce the inflation rate, $inflation$, which supplements the analysis when nominal values are taken into account but also reflects broader monetary conditions in EMEs, which may prove relevant in explaining FTS.

Third, we extend the dataset with a measure of public debt, *govtdebt*. Intuitively, fiscal sustainability may be correlated with EMEs' sovereign default risk and the cost of debt, so low dynamics of public debt should insulate a country from FTS events. At the same time, fiscal sustainability may have far-reaching effects for responses to adverse shocks and price stability. Exchange rate variability, calculated as monthly realized variance *usdrv*, serves as an approximation of a country's currency risk, as well as its exchange-rate flexibility. Lower exchange rate volatility was shown to compress local currency bond yields in EMEs, particularly in the post-GFC period (Gadanecz et al., 2018). As the last domestic variable, we include political stability rating, *polstab*, specified as changes in a country's World Bank Governance index relative to the US. Higher values of this index imply an upgrade in a country's political standing, which may be linked to an improvement in investors' perception of its safety.

Panel regressions are estimated using monthly frequency data and in an unbalanced setting, as both the coverage of identified FTS episodes and the availability of country-level variables differ across EMEs. When necessary, domestic variables are first differenced to obtain stationary series.[6] To adjust all variables into monthly frequency, three series originally available in annual frequency are interpolated using the cubic spline function. In those cases, instead of variables lagged one month, we introduce their values lagged 12 months. The adjusted maximum timespan of data for any EME in the sample covers the period from 2004:12 to 2020:12.

5.2 Baseline findings

The results of the baseline panel models, obtained for the entire sample of EMEs, are displayed in Table 6. Columns (1)–(4) contain coefficient estimates for FTS occurrence measure, while columns (5)–(8), estimates for FTS magnitude. In both cases, we develop the final models in four steps, based on the relationship between explanatory variables described in the previous section. Initially, the set of five global and three fundamental domestic variables are introduced in columns (1) and (5). As expected, global risk measures enter the regression with significant, positive estimates. There is, however, a notable difference with respect to the role of the *gecon* variable. Although an improvement in global economic conditions reduces the magnitude of FTS episodes, it does not affect their bare number. Additionally, the impact of the shadow interest rates is less pronounced for the magnitude measure. The coefficient on the *contaigion* variables

[6]Panel unit-root tests are available in Table A.2 in the Appendix.

has an expected significant and positive sign in all model specifications.

Out of the three initial country-level variables, only *reerov* turns out to be significant for both FTS^O and FTS^M indicators, which means that expected currency depreciation successfully predicts the occurrence of FTS and their intensity. However, measures of output and current account exhibit significant and negative estimates only for the magnitude of FTS. This implies that deteriorating macroeconomic fundamentals will predict more severe FTS events in a given country.

Table 6: Baseline panel estimation results: global and country-specific drivers of flight to safety

