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Accounting for Sovereign Tail Risk in Emerging Economies: The Role of Global and Domestic Risk Factors*

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Abstract

This paper employs a panel logistic regression to evaluate the role of global and domestic risk factors in explaining sovereign tail risk for 18 emerging economies (EMEs). Sovereign tail risk is defined as the likelihood of a sharp rise in sovereign credit risk. We find that both global and domestic risk factors are important for explaining sovereign tail risk, with explanatory power increasing with the severity of tail risk. Moreover, most of the risk factors have become more important following the global financial crisis. In particular, global liquidity conditions, US dollar appreciation, banking sector leverage, and economic growth are ranked as the major risk factors for sovereign tail risk among the EMEs. The result implies that a normalisation of the unconventional monetary policies adopted by advanced economies, which would tighten global liquidity and increase currency volatility further, could generate stronger headwinds for EMEs, particularly for those economies with higher banking sector leverage and weaker macroeconomic fundamentals.

JEL Classification: F34, G15

Keywords: Sovereign risk; tail risk; CDS spread; emerging markets; US monetary policy

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1. Introduction

The 2008 global financial crisis (GFC) and the subsequent Quantitative Easing programs adopted by the US Federal Reserve have had a profound impact on the international financial system. US monetary policy, which is regarded as a major determinant of capital flows, leverage, asset prices and credit growth globally (see Forbes and Warnock (2012) and Rey (2015)), has been the key global risk factor to emerging economies (EMEs). When the US normalises its monetary policy, these economies could suffer significant headwinds such as drastic capital outflows and a sharp correction in asset prices. Against this background, we look at sharp changes in asset returns and examine the contribution of global and domestic risk factors to sovereign credit risk in a group of emerging markets economies (EME).

Specifically, we assess the possibility of a sharp rise in an EME's sovereign credit default swap (CDS) spreads and its association with domestic and global risk factors in the pre- and post-crisis periods.[1,2] We find that some of these factors are not important when the increase in sovereign CDS spreads is mild, but can be significantly relevant when the increase in CDS spreads is high enough. Such phenomenon could be explained by a greater awareness of investors to changes in risk factors during periods of market turbulence, which results in a much stronger than usual response of the spread to risk factors. Traditional analysis, which focuses only on mean effects, may underestimate the contribution of risk factors to sovereign credit risk during periods of financial market turbulence.

In this study, we introduce the concept of sovereign tail risk and identify when the risk level becomes an issue of concern for an economy. Sovereign tail risk is defined as the likelihood of a sharp increase

[1] Sovereign CDS spreads are the price of the sovereign CDS contract. The contract is an insurance contract that insures the contract holder against a sovereign default. Its trading is mainly concentrated in the 5-year tenor, which is in contrast to the relatively short-tenor for other popular derivatives instruments such as foreign exchange options or interest rates swaps. See Augustin et al. (2014) for a comprehensive survey on sovereign CDS spreads.

[2] We focus on sovereign CDS contracts as opposed to measuring the underlying bond yield directly as the market liquidity for sovereign CDS market is well known to be even higher than the corresponding sovereign bond market (see Longstaff et al. (2011)).

in sovereign CDS spreads. A threshold level, usually based on a pre-specified percentile of its historical distribution on the right hand tail, can be set to identify sharp increases. We introduce a dummy variable called “exceedance” to indicate a sharp rise in the sovereign CDS spreads.[3] In contrast to using the spread directly, using a categorical approach via exceedance can avoid the linear assumptions made about shock transmissions from the covariates to the dependent variable. Instead, it focuses on the impact of large shocks that are typically of interest to policymakers and market participants. In particular, we study five episodes, which are regarded as stressful to illustrate the performance of EMEs through the lens of exceedance. The five episodes are: (1) The default of Lehman Brothers in September 2008; (2) The bailout of Greece in May 2010; (3) the escalation of the European debt crisis in September 2011; (4) the QE tapering tantrum in May 2013; and (5) the onset of the Russian oil crisis in December 2014.

To identify the determinants of sovereign tail risk, we use a fixed effect panel data logistic regression.[4] In addition to the common features of linear regressions, logistic regressions offer an estimate of the odds ratio, which helps identify the relative importance of different factors in the regression. For each risk factor, a higher odds ratio means that the factor contributes more to sovereign tail risk other things equal.[5] Moreover, since the tail risk can be perturbed by adjusting the assumed percentile of the distribution, our method offers a simple way to examine the explanatory power of contributory factors under different stress levels. Such a comparison is not feasible using ordinary least square (OLS) estimation, which is typically used in existing studies, because the OLS estimates are mean estimates by construction.

[3] The application of “exceedance” to financial stability analysis is first seen in Bae et al. (2003), which introduces a new approach to measuring contagion in financial markets.

[4] Forbes (2012) applies multivariate extreme value theory to analysis of the tails of stock price distributions in advanced economies. Using a panel logistic regression, the study identifies that both global and country-specific factors significantly determine the chance of a sharp price fall in stock market prices.

[5] The use of logistic regression and the accompanying odds ratio is very common in clinical studies. The odds of an event happening is the probability that the event will happen divided by the probability that the event will not happen. The odds ratio is a relative measure of risk, telling us how much more likely it is that someone who is exposed to a certain risk factor will develop a disease as compared to someone who is not exposed. A formal definition of odds ratio will be given later.

Three major results emerge from our analysis. First, both global and domestic risk factors are important in explaining sovereign credit risk, with explanatory power increasing with the threshold level. This empirical finding is consistent with the “wake-up” call hypothesis put forward by Goldstein (1998). During normal periods, investors may optimally neglect the vulnerability inherent in EMEs (such as economic fundamentals) and may only become aware of them when financial markets are stressful enough to trigger a “wake-up” call. Secondly, we find that most of risk factors have a larger impact on sovereign tail risk in the post-crisis period than in the pre-crisis period. The stronger association of risk factors during the post-crisis period supports the findings by Bruno and Shin (2015) and Rey (2015). These authors illustrate how US monetary policy can affect EMEs’ capital flows, banking sector leverage and asset returns. It is therefore not surprising that the contribution of risk factors is amplified given the ultra-loose US monetary conditions in the post-crisis period. Finally, by comparing the relative contribution of global and domestic risk factors to sovereign credit risk observed in five selected crisis episodes, we find that global risk factors play a more important role in explaining sovereign tail risk during the GFC and Greece bailout, while domestic risk factors explain more during the European debt crisis, QE tapering tantrum, and Russia oil crisis. The first two important domestic risk factors that we identified in the factor attribution analysis are banking sector leverage and economic growth. This implies that economies with higher banking sector leverage and weaker economic fundamentals are more vulnerable during times of market turbulence. Hence, relevant macro-prudential policies and an improvement in domestic fundamentals could help EMEs to lessen the adverse effect from potentially large external shocks.

