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Abstract

I develop a measure of changing tail risk perceptions based on global financial shocks reflecting 'flights-to-safety'. Large flight-to-safety shocks are defined as joint tail realizations of returns across major risky and safe asset classes. Flight-to-safety shocks are substantially distinct from VIX innovations, map to unexpected global events, inform future changes in world prices and interest rates, and reflect both risk sentiment and global demand. Estimating a multi-country structural VAR with country-specific heterogeneity, I show that global flight-to-safety shocks induce a sharp rise in sovereign risk and exchange market pressure, followed by a subsequent drop in economic activity in both emerging markets and the U.S. However, the macroeconomic effects of flight-to-safety shocks are far from uniform across emerging markets, with domestic financial factors moderating the transmission mechanism. Countries realizing larger sovereign risk adjustment or sharper currency depreciation from a flight-to-safety shock are subject to deeper subsequent economic contractions. The impact of flight-to-safety shocks on economic activity is four times larger for emerging markets with substantial presence in U.S. exchange traded funds. By contrast, leaning against the wind by aggressively expending international reserves limits the economic impact of global flight-to-safety shocks, with its effectiveness rising when the exchange rate is successfully stabilized.

Keywords: Tail Risk, Risk-off, Risk Sentiment, Global Shocks, Contagion, International Spillovers, Sovereign Risk, Monetary Policy, Capital Flows, Emerging Markets.

JEL Classifications: E44, F30, F44, F60, G15.

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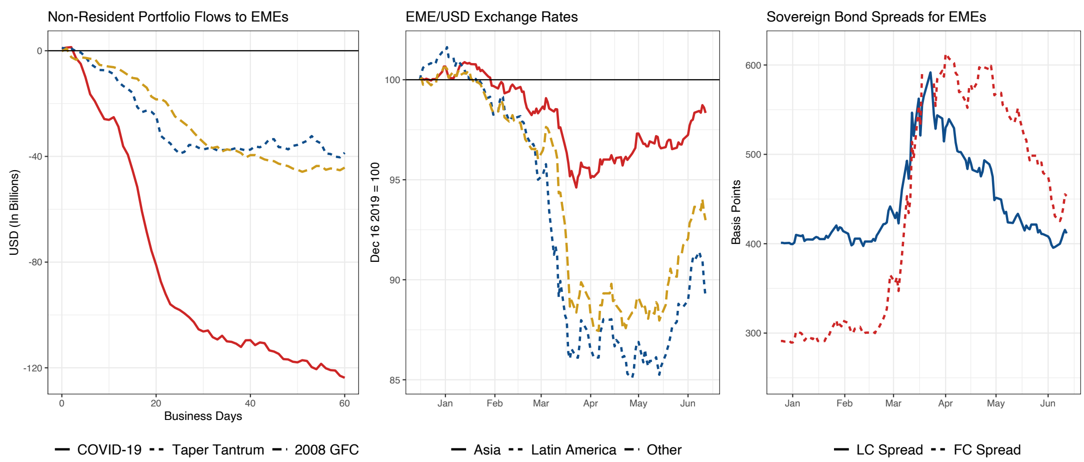
1 Introduction

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 particularly exposed, induced large and volatile capital outflows, currency depreciation, and sharply wider borrowing costs as presented in Figure 1. Despite the uniqueness of the pandemic shock, it shares the signatures of many unanticipated left-tail economic events: a 'flight-to-safety' or alternatively, 'risk-off'.[1] These refer to abrupt, violent swings across financial markets in the form of falling risky asset prices and rising safe asset prices associated with aggressive portfolio rebalancing of global investors. Flights-to-safety directly shape the evolution of the global financial cycle, reflecting both changing risk appetite and expectations over global demand. Flights-to-safety have increased in severity in the last decade amid an era of unprecedented global liquidity.[2]

Figure 1: COVID-19 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.

In this paper, I present a new measure of shocks to tail risk perceptions based on systematic features of global flight-to-safety episodes. These flight-to-safety shocks intend to capture unpredictable swings in global financial cycles, with large shocks especially reflecting re-evaluation of global tail risk. Specifically, large values of the measure captures joint tail realizations across a set of major risky and safe asset prices. My proposed methodology to identify flight-to-safety shocks is transparent, easily generalized and modifiable. Global flight-to-safety shocks carry distinct information apart from benchmark measures of global financial conditions, they are informative of future world prices and

[1]'Flight-to-safety' and 'global financial shock' are used interchangeably throughout the paper. Similarly, 'global financial cycles' and 'global financial conditions' are synonymous.

[2]See Figure 3.

interest rates, and map to historically disruptive events. While global flight-to-safety episodes have become a widely regarded financial phenomena, there is little evidence linking their impact to macroeconomic fluctuations. I show that global flight-to-safety shocks bear significant implications for the global economy. The impact of global flight-to-safety shocks on economic activity across emerging markets in particular are far from uniform, and I show that several domestic financial factors are significantly linked to this heterogeneity.

This paper makes two main contributions to the literature. First, it presents a new measure of financial shocks emphasizing tail risk perceptions by identifying global flights-to-safety. Second, it develops a multi-country structural VAR with country specific heterogeneity to model how emerging market dynamics respond to a global flight-to-safety shock. By exploiting country-specific heterogeneity, I identify several possible sources through which global shocks can shape macroeconomic dynamics.

I propose a method to identify shocks in to global financial markets which capture tail risk perceptions, by identifying global flights-to-safety behavior across risky and safe asset classes. While asset prices are largely unpredictable at short horizons, their distribution is not entirely unpredictable, and I exploit this feature to measure shifts in tail risk perceptions. Conceptually, as an asset's return grows too large to be justified by their conditional standard deviation/volatility, 1) the likelihood that it reflects an unanticipated shock rises towards certainty, and 2) the return reflects a realization in the tail of the conditional distribution. I identify daily asset price shocks within a asymmetric-GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model of conditional volatility, using this method across several major asset classes: equities, volatility, exchange rates, and interest rates. In a second step, I aggregate these asset-specific price shocks while imposing a condition such that their co-movement satisfies the covariance structure observed during flight-to-safety. I define this as rising volatility, rising safe asset prices, and rising safe-haven currency prices along with depreciating risky asset and risky currency prices. Moreover, the flight-to-safety condition can be made more conservative by imposing restrictions on both the covariance and the size of the shocks. Unlike known-unknown events such as monetary policy or macroeconomic news announcements, the events triggering global flight-to-safety shocks tend to be unknown-unknowns – unusual, unexpected, and unique. As such, large global flights-to-safety reflect changing tail risk perceptions. My approach admits to identifying such global flight-to-safety shocks in a systematic, transparent and general way.

Global flight-to-safety shocks represent a distinct source of variation from benchmark indices of global financial conditions (e.g. VIX). They map to economically disruptive events, inform contemporaneous and future changes in world commodity prices, interest rates, exchange rates and inflation expectations, therefore embedded in them are both components reflecting shifting risk sentiment and global demand. Using global flight-to-safety shocks as external instruments, I model their impact on emerging markets in a multi-country structural VAR. My modeling framework extends beyond standard approaches by allowing for country-specific heterogeneity (unlike panel VARs/regressions which pool information across countries), incorporating interdependencies between countries, and controlling for spillovers from advanced economies, namely the United States.

In response to a global flight-to-safety shock, emerging market sovereign spreads sharply widen, exchange market pressure rises, and a drop in economic activity follows. On average, industrial production contracts by 0.625 standard deviations, or four percent over an 18-month window following a 1-standard deviation global flight-to-safety shock. However, the effects of global flight-to-safety are far from uniform across countries, the heterogeneity being linked to domestic financial factors. The impact of global flight-to-safety shocks on economic activity is larger when flight-to-safety shocks also induce sharper sovereign spread adjustment and deeper currency depreciation upon impact. I also show that the impact of global flight-to-safety on economic activity is significantly amplified – roughly by a factor of 4 – in countries which have substantial presence in U.S. traded ETFs. By contrast, countries which more aggressively expend international reserves in response to a flight-to-safety shock are subject to less severe subsequent economic contractions. This buffering effect from policies that lean against the wind is strongest when the exchange rate is successfully stabilized.

This paper contributes to the active literature investigating the global macroeconomic implications of financial shocks and global financial cycles (Uribe and Yue [2006], Akinci [2013], Rey [2015], Aizenman et al. [2016], Caballero et al. [2019], Obstfeld et al. [2019], Kalemli-Ozcan [2019], Cesa-Bianchi et al. [2019], Miranda-Agrippino and Rey [2020]). This issue has received renewed attention in light of deep global financial integration occurring over the past two decades, and the concerns raised over global financial stability. My focus on emerging markets, which are particularly prone to global financial shocks, aligns closely with Uribe and Yue [2006], Akinci [2013], Caballero et al. [2019], and Obstfeld et al. [2019].

My work intends to extend upon from the prevailing literature, departing from it in several ways. First, by introducing a new measure of tail risk perceptions, I specifically quantify the financial and economic effects associated with global flights-to-safety or risk-off shocks, which I define, and subsequently show, as being distinct from more general financial fluctuations. This way, my work ties the literature on global financial cycles to that on flights-to-safety and risk-on/risk-off (Caballero and Krishnamurthy [2008], Beber et al. [2014], De Bock and de Carvalho Filho [2015b], Caballero and Kamber [2019], Baele et al. [2019]). On the development and measurement of financial shocks, my work also relates to Gilchrist and Zakrajsek [2012], Caballero et al. [2019] and Cesa-Bianchi et al. [2019], all of which introduce new, yet different measures of financial shocks, quantifying their macroeconomic impact. While the former two focus on country-specific measures of external finance premia, the latter develops a global measure of financial volatility. Like the latter, my measure intends to capture global shocks of a particular type.

Additionally, in modeling emerging market dynamics I allow for country-specific heterogeneity, thereby estimating both average pooled effects a la panel VARs while also showing that the effects of flight-to-safety shocks vary widely across countries. My modeling approach follows similar methods applied in Fernandez et al. [2017] and Cesa-Bianchi et al. [2019], the former quantifying the contribution of world commodity shocks and the latter studying the impact of global uncertainty shocks. Both allow for country-specific heterogeneity and highlight its importance. I use the country-specific variation admitted by my model to link differences in the macroeconomic impact of global flight-to-safety shocks to domestic financial factors, suggesting particular policy implications.

On the transmission and policy implications of global shocks, the association between wider sovereign spreads and subsequently deeper economic contractions induced by global flight-to-safety shocks is consistent the pass-through of global financial shocks depending on the sensitivity of domestic financial factors (Akinci [2013], Aizenman et al. [2016], Kalemli-Ozcan [2019]). That currency depreciation is associated with subsequently deeper contractions points to a financial channel of exchange rates associated with currency mismatch (Eichengreen and Hausmann [1999] Hofmann et al. [2019], Carstens and Shin [2019], Miranda-Agrippino and Rey [2020]), contrasting conventional wisdom related to the buffering effects of a flexible exchange rate as argued in Obstfeld et al. [2019], and rather, supportive of stabilization policies among financially developing countries Aghion et al. [2009]. The potential for an ETF channel to significantly amplify the effects of global flight-to-safety shocks is consistent with Converse et al. [2020] and more broadly the risks associated with volatile capital flows. The buffering effects of expending international reserves amid a global flight-to-safety shock are consistent with research citing the insurance benefits of reserves accumulation (Aizenman and Lee [2007], Jeanne and Ranciere [2011], Aizenman and Jinjarak). Although particularly novel about my findings is that it shows the buffering effects of leaning against the wind through *expending* reserves, beyond the signaling benefits of having large stocks of reserves.

Theoretically, global flights-to-safety may arise from unexpected news shocks to beliefs over global demand (Jaimovich and Rebelo [2009], Barsky and Sims [2011], Kurmann and Otrok [2013]) or shocks to global risk appetite or uncertainty (Bloom [2009], Fernández-Villaverde et al. [2011], Christiano et al. [2014] Alessandri and Mumtaz [2019], Cesa-Bianchi et al. [2019]. There is considerable theoretical and empirical evidence suggesting that news shocks and risk shocks are connected: large macroeconomic shocks arise from news shocks and endogenously generate time-varying risk premia (i.e. left-tail shocks, Danielsson and Shin [2003], Orlik and Veldkamp [2014], Cascaldi-Garcia and Galvao [2018], Berger et al. [2020]). Any attempt to empirically identify the effect of say, global financial shocks, will have to separate these two components, and my empirical results support views of the latter class of models. I investigate this issue further in the Online Supplement, Section S2.

The remainder of the paper is structured as follows: Section 2 describes the construction of global flight-to-safety shocks. Section 3 studies their impact on world prices and interest rates. Section 4 then introduces a multi-country VAR to investigate how global flight-to-safety shocks shape macroeconomic dynamics. Section 5 introduces measures of exchange market pressure – exchange rates and international reserves – into the VAR model. Section 6 discusses the heterogeneity in country-specific responses to global flight-to-safety shocks. Section 7 links country-specific heterogeneity to domestic financial factors as transmission mechanisms of global shocks. Section 8 specifically focuses on the role of U.S. ETFs as an amplifying mechanism of global flight-to-safety on emerging markets and Section 9 assess the joint explanatory power of financial factors as transmitters of global financial shocks in explaining differences in macroeconomic sensitivity. Section 10 concludes. In the Online Supplement, Section S2 discusses and separates global flight-to-safety shocks into both risk sentiment and global demand components, and investigates their relative contribution in affecting world prices and emerging market dynamics.

2 Global Flight-to-Safety Shocks

Macroeconomic shocks fall into two categories: Known-unknowns and unknown-unknowns. Stochastic realizations of a known event represent the former category. Some examples of these include monetary policy announcements, macroeconomic news releases, and elections – all of which are anticipated but can lead to surprises. The size of the surprise is often measured by daily or intra-day changes in asset prices around the known event. Recent advances in measuring these known-unknown shocks primarily come from high-frequency identification techniques.

By contrast, flight-to-safety (FTS) shocks fall into the category of unknown-unknowns. Unknown-unknowns refer to stochastic realizations stemming from completely unanticipated events. While these shocks present greater measurement challenges, they reflect some the the most impactful shocks to the macroeconomy. Some examples of these include the Lehman Brothers bankruptcy, the Arab Spring, and the COVID-19 pandemic. Qualitatively, they tend to have unique origins, reflecting tail risks. Thankfully, they leave behind highly similar patterns in the way they disrupt global financial markets. I exploit this feature to develop a measure of these unknown-unknown tail shocks, which I refer to as global flight-to-safety shocks.

The unexpected and idiosyncratic nature of global flights-to-safety makes them difficult to measure from any set of particular events the way known-unknowns can be identified. However, they do leave behind repeated, systematic signatures in global financial markets in the form of: falling risky asset prices, rising safe asset prices and rising volatility, at the same time. My approach for identifying flight-to-safety shocks specifically imposes this co-movement restriction across realized returns of major financial assets. Moreover, to measure the size of the shock, I consider the size of asset-specific return relative to their ex ante conditional distribution. These shocks are then aggregated across asset classes. Large shocks, therefore, reflect joint tail realizations across asset returns.

2.1 Stage 1: Measuring asset market shocks

I consider five global financial asset benchmarks due to their international presence: The Wilshire 5000 equity index, 10-year U.S. Treasury yields, the Japanese Yen/Australian Dollar exchange rate, the U.S. corporate high yield spread and the CBOE VIX index. The Wilshire 5000 index represents the broad U.S. stock market, while 10-year Treasuries are one of the worlds most sought after safe investments. The JPY/AUD exchange rate proxies for spot movements in the G10 carry trade. The Japanese yen acts famously as a safe haven currency, appreciating amid turmoil while the Australian Dollar tends to be risky in the sense that it covaries positively with global economic cycles. Therefore, the Yen tends to depreciate against the Australian Dollar during expansions times while appreciating during periods of global economic stress. 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 for global investor risk appetite, uncertainty. It specifically measures the option-implied expected forward 1-month volatility of the S&P 500 stock market index.[3]

One could easily add additional assets to the set A, for example, German bond yields to incorporate Europe's role as a financial center alongside the U.S.. Another consideration would be to include gold prices. However, I omit gold from the baseline estimation for several reasons. First, the price of gold tends to be strongly determined by other factors, like finite supply, the real interest rate and inflation. Second as a commodity, gold prices are subject to different demand forces than traditional financial assets and its market is dwarfed by the size of other safe asset markets. Lastly, the allocation of major global investors and intermediaries to gold is disproportionately small in comparison to safe financial assets. However, the persistence of gold's role as an alternative safe asset throughout history is impressive, therefore it can easily be incorporated in a simple extension.

[3]Notice that four of the five benchmark assets are U.S. centric and therefore, I make the naive assumption that global shocks are largely U.S. based. While this may reasonable in the current state, global economic centers shift over time. My approach is general enough such that one can easily add more financial benchmarks to the set, say from Europe or China to account for other important economic centers. Alternatively, this approach can be applied to construct region-specific flight-to-safety shocks.

Denote $r_{ad} \in \{r_{vd}, r_{sd}, r_{bd}, r_{jd}, r_{hd}\}$ as the daily return (logged-difference) of asset $a \in A = \{v, s, b, j, h\}$ over day d, where v refers to the VIX, s refers to the Wilshire 5000 index, b refers to the 10-year Treasury yield, j refers to the JPY/AUD exchange rate and h refers to the U.S. corporate high yield spread. The global FTS index is constructed as an aggregation of normalized daily innovations across these assets. I define daily shocks in each asset by comparing the realized return on day $d+1$, $r_{a,d+1}$, to the ex ante conditional volatility forecast for day $d+1$, made on day d:

$$Z_{ad} = \frac{r_{ad}}{E_{d-1}[\sigma_{ad}]}. \tag{1}$$

This step serves three important purposes. First, the volatility of returns vary substantially across assets and over time. Normalizing asset returns by their conditional volatility produces a transformation admits to comparing across assets classes and accounts for regime changes (i.e. volatility clustering). Second, under the assumption that $Z_{a,d+1}$ follows an i.i.d. standard normal distribution (it is, after all, a conditional z-score), the probability that return $r_{a,d+1}$ was unexpected rises in $Z_{a,d+1}$. Hence, large values of $Z_{a,d+1}$ are increasingly likely to reflect true exogenous shocks in the sense that they were unforeseeable. Third, large values of Z_{ad} are easily interpreted as tail-shocks. Therefore a key distinction of FTS shocks compared to more readily available measures of financial conditions is that it specifically captures shifts in *tail* risk perceptions. I later validate these interpretations by documenting that when large values of $Z_{a,d+1}$ are realized across assets a, they map to unexpected, globally disruptive events.