	FTS occurrence				FTS magnitude			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
dvix	0.021***	0.021***	0.020***	0.020***	0.021***	0.022***	0.021***	0.021***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
dusd	0.181***	0.180***	0.194***	0.193***	0.277***	0.265***	0.293***	0.278***
	(0.028)	(0.029)	(0.026)	(0.026)	(0.031)	(0.031)	(0.028)	(0.029)
dusrate	0.094**	0.077*	0.132***	0.124**	0.155**	0.072	0.141*	0.101
	(0.041)	(0.041)	(0.049)	(0.048)	(0.078)	(0.066)	(0.085)	(0.072)
gecon	-0.053	-0.040	-0.044	-0.037	-0.166***	-0.171***	-0.151***	-0.170***
	(0.034)	(0.038)	(0.034)	(0.038)	(0.039)	(0.050)	(0.039)	(0.049)
contagion	0.215***	0.213***	0.188***	0.185***	0.181***	0.187***	0.145**	0.151**
	(0.048)	(0.049)	(0.048)	(0.048)	(0.067)	(0.067)	(0.061)	(0.059)
indpro	0.038	0.040	0.069	0.070	-0.211**	-0.188*	-0.186**	-0.160*
	(0.070)	(0.067)	(0.070)	(0.069)	(0.103)	(0.099)	(0.085)	(0.083)
current	-0.009	-0.002	-0.005	0.001	-0.028**	-0.007	-0.021**	-0.001
	(0.009)	(0.009)	(0.006)	(0.001)	(0.013)	(0.010)	(0.009)	(0.007)
reerov	0.013***	0.013***	0.015***	0.015***	0.011***	0.011***	0.016***	0.015***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)	(0.003)
yield		0.022		0.015		0.105***		0.096***
		(0.023)		(0.018)		(0.036)		(0.032)
inflation		0.023		0.027*		0.026*		0.036**
		(0.015)		(0.015)		(0.015)		(0.014)
govtdebt			0.035**	0.039***			0.042**	0.049***
			(0.013)	(0.013)			(0.021)	(0.018)
usdrv			0.001**	0.001			0.003***	0.001***
			(0.000)	(0.001)			(0.001)	(0.000)
polstab			-0.006***	-0.006***			-0.006***	-0.006***
			(0.001)	(0.001)			(0.002)	(0.002)
Observations	3775	3775	3775	3775	3775	3775	3775	3775
Countries	21	21	21	21	21	21	21	21
Pseudo-R^2	0.062	0.072	0.077	0.079	0.111	0.118	0.116	0.122

Notes: The table presents the results of panel regressions for dependent variables FTS^O and FTS^M. Parameters estimates are obtained using the Poisson estimator with country-level fixed effects. Robust clustered standard errors are given in brackets. All country-level variables are lagged one month, except for *current*, *govdebt*, and *polstab* which are lagged 12 months. ***, **, and * denotes statistical significance at 0.01, 0.05, and 0.1 levels, respectively.

The inclusion of subsequent domestic variables reveals that *yield* and *inflation* are significant drivers of FTS magnitude but not their occurrence. It turns out that the number of FTS events is not related to prevailing levels of bond yield, but – given the construction of the FTS^M indicator – higher levels of yield translate to larger negative returns on FTS dates. Columns (2) and (6) lead to three additional findings. First, the CPI inflation shows a weak but positive impact on FTS magnitude, even though it is introduced in the model together with the yield level. Consequently, *inflation* brings in additional information, unrelated to the long-term yield, on the higher inflation rates – i.e., a greater monetary instability – driving FTS magnitude. Second, when the 10-year bond yield level enters the model, point estimates of the coefficient on the current account drop in absolute terms and become insignificant. Such interchangeability between *current* and *yield* seems to reflect the fact that the current account balance is a good predictor of sovereign yield levels. Third, the introduction of yield levels makes the measure of the US monetary policy, *dusrate*, redundant for the FTS^M indicator.

When we expand the model with the last set of variables, previously reported results remain largely intact, but we obtain strong evidence on three significant drivers of FTS. Higher public debt dynamics, *govtdebt*, tend to boost FTS occurrence and magnitude, while improvements in political stability, *polstab* lowers both indicators. The role of exchange rate variability of local currencies against the US, *usdrv*, is more robust for the FTS magnitude, with a definitive positive sign on its coefficient. It follows that the high realized variance of the exchange rate connects with stronger FTS events.

Our analysis shows that FTS instances and their magnitude in EMEs are affected by a combination of global and domestic factors. In this case, we find that the vast majority of potential FTS drivers that enter the panel regression model are significant, even after controlling for global factors and bond yield levels. Several domestic determinants stand out in the analysis as held in common for FTS^O and FTS^M indicators. One of them is the effective exchange rate overvaluation, which highlights the role of market expectations on local currency depreciation in triggering FTS episodes. This finding supplements Ghosh et al. (2014) who show that a similar measure is a robust predictor of capital surges, exceptionally large capital inflows to EMEs. We also find that dynamics of public debt and political stability show up as important drivers of FTS. This stands in contrast to a study on bond yield determinants by Habib et al. (2020), who find public debt to be a significant predictor of yields only in advanced economies. At the same time, the within pseudo-R^2 measures reported at the bottom of Table 7 are relatively low, they do not increase by much when additional domestic factors are introduced, and the explanatory power of the model is driven by global variables.

