Currency Returns, Credit Risk and its Proximity: Evidence from Sovereign Credit Default Swap*

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Abstract This paper examines whether credit risk and its proximity are priced in currency returns by making use of information in the term structure of sovereign credit default swap (CDS). Building upon and modifying a CDS pricing model, we construct two risk measures explaining different aspects of risk perception – "risk level", measured by the level of CDS curve, represents whether the expected loss given credit events is high or low, and "risk proximity", measured by the slope of CDS curve, captures how soon a specific credit event is likely to be materialized. Combining with asset pricing models for defaultable bonds and exchange rate, we set up the model where exchange rate is determined by credit risk level and proximity. Using a broad data set between 2004 and 2017 for 20 countries, we show that risk level and proximity individually can explain considerable amount of variation in currency returns and two risk measures together improves the predictive ability over a single CDS spread. Comparing the two, risk level broadly plays a stronger role during normal times, while risk proximity gains its significance when financial crisis is near in time. These findings suggest that not only credit risk level but also its proximity should be considered to better understand the exchange rate dynamics.

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1 Introduction

A large literature has documented the role of risk premium in explaining currency returns. As currency can be viewed as a class of financial assets in international portfolios, systematic sources of risk drive currency returns both across currencies and over time. Since investors with risky currencies should be compensated for bearing risk, whether risk is high or low – "risk level"– forecasts returns to holding that currency. Another aspect of risk that investors are aware of is whether risk is near or far in time – the so-called "risk proximity".[1] If a specific risky event is likely to be realized anytime soon, withdrawal of investment and portfolio re-balancing cause changes in the value of currency. Although both aspects of risk are perceived by investors and thus priced in currency returns, little attention has been paid to "risk proximity". This paper aims to evaluate the roles of these two different aspects of risk in explaining the currency movements by using the information embedded in the term structure of sovereign credit default swap.

Sovereign credit default swap (CDS) is a bilateral Over-the-Counter (OTC) insurance contract offering protection against the default of a referenced sovereign government. Protection buyer purchases insurance against contingent credit events by paying an annuity premium quarterly or bi-annually and protection seller compensates buyers for the losses given credit events.[2] Similar to other insurance contracts, CDS premium or spread naturally provides information about the riskiness of a referenced entity, in our case a sovereign.

Sovereign credit risk is closely related to currency risk. Intuitively, one of the biggest risk when holding financial assets issued in foreign currency is sovereign credit risk. Credit event such as a default may trigger a collapse of the banking system of a country, causing enormous losses on the value of assets denominated in that currency. Under floating exchange rate regime and free capital flow, obviously the price of insurance against credit events measures sovereign and currency risk well. Many researches empirically find that sovereign CDS spread reflects the market pricing of time-varying systematic risk from various origins. Pan and Singleton (2008) and Longstaff et al. (2011) show that global risk is a main driver of CDS spread, while Remolona et al. (2008) argue that local risk is also an important determinant. Stability of domestic financial system is also found to affect the CDS spread (Acharya et al., 2013).

[1] The term "risk proximity" is often used in risk management literature.

[2] In practice, there is no default in government bond. Instead, International Swap and Derivative Association (ISDA) references four types of credit events: acceleration, failure to pay, restructuring, and repudiation. Sovereign CDS has been increasing in use from early 2000s and as such, policy makers, regulators and investors monitor CDS spreads to gauge national financial stability. See Appendix for details about contractual provisions and statistics.

Sovereign CDS spread has advantage over other risk measures because it is directly observable. As currency risk is not observable, there have been several alternative approaches to circumvent this issue. Pioneered by Lustig and Verdelhan (2007), many finance literature on the carry-trade strategy consider systematic exchange risk as unobserved common factor.[3] They empirically show the portfolio constructed by the carry-trade strategy yields high returns due to latent risk measures. Another approach estimates currency risk by borrowing risk information from the other asset classes. Bekaert et al. (2007) point out that risk factors driving the premiums in the term structure of interest rates may also drive the risk premium in currency returns. Similarly, Chen et al. (2017) theoretically and empirically show that bond term premiums, which are separated out from the yield curve, are linked to currency risk premiums. Compared to these risk measures, sovereign CDS spread, by nature, is free from issues related to nonobservance and estimation because it is an observable price of credit risk determined by the interaction of protection buyers and sellers in the market. Recent researches in the aftermath of major global crises consider sovereign CDS as risk measure and relate to the carry-trade returns (Coudert and Mignon, 2013; Corte et al., 2014).[4]

Another useful feature of sovereign CDS to be pointed out is its term structure. There exist different sovereign CDS contract tenors from 1- to 10-years and all the tenors are actively traded in the market, unlike corporate CDS which is mostly concentrated in 5-year tenor contract.[5] Borrowing the concept of bond yield curve, we can construct the term structure of sovereign CDS and define CDS curve as CDS spreads against tenors. We pay attention to the term structure because it delivers more useful information over an single asset price as proven from recent researches. They attempt to explain currency movements in the net present value (NPV) framework by using the information from the term structures. Clarida et al. (2003) show that the term structure of FX forward premiums succeeds in predicting future spot exchange rates, while a single forward rate fails. Similarly, Chen and Gwati (2014) find that FX option term structure contains information about higher moments in exchange rate dynamics and helps forecast the currency returns. For the term structure of interest rates, as it embodies information about the time-varying risk as well as the expectation about future macroeconomic fundamentals, cross-country yield curve differences are examined to explain the currency behavior well (Chen and Tsang, 2013; Chen et al., 2017). While this line of research has shown that the measures extracted from the term structures

[3]The carry-trade is a strategy under which investors take long positions on high-yield currency and short positions on low interest rate currency. Other papers following this approach are Brunnermeier et al. (2009), Farhi et al. (2009), Lustig et al. (2011), Menkhoff et al. (2012) and many.

[4]Earlier work of Reihart (2002) also explores the effect of sovereign default events on currency crises, using credit rating data.

[5]See Appendix for details about statistics.

improve the forecasting ability, studies on what exactly these measures represent and how they drive the currency returns are scant. This paper explicitly investigates the implications of risk measures from CDS term structure and links to exchange rates by building a CDS pricing model and combining with insights from previous researches on exchange rates and defaultable bonds.

We first present the reduced-form model of CDS pricing where CDS spread is determined by current and expected future path of risk-free short rates, default probabilities and fractional losses given default over contract tenor. In order to summarize the term structure of CDS spreads and the shape of CDS curve, level and slope factors are constructed in the spirit of Nelson and Siegel (1987). Graphically, level captures the co-movement of various tenors of CDS spreads and slope reflects the gap between shortest- and longest-tenor CDS spreads. Interpreting the expressions for level and slope of CDS curve based on the CDS pricing model, we coin them as "risk level" and "risk proximity", respectively. Level of CDS curve is expressed as the weighted average of expected losses given default over different horizons. As an increase in level implies that expected losses, regardless of contract tenors, are escalated due to either higher default probabilities or larger loss rates, we can name it as risk level. Slope, defined as shortest- minus longest-tenor CDS spreads, provides information about the timing of credit events. We prove that if default probability in the long-run is higher than in the short-run, CDS curve is upward-sloping and slope is negative. Conversely, inverted CDS curve and positive slope are resulted from relatively higher default probability in the near term. In this regard, higher value of slope captures how soon the credit event is likely to be materialized – the so-called risk proximity.

We then link credit risk measures to currency returns by well-known finance literature. Applying the asset pricing model for defaultable bonds (Duffee and Singleton, 1999), we show that stochastic discount factor or pricing kernel is written as a function of risk-free rates, default probabilities and losses given default. Following Backus et al. (2001) that relate the ratio of home and foreign pricing kernels to exchange rate changes under no arbitrage condition, we iterate forward this relation to get the net present value (NPV) equation where exchange rate is determined by cross-country differences in pricing kernels in the current and future periods. Combining two, we demonstrate that exchange rate is determined by current and expected future path of risk-free rates, default probabilities and losses given default at home and abroad. Since this information is also contained in CDS spreads from short to long tenors and effectively summarized by level and slope of CDS curve, connection between credit risk measures and currency returns can be well-established. Therefore, theoretically, currency return should be determined by both credit risk level and proximity.

For the empirical test, we look at a broad data set of quarterly exchange rate changes against USD, three-month zero-coupon yields and the term structure of sovereign CDS for twenty countries from 2004 to 2017. Our sample countries mostly consist of emerging and developing countries because credit risk is particularly potential in these countries, compared to advanced countries. We first check if level and slope factors capture most of variation in entire sovereign CDS spreads of various tenors. Principal Component Analysis reveals that the first two principal components, which explain almost all of the variation in CDS curve, actually represent graphical level and slope respectively. Then, we proceed to examine the roles of different sets of sovereign credit risk measures including a single CDS spread, level and slope factors in explaining the exchange rate changes. The results confirms the existing findings in the recent finance literature as follows: 1) sovereign credit risk forecasts a large share of subsequent currency returns (Coudert and Mignon, 2013); 2) the effect of risk on currency movements is state-dependent (Clarida et al., 2009 among many) – an increase in sovereign credit risk results in positive currency returns under low volatility state, while leads to low returns or losses under high volatility state[6]; 3) the UIP puzzle is mitigated by reducing the omitted variable problem once incorporating credit risk measures in the regression.

This paper is distinctive in the following dimensions: 1) level and slope factors individually can explain considerable amount of the variation in currency movements; 2) the model with both level and slope factors outperform the model with a single CDS in explanatory power. These findings suggest that not only risk level but also risk proximity matters for currency returns and should not be ignored. Our results are similar to yet distinguished from previous term structure literature. While confirming that the term structure of an asset delivers more useful information about risk in addition to a single asset price, we make a progress by clearly interpreting that new information from the term structure is about different aspects of risk perception of market participants – risk level and proximity. To my knowledge, there has been no attempt to investigate the role of risk proximity in driving asset prices. Considering that investors are sensitive to how soon a bad event is actually likely to happen as well as how much the expected loss is, the concept of risk proximity may be one of the missing pieces in asset pricing model in general; 3) Comparing the role of risk level and proximity, the former explains currency behavior more consistently, while the latter catches up its role near the crises.

[6]Clarida et al.(2009) divide the sample periods into high, medium, low volatility and find that high interest rate currency pays high return during low volatility times, but low return during high volatility times. These results coincide with the findings in Brunnermeier et al. (2009) that under adverse financial market, as the carry-trades are unwound, dramatic depreciation happens for the high interest rate currency.

2 Theoretical Framework

2.1 Price of Credit Default Swap

In order to explore the informational contents contained in the term structure of CDS, we start by evaluating a price at time t of an m-tenor CDS (D_t^m).[7] Building upon and modifying continuous time pricing of CDS in Duffie et. al. (2003), we set up the pricing model in discrete time framework in order to analytically examine the meaning of CDS spreads and its term structure. The premium leg which is the present value of protection buyer's cash flow (V_t^{PB}) is given by[8]

$$V_t^{PB} = D_t^m + h_t exp(-r_t)0 + (1 - h_t) exp(-r_t) E_t(V_{t+1}^{PB}) \tag{1}$$

where r_t is risk-free short rate at time t, h_t is default probability between time t and $t+1$ conditional on information up to time t, and l_t is expected fractional loss at $t+1$ conditional on information up to time t. The CDS premium (D_t^m) is paid at the beginning of time t for the protection. If a credit event is triggered between time t and $t+1$, the contract is terminated and no more premium is paid. If not, the contract goes on to next period. Iterating forward the eq.(1), we get[9]

$$V_t^{PB} = D_t^m E_t \left[\sum_{j=0}^{m} exp\left(-\sum_{k=0}^{j} (r_{t+k-1} + h_{t+k-1}) \right) \right] \tag{2}$$

On the other hand, the contingent payment leg which is the present value of protection seller's cash flow (V_t^{PS}) is given by

$$V_t^{PS} = h_t exp(-r_t) l_t + (1 - h_t) exp(-r_t) E_t(V_{t+1}^{PS}) \tag{3}$$

If credit event is materialized between time t and $t+1$, the protection seller pays the notional amount equivalent to the loss given event at the end of time $t+1$, terminating the contract.

[7] We use the term "tenor" instead of "maturity" for CDS contract because the length of CDS contract is shorter than or equal to underlying bond maturity and the cash flow of CDS is fundamentally different from that of bond.

[8] We assume without loss of generality that CDS premium is paid on a yearly basis. This assumption enables us to relate annualized CDS spreads to annualized exchange rate changes and interest rate. However, the model can easily be translated into bi-annual or quarterly payment schemes.

[9] We define $r_{t-1} = h_{t-1} = 0$ and use the approximation of $exp(c) \simeq 1 + c$, for small c.

Iterating forward the eq.(3), we get

$$V_t^{PS} = E_t\left[\sum_{j=1}^{m} exp\left(-\sum_{k=1}^{j}(r_{t+k-1}+h_{t+k-2})\right)h_{t+j-1}l_{t+j-1}\right] \tag{4}$$

Granted that a fairly priced CDS at time t equates V_t^{PB} and V_t^{PS}, a price at time t of an m-tenor CDS (D_t^m) is expressed as

$$D_t^m = \frac{E_t\left[\sum_{j=1}^{m} exp\left(-\sum_{k=1}^{j}(r_{t+k-1}+h_{t+k-2})\right)h_{t+j-1}l_{t+j-1}\right]}{E_t\left[\sum_{j=0}^{m} exp\left(-\sum_{k=0}^{j}(r_{t+k-1}+h_{t+k-1})\right)\right]} \tag{5}$$

A single CDS spread of tenor m is a function of current and expected future path of risk-free short rates, default probabilities and fractional losses given default over the same tenor. So, we can rewrite the equation using general functional form ($g(.)$) as:

$$D_t^m = g(R_t^m, H_t^m, L_t^m) \tag{6}$$

where $R_t^m = [r_t, E_t r_{t+1}, ..., E_t r_{t+m}]'$, $H_t^m = [h_t, E_t h_{t+1}, ..., E_t h_{t+m}]'$, $L_t^m = [l_t, E_t l_{t+1}, ..., E_t l_{t+m}]'$.

2.2 Risk Level and Risk Proximity

To make use of information embedded in the term structure of CDS in effective and parsimonious way, we describe the shape of CDS curve with level and slope factors, borrowing the idea from bond yield curve model (Nelson and Siegel, 1987 among others).[10] Suppose sovereign CDS has tenors of $m = 1, 2, ..., n$. Level factor is defined as a CDS spread of the longest tenor, $L(D_t) = D_t^n$, and slope factor as the difference in CDS spreads between the shortest- and the longest-tenor, $S(D_t) = D_t^1 - D_t^n$. The meaning of level factor is straightforward. From eq.(5), it represents the weighted average of expected losses given default over short to long horizons. The weights for each period are just different from conventional discount rates. Since expected loss measures whether the risk embedded in that asset is high or low, let us refer to it as "risk level". An increase in level implies expected losses, regardless of contract tenors, are escalated due to either higher default probabilities or larger loss rates.

Now, let's examine the implication of slope factor. To motivate the idea with simple

[10]In Section 3, from Principal Component Analysis, we show that level and slope factors are actually the first two principal components which explain 99% of variation in entire CDS spreads at each time t.

example, we assume there are only two CDS spreads, D_t^1 and D_t^2, determined by:

$$D_t^1 = \frac{exp(-r_t)h_t l_t}{exp(-r_t - h_t)} \tag{7}$$

$$D_t^2 = \frac{exp(-r_t)h_t l_t + E_t[exp(-r_t - r_{t+1} - h_t)h_{t+1}l_{t+1}]}{exp(-r_t - h_t) + E_t[exp(-r_t - h_t - r_{t+1} - h_{t+1})]} \tag{8}$$

If the slope is negative or the CDS curve is upward-sloping, then $D_t^1 < D_t^2$. Simplifying the eq.(7) < (8) with the assumption of $l_t = l_{t+1}$, we obtain $h_t < E_t h_{t+1}$.[11] This implies that default probability next period (between $t+1$ and $t+2$) is expected to be higher than this period (between t and $t+1$). Conversely, for positive slope factor $D_t^1 > D_t^2$, or inverted CDS curve, default probability is relatively higher in the near-term, $h_t > E_t h_{t+1}$.

We derive the general expression which compares two adjacent CDS spreads, D_t^{m-1} and D_t^m for $m = 2, ..., n$. $D_t^{m-1} < D_t^m$ if and only if

$$h_t - E_t h_{t+m} + E_t \left[\sum_{j=1}^{m} exp\left(-\sum_{k=1}^{j} (r_{t+k} + h_{t+k-1}) \right) (h_{t+j} - h_{t+m}) \right] < 0 \tag{9}$$

And $D_t^{m-1} > D_t^m$ if and only if

$$h_t - E_t h_{t+m} + E_t \left[\sum_{j=1}^{m} exp\left(-\sum_{k=1}^{j} (r_{t+k} + h_{t+k-1}) \right) (h_{t+j} - h_{t+m}) \right] > 0 \tag{10}$$

If we assume monotonically increasing CDS spreads over tenors, $D_t^1 < D_t^2 < ... < D_t^n$, then we can prove that it must be $h_t < E_t h_{t+n}$.[12] We can interpret that if slope factor is negative, then default probability in the long-run is higher than that in the short-run. Similarly, with assumption of monotonically decreasing CDS curve, $D_t^1 > D_t^2 > ... > D_t^n$, the positive slope reflects that default is more likely to happen in the short-run compared to the long-run, $h_t > E_t h_{t+n}$. In this regard, higher value of slope measures how near in time a specific credit event is likely to be realized, as we coin this term as "risk proximity".[13]

[11] In credit default swap literature, fractional loss is conventionally assumed to be constant over time because it is determined by fundamentals of a referenced entity and thus estimated by historical recovery rate ($R = 1 - L$) in practice.

[12] Starting from $D_t^1 < D_t^2$ and using the obtained condition $h_t < E_t h_{t+1}$, we obtain the condition for $D_t^2 < D_t^3$ to be $h_t < E_t h_{t+2}$. Continuing this process sequentially to $D_t^{n-1} < D_t^n$, we end up with $h_t < E_t h_{t+n}$.

[13] The term "risk proximity" is often used in the risk management literature.

2.3 Sovereign Credit Risk and Exchange Rates

Consider a price at time t of a one-period zero-coupon government bond (P_t^1) which is subject to default risk (Duffie and Singleton, 1999) given by

$$P_t^1 = exp(-r_t - h_t l_t) \tag{11}$$

Compared to a default-free bond, a defaultable bond is like being priced using the default-adjusted discount rate, which is essentially the nominal short rate: $i_t = r_t + h_t l_t$.[14]

Following many popular models of asset prices, under the absence of arbitrage, we assume that a stochastic discount factor (SDF) or a pricing kernel of home country (M_{t+1}) which prices all assets is conditionally log-normal:

$$M_{t+1} = exp\left(-r_t - h_t l_t - \frac{1}{2}\lambda_t^{'}\lambda_t - \lambda_t^{'}\epsilon_{t+1}\right) \tag{12}$$

The term λ_t is time-varying price of risk associated with the sources of uncertainty ϵ_t. Assuming that the sources of uncertainty are r_t, h_t and l_t, we specify λ_t is a function of these state variables. Equivalently, we obtain a pricing kernel of foreign country (M_{t+1}^*) as

$$M_{t+1}^* = exp\left(-r_t^* - h_t^* l_t^* - \frac{1}{2}\lambda_t^{*'}\lambda_t^* - \lambda_t^{*'}\epsilon_{t+1}^*\right) \tag{13}$$

where λ_t^* is a function of r_t^*, h_t^* and l_t^*.

Now, let's investigate the linkage between sovereign credit risk and exchange rate. Backus et al. (2001) establish the condition under which home asset returns equate foreign asset returns denominated in home currency as[15]

$$\frac{S_{t+1}}{S_t} = \frac{M_{t+1}^*}{M_{t+1}} \tag{14}$$

where S_t is the spot exchange rate of home currency measured as per foreign currency. Defining the log of exchange rate $s_t \equiv logS_t$ and the log of pricing kernels $m_{t+1} \equiv logM_{t+1}$, $m_{t+1}^* \equiv logM_{t+1}^*$, no-arbitrage requires that expected exchange rate change is given by the expectation of difference between the log of foreign and home pricing kernels as specified in eq.(12) and (13), so that

$$E_t s_{t+1} - s_t = E_t(m_{t+1}^* - m_{t+1}) \tag{15}$$

[14] See Duffie and Singleton (1999) for discussion.
[15] See Backus et al. (2001) for discussion.

Iterating eq.(15) forward in terms of s_t, we get a net present value (NPV) equation where exchange rate is determined by the cross-country differences in pricing kernels in the current and the future:

$$
\begin{aligned}
s_t &= E_t \sum_{j=1}^{\infty} (m_{t+j} - m^*_{t+j}) \\
&= E_t \sum_{j=0}^{\infty} \left[-(r_{t+j} + h_{t+j} l_{t+j} - r^*_{t+j} - h^*_{t+j} l^*_{t+j}) - \frac{1}{2} \left(\lambda'_{t+j} \lambda_{t+j} - \lambda^{*'}_{t+j} \lambda^*_{t+j} \right) \right]
\end{aligned} \tag{16}
$$

Assuming that λ_t (λ^*_t) is a function of r_t, h_t, l_t (r^*_t, h^*_t, l^*_t) at each time t, exchange rate at time t depends on current and expected future path of risk-free rates, default probabilities and expected fractional losses at home and abroad. We can express this equation using general functional form ($h(.)$) as:

$$
s_t = h(R_t, H_t, L_t, R^*_t, H^*_t, L^*_t) \tag{17}
$$

where $R_t = [r_t, E_t r_{t+1}, ..., E_t r_{t+\infty}]'$, $H_t = [h_t, E_t h_{t+1}, ..., E_t h_{t+\infty}]'$, $L_t = [l_t, E_t l_{t+1}, ..., E_t l_{t+\infty}]'$, $R^*_t = [r^*_t, E_t r^*_{t+1}, ..., E_t r^*_{t+\infty}]'$, $H^*_t = [h^*_t, E_t h^*_{t+1}, ..., E_t h^*_{t+\infty}]'$ and $L^*_t = [l^*_t, E_t l^*_{t+1}, ..., E_t l^*_{t+\infty}]'$.

2.4 Linking Term Structure of CDS and Exchange Rates

From the eq.(17), we have shown that exchange rate is determined by state vectors $(R_t, H_t, L_t, R^*_t, H^*_t, L^*_t)$. Since sovereign CDS spreads contain information about the same state variables up to their tenors as in the eq.(6), the vectors of home CDS and foreign CDS over entire tenors ($D_t = [D^1_t, D^2_t, ..., D^n_t]'$, $D^*_t = [D^{1,*}_t, D^{2,*}_t, ..., D^{n,*}_t]'$), can be used as proxies for these state vectors. As we demonstrated that level and slope measures effectively summarize the CDS curve and provide more interesting interpretation of risk level and proximity, we propose to use level and slope instead of entire set of CDS spreads. Then, the eq.(17), using different general function ($f(.)$), becomes

$$
s_t = f(L(D_t), S(D_t), L(D^*_t), S(D^*_t)) \tag{18}
$$

Since nominal exchange rate is best approximated by a unit root process empirically, we focus our analyses on exchange rate change, $\Delta s_{t+m} = s_{t+m} - s_t$. So, we conduct the empirical studies to show how level and slope factors of sovereign CDS curve determine subsequent exchange rate changes in the following sections.

3 Basic Empirics

3.1 Data Description

Twenty sample countries are chosen on the basis of two criteria. First, sovereign CDS should be actively traded in the market. We select candidate countries in descending order by the trading volume reported by the Depository Trust and Clearing Corporation (DTCC).[16] Second, among the candidates, we exclude the countries whose exchange rate regime is not floating, based on the IMF Annual Report on Exchange Arrangements and Exchange Restrictions, 2016. Sample countries are Australia(AU), Brazil(BR), Chile(CL), Columbia(CO), Hungary(HU), Iceland(IS), Indonesia(ID), Israel(IL), Japan(JP), Korea(KR), Mexico(MX), Norway(NO), Peru(PE), Philippines(PH), Poland(PL), Romania(RO), South Africa(ZA), Sweden(SE), Thailand(TH), Turkey(TR) and the United States of America(US). Although our samples are mostly emerging and developing countries where sovereign credit risk is especially potential, we have complete set of both advanced and emerging economies over various continents including America, Asia, Europe, and Africa.

The main data we examine consists of monthly observations from January 2004 to June 2017 of the following series:[17] 1) spot exchange rate data: End-of-month exchange rates are obtained from the Bloomberg. We use the logged exchange rate, measured as per-dollar rate. Quarterly exchange rate change is expressed as $\Delta s_{t+3} = s_{t+3} - s_t$ and indicated as annualized percentage. Positive Δs_{t+3} means the depreciation of home currency against the US dollar and negative Δs_{t+3} means the appreciation; 2) zero coupon yield of three-month maturity: End-of-month zero coupon yields as annualized percentage are obtained from the Bloomberg.[18] Then, quarterly excess currency return is computed as $xr_{t+3} = i_t^3 - i_t^{3,US} - \Delta s_{t+3}$. Positive xr_{t+3} implies gain from the trade borrowing from the US and investing in home country and negative xr_{t+3} represents loss; 3) sovereign CDS data: Data on sovereign CDS spread is collected from the Bloomberg and the Datastream. We use sovereign CDS spreads with tenors of 1, 2, 3, 5, 7, 10 years, with USD as currency of denomination and in annuity basis point. CDS spreads are from the last trading day of each month.

Table 1 reports the summary statistics of our sample data. Considering potential structural breaks due to the Great Recession, the sample period is divided by two preliminary

[16] The Depository Trust and Clearing Corporation(DTCC) runs a warehouse for CDS trade confirmations accounting for around 90% of the total market and releases market data on the outstanding notional of CDS trades on a weekly basis.

[17] Sample periods are shorter for some countries due to data availability.

[18] For countries in which zero coupon yield data is not available, three-month interbank rates are obtained from central banks.

break dates – November 2007 and June 2009.[19] For the interpretation purpose, we label three sub-periods divided by two breaks as "Pre-Crisis", "Crisis"and "Post-Crisis". For quarterly exchange rate change Δs_{t+3} in **Panel A**, we observe that all currencies have appreciated before the Crisis except for IDR, JPY and ZAR, and all currencies except JPY have depreciated during the Crisis. This would be consistent with the idea that the US dollar (along the Japanese Yen) is commonly considered safe haven currencies. Behavior after the Crisis is differentiated across countries due to local and domestic events. For example, BRL, COP, HUF and ZAR have depreciated further, while ISK, ILS, KRW have appreciated. The volatility of exchange rate has been increased during the Crisis. After the Crisis, the standard deviation has decreased but still higher than the Pre-Crisis level for some countries reflecting persisted uncertainties. From **Figure 1**, we see episodes of exchange rate volatility, with the spike during the Great Financial Crisis and the European Fiscal Crisis. **Panel B** presents statistics on excess currency returns xr_{t+3}. Similar to exchange rate changes, most of the countries have shown high returns before the Crisis and low returns or losses during the Crisis.

