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Flights-to-safety and macroeconomic adjustment in emerging markets: The role of U.S. monetary policy

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ABSTRACT

This paper constructs a global financial flight-to-safety (FTS) index that measures risk-off/risk-on sentiment using daily asset prices disciplined with sign and magnitude restrictions. This FTS index is correlated with U.S. Dollar returns and global financial conditions but uncorrelated with high-frequency U.S. monetary policy shocks, providing a novel setup to jointly compare international financial and monetary spillovers under relatively mild identification assumptions. Estimates from a multi-country VAR show that FTS induce wider sovereign spreads, currency depreciation, and slower economic growth in emerging markets. Coincident U.S. monetary policy expansions offset these FTS spillovers by about 30% while coincident policy contractions magnify them, suggesting a prominent role for U.S. policy in shaping financial stability abroad.

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1. Introduction

Macroeconomic vulnerabilities to sharp swings in global financial conditions were once more highlighted by the COVID-19 pandemic. Concerns over a global public health crisis left emerging markets indiscriminately exposed, inducing large and volatile capital outflows, currency depreciation, and sharply wider borrowing costs as presented in Fig. 1. Despite the uniqueness of the pandemic, it shares the signatures of many unanticipated, left-tail economic events such as the 2008 Financial Crisis and the 2015 global growth scare: A 'flight-to-safety' or alternatively, 'risk-off' across global financial markets. These refer to abrupt market swings in the form of falling risky asset prices *and* a rotation into safe assets associated with aggressive portfolio rebalancing by global investors. Policy responses of the U.S. and other major central banks helped alleviate some of the most serious episodes of financial instability and the effects of these policies often propagated worldwide.[1]

This paper presents a new measure of changes to global financial risk appetite intended to capture the intensity and asymmetric nature of flights-to-safety originating in developed market financial centers. A flight-to-safety index is constructed over the 2000–2019 period at the daily frequency as joint tail realizations across risky and safe assets disciplined through sign and magnitude restrictions. Flights-to-safety are therefore distinguished from other shifts in financial market

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[1] Note that the 2020 COVID-19 shock at the onset in late February exhibited textbook flight-to-safety features, but by mid-March the indiscriminate selling of both risky and safe assets suggested that it turned to a flight-to-liquidity as it progressed.

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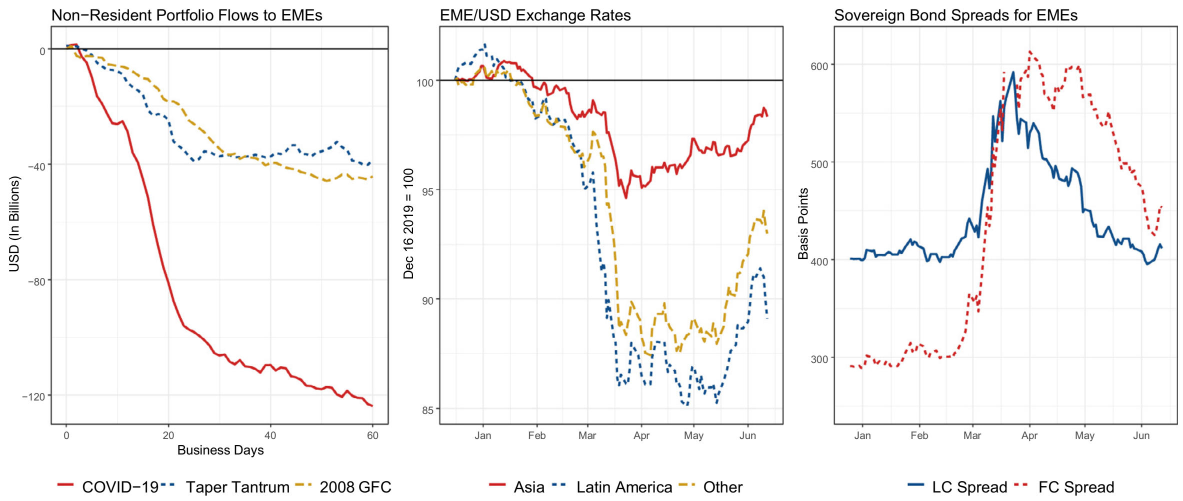

Fig. 1. COVID-19, Flight-to-Safety, and Emerging Markets. LHS: COVID-19 (Feb 19, 2020), Taper Tantrum (May 22, 2013), 2008 GFC-Lehman Bankruptcy (September 15, 2008). Center: Lower values imply depreciation vis-a-vis the USD. RHS: Local Currency (LC) and Foreign Currency (FC) Spreads. Data source: 2020 BIS Annual Economic Report.

sentiment that affect global financial conditions but do not generate the same flight-to-safety patterns. Moreover, unlike other financial risk measures that respond endogenously to monetary policy, the flight-to-safety index exhibits near-zero correlation with high frequency measures of U.S. monetary policy shocks, allowing for the joint examination of international financial and monetary spillovers under weaker identification assumptions than previous studies. That said, by focusing on flights-to-safety, this paper analyzes a specific subset of financial stress that is little correlated with monetary policy but it also does not rule out the interdependence between monetary policy and financial risk-taking through more general channels. In view of these considerations, the flight-to-safety index is used to investigate how global financial risk sentiment shapes macroeconomic dynamics in emerging markets, comparing their effects against the spillover effects from coincident but uncorrelated U.S. monetary policy shocks.

The focus on macroeconomic adjustment to global financial conditions builds on studies estimating financial spillovers within a multi-country vector autoregression (VAR) framework. In closely related papers, Cesa-Bianchi et al. (2020) shows that global financial volatility has a large and significant impact on real output growth in both advanced and emerging market economies. Chudik and Fratzscher (2011) compares the international spillover effects of U.S. funding and risk sentiment shocks separately identified using sign restrictions. I too examine global financial spillovers but unlike these studies, I focus on changes in financial market conditions specifically associated with flights-to-safety and the explicit role of U.S. monetary policy. Disentangling changes in financial conditions from monetary shocks is typically challenging because they endogenously shape each other. Maćkowiak (2007) does compare the effects of external shocks and U.S. monetary shocks on emerging markets in a structural VAR, identifying these shocks with short-run zero restrictions. They find a small role for U.S. monetary policy spillovers compared to external shock spillovers. Also using short-run restrictions, Akinci (2013) considers both the spillover effects of global financial conditions and U.S. monetary policy to emerging markets but again finds an important role for only financial conditions while U.S. monetary policy plays a negligible role.

Short-run structural VAR restrictions, however, are difficult to justify when it is unclear which shock leads the other, as in the case of shocks to monetary policy and financial conditions. Unlike Maćkowiak (2007) and Akinci (2013) which identify financial and monetary shocks separately by imposing short-run zero-restrictions, the flight-to-safety index and high-frequency identified U.S. monetary shocks are uncorrelated with one another. As a result, the effects of financial shocks identified from a VAR using the flight-to-safety index are insensitive to whether the flight-to-safety index is ordered before or after monetary policy shocks in the VAR. Contrasting previous studies, both flights-to-safety and U.S. monetary policy are found to have statistically and economically significant spillover effects across a broad set of emerging markets. Therefore the results agree with Cesa-Bianchi and Sokol (2022) which identifies both U.S. financial shocks and monetary policy shocks using external instruments and sign restrictions to find that both types of shocks spill over to financial and credit conditions in the United Kingdom.

This paper more broadly contributes to the literature on global financial spillovers and the international transmission of monetary policy. Miranda-Agrippino and Rey (2020) document the presence of a common factor in global asset prices and shows how U.S. monetary policy transmits through the financial cycle to affect financial conditions abroad. Some evidence suggests spill-backs from foreign monetary policy to the U.S. are also important (Ammer et al. (2019) and Spiegel (2022)). Cesa-Bianchi et al. (2018) points to U.S. intermediary leverage as a driver of global financial spillovers. Aizenman et al. (2016), Georgiadis (2016), Obstfeld et al. (2019), and Aizenman et al. (2020) show that the extent of financial spillovers depend on macroeconomic and institutional policy choices such as the exchange rate regime and financial openness, while

Converse et al. (2020) argue that spillovers are also linked to the financial development, specifically the growth of exchange traded funds. Like Ahmed and Zlate (2014) and Chari et al. (2020), my attention is focused on the impact of global financial spillovers on emerging market economies, but instead of studying the impact of financial conditions on capital flows, I build on studies such as Disyatat and Rungcharoenkitkul (2017) and Hofmann et al. (2020) by measuring the effects on emerging market sovereign spreads, exchange rates, and economic activity.

As the first contribution of this paper, a new financial index is presented which specifically captures sudden, unpredictable flights-to-safety. There is little consensus on how to systematically measure flight-to-safety or risk-off phenomena. Both discrete (Beber et al. (2014), Baele et al. (2019)) and continuous (Datta et al. (2017), Chari et al. (2020)) measures of flight-to-safety or 'risk-on/risk-off' have been proposed. Other studies rely on off-the-shelf measures of financial stress like the VIX index (De Bock and de Carvalho Filho (2015), Caballero and Kamber (2019)). I present a new approach to measure global flights-to-safety that starts with the key ingredient many of the prevailing measures share: Extreme co-movement between a carefully selected set of safe and risky asset market prices. I then depart from previous approaches in two crucial ways. First, the unpredictable component of these financial fluctuations is recovered using an asymmetric GARCH volatility model such that large flights-to-safety reflect tail-realizations across daily asset returns. Second, information is incorporated from multiple markets and economically motivated sign restrictions are imposed to sharply identify flights-to-safety. Specifically, using daily data, flights-to-safety or risk-off are identified as trading days where simultaneously: Equity markets fall, risky credit spreads widen, safe government bond yields fall, implied option volatility rises, and carry currencies unwind against safe haven currencies.

The flight-to-safety index is correlated with benchmark measures of financial risk appetite such as the VIX index, the global risk-off index of Datta et al. (2017) and the risk-on/risk-of index of Chari et al. (2020). It is also correlated with more general measures of financial conditions such as global realized stock market volatility (Cesa-Bianchi et al. (2020)), and the global financial cycle (Miranda-Agrippino and Rey (2020)). Yet these correlations are imperfect because the flight-to-safety index tries to isolate the component of financial fluctuations that specifically resemble flight-to-safety patterns. As a result, flights-to-safety are correlated with measures of financial conditions but they are distinctly uncorrelated with high-frequency identified monetary policy shocks. This implies that flights-to-safety differ from other types of changes in risk appetite caused by contractionary monetary policy surprises or interest rate 'tantrums' – cases associated with higher risk aversion and higher interest rates, because flights-to-safety are associated with higher risk aversion but lower interest rates (due to a rotation into safe assets). Flights-to-safety map to historically disruptive events and are associated with significant U.S. Dollar appreciation even after conditioning on the VIX index.

As a second contribution of this paper, new evidence is presented on the spillover effects of flights-to-safety on emerging markets. This is done within a multi-country VAR with country-specific heterogeneity to quantify the financial and macroeconomic impact of a global flight-to-safety. The modeling approach allows for interdependencies between emerging markets, spillovers from developed economies to emerging markets, and can embed global factors such as the flight-to-safety index and U.S. monetary policy shocks which affect all emerging markets but the degree of sensitivity to these factors might be country-specific. Global flights-to-safety significantly impact economic activity across emerging markets, and on average, the impact is substantially larger than that from changes in home-grown domestic financial conditions. Flights-to-safety induce rising sovereign spreads, currency depreciation and a reduction in FX reserves, followed by a contraction in economic activity. These effects persist after controlling for the VIX index or other global risk-off indices, are larger among more financially developed emerging markets, were present in the pre-2008 period, and remain significant under a battery of robustness checks.

Finally, using high-frequency identified U.S. monetary policy shocks from changes in Treasury futures prices around Federal Open Market Committee (FOMC) announcements, I demonstrate that contractionary U.S. monetary policy shocks impact emerging markets in the same way as flights-to-safety. This occurs despite monetary policy shocks and flights-to-safety exhibiting near-zero correlation. The effects of U.S. monetary policy and flights-to-safety compound, as expansionary (contractionary) U.S. monetary policy can help reduce (magnify) the extent of spillovers amid a global flight-to-safety by roughly 30%. These findings suggests that U.S. monetary policy reactions to sudden changes in financial conditions play a pivotal role in determining the extent of total spillovers to the rest of the world. An additional implication: Spillovers from contractionary U.S. monetary shocks are magnified when they inadvertently trigger a flight-to-safety, say due to investors perceiving a policy error.

The rest of the paper is structured as follows: Section 2 describes the construction of the flight-to-safety index and documents stylized facts. Section 3 presents the multi-country VAR model used to estimate the impact of flights-to-safety on emerging markets along with results. Section 4 extends the analysis to estimate spillovers from U.S. monetary policy to emerging markets. Section 5 concludes. The Appendix provides further details on data sources, robustness checks, and additional results.

2. Flight-to-Safety: A Cross-Asset Approach

The flight-to-safety (FTS) index presented here aims to capture the intensity of global flights-to-safety by pooling information from key international markets spanning major financial asset classes and by requiring a particular set of co-movements across these carefully selected markets to be realized. Six markets are considered due to their international presence: The Wilshire 5000 equity index; 10-year U.S. Treasury yields; 10-year German Bund yields; FX Carry index (long the New Zealand Dollar and Australian Dollar while short the Japanese Yen and Swiss Franc); U.S. corporate high yield spreads; the CBOE VIX index. These indices are considered for two main reasons: For broad international coverage across advanced economies, and for coverage across asset classes. The index, therefore, will have representation from major financial asset markets: Equities, options, government bonds, corporate credit, and currencies.

The market-capitalization weighted Wilshire 5000 index represents the broad U.S. stock market[2], while 10-year U.S. Treasuries and German Bunds are globally recognized safe assets. The FX Carry index captures the relative value of risky, high interest rate, procyclical currencies against safe, low interest rate, counter-cyclical currencies. The Japanese Yen and Swiss Franc act famously as safe havens, appreciating amid turmoil while the Australian and New Zealand Dollar tend to covary positively with global economic growth. The U.S. corporate high yield spread reflects the average financing premium faced by U.S. firms that are rated below investment grade. Finally, the VIX index is a common gauge of global investor risk appetite and demand for insuring equity market risk. It specifically measures the option-implied expected forward 1-month volatility of the S&P 500 stock market index.[3]

A measure of flight-to-safety will be estimated by relying on the cross-asset correlations typically observed during global flights-to-safety. The economics of FTS imply global portfolio rebalancing such that investors sell risky assets and buy safe assets in the face of a negative shock and/or rising uncertainty. To capture this flight-to-safety 'signature', a flight-to-safety or risk-off is defined as a period satisfying the following sign restrictions over any given trading day: Volatility (VIX) rises [**+**]; equities fall [**–**], Treasury and Bund yields fall [**–**], high yield credit spreads rise [**+**], carry currencies (AUD, NZD) depreciate against safe currencies (JPY, CHF) [**–**], as depicted in Table 1. The precise inverse is defined as risk-on behavior, so the final FTS index will capture both risk-on and risk-off movements.

While the above set of assets are meant to capture conventional flight-to-safety behavior as typically defined by practitioners, it is important to note that a rotation from risky to safe assets need not require increased demand for long-dated Treasuries or Bunds. Rather, the perception of what is safe and what is risky may change form over time. While long-dated bonds may match better the duration profile of risky assets like equities, Recent episodes suggest that, for example, a flight-to-safety may resemble investors rotating from risky assets into short-maturity risk-free debt instead of long-dated bonds and as such, clearly demarcating flights-to-safety may be more challenging at certain times over others.

2.1. Stage 1: Standardizing asset returns

The FTS index first requires estimating individual asset price changes before aggregating to the index level. Denote r_{kd}, $k \in \{1, \cdots, K\}$ as the daily return of asset k over day d. The $K = 6$ assets considered are those mentioned: The VIX, the Wilshire 5000 index, 10-year Treasury yields, 10-year German Bund yields, FX Carry, and U.S. corporate high yield spreads. All returns are in log-differences, except the two government yields, which are first-differences. The global FTS index is constructed as an aggregation of standardized daily changes across these assets. Standardized daily changes in each asset are defined by comparing the realized return on day d, denoted r_{kd}, to the square root of the conditional variance forecast for day d (i.e. the *ex ante* conditional volatility), made on day $d-1$:

$$Z_{kd} = \frac{r_{kd}}{\sqrt{E_{d-1}\left[\sigma^2_{kd}\right]}}. \tag{1}$$

This procedure resembles the approach of conditionally devolatizing price returns (Engle (2002)). A key difference is that the predicted, or *ex ante* day $d-1$ volatility is considered here, while devolatizing traditionally compares day d volatility to the day d return. This step serves three important purposes. First, return volatility varies substantially across assets and over time. Standardizing asset returns by their conditional volatility produces a transformation which admits comparison across assets classes and accounts for regime changes (e.g., volatility clustering). Second, under the assumption that Z_{kd} follows an i.i.d. distribution (it is, after all, a conditional z-score), the probability that return r_{kd} was unexpected rises in $|Z_{kd}|$. From the econometrician's perspective, large values of Z_{kd} are increasingly likely to reflect unexpected price movements in the sense that they are increasingly unlikely to occur under the prevailing distribution. Third, large values of Z_{kd} are naturally interpreted as tail realizations. The measure also has an institutional motivation: Large Z_{kd} can be seen as a breach of Value-at-Risk measures often used by financial institutions to assess market risk and determine portfolio leverage (Duffie and Pan (1997)).

While r_{kd} is observed, $E_{d-1}\left[\sigma^2_{kd}\right]$ is not and must be estimated. To estimate $E_{d-1}\left[\sigma^2_{kd}\right]$, a model for time-varying volatility must be specified. I assume that daily asset returns are mean zero with time-varying volatility following a GARCH process. (Bollerslev (1986)):

[2] Another common measure of U.S. stock market performance is the S&P 500 index, which covers fewer (500 firms) but larger publicly traded companies. Historical Wilshire 5000 and S&P 500 returns are highly correlated.

[3] Notice that four of the six benchmark assets are U.S. centric and therefore, I make the implicit assumption that global FTS are largely reflected in U.S. markets, and more generally across advanced economies. Similar interpretations are taken for the VIX when it is used as a gauge of global risk appetite. While this assumption may be reasonable, global economic centers shift over time. The approach taken in this paper is general enough such that one can easily add financial benchmarks from other countries to account for other important financial centers.