While r_{ad} is observed, σ_{ad} is not and must be estimated. To estimate $E_d[\sigma_{a,d+1}]$, a model which allows for time-varying volatility must be specified. I assume that asset returns are mean zero with time-varying volatility following a GARCH process (Bollerslev [1986]):

$$r_{ad} = \sigma_{ad} z_{ad}, \quad z_{ad} \sim \mathcal{N}(0, 1), \tag{2}$$

where the return sequence is mean zero, and split into a stochastic i.i.d component (z_{ad}) and a time-varying volatility component (σ_{ad}). Notice that our estimates of asset-specific shocks Z_{ad} is the same as z_{ad}, the exogenous component of asset returns under the specified model structure. I parameterize z_{ad} as being drawn from a normal distribution, hence conditional returns are normally distributed but the unconditional distribution are allowed to be fat-tailed[4]. Specifically the conditional variance at time d follows a GJR-GARCH(1,1) process:[5]

[4]One can parameterize z_{ad} 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. Alternatively one could use another model for time-varying volatility, for example stochastic (latent) volatility models. These typically rely on computationally intensive Bayesian approaches to estimate them and further assumptions

$$\sigma_{ad}^2 = \omega_a + \alpha_a \sigma_{a,d-1}^2 + (\beta_a + \gamma_a \mathbf{I}_{a,d-1}) r_{a,d-1}^2, \text{ where} \tag{3}$$

$$\mathbf{I}_{a,d-1} = \begin{cases} 0 & \text{if } r_{a,d-1} > 0 \\ 1 & \text{if } r_{a,d-1} < 0. \end{cases} \tag{4}$$

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 returns. The expected volatility for day $d+1$ conditional on day d information is computed as:

$$E_{d-1}[\sigma_{ad}] = \sqrt{E[\sigma_{ad}^2]} = \sqrt{\omega_a + \alpha_a \sigma_{a,d-1}^2 + (\beta_a + \gamma_a \mathbf{I}_{a,d-1}) r_{a,d-1}^2} \tag{5}$$

Referring back to Equation 1, I finally recover shocks to asset a by dividing its observed realization on day $d+1$ with the ex ante standard deviation for $d+1$. In other words, we simply ask: to what degree was the realized move justifiable under the prevailing (ex ante) forecast distribution? Larger values imply tail realizations, and equivalently returns which are less likely to be generated from the ex ante distribution.

As an alternative to the GARCH structure, a more recent alternative specification for time-varying volatility could adopt realized volatility (RV) models. For daily volatility estimates, realized volatility models require intra-day data. However, intra-day is not easily available for many financial assets going back over long histories. This limits the feasibility of constructing a daily FTS index which goes far back in history, but it is very possible to construct a monthly FTS index using realized volatilities measured with daily data. This approach is worth exploring and is left as an extension.

2.2 Stage 2: Rotation and aggregation to identify Flights-to-Safety

With asset-specific price shocks in hand, the next stage aggregates these shocks to develop a global shock measure while identifying flights-so-safety from broader financial market movements. The way this is done is by relying on the cross-asset correlations typically observed during global flights-to-safety. The economics of FTS imply global portfolio rebalancing such that risky assets are sold and safe assets bid in the face of rising uncertainty. To capture this flight-to-safety signature, I define a flight-to-safety as a period (day) when: VIX rises, stocks fall, Treasury yields fall, high yield credit spreads rise, and Japanese yen appreciates and the Australian Dollar depreciates - depicted in Table 1.

on prior distributions and estimation design. Despite their differences, GARCH, stochastic volatility, and realized volatility models, three workhorse models of time-varying volatility, perform quite similarly.

Table 1: Cross Asset Flight-to-Safety Behavior

Z_{ad}	Underlying	Asset Class	FTS Behavior
Z_{vd}	CBOE VIX Index	Volatility	+
Z_{sd}	Wilshire 5000 Stock Index	Equities	-
Z_{bd}	10-year U.S. Treasury Yield	Government Rates	-
Z_{hd}	U.S. High Yield Spread	Credit	+
Z_{jd}	JPY/AUD Exchange Rate	Currencies	-

With the Z_{ad} for all five assets, the global daily FTS index (FTS_d) is constructed as the rotated cross-section weighted average on each day d:

$$FTS_d = (w_v Z_{vd} + w_h Z_{hd} - w_s Z_{sd} - w_b Z_{bd} - w_c Z_{jd})\mathbf{1}_d, \quad \sum_{a \in A} w_a = 1, \tag{6}$$

where the rotations ensure that positive values of FTS_d coincide with fight-to-safety or risk-off, and negative values coincide with risk-on episodes. Hence, the shocks (Z_{ad}) corresponding to the VIX and high-yield credit spreads have positive weights w_a, while the rest have negative weights. I apply equal weights $w_a = 1/5$ but more generally, one can assign arbitrary weights w_a across assets. Similarly, an estimate of FTS_d can be obtained by taking the first principal component across asset shocks Z_{ad}. When doing so, the estimated signs on factor loadings typically coincide with those in Table 1, although an additional arbitrary rotation may be needed if the research wants positive values are to imply flight-to-safety episodes. In practice, there is very little difference between estimates of FTS_d obtained via PCA or the rotated cross-section average. Specifically, the FTS_d estimated as the cross-section average shares a correlation of over 0.98 with the PCA approach. The added benefit of taking cross-section averages is that it can be calculated each period without requiring information from the entire sample. A key advantage of the PCA approach is if the set of variables in Z_{ad} becomes very large, it may become more practical to identify the sign restrictions using PCA rather than imposing them one-by-one based on economic theory.

2.3 Imposing the flight-to-safety condition

To then identify flight-to-safety shocks, FTS_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 condition):

$$\mathbf{1}_d \begin{cases} 1 & \text{if } \{Z_{vd}, Z_{hd}\} > c \cap \{Z_{sd}, Z_{bd}, Z_{jd}\} < -c \quad \textit{`Risk-Off'} \\ 1 & \text{if } \{Z_{vd}, Z_{hd}\} < -c \cap \{Z_{sd}, Z_{bd}, Z_{jd}\} > c \quad \textit{`Risk-On'} \\ 0 & \text{otherwise,} \end{cases} \tag{7}$$

This way, I impose as a necessary condition that all 5 asset returns move in the direction consistent with flight-to-safety, with the size of the move necessarily larger than some threshold c. If asset price movements do not satisfy this restriction, there is no shock, and $FTS_d = 0$. If they do, the size of the shock is continuous, and can be positive ('risk-off') or negative ('risk-on'). To start, I set $c = 0$, meaning a flight-to-safety is identified simply based on directions of Z_{ad}, regardless of the size of the moves. One issue with this method is that some days may satisfy the FTS condition simply by random chance, and likely realize low values of FTS_d. This introduces noise into the FTS measure, therefore inducing attenuation bias when interested in the effects of flight-to-safety. One solution is to require a more conservative threshold for c, taking into account both the direction and size of cross-asset moves. Considering this alternative, I also set a threshold of $c = 1$, meaning that all 5 assets must have $|Z_{ad}| > 1$ on a given day (at least a 1-sigma) and also move in the direction consistent with flight-to-safety to count as an FTS shock.

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

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

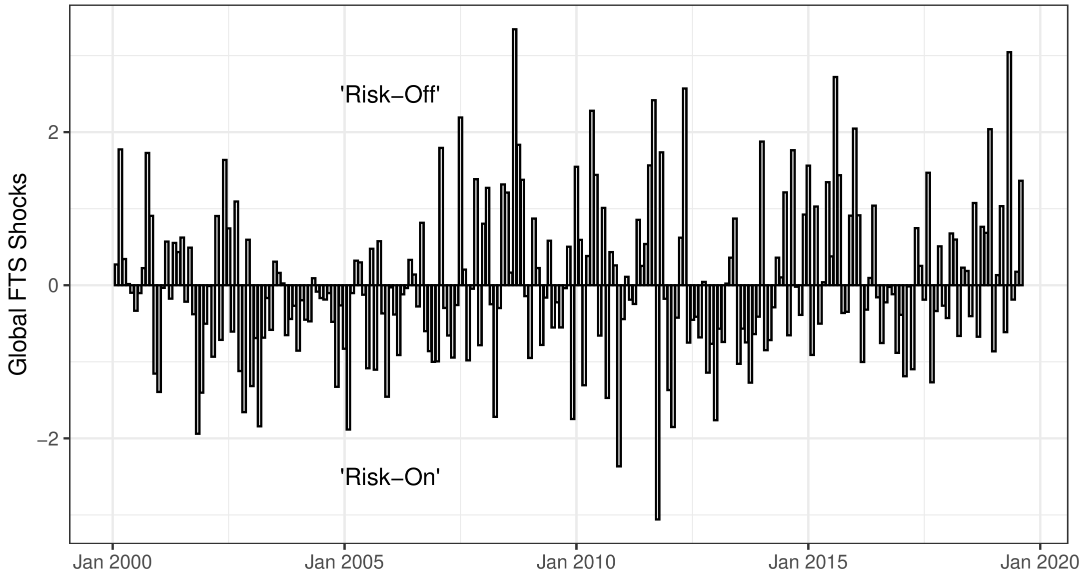
where $D(t)$ is the number of days in month t, and $FTS_d(t)$ denote daily global fight-to-safety measures corresponding to month t. By summing the daily values of FTS_d, which can be positive (risk-off), negative (risk-on) or zero (non-event), each months value in FTS_t can be interpreted as the net of the daily positive and negative FTS shocks. A large positive monthly value of FTS_t indicates that month had either/several large global flight-to-safety days (risk-off) relative to risk-on days and days which were neither risk-on or risk-off.

2.4 Flight-to-safety shocks: properties and stylized facts

From 2000 to 2019, of the 6,044 days in the sample, 11% have asset co-move in directions consistent with a flight-to-safety or 'risk-off', with 12.4% 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 accompanied by rising volatility, falling bond yields, rising credit spreads and depreciating risky currencies the average daily Wilshire 5000 return nearly doubles to -1.3%. Similar patterns apply across the other four assets. When the Australian Dollar depreciates (relative to JPY), it depreciates on average -0.6%. On risk-off days, the average depreciation increases to -1%. When the VIX index rises, it rises on average 4.2%. On a risk-off day, it rises on average 8.4%.

The VIX index is a common off-the-shelf gauge of global financial conditions. The

Figure 2: Time-Series of Global Flight-to-Safety Shocks (FTS_t)

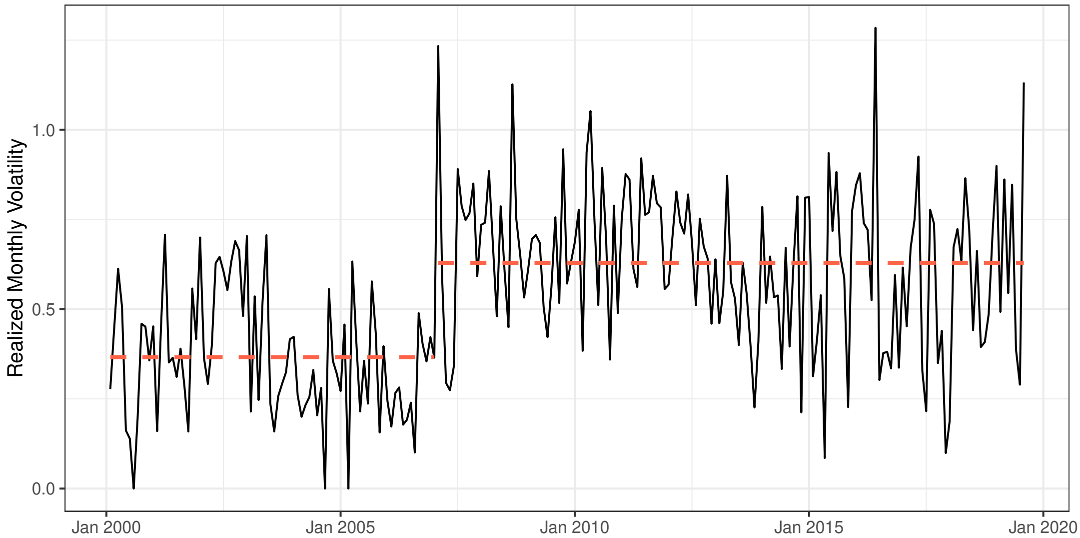


First order auto-correlation = 0.067. Series is normalized to have unit standard deviation.

way FTS shocks are designed, they can be interpreted as a subset of all VIX fluctuations: the VIX fluctuations which are 1) abnormally large and 2) coincide with large risk-off co-movements in other asset classes. Table 3 shows that FTS_t (which includes VIX innovations as a component) and changes in the VIX are indeed correlated, but quite imperfectly. Global FTS shocks can explain roughly 28% of the variation in log changes in the VIX (correlation of 0.53) suggesting that a majority of information content in the FTS_t measure is distinct from aggregate VIX innovations. Similarly global FTS shocks explain explain 39% of the variation in U.S. stock returns. These correlations weaken further when increasing the threshold to $c = 1$ which more conservatively identifies flight-to-safety episodes as tail shocks. On one hand, this highlights a rather substantive role of flight-to-safety in driving asset specific movements. Meanwhile, the relatively low R^2 between FTS shocks and U.S. stock returns and volatility suggests that this measure captures distinct information content relative to the benchmark fluctuations in global financial conditions.

FTS shocks do indeed capture shocks to global tail risk. Table 4 provides a list of dated days between 2000 and 2020 that, based on the daily measure FTS_d, are identified as the largest FTS shocks. The global nature of these shocks becomes apparent: the 'Chinese Correction' (2007), 'Brexit' (2016), U.S. President Trump political controversies (2017), Italian political tensions (2018), and the Lehman bankruptcy (2008) round out the top five daily global flights-to-safety. Using a different methodology, a similar list is reported in De Bock and de Carvalho Filho [2015a]. Several flight-to-safety episodes flagged by FTS_d are shared in their list, even though the methodologies differ. None of the ten

Figure 3: Realized Monthly Volatility of Daily Global Flight-to-Safety Shocks



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.

largest global FTS shocks correspond with the largest U.S. stock market crashes. Table 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 the popping 2000 Tech Bubble. Table 6 shows the top 10 largest percent changes in the VIX index – three overlap with the top 10 daily largest FTS shocks. The largest VIX shock reflects the 'VIXplosion' (2018), considered by many practitioners as a technical event caused by overcrowded short volatility positions. It's particularly interesting to point out that despite four of the 5 assets used to estimate FTS shocks FTS_t are U.S. based, they appear to do well in capturing shocks which are non-U.S. based, bearing global implications.

A time-series of monthly FTS shocks is shown in Figure 2. Unlike the standard VIX index or changes in the VIX, neither daily nor monthly measures of FTS shocks (FTS_d or FTS_t) exhibit significant serial correlation - an important feature which should be necessary, but not sufficient, in a measure of global FTS shocks. The volatility of FTS shocks have also markedly increased since 2007 (Figure 3). Each month the realized volatility is computed by taking the standard deviation of daily FTS_d shocks within that month. The volatility of FTS shocks after February 2007 is 75% larger than before 2007.

2.5 Discussion

Not only do large flights-to-safety consistently map back to well known globally disruptive events, they have large impacts on non-financial prices closely tied to economic fundamentals, namely commodity prices and inflation expectations. Taken together, this points to large financial shocks coinciding with shocks that affect beliefs over global demand. For example, flights-to-safety would be consistent with news shocks that induce renewed pessimism over global growth which endogenously increases risk aversion. This casts doubt on the assumption that large fluctuations in financial market indicators – not just flights-to-safety, but the VIX index, equity returns, volatility, or capital flows – are unbiased measures of risk preferences. However, it is often prohibitively difficult to separate the risk premia component from the fundamental component of asset price moves without imposing many, sometimes exceedingly controversial assumptions. While this is beyond the main scope of the paper, In Section S2, I attempt to separate the excess risk sentiment and global demand components embedded in global FTS shocks, subject to a number of assumptions.

An important observation is that the FTS measure differs substantially from VIX innovations. As shown, large values of global flight-to-safety specifically capture tail shocks which appear differ from extreme VIX movements. Why might the VIX and global flight-to-safety shocks differ? The VIX index measures the combination of two things. First, the amount of expected US uncertainty, and second, the pricing of this uncertainty (Bekaert and Hoerova [2014]). If flight-to-safety shocks are induced by changing preferences towards safety/risk, they will be correlated with the VIX since greater risk aversion would also directly influence the VIX through the pricing of uncertainty. If this change in risk preference is exogenous, and macro uncertainty did not structurally change along with it, then the part of the VIX which changes based on expected uncertainty would not be affected. However, these two components may be endogenous which complicates the issue, as changing risk perceptions can re-shape macro uncertainty and vice versa. However, global FTS shocks and VIX innovations would very likely not be identical. Consider mean-invariant volatility/uncertainty shocks (Bloom [2009]). These will directly affect the VIX through shifting macro uncertainty, but not directly affect the pricing of risk (though volatility may endogenously induce some change in either the nature of the risk being priced, or the pricing of risk). However, the effects on the two components of the VIX from a volatility shock will not be proportional to the effects captured within a FTS shock.