This study contributes to the literature on identifying determinants of sovereign credit risk in EMEs, which has been a topic of interest and debate. Using data on sovereign bond yields, Mauro et al. (2002), Geyer et al. (2004), Gonzalez-Rozada and Yeyati (2008) provide evidence that sovereign credit risk in EMEs is explained more by common global and financial market factors. Some recent studies extend this finding to sovereign CDS spreads. Remolona et al. (2008) and Pan and Singleton

(2008) find that global factors significantly explain sovereign CDS spreads.[6] Longstaff et al. (2011) find that sovereign CDS spreads of both developed and less-developed countries are explained more by global market factors, investment flows and risk premium than by domestic fundamentals. Remolona et al. (2015) find that the EMEs' sovereign CDS spread is driven mainly by global risk appetite, using principal component analysis. On the contrary, Hilscher and Nosbusch (2010) find that domestic fundamentals have substantial explanatory power for sovereign credit risk, even controlling for global factors and credit ratings. Moreover, Beirne and Fratzscher (2013) find that macro-economic fundamentals are highly significant but global factors (proxied by VIX) are not statistically significant. While these studies differ in their empirical design to analyse the average relationship between sovereign credit risk and its determinants, none of them have considered the possibility that the relationship could be nonlinear and different in the pre and post-crisis periods. We complement this research line by identifying determinants of sovereign tail risk with a hypothesis that both global and domestic risk factors contribute significantly to the sovereign risk of EMEs in times of crisis.

This paper is organised as follows. In section 2, we present our empirical model. Section 3 describes the data used, Section 4 discusses the results and the final section concludes.

[6] Remolona et al. (2008) decomposes the EMEs' sovereign CDS spreads into an expected loss component and a risk premium component. The authors find that sovereign CDS spreads are mostly risk premia, which are driven by global risk aversion. Pan and Singleton (2008) estimates the risk neutral default intensity for several EME, and find that it is highly correlated with the VIX index.

2. Empirical models

We assume that the sovereign CDS spread's exceedance can be explained by both global and domestic risk factors. Specifically, we consider a panel logistic regression:

$$Prob(Y_{it} = 1|G_t, L_{it}) = F[(\beta_1 G_t + \beta_2 L_{it}) + \alpha_i + \varepsilon_t] \quad (1)$$

where α_i is the country fixed effect to proxy for unobserved heterogeneity across the sample and F is a logistic function defined as F(z) = exp(z)/(1+exp(z)). This nonlinear functional form allows us to analyse the non-linear associations between a specific event and the risk factors being considered. In Eq. (1), Y_{it} is a dummy equal to 1 if economy *i* is experiencing an exceedance at time *t* (i.e., when the increase in sovereign CDS spreads fall within a predetermined percentile of its historical distribution). As discussed in the introduction, the level of risk can be easily perturbed by changing the assumed percentile to define exceedance.[7] G_t denotes a vector of global risk factors, such as changes in global risk aversion, global bond market conditions and the US dollar exchange rate.[8] L_{it} denotes a vector of local factors. The choice of L_{it} is motivated by previous studies which attempt to account for sovereign healthiness and the channels through which shocks are transmitted across countries. It includes net exports, net external claims of the banking sector, fund flows to the EMEs equity and bond funds, the leverage of the banking sector and the spread of the sovereign bond yields relative to the US Treasury for each EME.[9] We also examine an extension of Eq. (1) by differentiating the pre and post-crisis contribution of the factors considered to assess whether the relationship in Eq. (1) becomes different in the post-crisis period.[10]

7 For the comparison between exceedance and a general increase in sovereign credit risk, we also consider a benchmark case where Y_{it} is set to 1 when there is an increase of its sovereign CDS spreads

8 Another popular global risk factor is the funding liquidity risk, as proxied by the spread between the short-term US Treasury yields and the interbank rate, or referred as the TED spread. The TED spread measures the extent to which interbank lenders are willing to engage in lending activities. However, this indicator is not useful in most of our sample period because both the short-term US interest rates have been squeezed near the zero lower bound due to the quantitative easing programs.

9 Annex 1 provides the detailed definition of all the variables used in this study.

10 In the literature, there are growing concerns that global investors behave differently after the crisis of 2008. In particular, using the sovereign CDS spread, Remolona (2015) find break at the time of eruption of the global subprime crisis in Oct 2008. This motivates us to assess the risk based on the two subperiods separately.

Specifically,

$$Prob(Y_{it} = 1|G_t, L_{it}) = F[(\gamma_1 G_t + \gamma_2 L_{it}) * (1 - D_t) + (\gamma_3 G_t + \gamma_4 L_{it}) * D_t + \alpha_i \ + \varepsilon_t] \tag{2}$$

where $\mathrm{D_t}$ is dummy equal to 1 after the September 2008 (i.e., the onset of the GFC). These two equations can be rearranged to:

$$\frac{Prob(Y_{it} = 1|G_t, L_{it})}{1 - Prob(Y_{it} = 1|G_t, L_{it})} = \exp[(\beta_1 G_t + \beta_2 L_{it}) + \alpha_i + \varepsilon_t] \tag{3}$$

and

$$\frac{Prob(Y_{it} = 1|G_t, L_{it})}{1 - Prob(Y_{it} = 1|G_t, L_{it})} = \exp[(\gamma_1 G_t + \gamma_2 L_{it}) * (1 - D_t) + (\gamma_3 G_t + \gamma_4 L_{it}) * D_t + \alpha_i \ + \varepsilon_t] \tag{4}$$

The logistic regression allows us to find out the relative importance of each risk factor. Specifically, the coefficient of a risk factor in the logistic regression can be interpreted as the odds ratio of the factor which is a popular measure in epidemiology studies.[11] Conventionally when the risk factor is introduced in a binary fashion, the ratio measures how strongly the presence or absence of the exposure of the risk factor is associated with the dependent variable under consideration (i.e., sovereign tail risk).[12] In our context with continuous covariates, this is the ratio of odds at which exceedance occurs given a change in exposure to the risk factor *X*, relative to the odds of exceedance occurring without any change in *X*. Mathematically, the odds ratio of a risk factor *X* is defined as:

$$\text{odds ratio} = \frac{\text{odds}(X = x + \Delta x)}{\text{odds}(X = x)}$$
$$= \frac{Prob(Y_{it} = 1|X = x + \Delta x)}{1 - Prob(Y_{it} = 1|X = x + \Delta x)} \Big/ \frac{Prob(Y_{it} = 1|X = x)}{1 - Prob(Y_{it} = 1|X = x)}$$

[11] Similar to conventional multiple regressions, when the coefficient is not zero, the coefficient's sign determines whether the dependent variable (i.e. the probability, $Prob(Y_{it} = 1|G_t, L_{it})$, in a logistic regression) is increasing or decreasing as the independent variable (i.e. global and local risk factor in this study) increases. When the coefficient of a risk factor is zero, the probability is independent of the risk factor.

[12] An odds of an event is defined as the probability that the event occurs divided by the probability that the event does not occurs. An odds ratio is the ratio of two odds comparing the event under different conditions.

where Δx denotes an one-unit change in X, and factors other than X are being held as constant. Based on Eqs. (3) and (4), this expression can be simplified to $\exp(\beta_X \times \Delta x)$ where β_X is the coefficient of the risk factor X in the logistic regression. It is noteworthy that the odds ratio of an unimportant risk factor (i.e., $\beta_X = 0$) is equal to 1 since $\exp(0) = 1$. For a significant risk factor that increases (decreases) the likelihood of exceedance, the odds ratio will be larger (smaller) than 1. The simplified expression also suggests that a larger coefficient β_X (in magnitude) implies a multiplicatively larger difference between the two odds, and hence, a higher sensitivity to the risk factor X_{it}. In our model, the odds ratio simply measures the increase in the relative probability of having exceedance when one of the regressors increases by one standard deviation. As the odds ratio for an unimportant risk factor is always equal to one, it is useful to define the percentage change in the odds as:

$$\%\ \text{change in odds} = \exp(\beta_X \times \Delta x) - 1.$$

The percentage change in the odds offers an easier comparison between different risk factors in the regression. For risk factors that contribute positively (negatively) to the likelihood of exceedance, we would expect the percentage change in the odds to be positive (negative).