Table 1
Cross Asset Flight-to-Safety Behavior

Z_{kd}	Underlying	Asset Class	FTS Behavior	$w_k(avg)$	$w_k(PCA)$
Z_{1d}	CBOE VIX Index	Volatility	+	1/6	0.17
Z_{2d}	Wilshire 5000 Stock Index	Equities	–	1/6	0.18
Z_{3d}	10-year U.S. Treasury Yield	Government Rates	–	1/6	0.18
Z_{4d}	10-Year German Bund Yield	Government Rates	–	1/6	0.19
Z_{5d}	U.S. High Yield Spread	Credit	+	1/6	0.16
Z_{6d}	FX Carry*	Currencies	–	1/6	0.12

* FX Carry is an equally weighted index long New Zealand Dollar (NZD) and Australian Dollar (AUD) vis-à-vis the Swiss Franc (CHF) and Japanese Yen (JPY).

$$r_{kd} = \sqrt{E_{d-1}[\sigma^2_{kd}]} Z_{kd}, \quad Z_{kd} \sim N(0,1), \tag{2}$$

where the return sequence is split into a stochastic i.i.d component (Z_{kd}) and a time-varying volatility component (σ_{kd}). I parameterize Z_{kd} as being drawn from a standard normal distribution, hence conditional returns are normally distributed but the unconditional distribution is allowed to be fat-tailed.[4] Specifically the conditional variance at time d follows a GJR-GARCH (1,1) process:[5]

$$E_{d-1}[\sigma^2_{kd}] = \omega_k + \alpha_k E_{d-2}\left[\sigma^2_{k,d-1}\right] + (\beta_k + \gamma_k \boldsymbol{I}_{k,d-1}) r^2_{k,d-1}, \text{where} \tag{3}$$

$$\boldsymbol{I}_{k,d-1} = \begin{cases} 0, r_{k,d-1} \geq 0 \\ 1, r_{k,d-1} < 0. \end{cases} \tag{4}$$

The conditional volatility model under a GJR-GARCH extends the classical GARCH framework by allowing for asymmetric volatility, a well-known stylized fact of financial asset returns where the conditional variance of an asset is correlated with its returns. Allowing for conditionally asymmetric asset return variance is essential in this application due to the asymmetric nature of the flight-to-safety phenomena we wish to measure. The GJR-GARCH process is parameterized as (1,1) not just due to its simplicity, but also due to its heuristic appeal. GARCH(1,1) is equivalent to an infinite order autoregressive process and it has been shown that more complex volatility models do not strictly outperform a GARCH(1,1) benchmark (Hansen and Lunde, 2005).

From (3), the expected or *ex ante* volatility for day d conditional on day $d-1$ information is computed as $\sqrt{E_{d-1}[\sigma^2_{kd}]}$. Referring to (1), standardized changes to the price of asset k are recovered by dividing its observed realized return on day d by its *ex ante* conditional volatility. In other words, we ask: *To what degree was the realized asset change justified by its prevailing (ex ante) distribution?* Larger values imply tail realizations, and equivalently returns which are less likely to be generated from the *ex ante* distribution.

With Z_{kd} for all 6 components estimated, an aggregate measure, $\bar{Z}_d$ is constructed as the rotated cross-section average on each day d:

$$\bar{Z}_d = (w_1 Z_{1d} - w_2 Z_{2d} - w_3 Z_{3d} - w_4 Z_{4d} + w_5 Z_{5d} - w_6 Z_{6d}), \sum_{k \in K} w_k = 1, \tag{5}$$

where the rotations ensure that positive values of $\bar{Z}_d$ coincide with fight-to-safety or risk-off, and negative values coincide with risk-on episodes. Hence, the Z_{kd} vectors corresponding to the VIX and high-yield credit spreads are added, while the rest are subtracted. I apply equal weights $w_a = 1/6$ but more generally, one can assign arbitrary weights w_k across assets. Similarly, an estimate of $\bar{Z}_d$ can be obtained by taking the first principal component of Z_{kd}. The implicit weights assigned via PCA are reported in Table 1 under $w_k(PCA)$. In practice, there is very little difference between estimates of $\bar{Z}_d$ obtained via PCA or equal weighting. Specifically, the $\bar{Z}_d$ estimated as the cross-section average shares a correlation of over 0.98 with the PCA approach. Asymptotically, the cross-section average and 1st principal component converge to the same measure under true factor structure (likely in our case with financial market returns, Westerlund and Urbain (2015)), but note K is only 6 in this application. The added benefit of taking cross-section averages is that they can be calculated each period without requiring information from the entire (or future) sample. By contrast, a key advantage of the PCA approach is that it can "self-learn" weights in high-dimensional settings when the set of variables in Z_{kd} becomes large, which is not our case. But

[4] One can parameterize Z_{kd} as being drawn from a Student-T's distribution which allows for both fat tails in conditional and unconditional distributions, and the results are virtually unchanged.

[5] See Glosten et al. (1993) for the extension of GARCH to GJR-GARCH.

due to well-known presence of structural breaks in financial time series, PCA weights are likely to be unstable over time, under which the use of an equally weighted index becomes more pragmatic. Several studies document this robust feature of cross-section averaging (DeMiguel et al., 2009; Westerlund and Urbain, 2015; Karabiyik and Westerlund, 2021).

2.2. Stage 2: Imposing the Flight-to-Safety restrictions

In the next step to construct the FTS index, $\bar{Z}_d$ is multiplied by an indicator $\mathbf{1}_d$ which takes a value of 1 if that day's cross-asset co-movement was consistent with either flight-to-safety/risk-off or risk-on, and 0 otherwise (the flight-to-safety conditions shown in Table 1):[6]

$$FTS_d = \bar{Z}_d \mathbf{1}_d, \tag{6}$$

$$\mathbf{1}_d \begin{cases} 1 \ \mathit{if}\{Z_{1d}, Z_{5d}\} > c \ \cap \ \{Z_{2d}, Z_{3d}, Z_{4d}, Z_{6d}\} < -c & '\mathit{Risk-Off}' \\ 1 \ \mathit{if}\{Z_{1d}, Z_{5d}\} < -c \ \cap \ \{Z_{2d}, Z_{3d}, Z_{4d}, Z_{6d}\} > c & '\mathit{Risk-On}' \\ \quad 0 \quad \mathit{otherwise}. \end{cases} \tag{7}$$

These sign restrictions impose the condition that all 6 asset returns move in the direction consistent with flight-to-safety, with the size of the move necessarily larger than some threshold c (a magnitude restriction). If asset price movements do not satisfy this joint condition, there is no flight-to-safety, and $FTS_d = 0$. If the set of sign restrictions is satisfied, the size of FTS_d is continuous and can be positive ('risk-off') or negative ('risk-on'). As a baseline, $c = 0$, meaning a flight-to-safety is identified simply based on sign, regardless of magnitude. One drawback of this baseline is that some days may satisfy the FTS condition simply by random chance, though this becomes increasingly unlikely as the number of sign restrictions increase. Taking a more conservative threshold for c accounts for both the direction and size of cross-asset moves at the expense of omitting some true FTS days. As an alternative, a threshold of $c = 1$ is considered in Section 3.6, meaning that all components must have $|Z_{kd}| > 1$ on a given day (at least a 1-sigma move) and all components must also move in the direction consistent with a flight-to-safety. Note also that the threshold c can be further generalized, setting different c for each asset price series Z_{kd}. However, all of our measures fall along the same unit of measurement because they are standardized, so setting different c values may be more useful in situations dealing with non-standardized series.[7]

Finally, the daily FTS index FTS_d, can be aggregated to the monthly frequency, FTS_t:

$$FTS_t = \sum_{d=1}^{D(t)} FTS_d(t), \tag{8}$$

where $D(t)$ is the number of days in month t, and $FTS_d(t)$ denotes daily global fight-to-safety measures corresponding to month t. Similar approaches are used to aggregate daily monetary policy shocks to the monthly frequency. By summing the daily values of FTS_d, which can be positive (risk-off), negative (risk-on) or zero (non-event), each monthly index value of FTS_t can be interpreted as the net of the daily positive and negative FTS index values.

Because only six assets are in the set K which constructs the FTS index, it's important to assess the sensitivity of the index to excluding any single asset. Table 2 provides results from a leave-one-out analysis as a robustness check, showing that both the daily and monthly FTS series remain highly correlated with each series constructed as an aggregate of five of the six assets. Re-computing the index while excluding any one asset maintains a correlation of 0.89 or greater with the monthly FTS index constructed from all six assets, and 0.88 or higher for the daily index.

To assess the importance of the sign restrictions for the FTS index, the rotated average of the 6 standardized asset returns, i.e. $\bar{Z}_d$, is compared to the sign-restricted FTS index, FTS_d. Estimates from univariate regressions of the FTS index on this 'unrestricted' index show that the 'unrestricted' index explains 59% (57%) of the daily (monthly) variation in the benchmark FTS index with sign restrictions imposed. This result suggests that the sign restrictions meaningfully contribute to the FTS index. Naturally, there are many parameters that could be chosen differently in the construction of the FTS index. In Section 3.6, different iterations of the FTS index are considered.

2.3. Properties and stylized facts of the FTS index

A time-series of the monthly FTS index is shown in Fig. 2. From January 2000 through August 2019, of the 5,130 days in the sample, 9.6% are consistent with a flight-to-safety or 'risk-off', with 9.6% co-moving in a way consistent with 'risk-on'. Note that these proportions do not say anything about the size of the moves (recall $c = 0$). Risk-off days are also particularly special in the sense that asset price moves are significantly larger – statistically and economically – than usual. For the Wilshire 5000 stock index, the average daily negative return is −0.7%. On a risk-off day when negative equity returns are accom-

[6] Note that the rotation in the first stage captures risk-off versus risk-on while this second stage parses out all other (non risk-on/off) days.

[7] Moreover, given a particular target outcome variable (e.g. GDP growth), one could estimate a threshold c using maximum likelihood methods (MLE) as in Chudik et al. (2020). However, because the FTS index presented is a stand-alone measure, parameterizing c based on a particular outcome is not necessarily desirable in this context.

Table 2
FTS Index: Sensitivity Analysis

	Correlation with	
Excluding:	Daily FTS_d	Monthly FTS_t
CBOE VIX Index	0.95	0.96
Wilshire 5000 Stock Index	0.97	0.97
10-year U.S. Treasury Yield	0.97	0.96
10-Year German Bund Yield	0.92	0.93
U.S. High Yield Spread	0.96	0.95
FX Carry	0.88	0.89

Leave-one-out analysis constructs the FTS_d and FTS_t indices but only aggregating five of the six assets, excluding one at a time. Then the correlations are estimated against the full FTS index calculated with all six assets, to test whether the index is sensitive to leaving any particular asset out of the calculation.

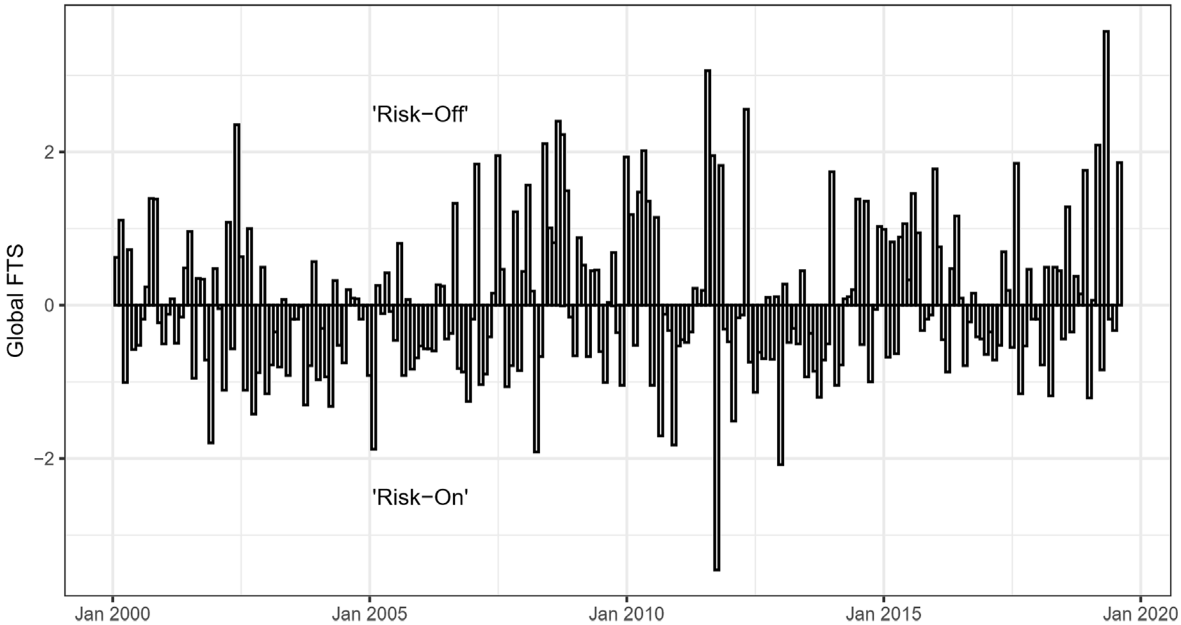

Fig. 2. Time-Series of Global Flight-to-Safety Index (FTS_t). First order auto-correlation = −0.012 and statistically indifferent from zero. Series is normalized to have unit standard deviation.

panied by rising volatility, falling bond yields, rising credit spreads and depreciating risky currencies, the average daily Wilshire 5000 return doubles to −1.4%. Similar patterns apply across the other markets. When the VIX index rises, it rises on average 5.3%. On a risk-off day, it rises on average 8.4%.

2.4. Flights-to-Safety and the U.S. Dollar

Table 3 shows that both advanced economy (AE) and emerging market (EM) U.S. Dollar indices appreciate significantly with the FTS index at both daily and monthly frequencies, and even after controlling for the VIX index. A 1-standard deviation positive FTS (risk-off) is associated with 0.211% and 0.243% monthly USD appreciation vis-a-vis AE and EM currencies, respectively. Dollar appreciation occurs *despite* long-term U.S. interest rates falling during FTS. Because the FTS index is constructed using estimates of otherwise unobserved component volatilities, it is subject to measurement error. Columns 2, 4, 6 and 8 report estimates under a model-free version of the FTS index, denoted *FTS(MF)*, described in Section 3.6.7 that does not introduce bias via generated regressors in the reported regressions.

2.5. The FTS index and its volatility

Unlike the VIX index or VIX changes, neither daily nor monthly measures of the FTS index (FTS_d or FTS_t) exhibit statistically significant serial correlation – a feature indicating the difficult-to-predict nature of these episodes. Specifically, the 1st

Table 3
Global Flights-to-Safety and U.S. Dollar Appreciation

	Daily Returns (%)				*Monthly Returns (%)*			
	AE/USD		EM/USD		AE/USD		EM/USD	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	−0.001	−0.001	0.008*	0.008*	−0.020	−0.020	0.119	0.119
	(0.006)	(0.006)	(0.005)	(0.005)	(0.100)	(0.100)	(0.076)	(0.076)
Lagged Δ USD (%)	−0.012	−0.011	0.053**	0.054**	0.319***	0.320***	0.386***	0.386***
	(0.016)	(0.016)	(0.025)	(0.025)	(0.059)	(0.059)	(0.070)	(0.067)
$\Delta \ln VIX(\%)$	0.0005	−0.0009	0.007***	0.007***	0.008	0.008	0.034***	0.035***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)	(0.008)	(0.008)	(0.007)
FTS	0.034***		0.091***		0.211**		0.243***	
	(0.009)		(0.007)		(0.098)		(0.092)	
FTS(MF)		0.045***		0.080***		0.226***		0.247***
		(0.010)		(0.008)		(0.086)		(0.091)
Observations	5,129	5,129	5,129	5,129	234	234	234	234
R^2	0.009	0.009	0.127	0.112	0.145	0.148	0.386	0.387
Adjusted R^2	0.008	0.008	0.126	0.111	0.134	0.136	0.378	0.379

Robust standard errors with *,**,*** corresponding to 10, 5, and 1 percent significance, respectively. USD returns are computed as log-changes from the previous period. AE index refers to the Nominal Major Currencies Index taken from FRED and consists of returns vis-vis the Euro Area, Canada, Japan, United Kingdom, Switzerland, Australia, and Sweden. EM index is the USD return vis-a-vis an equal weighted basket of currencies of: South Korea, Mexico, Brazil, India, Malaysia, South Africa, Taiwan, Thailand, Sri Lanka sourced from FRED. *FTS* is normalized to unit variance, while other variables are in percentages. *FTS (MF)* refers to the model-free FTS index described in 3.6.7 that is free of estimation error.

and 2nd order autocorrelation of the monthly series are very close to zero: −0.012 and −0.016, respectively. The volatility of FTS has also increased since 2007 (Fig. A.1 of the Appendix). Each month the realized volatility is computed by taking the standard deviation of daily FTS_d within that month. The volatility of FTS after February 2007 is roughly 60% larger than before 2007. The regime change in the severity of FTS coincides with the post 2008 Great Recession era and the onset of unprecedented monetary expansion and changing behavior of global capital flows (Ahmed and Zlate (2014)). Section A2 of the Appendix maps the largest daily FTS readings to economic events or news associated with them.

2.6. Comparison with other measures of financial stress

The FTS index is designed to be interpreted as a subset of more general global financial fluctuations: Those which are 1) abnormally large and 2) satisfy the fight-to-safety sign restrictions. Fig. 3 shows that the FTS index (x-axis) is indeed correlated with other measures of financial stress, but imperfectly so. These imperfect correlations suggest certain overlapping as broad financial indices respond during flights-to-safety. However, several types of adverse events that do *not* necessarily generate a flight-to-safety are also captured as fluctuations in broad measures of financial stress, e.g., monetary policy shocks, stagflation, taper tantrums, liquidity crunches, or non-fundamental shocks.[8] Therefore, the FTS index appears to isolate a specific type of financial risk that specifically generates the flight-to-safety pattern. This may be important if we believe that distinct patterns across financial markets bear different economic implications and contain different signals.