Panel C describes the statistics on interest rate differentials measured by cross-country differences in zero-coupon yield of three-month maturity as home minus US yield $i_t^3 - i_t^{3,US}$. Interest rate of home country is higher than that of the US and their gap has been widened during the Crisis. The volatility is very low, compared to that of exchange rate, implying that interest rate differential is not enough to generate the variation in currency movements and lending support on the view why more volatile variables are needed as explanatory variables in addition.

3.2 Principal Component Analysis of Term Structure of CDS

We describe the evolution of the term structure of sovereign CDS over sample period. **Figure 2** graphically shows sovereign CDS spreads of six different contract tenors. One immediately noticeable feature present in all countries is that all the CDS spreads co-move. During major global events when sovereign credit risk is mounted, CDS spreads jump up regardless of tenors. What is more interesting in this figure is that the gap between short- and long-tenor CDS spreads varies over time. Usually, the long-tenor CDS spread is higher than the short-tenor CDS spread due to longer exposure and higher uncertainty, but the gap becomes narrower or even inverted during the Global Financial Crisis. Level of CDS

[19] According to the NBER, the recession in the US is from December 2007 to June 2009. Although the recession periods in sample countries are not identical, we choose these breaks considering that no country was free from the massive impact of the Global Financial Crisis.

curve explains the co-movement of CDS spreads, while slope describes the difference between the shortest- and the longest-tenor CDS spreads. From this observation, we can draw two lessons: 1) the term structure of sovereign CDS contains more information than a single CDS spread; 2) level and slope of CDS curve summarize the shape of CDS curve well. In the previous section, we theoretically demonstrated that level reflects "risk level "and that slope captures "risk proximity". For example, consider the case of Iceland. As Iceland has experienced the financial crisis that involved the actual default of all three major commercial banks in the last 2008 to 2010, instant sovereign default was highly anticipated in the market, which was reflected in positive slope as well as skyrocketed level.

Now, we perform Principal Component Analysis and analyze that level and slope are indeed important two factors that determine the term structure of sovereign CDS. Let D_t denote the $N \times 1$ vector of sovereign CDS spreads at each time t, Ω be the $N \times N$ covariance matrix of D_t. The principal components are the linear combinations of D_t which account for as much variation in D_t as possible. That is,

$$\begin{aligned} PC_{1t} &= p_1^{'} D_t, \; where \; p_1 : eigenvector \; with \; the \; largest \; eigenvalue \; from \; \Omega \\ PC_{2t} &= p_2^{'} D_t, \; where \; p_2 : eigenvector \; with \; the \; second \; largest \; eigenvalue \; from \; \Omega \end{aligned}$$

The results are reported in **Table 2**. The first two principal components explain around 99% of variation in entire sovereign CDS spreads. The first principal component constitutes 84 - 98%, while the second principal component accounts for 2 - 15%. Due to strong co-movement of six CDS spreads, the large proportion explained by the first principal component is not surprising. Rather, the second principal component explains small but meaningful share of variation in the data. Turning to factor loadings on CDS spreads, the first principal component has roughly constant factor loadings across tenors, indicating that it is "level". On the other hand, the second principal component has positive factor loadings on short tenors and negative factor loadings on long tenors, implying that it is "slope" defined as short minus long tenor CDS. These findings suggest that two principal components coincide with geometrical level and slope of CDS curve as defined in Section 2. **Figure 3** confirms this relationship. Correlation between the first principal component and level is over 0.9 for all the countries and correlation between the second principal component and slope is mostly over 0.8. In the following empirical studies, we use two principal components instead of geometrical level and slope and denote them as "level" factor, $L(D_t)$, and "slope" factor, $S(D_t)$, respectively.[20]

[20]Since $PC_{1t} \approx D_t^{10}$ and $PC_{2t} \approx D_t^1 - D_t^{10}$, whether we use two principal components or literal level and

Table 3 describes the statistics for level and slope factors with potential structural breaks. During the Crisis, level has jumped up and slope has become flatter or even inverted. This implies that investors have perceived that huge loss from the credit event is highly likely to occur in the near future due to the impact from the Global Financial Crisis. In contrast, slope during the Post-Crisis period has quickly become as steep as in the Pre-Crisis period, while level has stayed up high. It can be interpreted that sovereign risk level was still high due to sluggish recovery of real economies and on-going financial uncertainties, but actual credit events were believed not to be realized near in time thanks to international efforts for securing the financial safety nets.

4 Main Results

4.1 Explaining the Currency Returns with Sovereign Credit Risk

We empirically examine whether sovereign credit risk factors perceived at the particular point in time can explain quarterly currency returns as predicted from the reduced-form model developed in Section 2. We also compare the explanatory power of different sets of risk measures: 1) one-year CDS spread, D_t^1; 2) level factor, $L(D_t)$, which captures risk level; 3) slope factor, $S(D_t)$, which implies risk proximity; 4) both level and slope factors, $L(D_t)$ and $S(D_t)$.[21] Specifically, the following regressions are estimated with structural breaks for each currency pairs:[22]

$$\text{Model 1:}\ \ \Delta s_{t+3} = \beta_0 + \beta_1 D_t^1 + \epsilon_{t+3} \tag{19}$$

$$\text{Model 2:}\ \ \Delta s_{t+3} = \beta_0 + \beta_1 L(D_t) + \epsilon_{t+3} \tag{20}$$

$$\text{Model 3:}\ \ \Delta s_{t+3} = \beta_0 + \beta_1 S(D_t) + \epsilon_{t+3} \tag{21}$$

$$\text{Model 4:}\ \ \Delta s_{t+3} = \beta_0 + \beta_1 L(D_t) + \beta_2 S(D_t) + \epsilon_{t+3} \tag{22}$$

slope does not make a big difference to our empirical studies.

[21] In our empirical study, we focus on home sovereign CDS spreads only. One reason is that we assume no default risk in the US, our foreign country. This assumption is realistic in that market participants rarely expect the default in the US assets. The other reason is that data on US sovereign CDS spreads only becomes available in recent years. However, later in this section, we conduct the robustness check by using the cross-country differences in credit risk factors.

[22] Test for endogenous structural breaks in the regression is performed based on Bai and Perron (2003) multiple break tests(with 15% trimming and 5 - 10% significance level). After identifying zero to two breaks, structural break dummy variables for each sub-period are incorporated into the regression.

Table 4 presents p-values from joint Wald test and adjusted R^2s.[23] As shown in the table, p-values are all below 5% with a few exceptions for Israel and Thailand. The hypothesis that sovereign credit risk factors have no information about three-month exchange rate change is strongly rejected, regardless of which set of risk measures are employed. The regressions generate high adjusted R^2s up to 60%. This is quite an impressive portion in light of the near-zero R^2 typical in this literature. We confirm the existing finding that sovereign credit risk accounts for a large share of currency returns (For example, Coudert and Mignon, 2013.).

Comparing the predictive ability of four different models, we first notice that the model with both level and slope factors (Model 4) can explain currency movements better than the model with one-year CDS spread (Model 1) in most countries. This finding lines up with with previous literature that term structures provide more useful information than a single asset price (Clarida et al., 2003; Chen and Tsang, 2013). One-year CDS spread may capture the amount of credit risk in the shortest run, but cannot say anything about the timing of risky events. In contrast, level and slope from the term structure of CDS, which capture both credit risk level and proximity, can together help more comprehensively evaluate the investors' perception of risk and thereby better forecast the currency returns. Another prominent feature is the performance of slope-only model (Model 3). Given that slope factor explains only small portion of the variation in entire CDS spreads as investigated in the Principal Component Analysis, its explanatory power is beyond expectation. This model performs better than one-year CDS model (Model 1) in 9 out of 20 countries and even better than level-only model (Model 2) in 8 out of 20 countries. These results lend support on our argument that foreign currency holders care not only how much of sovereign risk is expected from that currency, but also how near in time the risky event is expected to happen.

We further investigate the relation between credit risk measures and currency returns by employing two-state Markov-Switching model. Although structural break model estimates coefficients in sub-sample periods divided by break dates, the state-dependent relationship between variables might be averaged out in long sub-sample periods. This model is also silent about what each state represents. Alternatively, Markov-Switching model can show the state-dependency more clearly by allowing the regime to switch endogenously by unobserved yet comprehensive state factors. The model specification is as follows:

[23] To complement our analysis of the link between sovereign credit risk and currency movements, we also regress excess currency returns, xr_{t+3} on four sets of risk measures. The results remain qualitatively the same. The results are provided in Appendix.

$$\Delta s_{t+3} = \beta_{0,\xi_t} + \beta_{1,\xi_t} L(D_t) + \beta_{2,\xi_t} S(D_t) + \epsilon_{t+3}, \quad (23)$$
$$where\ \epsilon_{t+3}\ i.i.d.N(0, \sigma^2_{\xi_t})$$

$$\beta_{i,\xi_t} = \beta_{i,0}(1-\xi_t) + \beta_{i,1}\xi_t,\ for\ i = 0, 1$$
$$\sigma^2_{\xi_t} = \sigma^2_0(1-\xi_t) + \sigma^2_1 \xi_t$$
$$\xi_t = 0, 1$$
$$Pr[\xi_t = 0 | \xi_{t-1} = 0] = P_{00}$$
$$Pr[\xi_t = 1 | \xi_{t-1} = 1] = P_{11}$$

where ξ_t is state variable. After estimating the parameters by Maximum Likelihood Estimation (MLE), the filtered probabilities are computed by Hamilton filter (Hamilton, 1989).[24]

The regression results are reported in **Table 5**. We first observe that adjusted R^2s are very high up to 72%. Even though Markov-Switching model is estimated by Maximum Likelihood Estimation (MLE) which maximizes the log-likelihood of the model, we can compute adjusted R^2s from the linear combinations of two fitted values weighted by filtered probabilities of each state.[25] [26]

What does each regime imply? The volatility of state 1 appears to be relatively high compared to that of state 1 for all countries ($\sigma^2_0 < \sigma^2_1$). Consequently, state 0 represents "low volatility"state, and state 1 stands for "high volatility"state. We also explore when the volatility has been historically high by graphically checking the filtered probability of state 1 (P_1) as illustrated in **Figure 5**. High volatility states for sample countries commonly include major global crises such as the Global Financial Crisis and European Fis-

[24]Accurately, the model is estimated by Quasi-MLE. The model is not correctly specified because of auto-correlation in the error term due to overlapping data. However, it turns out that MLE estimates are consistent, while standard errors should be estimated by the robust covariance matrix. Specifically, let $\hat{\theta} = arg\min_{\theta\in\Theta} -lnL(\theta) = arg\min_{\theta\in\Theta} -lnf(y_t;\theta)$ and define the Gradient matrix evaluated at $\hat{\theta}$ as $G(\hat{\theta}) = \sum_{t=1}^{T} \frac{\partial}{\partial\theta} lnf(y_t;\hat{\theta}) = \sum_{t=1}^{T} G_t$, the Hessian matrix evaluated at $\hat{\theta}$ as $H(\hat{\theta}) = \sum_{t=1}^{T} \frac{\partial^2}{\partial\theta\partial\theta'} lnf(y_t;\hat{\theta})$. The robust covariance matrix in the existence of auto-correlation can be computed by $var(\hat{\theta}) = H(\hat{\theta})^{-1} J_P(\hat{\theta}) H(\hat{\theta})^{-1}$, where $J_P(\hat{\theta}) = \sum_{t=1}^{T} G_t G_t' + \sum_{i=1}^{p} w_i \left(\sum_{t=i+1}^{T} G_t G_{t-i}' + \sum_{t=i+1}^{T} G_{t-i} G_t' \right)$. P indicates that the approximation is curtailed at P lags of the auto-correlation, and w_i represents the weights with $\sum_{i=1}^{p} w_i = 1$.

[25]We obtain the estimated $\Delta\hat{s}_{t+3} = [\hat{\beta}_{0,0} + \hat{\beta}_{1,0} L(D_t) + \hat{\beta}_{2,0} S(D_t)]\hat{P}_0 + [\hat{\beta}_{0,0} + \hat{\beta}_{1,0} L(D_t) + \hat{\beta}_{2,0} S(D_t)]\hat{P}_1$ and compute the adjusted R^2 by using the residual sum of squares (RSS).

[26]Here, we do not report the goodness of fit measures from four different sets of risk factors as in Table 4. But, the model with both level and slope factors is also found to be superior to other models in terms of adjusted R^2 and AIC. The results can be provided upon request.

cal Crisis.[27] Moreover, it seems noteworthy that the persistence of high volatility state is country-dependent. The persistence is found to be low for countries like Korea, but high for countries such as Mexico, Peru. The value transition probability from state 1 to state 1 ($P_{11} = Pr[s_t = 1|s_{t-1} = 1]$) compares the country-specific persistence as it relates to the expected duration of high volatility state by $1/(1 - P_{11})$.[28] The lower transition probability (P_{11}) a country exhibits, the longer the high volatility state persists. Economic implication is that countries with relatively more persistent high volatility state have long struggled from the impact of the global crises, compared to countries with less persistence.

The coefficient estimates confirm the findings from recent empirical evidences on the carry-trade strategy (Clarida et al., 2009; Brunnermeier et al., 2009; Menkhoff et al., 2012). They show that when the volatility is low, currency with higher risk appreciates as investors demand compensation for holding risky currency. However, under high volatility, as investors abruptly unwind their portfolios in favor to safe haven currency, the value of currency with higher risk plummets. Since level and slope factors capture two types of riskiness – risk level and proximity, an increase in either level or slope or both is accompanied by significant appreciation of currency during low volatility state (state 0) and by depreciation or less appreciation of currency during high volatility state (state 1).[29] The concept of risk level and proximity give insights on sign-switching relation between credit risk and currency returns well. Recall that risk level is associated with the expected path of loss given credit events and risk proximity delivers information about the timing of actual credit event. During normal times when credit event is not likely to be realized shortly, both credit risk level and proximity forecast positive currency returns, as investors still hold that currency to be compensated for bearing risk. However, when the global crisis is about to be triggered, country with weak economic fundamentals is vulnerable to credit risk with potential default. Market participants with international portfolios anticipate that a default in this country is near in time and that expected loss is also escalated due to high default probability. Accordingly, they withdraw their investment and re-balance their portfolios so as to avoid highly probable losses, causing depreciation in the currencies of these countries.

[27] Since it is difficult to clearly define exact periods for these crises, we use the Chicago Board Options Exchange (CBOE) Volatility Index (VIX index) to identify highly volatile global financial market. Specifically, we indicate the periods when VIX index is greater than 20 along with the filtered probabilities.

[28] Expected duration of state 1: $E(D_{s_t=1}) = sum_{j=1}^{\infty} P_{11}^{j-1}(1 - P_{11}) = 1/(1 - P_{11})$. For Korea, $E(D_{s_t=1}) = 1/(1 - 0.780) = 4.54$ months. For Mexico, $E(D_{s_t=1}) = 1/(1 - 0.923) = 13.01$ months.

[29] We have the similar results from the regression of the excess currency return, xr_{t+3}. Higher level and slope factors give high positive returns during low volatility state, and incur losses or low returns during the high volatility state. The results are provided in Appendix.

4.2 Comparing the Role of risk level vs. Risk Proximity

We demonstrated that each of level and slope factor individually explains the subsequent currency movements well. Next question would be which of them accounts for more of variation in currency returns. From the structural break model, the explanatory power of level-only model is found to be higher than that of slope-only model in 12 out of 20 countries for full sample period. Risk level seems to broadly matter more than risk proximity. However, is it true regardless of the state of economy? In order to answer this question, we run the same regressions repeatedly with 36-month rolling windows.[30] **Figure 6** shows the time-varying adjusted R^2s from level-only and slope-only model. We first observe that the predictive ability of level factor is relatively higher for longer period of time. However, during the Global Financial Crisis around 2008 - 2009, slope factor explains more share of subsequent currency returns than level factor. This pattern is particularly apparent in developing countries such as Chile, Hungary, Indonesia, Israel, Korea, Mexico, Romania and South Africa.

We further compare the statistical significance of two factors from both level and slope model with the same rolling regression method.[31] $P-values$ of level and slope factors over sample periods are visualized in **Figure 7**. The contrast between normal times and crisis is obvious. Level factor is relatively more statistically significant during non-crisis periods, while slope factor picks up its significance during the crises. Again, this is especially true for developing countries.

These observations suggest that risk level is a main determinant during normal times and risk proximity plays more critical role during the crises. Intuitive explanation can be made by summing up the empirical findings so far. Suppose the economy is in low volatility states, which include the periods before and after the Global Financial Crisis. Level is relatively moderate and slope is steep. Investors are aware of some level of expected loss embedded by nature in the foreign asset subject to credit risk, but do not expect the actual event anytime soon. As a result, risk level mainly drives the currency returns, while risk proximity has little role. How about in high volatility states or near the Global Financial Crisis? Level is high and slope becomes flatter or inverted. Currency depreciates due to massive

[30] Specifically, we run the following regressions with 36-month rolling windows by OLS estimation: 1) Level-only model: $\Delta s_{t+3} = \beta_0 + \beta_1 L(D_t) + \epsilon_{t+3}$; 2) Slope-only model: $\Delta s_{t+3} = \beta_0 + \beta_1 S(D_t) + \epsilon_{t+3}$. We choose the window size of 36-month to obtain clear picture for the comparison of goodness of fit measures. However, the choice of window size does not affect our key interpretation.

[31] We run the following regressions with 36-month rolling windows by OLS estimation: $\Delta s_{t+3} = \beta_0 + \beta_1 L(D_t) + \beta_2 S(D_t) + \epsilon_{t+3}$. Then, $P-values$ of each regressor is computed for each window. If $P-value \leq 0.01$, we give "3". If $0.01 < P-value \leq 0.05$, we give "2". If $0.05 < P-value \leq 0.1$, we give "1". Otherwise, "0".

withdrawal of investments from the risky assets. Which is the main driver of re-weighting of investment from risky currencies to safe haven currencies: risk level or risk proximity? If investors perceive that a default is far from realization although expected loss is huge due to concurrent global devaluation of assets, they would require even more compensation rather than unwinding the position. However, if a specific credit event is almost surely to be immediately triggered, investors would unwind their position to avoid the losses, regardless of risk level. As a result, the link between risk proximity and currency returns becomes more pronounced for periods near major global crisis.

4.3 Risk-adjusted Uncovered Interest Rate Parity

This sub-section examines the role of sovereign credit risk in explaining the Uncovered Interest Rate Parity (UIP) puzzle. Since our reduced-form model is departed from exact UIP relation and based on the net present value (NPV) framework, we just briefly check whether the UIP puzzle is mitigated when incorporating credit risk factors as proxies for risk perceived at the current time t. Considering that one of the reasons for the UIP puzzle is ignoring risk premium, we expect that inclusion of credit risk measures would help correct the abnormal UIP coefficients. We start with the original UIP regression, which is also known as Fama Regression (Fama, 1984). This model is used as a benchmark to compare the results from our risk-adjusted UIP regression. We run the following regression and report the results in **Table 6**:

$$\Delta s_{t+3} = \beta_0 + \beta_1(i_t - i_t^*) + \epsilon_{t+3} \tag{24}$$

The null hypothesis that interest rate differentials has no information about subsequent exchange rate changes cannot be rejected and adjusted R^2s are close to zero. The UIP coefficients (β_1) are negative for seven countries, while positive for the other countries. The UIP puzzle is not as severe as in the existing empirical papers because our sample countries are mostly emerging economies and our sample period is relatively short including major global crises. Since our sample currencies are intrinsically risky, the deviation from the UIP relation is smaller as implied by Bansal and Dahlquist (2000) and Frankel and Poonawala (2010).[32] In addition, as shown from summary statistics, riskier currencies tend to depreciate more during the crisis. So, it is plausible to see positive coefficients when sample period is exposed to severe financial turmoil. However, since our objectives is to mitigate the UIP puzzle, we test whether the model augmented with risk premium pushes this coefficient to

[32] They find that the UIP coefficients are closer to 1 for emerging market currencies.

positive for negative coefficient countries and improves explanatory power.

Now, let us augment the UIP with risk premium, proxied by risk level (level factor) and proximity (slope factor). The regression equation is as follows:

$$\Delta s_{t+3} = \beta_0 + \beta_1(i_t - i_t^*) + \beta_2 L(D_t) + \beta_3 S(D_t) + \epsilon_{t+3} \quad (25)$$

The results are reported in **Table 7**. Compared to the results from the original UIP, we observe some improvement. Joint Wald test that regressors have no explanatory power cannot be rejected only for 5 countries at 10% significance level and the goodness of fit measures increase up to 26%. We also notice improvement in the UIP coefficients. Out of seven countries which showed negative coefficients in the UIP regression, four countries now have positive coefficients and one country has less negative coefficient. Negative coefficients on risk measures are also consistent with theoretical prediction. Assuming risk aversion instead of risk neutrality, economic agents require a higher expected return on relatively riskier cross-border investments because of risk premiums. So, when the risk premium is ignored in the empirical regression of UIP relation, it may cause the estimators to be biased due to the omitted variable problem (Obsfeld and Rogoff, 2001).[33] In this context, after incorporating risk premiums, measured by credit risk factors, the UIP puzzle could be mitigated.

4.4 Robustness Checks

We conduct extensive robustness checks to corroborate our key findings: 1) sovereign credit risk measures can explain considerable amount of variation in currency returns; 2) risk level and slope factors together explain the currency movements better than one-year CDS – both risk level and proximity play a role in forecasting currency returns; 3) relation between credit risk and currency returns are state-dependent; 4) risk level matters more during normal times, while risk proximity picks up its role near crises.

Over different horizons ($m = 1-, 3-, 6-, 12 - months$), we repeat the regressions of the exchange rate changes on four sets of credit risk measures (eq.(19), (20)(21) and (22)) with structural breaks. Adjusted R^2 results in **Table 8** are comparable to those in **Table 4**. All four sets of credit risk measures can explain sizable amount of variation in currency movements from monthly to yearly. Adjusted $R^2 s$ are very high up to 79% in yearly prediction,

[33] Suppose the true model is $\Delta s_{t+3} = \beta_0 + \beta_1(i_t - i_t^*) - \rho_t + \epsilon_{t+3}$, where ρ_t is time-varying risk premium. Risk premium is positively correlated with interest rate differential, as risk is generally higher in higher interest rate country, and negatively correlated with the exchange rate changes, as risk premium compensates the investors. So, if the estimated model regresses $\Delta s_{t+3} = \beta_0 + \beta_1(i_t - i_t^*) + \epsilon_{t+3}$, then β_1 is negatively biased, resulting in the UIP puzzle.

while relatively low in monthly prediction. Comparing the explanatory powers across models, the model with both level and slope factors consistently produces the highest goodness of fit. Markov-Switching model is also applied to different prediction horizons to check the state-dependent property of estimates. The results for monthly prediction reported in **Table 9** replicate all the findings from quarterly prediction: two regimes represent high and low volatility states, the persistence of high volatility state is country-dependent, and coefficient estimates are switching depending on the state of economy.

Until now, we relied on one country's CDS spreads rather than cross-country difference in CDS spreads when constructing credit risk measures, assuming no default risk in the US.[34] However, if there exist default risk, however small it is, relative credit risk of one country to the other should be taken into account in examining the bilateral currency movements. Here, we relax the assumption of no default in denominating country and explore whether our main results are preserved. Specifically, we define exchange rate against Japanese Yen. Cross-country differences in CDS spreads between home country and Japan are used to construct relative one-year CDS ($D_t^{1,R} = D_t^1 - D_t^{1,JP}$), relative level factor ($L(D_t^R) = L(D_t) - L(D_t^{JP})$), and relative slope factors($S(D_t^R) = S(D_t) - S(D_t^{JP})$).[35] Using these relative measures, we check the robustness of findings from structural break model and Markov-Switching model. The model specifications are the same except replacing one-country risk measures with cross-country differences. **Table 10** and **11** present the results consistent with our key findings. Whether we assume default risk in country of safe haven currency or not does not qualitatively affect our conclusions.

We compare the explanatory power and the statistical significance of level and slope factor with 36-months rolling windows. Voluminous regressions are performed for combinations of four horizons ($m = 1-, 3-, 6-, 12-months$), two denominating currencies (USD, JPY) and corresponding credit measures (only own country's credit risk, relative credit risk). **Figure 8** and **9** shows one example out of many results - the result from the regression of six-month exchange rate against JPY on the relative level and slope factors. All the other results from differently combined models are very similar. Overall, it seems safe to say that risk level counts more, in general, while risk proximity takes a pivotal role during the crisis.

[34] We admit that this assumption was partly due to the lack of CDS data for the US.

[35] Historical CDS data for Japan is available. Japanese yen is perceived as one of safe haven currencies, while the accumulated sovereign debt is highest in the world, implying potential credit risk. In this regard, Japan is a good sample country for this robustness check.

5 Conclusions

This paper relates sovereign credit risk level and proximity to currency returns. Theoretically, developing CDS pricing model and constructing the level and slope factors from the term structure of sovereign credit default swap (CDS) spreads, we show that level represents how high the expected loss is expected – risk level – and slope implies how soon the actual credit event is likely to be realized – risk proximity. Combining with asset pricing models for defaultable bonds and exchange rate, we set up the model where the spot exchange rate is determined by both credit risk level and proximity. Empirically, we examine that the explanatory power of the model with both level and slope factors improves over the model with a single CDS spread, supporting our view that risk level and proximity capture different aspects of risk perception of market participants. Their relative role relies on the state of economy as risk level matters more during normal times, while risk proximity cut a conspicuous figure near the crises. These findings suggest that market participants and policy authorities should closely monitor the movement of sovereign CDS spreads – not only level but also slope of CDS curves – to better understand the short-run currency behavior.

Of course, there are many remaining tasks. Although we have restricted attention in this paper to currency returns driven by credit risk due to clean measures of risk level and proximity from the term structure of CDS spreads, there is no reason why these measures cannot be obtained from the term structures of other asset classes such as bond yields and options. By investigating the pricing mechanism of different assets, we would be able to derive interesting interpretation from the time-varying shape of term structures. Another next step would be to go beyond the reduced-form asset pricing model and to develop the DSGE model. By incorporating the term structure of assets into otherwise general DSGE open economy model, we could have more insights on the connection between macroeconomic variables and asset prices.