We include the following global risk factors, and their expected signs are listed as follows:

1) Global risk appetite (or global liquidity) (*ΔVIX*): We use the Chicago Board Options Exchange Volatility Index (VIX) to proxy for global risk appetite. Following Bruno and Shin (2015) and Rey (2015), changes in VIX can also be used to proxy for global liquidity conditions, with a declining VIX representing abundant global liquidity, and vice versa. Under a period of elevated global risk or tightened global liquidity, it is conceivable that investors would typically require a higher risk premium. Higher risk premiums translate naturally to a higher CDS spread, which makes exceedance more likely to occur. As a result, we expect changes in VIX to contribute positively to the CDS spread in Eqs. (1) and (2).

2) Bond market volatility (*ΔMOVE*): As the underlying instrument of the sovereign CDS contract is the sovereign bond, it is conceivable that sovereign credit risk is related to aggregate bond market volatility, as represented by the Merrill Lynch's MOVE index. So we include changes in the MOVE index to examine whether exceedance in the EME's CDS spreads is affected by the bond market volatility. If so, we expect changes in the MOVE index to exert a positive impact in our regressions.
3) The US Dollar Index (*ΔUSD*): Druck et al. (2015) provide empirical evidence that a stronger US dollar (USD) has a negative effect on EME's growth through a commodity price channel. As the US dollar strengthens, dollar commodity prices fall and immediately affecting EMEs that are commodity exporters by depressing domestic demand. Druck et al. (2015) further argue that economies that rely on importing capital or inputs for domestic production will also be affected. To measure the movement of the USD, we use its value against a basket of major currencies including the euro (EUR), Japanese yen (JPY), British pound (GBP), Canadian dollar (CAD), Swiss franc (CHF) and Swedish krone (SEK). It is noteworthy that major commodity contracts are quoted in USD, so *ΔUSD* can also be used as a proxy to capture movements in commodity prices. Thus, we expect *ΔUSD* to contribute positively to the CDS spread in the specifications.[13]

We include the following domestic risk factors, and their expected signs are listed as follows:

1) Real GDP growth (*GDP*): Real GDP growth measures the economic performance of an economy. Other things equal, better economic fundamentals should help lower an economy's CDS spread and the chance of exceedance. Thus, we expect a negative coefficient for this variable in the specifications.
2) Inflation rate (*Inflation*): Although a mild inflationary environment is typically conducive to economic growth, hyperinflation is disruptive to financial stability. Aizenman et al. (2013a) find that lower inflation in Asia explains why Asian economies had a significantly lower CDS spreads than the

[13] To test whether the changes in US dollar index would have an opposite effect on oil importers, we therefore also include a dummy variable, which differentiate oil importers from exporters, and its interaction term with *ΔUSD* in the regression. However, we find that both the dummy and interaction term are insignificant at conventional significance levels.

Latin American economies during the GFC.[14] Therefore, we expect a positive coefficient for this variable in the specifications.

3) Net export to GDP (*Trade*): If an economy is persistently running a trade deficit, other things equal, its consumption and investment exceed its production. This implies that the economy is forced to borrow externally to finance its domestic consumption and investment's needs. The accumulated foreign debt would impair the overall repayment ability of the economy. Although trade is beneficial to growth, a higher trade exposure is a leading candidate for crisis transmission in the contagion literature (see Forbes (2012)). Given this ambiguous role of trade in assessing the financial stability of an economy, it is uncertain whether a higher net export to GDP ratio would necessarily imply a lower probability of exceedance.
4) International banks' net claims to GDP (*Banks' claim*): This variable determines whether an economy is a net borrower or lender to the international banking system. If an economy's bank is a net borrower from international banks, an inability to repay the debts may potentially affect the underlying sovereign since investors typically factor-in an expectation of bailouts, as suggested by Aizennman et al. (2013b). However, it is uncertain whether being persistently a net lender to the rest of the world is necessarily beneficial. This is because the economy with large net claims is more vulnerable to external shocks should its counterparty experience repayment difficulties or default. Hence, it is difficult to assess a priori whether higher bank exposure lowers the probability of exceedance.
5) Leverage of banking sector (*Leverage*): Previous studies such as Greenwood et. al (2011), Van Wincoop (2011) and Shin (2012) have shown that shocks to banks can be magnified significantly when banks' leverage is high. If the shock to banks of an economy cannot be mitigated, investors may worry about sovereign debt repayment. Thus, we expect a highly leveraged banking system to contribute positively to sovereign CDS spreads in the specifications. We measure *Leverage* by

[14] We also consider two alternative proxies for *Inflation* which replaces the year-on-year inflation rate with a dummy variable for hyperinflation. The first proxy defines the inflation dummy equal to 1 when inflation is larger than 10% and 0 otherwise. The second proxy defines the inflation dummy equal to 1 when inflation is larger than the country's period average and 0 otherwise. Both specifications do not alter the major regression results.

the asset-to-equity ratio of the banking system.

6) Net Bond and equity flow to GDP (*EPFR Flow*): This variable measures net inflows into an economy's stock and bond markets. This indicator measures the sanguineness of an economy's financial market from the perspective of international investors. An economy may attract inflows into its stock and bond market when the economic outlook is optimistic, and vice versa. As different financial markets within an economy display a high degree of co-movement, we hypothesize that net inflows will lower the likelihood of adverse CDS changes and contribute negatively to CDS spreads in the specifications. This measure can be thought as a proxy to measure flows of hot money.

7) UIP implied long run exchange rate expectation (*ΔFX expect*): The interest rate differential can be viewed as measuring exchange rate expectations given the uncovered interest rate parity (UIP) condition.[15] Although the validity of UIP in the short run is widely debated, Chinn and Meredith (2004) provide empirical evidence that UIP holds in long run. In this study, we use 10-year yield spreads of an economy relative to US Treasuries. We expect a long run depreciation expectation, as proxied by a widening of the interest rate differential, to contribute positively to CDS returns in the specifications.

The recent literature has argued that gross flows rather than net flows are more informative for understanding asset returns. In our empirical analysis, we have tried to replace net trade flows and net bank flows with their gross counterparts but the coefficients for the gross flow variables are not statistically significant.[16] Meanwhile, gross flow data for EPFR Flow are not available and preclude any further analysis.

[15] In the absence of arbitrage opportunities, UIP states that a higher interest rate currency is expected to depreciate relative to the lower interest rate currency.
[16] The details are available upon request.

3. Data

The data for this study includes EMEs' sovereign five-year CDS spreads. EMEs in our sample comprise Brazil, Chile, China, Colombia, Czech Republic, Malaysia, Mexico, Hong Kong, Hungary, Indonesia, Korea, Peru, Poland, Russia, South Africa, the Philippines, Thailand, and Turkey. These EMEs are considered to be important by Remolona et al. (2015) given that they satisfy at least one of the following criteria as of 2014, including: (1) A member of either the IMF's emerging or developing economies or World Bank's low and middle-income countries; (2) Constituents of Barclays, JP Morgan, Markit or Merrill Lynch emerging-market government bond indices; and (3) Stock of public debt exceeding USD 10 billion or long-term sovereign credit rating above BB/Ba. We obtain the EME CDS spreads from Bloomberg.