Global flights-to-safety can explain roughly 22% of the variation in log changes in the VIX (correlation of 0.47). The measure $GVOL_t$ is the change in logged global average equity realized volatility in the spirit of Cesa-Bianchi et al. (2020).[9] The FTS index can explain roughly 14% of the variation in $GVOL_t$ (correlation of 0.38). FTS_t is also imperfectly correlated with monthly changes in the global financial cycle of Rey (2015) and Miranda-Agrippino and Rey (2020), $GFCY_t$. Roughly 37% of the variation in $GFCY_t$ is explained by global flights-to-safety (correlation of −0.61).[10] Particularly interesting is that the FTS index, composed from just 6 components, exhibits the degree of correlation that it does with the global financial cycle, which is estimated using over 1,000 asset prices. The risk-on/risk-off index of Chari et al. (2020), $RORO_t$, and the global risk-off index of Datta et al. (2017), ROI_t, are financial indices that are more finely tuned to capture risk-off behavior like the FTS index. Both indices exhibit a high degree of correlation with the FTS index: The monthly FTS index can explain roughly 45% and 50% of the variation in $RORO_t$ and ROI_t, respectively. While the FTS index is correlated with these measures of financial conditions, it is also unique in important ways. Section 3 shows that the FTS index exhibits significant spillover effects to emerging markets even after controlling for other measures of financial conditions and Section 4 shows that the FTS index is uncorrelated with high-frequency identified monetary policy shocks.

[8] For instance, contractionary monetary policy shocks and liquidity shocks may result in falling equity prices and *rising* bond yields. A similar co-movement approach to disentangle shocks is used in Jarociński and Karadi (2020) who disentangle monetary information shocks using co-movements with equity returns.
[9] The measure is calculated by first computing monthly equity realized volatility from daily stock market index returns across 32 countries, and then taking the cross-section average to arrive at a global average realized volatility index. Finally for consistency, the measure is logged and then first-differenced.
[10] These correlations weaken further when increasing the FTS index threshold to $c = 1$ which more conservatively identifies flight-to-safety episodes as tail shocks.

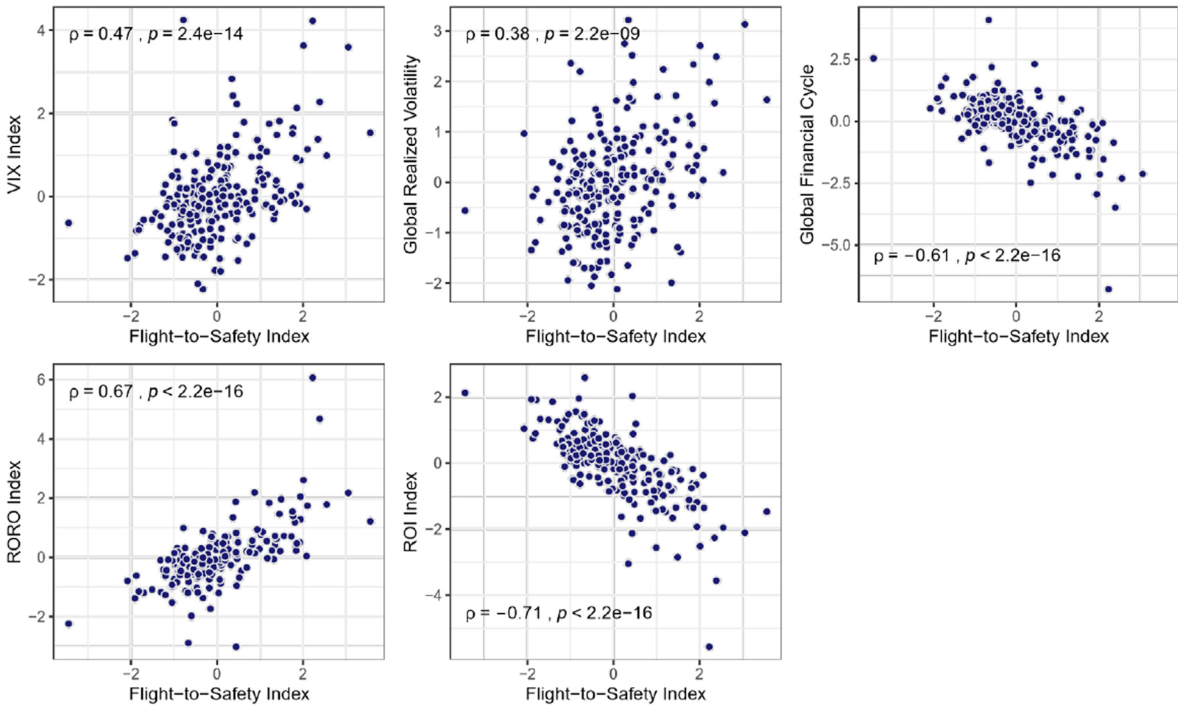

Fig. 3. Flight-to-Safety Index and other measures of Global Financial Stress. Top panel, LHS: Monthly changes in logged VIX index on the y-axis. Top panel, center: Monthly changes in logged global realized volatility, $GVOL_t$ from Cesa-Bianchi et al. (2020) on the y-axis. Top panel, RHS: Monthly changes in the global financial cycle, $GFCY_t$ from Miranda-Agrippino and Rey (2020) on the y-axis. Bottom panel, LHS: Risk-on/Risk-off index of Chari et al. (2020). Bottom panel, center: Global risk-off index of Datta et al. (2017). FTS index on the x-axis for all figures.

3. Global Flights-to-Safety and Emerging Markets

Recent debates and research in open-economy macroeconomics focus on the consequences of global financial spillovers propagating from advanced economies to emerging markets, many of the latter countries being vulnerable to external shocks due to deepening international financial integration.[11] This section revisits this issue, evaluating the dynamics of emerging markets following a global flight-to-safety, documenting both the financial and macroeconomic consequences for a broad set of countries. Table 4 reports the sample of countries considered in these exercises with further details on data and sources in Section A1 of the Appendix. The country list is based on monthly sovereign bond spreads and industrial production available through the World Bank's Global Economic Monitor database. The sample period ranges from January 2000 to August 2019.

Countries listed in bold are considered EM *Majors* and classified formally as such by MSCI, while non-bold countries tend to be smaller and less financially integrated, typically classified as Frontier Markets. The latter class of countries are referred to as EM *Minors*. Countries with incomplete data over the sample period are also relegated to the EM Minor group. EMs that do not have EMBI indices are noted with an asterisk and added to extend the sample. For these four countries, 5-year sovereign bond yield spreads to the 5-year U.S. Treasury yield are used to measure sovereign spreads.

3.1. The empirical multi-country model

Key modeling challenges of multi-country economic systems include accounting for 1) global common factors 2) network effects or spillovers between countries 3) spillovers from advanced countries to emerging markets, and 4) heterogeneous transmission of global shocks. The traditional modeling approaches used are panel regressions or VARs which estimate average effects or impulse response functions (IRF) to a global shock by pooling information across all countries in the sample. While pooling data across countries has the advantage of increasing statistical power, this approach has some drawbacks in this specific setting. First, it ignores slope heterogeneity across countries including the possibility that countries are differentially sensitive to global factors. When slope heterogeneity exists, panel estimates will be biased. Under an unbalanced panel, estimation relies on observations from countries with a larger observation set instead of giving each country equal

[11] See, for example, Uribe and Yue (2006), Akinci (2013), Caballero and Fernández (2019), Kalemli-Ozcan (2019), Cesa-Bianchi et al. (2020), Obstfeld et al. (2019).

Table 4
List of Countries

1–10	11–20	21–30	31–38
Argentina	El Salvador	Pakistan	Ukraine
Belarus	Gabon	**Peru**	Uruguay
Brazil	**Hungary**	**Philippines**	Venezuela
Chile	Indonesia	**Poland**	Vietnam
China	Iraq	**Russia**	India*
Colombia	Jordan	Senegal	Singapore*
Cote d' Ivoire	Kazakhstan	**South Africa**	S. Korea*
Croatia	Lithuania	Sri Lanka	Thailand*
Ecuador	**Malaysia**	Tunisia	
Egypt	**Mexico**	**Turkey**	

Countries in **bold** indicate EM 'majors' based on 1) EM classification by MSCI and 2) complete sample. Due to missing observations, Egypt and Indonesia are not considered in the EM major group. Non-bold countries defined as EM 'minors' most of which are typically considered frontier markets, or countries with incomplete data over the 2000–2019 period. Countries with '*' are used in an extended sample analysis as these countries do not have EMBI data available. As a substitute for the EMBI spread, the 5-year sovereign bond yield spread to U.S. Treasuries is used for these countries.

weight, and similar issues arise in a panel setting when the data exhibits significant heteroskedasticity across countries such that countries with more volatile observations more heavily influence the estimates. That including dynamics via lagged dependent variables along with fixed effects in a panel setting introduces bias in the estimates is also well known (Nickell (1981)).[12]

With these considerations in mind, I construct an unbalanced monthly data set on sovereign spreads and industrial production across 34 emerging markets from 2000 to 2019 to estimate a multi-country VAR.[13] This method has been applied successfully to large, heterogeneous macroeconomic panel data of similar size to address a variety of research questions (See for example Dees et al. (2007), Chudik et al. (2017), Hernandez-Vega (2019), Cesa-Bianchi et al. (2020)). Key differences between this modeling approach and the traditional panel VAR include allowing for country-specific heterogeneity, an important feature of the data as shown in Fernandez et al. (2017) and Cesa-Bianchi et al. (2020). Like the benchmark panel VAR, it can also be used to estimate average effects by averaging country-specific estimates over all countries or subsets of countries. The model also easily incorporates factor structure and spillovers between countries. Consider the baseline multi-country VAR:

$$\begin{bmatrix} FTS_t \\ \Delta Y_{US,t} \\ \Delta Y_{i',t} \\ \Delta y_{i,t} \\ \Delta S_{i',t} \\ \Delta s_{i,t} \end{bmatrix} = \begin{bmatrix} \theta_i^V \\ \theta_i^{US} \\ \theta_i^Y \\ \theta_i^y \\ \theta_i^S \\ \theta_i^s \end{bmatrix} + \Phi_i(L) \begin{bmatrix} FTS_{t-1} \\ \Delta Y_{US,t-1} \\ \Delta Y_{i',t-1} \\ \Delta y_{i,t-1} \\ \Delta S_{i',t-1} \\ \Delta s_{i,t-1} \end{bmatrix} + \begin{bmatrix} v_t \\ u_{i,t}^{US} \\ u_{i',t}^{Y} \\ u_{i,t}^{y} \\ u_{i',t}^{S} \\ u_{i,t}^{s} \end{bmatrix}, \tag{9}$$

where $\Delta s_{i,t}$ is the change in the log sovereign spread, a proxy for domestic financial conditions, of country i over month t. Country i's year-over-year change in industrial production (IP) in month t is given by $\Delta y_{i,t}$.[14] It's easy to see that a model with just these two variables represents a classic VAR(L) model. Country-specific lag polynomials are expressed as $\Phi_i(L)$ of finite order l. The number of lags are set to equal $l = 4$ months by comparing the sum or average Akaike Information Criteria over all 34 country VARs under varying lag lengths. The main results are not sensitive to alternative values of l and results using a lag length of 8 months are reported as a robustness check.[15] The specification is further extended by modeling cross-country linkages through $\Delta S_{i',t}$ and $\Delta Y_{i',t}$. These are cross-section averages of changes in the log sovereign spread and IP growth over all countries excluding country i. Specifically,

$$\Delta S_{i',t} = \sum\nolimits_{i' \neq i} w_{i'}^{s} \Delta s_{i',t}, \qquad \sum_{i'=1}^{N-1} w_{i'}^{s} = 1,$$

[12] See Rebucci (2010) for further comparison of the panel estimation approach with the mean group estimation approach applied in this paper.
[13] Data details are found in Section A1 of the appendix. An extended sample of 38 countries is studied in Section 3.6.
[14] IP growth rates are computed as year-over-year to remove seasonality, as several of the country IP series are not seasonally adjusted. This introduces a moving-average in the series, however this serial correlation is captured by the several lagged variables in the VAR.
[15] For $l = 1, 2, 3, \mathbf{4}, 5, 6, 7, 8$, the corresponding average AICs from the 34 estimated VARs are: 2553; 2476; 2434; **2430**; 2445; 2447; 2456; 2458, respectively.

$$\Delta Y_{i',t} = \sum\nolimits_{i' \neq i} w^y_{i'} \Delta y_{i',t}, \qquad \sum_{i'=1}^{N-1} w^y_{i'} = 1,$$

where $\Delta S_{i',t}$ is a weighted average of the spread change for countries not including i, $\Delta s_{i',t}$, weighted by $w^s_{i'}$. I follow Cesa-Bianchi et al. (2020) by setting equal weights, $w^s_{i'} = 1/(N-1)$ for all i', therefore $\Delta S_{i',t}$ can be interpreted as the cross-section average of sovereign spread changes, exclusive of country i. The same is done for $\Delta Y_{i,t}$, except Iraq is excluded from the calculations given large outlier values driven by the Iraq War in the early 2000′s. Other approaches to obtaining weights include weights based on economic activity, bilateral trade weights, capital flow weights, or estimating weights statistically via PCA for $w^s_{i'}$. [16] However, it is not clear which weight scheme is appropriate and asymptotically the weighting scheme does not matter (Pesaran, 2006) so long as there is no dominant unit among the set of countries – a condition typically satisfied as shown in Cesa-Bianchi et al. (2020). Moreover, because the correlations of these variables (e.g. sovereign spreads) across countries are so high due to the factor structure of macro and financial variables, alternative weight schemes make little difference to the results.

Including these global averages admit cross-country interdependencies without running into the 'Curse of Dimensionality' that most large VARs face. For example, $\Delta S_{i',t}$ and $\Delta Y_{i',t}$ can be thought of as the inclusion of lagged spreads and IP growth for all other countries in the equations for country i. Without any coefficient restriction, estimating a VAR(4) would entail the addition of $33 \times 4 \times 2 = 264$ additional lagged variables, exceeding the number of time-series observations. However, including cross-sectional averages implies a coefficient restriction such that lagged spreads and IP growth from all other countries in country i's equation have coefficients equal to $\Phi_i(L)\frac{1}{N-1}$. I also include $\Delta Y_{US,t}$, changes in U.S. economic activity, measured using the Chicago Fed National Activity Index (CFNAI) to account for macroeconomic spillovers between advanced economies and emerging markets.

3.2. Identification and estimation

FTS *shocks* are defined as the innovations υ_t, the residual component of the FTS index (FTS_t) in (9) based on short-run zero restrictions imposed through recursive ordering of the variables. As a benchmark, the FTS index is ordered first and identification of the FTS shock is achieved under the assumption that EMs take the FTS index as exogenous, an assumption often made in the small open economy literature. Such ordering allows the FTS index to impact all other variables in the VAR contemporaneously. In Section 3.6, an alternative and more conservative ordering is considered where the FTS index is ordered after relatively slow-adjusting measures of economic activity ($\Delta Y^{US}_t, \Delta Y_{i',t}, \Delta y_{i,t}$) but before the financial variables ($\Delta S_{i',t}, \Delta s_{i,t}$). Under this more conservative identification scheme, FTS shocks contemporaneously impact EM financial variables such as sovereign spreads but can only impact economic activity with a one-month lag. The results remain very similar under these alternative ordering schemes.

The large T dimension of the data allows the multi-country VAR to be estimated country-by-country, estimating country-specific VARs for 34 emerging markets. All variables are standardized to have zero mean and unit variance. This estimation procedure is akin to estimating a multi-country VAR following Cesa-Bianchi et al. (2020) and this modeling approach still allows estimation of average or pooled effects as done in traditional panel models. Estimating the average IRF over the panel is done using the Mean Group (MG) estimator of Pesaran and Smith (1995) and Chudik and Pesaran (2019).[17] Following Cesa-Bianchi et al. (2020), the horizon h mean group, or average, impulse response function for the endogenous variable, denoted X_{it}, to a 1 standard deviation (SD) FTS shock is computed as:

$$MGIRF(h) = \frac{1}{N}\sum_{i=1}^{N} E\left[X_{i,t+h}|\upsilon_t = 1, \omega_{t-1}\right] - \frac{1}{N}\sum_{i=1}^{N} E\left[X_{i,t+h}|\upsilon_t = 0, \omega_{t-1}\right]$$

$$= \frac{1}{N}\sum_{i=1}^{N} E\left[X_{i,t+h}|\upsilon_t = 1, \omega_{t-1}\right], \tag{10}$$

where $E[X_{i,t+h}|\upsilon_t = 1, \omega_{t-1}]$ is the horizon h impulse response of country i, denoted as the conditional expectation of $X_{i,t+h}$ given a 1-SD FTS shock ($\upsilon_t = 1$), and ω_{t-1} denotes the full information set available as of time $t-1$. Intuitively, the impulse response function of (10) examines how $X_{i,t+h}$ responds to a 1-standard deviation FTS shock at time t given the information available at time $t-1$, comparing it to a counterfactual scenario of no FTS shock ($\upsilon_t = 0$) at time t with the same information available at time $t-1$. The associated non-parametric cross-sectional standard errors are computed as:

$$SE(h) = \sqrt{\frac{1}{N}\frac{1}{N-1}\sum\nolimits_{i=1}^{N}\left(E\left[X_{i,t+h}|\upsilon_t = 1, \omega_{t-1}\right] - MGIRF(h)\right)^2} \tag{11}$$

[16] I test both and the factor estimated via averages and that via PCA are highly correlated, close to a coefficient of 1.

[17] Alternatively, the Common Correlated Effects Estimator (CCE) of Pesaran (2006) and Chudik and Pesaran (2015) can also be applied.

It can be easily seen that the MG IRF is the cross-section average of all i country-specific IRFs, each being denoted $E[X_{i,t+h}|v_t = 1, \omega_{t-1}]$, at each horizon h. 95% dispersion intervals for each horizon h which I report in the results are equal to

$$MGIRF(h) \pm 1.96 \times SE(h). \tag{12}$$

Given the unbalanced and heteroskedastic nature of the cross-country panel data, the MG estimate has an egalitarian advantage over the traditional panel estimator because it gives each country equal weighting in the estimation of the average affect, rather than determining weights based on within-country sample size. Sub-sample analyses are also considered to explore heterogeneity by separately examining EM Major and Minor country groups. Section 3.6 presents additional results using an extended sample of EMs.