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Table 1. Summary Statistics
for Exchange Rate, Excess Currency Return and Interest Rates

		AU	BR	CL	CO	HU	IS	ID	IL	JP	KR
Panel A: Exchange Rate Change (Δs_{t+3})											
Mean	Full	0.087	0.773	0.749	0.690	2.148	2.809	3.404	-1.784	0.370	-0.207
	Pre-Crisis	-4.307	-13.291	-6.286	-8.658	-4.760	-2.443	2.137	-4.955	0.272	-5.525
	Crisis	3.738	3.565	9.314	2.407	4.917	42.307	4.383	1.335	-9.483	16.465
	Post-Crisis	1.561	7.311	2.554	5.064	5.073	-2.606	3.845	-0.819	2.433	-0.926
SD	Full	27.644	33.594	23.711	28.927	30.373	33.081	20.228	16.901	21.064	22.155
	Pre-Crisis	16.441	18.87	15.075	21.793	19.446	25.529	15.957	13.512	15.585	12.853
	Crisis	59.086	60.240	48.206	49.812	59.310	67.001	41.599	30.490	28.362	46.174
	Post-Crisis	21.895	30.072	18.802	25.486	25.931	17.587	15.349	14.467	21.420	16.458
AR(1)		0.727	0.715	0.674	0.681	0.689	0.723	0.724	0.721	0.710	0.684
Panel B: Excess Currency Return (xr_{t+3})											
Mean	Full	2.700	10.349	1.060	2.469	2.329	4.392	3.027	3.144	-1.504	2.248
	Pre-Crisis	6.542	25.312	5.428	10.161	9.331	9.515	3.616	7.529	-3.578	6.364
	Crisis	0.065	7.295	-4.493	5.324	3.120	-28.057	5.009	0.790	8.896	-13.401
	Post-Crisis	1.296	3.411	0.973	-0.761	-1.371	8.433	2.325	2.116	-2.580	3.365
SD	Full	27.475	33.727	23.918	29.681	30.628	32.227	20.589	17.344	21.033	21.917
	Pre-Crisis	16.167	19.270	14.116	25.333	20.096	25.730	16.749	14.926	15.618	13.001
	Crisis	58.404	59.494	47.570	49.248	59.438	67.513	41.759	30.178	28.148	45.554
	Post-Crisis	22.076	30.173	18.527	25.411	26.056	17.706	15.654	14.332	21.379	16.550
AR(1)		0.725	0.717	0.653	0.673	0.691	0.704	0.722	0.712	0.711	0.675
Panel C: Interest Rate Differential ($i_t^3 - i_t^{3,US}$)											
Mean	Full	2.746	11.081	3.111	4.462	4.377	7.146	6.403	1.211	-1.134	2.009
	Pre-Crisis	2.235	12.021	0.486	2.972	4.571	7.072	5.753	0.618	-3.306	0.840
	Crisis	3.803	10.860	4.821	7.731	8.037	14.251	9.392	2.125	-0.587	3.064
	Post-Crisis	2.786	10.665	3.483	4.311	3.557	5.776	6.129	1.228	-0.179	2.373
SD	Full	1.273	2.729	1.981	1.706	3.058	3.182	2.061	1.224	1.607	1.328
	Pre-Crisis	1.188	3.737	0.801	1.301	3.200	1.959	2.230	0.808	1.303	1.202
	Crisis	1.162	1.690	2.179	1.301	1.824	3.284	2.813	0.853	0.785	1.015
	Post-Crisis	1.205	2.168	1.451	0.833	2.624	1.123	1.106	1.290	0.352	1.030
AR(1)		0.946	0.971	0.975	0.962	0.932	0.977	0.888	0.869	0.993	0.906

Note: 1. $\Delta s_{t+3} = s_{t+3} - s_t$ is the quarterly change of exchange rate, where s_t is the logged home currency price per USD. If Δs_{t+3} is positive, home currency is depreciated relative to USD. If Δs_{t+3} is negative, home currency is appreciated relative to USD. 2. $xr_{t+3} = i_t^3 - i_t^{3,US} - \Delta s_{t+3}$ is excess currency return, which is the return by investing in home currency from time t to $t+3$ with funding from foreign currency (US). If xr_{t+3} is positive, the investment yields gain. If xr_{t+3} is negative, the investment incurs loss. 3. $i_t^3 - i_t^{3,US}$ is the difference in three-month zero coupon yields or interbank interest rates in home and foreign country (US). 4. Sample period is from January, 2004 to June, 2017. All rates are reported in annualized percentage points. 5. Sample period is divided by two break dates, November,2007 and June, 2009. Sub-periods are reported as “Pre-Crisis”, “Crisis”and “Post-Crisis”, respectively. The break dates are chosen, considering the recession in the US is from December, 2007 to June, 2009 according to the NBER.

Table 1. Summary Statistics for Exchange Rate, Excess Currency Return and Interest Rates (Continued)

		MX	NO	PE	PH	PL	RO	ZA	SE	TH	TR
Panel A: Exchange Rate Change (Δs_{t+3})											
Mean	Full	3.856	1.423	-0.508	-0.856	-0.234	1.632	5.126	1.123	-1.043	7.380
	Pre-Crisis	-0.726	-6.906	-4.315	-8.176	-12.310	-7.396	2.268	-4.303	-4.622	-3.052
	Crisis	13.133	7.042	0.010	10.401	11.710	11.073	3.016	7.521	2.042	14.563
	Post-Crisis	4.276	4.485	1.309	0.544	3.429	4.266	7.002	2.558	0.135	11.185
SD	Full	23.208	24.744	11.549	12.552	31.887	25.732	30.799	24.232	12.602	28.181
	Pre-Crisis	10.312	18.470	7.998	11.808	21.866	21.315	27.972	19.032	12.886	26.331
	Crisis	45.484	45.005	20.704	15.392	62.454	42.635	56.594	45.896	15.493	48.375
	Post-Crisis	20.939	20.814	10.119	9.949	25.030	22.075	24.547	19.739	11.526	21.875
AR(1)		0.725	0.714	0.673	0.725	0.738	0.707	0.628	0.704	0.733	0.677
Panel B: Excess Currency Return (xr_{t+3})											
Mean	Full	0.546	-0.490	3.936	5.052	2.764	3.963	1.248	-1.082	2.264	1.778
	Pre-Crisis	5.165	6.221	5.370	11.140	13.622	14.489	2.608	3.172	4.252	16.610
	Crisis	-6.701	-3.932	5.216	-0.839	-7.158	0.114	7.139	-5.814	-0.437	-0.157
	Post-Crisis	-0.308	-3.178	2.950	3.179	-0.697	-0.571	-0.644	-2.265	1.811	-2.930
SD	Full	23.303	24.393	11.258	12.889	31.609	26.322	30.995	23.919	12.387	28.482
	Pre-Crisis	10.913	18.712	8.291	11.868	22.234	22.915	28.281	18.968	13.049	25.852
	Crisis	45.094	44.122	20.481	16.503	61.892	42.235	56.263	45.034	15.100	47.381
	Post-Crisis	21.276	20.811	9.943	11.486	25.030	22.312	24.879	19.764	11.404	22.289
AR(1)		0.726	0.706	0.655	0.716	0.734	0.721	0.630	0.699	0.722	0.678
Panel C: Interest Rate Differential ($i_t^3 - i_t^{3,US}$)											
Mean	Full	4.428	0.905	3.440	4.135	2.492	5.485	6.364	0.007	1.206	9.734
	Pre-Crisis	4.439	-0.685	1.055	2.964	1.313	7.093	4.876	-1.131	-0.370	11.206
	Crisis	6.432	3.110	5.226	9.562	4.552	11.186	10.155	1.706	1.605	14.406
	Post-Crisis	4.025	1.246	4.254	3.634	2.661	3.569	6.342	0.228	1.899	8.318
SD	Full	1.432	1.509	1.885	3.366	1.908	4.938	1.982	1.425	1.258	2.773
	Pre-Crisis	1.876	1.106	0.706	2.814	2.351	6.496	1.664	1.342	0.554	1.471
	Crisis	1.094	1.310	1.508	2.506	0.926	2.940	1.542	1.165	0.753	3.134
	Post-Crisis	0.760	0.775	1.109	2.713	1.328	2.786	0.947	1.021	0.825	1.460
AR(1)		0.976	0.971	0.978	0.882	0.974	0.932	0.973	0.962	0.979	0.935

Note: 1. $\Delta s_{t+3} = s_{t+3} - s_t$ is the quarterly change of exchange rate, where s_t is the logged home currency price per USD. If Δs_{t+3} is positive, home currency is depreciated relative to USD. If Δs_{t+3} is negative, home currency is appreciated relative to USD. 2. $xr_{t+3} = i_t^3 - i_t^{3,US} - \Delta s_{t+3}$ is excess currency return, which is the return by investing in home currency from time t to $t+3$ with funding from foreign currency (US). If xr_{t+3} is positive, the investment yields gain. If xr_{t+3} is negative, the investment incurs loss. 3. $i_t^3 - i_t^{3,US}$ is the difference in three-month zero coupon yields or interbank interest rates in home and foreign country (US). 4. Sample period is from January, 2004 to June, 2017. All rates are reported in annualized percentage points. 5. Sample period is divided by two break dates, November,2007 and June, 2009. Sub-periods are reported as "Pre-Crisis", "Crisis"and "Post-Crisis", respectively. The break dates are chosen, considering the recession in the US is from December, 2007 to June, 2009 according to the NBER.

Table 2. Principal Component Analysis for Term Structure of Sovereign Credit Default Swap Spreads

		AU	BR	CL	CO	HU	IS	ID	IL	JP	KR
Panel A: The first Principal Component (PC_{1t})											
Factor Loading	1Y	0.326	0.176	0.278	0.202	0.366	0.502	0.402	0.297	0.151	0.394
	2Y	0.337	0.314	0.351	0.291	0.414	0.451	0.421	0.359	0.223	0.415
	3Y	0.405	0.398	0.386	0.397	0.422	0.419	0.439	0.405	0.297	0.422
	5Y	0.458	0.473	0.453	0.482	0.421	0.384	0.410	0.457	0.435	0.414
	7Y	0.454	0.490	0.458	0.488	0.415	0.355	0.396	0.457	0.541	0.406
	10Y	0.448	0.498	0.485	0.497	0.409	0.309	0.379	0.447	0.598	0.399
Explained		88.277	95.662	95.952	92.826	97.111	98.397	96.249	94.779	95.068	97.156
$corr(PC_{1t}, D_t^{10})$		0.936	0.986	0.979	0.975	0.979	0.978	0.963	0.967	0.986	0.974
Panel B: The second Principal Component (PC_{2t})											
Factor Loading	1Y	0.428	0.604	0.471	0.635	0.648	0.562	0.556	0.546	0.515	0.512
	2Y	0.493	0.524	0.486	0.525	0.365	0.326	0.368	0.449	0.508	0.401
	3Y	0.330	0.312	0.357	0.262	0.134	0.035	0.178	0.300	0.449	0.243
	5Y	-0.040	-0.102	-0.024	-0.099	-0.202	-0.314	-0.194	-0.102	0.148	-0.191
	7Y	-0.357	-0.295	-0.412	-0.275	-0.379	-0.461	-0.424	-0.370	-0.217	-0.432
	10Y	-0.579	-0.407	-0.494	-0.409	-0.495	-0.515	-0.553	-0.512	-0.454	-0.542
Explained		11.240	4.032	3.638	6.627	2.777	1.501	3.354	4.948	4.403	2.760
$corr(PC_{2t}, D_t^1 - D_t^{10})$		0.922	0.541	0.668	0.687	0.974	0.566	0.987	0.846	0.423	0.996

		MX	NO	PE	PH	PL	RO	ZA	SE	TH	TR
Panel A: The first Principal Component (PC_{1t})											
Factor Loading	1Y	0.353	0.245	0.300	0.281	0.306	0.393	0.314	0.297	0.293	0.375
	2Y	0.391	0.313	0.389	0.348	0.376	0.423	0.363	0.344	0.344	0.418
	3Y	0.409	0.385	0.421	0.407	0.405	0.423	0.400	0.392	0.391	0.438
	5Y	0.432	0.471	0.445	0.458	0.447	0.413	0.446	0.465	0.456	0.428
	7Y	0.433	0.485	0.445	0.455	0.449	0.402	0.456	0.463	0.467	0.406
	10Y	0.426	0.488	0.430	0.466	0.447	0.395	0.451	0.458	0.466	0.380
Explained		94.952	84.182	91.443	95.159	95.512	97.231	91.700	93.910	90.816	89.679
$corr(PC_{1t}, D_t^{10})$		0.957	0.917	0.946	0.975	0.967	0.978	0.950	0.952	0.941	0.909
Panel B: The second Principal Component (PC_{2t})											
Factor Loading	1Y	0.530	0.368	0.543	0.648	0.536	0.605	0.620	0.418	0.535	0.595
	2Y	0.415	0.479	0.443	0.440	0.435	0.384	0.428	0.549	0.440	0.381
	3Y	0.250	0.414	0.266	0.218	0.277	0.134	0.221	0.276	0.335	0.146
	5Y	-0.094	0.078	-0.098	-0.131	-0.061	-0.232	-0.123	-0.018	-0.061	-0.185
	7Y	-0.389	-0.279	-0.425	-0.315	-0.359	-0.410	-0.353	-0.302	-0.353	-0.416
	10Y	-0.569	-0.616	-0.498	-0.472	-0.561	-0.496	-0.493	-0.597	-0.529	-0.521
Explained		4.734	14.808	7.432	4.674	4.143	2.649	7.960	5.415	8.987	9.516
$corr(PC_{2t}, D_t^1 - D_t^{10})$		0.954	0.856	0.900	0.801	0.846	0.997	0.921	0.830	0.887	0.994

Note: 1. Principal components are obtained as follows: 1)Let D_t denote the 6 x 1 vector of CDS spreads at each time t, Ω be the 6 x 6 covariance matrix of D_t; 2) The first principal component is $PC_{1t} = p_1^{'} D_t$, where p_1 is an eigenvector with the largest eigenvalue from Ω; 3) The second principal component is $PC_{2t} = p_2^{'} D_t$, where p_2 is an eigenvector with the second largest eigenvalue from Ω. 2. "Factor loadings" are p_1 and p_2, which represent the weight on each D_t^m of $m-$tenor. 3. "Explained" indicates how much of the variation in D_t is explained by each principal component. 4. In order to show the meaning of each principal component, we compute correlation between the first principal component and geometric level (D_t^{10}), and correlation between the second principal component and geometric slope ($D_t^1 - D_t^{10}$).

Table 3. Summary Statistics for Level and Slope factors of Sovereign CDS

		AU	BR	CL	CO	HU	IS	ID	IL	JP	KR
Panel A: Level factor = The first Principal Component ($L(D_t) = PC_{1t}$)											
Mean	Full	87.40	472.22	171.31	397.35	429.28	531.63	427.24	199.04	102.97	175.44
	Pre-Crisis	30.33	567.71	49.01	495.38	55.76	26.90	374.38	70.73	14.52	69.63
	Crisis	134.45	464.09	276.71	541.64	608.56	1375.72	882.01	286.31	83.05	453.56
	Post-Crisis	100.68	429.07	193.76	322.85	572.77	474.98	355.95	236.56	150.22	172.19
SD	Full	57.56	284.64	101.04	201.56	372.17	562.97	255.13	115.78	77.97	165.27
	Pre-Crisis	17.16	409.56	8.75	271.46	20.13	27.58	114.88	21.28	6.61	28.46
	Crisis	104.7	226.01	174.84	234.77	438.95	866.66	472.59	158.75	59.20	316.02
	Post-Crisis	34.43	204.99	44.76	95.38	319.05	325.36	83.67	82.79	58.42	77.16
AR(1)		0.883	0.906	0.919	0.894	0.967	0.956	0.900	0.947	0.958	0.919
Panel B: Slope factor = The second Principal Component ($S(D_t) = PC_{2t}$)											
Mean	Full	-24.84	-41.83	-30.85	-40.66	-75.21	-101.49	-170.32	-44.21	-5.87	-52.52
	Pre-Crisis	-12.89	-80.60	-12.27	-90.22	-24.15	-16.61	-179.86	-22.81	-1.05	-26.18
	Crisis	-11.59	17.61	-10.30	34.95	-28.94	-111.18	-151.12	-18.86	17.46	-31.20
	Post-Crisis	-32.20	-35.42	-41.49	-32.40	-108.83	-118.14	-170.74	-58.37	-12.85	-69.64
SD	Full	17.77	58.43	19.67	53.85	62.94	69.52	47.63	26.45	16.78	27.86
	Pre-Crisis	8.11	48.34	2.62	35.38	8.61	7.57	38.18	6.51	1.80	10.65
	Crisis	8.06	68.73	25.85	73.90	84.74	49.50	80.42	30.89	23.48	21.40
	Post-Crisis	17.9	47.72	12.31	29.39	49.43	67.09	41.18	20.35	14.20	21.04
AR(1)		0.940	0.885	0.864	0.944	0.911	0.916	0.800	0.904	0.918	0.912

		MX	NO	PE	PH	PL	RO	ZA	SE	TH	TR
Panel A: Level factor = The first Principal Component ($L(D_t) = PC_{1t}$)											
Mean	Full	265.88	43.09	315.21	426.51	195.97	403.92	350.44	66.65	216.73	486.88
	Pre-Crisis	162.97	14.42	309.80	638.08	41.87	97.68	143.21	33.29	88.22	497.33
	Crisis	462.37	50.90	480.71	655.31	315.65	777.71	567.41	109.36	354.31	709.23
	Post-Crisis	275.23	48.11	284.49	277.64	247.72	463.92	408.96	66.19	252.41	438.08
SD	Full	145.15	22.88	130.75	263.95	161.09	336.33	194.56	53.13	117.98	187.14
	Pre-Crisis	64.67	11.03	109.77	312.17	17.46	47.41	68.28	41.96	16.57	229.68
	Crisis	294.33	36.92	254.28	227.54	245.17	520.17	282.41	103.40	177.78	256.50
	Post-Crisis	63.93	15.38	62.11	77.89	122.96	245.92	112.52	31.66	65.01	97.76
AR(1)		0.906	0.903	0.867	0.921	0.948	0.943	0.942	0.874	0.920	0.800
Panel B: Slope factor = The second Principal Component ($S(D_t) = PC_{2t}$)											
Mean	Full	-79.91	-11.25	-86.60	-85.16	-42.50	-94.42	-76.18	-17.66	-45.75	-157.50
	Pre-Crisis	-67.50	-3.92	-124.72	-129.65	-15.68	-43.37	-50.16	-17.17	-23.56	-204.11
	Crisis	-54.73	1.53	-55.36	-2.86	-4.97	-75.80	-7.51	-1.37	0.38	-114.63
	Post-Crisis	-90.71	-15.46	-78.49	-79.67	-63.05	-120.44	-102.50	-21.00	-65.75	-144.63
SD	Full	32.41	8.51	37.27	58.50	33.55	55.52	57.32	12.76	37.11	60.96
	Pre-Crisis	29.03	3.52	43.84	46.02	6.84	18.67	24.48	22.20	4.10	37.44
	Crisis	26.39	5.78	27.57	92.87	40.06	71.63	84.10	4.74	39.66	100.41
	Post-Crisis	30.30	5.62	23.01	27.86	22.72	45.09	44.28	7.20	30.90	45.77
AR(1)		0.939	0.919	0.902	0.948	0.927	0.908	0.939	0.756	0.939	0.914

Note: 1. We denote the first principal component as “Level”factor and the second principal component as “Slope”factor. 2. Sample period is from January, 2004 to June, 2017. Sample period is short for some countries due to data availability. All values are in annuity in basis points. 3. Sample period is divided by two break dates, November,2007 and June, 2009. Sub-periods are reported as “Pre-Crisis”, “Crisis”and “Post-Crisis”, respectively. The break dates are chosen, considering the recession in the US is from December, 2007 to June, 2009 according to the NBER.

Table 4. Explaining the Currency Returns with Sovereign Credit Risk: Structural Break Model

	AU	BR	CL	CO	HU	IS	ID	IL	JP	KR
Model 1: $\Delta s_{t+3} = \beta_0 + \beta_1 D_t^1 + \epsilon_{t+3}$										
$p - value$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.000
$ad.R^2$	0.338	0.123	0.238	0.151	0.308	0.351	0.190	0.209	0.076	0.259
Model 2: $\Delta s_{t+3} = \beta_0 + \beta_1 L(D_t) + \epsilon_{t+3}$										
$p - value$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$ad.R^2$	0.278	0.228	0.400	0.270	0.298	0.348	0.168	0.121	0.155	0.344
Model 3: $\Delta s_{t+3} = \beta_0 + \beta_1 S(D_t) + \epsilon_{t+3}$										
$p - value$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.148	0.000	0.000
$ad.R^2$	0.229	0.113	0.464	0.119	0.354	0.315	0.333	0.008	0.228	0.411
Model 4: $\Delta s_{t+3} = \beta_0 + \beta_1 L(D_t) + \beta_2 S(D_t) + \epsilon_{t+3}$										
$p - value$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.162	0.000	0.000
$ad.R^2$	0.601	0.239	0.551	0.326	0.345	0.344	0.368	0.011	0.215	0.469

	MX	NO	PE	PH	PL	RO	ZA	SE	TH	TR
Model 1: $\Delta s_{t+3} = \beta_0 + \beta_1 D_t^1 + \epsilon_{t+3}$										
$p - value$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000
$ad.R^2$	0.140	0.313	0.165	0.278	0.187	0.215	0.176	0.231	0.087	0.110
Model 2: $\Delta s_{t+3} = \beta_0 + \beta_1 L(D_t) + \epsilon_{t+3}$										
$p - value$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.467	0.001
$ad.R^2$	0.128	0.259	0.241	0.266	0.209	0.172	0.257	0.238	-0.004	0.015
Model 3: $\Delta s_{t+3} = \beta_0 + \beta_1 S(D_t) + \epsilon_{t+3}$										
$p - value$	0.090	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.008	0.000
$ad.R^2$	-0.001	0.210	0.169	0.230	0.197	0.211	0.243	0.188	0.048	0.230
Model 4: $\Delta s_{t+3} = \beta_0 + \beta_1 L(D_t) + \beta_2 S(D_t) + \epsilon_{t+3}$										
$p - value$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.017	0.000
$ad.R^2$	0.135	0.380	0.278	0.322	0.312	0.173	0.338	0.173	0.045	0.342

Note: 1. We first regress quarterly exchange rate changes on four different sets of risk factors and then apply the Bai-Perron(2003) test(with 15% trimming and 5 - 10% significance level) to detect the multiple structural breaks in the regression. Zero to two breaks are detected depending on sample countries. 2. After identifying the break dates, structural break dummy variables for each sub-period are incorporated into the regression. 3. P-value is for the Wald test that factors jointly have no explanatory power 4. Adjusted R^2 is reported.

Table 5. Explaining the Currency Returns with Sovereign Credit Risk: Markov Switching Model

$$\Delta s_{t+3} = \beta_{0,\xi_t} + \beta_{1,\xi_t} L(D_t) + \beta_{2,\xi_t} S(D_t) + \epsilon_{t+3},\ \ where\ \epsilon_{t+3}\ i.i.d.N(0, \sigma^2_{\xi_t})$$

	AU	BR	CL	CO	HU	IS	ID	IL	JP	KR
$\beta_{0,0}$	-4.198	1.968	1.815	11.851	-12.176**	-14.430***	5.753	-16.928***	7.955**	-4.482
	(3.994)	(5.061)	(9.686)	(7.674)	(5.927)	(4.369)	(8.933)	(6.219)	(3.108)	(5.086)
$\beta_{0,1}$	97.863***	68.338***	-51.302***	130.680***	35.107	69.635*	59.529	10.136	-22.892***	6.124
	(16.376)	(13.859)	(6.179)	(23.621)	(32.727)	(36.905)	(49.895)	(7.418)	(7.459)	(12.501)
$\beta_{1,0}$	-0.163**	-0.052***	-0.061**	-0.062***	-0.019***	0.011***	-0.040***	-0.006	0.080**	-0.046***
	(0.072)	(0.014)	(0.026)	(0.017)	(0.006)	(0.003)	(0.006)	(0.017)	(0.031)	(0.012)
$\beta_{1,1}$	-0.467***	-0.056***	-0.112***	-0.222***	-0.005	-0.083**	0.005	0.006	0.084*	0.005
	(0.054)	(0.015)	(0.038)	(0.052)	(0.039)	(0.040)	(0.020)	(0.026)	(0.048)	(0.028)
$\beta_{2,0}$	-0.342***	-0.124**	-0.271**	-0.072	-0.174***	-0.055*	-0.058	-0.163***	-0.433**	-0.103
	(0.103)	(0.059)	(0.124)	(0.056)	(0.033)	(0.030)	(0.047)	(0.050)	(0.191)	(0.072)
$\beta_{2,1}$	0.863**	-0.007	-4.391***	0.476***	-0.130	-0.517	0.224	-0.119	-0.186	-0.456
	(0.428)	(0.062)	(0.664)	(0.131)	(0.142)	(0.329)	(0.299)	(0.140)	(0.198)	(0.746)
σ_0	12.654***	16.919**	15.783**	19.116**	17.858**	16.723**	9.541**	10.986**	12.376*	13.034
	(4.537)	(7.188)	(6.849)	(8.454)	(7.399)	(6.637)	(4.208)	(4.700)	(6.779)	(10.308)
σ_1	21.778*	26.913*	21.035	25.918**	29.949*	60.536	31.679	13.126**	15.273**	24.929
	(12.498)	(15.029)	(17.477)	(13.073)	(16.853)	(37.525)	(20.187)	(5.229)	(7.189)	(22.049)
P_{00}	0.942***	0.943***	0.982***	0.965***	0.952***	0.991***	0.965***	0.936***	0.833***	0.954
	(0.225)	(0.238)	(0.280)	(0.260)	(0.250)	(0.359)	(0.251)	(0.219)	(0.196)	(0.832)
P_{11}	0.883**	0.843***	0.893	0.893***	0.788***	0.897*	0.864***	0.844***	0.884***	0.780
	(0.356)	(0.215)	(0.572)	(0.322)	(0.241)	(0.524)	(0.285)	(0.260)	(0.290)	(0.522)
$ad.R^2$	0.687	0.716	0.526	0.559	0.625	0.457	0.296	0.650	0.651	0.557
AIC	8.685	9.236	8.695	9.166	9.171	8.953	8.219	8.207	8.659	8.573

Note: 1. The model is estimated by two-state Markov-Switching Model. After estimating the parameters by Maximum Likelihood Estimation (MLE), the filtered probabilities are computed by Hamilton filter. See the text for model specification. 2. Coefficient estimates are reported with the Newey-West standard errors in parentheses. Asterisks indicate significance levels at 1% (***), 5% (**), and 10% (*) respectively. 3. By using the filtered probabilities, we obtain the estimated $\Delta \hat{s}_{t+3} = [\hat{\beta}_{0,0} + \hat{\beta}_{1,0} L(D_t) + \hat{\beta}_{2,0} S(D_t)]\hat{P}_0 + [\hat{\beta}_{0,0} + \hat{\beta}_{1,0} L(D_t) + \hat{\beta}_{2,0} S(D_t)]\hat{P}_1$ and compute adjusted R^2 by using the residual sum of squares(RSS). 4. AIC is provided.