Data for global risk factors such as *ΔVIX, ΔUSD, ΔMOVE* and *ΔFX expect* are downloaded from Bloomberg. Data for domestic risk factors are obtained from different sources. GDP and inflation figures are from national statistics agencies consolidated by Bloomberg. Export and import data are obtained from IMF Direction of Trade Statistics (DOTS) database. International banking net claims is downloaded from the Bank for International Settlements. Banks' leverage is measured by the aggregate assets to equity ratio in the banking system which is based on the locally incorporated bank's balance sheet data downloaded from Bankscope database. Fund flows to EMEs' stock and bond markets are compiled by EPFR Global. According to EPFR Global, the monthly country fund flow data estimates the fund flows into or out of a country's stock and bond markets, regardless whether the funds are domiciled in onshore or offshore markets.[17]

Estimation is at a weekly frequency. We use Friday's closing price for the higher frequency variables

[17] According to EPFR Global, the country fund flows measures the net change in the fund size and investment destination of equity and bond funds worldwide. The fund coverage includes mutual funds, both open-ended and closed-end funds, Exchange Traded Funds and Variable Annuity/Insurance-Linked Funds.

(i.e., *ΔVIX, ΔMOVE* and *ΔFX expect*) to compute the weekly changes. Data for lower frequency variables are carried forward in each week and replaced when new information becomes available.[18] The sample period spans January 2005 to December 2014, providing a maximum of 521 observations. The beginning of the sample period is determined by data availability for the CDS spreads.

4. Empirical results

4.1 The relative importance of global and domestic risk factors

We set the threshold for identifying exceedance at the 95th percentile of the historical distribution of sovereign CDS spreads.[19] We also consider the zero spread, 50th and 90th percentiles as three alterative thresholds. The threshold for the zero spread and 50th percentile is used to assess the factors' contribution under a general increase in sovereign credit risk (or namely mean risk), while the threshold of the 90th and 95th percentile is used to assess the factors' contributions under tail risk.

Table 1 reports the estimates of the coefficients in Eq. (1) and the in percentage change in the odds for each threshold level. We find that both global and domestic risk factors are important in explaining sovereign credit risk, with explanatory power increasing with the threshold level. Empirically speaking, under mean risk, five variables including *ΔVIX, ΔMOVE, ΔUSD, EPFR Flow* and *ΔFX expect* are statistically significant at the 5% level with the expected sign. However, under tail risk, some domestic risk factors including *GDP, inflation* and *Leverage* that were previously insignificant are now significant at the 5% level with the expected sign. Moreover, we find that sovereign credit risk is increasingly sensitive to changes in some global and domestic risk factors under the tail risk. In particular, the odds ratio of *ΔVIX* is only 88% under mean risk, but it escalates sharply to 219% under tail risk. Moreover, the odds ratio of *ΔUSD* under tail risk is also significant and reaches 61%. This could be explained by

[18] *Trade* and *EPFR flow* are in monthly frequency, *Bank's claim* is quarterly frequency and *Leverage* is in annual frequency.
[19] Actual count of exceedance drops significantly when the threshold level is set at 99%. By definition, we would have only 6 exceedances out of the 521 observations for each economy. Hence, we opt to skip it for our empirical analysis.

the wake-up call hypothesis put forward by Goldstein (1998). The wake-up hypothesis postulates that investors would rationally neglect the structural weakness of economies during normal times. However, they will reassess the fundamentals and become more vigilant when new information arrives and triggers a wake-up call, which typically occurs during periods of market distress. Among the group of domestic risk factors, the sensitivity of *GDP* (47%) is found to be largest at the 95th percentile level, followed by *EPFR Flow* (35%), *ΔFX expect* (31%), *inflation* (17%), and *Leverage* (14%). Except for *ΔFX expect*, the sensitivities for other domestic risk factors are higher than those estimated under mean risk.[20] We also notice that model fit is better under tail risk, as illustrated by a higher Pseudo R-squared of the regressions.

The second finding of our paper is that most of risk factors have a larger impact on sovereign tail risk in the post-crisis period than in the pre-crisis period. As the effect of the factors is most pronounced under the tail risk, we focus on the 95th percentile level only. The upper and lower parts of Table 2 report the parameter estimates for pre and post-crisis periods respectively. Except for trade and banks' claim, all variables are estimated to be significant in the post-crisis period and largely consistent with the estimates reported in Table 1. *ΔVIX* has the largest sensitivity (218%), followed by *ΔUSD* (62%), *Leverage* (59%), *GDP* (44%), *EPFR Flow* (37%), *inflation* (23%), *ΔFX expect* (21%), and *ΔMOVE* (14%). Among these variables, the sensitivity of sovereign credit risk to *ΔVIX, GDP, Leverage, EPFR Flow* and *ΔFX expect* is found to be significantly higher (in absolute value) as suggested by the Wald test.[21] The higher sensitivity to *ΔVIX* post-crisis appears to support the arguments by Rajan (2014) that many EMEs have now become more sensitive to US monetary policy due to spillovers of US unconventional monetary policy. One of possible reason for the stronger effect of *ΔVIX* in the post-crisis period is that local banks in EMEs have become more exposed to global shocks due to their increased inter-linkages with global banks amid abundant global liquidity conditions after the GFC (see

[20] The weakening of *ΔFX expect* the tail may probably reflect its explanatory power is overshadowed by global risk factors, as well as other domestic risk factors.

[21] For each factor, we use the same standard deviation for the whole period to calculate the odds ratios such that the ratios are comparable for the pre-and post-crisis periods.

Bruno and Shin (2015) and Rey (2015)).

4.2 Model performance

To assess the in-sample performance of our model, we first calculate the in-sample estimated odds and then the probability of tail risk by simulating Eq. (2). The resulting time-series average is plotted in the top panel of Figure 1. As a comparison, we show plot the actual percentage of exceedance for the average EME in the lower panel. As can be seen, the average predicted probability generally moves in tandem with the actual percentage of exceedance. Moreover, the estimated probability registered a notable spike in the five crisis periods, which indicates the model is capable of capturing extreme events in the sovereign CDS market.

For the individual economy performance, we report the estimated probability of each economy in each of the five crisis episodes and the full post-crisis period and in Table 3. For each crisis episode, we also highlight the economies that have experienced exceedance historically and mark the corresponding probability in boldface. We can see the model is capable of capturing individual economic performance as the bold probabilities are generally larger. We can also check the average performance of our model during each episode by examining the average probability in the bottom row of Table 3. The estimated probability is found to be the largest in the GFC episode (100%), followed by Greece's bailout (97.7%), the Euro debt crisis (71.3%), the Russian oil crisis (39.3%) and the QE tapering tantrum (29.5%). The lower estimated probability in the QE tapering tantrum is likely because of the absence of a sudden surge in ΔVIX during the episode.[22] However, as the probability increases sharply from less than 1% in the three weeks prior to the tapering announcement (see Figure 1), this estimated probability should be considered large enough to signal a crisis. The last column of table 3

[22] As a reference, in the week that Ben S. Bernanke told Congress the Fed may cut the pace of bond purchases in May 2013, and the subsequent week followed, VIX only increased by 1.5 and 2.3 respectively. The change is mild compared to the double-digit change in VIX observed during the GFC.

counts the number of actual exceedance for each economy during the post-crisis period, while the adjacent figures denote the average estimated probabilities conditional on these actual exceedance counts. Given that the economy-wide average probability for the post-crisis period is found to be material at 42.9%, this suggests that our model has a reasonable explanatory power for sovereign tail risk.

4.3 Attribution of tail risks over time

The coefficient analysis in subsection 4.1 assesses the marginal impact of each of global and domestic risk factor holding other variables constant. To shed light on how these factors performed under tail risk in each of the selected crisis episodes, we estimate a factor attribution by decomposing the estimated odds found in subsection 4.2. For comparison, we also estimate a factor attribution under mean risk.