3.3. Main results

Fig. 4 traces the average or MG cumulative impulse response function of changes in logged sovereign spreads and IP growth to a 1-standard deviation *positive* FTS shock (i.e. 'risk-off'). Sovereign spreads react strongly, increasing about 0.50 standard deviations, and the response is front-loaded, displaying over-shooting behavior in the first few months following the shock. Economic activity significantly contracts over a period of roughly 18 months by about −0.70 standard deviations. All units are measured in standard deviations to correct for heteroskedasticity across countries. For the sake of interpretation, the 18-month cumulative response in IP growth is approximately a 4% average contraction across EMs. For comparison I also show that U.S. economic activity (thin solid line) significantly contracts following an FTS shock, reflecting the global nature of these episodes. Both the contraction and recovery of U.S. activity occurs faster than that of EMs. The dashed line indicates the response of EM economic activity to a 1-standard deviation idiosyncratic country spread shock.[18] The results indicate that the effects of global spillovers are substantially more potent than changes in country-specific financial conditions.

3.4. Exchange rates and international reserves

Exchange market pressure (EMP), introduced early on in Girton and Roper (1977) along with its many variants (Hossfeld and Pramor (2018)), is a useful gauge of international pressure on capital flows and the exchange rate either resisted through foreign exchange intervention or relieved through currency depreciation. EMP severity tends to capture periods of large, volatile capital inflows or outflows - often straining exchange rates and financial liquidity. Many recent studies highlight the role of global shocks in driving pressure on international markets via exchange or capital flow pressures across EMs.[19]

To consider the implications for EMP in the presence of global flights-to-safety, the multi-country VAR is augmented with two additional country-specific endogenous variables: Logged changes in USD exchange rates and international reserves which are ordered penultimately and last in the VAR, respectively. Global flights-to-safety and their international transmission suggests important interactions with EMP. Currency mismatch, for example, is a mechanism through which EMP may impact the real economy, as exchange rate depreciation increases the cost of foreign-denominated liabilities (Eichengreen and Hausmann (1999), Hofmann et al. (2020) and Carstens and Shin (2019)). Known as the financial channel of exchange rates, the pecuniary externality caused by currency depreciation in the presence of currency mismatch offsets the classical trade channel where depreciation is considered stimulative. For this reason I focus on USD exchange rates given the dominant role of the U.S. Dollar in the international monetary and price system.[20] Note that these exercises exclude Ecuador from the sample because it is a dollarized country while all other countries exhibit at least some exchange rate variation.

Fig. 5 traces the Mean Group IRF from a 1-SD FTS shock after extending the VAR in (9) to include exchange rates and international reserves. In addition to sovereign spreads widening and economic activity contracting, there is significant exchange market pressure across emerging markets. EMP manifests as both currency depreciation against the USD and as a significant reduction of international reserves across EMs.[21] Within the first few months, exchange rates depreciate on average 1.1%. After 10 months, reserves fall almost 2%. The effects on the exchange rate and international reserves are quite persistent, possibly linked to the persistent decline in economic activity but somewhat difficult to interpret given the heterogeneity in exchange rate regimes and financial openness across these countries, which is explored next.

3.5. Heterogeneity: Major and minor emerging markets

The country sample is clearly heterogeneous, particularly so in terms of financial development. The heterogeneous nature of the VAR model is beneficial since it can be used to study differential reactions to FTS among sub-groups of countries. To this end, the sample of EMs are split into 'EM Majors' and 'EM Minors' as highlighted in Table 4. Majors consist of 14 coun-

[18] The recursive structure of the VAR designs the country spread shock to be contemporaneously uncorrelated with the FTS index, US economic activity and domestic economic activity.

[19] See Fratzscher (2012), Aizenman and Binici (2016), Goldberg and Krogstrup (2018).

[20] The majority of trade is invoiced in USD, most countries peg to the USD, most international reserves are held in USD, most international financing is denominated in USD.

[21] Because the currency and asset composition of international reserves is typically confidential, the response of reserves is likely composed of both a valuation effect and a flow effect.

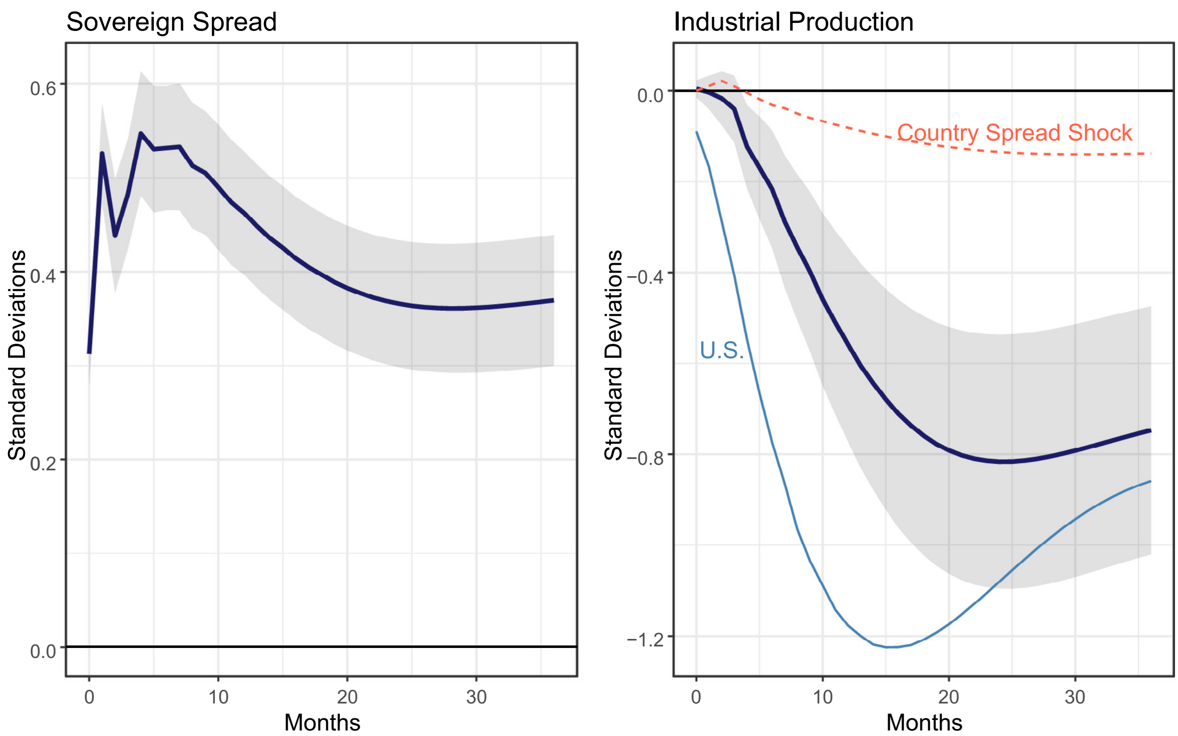

Fig. 4. EM Average Response to a 1-Standard Deviation FTS Shock (Solid, Thick), EM Response to a Country-Specific Sovereign Spread Shock (Dashed), U.S. Response to a 1-Standard Deviation FTS Shock (Solid, Thin). Cumulative MG Response (Equation (10)) to a 1-standard deviation flight-to-safety shock identified from the VAR (solid), and idiosyncratic country-specific sovereign spread shock (dashed). 95% non-parametric dispersion bands as computed in Equation (12). Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Thin solid line in RHS figure is the IRF of U.S. national economic activity.

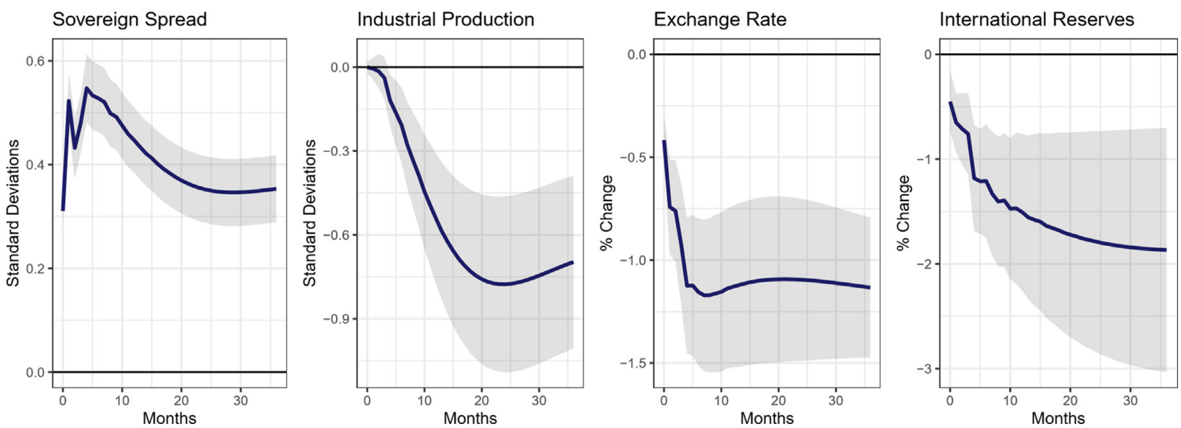

Fig. 5. Emerging Markets: Average Response to a 1-Standard Deviation FTS Shock. Cumulative MG Response (Equation (10)) to a 1-standard deviation flight-to-safety shock identified from the VAR.. 95% non-parametric dispersion bands as computed in Equation (12). Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes.

tries which by MSCI definition fall into the 'Emerging Markets' category given their relatively high degree of financialization and the larger investor portfolio allocations to these countries. Moreover, the Majors necessarily have data spanning the entire 2000–2019 period. The remaining 19 countries (excluding Ecuador) classified as 'EM Minors' are typically considered 'Frontier Markets' based on organization classifications such as MSCI and the IMF, but also include countries with incomplete samples that are otherwise considered EMs by MSCI.

Table 5 reports some key summary statistics on the two sub-groups of countries. EM Majors tend to grow substantially faster, with a median YoY industrial production growth rate of 3.9% versus 2.7% for EM Minors. Majors also have substan-

Table 5
Summary Statistics for EM Majors and EM Minors

		Median	Median	MAD	MAD
	N	YoY IP (%)	EMBI Spread	FX (%)	Int'l Reserves (%)
EM Majors	14	3.9	248.25	1.9	2.1
EM Minors	19	2.7	669.41	0.7	4.8

Within-group medians reported for YoY industrial production growth (percent) and EMBI sovereign spreads (in basis points). Median absolute deviations (MAD) are used to measure volatility that is robust to outliers for monthly exchange rate returns against the USD and monthly international reserves growth.

tially lower sovereign spreads (roughly 248 basis points versus 669). EM Majors tend to have more flexible exchange rates based on monthly median absolute deviations of exchange rate returns of 1.9%, roughly three times that of EM Minors (0.7%). By contrast, EM Minors exhibit more than twice the volatility of EM Majors in their monthly changes in international reserves (4.8% versus 2.1%, respectively).

Fig. 6 plots the average IRF following an FTS shock for the EM Major subgroup in the top row with solid lines, while the bottom row plots the average IRF for the EM Minors with dashed lines. A few patterns emerge: The impact on sovereign spreads, industrial production, and exchange rates is larger for EM Majors than EM Minors, while the reduction of international reserves is slightly greater for EM Minors. Notably, the impact of FTS on industrial production is roughly 3 times as large for EM Majors than Minors. The response of EM Minors to FTS shocks is also more heterogeneous (i.e. wider confidence bands) than the response of EM Majors. These differential impacts are consistent with EM Majors being substantially more exposed to global financial conditions than EM Minors, and the fact that EM Majors have currencies that float to a greater extent than EM Minors. Despite these differences across sub-samples, the estimated impacts are statistically and economically significant for both groups.

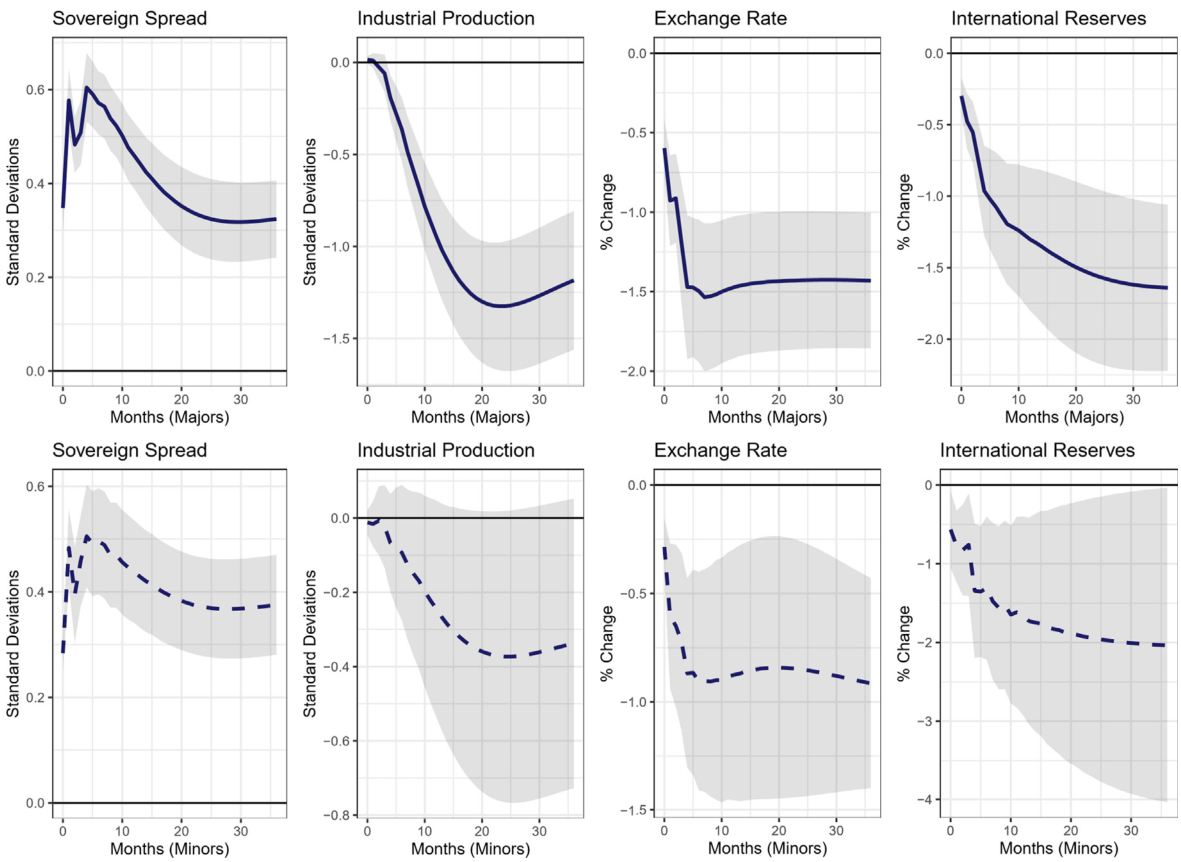

Fig. 6. Emerging Market Majors (Solid) and Minors (Dashed): Average Response to a 1-Standard Deviation FTS Shock. Cumulative MG Response (Equation (10)) to a 1-standard deviation flight-to-safety shock identified from the VAR. 95% non-parametric dispersion bands as computed in Equation (12). Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes. EM Majors include: Brazil, Chile, China, Colombia, Hungary, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Turkey. EM Minors include: Argentina, Belarus, Cote d' Ivoire, Croatia, Egypt, El Salvador, Gabon, Indonesia, Iraq, Jordan, Kazakhstan, Lithuania, Pakistan, Senegal, Sri Lanka, Tunisia, Ukraine, Uruguay, Venezuela, Vietnam.

3.6. Robustness

In this section, a battery of robustness checks is conducted. The results indicate that the main result is robust to varying the sample period, controlling for other measures of financial stress, ordering of the variables in the VAR model, alternative constructions of the FTS index, and alternative model specifications.

3.6.1. Pre-2008 period

An important question regarding generalizability of the main result is whether the impact of FTS is mainly driven by the 2008 crisis period or not. To examine this, the sample period is truncated at December 2007. Using the EM Majors sub-group of countries which have observations spanning the entire period, Fig. A.3 plots average IRFs following a FTS shock using only the 2000–2007 sample period. The resulting IRFs are resemble the full-sample IRFs, with significant increases in EM sovereign risk and decreases in economic activity, exchange rates and international reserves.

3.6.2. Controlling for the VIX index

How complementary is the FTS index to conventional financial stress measures like the VIX index? To answer this question, an FTS index that is uncorrelated with changes in the VIX is constructed. First, the daily FTS index is constructed excluding the VIX index. Second, the monthly non-VIX FTS index is regressed on monthly VIX changes, resulting in a measure of FTS residuals that are orthogonal to VIX changes. This non-VIX FTS index then replaces the standard FTS index in the multi-country VAR model. Fig. A.4 traces the average IRF across EMs following a shock to the non-VIX FTS. While the responses of EM variables are unsurprisingly smaller, they remain statistically and economically significant, indicating that the FTS index captures relevant and distinct information that is not captured by the VIX index.

3.6.3. Ordering of the FTS index in the VAR

A more conservative VAR ordering is considered where it is assumed that FTS can only impact economic activity with a lag. Specifically, FTS shocks are identified from a VAR where FTS_t is ordered after U.S. economic activity ($\Delta Y_{US,t}$), EM average economic activity ($\Delta Y_{i',t}$), and EM country-specific economic activity ($\Delta y_{i,t}$) in the VAR shown in (9). Fig. A.5 shows that the IRF responses under this more conservative VAR ordering scheme are very similar to the benchmark results.

3.6.4. Alternative FTS magnitude restrictions

The benchmark FTS index relies on sign restrictions but sets the magnitude restriction to $c = 0$, which may result in more false-positive FTS days than desired. Setting a more conservative magnitude restriction of $c = 1$ will reduce the noise in the FTS index, though at the cost of possibly missing some true FTS episodes. Fig. A.6 shows that the baseline results broadly remain intact when using an FTS index with more conservative magnitude restrictions. The decrease in the exchange rate and international reserves is relatively smaller but remains significant.

3.6.5. Including additional assets in the FTS index

The number of assets included in the FTS index can be expanded, though this requires some careful consideration. As an example, three additional assets are incorporated into the FTS index: The Nikkei 225 index (international equities, Japan), world spot gold prices, and the advanced economy U.S. Dollar index. No emerging market related variables are considered to maintain the assumption that EMs take the FTS index as exogenous. During a flight-to-safety, risky Japanese equities are expected to sell off ($-$), while both gold and the Dollar are expected to appreciate (+).