Table 5. Explaining the Currency Returns with Sovereign Credit Risk: Markov Switching Model (Continued)

$$\Delta s_{t+3} = \beta_{0,\xi_t} + \beta_{1,\xi_t} L(D_t) + \beta_{2,\xi_t} S(D_t) + \epsilon_{t+3},\ \ where\ \epsilon_{t+3}\ i.i.d.N(0, \sigma^2_{\xi_t})$$

	MX	NO	PE	PH	PL	RO	ZA	SE	TH	TR
$\beta_{0,0}$	4.237	82.263***	7.944***	2.576	-17.702***	-18.356***	-4.807	-5.645	16.052***	5.885
	(4.371)	(9.919)	(1.870)	(3.615)	(5.140)	(5.751)	(4.214)	(3.631)	(4.222)	(16.161)
$\beta_{0,1}$	79.158**	-3.358	7.460	-5.527	50.751**	4.417	49.700***	62.594***	-11.750***	-1.196
	(39.635)	(5.957)	(7.970)	(12.627)	(23.429)	(9.072)	(9.636)	(16.367)	(2.291)	(46.904)
$\beta_{1,0}$	-0.043***	0.081	-0.039***	-0.007	-0.020	-0.005	-0.049***	-0.152***	-0.017	-0.026
	(0.008)	(0.238)	(0.003)	(0.005)	(0.013)	(0.007)	(0.009)	(0.033)	(0.011)	(0.020)
$\beta_{1,1}$	-0.046	-0.183**	0.000	0.084***	0.034	0.028***	-0.043**	-0.195***	0.005	0.022
	(0.042)	(0.081)	(0.005)	(0.026)	(0.047)	(0.009)	(0.020)	(0.075)	(0.008)	(0.056)
$\beta_{2,0}$	-0.025	3.514***	0.003	-0.006	-0.236***	-0.088***	-0.147*	-0.239*	-0.059	-0.007
	(0.054)	(0.887)	(0.012)	(0.028)	(0.071)	(0.032)	(0.080)	(0.128)	(0.048)	(0.051)
$\beta_{2,1}$	0.427**	-0.669***	0.029	0.317***	0.318**	-0.112	0.045	1.356*	-0.086***	-0.215
	(0.205)	(0.208)	(0.058)	(0.116)	(0.133)	(0.095)	(0.138)	(0.721)	(0.027)	(0.240)
σ_0	11.083**	16.066*	4.192*	9.294**	17.906**	15.737**	16.695*	13.880**	6.596**	15.089*
	(5.520)	(9.131)	(2.178)	(3.816)	(7.371)	(7.626)	(8.620)	(5.945)	(2.947)	(7.748)
σ_1	26.617*	16.546**	13.795**	15.840*	27.974	19.090*	24.670	18.352*	7.900**	24.225
	(15.600)	(6.624)	(6.676)	(9.030)	(18.762)	(10.800)	(16.364)	(9.594)	(3.404)	(15.114)
P_{00}	0.961***	0.773***	0.933***	0.991***	0.941***	0.896***	0.905***	0.932***	0.773***	0.916***
	(0.287)	(0.274)	(0.264)	(0.314)	(0.211)	(0.177)	(0.213)	(0.208)	(0.196)	(0.181)
P_{11}	0.923*	0.957***	0.923***	0.972**	0.762***	0.811***	0.855	0.876***	0.924***	0.847**
	(0.484)	(0.298)	(0.238)	(0.489)	(0.220)	(0.183)	(0.776)	(0.247)	(0.190)	(0.397)
$ad.R^2$	0.516	0.620	0.262	0.198	0.665	0.667	0.656	0.672	0.708	0.682
AIC	8.527	8.804	7.281	7.729	9.220	9.020	9.261	8.739	7.461	9.105

Note: 1. The model is estimated by two-state Markov-Switching Model. After estimating the parameters by Maximum Likelihood Estimation (MLE), the filtered probabilities are computed by Hamilton filter. See the text for model specification. 2. Coefficient estimates are reported with the Newey-West standard errors in parentheses. Asterisks indicate significance levels at 1% (***), 5% (**), and 10% (*) respectively. 3. By using the filtered probabilities, we obtain the estimated $\Delta \hat{s}_{t+3} = [\hat{\beta}_{0,0} + \hat{\beta}_{1,0} L(D_t) + \hat{\beta}_{2,0} S(D_t)]\hat{P}_0 + [\hat{\beta}_{0,0} + \hat{\beta}_{1,0} L(D_t) + \hat{\beta}_{2,0} S(D_t)]\hat{P}_1$ and compute adjusted R^2 by using the residual sum of squares(RSS). 4. AIC is provided.

Table 6. Uncovered Interest Rate Parity:

OLS

$$\Delta s_{t+3} = \beta_0 + \beta_1(i_t^3 - i_t^{3,US}) + \epsilon_{t+3}$$

	AU	BR	CL	CO	HU	IS	ID	IL	JP	KR
β_0	-9.299	2.702	-7.894*	-6.550	3.670	-21.789*	10.691	-5.717**	1.217	-7.400**
	(7.665)	(15.105)	(4.589)	(10.875)	(4.843)	(12.962)	(8.573)	(2.752)	(3.427)	(3.561)
β_1	3.482	-0.189	3.182*	1.915	-0.330	3.313	-1.214	3.049	0.747	3.524
	(3.442)	(1.429)	(1.759)	(2.691)	(1.384)	(2.030)	(1.595)	(1.877)	(1.305)	(2.178)
$p-value$	0.058	0.850	0.002	0.187	0.690	0.000	0.126	0.012	0.472	0.008
$ad.R^2$	0.018	-0.006	0.061	0.005	-0.005	0.102	0.009	0.036	-0.003	0.038

	MX	NO	PE	PH	PL	RO	ZA	SE	TH	TR
β_0	6.387	-3.964	-4.563*	-1.368	-7.671*	3.135	11.634	0.249	-3.698	16.852
	(12.260)	(3.621)	(2.557)	(2.508)	(4.139)	(4.919)	(15.333)	(3.204)	(2.386)	(17.499)
β_1	-0.600	5.273*	1.277	0.122	2.940	-0.330	-1.021	5.472**	2.175*	-0.916
	(3.180)	(2.876)	(0.783)	(0.489)	(2.470)	(1.121)	(2.632)	(2.512)	(1.208)	(1.966)
$p-value$	0.646	0.000	0.011	0.682	0.027	0.503	0.407	0.000	0.006	0.276
$ad.R^2$	-0.005	0.082	0.037	-0.005	0.025	-0.004	-0.002	0.092	0.042	0.001

Note: 1. The model is estimated by OLS. 2. Coefficient estimates are reported with the Newey-West standard errors in parentheses. Asterisks indicate significance levels at 1% (***), 5% (**), and 10% (*) respectively. 3. P-value is for the Wald test that factors jointly have no explanatory power 4. Adjusted R^2 is reported.

Table 7. Risk-adjusted Uncovered Interest Rate Parity: OLS

$$\Delta s_{t+3} = \beta_0 + \beta_1(i_t^3 - i_t^{3,US}) + \beta_2 L(D_t) + \beta_3 S(D_t) + \epsilon_{t+3}$$

	AU	BR	CL	CO	HU	IS	ID	IL	JP	KR
β_0	-18.366***	-26.103	-2.481	-0.760	-16.526**	-27.705*	-10.089	-9.667*	-5.617	-2.557
	(6.135)	(17.977)	(6.724)	(11.786)	(7.581)	(15.897)	(11.084)	(5.629)	(7.618)	(4.305)
β_1	10.401***	5.758**	5.551***	6.381*	2.294	4.081	-1.355	3.711	-0.873	6.506*
	(3.814)	(2.616)	(2.142)	(3.334)	(1.744)	(2.482)	(1.809)	(2.276)	(1.945)	(3.351)
β_2	-0.258***	-0.066**	-0.109***	-0.078***	-0.014	-0.007	-0.008	-0.007	0.037	-0.037**
	(0.059)	(0.026)	(0.038)	(0.025)	(0.011)	(0.011)	(0.011)	(0.023)	(0.045)	(0.018)
β_3	-0.530***	0.149**	-0.215*	-0.068	-0.199***	-0.041	-0.147***	-0.101	-0.212	0.083
	(0.139)	(0.066)	(0.121)	(0.058)	(0.062)	(0.046)	(0.044)	(0.078)	(0.153)	(0.094)
$p-value$	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.020	0.132	0.001
$ad.R^2$	0.256	0.133	0.258	0.131	0.120	0.105	0.127	0.048	0.017	0.084

	MX	NO	PE	PH	PL	RO	ZA	SE	TH	TR
β_0	3.154	4.372	-4.751	0.487	-12.829**	-6.535	-2.767	9.930	-3.611	20.200
	(11.723)	(7.720)	(4.604)	(4.600)	(5.308)	(7.660)	(16.049)	(7.600)	(4.017)	(18.569)
β_1	0.061	7.558**	2.286***	0.325	3.647	-0.370	2.827	7.024**	2.364	-0.179
	(3.514)	(3.215)	(0.822)	(0.795)	(3.619)	(1.296)	(3.273)	(2.878)	(1.663)	(2.611)
β_2	-0.015	-0.433***	-0.029***	-0.006	-0.016	0.007	-0.056**	-0.136**	-0.011	-0.024
	(0.021)	(0.151)	(0.011)	(0.005)	(0.035)	(0.012)	(0.027)	(0.063)	(0.015)	(0.029)
β_3	-0.054	-0.682***	-0.066**	0.001	-0.158	-0.073	-0.126**	0.044	-0.048	-0.004
	(0.083)	(0.256)	(0.031)	(0.029)	(0.117)	(0.059)	(0.061)	(0.225)	(0.037)	(0.068)
$p-value$	0.545	0.000	0.000	0.515	0.017	0.131	0.000	0.000	0.005	0.361
$ad.R^2$	-0.006	0.227	0.143	-0.004	0.045	0.017	0.106	0.160	0.061	0.002

Note: 1. The model is estimated by OLS. 2. Coefficient estimates are reported with the Newey-West standard errors in parentheses. Asterisks indicate significance levels at 1% (***), 5% (**), and 10% (*) respectively. 3. P-value is for the Wald test that factors jointly have no explanatory power 4. Adjusted R^2 is reported.

Table 8. Explaining the Currency Returns over Different horizons: Structural Break Model

Model 1: $\Delta s_{t+m} = \beta_0 + \beta_1 D_t^1 + \epsilon_{t+m}$
Model 2: $\Delta s_{t+m} = \beta_0 + \beta_1 L(D_t) + \epsilon_{t+m}$
Model 3: $\Delta s_{t+m} = \beta_0 + \beta_1 S(D_t) + \epsilon_{t+m}$
Model 4: $\Delta s_{t+m} = \beta_0 + \beta_1 L(D_t) + \beta_2 S(D_t) + \epsilon_{t+m}$

	AU	BR	CL	CO	HU	IS	ID	IL	JP	KR
$m = 1$										
Model 1	0.075	0.025	0.151	0.054	0.043	0.245	0.158	0.024	0.031	0.180
Model 2	0.088	0.039	0.184	0.067	0.036	0.250	0.160	0.027	0.022	0.194
Model 3	0.009	0.045	0.158	0.030	0.035	0.262	0.127	0.027	0.051	0.071
Model 4	0.080	0.085	0.187	0.083	0.047	0.257	0.159	0.029	0.050	0.187
$m = 3$										
Model 1	0.338	0.123	0.238	0.151	0.308	0.351	0.190	0.209	0.076	0.259
Model 2	0.278	0.228	0.400	0.270	0.298	0.348	0.168	0.121	0.155	0.344
Model 3	0.229	0.113	0.464	0.119	0.354	0.315	0.333	0.008	0.228	0.411
Model 4	0.601	0.239	0.551	0.326	0.345	0.344	0.368	0.011	0.215	0.469
$m = 6$										
Model 1	0.501	0.331	0.481	0.354	0.547	0.560	0.400	0.285	0.315	0.534
Model 2	0.483	0.485	0.604	0.401	0.528	0.559	0.390	0.207	0.346	0.581
Model 3	0.297	0.317	0.540	0.320	0.519	0.420	0.308	0.279	0.364	0.536
Model 4	0.595	0.545	0.643	0.477	0.553	0.506	0.466	0.323	0.391	0.634
$m = 12$										
Model 1	0.493	0.625	0.671	0.744	0.493	0.673	0.666	0.433	0.484	0.730
Model 2	0.506	0.705	0.649	0.663	0.471	0.659	0.568	0.452	0.535	0.712
Model 3	0.448	0.524	0.380	0.418	0.467	0.514	0.477	0.449	0.478	0.495
Model 4	0.554	0.769	0.672	0.781	0.500	0.670	0.671	0.546	0.555	0.787

Note: 1. For robustness checks, we run the same regression equations in **Table 4** over different horizons ($m = 1-, 3-, 6-, 12-$month) and report the adjusted R^2. 2. Four sets of risk factors are considered as regressors and the Bai-Perron(2003) test(with 15% trimming and 5 - 10% significance level) is applied to detect the multiple structural breaks in the regression. After identifying from zero to two breaks, structural break dummy variables for each sub-period are incorporated into the regression.

Table 8. Explaining the Currency Returns over Different horizons: Structural Break Model (Continued)

Model 1: $\Delta s_{t+m} = \beta_0 + \beta_1 D_t^1 + \epsilon_{t+m}$
Model 2: $\Delta s_{t+m} = \beta_0 + \beta_1 L(D_t) + \epsilon_{t+m}$
Model 3: $\Delta s_{t+m} = \beta_0 + \beta_1 S(D_t) + \epsilon_{t+m}$
Model 4: $\Delta s_{t+m} = \beta_0 + \beta_1 L(D_t) + \beta_2 S(D_t) + \epsilon_{t+m}$

	MX	NO	PE	PH	PL	RO	ZA	SE	TH	TR
$m = 1$										
Model 1	0.113	0.055	0.095	0.054	0.087	0.053	0.037	0.079	0.047	0.044
Model 2	0.114	0.072	0.080	0.062	0.086	0.073	0.037	0.067	0.033	0.031
Model 3	0.021	0.023	0.056	0.055	0.021	0.040	0.039	0.019	0.020	0.038
Model 4	0.108	0.059	0.082	0.059	0.083	0.075	0.054	0.087	0.048	0.036
$m = 3$										
Model 1	0.140	0.313	0.165	0.278	0.187	0.215	0.176	0.231	0.087	0.110
Model 2	0.128	0.259	0.241	0.266	0.209	0.172	0.257	0.238	-0.004	0.015
Model 3	-0.001	0.210	0.169	0.230	0.197	0.211	0.243	0.188	0.048	0.230
Model 4	0.135	0.380	0.278	0.322	0.312	0.173	0.338	0.173	0.045	0.342
$m = 6$										
Model 1	0.314	0.509	0.352	0.473	0.455	0.398	0.353	0.503	0.210	0.348
Model 2	0.258	0.525	0.385	0.468	0.472	0.368	0.404	0.506	0.247	0.306
Model 3	0.330	0.392	0.375	0.369	0.391	0.365	0.423	0.334	0.291	0.463
Model 4	0.366	0.624	0.444	0.545	0.471	0.417	0.497	0.511	0.270	0.578
$m = 12$										
Model 1	0.532	0.502	0.686	0.711	0.612	0.508	0.500	0.533	0.542	0.548
Model 2	0.483	0.527	0.698	0.699	0.634	0.491	0.591	0.557	0.557	0.472
Model 3	0.437	0.409	0.617	0.535	0.564	0.424	0.460	0.288	0.390	0.453
Model 4	0.568	0.555	0.725	0.732	0.639	0.505	0.681	0.564	0.559	0.582

Note: 1. For robustness checks, we run the same regression equations in **Table 4** over different horizons ($m = 1-, 3-, 6-, 12-$month) and report the adjusted R^2. 2. Four sets of risk factors are considered as regressors and the Bai-Perron(2003) test(with 15% trimming and 5 - 10% significance level) is applied to detect the multiple structural breaks in the regression. After identifying from zero to two breaks, structural break dummy variables for each sub-period are incorporated into the regression.

Table 9. Explaining the Currency Returns over Different Horizons: Markov Switching Model

$$\Delta s_{t+m} = \beta_{0,\xi_t} + \beta_{1,\xi_t} L(D_t) + \beta_{2,\xi_t} S(D_t) + \epsilon_{t+m},\ \ where\ \epsilon_{t+m}\ i.i.d.N(0, \sigma^2_{\xi_t})$$

	AU	BR	CL	CO	HU	IS	ID	IL	JP	KR
$\beta_{0,0}$	1.384	-12.973	-54.970***	2.615	-8.234	-14.315*	26.023**	-1.144	1.470	6.369
	(6.184)	(7.984)	(7.098)	(6.651)	(5.882)	(7.424)	(10.161)	(4.974)	(4.902)	(6.101)
$\beta_{0,1}$	123.417**	82.096**	-6.212	53.420	67.195	2.201	-97.073***	-20.680	-9.244	-19.878
	(51.484)	(33.780)	(6.742)	(35.313)	(61.063)	(32.953)	(24.842)	(12.619)	(8.154)	(18.778)
$\beta_{1,0}$	-0.260***	0.008	0.847***	-0.023	-0.029**	0.013*	-0.077***	-0.112	-0.148	-0.126***
	(0.058)	(0.012)	(0.028)	(0.018)	(0.012)	(0.007)	(0.011)	(0.069)	(0.120)	(0.016)
$\beta_{1,1}$	-0.008	-0.115**	-0.047*	-0.107	-0.056	-0.088	0.025*	0.040	0.030	0.173***
	(0.104)	(0.055)	(0.026)	(0.074)	(0.058)	(0.069)	(0.015)	(0.035)	(0.056)	(0.036)
$\beta_{2,0}$	-0.524***	0.024	-1.487***	-0.035	-0.167***	-0.053	-0.004	-0.242	-1.694*	-0.101
	(0.191)	(0.077)	(0.156)	(0.090)	(0.056)	(0.048)	(0.052)	(0.208)	(0.864)	(0.092)
$\beta_{2,1}$	2.243*	0.226	-0.383***	0.137	-0.257	-1.257*	-0.650***	-0.360*	0.064	-0.105
	(1.356)	(0.145)	(0.136)	(0.217)	(0.269)	(0.757)	(0.136)	(0.200)	(0.220)	(0.312)
σ_0	33.541**	31.895*	21.085	26.239**	33.993***	35.297***	20.814**	17.581**	24.115**	22.853**
	(13.541)	(17.139)	(19.498)	(11.974)	(12.661)	(13.349)	(8.359)	(7.599)	(11.221)	(11.408)
σ_1	54.078	67.545**	31.998***	63.728**	89.880*	103.548	27.827*	37.067**	37.081**	40.233*
	(39.964)	(30.734)	(11.279)	(27.917)	(47.810)	(66.021)	(16.336)	(15.633)	(15.058)	(23.643)
P_{00}	0.912***	0.863***	0.309	0.936***	0.966***	0.989**	0.853**	0.967***	0.961***	0.690
	(0.286)	(0.329)	(0.790)	(0.277)	(0.290)	(0.389)	(0.338)	(0.343)	(0.351)	(0.706)
P_{11}	0.301	0.812**	0.977***	0.926***	0.842**	0.868*	0.397	0.964***	0.970***	0.375
	(0.541)	(0.369)	(0.257)	(0.331)	(0.384)	(0.487)	(0.364)	(0.348)	(0.353)	(0.400)
$ad.R^2$	0.493	0.215	0.381	0.042	0.245	0.219	0.626	0.100	0.115	0.528
AIC	10.335	10.737	9.989	10.444	10.510	10.380	9.418	9.502	9.853	9.820

Note: 1. For robustness checks, we estimate the same model in **Table 5** over different horizons. Here, estimation results for $m = 1-$month are reported. Results for $m = 6-, 12-$month can be provided upon request. 2. The model is estimated by two-state Markov-Switching Model. After estimating the parameters by Maximum Likelihood Estimation (MLE), the filtered probabilities are computed by Hamilton filter. 3. Coefficient estimates are reported with the standard errors in parentheses. Asterisks indicate significance levels at 1% (***), 5% (**), and 10% (*) respectively. 4. Adjusted R^2 and AIC are reported.

Table 9. Explaining the Currency Returns over Different Horizons: Markov Switching Model (Continued)

$$\Delta s_{t+m} = \beta_{0,\xi_t} + \beta_{1,\xi_t} L(D_t) + \beta_{2,\xi_t} S(D_t) + \epsilon_{t+m},\ where\ \epsilon_{t+m}\ i.i.d.N(0, \sigma^2_{\xi_t})$$

	AU	BR	CL	CO	HU	IS	ID	IL	JP	KR
$\beta_{0,0}$	1.384	-12.973	-54.970***	2.615	-8.234	-14.315*	26.023**	-1.144	1.470	6.369
	(6.184)	(7.984)	(7.098)	(6.651)	(5.882)	(7.424)	(10.161)	(4.974)	(4.902)	(6.101)
$\beta_{0,1}$	123.417**	82.096**	-6.212	53.420	67.195	2.201	-97.073***	-20.680	-9.244	-19.878
	(51.484)	(33.780)	(6.742)	(35.313)	(61.063)	(32.953)	(24.842)	(12.619)	(8.154)	(18.778)
$\beta_{1,0}$	-0.260***	0.008	0.847***	-0.023	-0.029**	0.013*	-0.077***	-0.112	-0.148	-0.126***
	(0.058)	(0.012)	(0.028)	(0.018)	(0.012)	(0.007)	(0.011)	(0.069)	(0.120)	(0.016)
$\beta_{1,1}$	-0.008	-0.115**	-0.047*	-0.107	-0.056	-0.088	0.025*	0.040	0.030	0.173***
	(0.104)	(0.055)	(0.026)	(0.074)	(0.058)	(0.069)	(0.015)	(0.035)	(0.056)	(0.036)
$\beta_{2,0}$	-0.524***	0.024	-1.487***	-0.035	-0.167***	-0.053	-0.004	-0.242	-1.694*	-0.101
	(0.191)	(0.077)	(0.156)	(0.090)	(0.056)	(0.048)	(0.052)	(0.208)	(0.864)	(0.092)
$\beta_{2,1}$	2.243*	0.226	-0.383***	0.137	-0.257	-1.257*	-0.650***	-0.360*	0.064	-0.105
	(1.356)	(0.145)	(0.136)	(0.217)	(0.269)	(0.757)	(0.136)	(0.200)	(0.220)	(0.312)
σ_0	33.541**	31.895*	21.085	26.239**	33.993***	35.297***	20.814**	17.581**	24.115**	22.853**
	(13.541)	(17.139)	(19.498)	(11.974)	(12.661)	(13.349)	(8.359)	(7.599)	(11.221)	(11.408)
σ_1	54.078	67.545**	31.998***	63.728**	89.880*	103.548	27.827*	37.067**	37.081**	40.233*
	(39.964)	(30.734)	(11.279)	(27.917)	(47.810)	(66.021)	(16.336)	(15.633)	(15.058)	(23.643)
P_{00}	0.912***	0.863***	0.309	0.936***	0.966***	0.989**	0.853**	0.967***	0.961***	0.690
	(0.286)	(0.329)	(0.790)	(0.277)	(0.290)	(0.389)	(0.338)	(0.343)	(0.351)	(0.706)
P_{11}	0.301	0.812**	0.977***	0.926***	0.842**	0.868*	0.397	0.964***	0.970***	0.375
	(0.541)	(0.369)	(0.257)	(0.331)	(0.384)	(0.487)	(0.364)	(0.348)	(0.353)	(0.400)
$ad.R^2$	0.493	0.215	0.381	0.042	0.245	0.219	0.626	0.100	0.115	0.528
AIC	10.335	10.737	9.989	10.444	10.510	10.380	9.418	9.502	9.853	9.820

Note: 1. For robustness checks, we estimate the same model in **Table 5** over different horizons. Here, estimation results for $m = 1-$month are reported. Results for $m = 6-, 12-$month can be provided upon request. 2. The model is estimated by two-state Markov-Switching Model. After estimating the parameters by Maximum Likelihood Estimation (MLE), the filtered probabilities are computed by Hamilton filter. 3. Coefficient estimates are reported with the standard errors in parentheses. Asterisks indicate significance levels at 1% (***), 5% (**), and 10% (*) respectively. 4. Adjusted R^2 and AIC are reported.

Table 10. Explaining the Currency Returns with Relative Credit Risk Measures: Structural Break Model

Model 1: $\Delta s_{t+m} = \beta_0 + \beta_1 D_t^{1,R} + \epsilon_{t+m}$
Model 2: $\Delta s_{t+m} = \beta_0 + \beta_1 L(D_t^R) + \epsilon_{t+m}$
Model 3: $\Delta s_{t+m} = \beta_0 + \beta_1 S(D_t^R) + \epsilon_{t+m}$
Model 4: $\Delta s_{t+m} = \beta_0 + \beta_1 L(D_t^R) + \beta_2 S(D_t^R) + \epsilon_{t+m}$

	AU	BR	CL	CO	HU	IS	ID	IL	KR	MX
$m = 1$										
Model 1	0.012	0.014	0.120	0.009	0.062	0.228	0.092	0.061	0.185	0.051
Model 2	0.021	0.011	0.179	0.011	0.069	0.234	0.087	0.080	0.189	0.031
Model 3	0.043	0.046	0.116	0.026	0.048	0.266	0.061	0.046	0.051	0.020
Model 4	0.050	0.040	0.175	0.035	0.065	0.256	0.082	0.098	0.180	0.055
$m = 3$										
Model 1	0.047	0.055	0.160	0.029	0.416	0.313	0.179	0.286	0.263	0.066
Model 2	0.078	0.062	0.231	0.043	0.367	0.318	0.177	0.291	0.307	0.047
Model 3	0.100	0.062	0.309	0.074	0.390	0.319	0.093	0.106	0.367	0.040
Model 4	0.095	0.117	0.322	0.079	0.445	0.323	0.268	0.287	0.374	0.054
$m = 6$										
Model 1	0.232	0.241	0.320	0.264	0.612	0.484	0.357	0.423	0.482	0.254
Model 2	0.322	0.261	0.368	0.264	0.588	0.522	0.379	0.366	0.475	0.210
Model 3	0.328	0.251	0.298	0.299	0.526	0.521	0.322	0.281	0.533	0.192
Model 4	0.358	0.322	0.420	0.333	0.616	0.572	0.394	0.359	0.556	0.318
$m = 12$										
Model 1	0.467	0.447	0.429	0.439	0.728	0.701	0.603	0.650	0.600	0.426
Model 2	0.541	0.495	0.475	0.351	0.723	0.710	0.605	0.611	0.587	0.486
Model 3	0.526	0.387	0.263	0.388	0.553	0.630	0.500	0.456	0.610	0.363
Model 4	0.613	0.601	0.476	0.626	0.733	0.753	0.649	0.607	0.670	0.497

Note: 1. For robustness check, we run the same regression equations in **Table 4** for different currency pairs with relative credit risk measures over different horizons ($m = 1-, 3-, 6-, 12-$month) and report the adjusted R^2. 2. Key differences are: (i) exchange rate is defined as per-Japanese Yen rate instead of per-US Dollar rate, (ii) relative sovereign credit risk measures are used as explanatory variables. Relative CDS spreads are defined as $D_t^R = D_t - D_t^{JP}$. Relative level, $L(D_t^R)$ and relative slope, $S(D_t^R)$ are defined accordingly. 3. Bai-Perron(2003) test(with 15% trimming and 5 - 10% significance level) is applied to detect the multiple structural breaks in the regression. After identifying from zero to two break dates, structural break dummy variables for each sub-period are incorporated into the regression.