Figure 2 shows the factor attributions under mean risk (left panel) and tail risk (right panel) under the five crisis episodes. The percentage reported next to each economy is the total share of global risk factors contributing to the odds (in logarithm), which is the sum of all global risk factors' contribution in absolute terms divided by the sum of all the factors' contribution and the fixed effect in absolute terms. We use this percentage to rank the order of the listed economies in each of the charts accordingly. This percentage measures to what extent global risk factors explain the total variations of the estimated odds ratio. All insignificant factors, together with the fixed effect terms are grouped together in the category "Others" shown in the chart.

During the GFC, global risk factors explain the total variation of the estimated odds substantially under mean risk (left panel). The share of global risk factors of all EMEs is 78% on average (Figure 2a), with a range of between 64% and 87%. *VIX* has the largest contribution to the total variation in all EMEs among all risk factors. The contribution of domestic risk factors is significant, but their total contribution remains much lower than that of global risk factors. However, the share of global risk factors declines notably under tail risk (right panel), with the average share edging down to 59% (Figure 2b). *VIX* is again the risk factor contributing the most to the total variation but leverage also contributes notably in some EMEs.

In other crisis episodes, the contribution of global risk factors at the tail risk is also much smaller than under mean risk. The share of global risk factors as indicated by the average percentage for all EMEs is 56% (Figure 2d), 42% (Figure 2f), 21% (Figure 2h), and 37% (Figure 2i) for in the Greece bailout, euro debt crisis, QE tapering tantrum, and Russian oil crisis respectively. Except for the Greece bailout episode, *VIX* is no longer the largest risk factor for the EMEs, instead *Leverage* makes the largest contribution for most of the EMEs. Hence, the third finding of our paper is that while global risk factors play a key role for EMEs' sovereign credit risk, domestic risk factors can also be more important for explaining sovereign tail risk in EMEs.

5. Conclusion

Based on experience of the EMEs, this paper investigates the determinants of sovereign tail risk. Using a panel logistic regression, we find that both domestic and global risk factors are more important for explaining sovereign credit risk at a higher threshold level and become more important after the GFC. Global risk appetite, US dollar appreciation, banking sector leverage, and economic growth are key risk factors of sovereign tail risk in the post-crisis period. Comparing the relative importance of significant risk factors in the five crisis episodes, we find that global risk factors play a more important role in explaining the sovereign tail risk during the GFC and Greece bailout, while domestic risk factors explain more of the change in sovereign risk during the European debt crisis, the QE tapering tantrum, and the Russia oil crisis. This result reflects that while global risk factors play a key role in propagating financial shocks amongst EMEs, domestic risk factors can be more important for explaining sovereign tail risk among EMEs.

Our results have important policy implications for EMEs. Against the backdrop of increasing global stock market volatility and an expected US dollar appreciation, the normalisation of monetary policies in advanced economies may generate significant headwinds for EMEs, particularly for those economies with higher banking sector leverage and weaker macroeconomic fundamentals. To ensure a tranquil transition, EMEs should concentrate on macroprudential policies aimed at limiting banks' leverage and improving economic fundamentals to help lessen the adverse fallout from external risk developments.[23]

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[23] See Galati and Moessner (2013) for a review of macroprudential policies and its effectiveness in dealing with systemic risk arising from a leveraged banking system.

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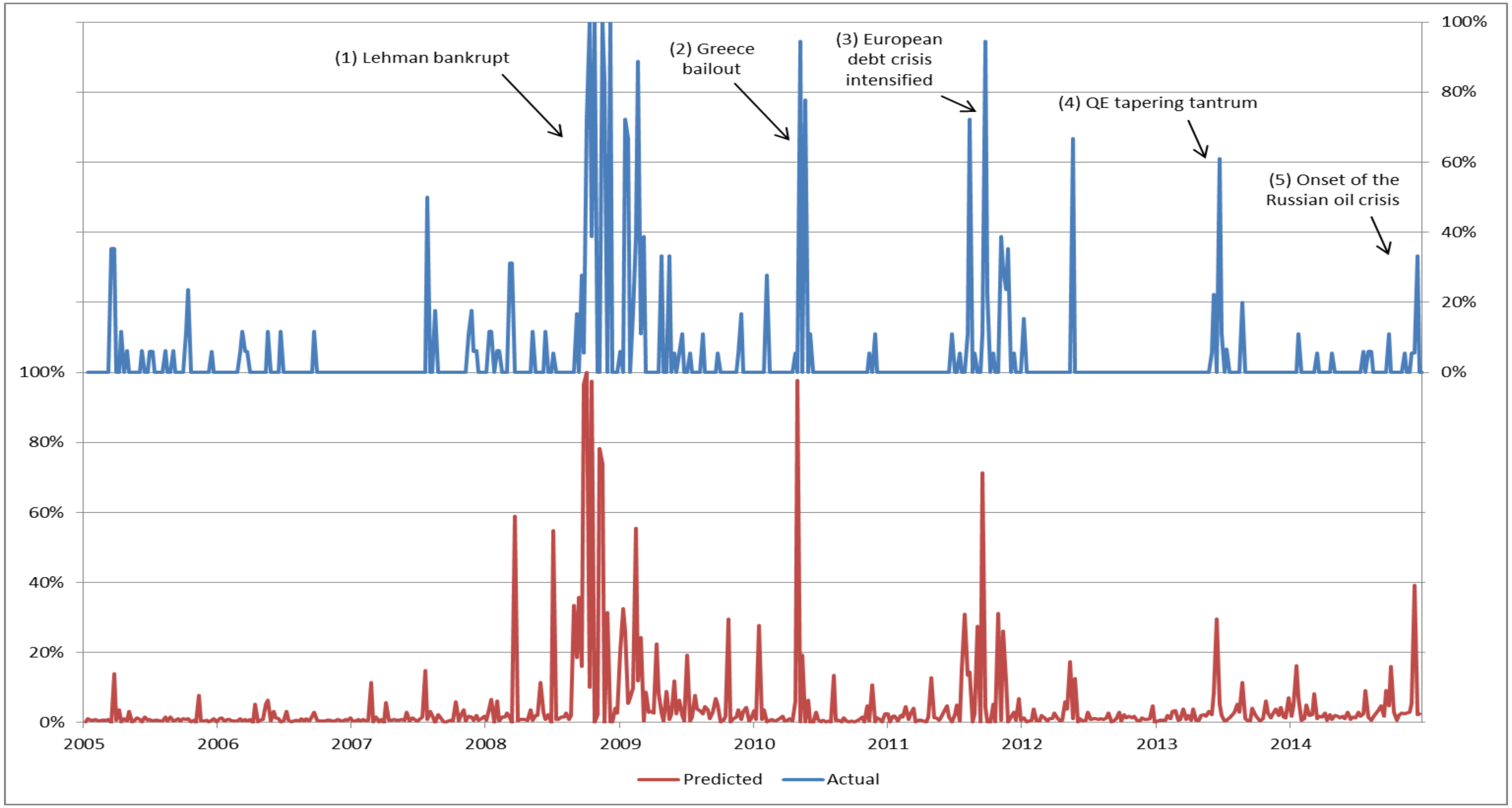
Figure 1 Actual exceedance and estimated probabilities for the average EME