Hence, the results we obtain from panel models reveal an interesting interplay between global and domestic variables associated with FTS occurrence and magnitude. On the one hand, we find that FTS experienced by EMEs are driven chiefly by global "push" factors. This corroborates both the importance of the global financial cycle (Miranda-Agrippino and Rey, 2020) for EME and the role of global stops for portfolio-debt flows Eichengreen et al. (2018), but using an entirely different methodological approach and a sample of economies. Within this group of variables, however, macroeconomic factors seem relatively more important than financial and monetary ones for the magnitude of FTS, as indicated by the behaviour of the global economic indicator (*gecon*) that is found to be insignificant for the FTS^O indicator. On the other hand, our results lend support to the notion that the role of country-specific "pull" factors, in particular economic fundamentals, is more pronounced for the FTS magnitude indicator than the mere occurrence of FTS events. With some limitations, this echoes the findings of Ghosh et al. (2014) and Gelos et al. (2022) and indicates that domestic conditions and policies may mitigate the risks of abrupt flights to safety from EMEs in the face of global shocks.

It must be noted that conclusions based on the baseline model presented in this section remain essentially unchanged when regressions are obtained using different panel data estimators. Those results are summarized in Table A.3 in the Appendix. We first re-estimate the FE-Poisson model using the FTS^O indicator expressed as frequency (share of FTS days in the total number of days) rather than count data. Next, we employ a regular within estimator with panel-corrected standard errors. Compared to the baseline specification, the OLS produces coefficient estimates with signs and statistical significance matching those in FE-Poisson regressions. Lastly, to further account for a potential overdispersion of our outcome variables, we employ the negative binomial estimator, which may be considered a more flexible modification of the Poisson model. Also, in this case, our baseline results hold.

5.3 Analysis in subsamples

This subsection provides additional evidence on drivers of FTS indicators in a panel of EMEs. We proceed in three steps. First, we re-run the baseline model on a sample of countries that excludes the so-called "fragile five" economies: Brazil, India, Indonesia, South Africa, and Turkey. As those economies proved highly susceptible to changes in global risk factors, it is worthwhile checking if they bend the results of the entire panel of EMEs. Second, we single out a subsample of EMEs by eliminating countries with relatively high GDP per capita, i.e., three EU economies: Czechia, Hungary, and Poland, along with Israel and Korea. Those economies may benefit from their higher levels of economic and financial development, which may result in their ability to produce sovereign assets that are safer than in remaining EMEs. Third, similarly to the VAR analysis in Section 4.2, we re-estimate panel regressions for the post-GFC period, starting in January 2010. This also allows us to evaluate whether the importance of identified factors shifted after the crisis. Another advantage of this step is that panel data used in the estimation become more balanced.

Table 7 displays parameter estimates in three subsamples. Columns (1) and (4) indicate that the exclusion of 'fragile five' economies from the sample does not alter our general findings. The effects of global factors remain similar, with the *gecon* index being more important for FTS magnitude. Aside from the *polstab* variable in the regression for FTS^M, the results are coherent with the benchmark. This is reassuring given that one might speculate whether large, sudden changes in bond yield observed in Turkey or Brazil are decisive for the baseline outcomes. The results from the subsample of countries that excludes economies with a higher level of development – columns (2) and (5) – are highly comparable to the benchmark ones for all covariates apart from one. The coefficient on the *indpro* variable in the FTS^M regression loses statistical significance. This suggests that the magnitude of FTS events in countries with lower GDP *per capita* is less affected by output growth.