It's worth noting an important methodological limitation of this approach. Namely the volatility estimation takes into account the full sample, which poses two issues. In contrast to out-of-sample forecasts, full-sample estimation induces potential 'look-ahead' bias. This poses an issue if one's primary objective is to forecast. On the other hand, this is less of an issue if one's goal is to combine ex ante and ex post information for explanatory purposes. A potential solution to this problem would be to formulate a strategy to generate out-of-sample volatility forecasts on a recursive basis. One way would be to keep the GARCH formulation but require taking a stance on additional parameters (rolling procedure, window size). This comes with impose a greater computational burden and substantially reduced the statistical power from estimating over smaller samples. For robustness, I include an analysis exclusively using the post 2009 sample analysis where I estimate FTS_t in a fully out-of-sample fashion.

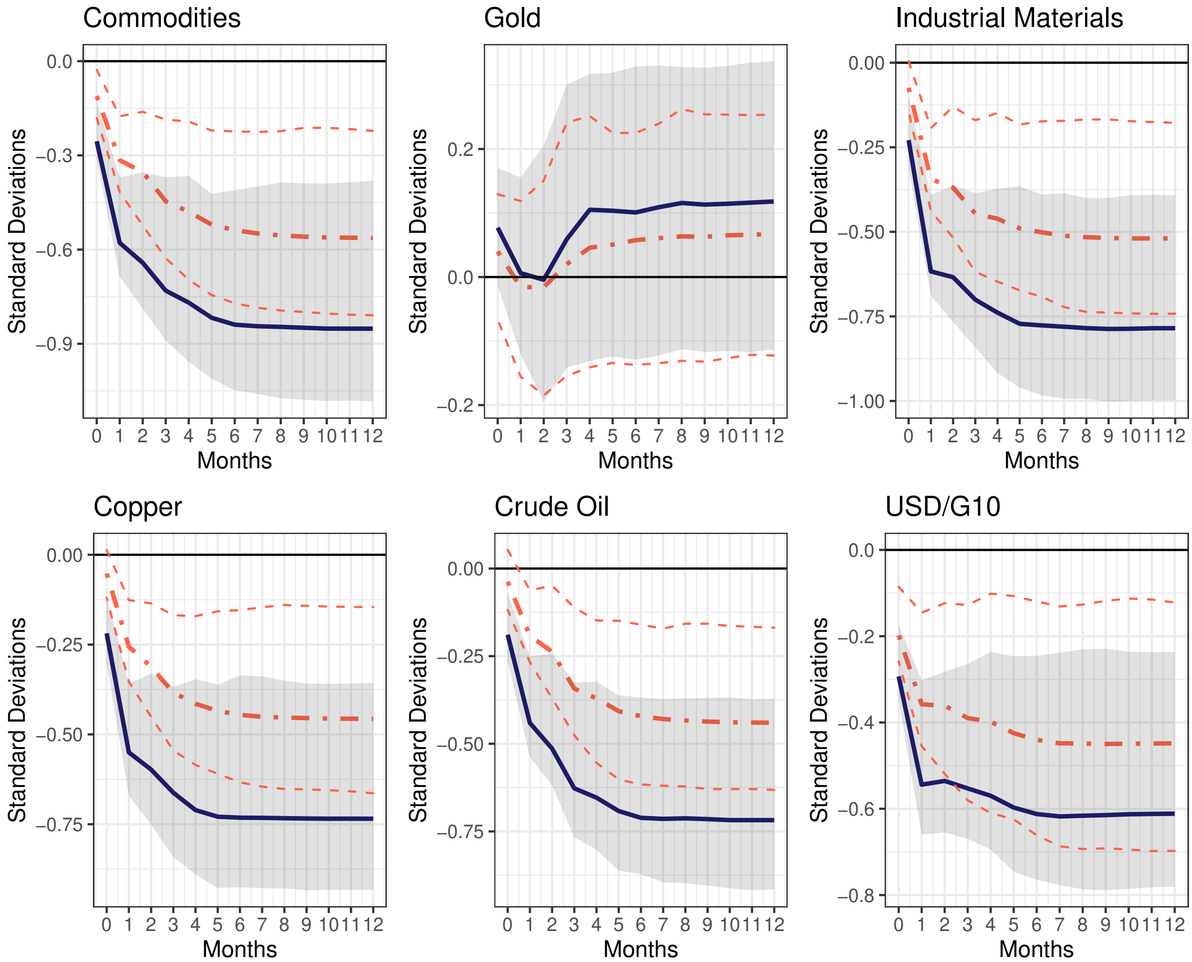
3 Global Flights-to-Safety Shocks and World Prices

Table 2 reports R^2 statistics from auto-regressions of different global market prices augmented with FTS_{t-1} (column 2) and FTS_t and FTS_{t-1} (column 3). Some of these variables are included in the construction of FTS_t (VIX, stock returns, high-yield credit spreads, 10-year yields, AUD/JPY exchange rate), but I focus on the relationship between *lagged* FTS shocks, FTS_{t-1} and current values of these variables. What is striking is the significant information content of FTS_{t-1} across many financial and non-financial market prices. Past month's flight-to-safety shock is significantly informative of one-month ahead changes in the VIX, U.S. 10-year yields, U.S. risky credit spreads, the JPY/AUD exchange rate, crude oil, broad commodities, and U.S. inflation expectations. What's more is that FTS_{t-1} is more significantly associated with month t changes across these global indicators than their own lagged $t-1$ value for a majority of the above. By contrast, the U.S. dollar is not significantly led by FTS_{t-1}, but the contemporaneous association with FTS_t is highly significant.

To simulate the response to a global flight-to-safety shock, I estimate a second-order structural vector auto-regression (SVAR) of monthly log-differences of U.S. short and medium term yields, USD exchange rates, commodities, and U.S. inflation expectations where FTS shocks, FTS_t, are identified recursively. FTS shocks impact all variables contemporaneously, consistent with the potent nature of unusual or unexpected events which trigger flights-to-safety. I trace two sets of impulse responses. The first is the response to a 1-standard deviation FTS shock, and the second is the response to a 1-standard deviation FTS shock from an SVAR which controls for contemporaneous log VIX changes. The purpose of the latter is to test whether FTS shocks indeed contain information distinct to VIX innovations. Controlling for contemporaneous VIX changes is a conservative approach, as it attributes the correlation between the VIX and FTS shocks as being caused by the VIX index, and not FTS.

Figure 4 traces the impulse responses of a 1-SD FTS shock on a variety of commodity prices, gold, and the USD exchange rate vis-a-vis the G10. The solid line is the response to a 1-SD FTS shock, FTS_t and the dashed line is the response when controlling for VIX innovations. Figures 13 and 14 provide additional IRFs for U.S. interest rates, inflation expectations and additional commodity prices.

Figure 4: Response to a 1-Standard Deviation FTS Shock (Solid) and after controlling for changes in logged VIX (dashed)



Cumulative response (in standard deviations) to a 1-standard deviation structural flight-to-safety (FTS) shock, FTS_t, (solid), and after controlling for contemporaneous changes in logged VIX (dashed). 90% bootstrapped confidence bands.

Most responses exhibit highly significant adjustment for several months following an FTS shock, U.S. yields fall along the entire short end of the maturity curve. The impact on inflation expectations are completely dynamic in the sense that they do not respond contemporaneously, but respond significantly with a lag to FTS shocks. Commodity prices fall and the U.S. Dollar appreciates in response to an FTS shock, both in time 0 and subsequent months. The response of commodities is sharp across metals and energy. The impact of FTS shocks are much less potent among soft commodities (Figure 14, soybeans, coffee, sugar, lumber). The effect on gold is statistically indifferent from zero. This may be somewhat surprising given that some view the yellow metal as a safe haven.

The dashed lines trace the same impulse response functions but in a VAR which controls for contemporaneous log VIX changes. Importantly, nearly all of the significant responses to an FTS shock remain significant, although less pronounced suggesting that FTS shocks indeed contain information distinct from standard measures of financial risk. Figure 15 shows that the results are robust to an FTS index identified under a more conservative flight-to-safety condition of $c = 1$, where both direction of asset price moves and also size are taken into account.

4 Global Flights-to-Safety and Emerging Markets

Recent debate and research focuses the consequences of global financial shocks on emerging markets (EMs), many of which are left particularly vulnerable from growing financial integration. I revisit this issue, specifically to evaluating the dynamics of emerging markets in response to a global flight-to-safety shock. I collect monthly data on sovereign spreads and industrial production across 34 emerging markets from 2000 to 2019.[6] I build on several recent studies have investigated the global transmission of world financial shocks on EM dynamics (Uribe and Yue [2006], Akinci [2013], Caballero et al. [2019], Kalemli-Ozcan [2019], Cesa-Bianchi et al. [2019], Obstfeld et al. [2019]). The traditional modeling approach used is a panel regression or VAR which estimates average effects and impulse response functions (IRF) to a global shock by pooling information across all countries. While pooling has the advantage of increasing statistical power, it ignores vital heterogeneity across countries, which surely exists among EMs. A key difference in my modeling approach is that I allow for country-specific heterogeneity, following an approach similar to Cesa-Bianchi et al. [2019]. I further show that this heterogeneity can be used to identify potential transmission mechanisms through which global shocks transmit to the real economy.

In view of this consideration, I propose a heterogeneous multi-country VAR which combines elements from the Global Vector Autoregressive (GVAR) Pesaran et al. [2004] and Factor-augmented Vector Autoregressive (FAVAR) Bernanke et al. [2005] frameworks. Like the benchmark panel VAR, it can be used to report average effects by pooling results across countries. However, like Fernandez et al. [2017] and Cesa-Bianchi et al. [2019], my approach builds on previous analyses by also allowing for country-specific heterogeneity. 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 shocks. Consider the baseline model which incorporates these features:

[6] Data details are found in Section S1.

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

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 $\Delta y_{i,t}$. 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. I set the number of lags equal to $\ell = 4$ months. The specification is extended by modeling cross-country linkages through $\Delta \mathcal{S}_{i',t}$ and $\Delta \mathcal{Y}_{i',t}$. These are cross-section averages of changes in the log sovereign spread and year-over-year IP growth over all countries excluding country i. Specifically,

$$\Delta \mathcal{S}_{i',t} = \Delta s^*_{i',t} = \sum_{i' \neq i} w^s_{i'} \Delta s_{i',t}, \qquad \sum_{i'=1}^{N-1} w^s_{i'} = 1,$$

$$\Delta \mathcal{Y}_{i',t} = \Delta y^*_{i',t} = \sum_{i' \neq i} w^y_{i'} \Delta y_{i',t}, \qquad \sum_{i'=1}^{N-1} w^y_{i'} = 1,$$

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 set 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 $\Delta \mathcal{Y}_{i,t}$, except I exclude Iraq from the calculations given large outlier values driven by the Iraq War in the early 2000's. Another approach to obtaining weights would be to apply GDP weights, bilateral trade-weights or capital flow weights for $w^s_{i'}$. However, in this particular setting, because cross-country correlations are high, these alternatives make no practical difference.

Because sovereign spreads and economic activity exhibit strong co-movement across emerging markets, $\Delta \mathcal{S}_{i',t}$ and $\Delta \mathcal{Y}_{i',t}$ can also be thought of as approximations of the common global factors governing sovereign spreads and IP growth, respectively, admitting a FAVAR interpretation. As such, one can alternatively estimate $\Delta \mathcal{S}_{i',t}$ and $\Delta \mathcal{Y}_{i',t}$ using Principal Components Analysis (PCA), with both the PCA approaches and the cross-section averaging approach often yielding similar estimates.[7]

Moreover, including these global averages admit for cross-country interdependencies

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

without running into the 'Curse of Dimensionality' issue most large VARs face (hence, also admitting to a GVAR interpretation). For example, $\Delta\mathcal{S}_{i',t}$ and $\Delta\mathcal{Y}_{i',t}$ 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 observations. However, including cross-sectional averages imply a coefficient restriction such that lag l 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 $\Delta\mathcal{Y}_{US,t}$ changes in U.S. economic activity, measured using the Chicago Fed National Activity Index (CFNAI) to account for spillovers between advanced economies and emerging markets.

Finally, FTS shocks FTS_t enter the system as an external instrument (Stock and Watson [2012], Stock and Watson [2018]). Moreover, notice that FTS shocks are treated as a common shock across all countries to which countries can respond deferentially (as reflected in the country-specific coefficients θ_i^V), and the shock is identified recursively. That is, FTS_t can be viewed as a common factor that unlike $\mathcal{S}_{i',t}$ and $\Delta\mathcal{Y}_{i',t}$ is completely external to the system. Recall that FTS_t is measured from financial variables either based out of the U.S. or advanced economies, while the endogenous variables in Equation 9 belong to emerging markets except for $\Delta\mathcal{Y}_{US,t}$.

4.1 Estimating the multi-country SVAR and impulse responses

FTS shocks FTS_t enter the system as an external instrument. The shock FTS_t is structural, in that it is identified under the recursive assumption that FTS_t contemporaneously affects fast-moving financial variables $\Delta s_{i,t}$ and $\Delta\mathcal{S}_{i',t}$, while slower-moving macroeconomic variables $\Delta y_{i,t}$, $\mathcal{Y}_{i',t}$ and $\mathcal{Y}_{US,t}$ respond to FTS shocks with a lag. In effect, this requires the FTS shock variable FTS_t to be contemporaneously orthogonalized against the three slow-moving economic activity variables. The results are robust to alternative ordering restrictions, specifically one such that FTS_t contemporaneously affects all other variables but no other variable contemporaneously affects FTS_t. Because we are mainly concerned with the effect of an FTS shock, the ordering of other variables in the system is irrelevant.

The large T dimension of the data allows the multi-country SVAR to be estimated country-by-country, estimating country-specific SVARs for 34 emerging markets. This estimation procedure is akin to estimating a Global VAR (Pesaran et al. [2004], Chudik and Pesaran [2016]) with similar approaches also being applied in Fernandez et al. [2017] and Cesa-Bianchi et al. [2019]. A key advantage of this modeling approach which departs from conventional panel VARs is that the coefficients are heterogeneous – they are allowed to be country-specific. Given the economic uniqueness across countries particularly observed among EMs, The pooling restriction imposed with panel VARs may be an overly restrictive and unrealistic assumption. The heterogeneous modeling approach still allows estimation of average or pooled effects as done in traditional panel models. Estimating the average IRF over the panel is simple using the Mean Group (MG) estimator of Pesaran and Smith [1995] and Chudik and Pesaran [2019].[8] The horizon h mean group impulse response function for the endogenous variable, denoted X_{it}, to a 1-SD FTS shock is computed as:

$$\begin{aligned} MGIRF(h) &= \frac{1}{N}\sum_{i=1}^{N} E[X_{i,t+h}|FTS_t = 1] - \frac{1}{N}\sum_{i=1}^{N} E[X_{i,t+h}|FTS_t = 0] \\ &= \frac{1}{N}\sum_{i=1}^{N} E[X_{i,t+h}|FTS_t = 1], \end{aligned} \tag{10}$$

with associated non-parametric cross-sectional standard errors computed as:

$$SE(h) = \sqrt{\frac{1}{N}\frac{1}{N-1}\sum_{i=1}^{N}\Big(E[X_{i,t+h}|FTS_t = 1] - MGIRF(h)\Big)^2}. \tag{11}$$

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

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

These methods have been applied successfully to large, heterogeneous macroeconomic panel data of similar size to address a variety of research questions.[9]

4.2 The average response to a global flight-to-safety shock

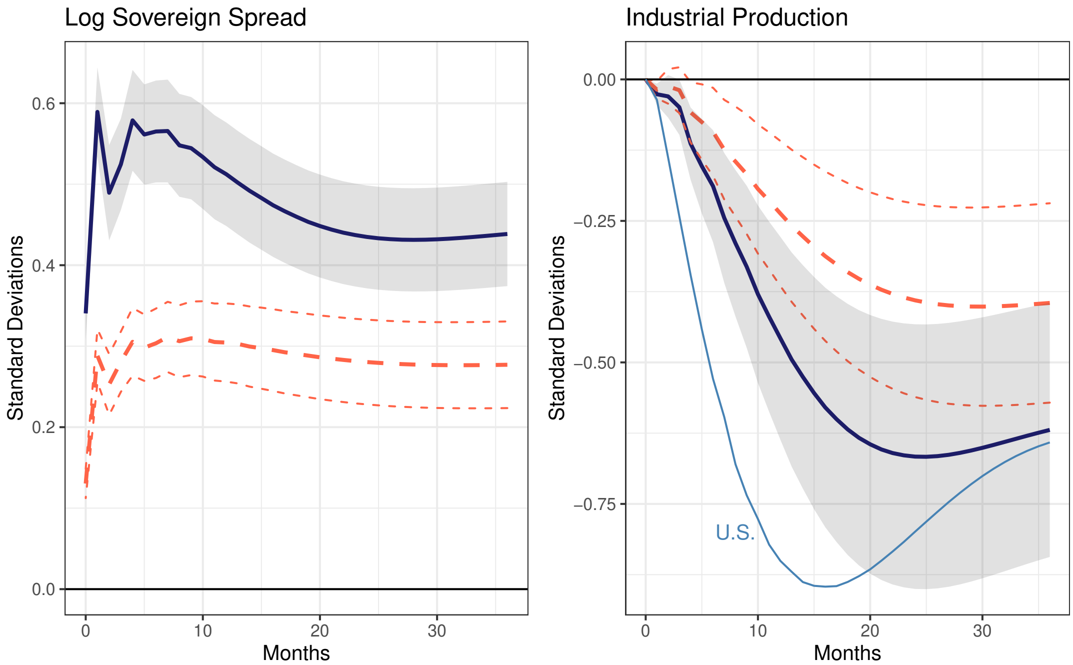
I first estimate the model with the aggregate FTS shock, FTS_t, and then in a second set of estimations, I control for contemporaneous changes in the log VIX as a robustness check. We first examine the pooled dynamics across EMs in response to a global flight-to-safety shock (dashed lines).

Figure 5 traces the pooled, or MG estimate impulse response of both logged sovereign spreads and IP growth to a 1-standard deviation FTS_t shock (solid), and also the response after controlling for contemporaneous VIX changes (dashed). Sovereign spreads react strongly and the response is front-loaded, displaying over-shooting behavior in the first

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

[9] See for example Dees et al. [2007], Chudik et al. [2017],Hernandez-Vega [2019], Cesa-Bianchi et al. [2019].