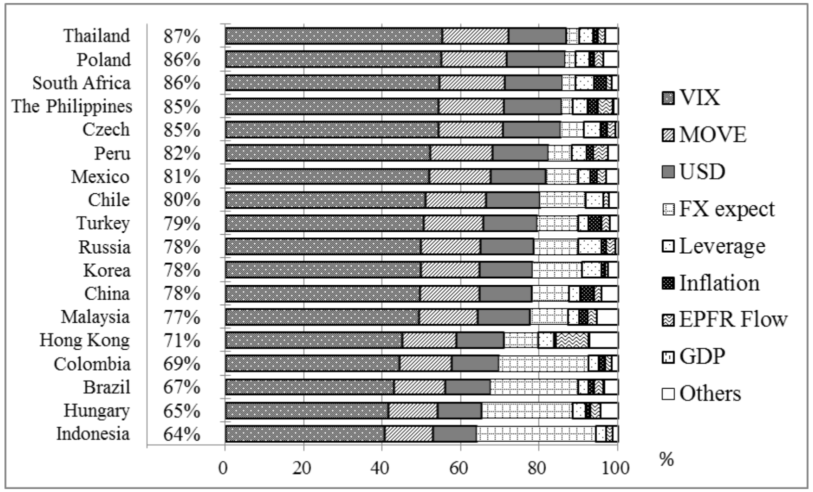


Notes: Actual exceedance is computed as dividing the total count of exceedance for all EMEs in a particular week by the number of EMEs. The estimated probability is found by averaging each EME's predicted probability from Eq. (2).

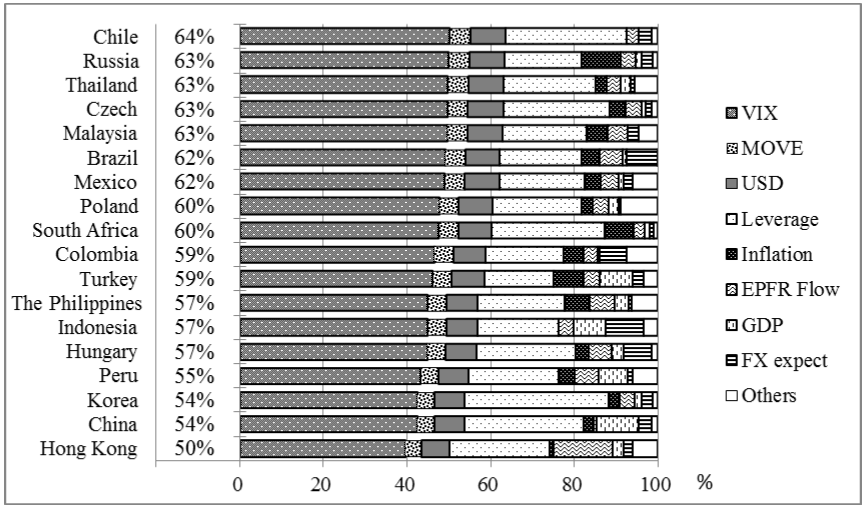
Figure 2 Attributions of risk factors under different risk levels in each of the crisis episode

mean risk (positive change in CDS spreads)	*tail risk (change in CDS spreads exceeding 95th percentile)*

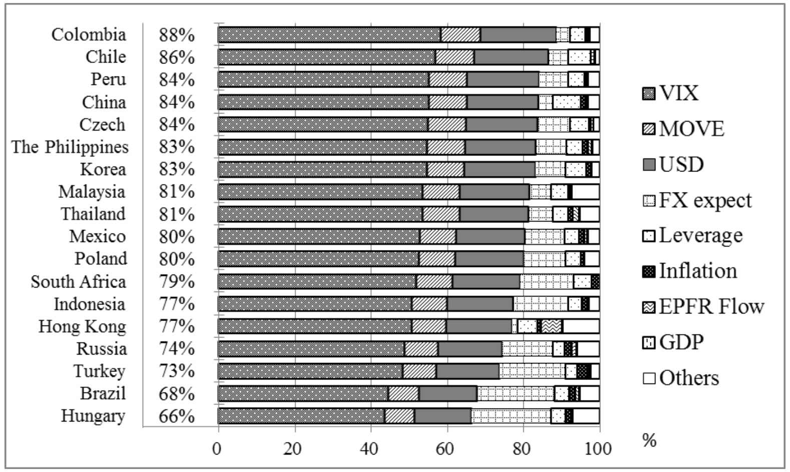
(a) GFC (78%)



(b) GFC (59%)



(c) Greece bailout (79%)



(d) Greece bailout (56%)

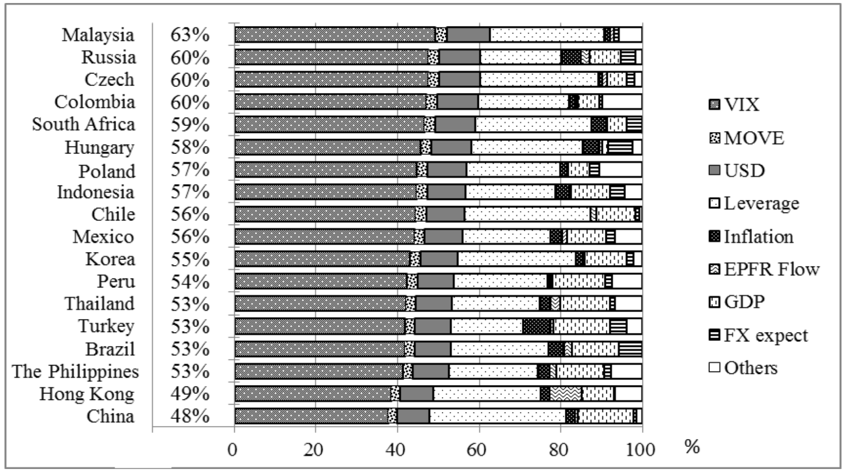
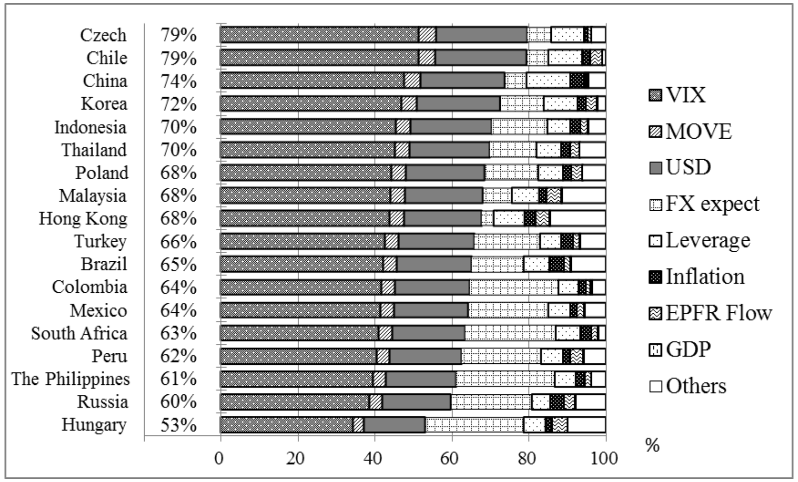