Moving to estimation results for the post-GFC period, we investigate two specifications already used in the baseline model. All explanatory variables are introduced in columns (3) and (7), while models in columns (4) and (8) exclude *yield* and $inflation$ variables from the setup. It must be noted right away that there is a considerable increase in coefficients on *dusd* and *dusrate*, compared to whole-sample estimates. The same is true for the *dvix* variables in the regression for FTS^M. Taken together, this implies a stronger impact of the US monetary policy and the dollar on FTS, substantiating our previous findings. On the contrary, several factors lose statistical significance in the post-GFC period, especially when it comes to explaining the magnitude of FTS events. Coefficients on variables related to macroeconomic stability, *gecon*, *indpro*, and $inflation$, all become insignificant. Additionally, *polstab* ceased to be a relevant

Table 7: Analysis in subsamples: global and country-specific drivers of flight to safety

	Occurrence				Magnitude			
	Exc. fragile 5	Exc. high GDPpc	Post-GFC: 2010-2020	Post-GFC: 2010-2020	Exc. fragile 5	Exc. high GDPpc	Post-GFC: 2010-2020	Post-GFC: 2010-2020
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
dvix	0.022***	0.017***	0.019***	0.020***	0.021***	0.020***	0.031***	0.032***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)	(0.004)
dusd	0.183***	0.211***	0.273***	0.273***	0.259***	0.274***	0.375***	0.374***
	(0.032)	(0.025)	(0.031)	(0.031)	(0.035)	(0.030)	(0.037)	(0.037)
dusrate	0.160***	0.127**	0.318***	0.321***	0.139	0.128	0.367***	0.365***
	(0.058)	(0.053)	(0.054)	(0.074)	(0.090)	(0.090)	(0.097)	(0.098)
gecon	0.001	-0.038	0.020	0.046	-0.172**	-0.185***	-0.010	0.037
	(0.047)	(0.046)	(0.042)	(0.040)	(0.070)	(0.054)	(0.041)	(0.046)
contagion	0.201***	0.173***	0.096	0.114*	0.199***	0.111	0.107*	0.131**
	(0.053)	(0.058)	(0.064)	(0.065)	(0.062)	(0.072)	(0.056)	(0.061)
indpro	0.013	0.151	0.121	0.112	-0.234***	-0.031	0.112	0.051
	(0.057)	(0.100)	(0.075)	(0.072)	(0.081)	(0.092)	(0.134)	(0.100)
current	0.002	0.005	0.011	-0.004	0.001	0.001	-0.012	-0.041*
	(0.009)	(0.008)	(0.015)	(0.015)	(0.007)	(0.007)	(0.017)	(0.021)
reerov	0.016***	0.012***	0.020***	0.019***	0.016***	0.013***	0.022***	0.019***
	(0.003)	(0.002)	(0.005)	(0.005)	(0.004)	(0.003)	(0.004)	(0.005)
yield	0.026	-0.005	0.078**		0.122***	0.072*	0.146***	
	(0.023)	(0.020)	(0.034)		(0.041)	(0.041)	(0.051)	
inflation	0.027	0.024	0.014		0.029**	0.038**	0.012	
	(0.020)	(0.016)	(0.016)		(0.014)	(0.016)	(0.016)	
govtdebt	0.046***	0.023*	0.043***	0.055***	0.074***	0.035*	0.076***	0.097***
	(0.014)	(0.013)	(0.014)	(0.018)	(0.019)	(0.021)	(0.015)	(0.023)
usdrv	0.001**	0.000	0.001	0.002*	0.002**	0.001**	0.002*	0.003***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
polstab	-0.005***	-0.005***	-0.002	-0.001	-0.005	-0.006***	-0.002	0.000
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)
Observations	2893	2810	2730	2730	2893	2810	2730	2730
Countries	16	16	21	16	16	16	21	21
Pseudo-R^2	0.077	0.079	0.075	0.073	0.121	0.124	0.107	0.102

Notes: The table presents the results of panel regressions for dependent variables FTS^O and FTS^M. Parameters estimates are obtained using the Poisson estimator with country-level fixed effects. Robust clustered standard errors are given in brackets. See also: Table 6. 'Exc. fragile 5' subsample excludes Brazil, India, Indonesia, South Africa, and Turkey. 'Exc. high GDPpc' subsample excludes Czechia, Hungary, Israel, Korea and Poland. 'Post-crisis: 2010-2020' subsample spans from 2010:01 to 2020:12. ***, **, and * denotes statistical significance at 0.01, 0.05, and 0.1 levels, respectively.

driver for both FTS^O and FTS^M indicators.