There are some caveats, however. Because most assets are priced in Dollars, including gold, Dollar appreciations have been and often are accompanied by drops in the price of gold, so it is not always clear that a flight-to-safety episode appreciates gold *if* the Dollar appreciates too, as exhibited during the 2008 Financial Crisis. Second, introducing international assets at the daily frequency requires careful consideration of the recorded hour in which the daily price is recorded because globally, different markets are open during different hours. Therefore, introducing gold and the Dollar jointly and introducing additional international variables at the daily frequency add complexity to the FTS-identification problem.

Fig. A.7 reports the average EM IRF following an FTS shock after introducing the additional asset market variables. While the EM response to FTS is slightly weaker, it remains statistically and economically significant. Introducing three additional variables, along with the necessary sign restrictions, reduces substantially the number of FTS days identified despite leaving the magnitude threshold unchanged at $c = 0$. Moreover, this version of the FTS index is only weakly associated with the VIX, with a correlation coefficient of 0.23.

3.6.6. Local projection specification

To test the robustness of the results to model specification, local projections (Jordà, 2005) are considered as an alternative to the multi-country VAR model. Local projections of the following form are estimated for each country:

$$Y_{i,t+h} = \alpha_i(h) + \sum_{p=0}^{1} \beta_{i1p}(h) FTS_{t-p} + \sum_{p=1}^{2} \beta_{i2p}(h) Y_{i,t-p} + e_{i,t+h} \tag{13}$$

where the outcome variable $Y_{i,t+h}$ corresponds to either: EMBI spreads, industrial production, exchange rates or international reserves. The effect of FTS on the outcome is captured by the sequence of $h = 0, \ldots, 36$ local projection estimates of the coefficient $\beta_{i10}(h)$. The coefficients are averaged across the 34 countries to arrive at MG local projections, shown in Fig. A.8. The local projection estimates reveal a similar picture to that of the baseline multi-country VAR specification, where sovereign spreads significantly rise following an FTS shock while industrial production, the exchange rate, and international reserves all fall.

3.6.7. Assessing the scope of estimation error

Due to the multi-stage approach of estimating FTS spillovers to EMs, the main result suffers from the well-known generated regressors problem, potentially biasing the estimates and standard errors of the VAR model due to estimation error introduced in the first stage when the FTS index is constructed, since the FTS index construction relies on estimating otherwise unobserved volatilities of its underlying components. There is no obvious solution to deal with this problem. One possible solution is to bootstrap the entire multi-stage procedure which can help correct the standard errors on VAR IRFs. However, given the six separate FTS components this is not a trivial task.

As a parsimonious alternative, I present a model-free version of the monthly FTS index which is derived from the VIX index that is not subject to the generated regressors problem. Using this model-free measure, we can compare the IRF confidence bands to the benchmark confidence bands and gauge the extent of bias introduced by first-stage estimation error. Denote this model-free FTS index $FTS_t(MF)$, which is defined as:

$$FTS_t(MF) = \sum_{d=1}^{D(t)} \Delta \ln VIX_d(t) \mathbf{1}_d \tag{14}$$

Where the $FTS_t(MF)$ index of month t is equal to the sum of the product of daily VIX changes multiplied by the daily indicator flagging risk-on/risk-off days. The indicator $\mathbf{1}_d$, as previously defined, imposes the flight-to-safety condition, thereby identifying risk-off and risk-on days using the daily returns across the candidate assets and days which are neither risk-off or risk-on receive a value of 0. This model-free version of the FTS index does not introduce any estimation error because underlying asset-level conditional volatilities are not required. The monthly $FTS_t(MF)$ and the benchmark FTS_t index share a correlation of 0.87. Fig. A.9 shows the EM responses to FTS shocks using this model-free measure. Notably, the estimates and corresponding confidence bands are very similar to the baseline results, implying that the generated regressor problem of the baseline analysis is not material.

3.6.8. Extending the sample of EMs

Additional countries are added to the sample that otherwise do not have EMBI sovereign spread indices. This extended sample adds the following EMs to the current sample: India, South Korea, Singapore, Thailand. Because these countries do not have EMBI spreads, the sovereign spread variable used in the VAR for these countries is the 5-year sovereign bond yield minus the 5-year U.S. Treasury yield. Fig. A.10 reports IRFs using a full sample incorporating these additional countries.

3.6.9. Increasing the VAR lag length

While the lag length of 4 was selected via AIC, as an additional robustness check Fig. A.11 reports IRFs under a VAR model that extends the lag length from 4 months to 8 months.

3.6.10. Conditioning on the Datta et al. (2017) Global Risk-off Index

In an exercise to further test the incremental information content of the FTS index, Fig. A.12 reports IRFs following FTS shocks that are orthogonal to the global risk-off index (ROI) of Datta et al. (2017). The global ROI and the FTS index are indeed significantly correlated as pointed out in Fig. 3. However, the FTS index still contains distinct information as its component that is uncorrelated with the global ROI also has a significant effect on emerging market financial conditions and economic activity.

4. The Role of U.S. Monetary Policy

The literature on global financial cycles investigates the causal role of U.S. monetary policy driving global financial conditions. However, here we ask whether counter-cyclical or *reactionary* U.S. monetary policies offset some of the destabilizing nature of tighter global financial conditions. To this end, I present an application of the FTS index that aims to contribute to the literature comparing spillover effects of financial conditions and U.S. monetary policy (Maćkowiak (2007), Akinci (2013), Cesa-Bianchi and Sokol (2022)).

4.1. High-frequency identification

I consider both measures of conventional and unconventional monetary policy shocks by using high-frequency (30-minute) changes in Treasury futures contract prices around Federal Open Market Committee (FOMC) announcements following Kuttner (2001), Gertler and Karadi (2015) and others. Specifically, I consider the 3-month Treasury futures price which is converted to yield changes to capture conventional monetary policy shocks. The data is provided by the Bank for International Settlements and used in Kearns et al. (2023). I rely on changes in longer-dated futures, specifically the 10-year futures log price, to capture changes in unconventional monetary policy which typically targets interest rates at longer maturities but also captures Fed information effects.[22] Similar use of longer-dated futures to capture unconventional monetary shocks such as quantitative easing or forward guidance are considered in Gilchrist et al. (2019) and Kearns et al. (2023). These high-frequency observations are then aggregated to the monthly frequency by summing all shocks within each month. Months without an FOMC meeting or observed shock are given a value of zero.

Correlations between monthly high-frequency shocks to the 3-month and 10-year futures are statistically indifferent from zero, thus uncorrelated with each other (Table 6). These monetary policy shocks are also uncorrelated with the FTS index. The correlation between 3-month (conventional) shocks and FTS is 0.042 while the correlation between 10-year (unconventional) shocks and FTS is 0.038. All correlations are statistically insignificant. This feature differs from the literature on global financial cycles showing that monetary policy shocks are correlated with broader measures of risk appetite or financial conditions such as the VIX index (Miranda-Agrippino and Rey (2020)), and provides further support that unlike most financial indices, the FTS index is little correlated with monetary policy shocks. This distinct setup of uncorrelated financial and monetary fluctuations allows for testing their effects jointly under less strict identifying assumptions than previous studies.

4.2. Incorporating U.S. monetary policy shocks

The multi-country VAR in (9) with EMP variables is further augmented with conventional and unconventional U.S. monetary policy shocks, bringing the total number of variables in the VAR to eight. Given that these monetary shocks are externally identified, I order them first in the VAR, with the 3-month shock first, the 10-year shock second, and the FTS index third. This way, unconventional monetary policy shocks are defined as changes in 10-year rate changes that are orthogonal to changes in the 3-month rate around FOMC announcements. As noted earlier, the correlation between the three series is almost zero, so their ordering is not consequential, and results are unchanged when the FTS index or unconventional monetary policy shocks are ordered first.

4.3. The effects of U.S. monetary policy spillovers

The top row of Fig. 7 reports MG IRFs following a 1-standard deviation *expansionary* conventional monetary policy shock, with a contractionary shock producing IRFs that are symmetric but flipped. The average effect on EMs is almost the precise inverse of the impact of an FTS shock: Sovereign spreads compress, exchange rates appreciate, and economic activity expands, *despite* near-zero correlation between monetary policy shocks and the FTS index. This also implies that contractionary U.S. monetary shocks affect emerging markets similarly to positive FTS index values, i.e., risk-off episodes.

The bottom row of Fig. 7 reports the MG IRFs following a 1-standard deviation expansionary unconventional monetary policy shock. Again, EMs respond inversely to their response to a risk-off FTS shock despite these two shocks being uncorrelated. Compared to a conventional monetary expansion, unconventional shocks show a smaller impact on sovereign spreads, but a larger impact on alleviating exchange market pressure both in the form of currency appreciation and international reserves accumulation. The two different types of U.S. monetary shocks exhibit similar sized effects on EM economic activity, which are about 2–3 times smaller in absolute terms than that of a comparably sized (1-standard deviation) FTS shock.

4.4. Pre-2008 period

Fig. A.13 in the Appendix plots the response of EM Majors to a 1-standard deviation expansionary conventional monetary policy shock but only considering the pre-2008 sample period before the Fed was constrained by the zero lower bound. The unconventional (10-year) shocks are removed from this VAR, as previously mentioned the 10-year shocks may be contaminated with other information released by the Fed and as a result, is a noisy measure of unconventional monetary policy. In the pre-2008 sample, while the impact on exchange rates is muted, expansionary U.S. monetary policy still led to significant compression in EM sovereign spreads and an expansion in economic activity.

4.5. Heterogeneous spillovers

Fig. A.14 splits the countries into EM Majors and Minors and traces their respective responses to an expansionary conventional monetary policy shock, while Fig. A.15 traces their respective responses to an expansionary unconventional monetary policy shock. The Major-Minor split reveals that for both conventional and unconventional U.S. monetary policy

[22] While conventional shocks are interpreted as standard shocks to the Fed policy rate, unconventional shocks are a bit more ambiguous: They can reflect forward guidance over the future path of the short rate, and/or the pricing of quantitative easing policies, and/or they can reflect Fed communication related to expected future economic conditions. I do not take a stance on which specific source is driving unconventional policy shocks, but importantly these shocks have gained prevalence since the conventional policy interest rate became constrained at the zero lower bound.

Table 6
Correlations between U.S. Monetary Shocks and the FTS Index

	3-Month Treasury Shocks	10-Year Treasury Shocks	FTS Index
3-Month Treasury Shocks	1	–	–
10-Year Treasury Shocks	0.046	1	–
FTS Index	0.042	0.038	1

Sample correlations reported for monthly contractionary monetary policy shocks and FTS index. U.S. monetary policy shocks are identified as changes in futures contract prices around FOMC announcements. All correlations are statistically insignificant.

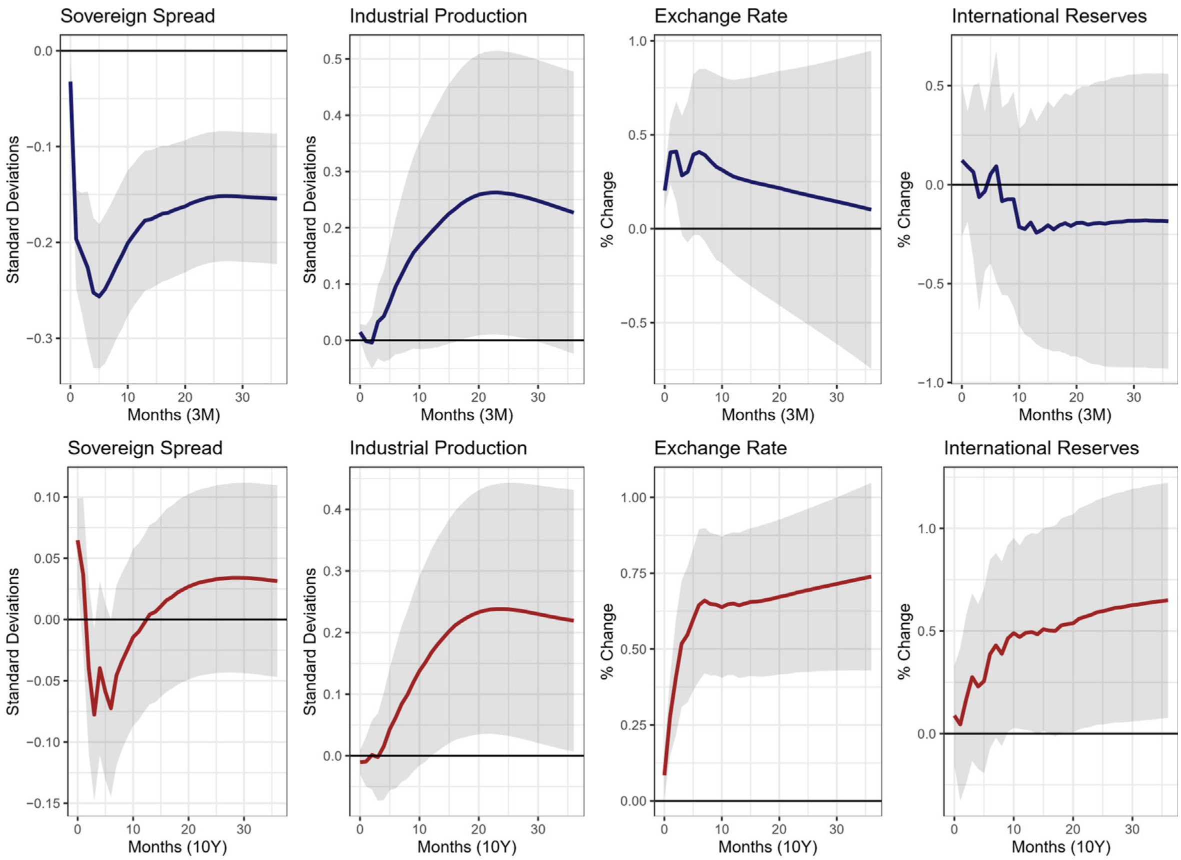

Fig. 7. Emerging Markets: Average Response to a 1-Standard Deviation Expansionary *Conventional* (top row, 3M) and *Unconventional* (bottom row, 10Y) U.S. Monetary Policy Shock. Cumulative MG Response (Equation (10)) to a 1-standard deviation expansionary conventional and unconventional U.S. monetary policy shock. U.S. monetary shocks are recovered from 3-month and 10-year Treasury futures contract yield and log price changes, respectively, within a 30-minute window of FOMC announcements and then aggregated to the monthly frequency. 95% non-parametric dispersion bands as computed in Equation (12). Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes.

spillovers are much more potent on EM Majors, while the responses of EM Minors are mostly (but not always) statistically insignificant. Interestingly, the heterogeneous responses to monetary policy shocks matches the heterogenous response of EMs to FTS shocks in that EM majors appear particularly exposed to both flights-to-safety and U.S. monetary policy.

4.6. Policy implications

To summarize, FTS and U.S. monetary policy shocks have similar spillover effects on EMs despite being uncorrelated with each other. This result suggests that the overall size and impact of global financial conditions on EMs is at least partly determined by the U.S. monetary policy stance. Based on the estimates presented in this paper, a contractionary monetary policy shock occurring alongside an adverse flight-to-safety would induce an impact on EMs roughly 30% more severe than a flight-to-safety alone, while an expansionary monetary policy response would reduce the effects of a coincident flight-to-safety by a similar magnitude. These results starkly contrast Maćkowiak (2007) and Akinci (2013) which find a large role for external financial shocks but only a small role of U.S. monetary policy spillovers to EMs. The results are therefore more in line with Cesa-Bianchi and Sokol (2022) which finds important dual roles for both financial and U.S. monetary policy spillovers to the United Kingdom.

It's worth noting once again, however, that the FTS index does not reflect all kinds of financial stress but rather is a special case of financial stress that is little correlated with monetary policy shocks. More generally, it is difficult to compare the effects of monetary and financial spillovers jointly because they endogenously affect each other. U.S. monetary policy affects global financial conditions. Moreover, loose monetary policy can incentivize excessive risk-taking and lead to financial vulnerabilities down the road but at the same time, monetary policy tends to be responsive to financial shocks. Flights-to-safety may also reflect asset price reactions to expected monetary policy changes (e.g. policy errors). Monetary tightening itself can trigger a flight-to-safety to the extent the tightening is perceived as a policy error by investors that will adversely impact economic activity. This backdrop implies that the effects of contractionary monetary policy shocks can be magnified when they trigger a flight-to-safety across financial markets. As a result, monetary policy and financial conditions are intimately connected and difficult to separate. While under this setup we can more sharply separate the relative sizes of financial and U.S. monetary policy spillovers, it is important to appreciate the complexity of the endogeneity problem at hand.

5. Concluding Remarks

This paper presents a new measure of global financial risk sentiment representing flights-to-safety and estimates their global impact on a broad set of countries. Global flights-to-safety significantly impact macroeconomic dynamics in the U.S. and in emerging markets. Flights-to-safety induce wider sovereign spreads, exchange rate depreciation against the Dollar, a reduction in FX reserves, and a contraction in economic activity across EMs. The effects of FTS persist after controlling for the other financial indices and they remain present under a variety of robustness checks.

The extant literature focuses on U.S. monetary policy's role in dictating global financial conditions. But the endogenous nature of financial conditions makes it difficult to empirically compare the importance of financial and monetary spillovers. Unlike most indicators of financial stress, the FTS index is uncorrelated with high-frequency U.S. monetary policy shocks, providing a unique setup to compare these two spillovers jointly. I find that both expansionary conventional and unconventional U.S. monetary policy shocks have an effect on EMs that is opposite to a risk-off flight-to-safety such that expansionary U.S. monetary policy following a FTS can reduce FTS-driven financial and economic volatility by about 30%. Conversely, to the extent that a contractionary U.S. monetary policy shock is perceived as a policy error thereby triggering a flight-to-safety, total spillovers to EMs are substantially magnified under a contractionary U.S. monetary policy coinciding with a flight-to-safety. These results suggest that the extent to which U.S. monetary policy reacts to global financial conditions plays a prominent role in shaping financial and macroeconomic stability abroad.