Figure 5: Emerging Markets: Average Response to a 1-Standard Deviation FTS Shock (Solid) and after controlling for changes in logged VIX (Dashed)



Cumulative MG Response (Equation 10) to a 1-standard deviation structural flight-to-safety shock, FTS_t (solid), and after controlling for contemporaneous VIX innovations (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 line in RHS figure is the IRF of U.S. national economic activity.

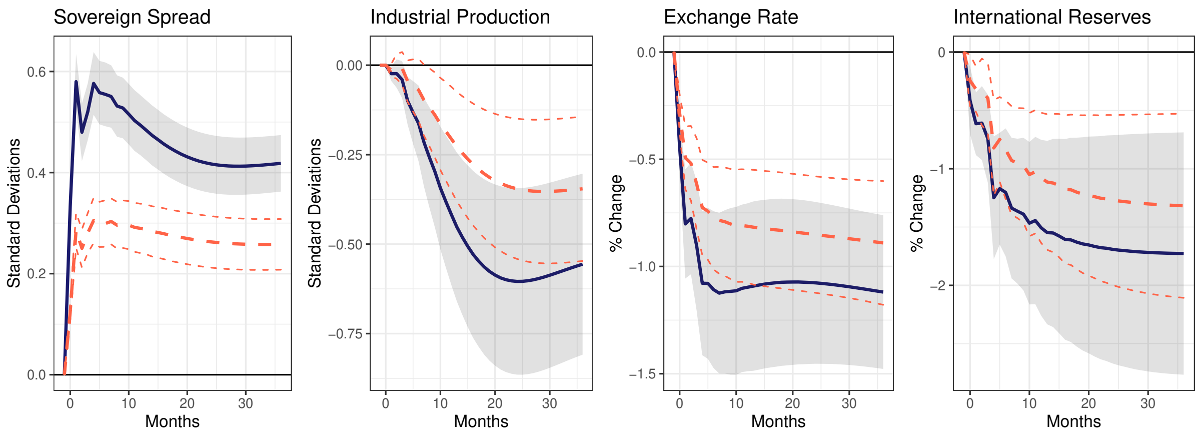
few months following the shock. Economic activity significantly contracts over about 18 months. All units are measured in standard deviations to correct for heteroscedasticity across countries. For the sake of interpretation, the 18-month cumulative response in IP growth is approximately equivalent to a 4% contraction. For comparison I also show that U.S. economic activity significantly contracts with a lag following an FTS shock, with the total contraction occurring faster and a sharper rebound after 12 months.

Both the response in sovereign spreads and the subsequent contraction in IP growth remain significant after controlling for changes in the VIX index, suggesting a distinct role for FTS shocks in shaping macroeconomic dynamics. Figure 16 shows that these results are robust to an FTS index identified under a more conservative flight-to-safety condition of $c = 1$, where both direction of asset price moves and also size are taken into account.

5 Incorporating Exchange Market Pressure

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 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.[10]

Figure 6: Emerging Markets: Average Response to a 1-Standard Deviation FTS Shock (Solid) and after controlling for changes in logged VIX (Dashed)



Cumulative MG Response (Equation 10) to a 1-standard deviation structural flight-to-safety shock, FTS_t before (solid) and after controlling for contemporaneous VIX innovations (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. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes.

To consider the implications of EMP in the presence of global flights-to-safety, I augment the multi-country VAR with two additional country-specific endogenous variables: logged changes in USD exchange rates and international reserves. Global flight-to-safety shocks likely bear implications for EMP and its interaction with economic activity. 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. [2019], 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 depreciations are considered stimulative. For this reason I focus on USD exchange rates given the recent evidence on the overwhelming role of the U.S. Dollar in the international monetary and price system.[11]

Figure 6 traces the Mean Group IRF from a 1-SD FTS shock (solid) and when controlling for VIX changes (dashed) from the model including exchange rates and international

[10] Fratzscher [2012], Aizenman and Binici [2016], Goldberg and Krogstrup [2018].

[11] 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.

reserves. In addition to sovereign spreads widening and economic activity contracting, there is significant exchange market pressure across emerging markets. EMP manifests as both currencies rapidly depreciating against the USD and significant reserves expenditure. Within the first few months, exchange rates depreciate on average of 1.1%. After 10 months, reserves growth drops an average of 1.5%. Both of these effects remain significant when controlling for changes in the VIX.

The results of large pass-through of global shocks to domestic financial conditions, exchange rates and subsequent economic activity corroborate the evidence reported in several of the studies mentioned. However, notably I show that FTS shocks, interpreted as tail risk perceptions, carry effects distinct from benchmark changes in global financial conditions. In fact, roughly half of the impact on sovereign spreads and economic activity is attributed uniquely to FTS shocks after controlling for the VIX. More than half of the response in EMP continues to be attributed to FTS shocks. Figure 17 shows that the results are robust to an FTS index identified under a more conservative flight-to-safety condition of $c = 1$, where both direction of asset price moves and also size are taken into account.

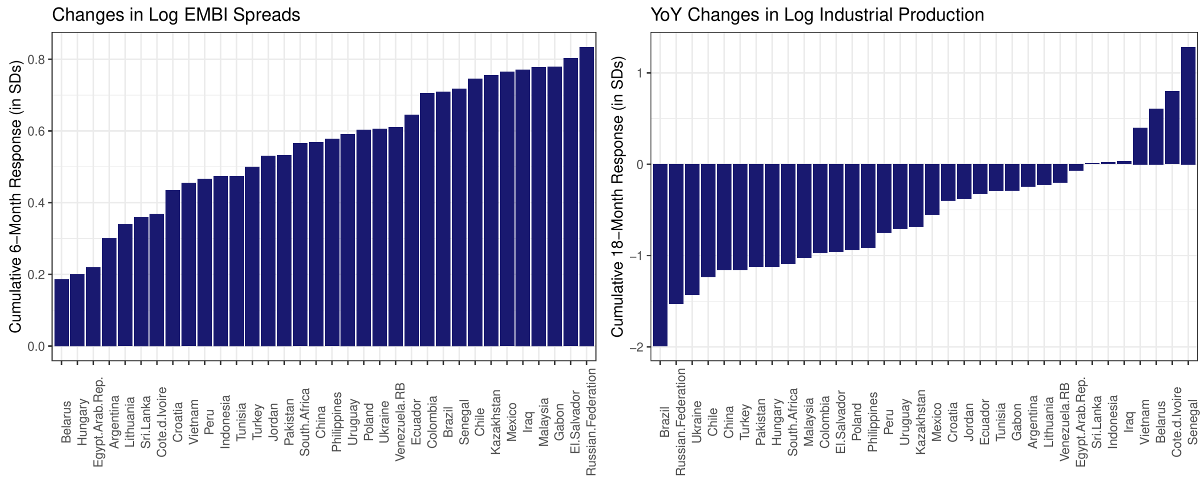
6 Global Flight-to-Safety and Cross-Country Heterogeneity

Global financial shocks exhibit significant *average* effects on domestic financial conditions, exchange market pressure, and subsequent economic activity across emerging markets. While much of the literature focuses on such pooled estimates, in reality different countries are likely to bear differential exposure to fluctuations in global financial markets. This section highlights the degree of heterogeneity in country-specific responses to a global FTS shock.

Country-specific responses over select horizons are reported in Figure 7 for sovereign spreads (cumulative 6-month impact) and IP growth (cumulative 18-month impact). Country-specific responses in exchange rates (6-month cumulative) and reserves (6-month cumulative) are shown in Figure 8. Indeed, the way EMs respond to a global FTS shock varies widely. One common pattern, however, is that sovereign spreads unambiguously rise in response to a global FTS shock, most currencies depreciate, most countries expend reserves, and most countries realize subsequent economic contractions. But the size of these effects are far from uniform across countries.

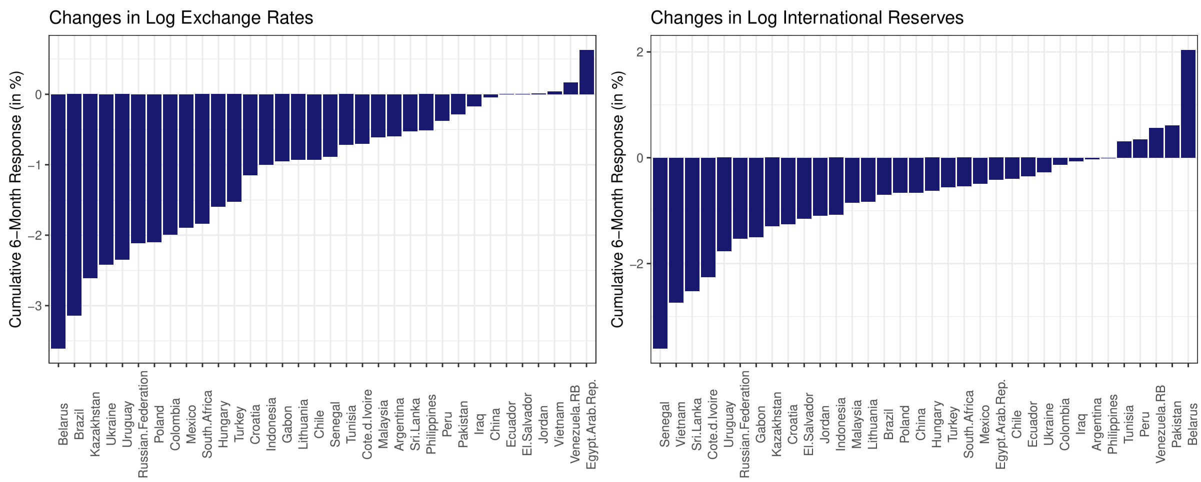
For instance, the sovereign spread responses of Belarus and Egypt are smaller than that of Russia and El Salvador by a factor of four. The likes of Brazil and Russia are estimated to realize significantly deep contractions in industrial production over 18 months, while there is no significant link between global FTS shocks and economic activity

Figure 7: Country-specific Response to a 1-Standard Deviation FTS Shock



Cumulative Response (in standard deviations) to a 1-standard deviation structural flight-to-safety (FTS) shock, FTS_t. 6-month cumulative change in log sovereign spreads (LHS) and 18-month cumulative change in industrial production (RHS).

Figure 8: Country-specific Response to a 1-Standard Deviation FTS Shock



Cumulative Response (in percent) to a 1-standard deviation structural flight-to-safety (FTS) shock, FTS_t. 6-month ahead cumulative impact on exchange rates (LHS) and international reserves (RHS).

in Vietnam and Indonesia, among other countries. Exchange rates tend to depreciate in response to an FTS shock, but to varying degrees. Belarus, Brazil and Kazakhstan round out the most sensitive countries. Brazil operates a flexible exchange rate, while the other two countries tend to operate managed exchange rates, yet the propensity to depreciate the exchange rate in response to a global FTS shock is high among these countries. By contrast, Egypt, Argentina, Vietnam and Venezuela exchange rates are insensitive to financial shocks.[12] International reserves exhibit similar patterns – across most countries, reserves are expended yet to varying degrees in response to a global FTS shock.

7 The Transmission of Global Shocks through Domestic Financial Factors

Emerging Markets, on average, are subject to significant adjustments in response to a global flight-to-safety yet the effects vary widely across countries. An issue worth exploring then is whether these cross-country heterogeneities are systematically linked. That is, can we infer particular transmission channels which moderate the transmission of global FTS shocks to emerging market economies? Are global FTS shocks amplified through their effect on domestic financial conditions (i.e. wider sovereign spreads, or currency depreciation)?

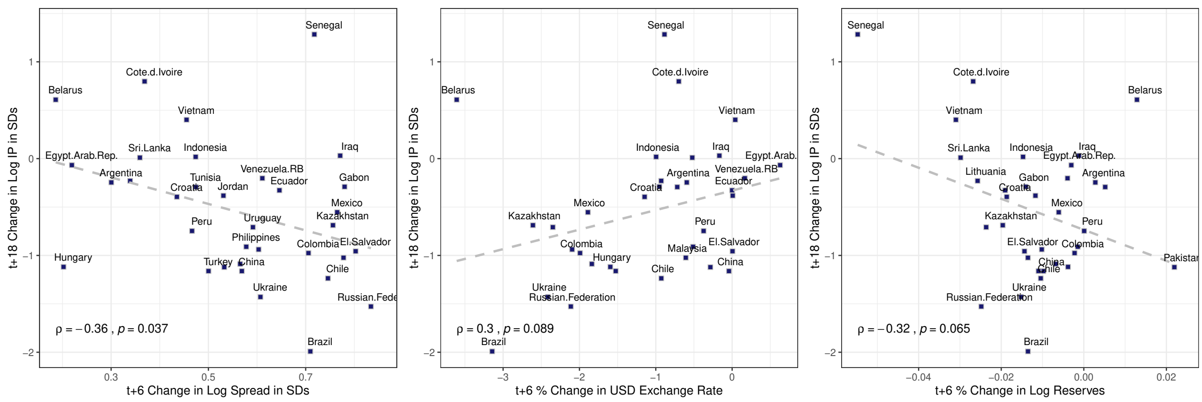
Explicit identification of transmission channels at the international macro level remains a challenge. Generally speaking, there are two main approaches. The first is to develop a structural model while the second is a reduced form approach. An example of the reduced form approach is taken in Akinci [2013] when attempting to quantify whether or not global financial shocks transmit to the real economy through their effect on domestic financial conditions. A basic counterfactual exercise is done by comparing the variance decomposition of a financial shock to real economic activity under the baseline VAR, to the same variance decomposition after shutting down effect of financial shocks on sovereign spreads (i.e. setting the coefficients in the sovereign spread equations associated with global financial shocks equal to zero). The results suggest that indeed, global shocks are amplified through their effect on sovereign spreads. However, the author also notes that this counterfactual exercise is subject to the Lucas Critique, as it is questionable whether all other coefficients characterizing the system would in fact stay constant when shutting one particular channel completely down.

Given the heterogeneity provided by my modeling approach, I extend upon the approach of Akinci [2013] by exploiting cross-country differences to infer potential transmission channels. By comparing countries with differential responses to FTS shocks, we can potentially identify transmission mechanisms without imposing such controversial restrictions on the counterfactual estimation. For example, I investigate whether the impact of FTS shocks on economic activity is significantly stronger for the subset of countries with highest sovereign spread sensitivity to FTS shocks.

Figure 9 LHS shows across the 34 countries in the panel, the 6-month cumulative change in the log sovereign spread against the 18-month cumulative change in industrial production induced by a 1-SD FTS shock. The LHS correlation coefficient equals -0.36

[12] Venezuela is a special case as the currency has been subject to periodic episodes of hyperinflation.

Figure 9: Heterogeneous Impact of Global FTS Shocks: 6-month change in Sovereign Spreads vs. 18-month change in Economic Activity



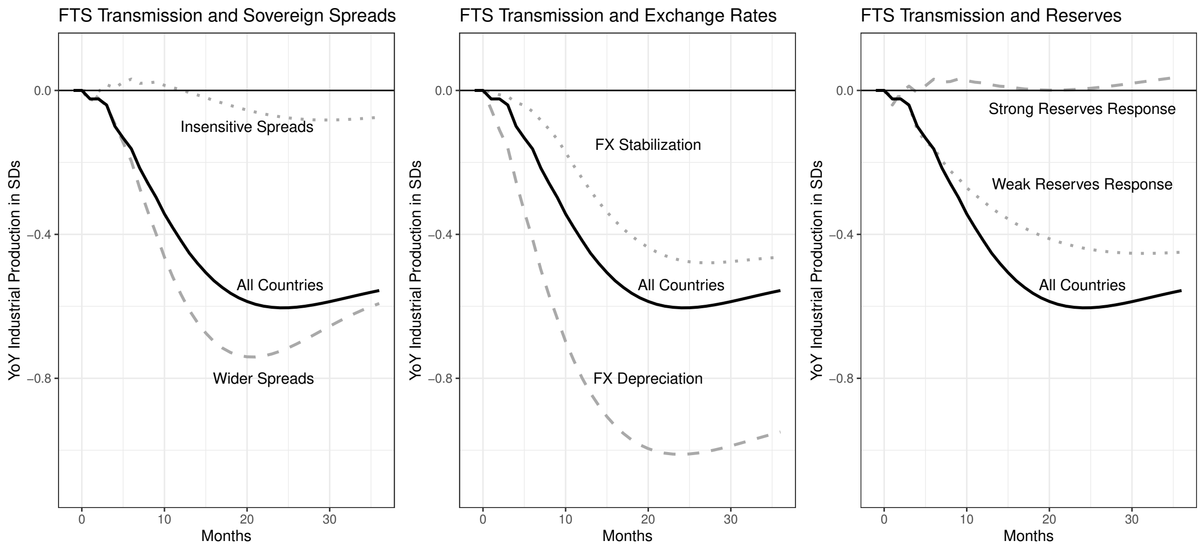
Cumulative Responses (in standard deviations) to a 1-standard deviation structural flight-to-safety (FTS) shock, FTS_t.

and is statistically significant. Countries which realize wider sovereign spread adjustment in response to an FTS shock are subject to deeper subsequent economic contractions. Similarly, the center figure shows that countries which experience greater currency depreciation vis-a-vis the USD amid an FTS shock also realize larger subsequent IP contractions. By contrast,the RHS figure shows that countries which more aggressively expend reserves also realize shallower subsequent contractions in industrial production. Taken together, these associations suggest that the impact of FTS shocks on the real economy are moderated by the sensitivity of domestic financial factors to FTS shocks.