Table 10. Explaining the Currency Returns with Relative Credit Risk Measures: Structural Break Model (Continued)

Model 1: $\Delta s_{t+m} = \beta_0 + \beta_1 D_t^{1,R} + \epsilon_{t+m}$
Model 2: $\Delta s_{t+m} = \beta_0 + \beta_1 L(D_t^R) + \epsilon_{t+m}$
Model 3: $\Delta s_{t+m} = \beta_0 + \beta_1 S(D_t^R) + \epsilon_{t+m}$
Model 4: $\Delta s_{t+m} = \beta_0 + \beta_1 L(D_t^R) + \beta_2 S(D_t^R) + \epsilon_{t+m}$

	NO	PE	PH	PL	RO	ZA	SE	TH	TR	US
$m = 1$										
Model 1	0.028	0.055	0.009	0.084	0.067	0.029	0.021	0.071	0.007	0.112
Model 2	0.025	0.053	0.020	0.096	0.106	0.022	0.018	0.064	0.003	0.082
Model 3	0.006	0.034	0.010	0.024	0.059	0.023	0.012	0.032	0.029	0.036
Model 4	0.015	0.069	0.024	0.091	0.136	0.022	0.026	0.056	0.023	0.074
$m = 3$										
Model 1	0.103	0.192	0.081	0.256	0.243	0.050	0.046	0.137	0.004	0.129
Model 2	0.144	0.144	0.132	0.238	0.251	0.027	0.018	0.236	0.096	0.116
Model 3	0.190	0.006	0.107	0.205	0.212	0.262	0.267	0.209	0.362	0.118
Model 4	0.211	0.143	0.157	0.298	0.287	0.325	0.255	0.266	0.364	0.110
$m = 6$										
Model 1	0.244	0.316	0.269	0.448	0.448	0.368	0.254	0.295	0.274	0.349
Model 2	0.129	0.256	0.239	0.443	0.446	0.337	0.278	0.289	0.240	0.395
Model 3	0.294	0.237	0.297	0.338	0.367	0.416	0.347	0.325	0.520	0.444
Model 4	0.350	0.369	0.337	0.470	0.491	0.438	0.421	0.320	0.520	0.438
$m = 12$										
Model 1	0.376	0.369	0.397	0.635	0.658	0.382	0.416	0.398	0.378	0.679
Model 2	0.386	0.421	0.379	0.604	0.659	0.397	0.480	0.398	0.358	0.690
Model 3	0.386	0.569	0.486	0.510	0.556	0.307	0.421	0.406	0.376	0.689
Model 4	0.520	0.595	0.508	0.646	0.721	0.497	0.520	0.405	0.398	0.694

Note: 1. For robustness check, we run the same regression equations in **Table 4** for different currency pairs with relative credit risk measures over different horizons ($m = 1-, 3-, 6-, 12-$month) and report the adjusted R^2. 2. Key differences are: (i) exchange rate is defined as per-Japanese Yen rate instead of per-US Dollar rate, (ii) relative sovereign credit risk measures are used as explanatory variables. Relative CDS spreads are defined as $D_t^R = D_t - D_t^{JP}$. Relative level, $L(D_t^R)$ and relative slope, $S(D_t^R)$ are defined accordingly. 3. Bai-Perron(2003) test(with 15% trimming and 5 - 10% significance level) is applied to detect the multiple structural breaks in the regression. After identifying from zero to two break dates, structural break dummy variables for each sub-period are incorporated into the regression.

Table 11. Explaining the Currency Returns with Relative Credit Risk Measures: Markov Switching Model

$$\Delta s_{t+3} = \beta_{0,\xi_t} + \beta_{1,\xi_t} L(D_t^R) + \beta_{2,\xi_t} S(D_t^R) + \epsilon_{t+3},\ where\ \epsilon_{t+3}\ i.i.d.N(0, \sigma^2_{\xi_t})$$

	AU	BR	CL	CO	HU	IS	ID	IL	KR	MX
$\beta_{0,0}$	-1.500	-3.884	194.793***	12.164*	-1.144	-10.159	8.977	-4.538	-7.048*	7.013
	(5.150)	(6.256)	(4.770)	(6.577)	(4.259)	(82.634)	(5.522)	(5.852)	(4.061)	(8.241)
$\beta_{0,1}$	145.383***	51.372*	-1.544	-18.630	121.121***	-42.605	69.980**	8.573	16.998	61.839
	(35.944)	(27.257)	(5.665)	(23.589)	(31.544)	(14246)	(32.406)	(13.692)	(14.873)	(56.484)
$\beta_{1,0}$	-0.108	-0.016	-0.240***	-0.073***	-0.034***	0.016	-0.032***	-0.028	0.025	-0.024
	(0.164)	(0.012)	(0.015)	(0.019)	(0.009)	(0.075)	(0.012)	(0.019)	(0.018)	(0.027)
$\beta_{1,1}$	-1.271	0.026	-0.042	0.134	-0.114***	-0.061	-0.156***	0.025	-0.016	0.018
	(1.827)	(0.056)	(0.044)	(0.088)	(0.029)	(2.347)	(0.014)	(0.090)	(0.049)	(0.053)
$\beta_{2,0}$	0.264	0.041	0.718***	-0.014	-0.063	0.004	0.000	0.048	0.107	0.108
	(0.561)	(0.076)	(0.209)	(0.064)	(0.049)	(0.389)	(0.003)	(0.151)	(0.088)	(0.107)
$\beta_{2,1}$	0.410	-0.472*	-0.216	-0.158	-0.014	-1.067	-0.685***	0.081	-0.032	0.145
	(5.670)	(0.265)	(0.194)	(0.335)	(0.087)	(68.813)	(0.163)	(0.332)	(0.318)	(0.421)
σ_0	22.621**	24.317**	0.257*	17.910**	21.485**	21.284	21.835***	11.052	10.848**	24.080**
	(9.772)	(9.960)	(0.150)	(7.286)	(8.943)	(20.940)	(8.443)	(6.701)	(4.896)	(10.201)
σ_1	39.421	44.554	23.703**	44.976*	34.237**	102.425	24.980**	35.177*	42.980	45.227
	(38.186)	(30.309)	(9.302)	(24.445)	(15.273)	(1047)	(11.132)	(19.274)	(31.069)	(36.621)
P_{00}	0.993***	0.957***	0.404	0.902***	0.976***	0.989	0.993***	0.905***	0.927***	0.971***
	(0.352)	(0.237)	(0.736)	(0.208)	(0.237)	(8.872)	(0.359)	(0.234)	(0.240)	(0.242)
P_{11}	0.888	0.789***	0.991***	0.793***	0.862**	0.898	0.817*	0.896***	0.865**	0.818**
	(0.830)	(0.293)	(0.308)	(0.209)	(0.352)	(11.933)	(0.478)	(0.263)	(0.391)	(0.352)
$ad.R^2$	0.533	0.567	0.441	0.329	0.576	0.139	0.453	0.092	0.248	0.444
AIC	9.284	9.782	9.181	9.611	9.418	9.514	9.187	9.125	8.993	9.600

Note: 1. For robustness checks, we estimate the same model in **Table 5** for different currency pairs with relative credit risk measures over different horizons ($m = 1-, 3-, 6-, 12-$month): (i) exchange rate is defined as per-Japanese Yen rates instead of per-US Dollar rates, (ii) relative sovereign credit risk measures are used as explanatory variables. Relative CDS spreads are defined as $D_t^R = D_t - D_t^{JP}$. Relative level, $L(D_t^R)$ and relative slope, $S(D_t^R)$ are defined accordingly. 2. Here, estimation results for $m = 3-$month are reported. Results for $m = 1-, 6-, 12-$month can be provided upon request.

Table 11. Explaining the Currency Returns with Relative Credit Risk Measures: Markov Switching Model (Continued)

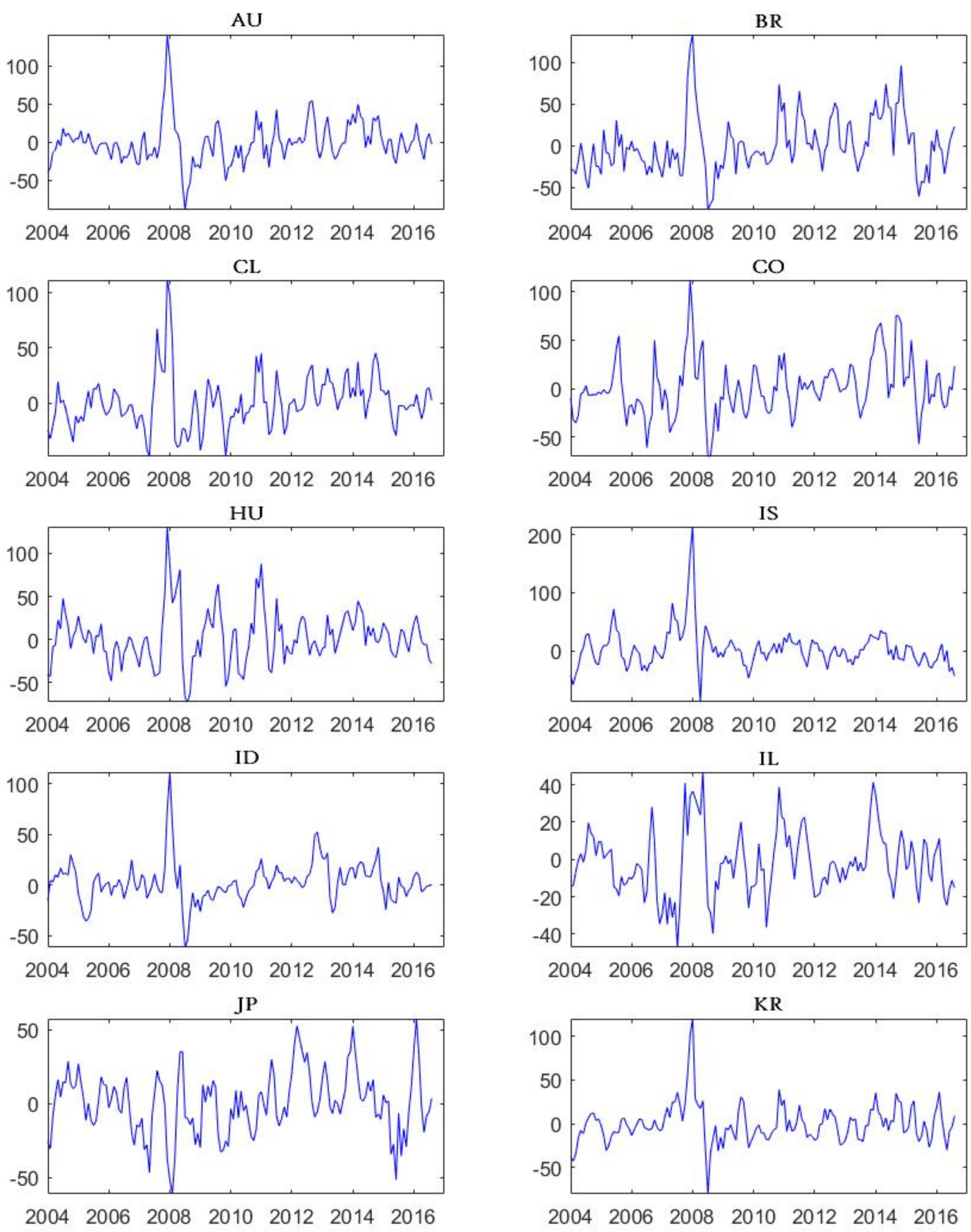
$$\Delta s_{t+3} = \beta_{0,\xi_t} + \beta_{1,\xi_t} L(D_t^R) + \beta_{2,\xi_t} S(D_t^R) + \epsilon_{t+3},\ where\ \epsilon_{t+3}\ i.i.d.N(0, \sigma^2_{\xi_t})$$

	NO	PE	PH	PL	RO	ZA	SE	TH	TR	US
$\beta_{0,0}$	162.424***	10.026**	-1.182	-5.646	-7.853	5.297	-4.685	-29.825***	36.254***	-4.123
	(3.182)	(4.119)	(14.992)	(6.147)	(6.481)	(9.448)	(4.344)	(8.468)	(9.766)	(2.736)
$\beta_{0,1}$	-1.646	-53.181***	5.532	51.285	23.095	80.858**	59.802	6.674	-142.800***	7.919
	(3.997)	(15.157)	(67.009)	(87.871)	(14.330)	(39.488)	(36.439)	(8.326)	(20.944)	(6.793)
$\beta_{1,0}$	1.010***	-0.003	0.005	-0.063***	-0.002	-0.077***	0.058	0.268***	-0.070***	-0.043
	(0.038)	(0.020)	(0.018)	(0.023)	(0.009)	(0.029)	(0.075)	(0.051)	(0.018)	(0.048)
$\beta_{1,1}$	-0.005	0.053	0.009	0.018	0.057*	-0.095	-0.015	-0.051***	0.175***	0.130
	(0.054)	(0.054)	(0.119)	(0.237)	(0.031)	(0.062)	(0.066)	(0.018)	(0.021)	(0.085)
$\beta_{2,0}$	-1.795***	0.119*	0.081	0.094	0.066	-0.092	-0.069	0.124	0.050	-0.157**
	(0.178)	(0.062)	(0.123)	(0.164)	(0.074)	(0.075)	(0.225)	(0.146)	(0.056)	(0.078)
$\beta_{2,1}$	-0.046	-0.555**	-0.253	0.104	0.069	-0.098	1.559*	-0.126	-0.922***	-0.042
	(0.274)	(0.225)	(0.748)	(0.445)	(0.206)	(0.276)	(0.906)	(0.105)	(0.074)	(0.252)
σ_0	5.680	12.532**	18.654	18.352	18.825**	22.799**	18.289**	20.876*	24.901**	7.925
	(5.165)	(5.045)	(12.014)	(13.008)	(7.913)	(9.518)	(8.878)	(12.580)	(11.505)	(5.142)
σ_1	23.682**	34.505	21.708	43.676	31.302	39.292	36.477*	11.632	25.385	26.369**
	(9.393)	(21.867)	(13.470)	(37.754)	(21.472)	(27.766)	(19.814)	(7.429)	(16.061)	(11.743)
P_{00}	0.590	0.956***	0.972	0.950**	0.924***	0.958***	0.944***	0.880***	0.957***	0.795***
	(0.464)	(0.247)	(1.335)	(0.412)	(0.175)	(0.271)	(0.242)	(0.262)	(0.280)	(0.212)
P_{11}	0.961***	0.860***	0.895	0.811***	0.822***	0.805***	0.827***	0.845***	0.744**	0.874***
	(0.171)	(0.271)	(0.903)	(0.305)	(0.217)	(0.275)	(0.259)	(0.225)	(0.373)	(0.277)
$ad.R^2$	0.500	0.162	0.394	0.592	0.567	0.583	0.497	0.464	0.567	0.066
AIC	9.302	8.683	8.966	9.439	9.481	9.649	9.403	8.797	9.603	8.902

Note: 1. For robustness checks, we estimate the same model in **Table 5** for different currency pairs with relative credit risk measures over different horizons ($m = 1-, 3-, 6-, 12-$month): (i) exchange rate is defined as per-Japanese Yen rates instead of per-US Dollar rates, (ii) relative sovereign credit risk measures are used as explanatory variables. Relative CDS spreads are defined as $D_t^R = D_t - D_t^{JP}$. Relative level, $L(D_t^R$ and relative slope, $S(D_t^R$ are defined accordingly. 2. Here, estimation results for $m = 3-$month are reported. Results for $m = 1-, 6-, 12-$month can be provided upon request.

Figure 1: Exchange Rate Change

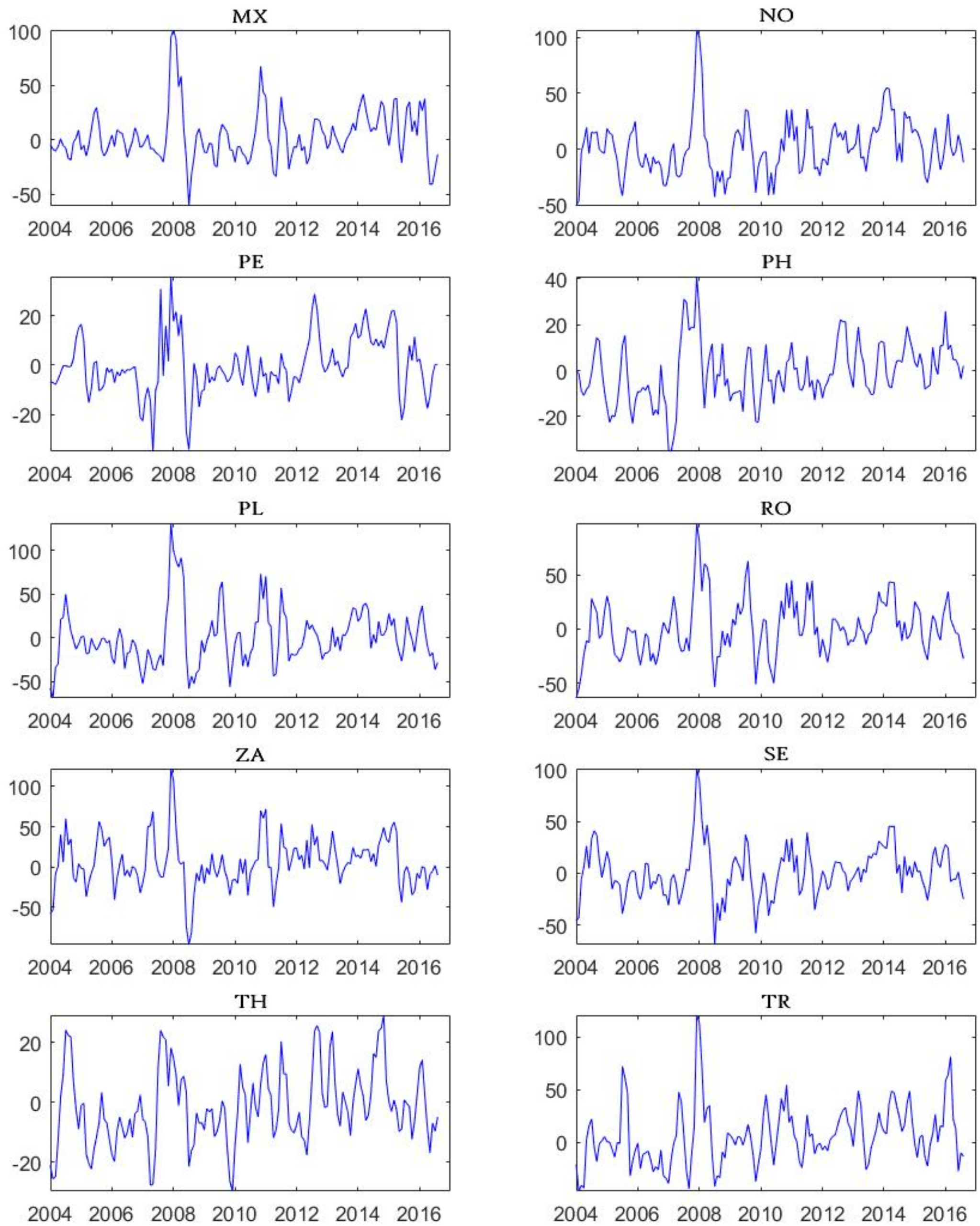
(Annualized %; Home Currency/USD)



Note: 1. **Figure 1** shows the quarterly change of exchange rate, $\Delta s_{t+3} = s_{t+3} - s_t$, where s_t is the logged home currency price per USD. 2. Sample period is from January, 2004 to June, 2017. All rates are in annualized percentage points.

Figure 1: Exchange Rate Change (Continued)

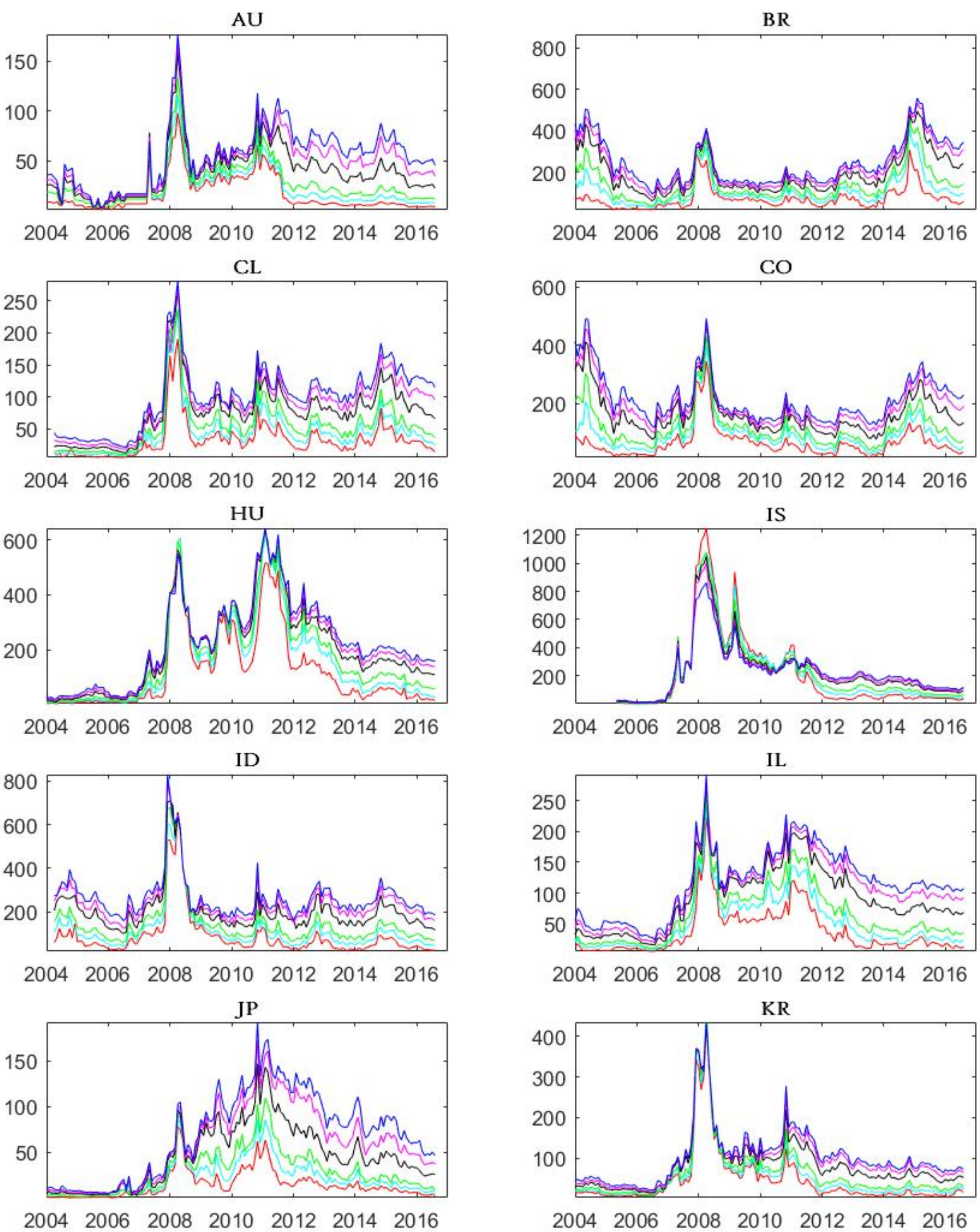
(Annualized %; Home Currency/USD)



Note: 1. **Figure 1** shows the quarterly change of exchange rate, $\Delta s_{t+3} = s_{t+3} - s_t$, where s_t is the logged home currency price per USD. 2. Sample period is from January, 2004 to June, 2017. All rates are in annualized percentage points.

Figure 2: Sovereign Credit Default Swap

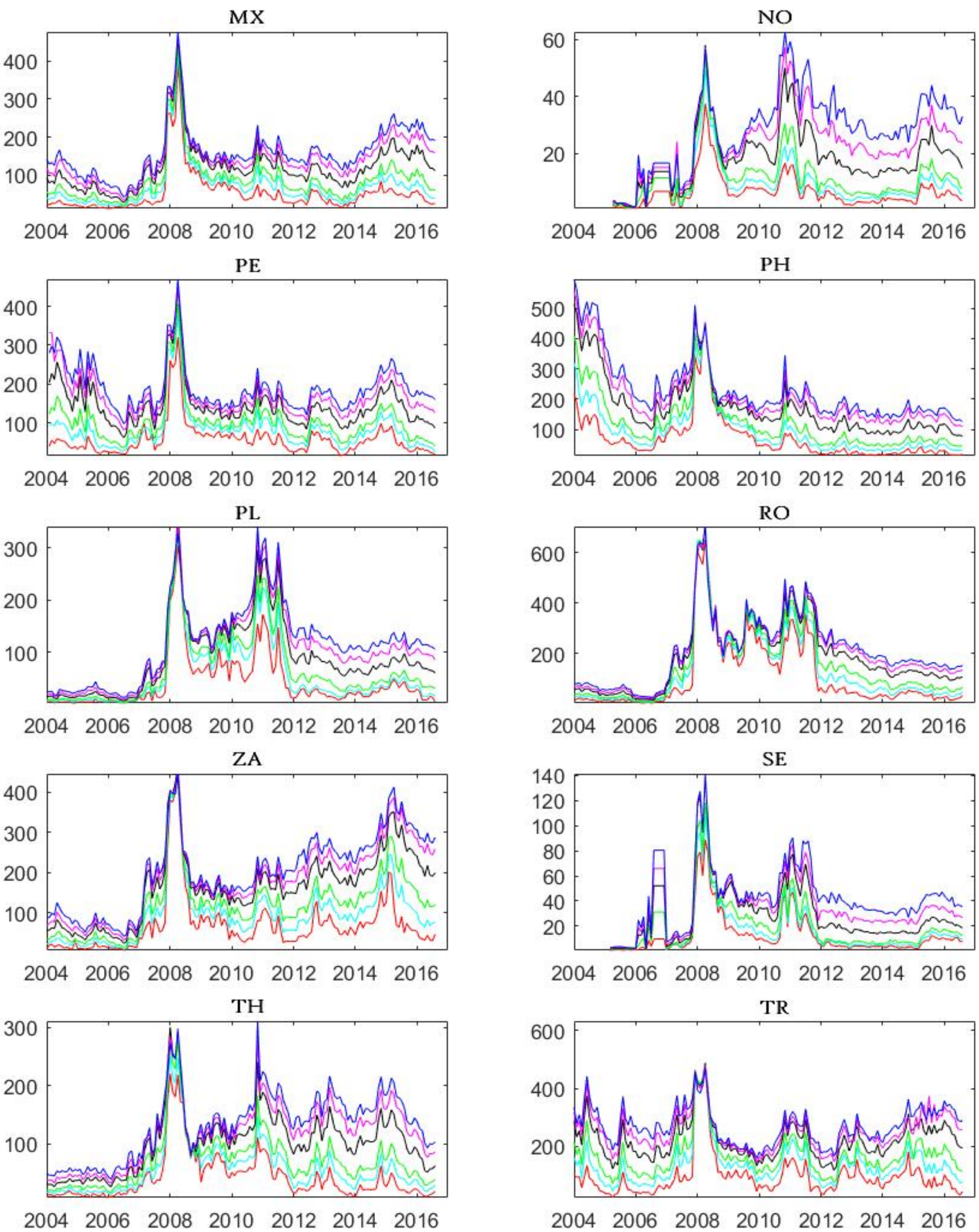
(Basis Point)



Note: 1. **Figure 2** shows sovereign credit default swap (CDS) spreads of 1, 2, 3, 5, 7, 10 years tenor: Red for 1 year, Cyan for 2 year, Green for 3 year, Black for 5 year, Magenta for 7 year and Blue for 10 year tenor CDS spread. 2. Sample period is from January, 2004 to June, 2017, but shorter for some countries. All values are in annuity basis points.