Data availability

Data will be made available on request.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

A.1. Data

Data is collected from a variety of sources. To construct the FTS index, the underlying daily data on the VIX Index, Wilshire 5000 index, 10-year Treasury yields, U.S. corporate high yield spreads, and exchange rates are taken from the FRED database while daily data on the 10-year German Bund yield is from Bloomberg. The daily data spans January 2000 to August 2019 and is plotted in levels in Fig. A.2. The daily data is eventually transformed to construct the FTS variable and then aggregated to a monthly frequency for further analysis. Daily data to construct AE and EM Dollar exchange rate indices were taken from the FRED database.

Monthly average sovereign spreads are measured with J.P. Morgan EMBI indices from the World Bank Global Economic Monitor. The sample contains monthly data on spreads for 34 countries over the period January 2000 to August 2019. All countries have at least 99 observations, Log changes in EMBI spreads are computed as:

$$\Delta s_{it} = \ln(\frac{S_{it}}{S_{i,t-1}})$$

where S_{it} is the average EMBI spread level for country i over month t. Because the analysis relies on changes in the log EMBI spread, the bulk of summary statistics are reported on Δs_{it}. Table A.1 reports summary statistics on changes in sovereign spreads across countries. Outlier observations of logged EMBI changes greater than + 200% or less than −100% are removed. To extend the sample of countries to include prominent EMs that do not have EMBI spreads available, monthly 5-year local sovereign bond spreads to the 5-year U.S. Treasury yield are constructed using data from Reuters. These countries are: India, South Korea, Singapore, and Thailand. The 5-year yield spread is replaces the EMBI spread in the VAR models for these countries.

Monthly industrial production data across countries is taken from the World Bank.

Year-on-year changes in log industrial production are computed as:

$$\Delta y_{it} = \ln(\frac{Y_{it}}{Y_{i,t-12}})$$

where Y_{it} is the nominal industrial production of country i in month t. This also helps reduce seasonality of the time series. Summary statistics for year-over-year changes in log industrial production are reported in Table A.2. Iraq experienced very large swings in industrial production during the early 2000′s when it was invaded and under military occupation. This is visible in the summary statistics. Table A.3 reports summary statistics on select commodity and financial market variables at the monthly frequency. The values are monthly average changes, not end-of-month changes.

For emerging markets, country-specific measures of nominal USD exchange rates are from the IMF. These are monthly averages, with changes in log exchange rates interpreted as log returns. Positive changes in denote domestic appreciation vis-a-vis the USD. Country-specific measures of international reserves are taken from the IMF as well. These are denominated in USD. Reserves growth rates are computed as changes in log monthly reserves, where positive monthly growth denotes reserves accumulation.

Data on daily equity index prices across 32 countries are taken from Bloomberg to construct the global average realized volatility measure, $GVOL_t$, similar to that of Cesa-Bianchi et al. (2020). Data on monthly estimates of the global financial cycle from Miranda-Agrippino and Rey (2020), $GFCY_t$, are available through the authors' website. The global risk-off/risk-on indices of Datta et al. (2017) and Chari et al. (2020) were provided by the authors. High-frequency monetary policy shocks are derived from intra-day (30-minute) changes in Treasury futures contract prices around FOMC announcements. These refer to 3-month and 10-year U.S. Treasury futures traded on the Chicago Mercantile Exchange, and were provided by the Bank for International Settlements.

A.2. Events Underlying the Largest Flights-to-Safety

Comparing extreme values of the FTS index shows that it indeed captures global tail risk. Table A.4 provides a list of dates between 2000 and 2020 that, based on the daily measure FTS_d, are identified as the largest flights-to-safety. The global nature of these episodes become apparent: 'Brexit' (2016), 'Chinese Correction' (2007), U.S. President Trump political controversies (2017), the Lehman bankruptcy (2008), and the Arab Spring (2011) round out the top five daily global flights-to-safety. If we included early 2020 in the calculation, January 27 and February 24, 2020, the onset of the COVID-19 global pandemic, would have both scored within the top ten largest FTS_d readings since 2000, respectively the tenth and fourth largest. Using a different methodology, a similar list is reported in De Bock and de Carvalho Filho (2015). Several flight-to-safety episodes flagged by FTS_d are shared in their lists despite differing methodologies. None of the ten largest FTS days correspond with the largest U.S. stock market crashes. Table A.5 lists the top 10 largest daily stock market percent declines between the same period. Most of the largest stock market crashes occurred during the 2008 Global Financial Crisis, and another during the 2000 Tech Bubble. Table A.6 shows the top 10 largest percent changes in the VIX index – three overlap with the top 10 daily largest FTS days. The largest VIX change reflects the 'Volmageddon' (2018), considered by many practitioners as a technical, non-fundamental event caused by overcrowded short volatility positions, highlighting the influence of non-fundamental movements on financial stress indicators.

Table A1
Summary Statistics for Changes in Log EMBI Spread

Country	*T* (Start Date)	Min	Max	Mean	Median	SD	Median Level
Argentina	235 (Feb 2000)	−0.730	0.686	0.009	−0.004	0.139	722.793
Belarus	107 (Oct 2010)	−0.248	0.511	−0.007	−0.014	0.116	625.614
Brazil	235 (Feb 2000)	−0.204	0.525	−0.005	−0.019	0.103	270.003
Chile	235 (Feb 2000)	−0.368	0.487	−0.000	−0.002	0.096	139.650
China	235 (Feb 2000)	−0.808	0.659	0.002	0.000	0.127	138.411
Colombia	235 (Feb 2000)	−0.255	0.670	−0.004	−0.020	0.112	216.005
Cote d'Ivoire	235 (Feb 2000)	−0.453	0.305	−0.003	−0.005	0.075	1106.238
Croatia	235 (Feb 2000)	−0.270	0.371	−0.045	−0.070	0.103	257.671
Ecuador	235 (Feb 2000)	−0.769	0.806	−0.007	−0.016	0.139	788.271
Egypt	217 (Aug 2001)	−0.561	0.986	0.010	−0.010	0.187	349.198
El Salvador	208 (May 2002)	−0.216	0.550	0.003	−0.006	0.093	376.053
Gabon	140 (Jan 2008)	−0.267	0.646	0.003	−0.006	0.126	425.400
Hungary	235 (Feb 2000)	−0.709	0.823	0.001	−0.002	0.167	123.800
Indonesia	182 (Jul 2004)	−0.300	0.733	−0.004	−0.017	0.113	239.111
Iraq	160 (May 2006)	−0.231	0.346	0.000	−0.003	0.095	520.688
Jordan	103 (Feb 2011)	−0.348	0.374	−0.000	0.010	0.081	382.145
Kazakhstan	146 (Jul 2007)	−0.279	0.669	0.001	−0.010	0.133	298.227
Lithuania	117 (Dec 2009)	−0.459	0.395	−0.020	−0.023	0.151	123.726
Malaysia	235 (Feb 2000)	−0.284	0.589	−0.001	−0.007	0.104	141.806
Mexico	235 (Feb 2000)	−0.221	0.584	−0.001	−0.010	0.092	219.976
Pakistan	218 (Jul 2001)	−0.525	0.523	−0.041	−0.024	0.179	512.429
Peru	235 (Feb 2000)	−0.248	0.663	−0.005	−0.019	0.115	194.396
Philippines	235 (Feb 2000)	−0.226	0.561	−0.006	−0.007	0.101	217.405
Poland	235 (Feb 2000)	−0.671	0.582	−0.007	0.008	0.138	109.399
Russia	235 (Feb 2000)	−0.266	0.629	−0.010	−0.025	0.117	241.053
Senegal	99 (Jun 2011)	−0.166	0.213	−0.001	−0.003	0.077	450.697
South Africa	235 (Feb 2000)	−0.261	0.650	0.001	−0.004	0.110	236.514
Sri Lanka	141 (Dec 2007)	−0.285	0.658	−0.001	−0.009	0.115	412.982
Tunisia	207 (Jun 2002)	−0.525	0.481	−0.018	−0.049	0.123	209.755
Turkey	235 (Feb 2000)	−0.241	0.532	0.001	−0.008	0.108	305.410
Ukraine	231 (Jun 2000)	−0.475	0.974	−0.006	−0.012	0.148	620.636
Uruguay	218 (Jul 2001)	−0.340	0.576	−0.002	−0.019	0.114	230.800
Venezuela	235 (Feb 2000)	−0.209	0.605	0.011	0.001	0.109	1038.486
Vietnam	164 (Jan 2006)	−0.283	0.665	−0.002	−0.005	0.137	249.750

Summary statistics for Δs_{it} (Equation (9)), monthly changes in the log EMBI spread. Column 8, Median Level, reports the median level of each country's EMBI spread. SD refers to standard deviation. All time series end in August 2019 but beginning date varies.

Table A2
Summary Statistics for Year-over-Year Change in Log Industrial Production

Country	*T* (Start Date)	Min	Max	Mean	Median	SD
Argentina	235 (Feb 2000)	−0.222	0.245	0.022	0.023	0.078
Belarus	151 (Feb 2007)	−0.109	1.997	0.259	0.136	0.436
Brazil	235 (Feb 2000)	−0.170	0.190	0.012	0.013	0.064
Chile	235 (Feb 2000)	−0.131	0.140	0.021	0.027	0.044
China	235 (Feb 2000)	0.038	0.207	0.116	0.114	0.044
Colombia	235 (Feb 2000)	−0.143	0.163	0.025	0.020	0.054
Cote d'Ivoire	195 (Jun 2003)	−0.501	0.581	0.027	0.035	0.163
Croatia	235 (Feb 2000)	−0.142	0.131	0.014	0.017	0.052
Ecuador	235 (Feb 2000)	−0.170	0.491	0.043	0.050	0.078
Egypt	175 (Feb 2005)	−0.145	0.410	0.044	0.034	0.081
El Salvador	235 (Feb 2000)	−0.046	0.079	0.014	0.014	0.023
Gabon	235 (Feb 2000)	−0.377	0.426	−0.005	0.018	0.137
Hungary	235 (Feb 2000)	−0.302	0.291	0.046	0.056	0.087
Indonesia	235 (Feb 2000)	−0.136	0.345	0.040	0.038	0.053
Iraq	235 (Feb 2000)	−0.830	11.500	0.144	0.087	0.860
Jordan	235 (Feb 2000)	−0.229	0.286	0.022	0.015	0.078
Kazakhstan	235 (Feb 2000)	−0.096	0.414	0.072	0.059	0.083
Lithuania	235 (Feb 2000)	−0.260	0.381	0.048	0.050	0.088
Malaysia	235 (Feb 2000)	−0.176	0.234	0.042	0.040	0.063
Mexico	235 (Feb 2000)	−0.177	0.148	0.016	0.022	0.048
Pakistan	235 (Feb 2000)	−0.195	0.319	0.049	0.039	0.084
Peru	235 (Feb 2000)	−0.141	0.222	0.037	0.037	0.073
Philippines	235 (Feb 2000)	−0.287	0.360	0.025	0.025	0.110

(*continued on next page*)

Table A2 (*continued*)

Country	*T* (Start Date)	Min	Max	Mean	Median	SD
Poland	235 (Feb 2000)	−0.153	0.234	0.054	0.055	0.059
Russia	235 (Feb 2000)	−0.170	0.263	0.037	0.040	0.054
Senegal	151 (Feb 2007)	−0.224	0.609	0.060	0.042	0.127
South Africa	235 (Feb 2000)	−0.232	0.100	0.012	0.018	0.051
Sri Lanka	104 (Jan 2011)	−0.143	0.193	0.025	0.020	0.059
Tunisia	235 (Feb 2000)	−0.177	0.165	0.007	0.000	0.050
Turkey	235 (Feb 2000)	−0.240	0.294	0.055	0.065	0.092
Ukraine	200 (Jan 2003)	−0.308	0.221	0.011	0.023	0.107
Uruguay	200 (Jan 2003)	−0.311	0.572	0.048	0.037	0.127
Venezuela	235 (Feb 2000)	−0.648	1.832	−0.045	−0.015	0.229
Vietnam	128 (Jan 2009)	−0.504	0.679	0.104	0.103	0.214

Summary statistics for Δy_{it} (Equation (9)). Iraq's large minimum and maximum driven by the war period in the early 2000 s. SD refers to standard deviation.

Table A3
Summary Statistics for Select Financial and Commodity Market Variables

Market Variable (Monthly)	*T*	Mean	SD	Min	Pctl(25)	Pctl(75)	Max
VIX	235	−0.001	0.167	−0.373	−0.098	0.068	0.708
U.S. High Yield Credit Spread	235	−0.0005	0.088	−0.223	−0.059	0.043	0.486
Wilshire 5000 Index	235	0.0002	0.002	−0.008	−0.001	0.002	0.005
3-month Treasury Yield	235	−0.004	0.329	−1.738	−0.072	0.065	2.025
2-year Treasury Yield	235	−0.006	0.124	−0.568	−0.070	0.061	0.316
5-year Treasury Yield	235	−0.006	0.100	−0.411	−0.058	0.046	0.360
10-year Treasury Yield	235	−0.006	0.070	−0.378	−0.046	0.034	0.194
1-year Inflation Expectations	235	−0.0001	0.004	−0.013	−0.002	0.002	0.017
2-year Inflation Expectations	235	−0.0001	0.002	−0.006	−0.001	0.001	0.008
10-year Inflation Expectations	235	−0.007	0.101	−0.368	−0.067	0.059	0.253
USD Exchange Rate	235	−0.0002	0.017	−0.048	−0.011	0.011	0.064
Copper Price	235	0.005	0.065	−0.354	−0.025	0.038	0.230
WTI Crude Oil Price	235	0.003	0.087	−0.332	−0.045	0.060	0.214
Gold Price	235	0.007	0.037	−0.124	−0.016	0.032	0.115

Inflation expectations are monthly changes (not logged). All others are monthly changes in logs. Inflation expectations are estimated using the method of Haubrich et al. (2012).

Table A4
Largest Daily Global FTS Shocks, 2000–2019

Description	Date	FTS_d
1. British referendum votes to exit E.U.	2016–06-24	4.89
2. Chinese Correction: Authorities announced plans to curb speculation	2007–02-27	4.74
3. U.S. President Trump controversy	2017–05-17	3.44
4. Lehman Brothers Bankruptcy	2008–09-15	3.33
5. Arab Spring - Instability in the Middle East and North Africa	2011–02-22	3.15
6. Italian political tensions, speculation of E.U. exit	2018–05-29	3.12
7. ECB announces no new emergency support for Greece; Greece calls for bailout referendum	2015–06-29	3.05
8. S&P downgraded Greece's credit rating to'junk'	2010–04-27	3.04
9.GFC: Congress rejects bank bailout bill	2008–09-29	2.71
10. U.S. - China trade war intensifies	2019–08-05	2.61

February 24, 2020 would rank #4 and January 27, 2020 would rank #10 if the index was re-estimated through Feb 28, 2020 to account for the onset of the COVID-19 global pandemic.

Table A5
Largest Daily Percent Wilshire 5000 Declines, 2000–2019

Description	Date	Change
1. GFC: NBER confirms U.S. recession	2008–12-01	−9.6%
2. 2008 GFC	2008–10-15	−9.4%
3. GFC: Congress rejects bank bailout bill	2008–09-29	−8.75%
4. 2008 GFC	2008–10-09	−7.8%
5. U.S. credit downgrade from AAA to AA + by S&P	2011–08-08	−7.2%
6. 2008 GFC	2008–11-20	−7.1%
7. Tech Bubble Crash	2000–04-14	−6.6%
8. 2008 GFC	2008–11-19	−6.6%
9. 2008 GFC	2008–10-22	−6.1%
10. GFC: Fed communicates negative outlook	2008–10-07	−5.9%

Table A6
Largest Daily Log VIX (Percent) Changes, 2000–2019

Description	Date	Change
1. "Volmageddon"	2018–02-05	+76.8%
2. Chinese Correction: Authorities announced plans to curb speculation	2007–02-27	+49.6%
3. U.S. credit downgrade from AAA to AA + by S&P	2011–08-08	+40.5%
4. British referendum votes to exit E.U.	2016–06-24	+40.1%
5. China slowdown	2015–08-21	+38.1%
6. U.S. President Trump controversy	2017–05-17	+38.1%
7.China introduces new exchange rate mechanism ahead of potential Fed hike	2015–08-24	+37.3%
8. N. Korea announces plans to attack the U.S. Naval Base Guam	2017–08-10	+36.7%
9. U.S. China Trade war concerns	2018–10-10	+36.4%
10. Boston Marathon terrorist attack	2013–04-15	+35.9%

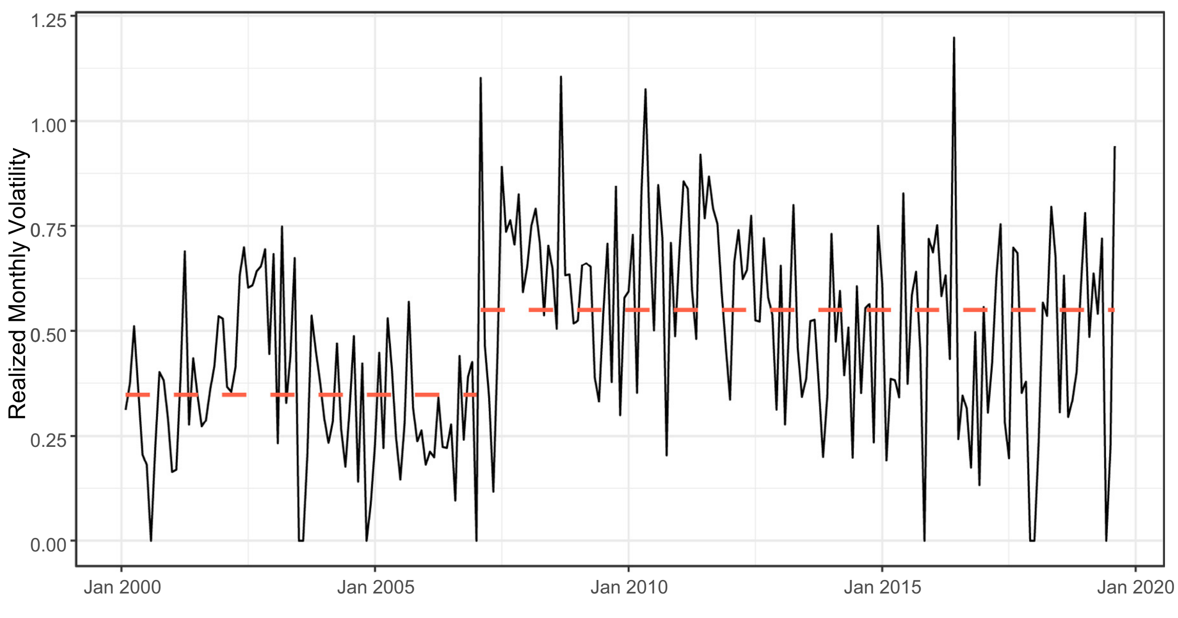

Fig. A1. Realized Monthly Volatility of Daily Global Flight-to-Safety Index. Each month's realized volatility of FTS is computed as the standard deviation of daily values of FTS_d for each month. Structural break occurs in February 2007.