Figure 10 offers an alternative perspective, tracing the heterogeneity in IP responses by binning countries based on their domestic financial factor sensitivity. The LHS compares counties which exhibit high sovereign spread sensitivity to FTS shocks against those which exhibit low sensitivity, tracing the two groups IP growth response to an FTS shock. Similar IRFs are reported comparing countries with sensitive exchange rates to those which have stable, or insensitive exchange rates to FTS shocks (center chart), and countries which tend to use international reserves to buffer against FTS shocks to those which don't (RHS chart). The first two figures both show that countries where sovereign spreads or exchange rates respond less to an FTS shock, economic activity also contracts less on average over the longer run. At the same time, countries which more aggressively expend reserves, 'leaning against the wind' during a global FTS shock, exhibit a much weaker impact of FTS shocks on economic activity.

The evidence of sovereign spreads amplifying the impact of global shocks on the domestic economy corroborates the findings of Akinci [2013] and Caballero et al. [2019], while the buffering effects of expending international reserves is in line with Aizenman and Lee [2007] and Jeanne and Ranciere [2011] among others. However, more controversial is the finding of contractionary impact of exchange rate depreciation. Our findings point

Figure 10: Heterogeneous Impact of Global FTS Shocks on Industrial Production comparing Countries with high versus low financial sensitivities



MG IRF (Equation 10) of top 7 vs. bottom 7 countries in terms of 6-month response to an FTS shock in financial variables: sovereign spreads (LHS), exchange rate (center), international reserves (RHS). Dotted (dashed) line refers to low (high) sensitivity group. Solid line is the all-country MG IRF.

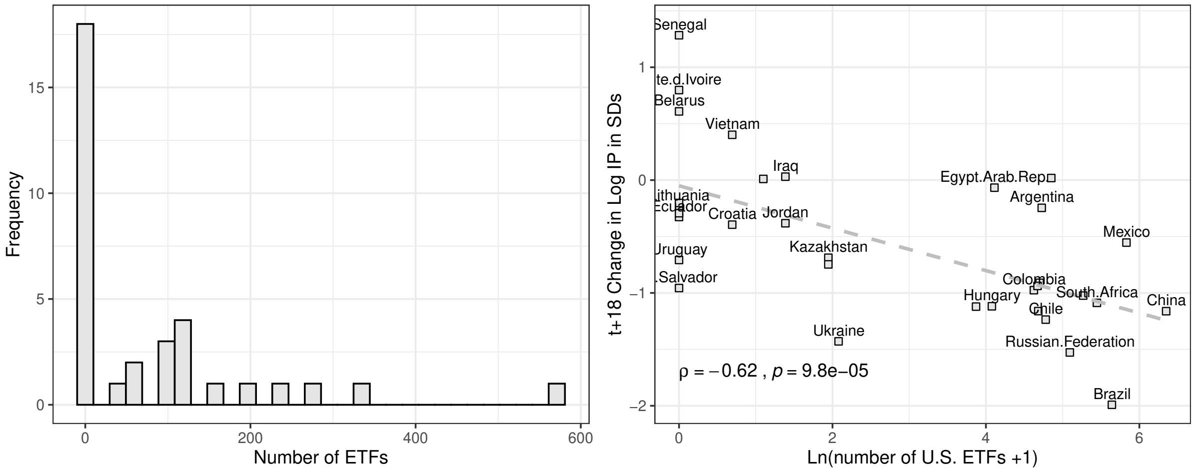
towards a financial channel of exchange rates, corroborating Rey [2015] and Hofmann et al. [2019], contrary to Obstfeld et al. [2019] who show that exchange rate flexibility buffers against global financial shocks.

8 Do ETFs Amplify the Impact of Flight-to-Safety Shocks?

The extent to which FTS shocks eventually impact economic activity in emerging markets suggestively depend on the sensitivity of domestic financial factors. An additional factor which has received significant attention as of late in the context of global financial cycles is the role of capital control and macroprudential policies which regulate financial openness. Specifically the advent of exchange-traded funds (ETFs) in advanced economies gives global investors considerable access EM investments with the promise of superior liquidity. With this comes the potential for much greater capital flow volatility. In recent work, Converse et al. [2020] document that equity and bond ETF flows are significantly more sensitive to global financial conditions than mutual fund flows, bearing macroeconomic implications for gross capital flow movements as the market share of ETFs continues to rise.

In consideration of this view, I investigate whether the impact of FTS shocks differ systematically in countries which have either equity or bond ETFs available for trade on

Figure 11: Average Response to a 1-Standard Deviation FTS Shock for Countries with U.S. ETFs (Solid) and those without (Dashed)



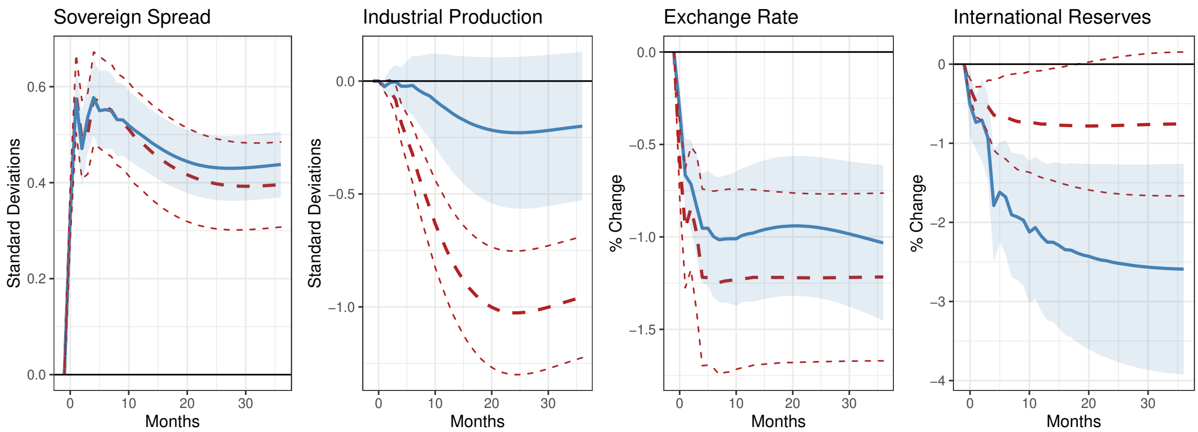
LHS: Frequency distribution of the number of U.S. ETFs a country has presence within (as of October 2020). Source: etfdb.com. RHS: x-axis plots the ln(number of U.S. ETFs +1) against the 18-month cumulative IP growth response to a 1-SD FTS shock.

U.S. exchanges compared to those which do not. These countries, by virtue of selection, are likely to have more advanced financial markets and more open capital accounts. Greater financial development implies that these countries enjoy lower rates on average. At the same time, these countries may be particularly sensitive to flight-to-safety shocks and associated sudden capital outflows as global investors withdraw capital from emerging markets, deemed risky investments. Table S.4 provides the number of U.S. traded ETFs granting exposure to each country in the sample as of October 2020. Brazil, China, Mexico and South Africa each have more than 200 U.S. traded ETFs which at least some financial assets based in those countries. By contrast, several countries have little or no investment through U.S. ETF holdings: Belarus, Cote d'Ivoire, Croatia, Ecuador, Vietnam, among others. A clear demarcation is observed between Ukraine, which a U.S. investor can gain exposure through 7 ETFs and the next country Pakistan, for which the number of ETFs jump to 47.

Figure 11 shows the frequency distribution (LHS) of countries by number of U.S. based ETFs. Roughly half of the countries have little or no ETF presence in the United States. On the RHS, the relationship between the logged number of ETFs per country on the x-axis and the response of IP growth to a FTS shock is plotted. It's quite clear from a cursory look that economic contractions induced bye global FTS shocks are deeper in countries with greater presence among U.S. ETFs.

Figure 12 traces the IRFs to a 1-SD FTS shock for two different groups of EMs. The dashed line refers to countries with a substantial presence in the U.S. ETF space (Argentina, Brazil, Chile, China, Colombia, Egypt, Hungary, Indonesia, Malaysia, Mexico,

Figure 12: Average Response to a 1-Standard Deviation FTS Shock for Countries with U.S. ETF presence (dashed) and those with (solid)



Cumulative MG response (Equation 10) to a 1-standard deviation structural flight-to-safety shock, FTS_t. 95% dispersion bands as computed in Equation 12. Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative exchange rate response equals percent depreciation against the USD. International Reserves as log monthly change. Countries with U.S. ETF presence: Argentina, Brazil, Chile, China, Colombia, Egypt, Hungary, Indonesia, Malaysia, Mexico, Pakistan, Philippines, Poland, Russia South Africa, Turkey.

Pakistan, Philippines, Poland, Russia, South Africa, and Turkey). The solid line is the MG IRF for countries with little to no ETF presence (Belarus, Cote d'Ivoire, Croatia, Ecuador, El Salvador, Gabon, Iraq, Jordan, Kazakhstan, Lithuania, Peru, Senegal, Sri Lanka, Tunisia, Ukraine, Uruguay, Venezuela, and Vietnam). The minimum number of ETFs available among the countries with substantial presence is 47 (Pakistan) and the max is China (571). The minimum for the group with low ETF presence is zero (Belarus, Cote d'Ivoire, Ecuador, Gabon, Lithuania, Senegal, Tunisia, Uruguay, Venezuela) and the maximum is Ukraine with 7 ETFs.

Despite similar responses in sovereign spreads to a global FTS shock, The group of countries with heavy ETF presence are subject to significantly deeper – roughly four times deeper – economic contractions than the group without U.S. ETF presence. While both groups of countries experience heavy exchange market pressure following a global FTS shock, the groups differ by whether the pressure is relieved through currency depreciation or expending reserves. Countries with heavy ETF presence realize relatively sharper currency depreciation while expending relatively less international reserves, with the reverse holding for the group without an ETF presence.

This evidence corroborates Converse et al. [2020] in that the growth of ETFs poses a potential amplification mechanism for the transmission of global shocks, and that this stretches beyond global financial fluctuations, affecting the real economy in countries with substantial links to U.S. ETFs.

9 Cross-Sectional Regression of Macro Sensitivity on Domestic Financial Factors

Taking stock of the systematic heterogeneities between domestic financial factors and the transmission of global shocks, there is evidence suggesting that a global FTS shock can induce deeper subsequent contractions in IP growth when the early response in sovereign spreads are sharper, when the exchange rate depreciates more, or when there is greater U.S. ETF presence. Meanwhile, actively using international reserves in response to an FTS shock is associated with a buffering effect on IP growth. These domestic financial factors may interact with each other. To analyze the joint influence of these financial factors on the medium-run impact of FTS shocks on economic activity, I propose the following cross-sectional regression:

$$E_i[\Delta y_{i,t,t+18}|FTS_t] = \alpha + \beta_1 E_i[\Delta s_{i,t,t+6}|FTS_t] + \beta_2 E_i[\Delta fx_{i,t,t+6}|FTS_t] + \beta_3 E_i[\Delta res_{i,t,t+6}|FTS_t] + \beta_4 \ln(ETF_i + 1) + e_i, \quad (13)$$

where the dependent variable $E_i[\Delta y_{i,t,t+18}|FTS_t]$ is country i's cumulative response in IP growth to a 1-SD FTS shock after 18 months. $E_i[\Delta s_{i,t,t+6}|FTS_t]$, $E_i[\Delta fx_{i,t,t+6}|FTS_t]$, and $E_i[\Delta res_{i,t,t+6}|FTS_t]$ are the 6-month cumulative response of country i's sovereign spread, USD exchange rate, and international reserves to a 1-SD FTS shock, respectively. Finally ETF_i is the number of U.S. traded ETF's country i maintains a presence within. Standard errors are robust to heteroscedasticity. Note that both the dependent variable and the independent variables are estimates, thus subject to measurement error. In the case of uncorrelated measurement error, attenuation will bias the coefficients estimated by least squares towards zero. Therefore, a most plausible scenario is one where the standard errors are biased upwards and the point estimates are biased downwards, thus estimated associations are actually stronger than the estimates from Equation 13 imply.

Table 7 reports the regression results from estimating Equation 13. Deeper subsequent IP growth contractions are associated with countries which initially realize wider sovereign spreads or currency depreciation in response to a FTS shock, but the association between FX depreciation and subsequent IP growth becomes statistically insignificant. Countries which expend more reserves as a buffer against an FTS shock realize economic contractions which are comparatively benign. Moreover, having a larger presence in the U.S. ETF investable space is associated with deeper economic contractions following flights-to-safety, and this relationship is highly significant and robust.

Finally, to consider the interaction of international reserves and exchange rate movements which together characterize total exchange market pressure, I include the interaction term, $E_i[\Delta fx_{i,t,t+6}|FTS_t] \times E_i[\Delta res_{i,t,t+6}|FTS_t]$, which is abbreviated in the table for succinctness. The interaction term is highly significant and negative, while the marginal effect of exchange rate depreciation is insignificant,and the marginal effect of expending reserves is highly significant. Therefore a possible interpretation of the three estimates is that expending reserves (i.e. leaning against the wind) buffers against the real economic impact following a global FTS shock, and this effect weakens with greater coincident exchange rate depreciate. In other words, following a global FTS shock, the buffering effects of expending reserves on subsequent economic growth is most effective when the exchange rate is successfully stabilized.

Taken together, these domestic financial factors explain up to 63% of variance in the macroeconomic sensitivity to a global FTS shock across emerging markets.

10 Concluding Remarks

This paper presents a new measure of shocks to tail risk perceptions reflecting flight-to-safety. The largest daily FTS shocks do not correspond with the largest stock market crashes nor a majority of the largest jumps in the VIX index. Flight-to-safety shocks do map to economically disruptive historical events, inform current and future changes in interest rates, exchange rates, commodities and inflation expectations, containing both components reflecting shifting risk sentiment and global demand. In Section S2 of the Online Supplement, I further investigate the separation of FTS shocks into excess risk sentiment and global demand components.

Using global FTS shocks as an external instrument, I investigate the way they shape macroeconomic dynamics in a panel of 34 emerging markets and the U.S.. I extend prevailing modeling approaches by estimating a multi-country structural VAR which allows for country-specific heterogeneity, and common factors which capture spillovers between countries and from the U.S. in both economic and financial fluctuations. In response to a global FTS shock, sovereign spreads widen dramatically, exchange market pressure increases and economic activity subsequently contracts in both emerging markets and the U.S. These effects are robust to controlling for fluctuations in the VIX index, implying that global FTS shocks, specifically capturing macro tail shocks, pose distinct implications for the global economy.

I further show that there is significant country-specific heterogeneity in the impact of FTS shocks across EMs. Countries realizing sharper adjustment in their sovereign spreads and greater currency depreciation are subject to deeper subsequent economic contractions. Meanwhile, countries which aggressively expend international reserves, leaning against the wind in response to an FTS shock, are subject to smaller subsequent economic contractions, especially when the exchange rate is successfully stabilized. Moreover, the impact of FTS shocks on economic growth is significantly amplified among countries with substantial presence within U.S. traded ETFs.

The role of domestic financial factors moderating the pass-through of global shocks to local economic conditions coincides with the findings of Aizenman et al. [2016] and Kalemli-Ozcan [2019] among others. Overall, these findings suggest an important role for macroprudential and monetary policies to buffer against external shocks in a financially integrated world. Namely, international reserves may be an important policy in the central bank tool kit. The transmission of global shocks and by affecting sovereign risk premia introduces a particularly complicated trade-off faced by governments which rely on international capital markets for financing. The amplification mechanism of global shocks through highly volatile investment flows, particularly through ETFs, also warrants further research given the rapidly expanding footprint of the industry.