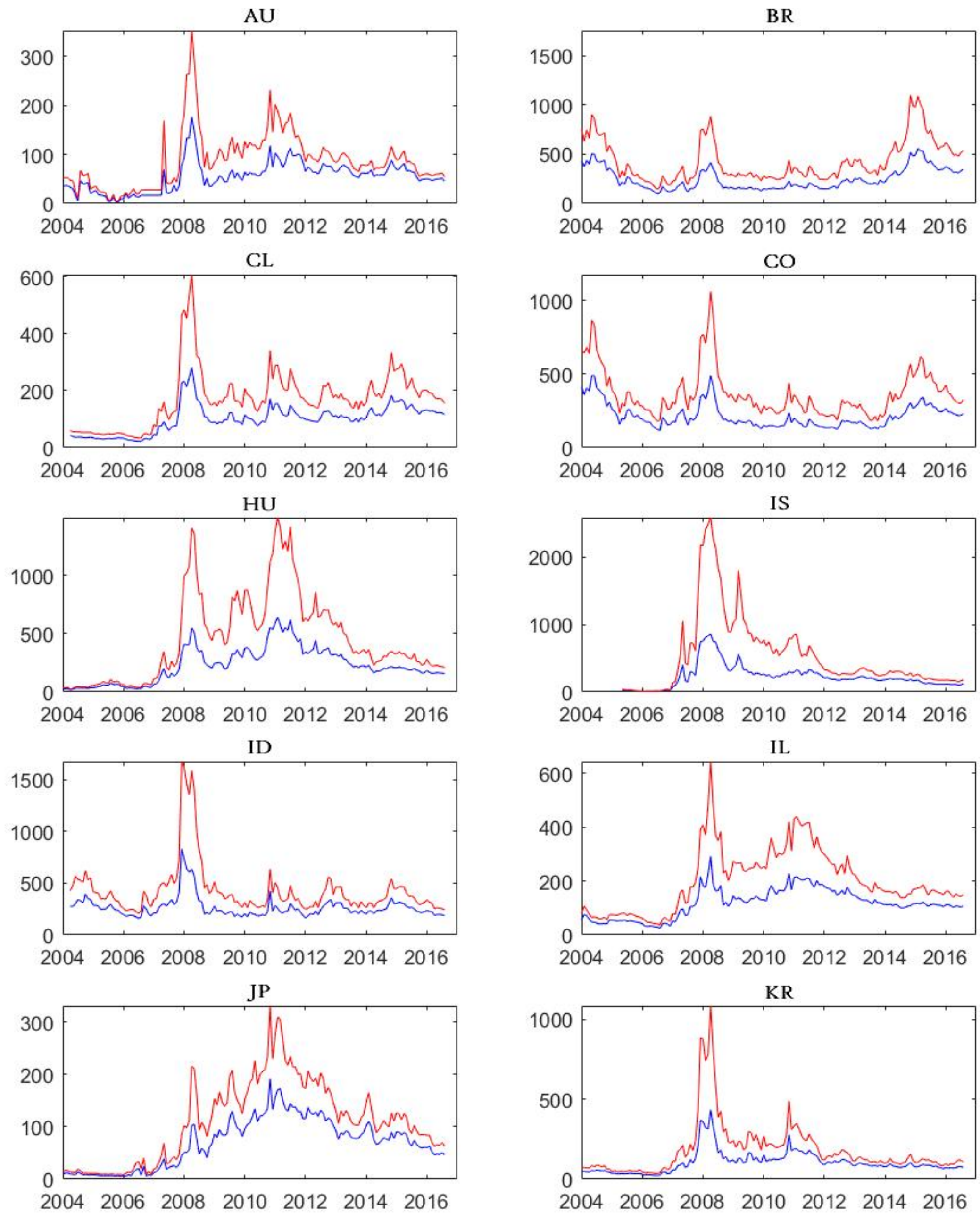
Figure 2: Sovereign Credit Default Swap (Continued)

(Basis Point)



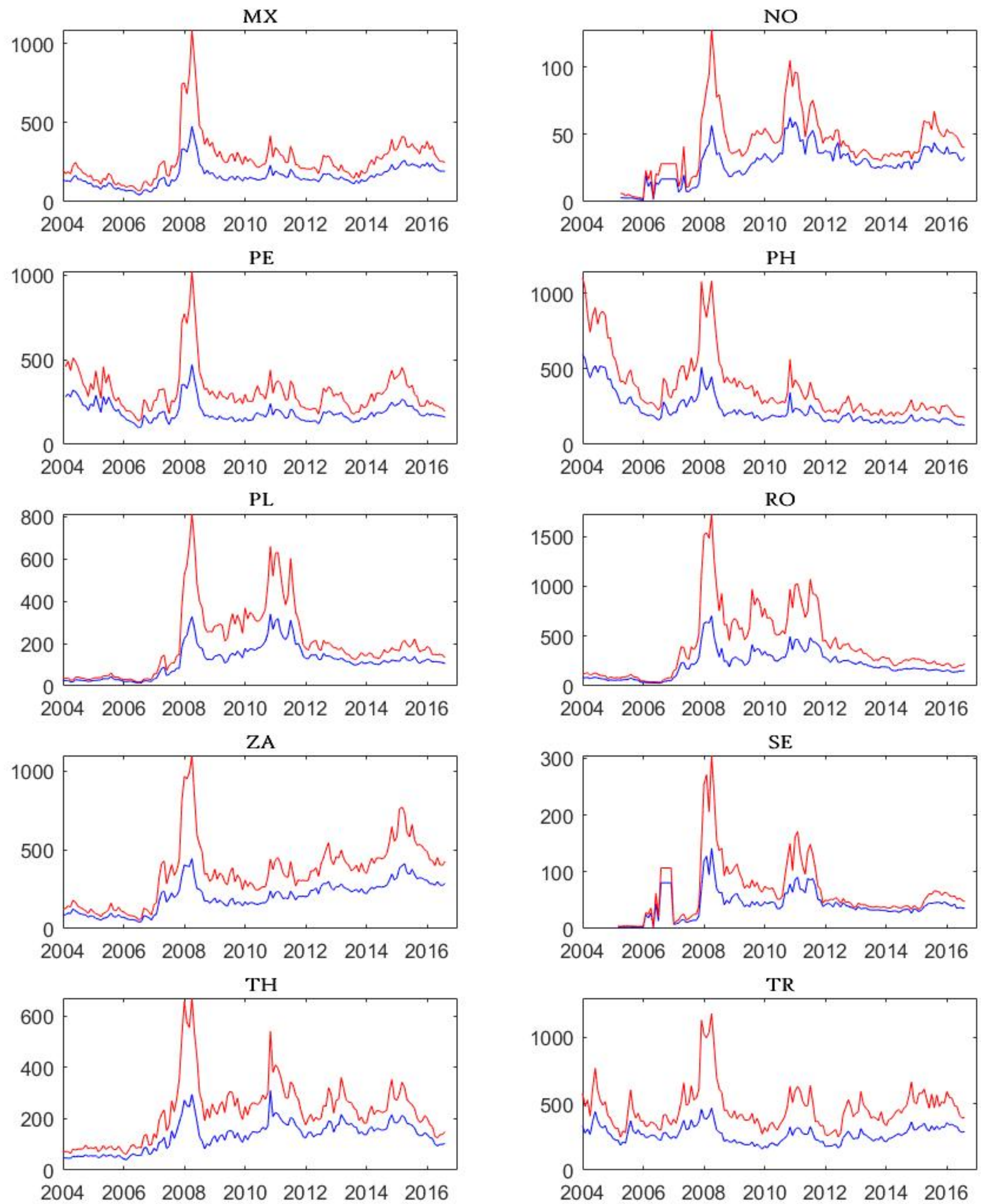
Note: 1. **Figure 2** shows sovereign credit default swap (CDS) spreads of 1, 2, 3, 5, 7, 10 years tenor: Red for 1 year, Cyan for 2 year, Green for 3 year, Black for 5 year, Magenta for 7 year and Blue for 10 year tenor CDS spread. 2. Sample period is from January, 2004 to June, 2017, but shorter for some countries. All values are in annuity basis points.

Figure 3: Correlation between the first Principal Component and D_t^{10}



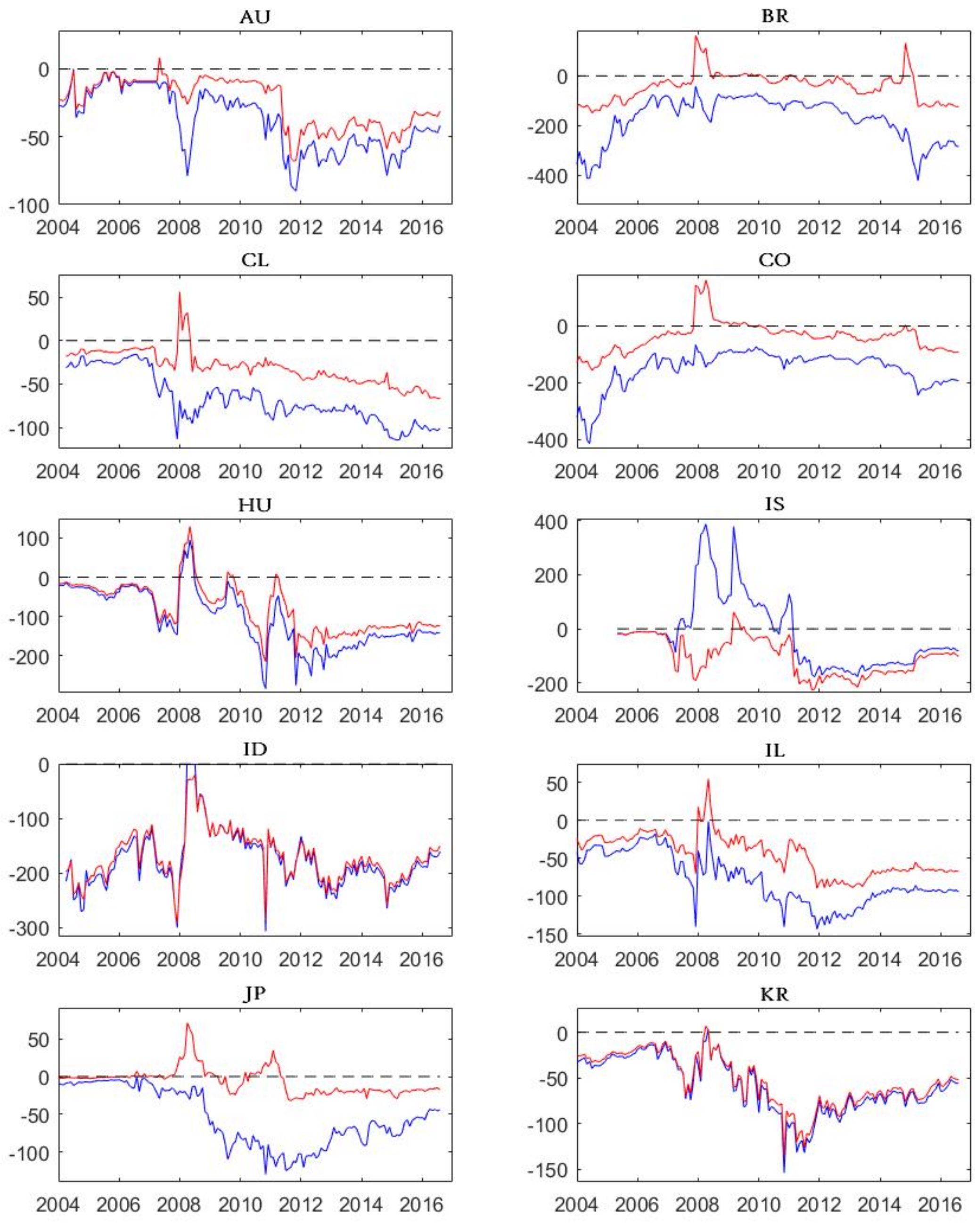
Note: 1. **Figure 3** shows time series of the first principal component of sovereign CDS, along with 10-year tenor CDS spreads (D_t^{10}): Red line for the first Principal Component and Blue for D_t^{10}. 2. Sample period is from January, 2004 to June, 2017, but shorter for some countries. All values are in annuity basis points.

Figure 3: Correlation between the first Principal Component and D_t^{10} (Continued)



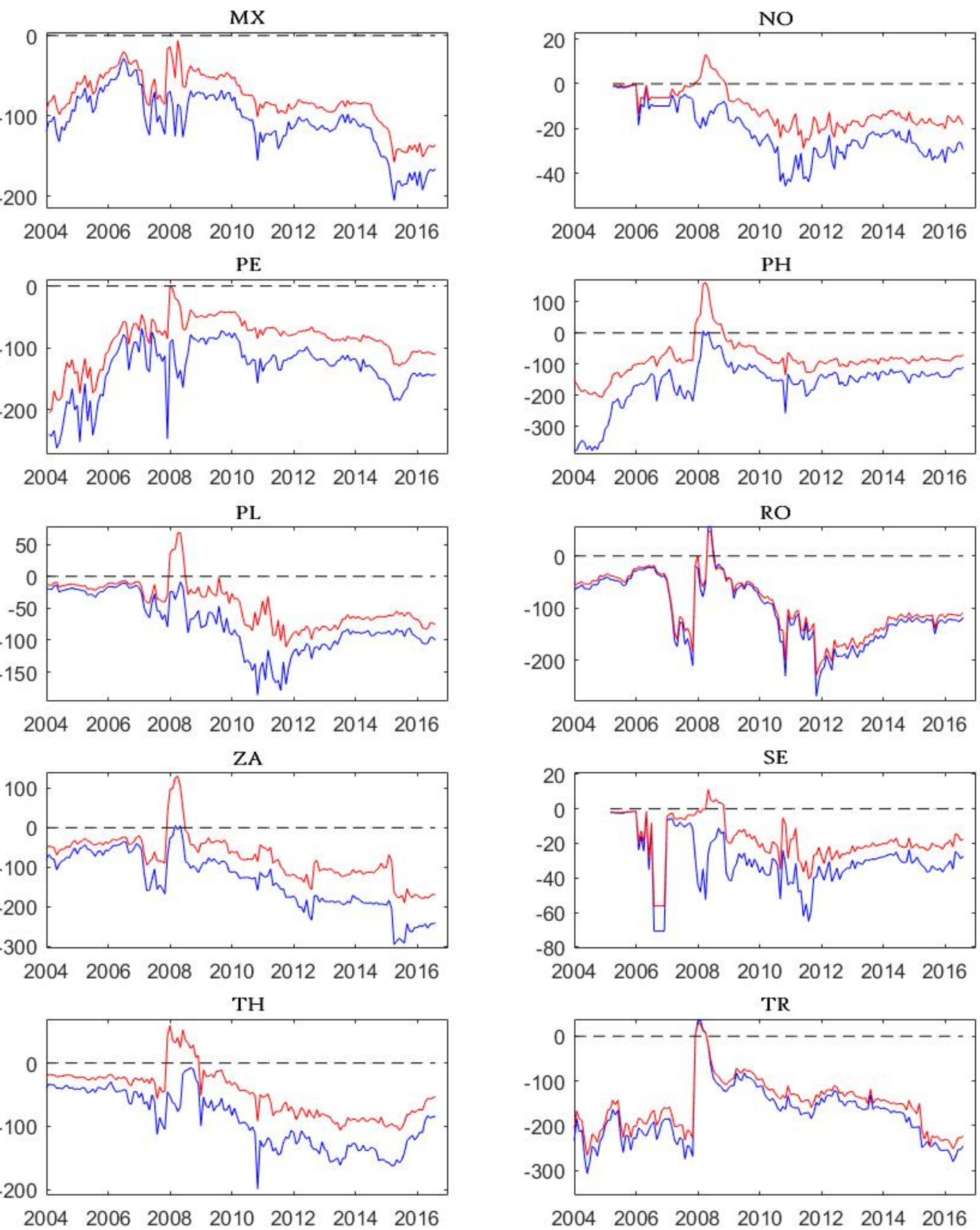
Note: 1. **Figure 3** shows time series of the first principal component of sovereign CDS, along with 10-year tenor CDS spreads (D_t^{10}): Red line for the first Principal Component and Blue for D_t^{10}. 2. Sample period is from January, 2004 to June, 2017, but shorter for some countries. All values are in annuity basis points.

Figure 4: Correlation between the second Principal Component and $D_t^1 - D_t^{10}$



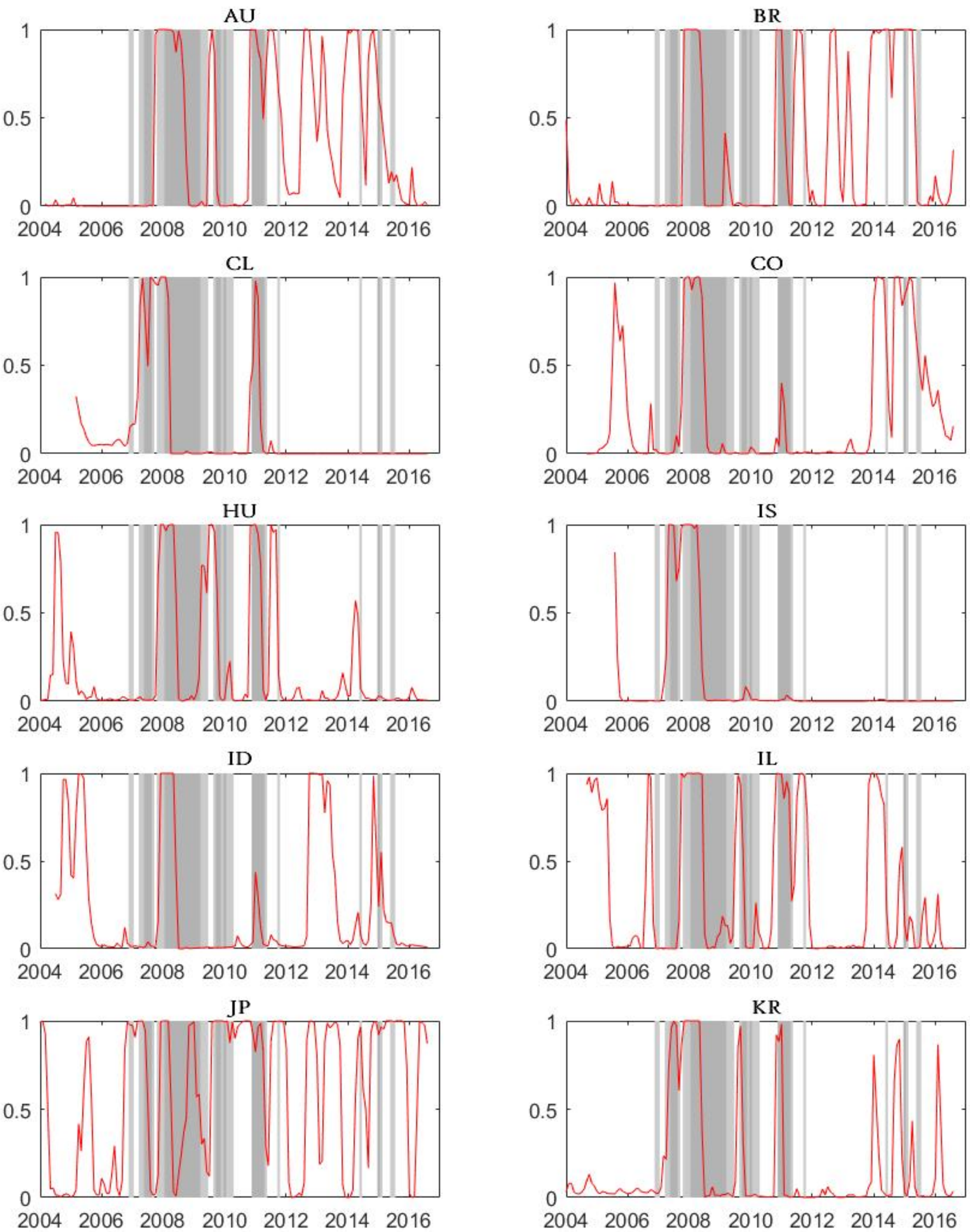
Note: 1. **Figure 4** shows time series of the second principal component of sovereign CDS, along with the difference between 1-year and 10-year tenor CDS spreads ($D_t^1 - D_T^{10}$): Red line for the second Principal Component and Blue for $D_t^1 - D_t^{10}$. Positive value implies an inverted CDS curve. 2. Sample period is from January, 2004 to June, 2017, but shorter for some countries. All values are in annuity basis points.

Figure 4: Correlation between the second Principal Component and $D_t^1 - D_t^{10}$ (Continued)



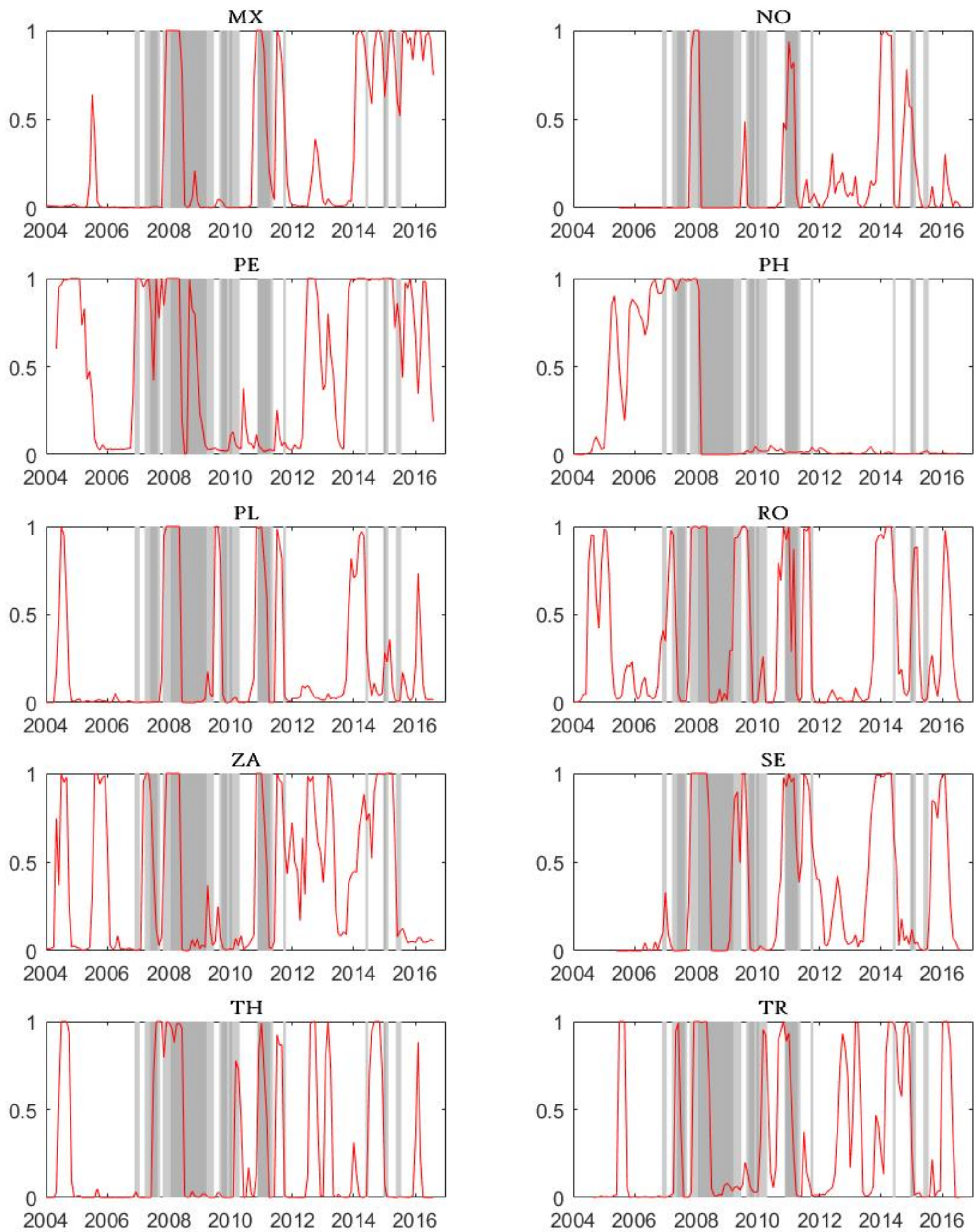
Note: 1. **Figure 4** shows time series of the second principal component of sovereign CDS, along with the difference between 1-year and 10-year tenor CDS spreads ($D_t^1 - D_T^{10}$): Red line for the second Principal Component and Blue for $D_t^1 - D_t^{10}$. Positive value implies an inverted CDS curve. 2. Sample period is from January, 2004 to June, 2017, but shorter for some countries. All values are in annuity basis points.