Hence, the results obtained for the post-GFC period suggest that the role of growth and economic fundamentals in driving FTS diminished at the expense of financial factors. Additionally, the relationship between vulnerability (or resilience) to FTS and domestic factors in EMEs seems to have weakened. As such, our findings support the notion of a 'fickleness' of financial flows in the global economy, the tendency of investors to quickly exit a country during distress (the 'risk on-off' behaviour) and results in a sharp reversal of cross-border flows (Aizenman et al., 2021; Caballero and Simsek, 2020). This implies, in turn, that EMEs may find it increasingly harder to insulate from destabilizing global shocks, and there is a need for policies that would reduce the volatility of financial flows experienced by these economies.

6 Conclusions

The recurrence of sharp financial outflows and flight to safety episodes have become a crucial trait of EMEs in the international financial system. By focusing on extreme movements in long-term sovereign bond returns, this paper explores the properties of cross-border FTS incidences in EMEs and seeks to understand their global and local drivers. We employ an adaptable shift-detection outlier algorithm on daily data and 21 important EMEs over the period 2002-2021 to construct novel indicators of FTS occurrence and magnitude. These measures are next used to investigate FTS events, both as group indicators and at the country level.

Our analysis shows that FTS episodes in bond markets across EMEs map well into worldwide risk-off shocks, international uncertainty, and business-cycle measures. VAR models estimated using FTS measures aggregated for all EMEs shows that they firmly respond to shocks to VIX, which also explain a sizeable fraction of their occurrence and magnitude. However, we find that the relative role of the US dollar fluctuations for FTS has increased in the period following the GFC. This supports recent accounts that underline the importance of the US dollar for driving the behaviour of financial intermediaries and its consequences for cross-border financial flows.

Although global factors play a leading role in explaining FTS across EMEs, domestic variables, both fundamental and financial ones, also matter for a country's susceptibility to FTS. Using fixed-effect Poisson panel regressions, we demonstrate that a set of country-specific factors – macroeconomic and external stability, real exchange rate overvaluation, public indebtedness, and political standing – serve as significant drivers of FTS. The role of domestic factors is found to be more pronounced for the magnitude of FTS that a country experiences rather than its mere occurrence. At the same time, a sizeable fraction of FTS events remains idiosyncratic and appears difficult to explain with domestic factors. This tendency becomes even more noticeable in the post-2010 period.

Our findings posit that EMEs' exposure to FTS events is an important epitome of their more general vulnerability to global risk factors and the uneasy dynamics of financial flows between emerging and advanced economies. However, the nonnegligible role of the country-specific factors that we find for the magnitude of FTS experienced by EMEs indicates that improvement in domestic conditions may shield, at least partially, sovereign bond markets in EMEs from adverse global shocks. It is then justified to discuss improvement in their policy frameworks, such as changes in monetary arrangements or macroprudential tools, to mitigate the sensitivity to FTS incidences. Consequently, possible extensions to this study may take a closer look into the role of various macroeconomic policies in alleviating FTS pressures experienced by EMEs. Additionally, more granular data on specific transactions in bond markets could be employed to further explore the origins of FTS episodes.