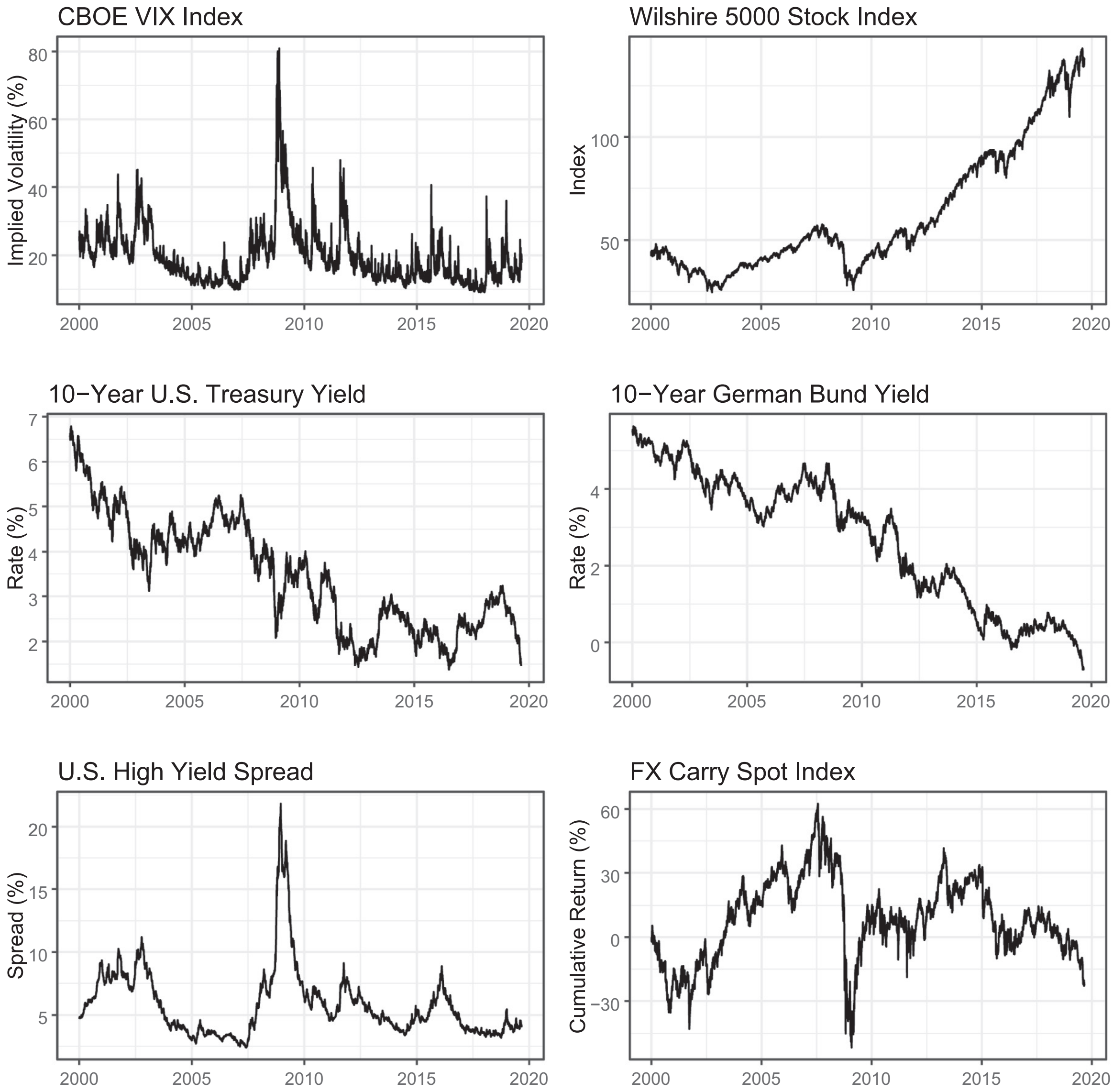

Fig. A2. Daily Time Series in Levels of FTS Constituents. Details on the data including sources are in Section A1 of the Appendix. FX Carry index is the equal-weighted average return from a position that is long New Zealand Dollar and Australian Dollar vis-a-vis the Swiss Franc and Japanese Yen.

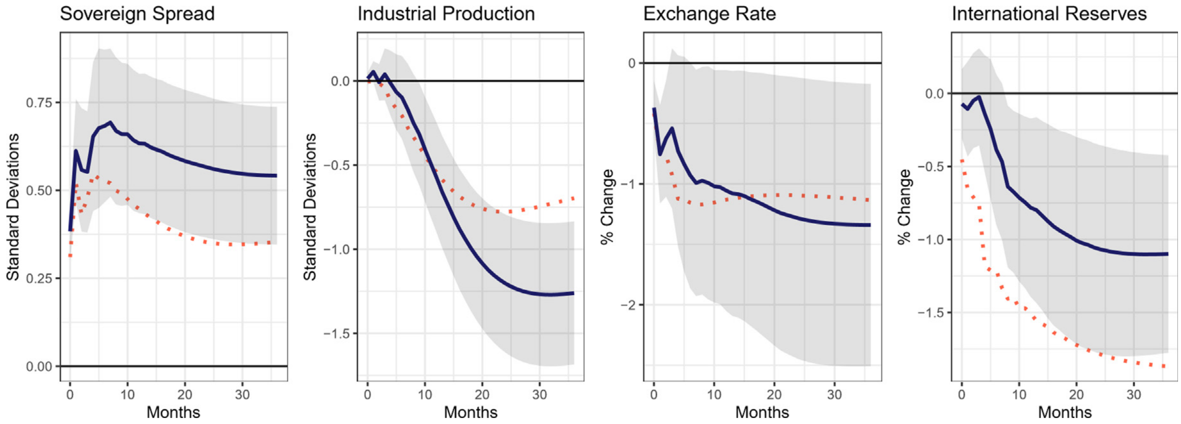

Fig. A3. Emerging Market Majors: Average Response to a 1-Standard Deviation FTS Shock, Pre-2008 Sample. Cumulative MG Response (Equation (10)) to a 1-standard deviation flight-to-safety shock identified from the VAR. 95% non-parametric dispersion bands as computed in Equation (12). Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes. EM Majors include: Brazil, Chile, China, Colombia, Hungary, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Turkey. Sample truncated to end in December 2007. Dashed lines correspond to the IRF estimate from the baseline result in Fig. 5.

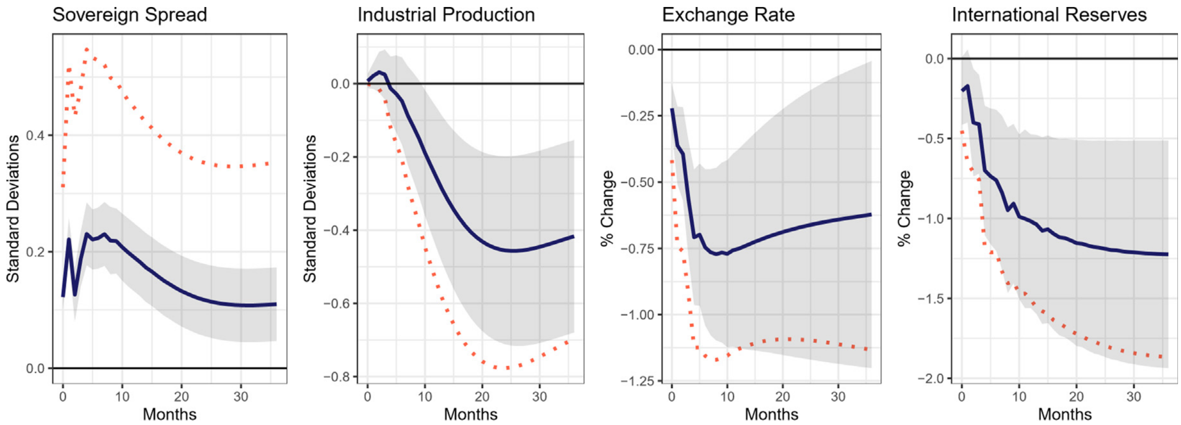

Fig. A4. Emerging Markets: Average Response to a 1-Standard Deviation FTS Shock that is Orthogonal to VIX Changes. Cumulative MG Response (Equation (10)) to a 1-standard deviation flight-to-safety shock identified from the VAR. Daily FTS construction excludes the VIX index and Monthly FTS is orthogonal to VIX changes. 95% non-parametric dispersion bands as computed in Equation (12). Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes. Dashed lines correspond to the IRF estimate from the baseline result in Fig. 5.

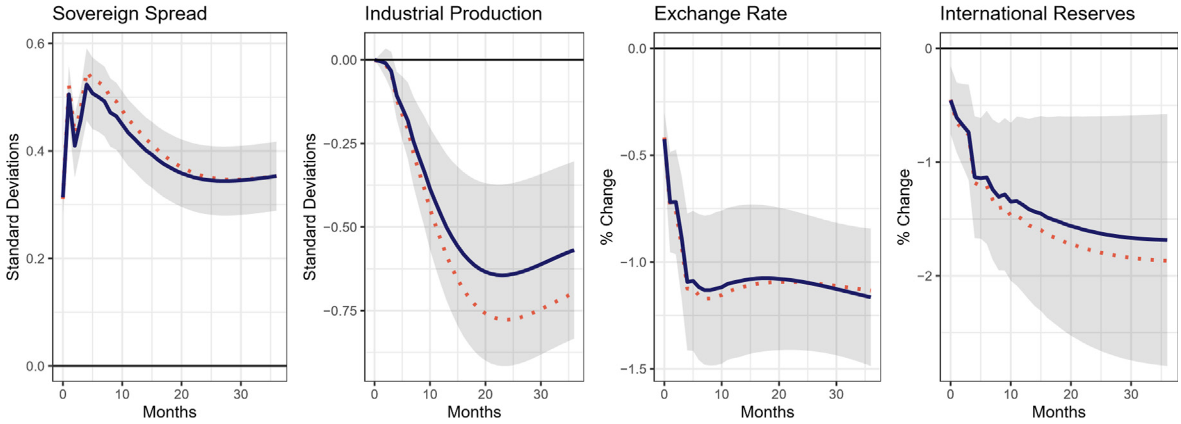

Fig. A5. Emerging Markets: Average Response to a 1-Standard Deviation FTS Shock, FTS ordered after Industrial Production Measures. Cumulative MG Response (Equation (10)) to a 1-standard deviation flight-to-safety shock identified from the VAR. FTS is ordered after U.S. and EM IP in the VAR. 95% non-parametric dispersion bands as computed in Equation (12). Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes. Dashed lines correspond to the IRF estimate from the baseline result in Fig. 5.

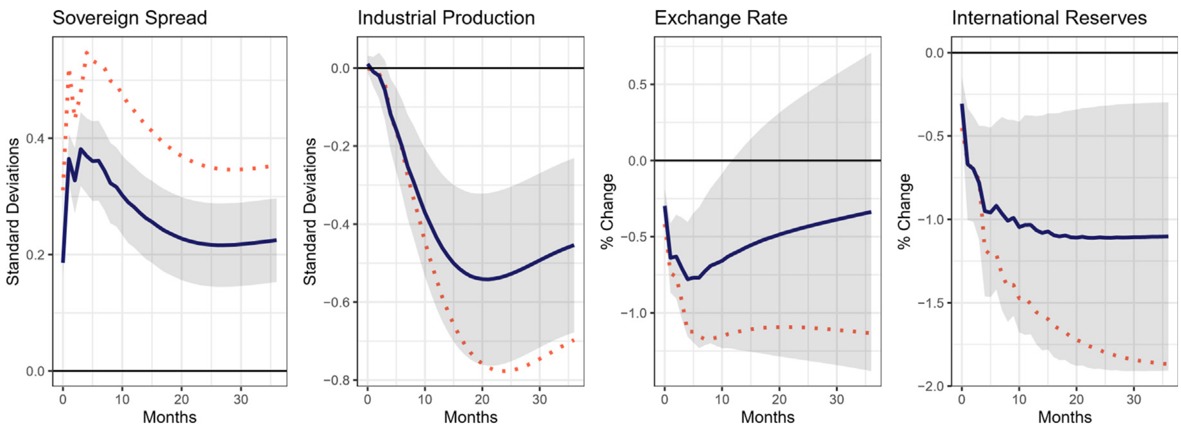

Fig. A6. Emerging Markets: Average Response to a 1-Standard Deviation FTS Shock with Magnitude Threshold $c = 1$. Cumulative MG Response (Equation (10)) to a 1-standard deviation flight-to-safety shock identified from the VAR constructed with a magnitude threshold of $c = 1$. 95% non-parametric dispersion bands as computed in Equation (12). Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes. Dashed lines correspond to the IRF estimate from the baseline result in Fig. 5.

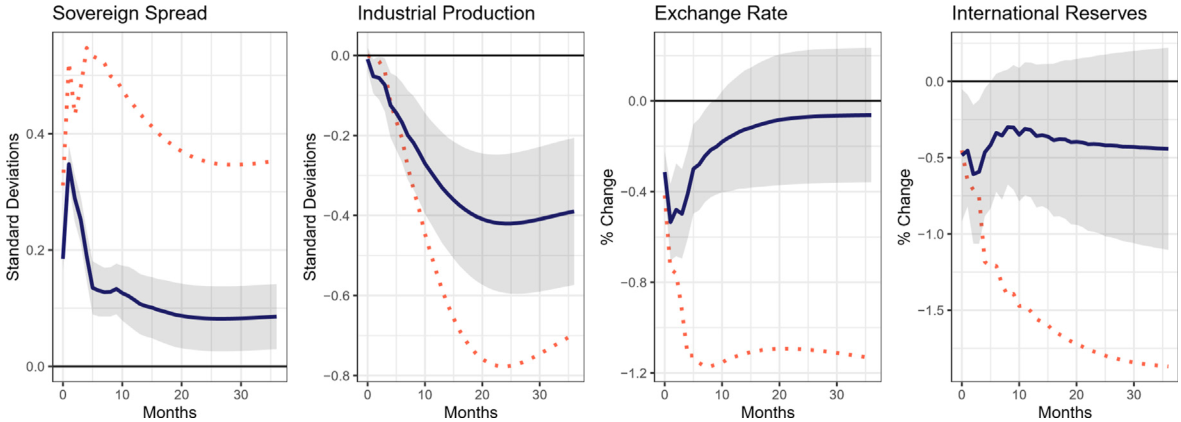

Fig. A7. Emerging Markets: Average Response to a 1-Standard Deviation FTS Shock Constructed with Additional Variables. Cumulative MG Response (Equation (10)) to a 1-standard deviation flight-to-safety shock identified from the VAR. FTS_t construction extended to include the Nikkei 225 equity index, gold prices, and advanced economy Dollar index. 95% non-parametric dispersion bands as computed in Equation (12). Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes. Dashed lines correspond to the IRF estimate from the baseline result in Fig. 5.

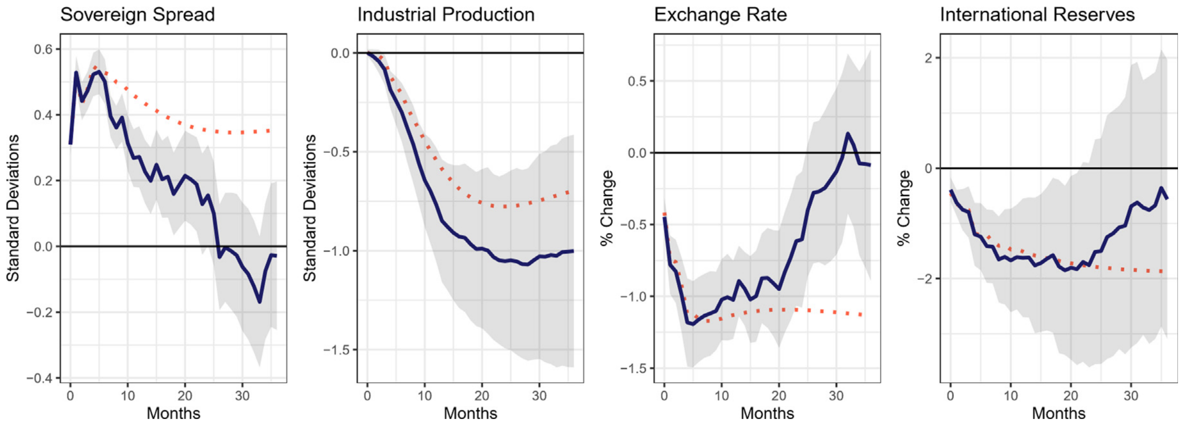

Fig. A8. Emerging Markets: Average Response to a 1-Standard Deviation FTS Shock via Local Projections. Cumulative MG Response (Equation (10)) to a 1-standard deviation flight-to-safety shock via local projections (Equation (13)). 95% non-parametric dispersion bands as computed in Equation (12). Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes. Dashed lines correspond to the IRF estimate from the baseline result in Fig. 5.