Figure 5: Probability in State 1



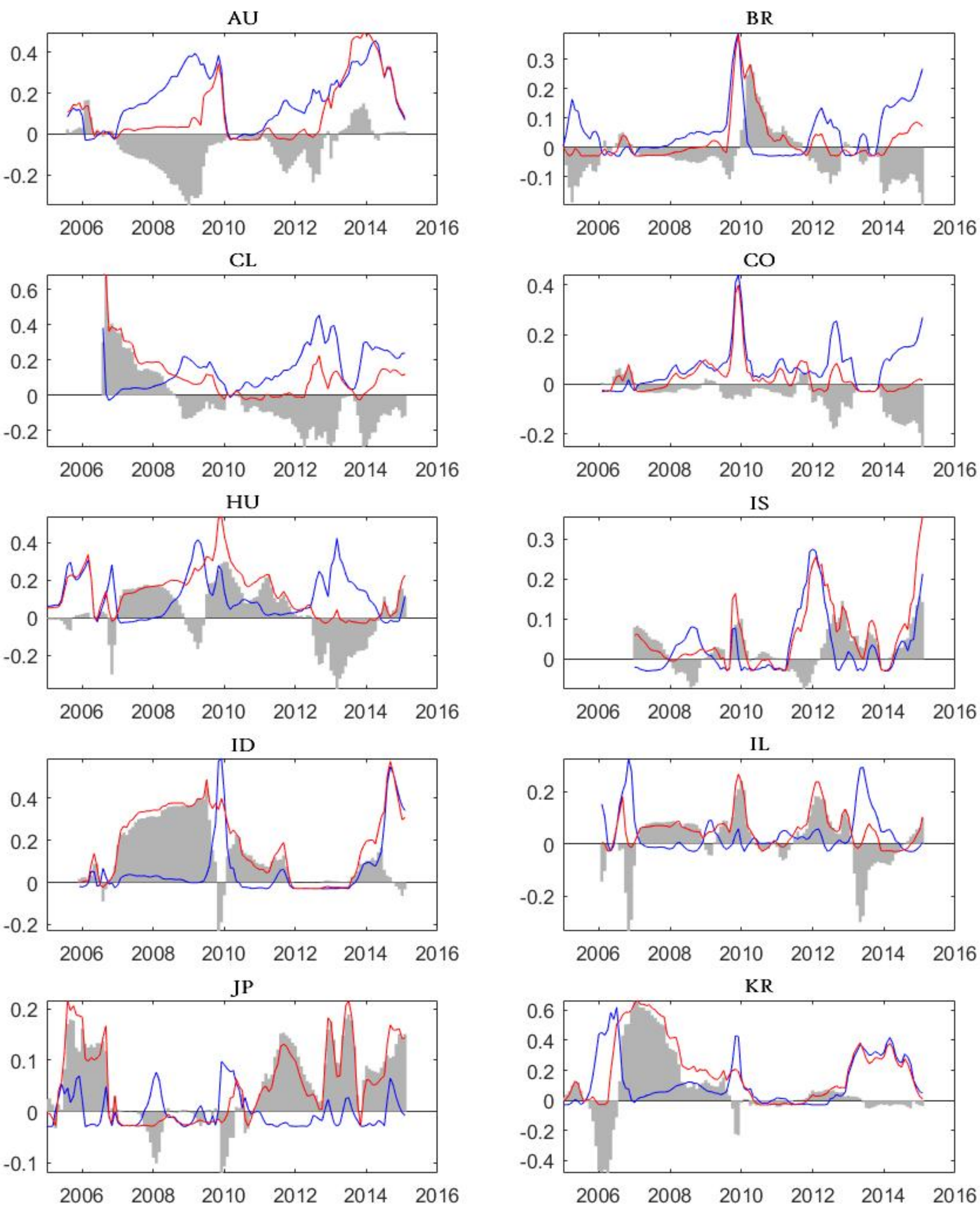
Note: 1. **Figure 5** shows the filtered probability in state 1 from Markov-Switching model estimation: $\Delta s_{t+3} = \beta_{0,\xi_t} + \beta_{1,\xi_t} L(D_t) + \beta_{2,\xi_t} S(D_t) + \epsilon_{t+3},\ where\ \epsilon_{t+3}\ i.i.d.N(0, \sigma^2_{\xi_t})$. State 1 represents "high volatility"state. 2. Dark shades show the months when VIX index is greater than 25 and light shades show the months when VIX index is between 20 and 25.

Figure 5: Probability in State 1 (Continued)



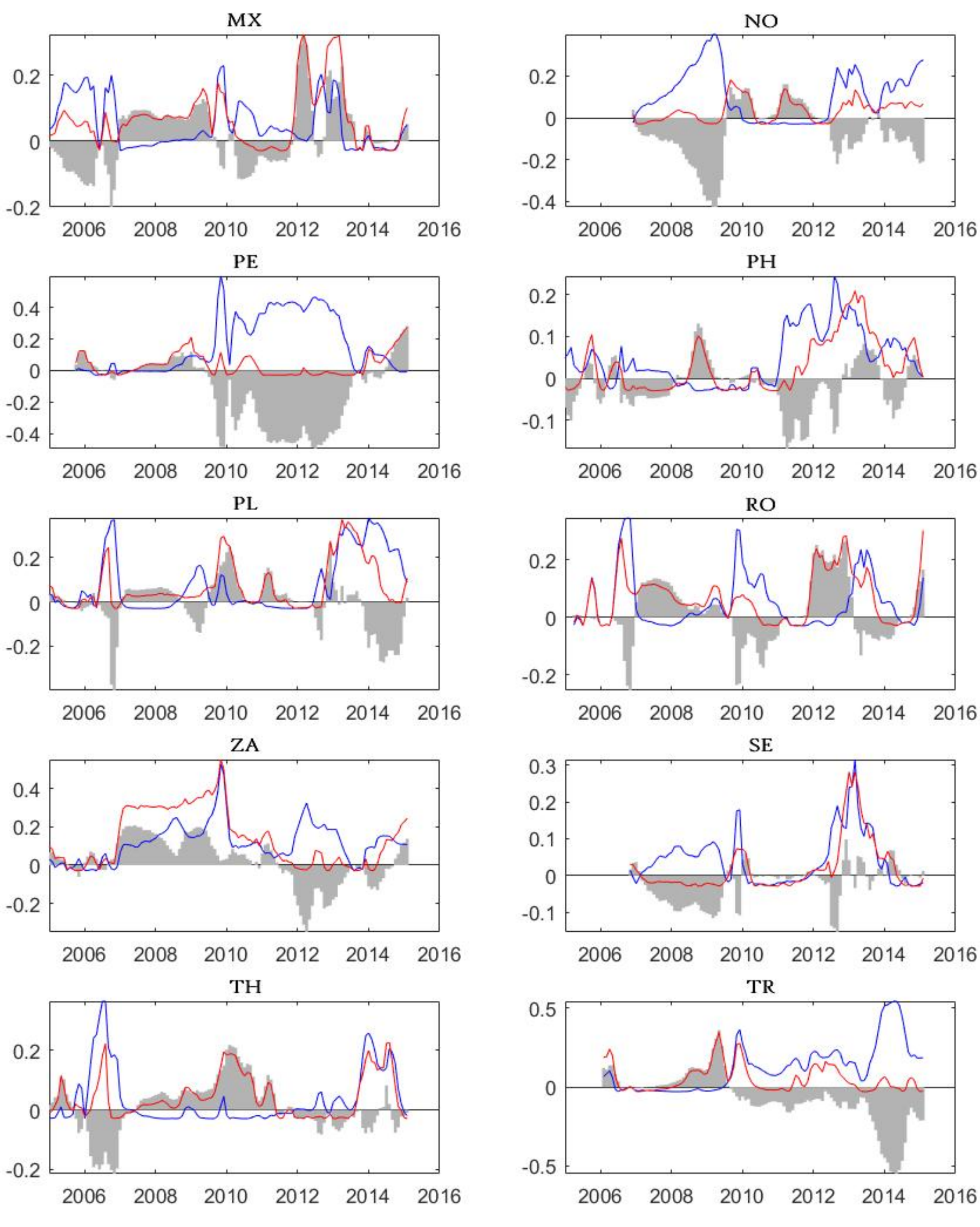
Note: 1. **Figure 5** shows the filtered probability in state 1 from Markov-Switching model estimation: $\Delta s_{t+3} = \beta_{0,\xi_t} + \beta_{1,\xi_t} L(D_t) + \beta_{2,\xi_t} S(D_t) + \epsilon_{t+3},\ where\ \epsilon_{t+3}\ i.i.d.N(0, \sigma^2_{\xi_t})$. State 1 represents "high volatility"state. 2. Dark shades show the months when VIX index is greater than 25 and light shades show the months when VIX index is between 20 and 25.

Figure 6: Comparing the Adjusted R^2 over 36-month Rolling Windows: Level or Slope?



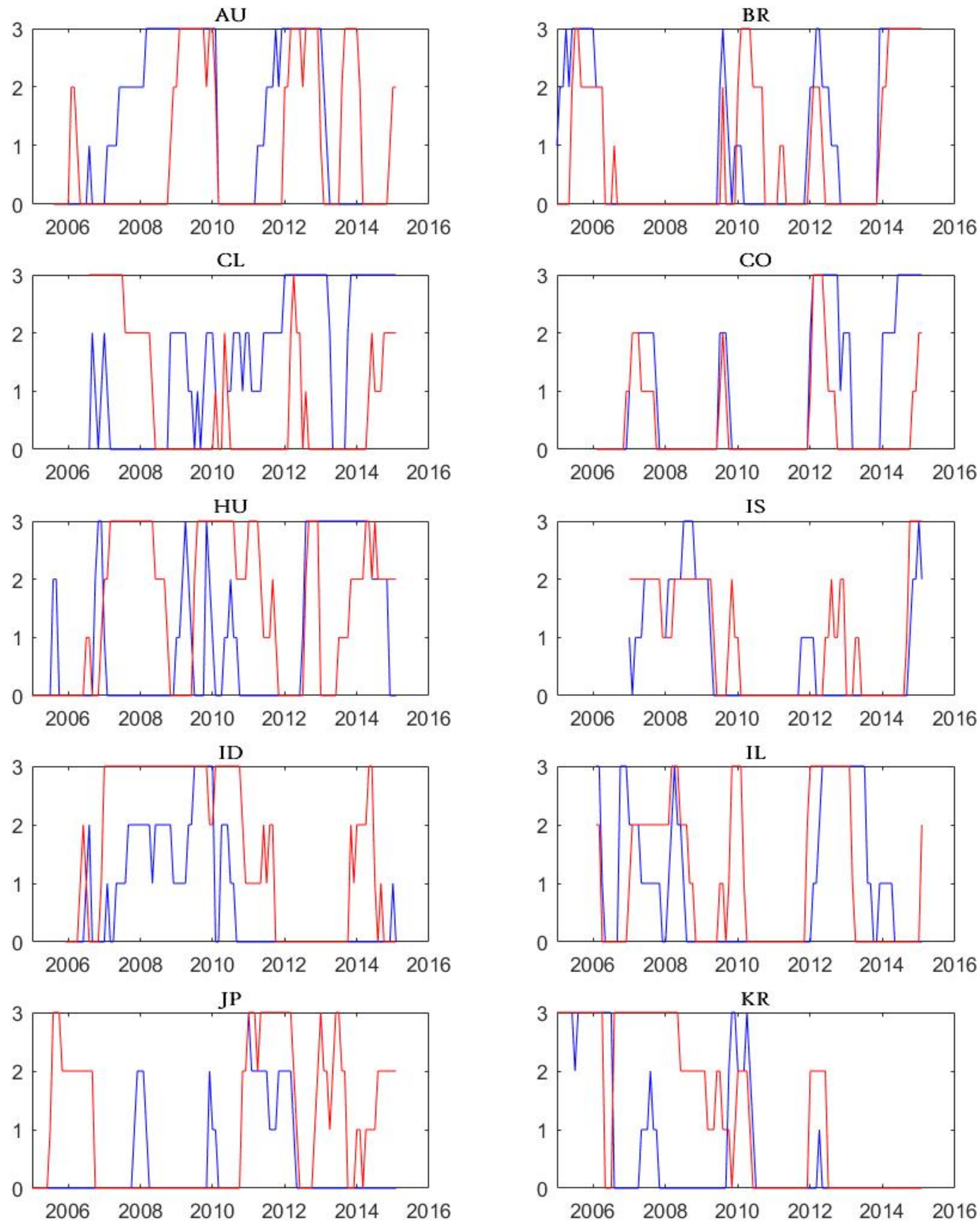
Note: 1. **Figure 6** compares the goodness of fit measures (*adjusted* R^2) over 36-month rolling windows from two models: 1) Level-only model: $\Delta s_{t+3} = \beta_0 + \beta_1 L(D_t) + \epsilon_{t+3}$; 2) Slope-only model: $\Delta s_{t+3} = \beta_0 + \beta_1 S(D_t) + \epsilon_{t+3}$. 2. Blue line represents adjusted R^2s from level-only model and Red line shows adjusted R^2s from slope-only model. Gray bar graph shows the difference in adjusted R^2s from two models defined as "adjusted R^2 from slope-only model − adjusted R^2 from level-only model". If the difference is positive, slope-model explains relatively more than level-only model for that regression window. 3. X-axis represents the midpoint of each window.

Figure 6: Comparing the Adjusted R^2 over 36-month Rolling Window: Level or Slope? (Continued)



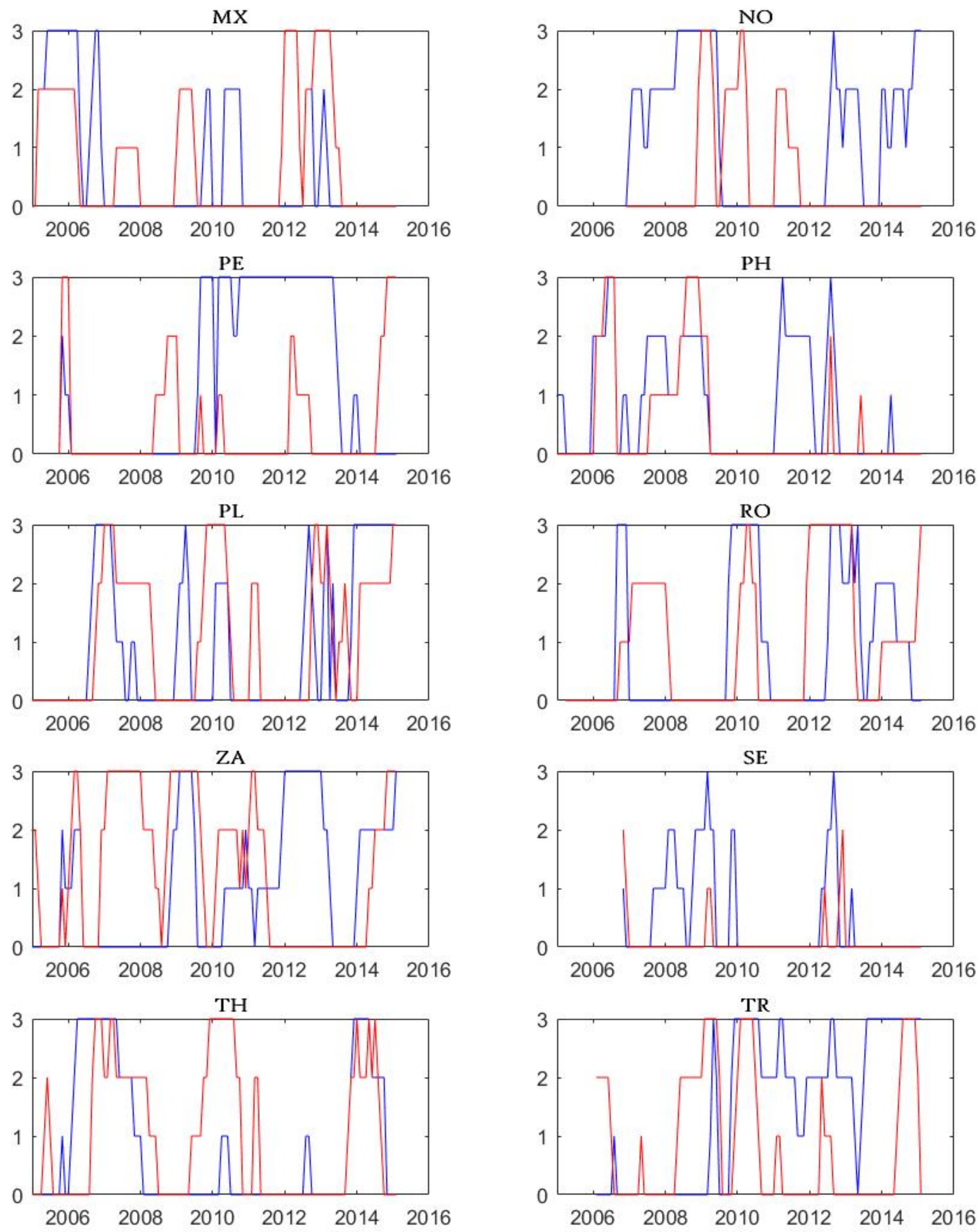
Note: 1. **Figure 6** compares the goodness of fit measures (*adjusted* R^2) over 36-month rolling windows from two models: 1) Level-only model: $\Delta s_{t+3} = \beta_0 + \beta_1 L(D_t) + \epsilon_{t+3}$; 2) Slope-only model: $\Delta s_{t+3} = \beta_0 + \beta_1 S(D_t) + \epsilon_{t+3}$. 2. Blue line represents adjusted R^2s from level-only model and Red line shows adjusted R^2s from slope-only model. Gray bar graph shows the difference in adjusted R^2s from two models defined as "adjusted R^2 from slope-only model − adjusted R^2 from level-only model". If the difference is positive, slope-model explains relatively more than level-only model for that regression window. 3. X-axis represents the midpoint of each window.

Figure 7: Comparing the $P - values$ over 36-month Rolling Windows: Level or Slope?



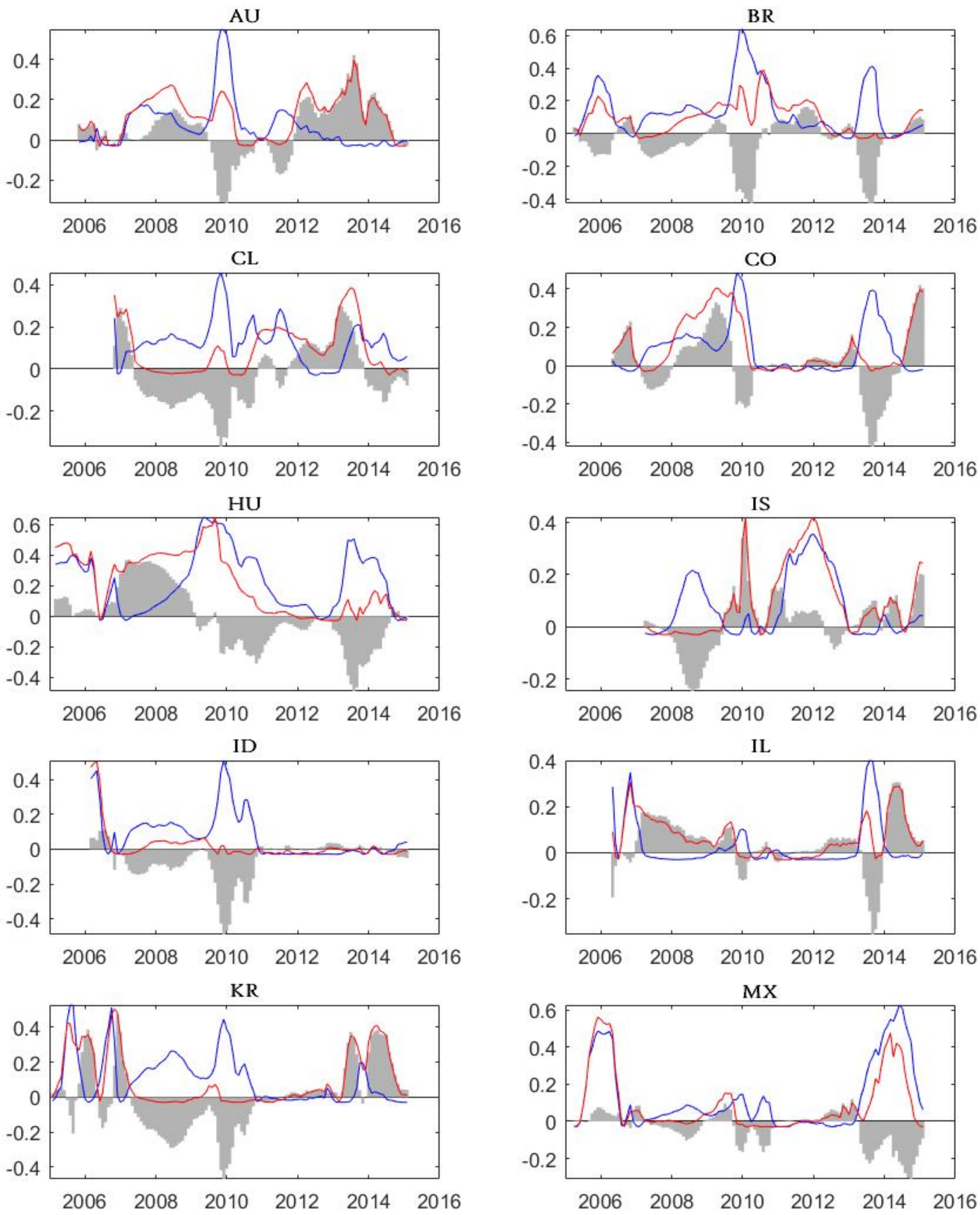
Note: 1. **Figure 7** compares the statistical significance ($P - value$) over 36-month rolling windows of level and slope factors. From the regression of $\Delta s_{t+3} = \beta_0 + \beta_1 L(D_t) + \beta_1 S(D_t) + \epsilon_{t+3}$, we obtain $P - values$ for level and slope factors. If $P - value \leq 0.01$, we give "3". If $0.01 < P - value \leq 0.05$, we give "2". If $0.05 < P - value \leq 0.1$, we give "1". Otherwise, "0". 2. Blue line for level factor and Red line for slope factor. 3. X-axis represents the midpoint of each window.

Figure 7: Comparing the $P - values$ over 36-month Rolling Windows: Level or Slope? (Continued)



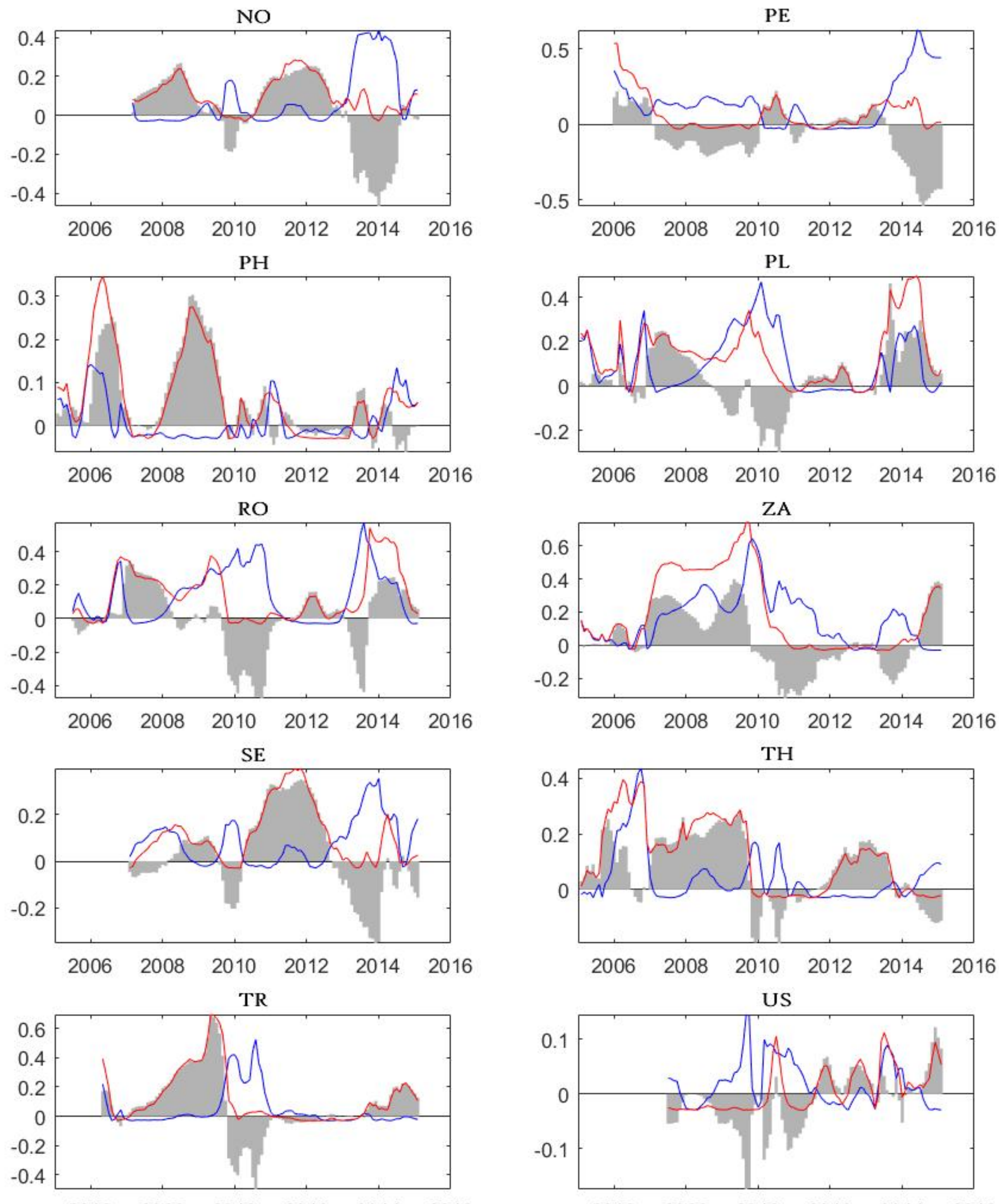
Note: 1. **Figure 7** compares the statistical significance ($P - value$) over 36-month rolling windows of level and slope factors. From the regression of $\Delta s_{t+3} = \beta_0 + \beta_1 L(D_t) + \beta_1 S(D_t) + \epsilon_{t+3}$, we obtain $P - values$ for level and slope factors. If $P - value \leq 0.01$, we give "3". If $0.01 < P - value \leq 0.05$, we give "2". If $0.05 < P - value \leq 0.1$, we give "1". Otherwise, "0". 2. Blue line for level factor and Red line for slope factor. 3. X-axis represents the midpoint of each window.

Figure 8: Comparing the Adjusted R^2 over 36-month Rolling Windows: Relative Level or Relative Slope?