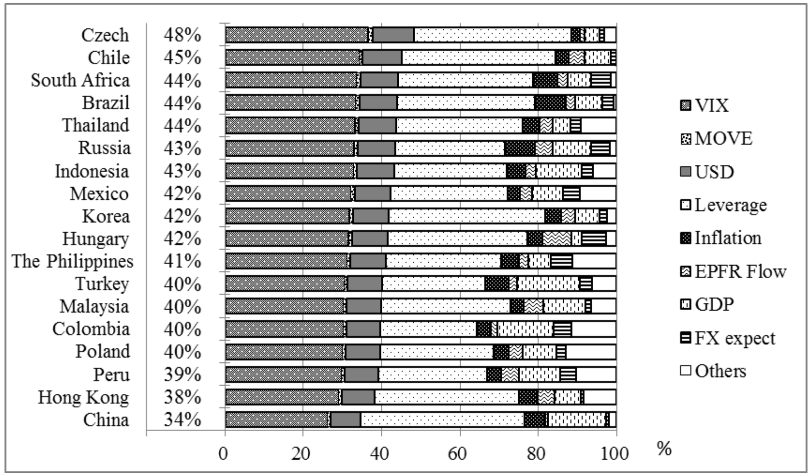
Figure 2 (cont')

mean risk (positive change in CDS spreads)	*tail risk (change in CDS spreads exceeding 95th percentile)*

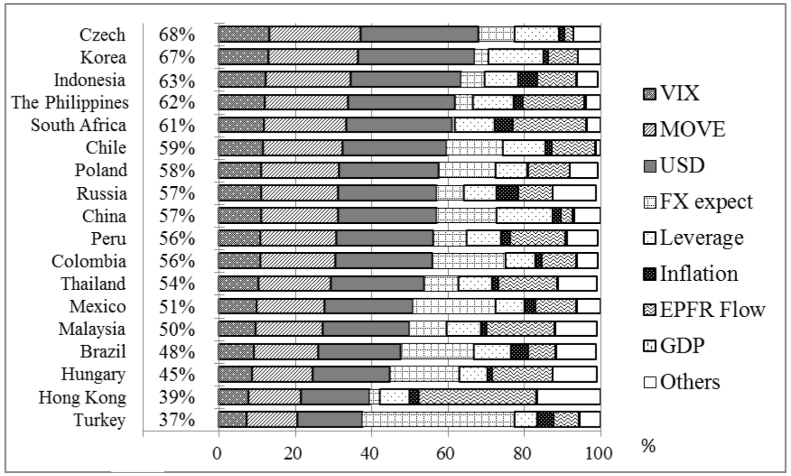
(e) European debt crisis (67%)



(f) European debt crisis (42%)



(g) QE tapering tanturm (55%)



(h) QE tapering tanturm (21%)

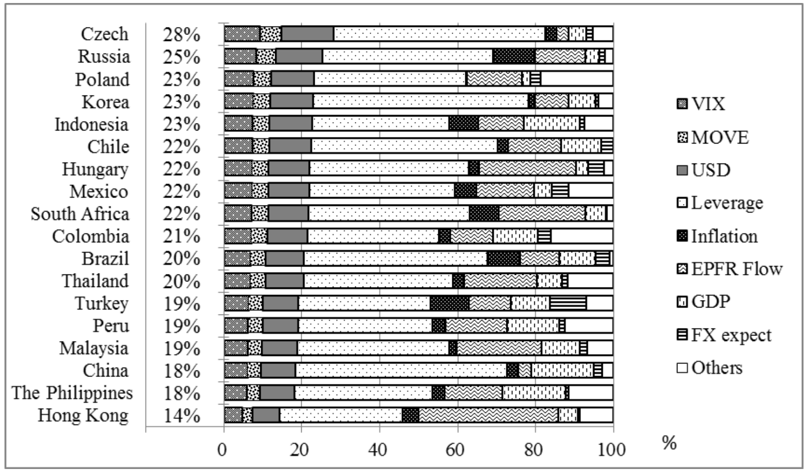
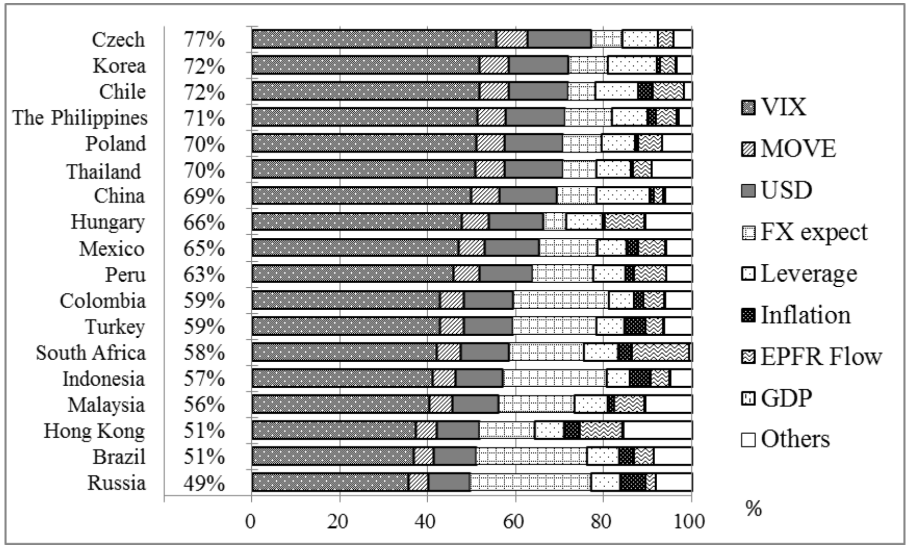
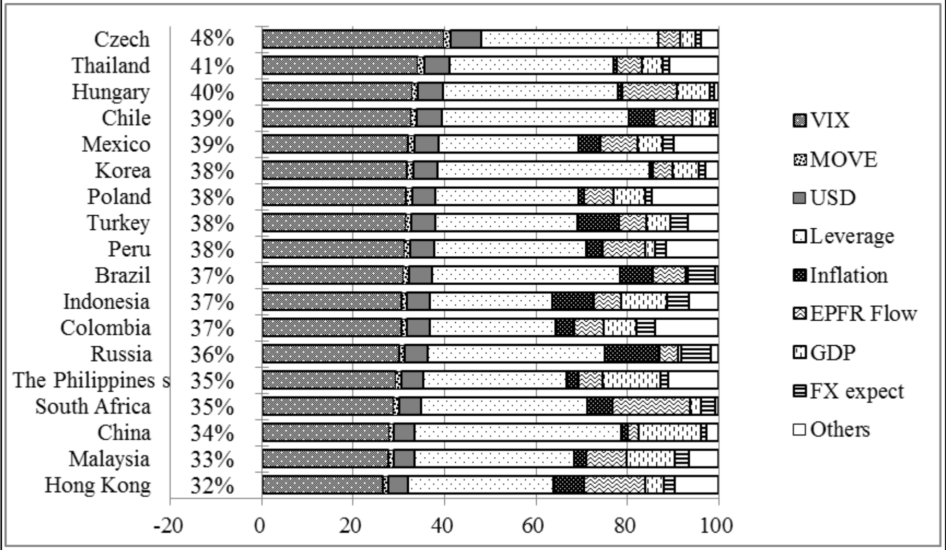


Figure 2 (cont')

mean risk (positive change in CDS spreads)	*tail risk (change in CDS spreads exceeding 95th percentile)*
(i) Russian oil crisis (63%)	(j) Russian oil crisis (37%)





Note: The figures in the parenthesis denote the average share of global risk factors amongst the EMEs

Table 1 Estimates of the panel logistic regression specified in Eq. (1) at different levels of risk