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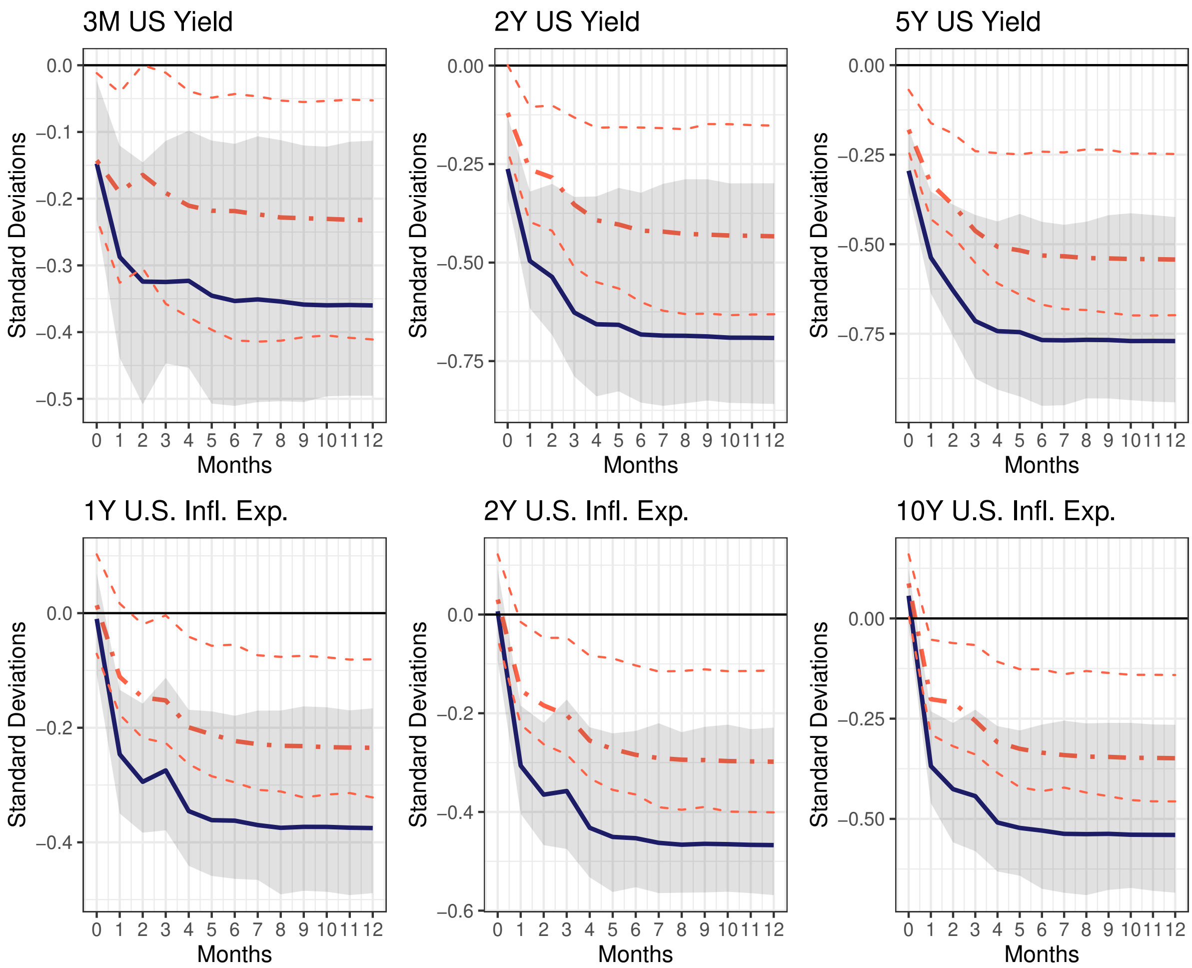
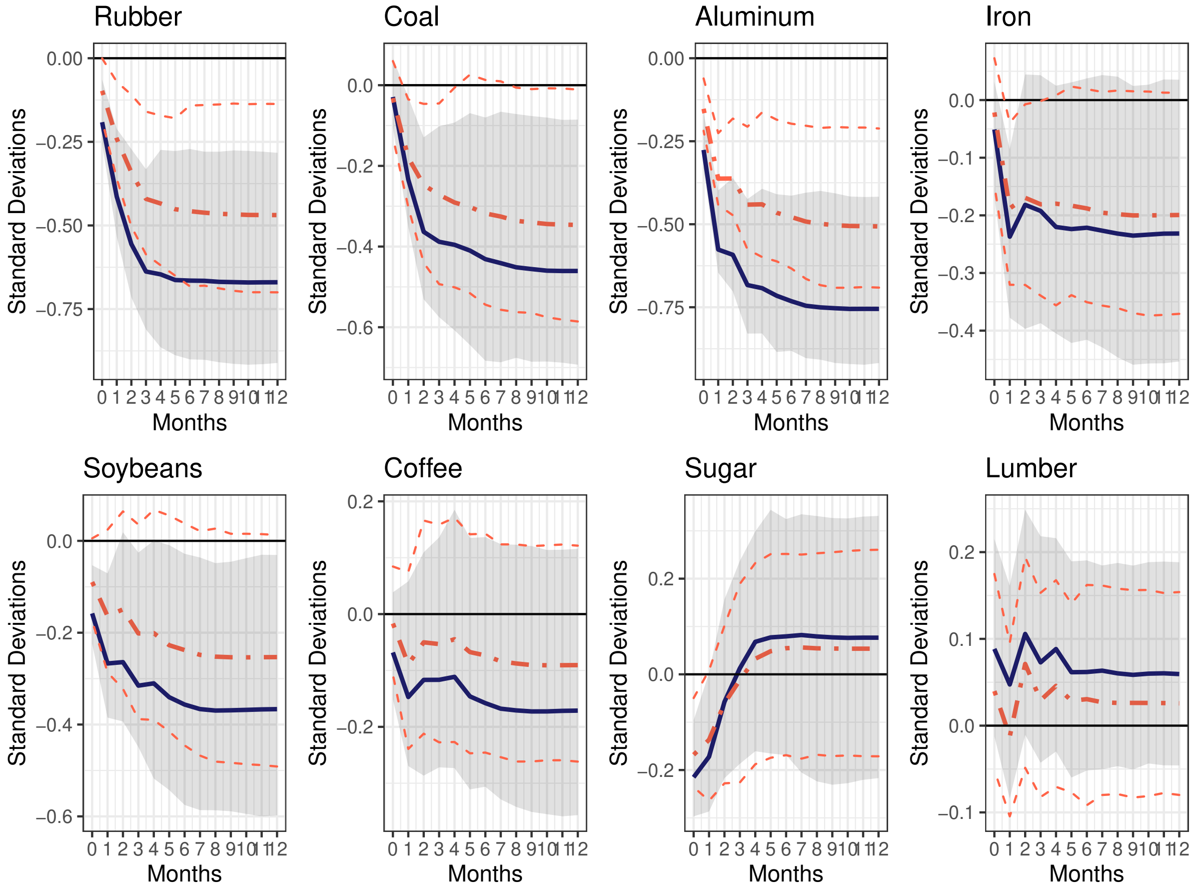
Figure 13: Response to a 1-Standard Deviation FTS Shock (Solid) and after controlling for changes in log VIX (dashed)



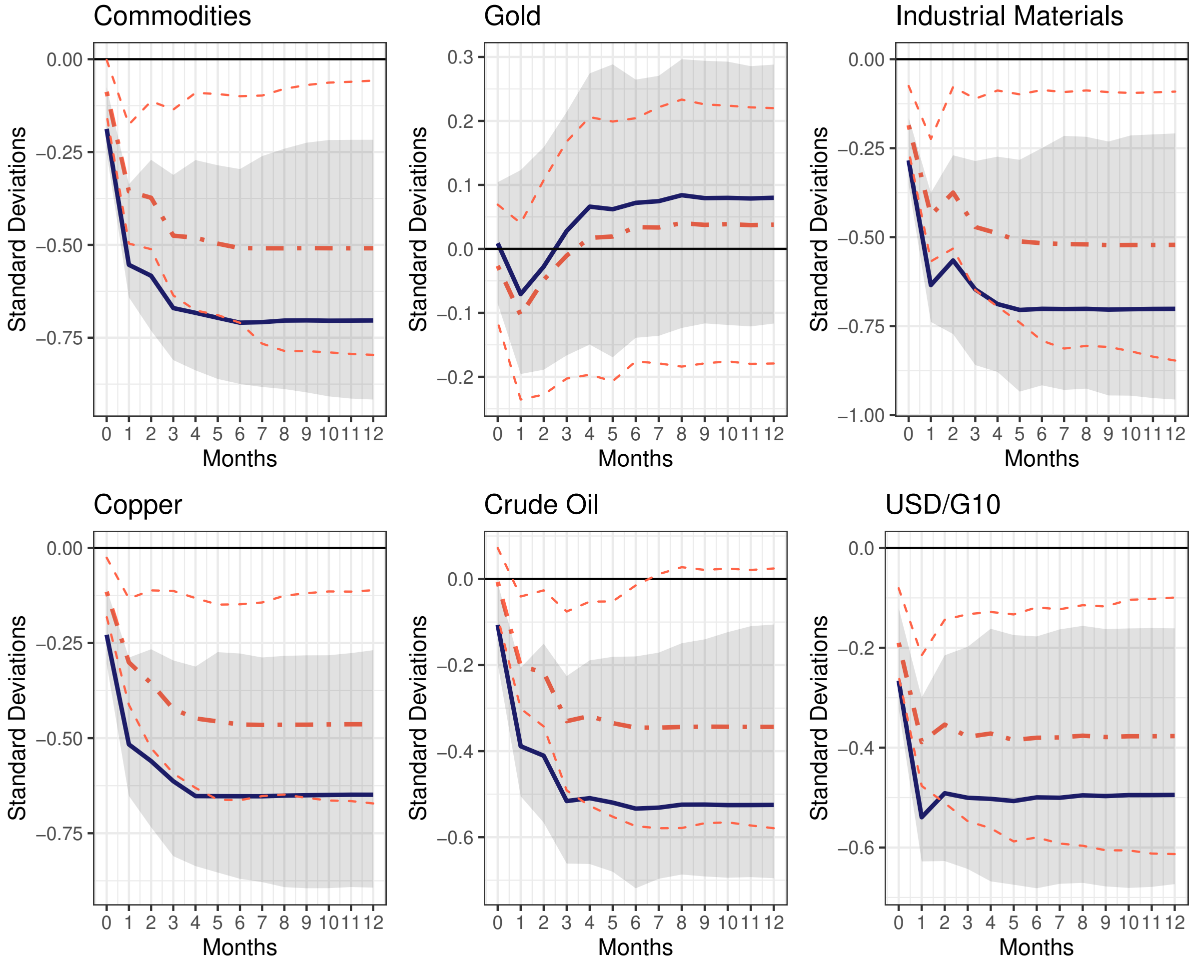
Cumulative response (in standard deviations) to a 1-standard deviation structural flight-to-safety (FTS) shock, FTS_t, (solid), and after controlling for contemporaneous changes in logged VIX (dashed). 90% bootstrapped confidence bands.

Figure 14: Response to a 1-Standard Deviation FTS Shock (Solid) and after controlling for changes in log VIX (dashed)



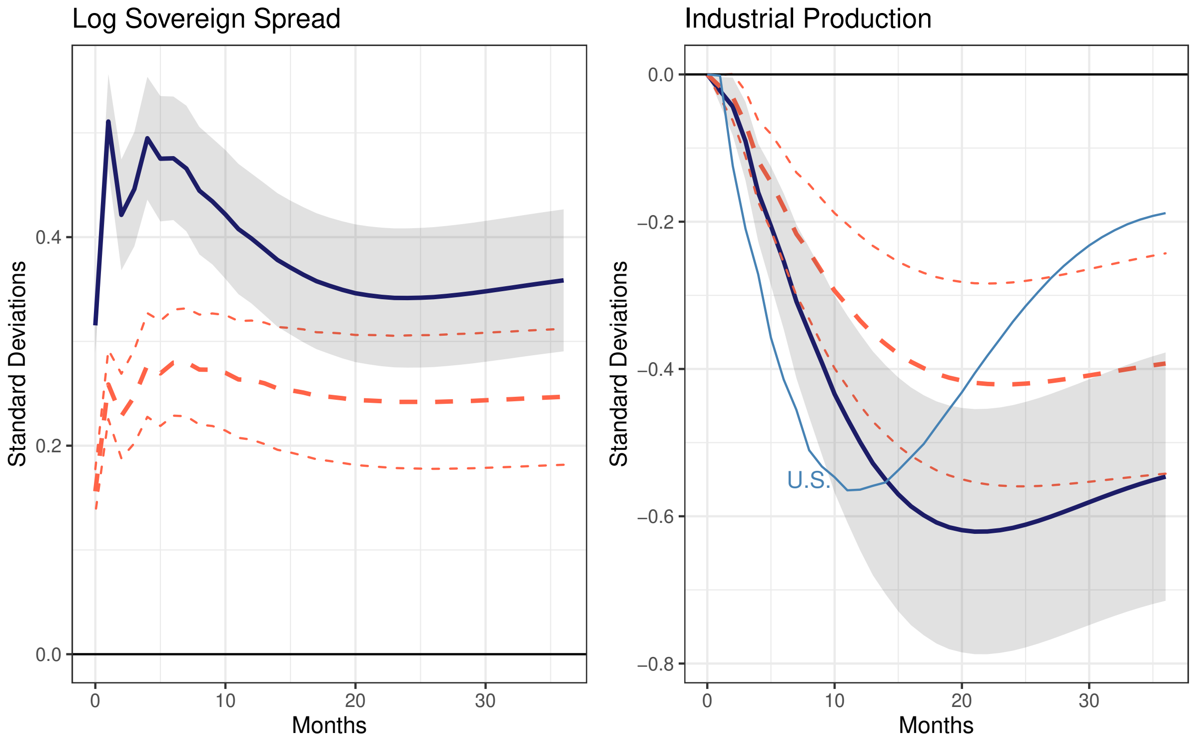
Cumulative response (in standard deviations) to a 1-standard deviation structural flight-to-safety (FTS) shock, FTS_t, (solid), and after controlling for contemporaneous changes in logged VIX (dashed). 90% bootstrapped confidence bands.

Figure 15: Setting FTS Condition threshold $c = 1$, Response to a 1-Standard Deviation FTS Shock (Solid) and after controlling for changes in log VIX (dashed)



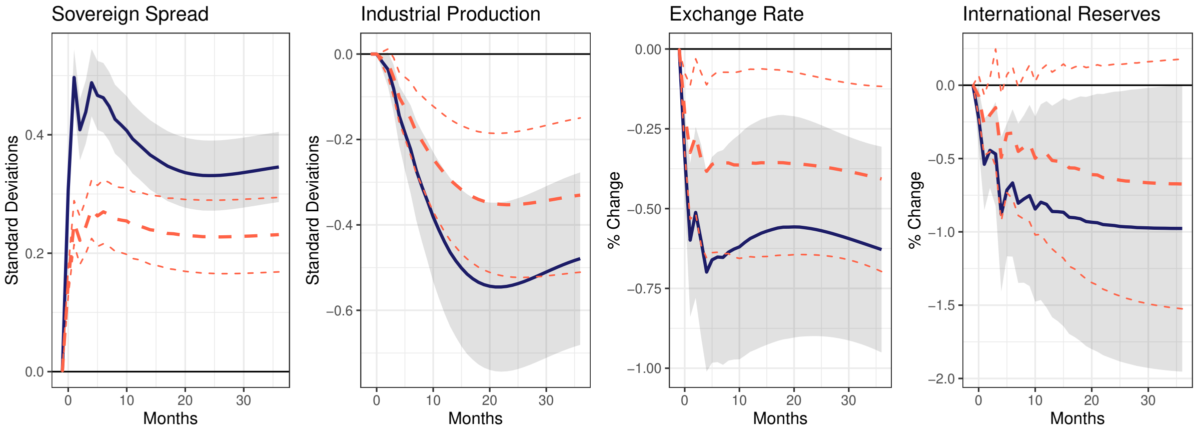
Cumulative response (in standard deviations) to a 1-standard deviation structural flight-to-safety (FTS) shock, FTS_t, (solid), and after controlling for contemporaneous changes in logged VIX (dashed). 90% bootstrapped confidence bands.

Figure 16: Setting FTS Condition threshold $c = 1$, Response to a 1-Standard Deviation FTS Shock (Solid) and after controlling for changes in log VIX (dashed)



Cumulative MG Response (Equation 10) to a 1-standard deviation structural flight-to-safety shock, FTS_t before (solid) and after controlling for contemporaneous VIX innovations (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.

Figure 17: Setting FTS Condition threshold $c = 1$, Response to a 1-Standard Deviation FTS Shock (Solid) and after controlling for changes in log VIX (dashed)



Cumulative MG Response (Equation 10) to a 1-standard deviation structural flight-to-safety shock, FTS_t before (solid) and after controlling for contemporaneous VIX innovations (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. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes.

Table 2: R^2 estimates of autoregressions augmented with FTS_{t-1}

	Monthly Changes in:	AR(1)	AR(1)+FTS_{t-1}	AR(1)+FTS_{t-1}+FTS_t
1	CBOE VIX Index	0.00	0.02**	0.30**
2	Wilshire 5000 Index	0.01	0.01	0.40*
3	10-year U.S.Yield	0.05	0.11***	0.19***
4	U.S. High Yield Spread	0.11	0.22***	0.44***
5	USD/G10 Exchange Rate	0.13	0.14	0.19
6	JPY/AUD Exchange Rate	0.09	0.18***	0.35***
7	WTI Crude Oil	0.07	0.11***	0.15***
8	Copper	0.18	0.20***	0.20***
9	1-year U.S. Infl. Exp.	0.05	0.11***	0.11***
10	10-year U.S. Infl. Exp.	0.00	0.18***	0.18***

R^2 from an AR(1) regression and that of an AR(1) augmented with FTS_{t-1} and FTS_t. Monthly data. *,**,*** reflects significance of FTS_{t-1} estimate at the 10%, 5%, and 1% level, respectively. All variables are in logs except U.S. inflation expectations.

Table 3: Correlations of FTS Shocks and Macro-Financial Aggregates

	FTS_t	VIX	Stocks	U.S. 10Y Yield	USD/G10	Oil	U.S. Unemp.	U.S. NA	EM IP
FTS_t	1								
VIX	0.534	1							
Stocks	-0.625	-0.613	1						
10Y UST	-0.294	-0.22	0.185	1					
USD/G10	-0.279	-0.195	0.292	-0.055	1				
Oil	-0.218	-0.236	0.203	0.34	-0.357	1			
U.S. Unemp.	0.172	0.1	-0.309	-0.127	0.13	-0.184	1		
U.S. NA	-0.228	-0.133	0.338	0.138	-0.221	0.235	-0.87	1	
EM IP	-0.097	-0.011	0.12	-0.016	-0.153	0.206	-0.355	0.449	1

Correlations of FTS shocks with log changes in the VIX, Wilshire 5000 equity index, 10 Year U.S. Treasury Yields, USD/G10 index (negative is USD appreciation), WTI crude oil, 6-month forward change in U.S. Unemployment (US UR), 6-month forward change in U.S. national activity (U.S. NA), 6-month forward change in emerging market log Industrial Production (EM IP), respectively.

Table 4: Largest Daily Global FTS Shocks, 2000-2019

Description	Date	FTS_d
1. Chinese Correction: Authorities announced plans to curb speculation	2007-02-27	5.34
2. British referendum votes to exit E.U.	2016-06-24	5.20
3. U.S. President Trump controversy	2017-05-17	4.11
4. Italian political tensions, speculation of E.U. exit	2018-05-29	3.48
5. Lehman Brothers Bankruptcy	2008-09-15	3.47
6. Arab Spring - Instability in the Middle East and North Africa	2011-02-22	3.29
7. ECB announces no new emergency support for Greece; Greece calls for bailout referendum	2015-06-29	3.24
8. Global growth pessimism communicated by the Fed	2019-03-22	2.98
9. S&P downgraded Greece's credit rating to 'junk'	2010-04-27	2.98
10. U.S. - China trade war intensifies	2019-08-05	2.95

Table 5: 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 6: Largest Daily Log VIX (Percent) Changes, 2000-2019

Description	Date	Change
1. 'VIXplosion	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 controversey	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%

Table 7: Domestic Financial Factors and the Impact of FTS shocks on Economic Activity

	Dependent variable:				
	18-Month Response of IP Growth				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.217	0.361	0.308	0.519	0.104
	(0.364)	(0.369)	(0.390)	(0.327)	(0.309)
6M Spread Response	-1.369^{**}	-1.278^{*}	-1.632^{**}	-1.272^{**}	-0.836
	(0.655)	(0.731)	(0.750)	(0.563)	(0.590)
6M FX Response		18.118	17.244	12.300	1.232
		(12.617)	(14.885)	(11.071)	(7.251)
6M Reserves Response			-20.640^{**}	-12.597	-29.596^{***}
			(10.235)	(9.674)	(10.136)
$\ln(ETF_i + 1)$				-0.140^{***}	-0.115^{***}
				(0.044)	(0.035)
6M FX $\times$ 6M Reserves					$-1{,}716.504^{***}$
					(523.335)
Observations	34	34	34	34	34
R^2	0.129	0.199	0.361	0.540	0.627
Adjusted R^2	0.102	0.148	0.297	0.476	0.560

Robust standard errors. *, **, *** correspond to significance at the 10, 5, and 1 percent level, respectively. Dependent variable is the cumulative 18-month expected response of IP growth (in SDs) to a 1-SD FTS shock (Dependent and independent variable descriptions found in Equation 13). The final independent variable is the interaction of the 6-month cumulative response of country i's exchange rate to a 1-SD FTS shock and the 6-month cumulative response of country i's international reserves. IP growth and changes in log spreads are in units of standard deviations. Exchange rate and reserves are in log changes.