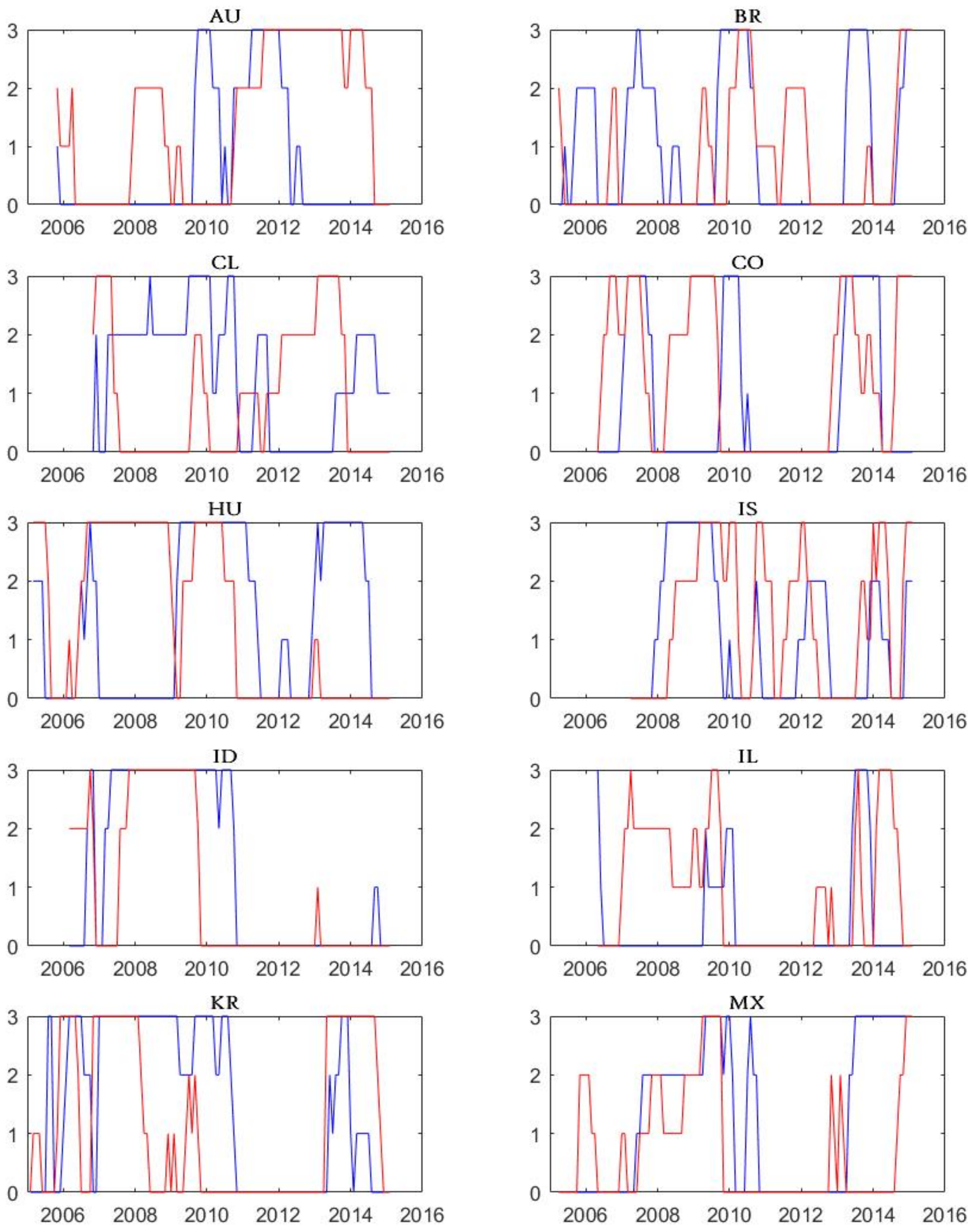
Note: 1. **Figure 8** is the robustness check for **Figure 6**: 1) Relative Level-only model: $\Delta s_{t+m} = \beta_0 + \beta_1 L(D_t^R) + \epsilon_{t+m}$; 2) Slope-only model: $\Delta s_{t+m} = \beta_0 + \beta_1 S(D_t^R) + \epsilon_{t+m}$. Here, we show the results from JPY as denominating currency, with relative risk measures as regressors, and for $m = 6-$month. The results from USD and/or over different horizons ($m = 1-, 3-, 12-$month) can be provided upon request. 2. Blue line: adjusted R^2 from level-only model, Red line: adjusted R^2 from slope-only model. Gray bar: adjusted R^2 from slope-only model $-$ adjusted R^2 from level-only model.

Figure 8: Comparing the Adjusted R^2 over 36-month Rolling Window: Relative Level or Relative Slope? (Continued)



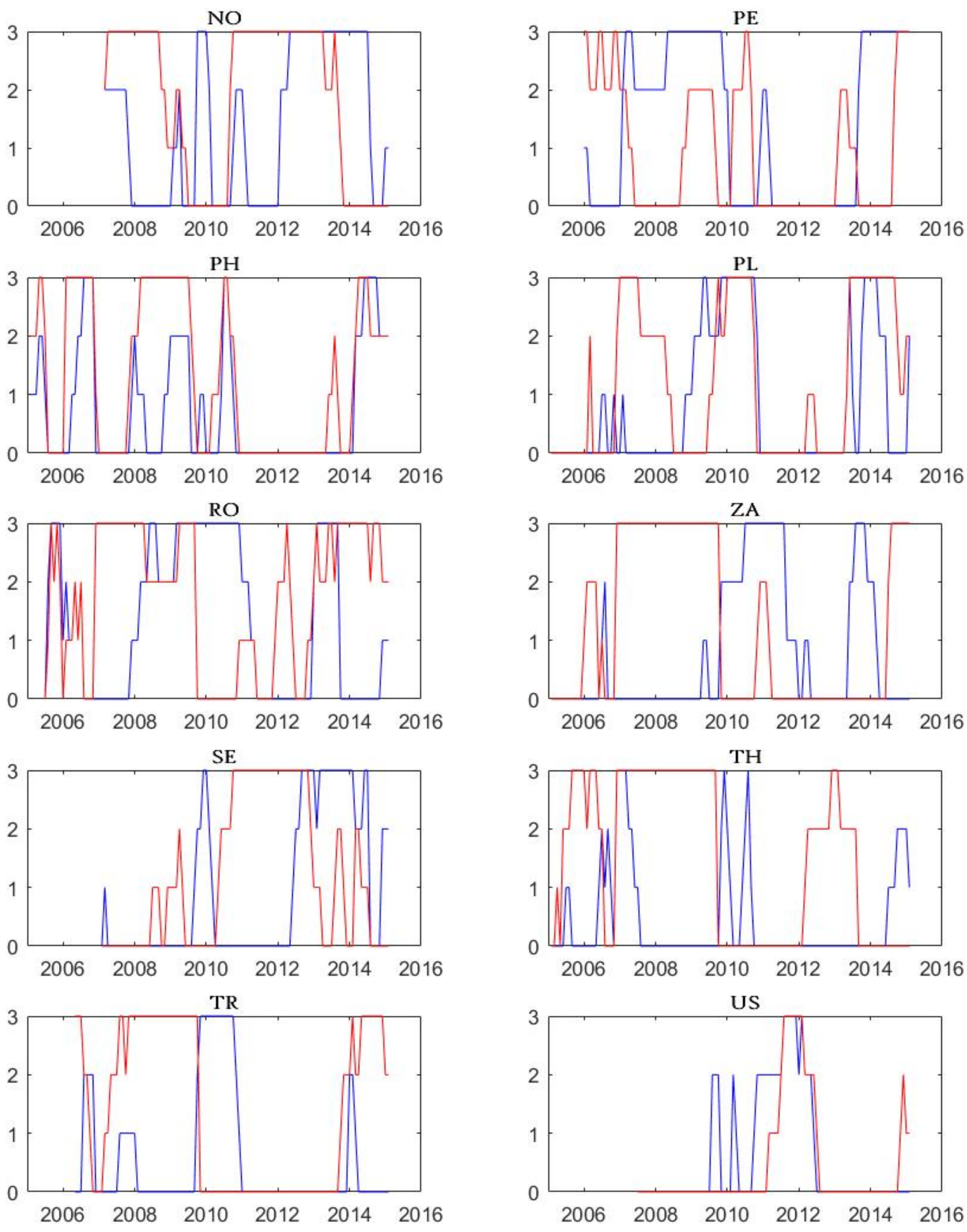
Note: 1. **Figure 8** is the robustness check for **Figure 6**: 1) Relative Level-only model: $\Delta s_{t+m} = \beta_0 + \beta_1 L(D_t^R) + \epsilon_{t+m}$; 2) Slope-only model: $\Delta s_{t+m} = \beta_0 + \beta_1 S(D_t^R) + \epsilon_{t+m}$. Here, we show the results from JPY as denominating currency, with relative risk measures as regressors, and for $m = 6-$month. The results from USD and/or over different horizons ($m = 1-, 3-, 12-$month) can be provided upon request. 2. Blue line: adjusted R^2 from level-only model, Red line: adjusted R^2 from slope-only model. Gray bar: adjusted R^2 from slope-only model $-$ adjusted R^2 from level-only model.

Figure 9: Comparing the $P-values$ over 36-month Rolling Windows: Relative Level or Relative Slope?



Note: 1. **Figure 9** is the robustness check for **Figure 7**. From the regression of $\Delta s_{t+m} = \beta_0 + \beta_1 L(D_t^R) + \beta_1 S(D_t^R) + \epsilon_{t+m}$, we obtain $P-values$ for level and slope factors. If $P-value \leq 0.01$, we give "3". If $0.01 < P-value \leq 0.05$, we give "2". If $0.05 < P-value \leq 0.1$, we give "1". Otherwise, "0". Here, we show the results from JPY as denominating currency, with relative risk measures as regressors, and for $m = 6-$month. The results from USD and/or over different horizons ($m = 1-, 3-, 12-$month) can be provided upon request. 2. Blue line for level factor and Red line for slope factor.

Figure 9: Comparing the $P - values$ over 36-month Rolling Windows: Relative Level or Relative Slope? (Continued)



Note: 1. **Figure 9** is the robustness check for **Figure 7**. From the regression of $\Delta s_{t+m} = \beta_0 + \beta_1 L(D_t^R) + \beta_1 S(D_t^R) + \epsilon_{t+m}$, we obtain $P - values$ for level and slope factors. If $P - value \leq 0.01$, we give "3". If $0.01 < P - value \leq 0.05$, we give "2". If $0.05 < P - value \leq 0.1$, we give "1". Otherwise, "0". Here, we show the results from JPY as denominating currency, with relative risk measures as regressors, and for $m = 6-$month. The results from USD and/or over different horizons ($m = 1-, 3-, 12-$month) can be provided upon request. 2. Blue line for level factor and Red line for slope factor.

Appendix

What is Sovereign Credit Default Swap?

Sovereign Credit Default Swap (CDS) is a bilateral Over-the-Counter(OTC) agreement in which protection buyer purchases insurance against contingent credit events by paying an annuity premium quarterly or bi-annually and protection seller compensates for the loss given credit events. Protection buyers are usually banks, security firms and hedge funds and protection sellers are mostly insurance companies and banks. In practice, there is no default in government bond. Instead, International Swap and Derivative Association (ISDA) references four types of credit events: acceleration, failure to pay, restructuring, and repudiation.

There are three types of cash flows associated with CDS contract. 1) If there is no credit event until the end of the contract, only protection buyer pays an annuity premium for the contract tenor. The protection seller pays nothing. 2) If one of the credit events is triggered prior to the tenor, the buyer pays an annuity premium until the credit event happens and the contract terminates. The seller compensates the buyer for its loss given a credit event. There are two types of settlement. In the physical settlement, the buyer provides the seller the deliverable obligations of the reference entity and the seller pays the buyer a cash payment amounting to its full aggregate notional amount. In cash settlement, the seller pays the buyer a cash payment amounting to a full in market value of a debt obligation of the reference entity. 3) Each counter party of CDS contract can unwind the contract prior to the tenor. In order to unwind the contract, they need to agree on early termination or assignment to another counter party or they can offset the transaction in the market. In any case, they need to pay or receive the Mark-to-Market value, which is the present value of difference in annuity payment over remaining contract period. For example, if the CDS tightens, the buyer needs to pay the Mark-to-Market value to seller.

Sovereign CDS has been increasing in use from early 2000s. According to the Bank for International Settlement (BIS) statistics, sovereign CDS exploded from 6.4 trillion dollars in 2004 to a peak of 58.2 trillion dollars in 2007. The amount has since come down because the credit derivatives were central to the 2007-2009 financial crisis.

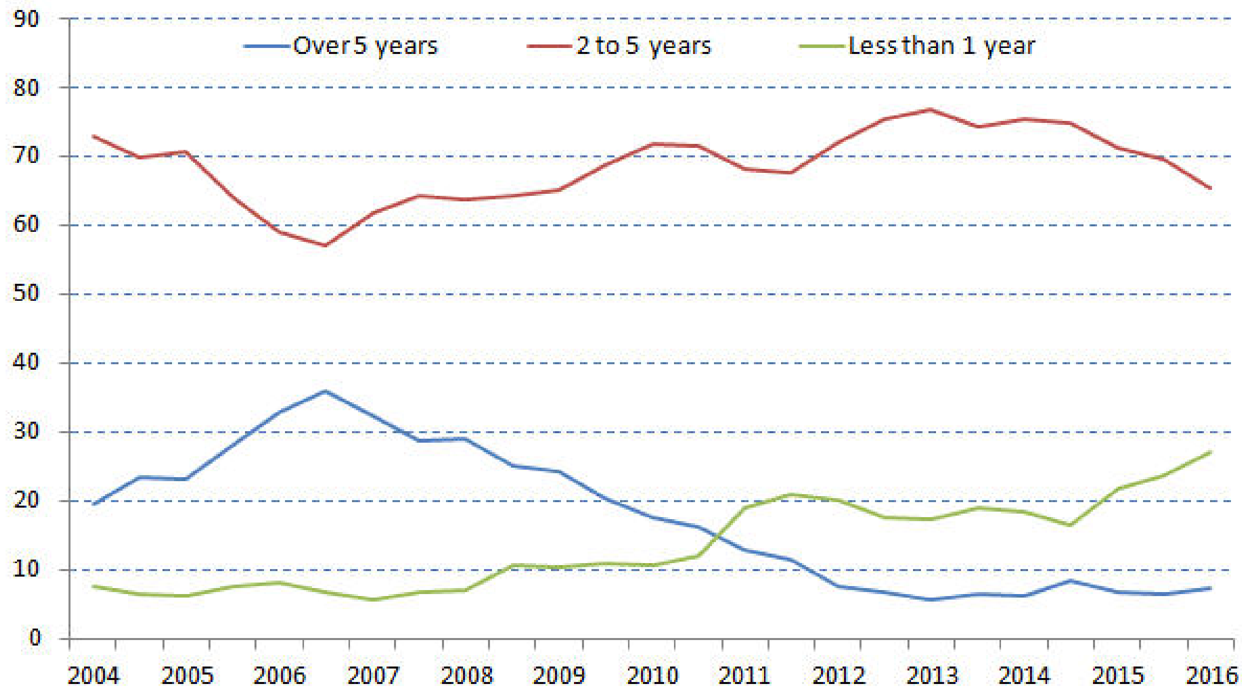
Sovereign CDS: Outstanding notional amount (billion USD)

2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
6396	13908	28650	58244	41883	32693	29898	28626	25068	21020	16399	12294	9857

Note: 1. Each number represents the gross notional amount outstanding in the second half of each year. 2. source: www.bis.org

While corporate CDS is mostly concentrated around five-year contracts, sovereign CDS is well diversified over different tenors. Based on the BIS statistics, we compute market shares of each tenor contract from 2004 to 2016. The total volume of notional amount outstanding with tenor less than one year consist 12.01%, with tenor between two to five years 67.10% and with tenor over five years 20.88%. The interesting feature is that after 2011, short tenors have gradually been trading more relative to long tenors.

Market of sovereign CDS over different tenors (% in volume)



Note: 1. Market share is computed as total volume of notional amount outstanding of each tenor group compared that of all tenors. 2. source: www.bis.org

Appendix Tables

Table A1. Explaining the Excess Currency Returns with Sovereign Credit Risk: Structural Break Model

	AU	BR	CL	CO	HU	IS	ID	IL	JP	KR
Model 1: $xr_{t+3} = \beta_0 + \beta_1 D_t^1 + \epsilon_{t+3}$										
$p-value$	0.000	0.006	0.000	0.002	0.005	0.000	0.000	0.032	0.033	0.000
$ad.R^2$	0.126	0.059	0.176	0.098	0.086	0.244	0.176	0.055	0.056	0.192
Model 2: $xr_{t+3} = \beta_0 + \beta_1 L(D_t) + \epsilon_{t+3}$										
$p-value$	0.000	0.002	0.000	0.000	0.004	0.000	0.000	0.007	0.027	0.000
$ad.R^2$	0.131	0.074	0.217	0.147	0.093	0.250	0.186	0.081	0.060	0.212
Model 3: $xr_{t+3} = \beta_0 + \beta_1 S(D_t) + \epsilon_{t+3}$										
$p-value$	0.003	0.002	0.000	0.011	0.002	0.000	0.000	0.030	0.014	0.003
$ad.R^2$	0.100	0.075	0.180	0.074	0.100	0.280	0.221	0.056	0.071	0.097
Model 4: $xr_{t+3} = \beta_0 + \beta_1 L(D_t) + \beta_2 S(D_t) + \epsilon_{t+3}$										
$p-value$	0.000	0.000	0.000	0.000	0.011	0.000	0.000	0.003	0.052	0.000
$ad.R^2$	0.245	0.127	0.212	0.149	0.087	0.273	0.230	0.111	0.058	0.199

	MX	NO	PE	PH	PL	RO	ZA	SE	TH	TR
Model 1: $xr_{t+3} = \beta_0 + \beta_1 D_t^1 + \epsilon_{t+3}$										
$p-value$	0.000	0.010	0.000	0.000	0.002	0.001	0.019	0.013	0.008	0.004
$ad.R^2$	0.164	0.092	0.130	0.101	0.102	0.108	0.067	0.086	0.070	0.085
Model 2: $xr_{t+3} = \beta_0 + \beta_1 L(D_t) + \epsilon_{t+3}$										
$p-value$	0.000	0.013	0.000	0.000	0.001	0.001	0.007	0.018	0.003	0.005
$ad.R^2$	0.167	0.087	0.137	0.110	0.111	0.112	0.083	0.081	0.085	0.081
Model 3: $xr_{t+3} = \beta_0 + \beta_1 S(D_t) + \epsilon_{t+3}$										
$p-value$	0.007	0.046	0.012	0.000	0.033	0.000	0.013	0.043	0.086	0.000
$ad.R^2$	0.085	0.062	0.068	0.097	0.056	0.133	0.073	0.063	0.030	0.124
Model 4: $xr_{t+3} = \beta_0 + \beta_1 L(D_t) + \beta_2 S(D_t) + \epsilon_{t+3}$										
$p-value$	0.000	0.015	0.000	0.000	0.001	0.001	0.001	0.015	0.008	0.000
$ad.R^2$	0.161	0.099	0.143	0.160	0.125	0.134	0.123	0.098	0.084	0.200

Note: 1. This table is Appendix to **Table 4**. Instead of regressing quarterly exchange rate changes, we regress quarterly excess currency returns ($xr_{t+3} = i_t^3 - i_t^{3,US} - \Delta s_{t+3}$) on four different sets of risk factors and then apply the Bai-Perron(2003) test(with 15% trimming and 5 - 10% significance level) to detect the multiple structural breaks in the regression. Zero to two breaks are detected. 2. After identifying the break dates, structural break dummy variables for each sub-period are incorporated into the regression. 3. P-value is for the Wald test that factors jointly have no explanatory power 4. Adjusted R^2 is reported.

Table A2. Explaining the Excess Currency Returns with Sovereign Credit Risk: Markov Switching Model

$$xr_{t+3} = \beta_{0,\xi_t} + \beta_{1,\xi_t} L(D_t) + \beta_{2,\xi_t} S(D_t) + \epsilon_{t+3},\ \ where\ \epsilon_{t+3}\ i.i.d.N(0, \sigma^2_{\xi_t})$$

	AU	BR	CL	CO	HU	IS	ID	IL	JP	KR
$\beta_{0,s_t=0}$	0.316	20.160***	7.772	0.127	13.728**	19.154***	-23.066***	1.454	-6.194	-5.208
	(6.738)	(7.756)	(6.919)	(1.780)	(6.635)	(7.231)	(5.443)	(4.699)	(5.022)	(5.249)
$\beta_{0,s_t=1}$	-123.409*	-67.085*	286.073**	-47.404	-36.819	9.560	106.143***	19.100	11.261	-24.284
	(68.505)	(34.648)	(138.493)	(33.826)	(42.827)	(55.303)	(23.733)	(12.487)	(8.659)	(28.763)
$\beta_{1,s_t=0}$	0.267***	-0.003	0.056**	0.022*	0.027***	-0.010	0.081***	0.160***	0.157	0.121***
	(0.062)	(0.012)	(0.026)	(0.013)	(0.009)	(0.007)	(0.012)	(0.054)	(0.113)	(0.014)
$\beta_{1,s_t=1}$	0.074	0.114**	0.127	0.108	-0.103**	0.100	-0.021	-0.035	-0.032	-0.131***
	(0.391)	(0.056)	(0.297)	(0.073)	(0.051)	(0.064)	(0.014)	(0.035)	(0.057)	(0.031)
$\beta_{2,s_t=0}$	0.556***	-0.086	0.411***	0.017	0.179***	0.060	0.000	0.397**	1.596*	0.102
	(0.206)	(0.084)	(0.145)	(0.086)	(0.052)	(0.045)	(0.006)	(0.169)	(0.825)	(0.079)
$\beta_{2,s_t=1}$	-2.181	-0.235	13.605***	-0.123	-0.092	1.368*	0.682***	0.327*	-0.165	-0.438***
	(1.429)	(0.143)	(5.272)	(0.220)	(0.320)	(0.813)	(0.129)	(0.193)	(0.227)	(0.073)
$\sigma_{s_t=0}$	33.878***	30.122*	31.209***	25.245**	36.370***	32.841***	21.893**	16.697**	24.096**	23.734**
	(1.092)	(17.625)	(11.662)	(11.515)	(13.747)	(12.589)	(8.728)	(7.794)	(11.213)	(9.296)
$\sigma_{s_t=0}$	53.792***	67.357**	50.947	63.785**	68.482	101.608	26.347*	36.746**	36.562**	48.133**
	(1.343)	(29.846)	(40.834)	(27.533)	(43.136)	(64.414)	(15.840)	(15.574)	(15.088)	(23.283)
P_{00}	0.910***	0.845**	0.983***	0.937***	0.861***	0.987**	0.856***	0.961***	0.961***	0.856***
	(0.240)	(0.346)	(0.286)	(0.275)	(0.286)	(0.398)	(0.318)	(0.355)	(0.353)	(0.320)
P_{11}	0.301	0.826**	0.737	0.944***	0.000	0.859*	0.410	0.965***	0.968***	0.469
	(0.377)	(0.359)	(0.581)	(0.332)	(0.414)	(0.511)	(0.374)	(0.345)	(0.358)	(0.389)
$ad.R^2$	0.420	0.211	0.391	0.036	0.523	0.229	0.634	0.116	0.149	0.512
AIC	10.377	10.764	10.020	10.462	10.548	10.293	9.487	9.529	9.826	9.836

Note: 1. This table is Appendix to **Table 5**. The model is estimated by two-state Markov-Switching Model. After estimating the parameters by Maximum Likelihood Estimation (MLE), the filtered probabilities are computed by Hamilton filter. 2. Coefficient estimates are reported with the Newey-West standard errors in parentheses. Asterisks indicate significance levels at 1% (***), 5% (**), and 10% (*) respectively. 3. By using the filtered probabilities, we obtain the estimated xr_{t+3} and compute the adjusted R^2 by using the residual sum of squares(RSS). 4. AIC is provided.

Table A2. Explaining the Excess Currency Returns with Sovereign Credit Risk: Markov Switching Model (Continued)

$$xr_{t+3} = \beta_{0,\xi_t} + \beta_{1,\xi_t} L(D_t) + \beta_{2,\xi_t} S(D_t) + \epsilon_{t+3},\ \ where\ \epsilon_{t+3}\ i.i.d.N(0,\sigma^2_{\xi_t})$$

	MX	NO	PE	PH	PL	RO	ZA	SE	TH	TR
$\beta_{0,s_t=0}$	-3.066	8.826	-10.120**	-8.322	13.088**	-0.073	24.788***	-0.451	3.552	-18.679***
	(7.704)	(7.488)	(5.011)	(5.595)	(6.664)	(4.694)	(9.164)	(7.118)	(3.065)	(0.649)
$\beta_{0,s_t=1}$	-51.812	-56.382*	-11.617	29.405	-139.945	58.327**	-11.451	-30.921	4.364	-28.081**
	(49.163)	(30.930)	(27.870)	(18.896)	(108.090)	(23.676)	(15.053)	(34.883)	(5.377)	(11.331)
$\beta_{1,s_t=0}$	0.073***	0.168	0.068***	0.007	0.063**	0.034***	0.124***	0.246***	0.013	0.418***
	(0.014)	(0.152)	(0.018)	(0.007)	(0.025)	(0.009)	(0.022)	(0.080)	(0.016)	(0.001)
$\beta_{1,s_t=1}$	0.007	0.636	0.025	-0.043	0.154	-0.138***	0.027	0.122	0.003	0.051***
	(0.068)	(0.508)	(0.038)	(0.033)	(0.210)	(0.030)	(0.027)	(0.231)	(0.018)	(0.016)
$\beta_{2,s_t=0}$	0.065	1.020***	0.093**	-0.075	0.304***	0.028	0.156*	0.375	-0.046	2.066***
	(0.090)	(0.387)	(0.037)	(0.057)	(0.105)	(0.044)	(0.080)	(0.246)	(0.035)	(0.005)
$\beta_{2,s_t=1}$	-0.312	-0.760	-0.054	0.123	-0.408	0.275	0.199*	-0.324	0.120**	-0.073
	(0.333)	(1.680)	(0.212)	(0.104)	(0.617)	(0.211)	(0.115)	(1.282)	(0.059)	(0.049)
$\sigma_{s_t=0}$	19.633**	29.742**	12.306**	16.332**	37.554***	32.089**	17.851	28.911**	5.160	0.349
	(9.989)	(13.007)	(4.936)	(7.128)	(14.449)	(13.559)	(13.570)	(13.495)	(3.509)	(0.288)
$\sigma_{s_t=0}$	50.832*	57.059*	32.801*	25.144**	76.961	41.684*	53.826***	59.909*	21.908***	34.081***
	(26.296)	(31.700)	(16.869)	(11.228)	(50.086)	(23.139)	(20.643)	(34.183)	(8.363)	(10.884)
P_{00}	0.917***	0.941***	0.977***	0.987**	0.959***	0.753***	0.137	0.927***	0.506	0.973***
	(0.351)	(0.294)	(0.311)	(0.401)	(0.322)	(0.284)	(0.724)	(0.355)	(0.457)	(0.235)
P_{11}	0.800*	0.845**	0.948**	0.979**	0.689	0.232	0.738**	0.782	0.834***	0.000
	(0.465)	(0.429)	(0.483)	(0.426)	(0.519)	(0.516)	(0.306)	(0.482)	(0.252)	(8.608)
$ad.R^2$	0.274	0.128	0.046	0.032	0.419	0.511	0.429	0.133	0.080	0.359
AIC	9.726	10.240	8.539	8.885	10.582	10.313	10.875	10.256	8.770	10.115

Note: 1. This table is Appendix to **Table 5**. The model is estimated by two-state Markov-Switching Model. After estimating the parameters by Maximum Likelihood Estimation (MLE), the filtered probabilities are computed by Hamilton filter. 2. Coefficient estimates are reported with the Newey-West standard errors in parentheses. Asterisks indicate significance levels at 1% (***), 5% (**), and 10% (*) respectively. 3. By using the filtered probabilities, we obtain the estimated xr_{t+3} and compute the adjusted R^2 by using the residual sum of squares(RSS). 4. AIC is provided.