Threshold	Zero Spread		50th percentile		90th percentile		95th percentile	
Risk level	Mean risk		Mean risk		Tail risk		Tail risk	
	Coeff.	%change in odds[1]	Coeff.	%change in odds[1]	Coeff.	%change in odds[1]	Coeff.	%change in odds[1]
Full period (2005-2014)								
ΔVIX	0.184*** (0.010)	88%	0.185*** (0.010)	89%	0.274*** (0.02)	157%	0.337*** (0.020)	219%
ΔMOVE	0.021*** (0.003)	22%	0.019*** (0.003)	20%	0.027*** (0.004)	30%	0.017*** (0.005)	18%
ΔUSD	0.363*** (0.031)	40%	0.363*** (0.031)	40%	0.490*** (0.051)	57%	0.516*** (0.067)	61%
GDP	-0.008 (0.009)	-2%	-0.002 (0.009)	-1%	-0.178*** (0.014)	-40%	-0.222*** (0.019)	-47%
Inflation	0.025* (0.015)	5%	0.009 (0.015)	2%	0.109*** (0.025)	22%	0.083** (0.036)	17%
Trade	-1.165 (0.743)	-4%	-1.367* (0.744)	-5%	2.103 (1.479)	8%	-0.319 (2.345)	-1%
Banks' claim	-0.294 (0.176)	-2%	-0.258 (0.176)	-2%	-0.005 (0.330)	0%	-0.215 (0.469)	-2%
Leverage	0.005 (0.017)	1%	0.022 (0.017)	3%	0.031 (0.033)	4%	0.098** (0.048)	14%
EPFR Flow	-15.014*** (2.025)	-16%	-14.485*** (2.028)	-15%	-31.843*** (3.802)	-30%	-37.659*** (4.968)	-35%
ΔFX expect	1.531*** (0.068)	50%	1.476*** (0.068)	48%	1.626*** (0.096)	54%	1.008*** (0.115)	31%
Country Fixed Effect	Y		Y		Y		Y	
Pseudo R2	0.1258		0.1231		0.2973		0.3933	

Notes: (1) $\%\text{ change in odds} = \exp(\beta_X \times \Delta x) - 1$ where β_X is the coefficient of the risk factor *X* and Δx is a one-SD change in the risk factor *X*. (2) ***, ** and * indicate significance at 1%, 5% and 10% levels respectively.

Table 2 Estimates of the panel logistic regression specified in Eq. (2) at the 95th percentile

	Coeff.	%change in odds[1,2]	Wald test[24] (p-value)
Pre-crisis (2005-Aug2008)			
ΔVIX	0.219*** (0.063)	113%	
ΔMOVE	0.039** (0.015)	46%	
ΔUSD	0.357* (0.210)	39%	
GDP	-0.022 (0.074)	-6%	
Inflation	0.183** (0.078)	40%	
Trade	-5.133 (3.709)	-18%	
Banks' claim	-0. 430 (1.224)	-3%	
Leverage	0.137** (0.058)	20%	
EPFR Flow	0.487 (20.390)	1%	
ΔFX expect	1.796*** (0.337)	61%	
Post-crisis (Sep2008-2014)			
ΔVIX	0.335*** (0.022)	218%	0.08*
ΔMOVE	0.014** (0.005)	14%	0.11
ΔUSD	0.523*** (0.073)	62%	0.45
GDP	-0.205*** (0.022)	-44%	0.01**
Inflation	0.110*** (0.040)	23%	0.37
Trade	1.388 (2.533)	5%	0.10
Banks' claim	-0.404 (0.495)	-3%	0.98
Leverage	0.348*** (0.067)	59%	0.00***
EPFR Flow	-41.127*** (5.258)	-37%	0.05***
ΔFX expect	0.705*** (0.125)	21%	0.00***
Country Fixed Effect		Y	
Pseudo R2		0.4129	

Notes: (1) $\%\ \text{change in odds} = \exp(\beta_X \times \Delta x) - 1$ where β_X is the coefficient of the risk factor *X* and Δx is a one-SD change in the risk factor *X*; (2) In calculating the odd ratios in both pre-and post-crisis period, we use the full period standard deviation of the risk factors to facilitate comparison;(3) ***, ** and * indicate significance at 1%, 5% and 10% levels respectively.

[24] This reports the probability of rejecting the null hypothesis that pre-crisis estimate of the explanatory variables is different from the respective post-crisis estimate.

Table 3 Predicted probability for EME in the post-crisis period based on the specification for the post-crisis period in Eq.(2)

	GFC (Oct 2008 wk2)	Greece bailout (May 2010 wk1)	Euro debt crisis (Sep 2011 wk4)	QE tapering tantrum (Jun 2013 wk3)	Russian oil crisis (Dec 2014 wk2)	Full post-crisis period (Sep 2008 - Dec 2014)	
Economy	Estimated probability					Average probability	Exceedance count
Brazil	**100.0**	**97.8**	**73.4**	**31.4**	**69.3**	49.1	17
Chile	**99.9**	**97.7**	**69.9**	**13.6**	42.8	35.2	22
China	**99.9**	**98.9**	**81.2**	16.7	28.3	39.1	23
Colombia	**100.0**	**98.5**	**60.1**	**21.0**	**37.8**	49.2	15
Czech	**100.0**	**98.0**	**62.4**	11.3	10.3	36.9	21
Hong Kong	**100.0**	**98.8**	59.0	**77.9**	37.0	45.4	22
Hungary	**100.0**	**99.4**	**90.0**	**40.7**	21.0	45.8	25
Indonesia	**100.0**	**97.2**	**55.5**	**10.3**	24.7	25.1	19
Korea	**100.0**	**96.7**	**77.7**	17.6	30.6	51.5	23
Malaysia	**100.0**	**99.2**	**75.3**	**37.8**	43.5	39.9	22
Mexico	**100.0**	**97.8**	**74.2**	**40.2**	**37.5**	46.7	22
Peru	**100.0**	**95.8**	**79.9**	**26.9**	**60.7**	48.8	17
Philippines	**100.0**	**96.3**	**84.5**	21.8	21.9	54.5	16
Poland	**100.0**	**99.1**	**82.0**	37.7	27.8	36.7	25
Russia	**100.0**	**97.2**	**65.3**	**23.5**	**75.5**	40.3	26
South Africa	**100.0**	**99.0**	**75.6**	**36.5**	**76.8**	43.0	22
Thailand	**100.0**	97.5	**81.9**	34.7	30.2	41.8	21
Turkey	**100.0**	**94.3**	**34.5**	**31.5**	32.1	44.0	18
Column average/ Total count	100	97.7	71.3	29.5	39.3	42.9	376

Note: Bold probability indicates the corresponding economy has experienced exceedance in that crisis episode. The average probability for each economy is conditional on whether the economy has experienced exceedance historically.

Annex 1 Variables used in Eq. (1)

Variable	*Definition*	*Source*
Dependent variable		
Y_{it}	Equal to one when the weekly changes in the sovereign CDS spreads fall in the worst 5% tail of its historical distribution	*Bloomberg*
Global risk factors		
ΔVIX	Weekly changes in CBOE Volatility Index	*Bloomberg*
ΔMOVE	Weekly changes in the Merrill Lynch's MOVE Index	*Bloomberg*
ΔUSD	Weekly changes in the US spot dollar index	*Bloomberg*
Domestic risk factors		
GDP	Year-on-year real GDP growth	*Bloomberg*
Inflation	Year-on-year inflation rate	*Bloomberg*
Trade	(Export – Import) / GDP	*IMF DOTS*
Banks' claim	(External claims – External liabilities) / GDP	*BIS Statistics*[25]
Leverage	Average asset-to-equity ratios of banks	*Bankscope*
EPFR Flow	Country net flow / GDP	*EPFR*
ΔFX expect	Weekly changes in the spread of 10-year government bond yields over 10-year US Treasury yield	*Bloomberg*

[25] BIS locational banking statistics. Table A3.1 of Cross-border positions, by residence and sector of counterparty