Online Supplement to
"Global Fight-to-Safety Shocks"

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October 12, 2020

This Online Supplement is organized in four sections. Section S1 provides detail on relevant data and sources. Section S2 describes a method to separate excess risk sentiment from the global demand component embedded in Flight-to-Safety shocks, and then provides supplementary results.

S1 Data

Data is collected from a variety of sources. To construct global flight-to-safety shocks, the underlying daily data on the VIX Index, Wilshire 5000 index, 10-year Treasury yields, U.S. corporate high yield spreads, and AUD/JPY exchange rate are taken from the FRED database. The daily data is eventually aggregated to a monthly frequency for further analysis.

Monthly average sovereign spreads are measured with J.P. Morgan EMBI indices. The sample contains monthly data on spreads for 34 countries over the period 2000-2019. 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 S.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.

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. Summary statistics for year-over-year changes in log industrial production are reported in Table S.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 her summary statistics.

Table S.3 report summary statistics on select commodity and financial market variables at the monthly frequency. The values are monthly average changes, not end-of-month changes. It includes all components used to construct the global FTS index along with interest rates and commodities.

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.

Table S.1: Summary Statistics for Changes in Log EMBI Spread

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

Table S.2: Summary Statistics for Year-over-Year Change in Log Industrial Production

Country	T	Min	Max	Mean	Medan	SD
Argentina	235	-0.222	0.245	0.022	0.023	0.078
Belarus	151	-0.109	1.997	0.259	0.136	0.436
Brazil	235	-0.170	0.190	0.012	0.013	0.064
Chile	235	-0.131	0.140	0.021	0.027	0.044
China	235	0.038	0.207	0.116	0.114	0.044
Colombia	235	-0.143	0.163	0.025	0.020	0.054
Cote d'Ivoire	195	-0.501	0.581	0.027	0.035	0.163
Croatia	235	-0.142	0.131	0.014	0.017	0.052
Ecuador	235	-0.170	0.491	0.043	0.050	0.078
Egypt	175	-0.145	0.410	0.044	0.034	0.081
El Salvador	235	-0.046	0.079	0.014	0.014	0.023
Gabon	235	-0.377	0.426	-0.005	0.018	0.137
Hungary	235	-0.302	0.291	0.046	0.056	0.087
Indonesia	235	-0.136	0.345	0.040	0.038	0.053
Iraq	235	-0.830	11.500	0.144	0.087	0.860
Jordan	235	-0.229	0.286	0.022	0.015	0.078
Kazakhstan	235	-0.096	0.414	0.072	0.059	0.083
Lithuania	235	-0.260	0.381	0.048	0.050	0.088
Malaysia	235	-0.176	0.234	0.042	0.040	0.063
Mexico	235	-0.177	0.148	0.016	0.022	0.048
Pakistan	235	-0.195	0.319	0.049	0.039	0.084
Peru	235	-0.141	0.222	0.037	0.037	0.073
Philippines	235	-0.287	0.360	0.025	0.025	0.110
Poland	235	-0.153	0.234	0.054	0.055	0.059
Russian	235	-0.170	0.263	0.037	0.040	0.054
Senegal	151	-0.224	0.609	0.060	0.042	0.127
South Africa	235	-0.232	0.100	0.012	0.018	0.051
Sri Lanka	104	-0.143	0.193	0.025	0.020	0.059
Tunisia	235	-0.177	0.165	0.007	0.000	0.050
Turkey	235	-0.240	0.294	0.055	0.065	0.092
Ukraine	200	-0.308	0.221	0.011	0.023	0.107
Uruguay	200	-0.311	0.572	0.048	0.037	0.127
Venezuela	235	-0.648	1.832	-0.045	-0.015	0.229
Vietnam	128	-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 2000s. SD refers to standard deviation.

Table S.3: Summary Statistics for Select Financial and Commodity Market Variables

Market Variable	N	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
JPY/AUD Exchange Rate	235	0.0002	0.034	−0.241	−0.015	0.020	0.082
10-year Treasury Yield	235	−0.006	0.070	−0.378	−0.046	0.034	0.194
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
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/G10 Exchange Rate	235	−0.0002	0.019	−0.050	−0.013	0.013	0.082
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 S.4: U.S. Traded ETFs Granting Exposure to an EM Country

	Country	Number of ETFs
1	Argentina	112
2	Belarus	0
3	Brazil	281
4	Chile	118
5	China	571
6	Colombia	101
7	Cote d'Ivoire	0
8	Croatia	1
9	Ecuador	0
10	Egypt	60
11	El Salvador	0
12	Gabon	0
13	Hungary	58
14	Indonesia	127
15	Iraq	3
16	Jordan	3
17	Kazakhstan	6
18	Lithuania	0
19	Malaysia	193
20	Mexico	340
21	Pakistan	47
22	Peru	6
23	Philippines	109
24	Poland	106
25	Russia	162
26	Senegal	0
27	South Africa	231
28	Sri Lanka	2
29	Tunisia	0
30	Turkey	107
31	Ukraine	7
32	Uruguay	0
33	Venezuela	0
34	Vietnam	1

Source: etfdb.com. Data collected as of October 2020.

S2 Flight-to-Safety, Excess Risk Sentiment, and Global Demand

Large global shocks measured with asset prices reflect both risk sentiment and global demand - the latter referring to changing beliefs over future fundamentals. It's evident that global FTS shocks, a product of asset price movements, exhibits clear links to global demand shown by their impact on commodity prices and U.S. inflation expectations and also by the economic relevance of the events triggering them. While the impact of FTS shocks itself is the main focus of this paper, I also isolate the effects induced by the excess risk sentiment component of FTS shocks to better understand the macroeconomic implications of global risk sentiment.

In this section I propose a simple reduced-form separation of FTS shocks into their global demand and excess risk sentiment components. This is accomplished by estimating a principal components regression (PCR) of global FTS shocks on the common factor in world commodity prices, an established proxy for global demand. The obtained residual then reflects the component of global FTS that is left unexplained by the contemporaneous adjustment in commodity prices, which I refer to as excess risk sentiment. More explicitly, I define excess risk sentiment as the component of risk affecting financial asset prices as pure risk premia; it is *excess* in that it has no causal effect on fundamental global demand and simply serves to compensate risk aversion.

Suppose FTS shocks were made up of two orthogonal components,

$$FTS_t = G_t + V_t, \tag{S.1}$$

where G_t reflects global demand, and V_t is the excess risk sentiment. It's 'excess' because it is the risk sentiment reflected in asset prices above and beyond whatever effect risk has had on global demand (which is absorbed in G_t). However these two components are unobserved, and therefore must be estimated. Therefore to recover the excess risk sentiment component, I regress FTS_t on an estimate for global demand $\widehat{G}_t$, which I measure as the common factor in commodity prices:

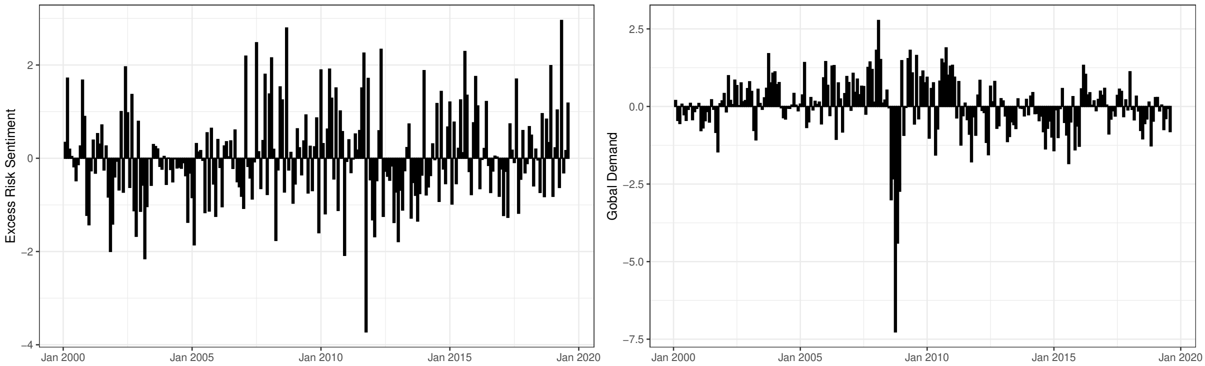
$$FTS_t = \underbrace{\hat{\beta}\boldsymbol{\gamma}\Delta\mathbf{C}_t}_{\widehat{G}_t} + \epsilon_t^V, \quad \widehat{V}_t = \epsilon_t^V, \tag{S.2}$$

where

$$\boldsymbol{\gamma}\Delta\mathbf{C}_t = \sum_{k=1}^{K} \gamma_k \Delta c_{k,t}. \tag{S.3}$$

$\Delta\mathbf{C}_t$ is a $T \times k$ matrix of log returns from a broad set of k commodity prices, and coefficients γ_k as set such $\boldsymbol{\gamma}'\Delta\mathbf{C}_t$ reflects the first principal component of the space of

Figure S.1: Separating Global Flights-to-Safety Shocks into Excess Risk Sentiment ($\widehat{V}_t$) and Global Demand ($\widehat{G}_t$)



Both series are normalized to have unit standard deviation.

commodity returns (i.e. the vector which maximizes the variance across the space of commodities). Specifically, I estimate $\widehat{G}_t$ using Principal Components Analysis (PCA) over a broad set of 66 commodity prices. The first principal component is our estimate of $\widehat{G}_t$. Each commodity price series is log-differenced and standardized. Then, by then regressing FTS_t on the common commodity factor, I define the obtained residual ϵ_t^V as excess risk sentiment $\widehat{V}_t$.

Figure S.1 shows the decomposition of FTS shocks into risk premia and global demand, respectively. Starkly, the 2008-2009 global financial crisis is identified as a large, negative global demand shock. October 2008, November 2008, and August 2008 reflect a -7.26, -4.4, and -3 standard deviation global demand shock, respectively. These are identified as having little risk sentiment component. Meanwhile, September 2008 reflects a joint risk sentiment (+2.79 SDs) and global demand shock (-2.33 SDs). Meanwhile, May 2019 reads as a 2.95 standard deviation risk sentiment shock and -0.74 standard deviation global demand shock, amid the U.S. - China trade tensions. June 2002 reflects a 2-standard deviation risk sentiment shock amid the Dot Com bubble bursting.

S2.1 World prices and the excess risk component of FTS shocks

Figures S.3, S.4, and S.5 trace IRFs from a 1-SD FTS shock, and also a 1-SD shock to the excess risk sentiment component, V_t (dashed) on world prices. The risk sentiment channel is responsible for 50% of the total response among commodities. For the U.S. Dollar, roughly half of the response during flights-to-safety is driven by risk sentiment, which is surprisingly low given the active debate over its role as a prominent indicator of global financial risk. By contrast, the impact of FTS shocks on U.S. interest rates is predominantly driven by excess risk sentiment.

Relative to financial asset prices, the global demand channel contributes significantly to the total response of commodities and the U.S. Dollar during flights-to-safety. This is the case *despite* excess risk sentiment shocks accounting for most of the variation in flights-to-safety. The response in gold *increases* after isolating the risk shock. Gold prices is most interesting - appreciating significantly when isolating the risk sentiment component, validating its role as a safe haven commodity. It also implies that gold prices covary positively with risk shocks *and* global demand shocks. Because global FTS shocks tend to act as joint shocks to demand and risk sentiment, the response to a total FTs shock hides the significant effect of the risk sentiment channel on gold. By contrast, another safe haven asset, the U.S. Dollar, appreciates in response to heightened risk sentiment or lower global demand. So while gold may provide a hedge against rising uncertainty (but not weaker global demand), the U.S. Dollar provides a hedge against both greater uncertainty and weaker global demand.

S2.2 Emerging Markets and the excess risk component of FTS shocks

Figure S.6 shows the impact of a 1-SD FTS shock on emerging markets, along with the isolated excess risk component (dashed). Most of the response in sovereign spreads is driven by risk sentiment, while about half of the response in industrial production growth is attributed to risk sentiment, the other attributed to global demand. Similarly, the response observed in exchange market pressure (exchange rates and international reserves) is driven by a mix of both risk sentiment and global demand.

S2.3 Endogeneity and assumptions for separating excess risk sentiment component of global FTS shocks

The reduced-form approach to recover a measure of global excess risk sentiment has the advantage of being convenient, robust and practical. The separation issue, however is subject to complications when taking into account the presence of endogeneity: changing risk perceptions themselves can affect global demand (Bloom [2009] Caballero and Simsek [2020]) and vice versa. Like asset prices, global FTS shocks, therefore, likely contain both a global demand and risk sentiment component, and the two may be correlated with one another. For the principal-components regression approach to consistently estimate true excess risk sentiment, there are a number of underlying conditions that must be satisfied:

1. The 1st principal component (PC) of commodity price returns reflects global demand.
2. Weak exogeneity of excess risk sentiment.
3. Commodity prices do not pay risk premium on aggregate risk.

I discuss these issues here to acknowledge the limitations associated with them and evaluate how reasonable each assumption may be. The second issue, weak exogeneity of excess risk sentiment implies that global demand is not contemporaneously impacted by *excess* risk sentiment, but can be impacted with a lag. Point 3 follows from points 1 and 2. If the 1st PC of commodity returns is in fact a proxy for global demand and is additionally not influenced by excess risk premia the way financial asset prices are, we should observe that investors in particularly pro-cyclical commodities are *not* compensated for the aggregate risk they bear. Importantly, point 3 is empirically testable.

The 1st PC of commodity price returns reflects global demand

The common factor in commodity prices, to proxy global demand, G_t, must first reflect fluctuations in global demand. Recent and building evidence suggests this condition is validated (Kilian [2009], Kilian and Zhou [2018] Delle Chiaie et al. [2018], Alquist et al. [2020]). Importantly, global demand shocks are also not the same as fluctuations in global activity. Global demand shocks can exhibit more volatility and move significantly faster in reflecting information than, say, real GDP. This means that controlling for global demand is not the same as regressing FTS_t on slow-moving macroeconomic aggregates. Commodity prices exhibit the unique feature of being both tied to the fundamental economy and adjusting at a relatively fast pace (Bailey and Chan [1993], Hong and Yogo [2012]). In fact, some highly financialized commodity markets, like crude oil, respond to information at the speed of liquid financial markets. Less liquid commodity markets may exhibit stickier prices, but often these prices still adjust faster than macroeconomic aggregates.

Weak exogeneity excess risk sentiment

For illustration, suppose FTS shocks can be decomposed into asset price movements reflecting: global demand G_t the component of risk sentiment that affects global demand ρ_t^G (non-excess risk sentiment), and excess or idiosyncratic risk sentiment component V_t,

$$FTS_t = G_t + V_t, \tag{S.4}$$

$$G_t = \widetilde{G}_t - \rho_t^G, \tag{S.5}$$

where

$$cov(G_t, V_t) = 0, \quad cov(\widetilde{G}_t, \rho_t^G) < 0, \quad cov(\rho_t^G, V_t) = 0.$$

Here, total global demand G_t can be decomposed into the "pure" demand effect given by $\widetilde{G}_t$ and non-excess rising risk premia ρ_t^G. Similarly, total risk premia is the sum of ρ_t^G and excess risk sentiment V_t.

A crucial condition to satisfy the assumption of weak exogoneity is that non-excess risk sentiment that impacts global demand ρ_t^G is contemporaneously uncorrelated with excess risk sentiment V_t. Why might this condition be satisfied? Under the rationale that FTS shocks tend source from unique, unusual events. These events are unpredictable. And while the overall "flight-to-safety" signature is similar across these events, the underlying components – global demand, non-excess and excess risk sentiment – driving the flight-to-safety can differ drastically. For example, it may be that the FTS Shock induced by the September 11 terrorist attack was mostly a risk sentiment shock, while FTS during the 2008 Global Financial Crisis were contained a larger global demand shock component. Following the same logic, excess risk sentiment may differ from non-excess risk sentiment from shock to shock in an uncorrelated way. For instance, excess risk sentiment may be more related to technical market conditions or intermediary leverage prior to the FTS shock, while non-excess risk sentiment may be more associated with the degree of macroeconomic uncertainty caused by an unexpected news shock, therefore having a stronger impact on growth.

Why might this condition be violated? Excess and non-excess risk sentiment driving asset prices may be correlated over the business cycle. If excess risk sentiment is determined by intermediary leverage, and that leverage varies systematically with the business cycle, the assumption of excess risk premia and non-excess risk premia being uncorrelated would be violated.

Commodity prices do not pay risk premium on aggregate risk

This condition which follows from the previous assumptions has the advantage of being empirically testable. That is, consistent separation of excess risk sentiment component of FTS shocks from global demand using commodity prices, requires that commodity prices only adjust to changing global demand and *not* to excess risk premia. This is unlike financial asset prices, since asset prices adjust to global demand but are also sensitive to investor risk sentiment. Non-excess risk sentiment *can* impact commodity prices indirectly by causally impacting global demand, but excess changes in risk sentiment do not reflect themselves in commodity prices.