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Appendix

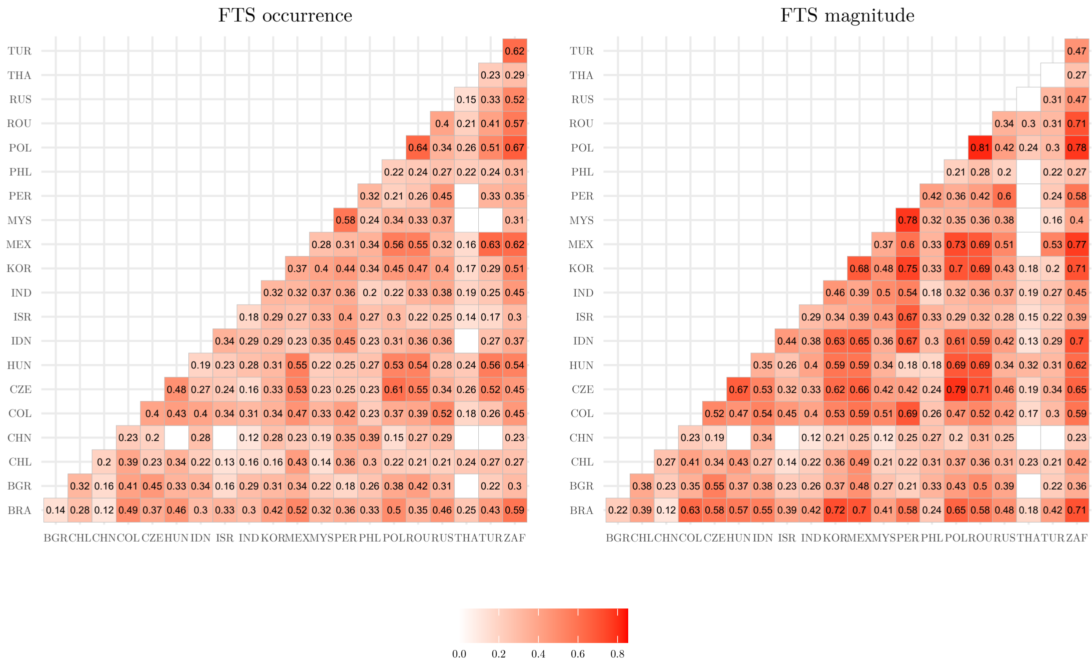
The Appendix provides additional tables and graphs referenced in the main body of the paper.

Table A.1: Descriptive statistics for 10-year sovereign bond returns

	Start date	Observations	Mean	St. dev.	Skewness	Kurtosis
Brazil	2002/01/01	5020	-0.014	2.168	-4.354***	75.253***
Bulgaria	2006/04/18	3902	0.009	0.759	0.232***	15.600***
Chile	2007/04/02	3653	-0.003	0.608	-0.435***	8.251***
China	2002/06/05	4911	0.005	0.345	0.613***	16.985***
Colombia	2002/09/18	4846	0.014	1.143	-0.451***	47.847***
Czechia	2002/01/01	5020	0.016	0.625	-0.232***	7.987***
Hungary	2002/01/01	5020	0.006	1.097	-0.558***	9.484***
Indonesia	2003/05/16	4664	-0.001	1.096	-1.619***	79.554***
Israel	2002/04/01	4950	0.016	0.952	-2.165***	112.818***
India	2002/01/01	5020	-0.005	0.510	-0.670***	15.574***
Korea	2002/01/01	5020	0.013	0.565	-0.045	20.894***
Mexico	2002/01/01	5020	-0.010	0.890	-0.650***	13.047***
Malaysia	2002/01/01	5020	-0.001	0.426	-0.538***	8.968***
Peru	2010/09/07	2756	-0.008	0.444	-0.726***	33.606***
Philippines	2002/01/01	5020	0.021	0.874	-1.036***	19.761***
Poland	2002/01/01	5020	0.0136	0.806	-0.695***	13.909***
Romania	2007/08/20	3553	-0.006	0.981	-0.146***	12.801***
Russia	2003/04/02	4696	-0.008	1.616	-2.447***	48.903***
Thailand	2002/01/01	5020	0.013	0.469	-0.264***	18.162***
Turkey	2010/01/29	2914	-0.080	1.758	-2.688***	41.913***
South Africa	2002/01/01	5020	0.000	1.134	-0.518***	8.823***
United States	2002/01/01	5020	0.006	0.379	-0.074**	5.711***

Notes: The table shows descriptive statistics for 10-year bond returns changes used for the detection of FTS. *** and ** denote statistical significance at the 0.01 and 0.05 levels, respectively.