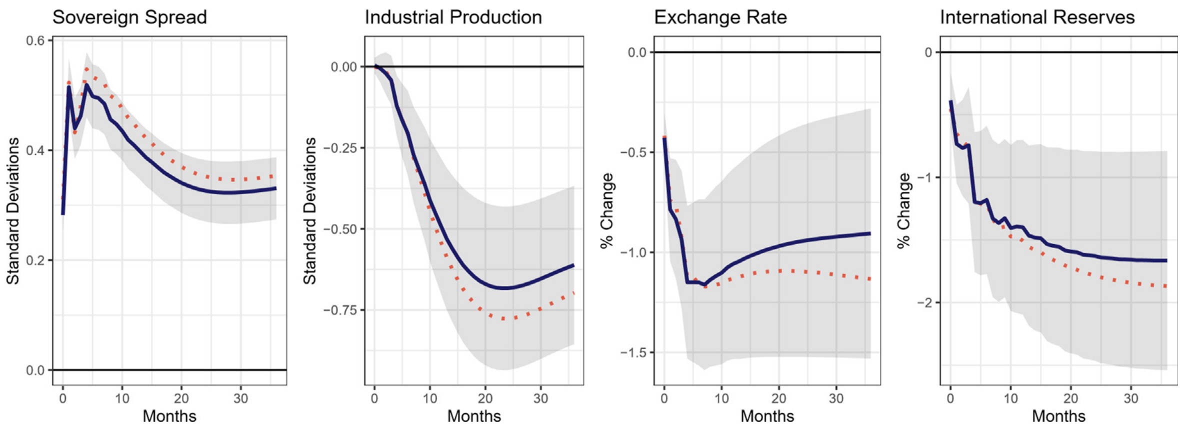

Fig. A9. Emerging Markets: Average Response to a 1-Standard Deviation FTS Shock using Model-Free FTS. Cumulative MG Response (Equation (10)) to a 1-standard deviation model-free flight-to-safety shock defined in Equation (14) and identified from the VAR. 95% nonparametric dispersion bands as computed in Equation (12). Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes. Dashed lines correspond to the IRF estimate from the baseline result in Fig. 5.

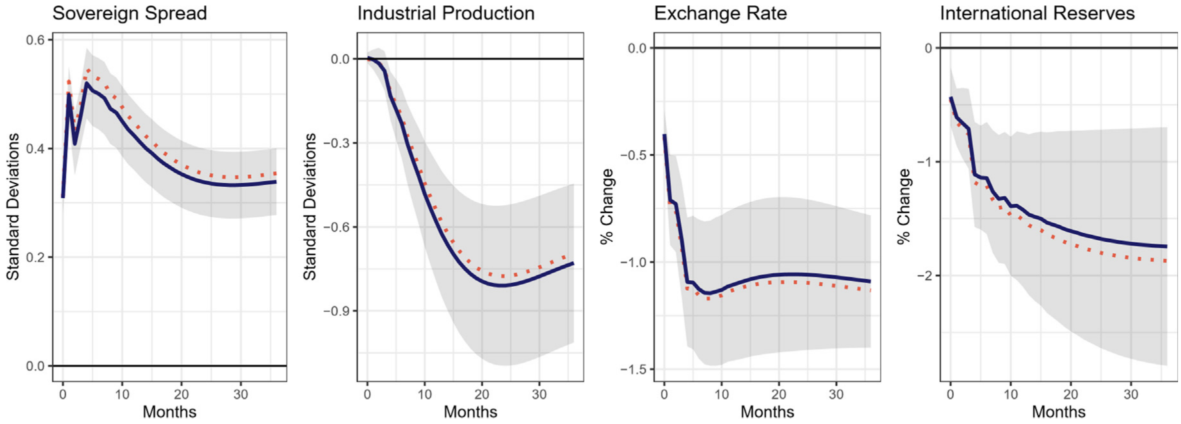

Fig. A10. Emerging Markets: Average Response to a 1-Standard Deviation FTS Shock using Extended Country Sample. Cumulative MG Response (Equation (10)) to a 1-standard deviation flight-to-safety shock identified from the VAR. 95% non-parametric dispersion bands as computed in Equation (12). Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes. Extended sample includes India, S. Korea, Singapore, Thailand. Dashed lines correspond to the IRF estimate from the baseline result in Fig. 5.

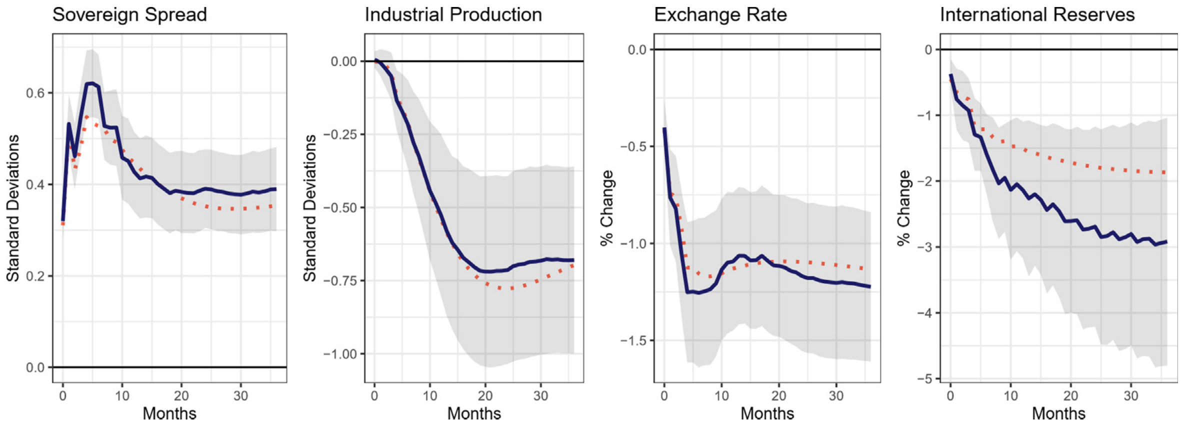

Fig. A11. Emerging Markets: Average Response to a 1-Standard Deviation FTS Shock under VAR with 8 Lags. Cumulative MG Response (Equation (10)) to a 1-standard deviation flight-to-safety shock identified from the VAR. 95% non-parametric dispersion bands as computed in Equation (12). Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. VAR is estimated with 8 lags. Dashed lines correspond to the IRF estimate from the baseline result in Fig. 5.

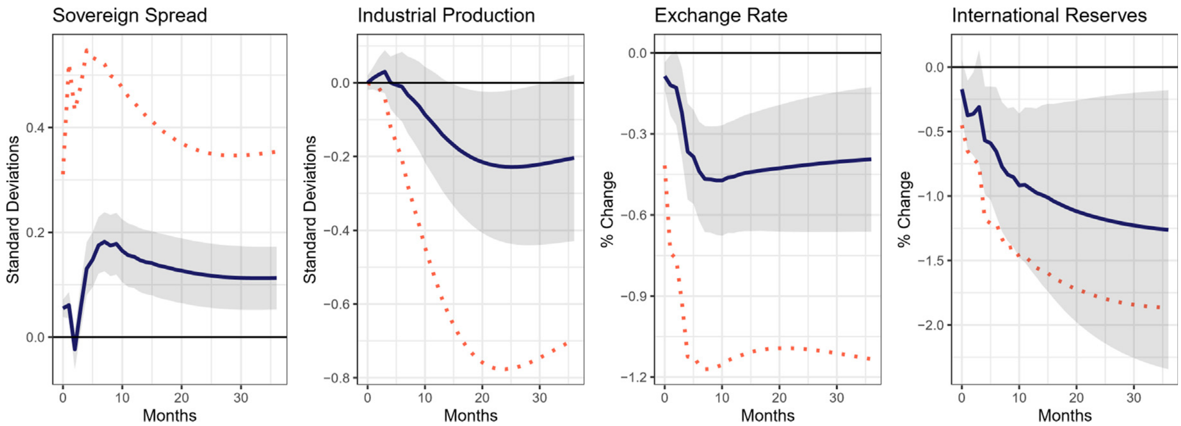

Fig. A12. Emerging Markets: Average Response to a 1-Standard Deviation FTS Shock that is Orthogonal to the Risk-Off Index of Datta et al. (2017). Cumulative MG Response (Equation (10)) to a 1-standard deviation flight-to-safety shock identified from the VAR. Risk-Off Index is taken from Datta et al. (2017). 95% non-parametric dispersion bands as computed in Equation (12). Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes. Dashed lines correspond to the IRF estimate from the baseline result in Fig. 5.

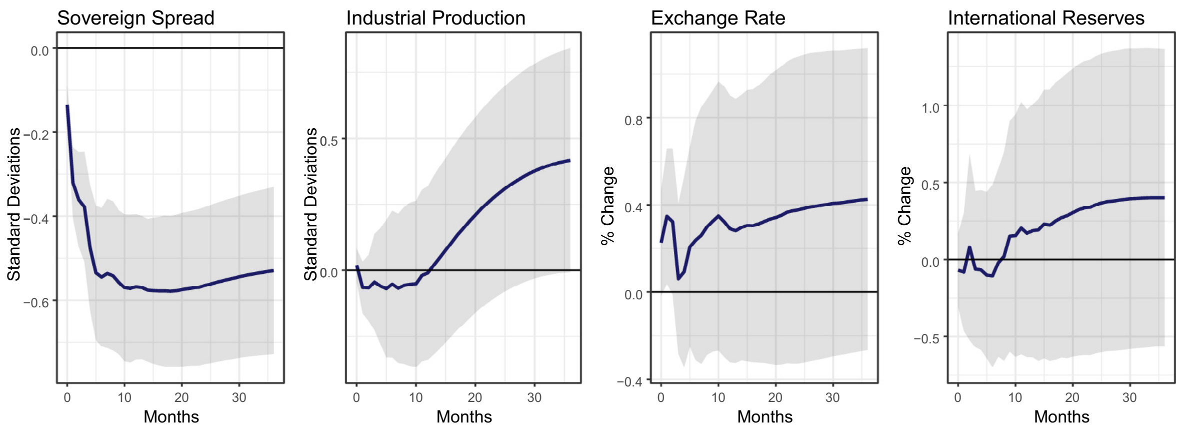

Fig. A13. Emerging Market Majors: Average Response to a 1-Standard Deviation *Conventional* U.S. Monetary Policy Shock, Pre-2008 Sample. Cumulative MG Response (Equation (10)) to a 1-standard deviation expansionary conventional U.S. monetary policy shock. U.S. monetary policy shocks are recovered from Treasury futures contract yield changes within a 30-minute window of FOMC announcements and then aggregated to the monthly frequency. 95% non-parametric dispersion bands as computed in Equation (12). Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes. EM Majors include: Brazil, Chile, China, Colombia, Hungary, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Turkey. Sample truncated to end in December 2007.

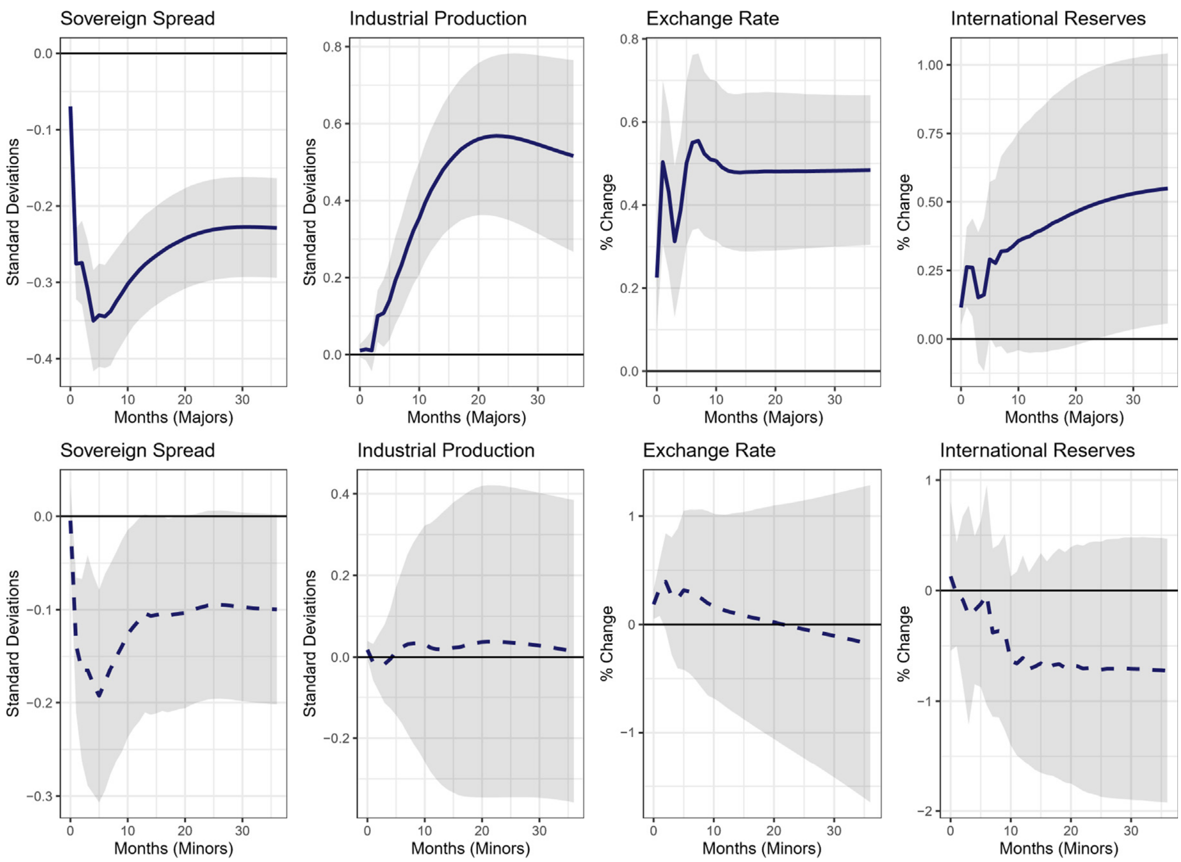

Fig. A14. Emerging Market Majors (Solid) and Minors (Dashed): Average Response to a 1-Standard Deviation Expansionary *Conventional* U.S. Monetary Policy Shock. Cumulative MG Response (Equation (10)) to a 1-standard deviation expansionary conventional U.S. monetary policy shock. U.S. monetary shocks are recovered from 3-month Treasury futures contract yield changes within a 30-minute window of FOMC announcements and then aggregated to the monthly frequency. 95% non-parametric dispersion bands as computed in Equation (12). Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes. EM Majors include: Brazil, Chile, China, Colombia, Hungary, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Turkey. EM Minors include: Argentina, Belarus, Cote d' Ivoire, Croatia, Egypt, El Salvador, Gabon, Indonesia, Iraq, Jordan, Kazakhstan, Lithuania, Pakistan, Senegal, Sri Lanka, Tunisia, Ukraine, Uruguay, Venezuela, Vietnam.

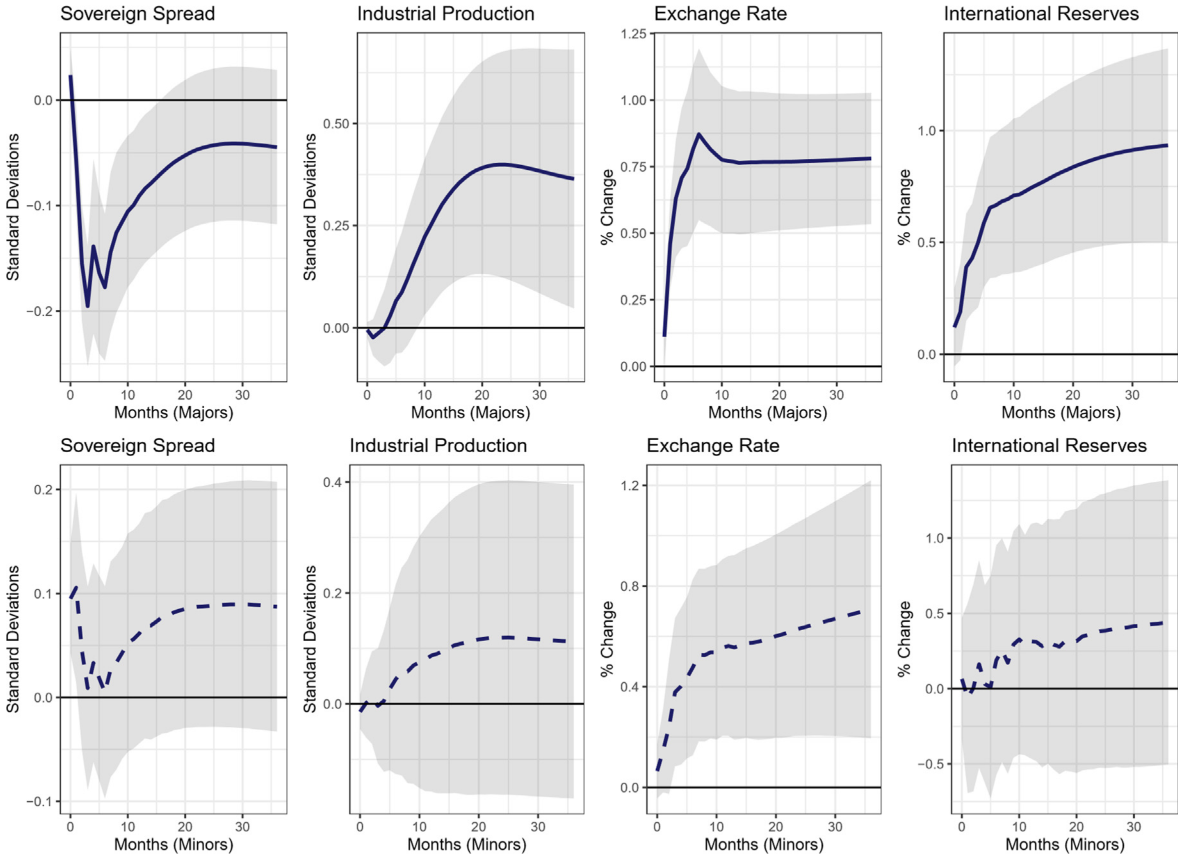

Fig. A15. Emerging Market Majors (Solid) and Minors (Dashed): Average Response to a 1-Standard Deviation Expansionary *Unconventional* U.S. Monetary Policy Shock. Cumulative MG Response (Equation (10)) to a 1-standard deviation expansionary unconventional U.S. monetary policy shock. U.S. monetary shocks are recovered from 10-year Treasury futures contract log price changes within a 30-minute window of FOMC announcements and then aggregated to the monthly frequency. 95% non-parametric dispersion bands as computed in Equation (12). Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes. EM Majors include: Brazil, Chile, China, Colombia, Hungary, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Turkey. EM Minors include: Argentina, Belarus, Cote d' Ivoire, Croatia, Egypt, El Salvador, Gabon, Indonesia, Iraq, Jordan, Kazakhstan, Lithuania, Pakistan, Senegal, Sri Lanka, Tunisia, Ukraine, Uruguay, Venezuela, Vietnam.

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