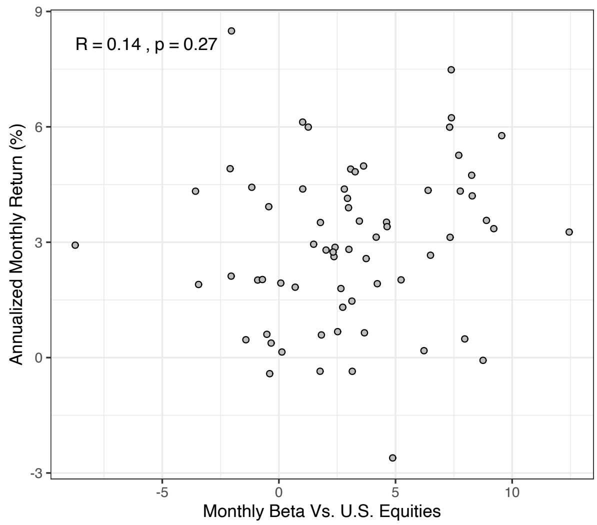
To put another way, commodity investors are not compensated for taking on aggregate risk the way it financial assets compensate holders for bearing the same risk. For this assumption to be violated, heightened risk aversion must directly cause changes to commodity prices above and beyond any effect transmitting through risk aversion's effect on global growth prospects. A violation of this assumption would imply that particularly pro-cyclical commodities exhibit excess returns. I argue that considerable evidence suggests that this assumption is reasonably satisfied. Even at face value, Table S.5 shows annualized returns on commodity ETF investments which invest in futures against the S&P 500 since 2000. Crude oil, copper, and broad commodity prices all exhibit a high degree of procyclical behavior. Despite this, an investment any of these commodities would have yielded negative annual returns over the past decade. Evidence of no aggregate risk premia applies for broad commodity spot returns too. Figure S.2 shows that for a set of 66 spot commodity returns from 2000-2019, U.S. equity betas are essentially uncorrelated with average returns. If aggregate risk premia was priced in the cross-section of commodities, commodities with higher betas would exhibit significantly higher average returns historically.

Table S.5: Commodity Futures Annualized Excess Returns

Date Range	Commodity	Average Return	Daily S&P 500 Beta
2007-2020	WTI Crude Oil	-19.2%	0.76
2011-2020	Copper	-3.5%	0.42
2007-2020	Commodity Basket	-3.9%	0.43
2007-2020	S&P 500	6.16%	1

Daily log returns, annualized. Data taken from ETFs: USO, CPER, DBC, respectively.

Figure S.2: Cross Section of Monthly Commodity Spot Return Betas, 2000-2019



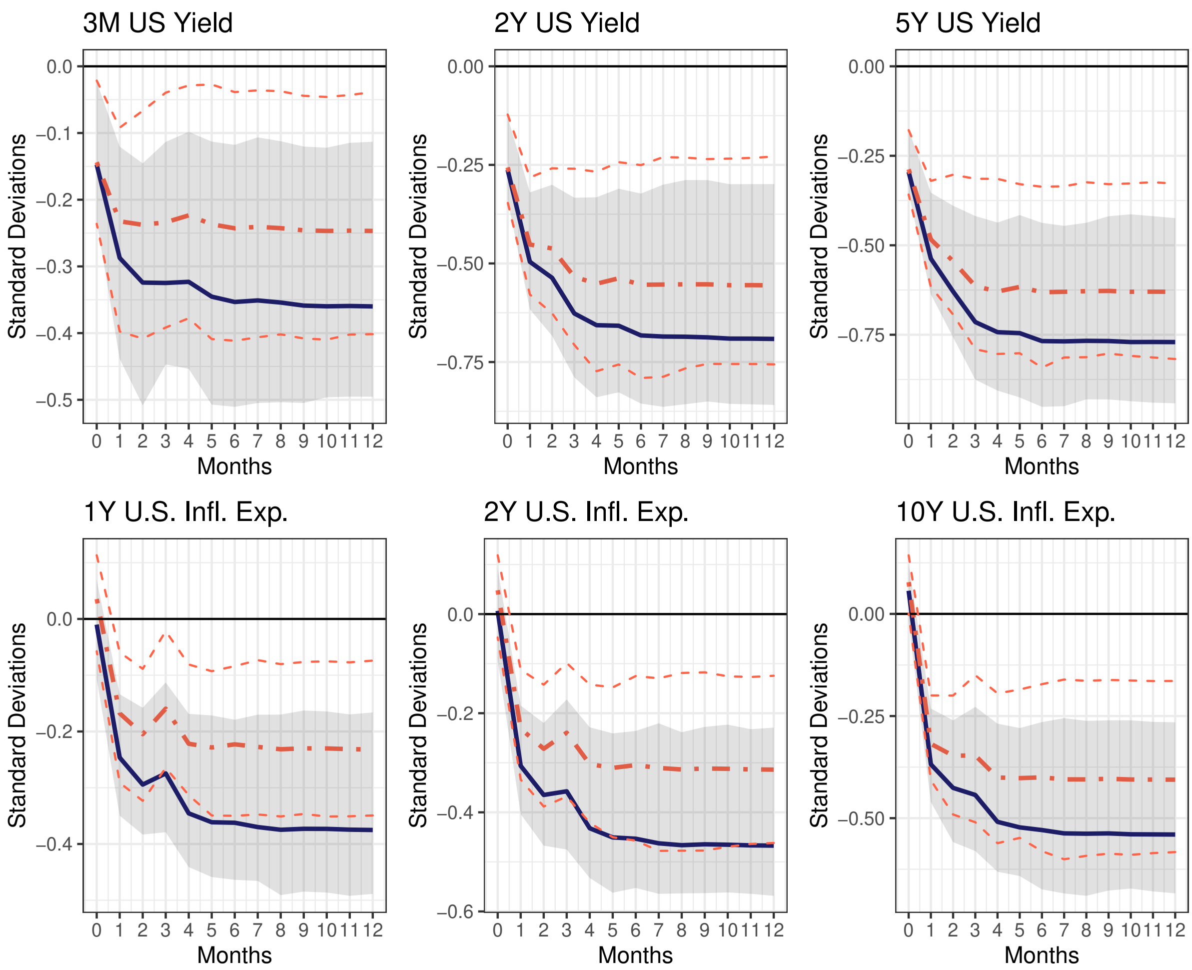
Returns are annualized. U.S. Equity index used is the Wilshire 5000.

More rigorous evidence that commodity investments do not compensate for taking on aggregate risk has been documented over several decades (Dusak [1973], Feldman and Till [2006], Erb and Harvey [2006]). Rather, commodity risk premia has been linked to producer hedging demand[S1], which is an idiosyncratic supply-side phenomena and other factors like momentum (Hirshleifer [1988], Gorton and Rouwenhorst [2006], Gorton

[S1]This comes from The Theory of Storage: in the face of low inventories, commodity prices and volatility rise due to risk of 'stock-out'. As a result, consumers of the commodity store supply at elevated levels. To hedge their production, risk-averse producers must provide additional compensation to counterparties as incentive to enter into commodity futures contracts.

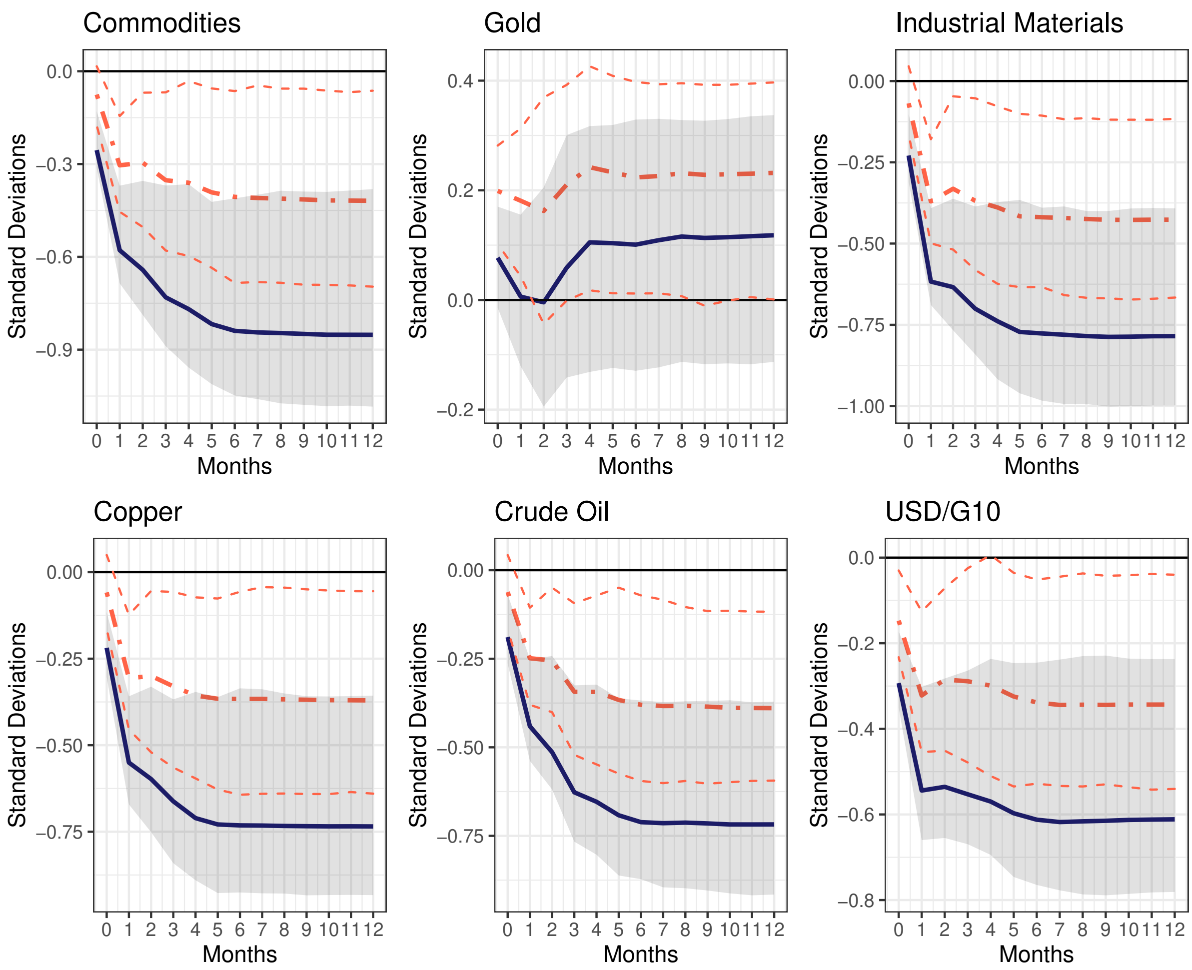
et al. [2013], Szymanowska et al. [2014]). Some commodities like energy and metals are more sensitive to global economic conditions than others (e.g. agriculture). There is some evidence of positive excess returns among energy and metals, but *not* related to associated aggregate risk. Rather, these commodities have higher expected returns during business cycle peaks when inventory is low, supportive of the producer hedging theory (Fama and French [1988], Kucher and Kurov [2014], Duncombe et al. [2018]). This goes in the opposite direction of what standard asset pricing theory would imply.

Figure S.3: Response to a 1-Standard Deviation FTS Shock (Solid) and the excess risk sentiment component (Dashed)



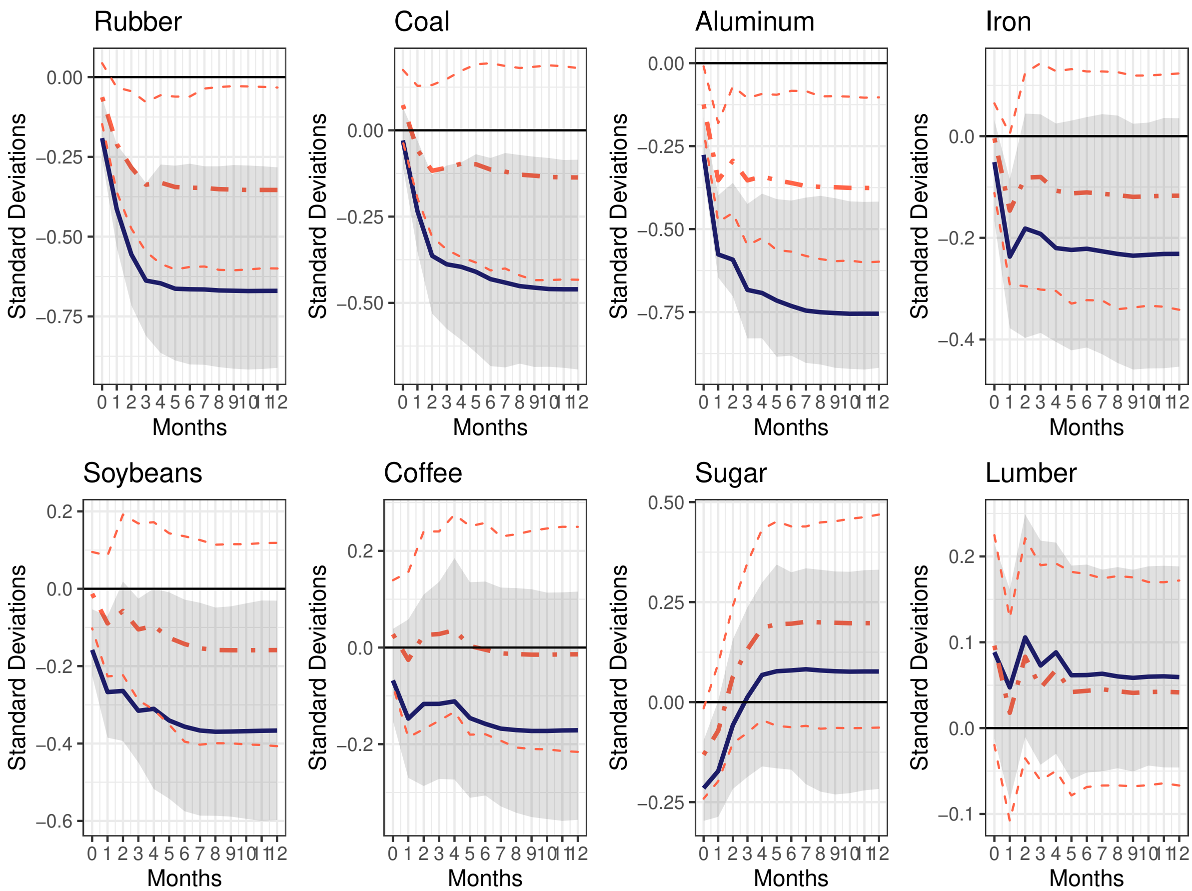
Cumulative Response (in standard deviations) to a 1-standard deviation: structural flight-to-safety (FTS) shock, FTS_t, (solid), and the component attributed to the excess risk sentiment component of FTS, V_t (dashed). 90% bootstrapped confidence bands.

Figure S.4: Response to a 1-Standard Deviation FTS Shock (Solid) and the excess risk sentiment component (Dashed)



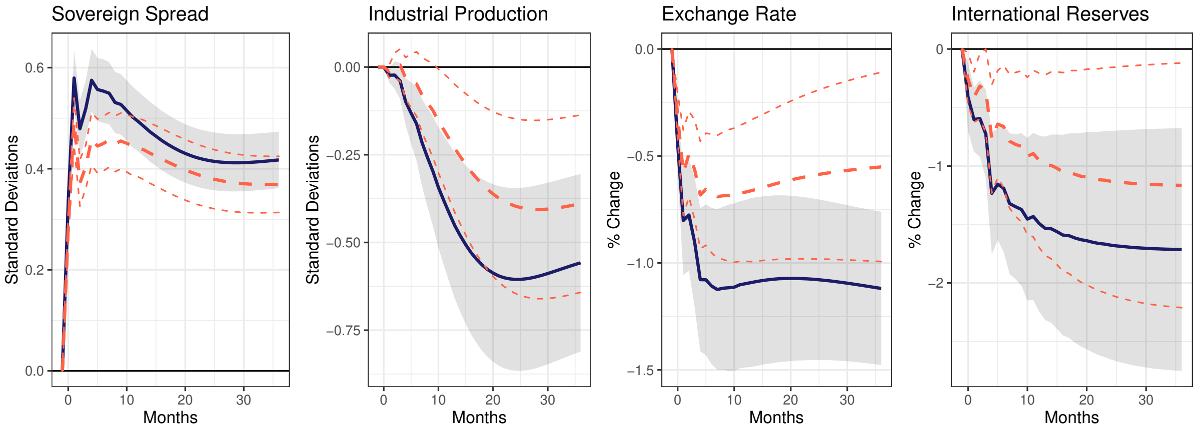
Cumulative Response (in standard deviations) to a 1-standard deviation: structural flight-to-safety (FTS) shock, FTS_t, (solid), and the component attributed to the excess risk sentiment component of FTS, V_t (dashed). 90% bootstrapped confidence bands.

Figure S.5: Response to a 1-Standard Deviation FTS Shock (Solid) and the excess risk component (Dashed)



Cumulative Response (in standard deviations) to a 1-standard deviation: structural flight-to-safety (FTS) shock, FTS_t, (solid), and the component attributed to the excess risk sentiment component of FTS, V_t (dashed). 90% bootstrapped confidence bands.

Figure S.6: Response to a 1-Standard Deviation FTS Shock (Solid) and the excess risk component (Dashed)



Cumulative MG Response (Equation 10) to a 1-standard deviation: structural flight-to-safety (FTS) shock, FTS_t, (solid), and the component attributed to the excess risk sentiment component of FTS, V_t (dashed). 95% dispersion intervals as computed in Equation 12. Sovereign spreads and Industrial Production response in standard deviations. Exchange rate and international reserves response in percent. Negative exchange rate movement is local depreciation vis-a-vis USD.