Figure A.1: Correlation matrices for FTS indicators among EMEs



Notes: Correlation matrices display simple correlation coefficients of FTS measures in monthly frequency using the longest available period for any given pair of economies. Blank blocks show the lack statistical significance at the 0.1 level.

Table A.2: The results of panel unit root tests

	Im-Pesaran-Shin	Maddala-Wu	Choi
indpro	-12.146***	273.09***	25.214***
current	-2.142**	67.084**	2.737***
reer	-5.295***	97.025***	6.004***
yield	-1.526*	65.87**	2.604***
inflation	-4.572***	92.722***	5.534***
govtdebt	-3.471***	79.74***	4.118***
usdrv	-26.613***	879.94***	91.427***
polstab	-6.071***	121.57***	8.681***

Notes: The table displays the Madalla-Wu and Choi panel unit root statistics for country-level variables in an unbalanced panel. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

Table A.3: Alternative estimators: global and country-specific drivers of flight to safety

	Occurrence			Magnitude	
	Poisson (frequency)	OLS (PCSE)	Negative binomial	OLS (PCSE)	Negative binomial
	(1)	(2)	(3)	(4)	(5)
dvix	0.019***	0.029***	0.022***	0.505***	0.021***
	(0.003)	(0.003)	(0.003)	(0.080)	(0.004)
dusd	0.190***	0.088***	0.191***	1.218***	0.279***
	(0.026)	(0.014)	(0.027)	(0.241)	(0.029)
dusrate	0.121**	0.075***	0.133***	0.884**	0.101
	(0.049)	(0.022)	(0.048)	(0.347)	(0.072)
gecon	-0.041	-0.087***	-0.043	-2.123***	-0.170***
	0.037	(0.130)	(0.042)	(0.502)	(0.049)
contagion	0.186***	0.079***	0.181***	0.383*	0.151**
	(0.048)	(0.019)	(0.050)	(0.220)	(0.058)
indpro	0.063	-0.011	0.071	-1.061**	-0.160*
	(0.068)	(0.025)	(0.070)	(0.483)	(0.083)
current	0.002	0.000	0.003	-0.020	-0.001
	(0.008)	(0.005)	(0.008)	(0.087)	(0.007)
reerov	0.015***	0.007***	0.015***	0.076***	0.015***
	(0.002)	(0.002)	(0.003)	(0.026)	(0.003)
yield	0.014	0.006	0.014	0.394***	0.096***
	(0.019)	(0.008)	(0.019)	(0.125)	(0.032)
inflation	0.029**	0.014*	0.031**	0.179*	0.036**
	(0.015)	(0.007)	(0.015)	(0.100)	(0.014)
govtdebt	0.039***	0.016***	0.039***	0.177**	0.049***
	(0.012)	(0.006)	(0.012)	(0.080)	(0.018)
usdrv	0.001*	0.001	0.001	0.036**	0.001***
	(0.001)	(0.001)	(0.001)	(0.015)	(0.000)
polstab	-0.006***	-0.002***	-0.006***	-0.016**	-0.006***
	(0.001)	(0.001)	(0.001)	(0.007)	(0.002)
Observations	3775	3775	3775	3775	3775
Countries	21	21	21	21	21
Pseudo-R^2	0.103		0.061		0.122
R^2		0.130		0.218	

Notes: The table presents results for the baseline panel regressions, see Table 6), using alternative panel data estimators. Poisson (frequency) is the baseline FE-Poisson estimator used on the frequency of FTS (share of days in a month) rather than the count data as the dependent variable. OLS (PCSE) is obtained using a standard within estimator with panel corrected standard errors à la Beck and Katz. Negative binomial models are estimated with clustered robust standard errors. All panel regressions include country-level fixed effects. ***, **, and * denotes statistical significance at 0.01, 0.05, and 0.1 levels, respectively.