International Review of Economics and Finance 41 (2016) 371–390

Contents lists available at ScienceDirect

International Review of Economics and Finance

journal homepage: www.elsevier.com/locate/iref

Global risk spillover and the predictability of sovereign CDS spread: International evidence☆

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ARTICLE INFO

Article history:
Received 29 June 2014
Received in revised form 9 March 2015
Accepted 28 October 2015
Available online 5 November 2015

JEL classification:
G1
G14
G15

Keywords:
Spillover
Contagion
Sovereign CDS
Granger causality
Out-of-sample forecast

ABSTRACT

Using an error correction model, we document strong evidence of Granger causality in mean from the S&P option market to the sovereign CDS market in 98% of the 56 sovereigns we investigate. Tests under conditional heteroskedasticity provide further evidence of the risk spillover effect from the S&P index option market to the CDS market in mean, variance, and value-at-risk. The strong spillover effect during the recent financial crisis implies that global shocks first affect the S&P option market and then spill over to the sovereign CDS market. We demonstrate that our results are quite robust.

1. Introduction

The role of sovereign debt in the recent financial crisis has placed sovereign credit default swaps (CDS) in the limelight. As the sovereign debt market rapidly increases in size, the importance of sovereign credit risk and factors that explain it are receiving more attention (see Gande & Parsley, 2005; Remolona, Scatigna, & Wu, 2008; Hilscher & Nosbusch, 2010; Longstaff, Pan, Pedersen, & Singleton, 2011). In particular, the contagion effect created by a financial crisis can have a severe impact on sovereign credit risk and lead to global risk spillover (Longstaff, 2010).[1]

In the recent literature, Pan and Singleton (2008) and Longstaff et al. (2011) document that besides the country-specific component, the sovereign CDS spreads contain another component that is attributed to global risk. Rapach, Strauss, and Zhou (2013) find that the US stock market leads the rest of the world in reflecting market information. Our research question arises from a

☆ We acknowledge the useful comments of Henk Berkman, Ben Jacobson, Ben Marshall, John Wei, and other participants at the first VUW-WISE Symposium in Experimental Economics and Finance (Xiamen, 2012), the International Conference on Systemic Risk (Sydney, 2013), Victoria University of Wellington Finance Workshop (Wellington, 2013) and the World Finance and Banking Symposium (Beijing, 2013). We also appreciate the excellent research assistance provided by Duminda Kuruppuarachchi. Lin acknowledges the financial support from National Natural Science Fund of China (Grant Nos. 71301137, 71371161, 71101121) and the Humanities and Social Science Fund of Chinese Ministry of Education (Grant No. 11JYC790014).

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[1] Other studies include Forbes and Rigobon (2002), Bekaert et al. (2005), Syllignakis and Kouretas (2011), Guo, Chen, and Huang (2011), Gorea and Radev (2014), Morales and Andreosso-O'Callaghan (2014) and Suh (2015).

http://dx.doi.org/10.1016/j.iref.2015.10.047
1059-0560/

combination of these two findings; that is, while the entire CDS market may be affected by a global shock, is there a leading market, such as the S&P index option market, that reflects new information quickly facilitating price discovery in the CDS market? Our study hypothesises that new information from the global shock affects the S&P index option market before spilling over to the global CDS market. If this hypothesis is true, then we should find a significant causal relationship between the S&P index option market and the sovereign CDS market. The reasoning behind our intuition stems from the liquidity of the S&P index option market[2] together with evidence of informed trading in the option market that can be used to predict future stock market returns.[3] This is consistent with the view that information about future risk is reflected in the S&P index option market first and then spills over to other less liquid markets, such as the sovereign CDS market. Our paper documents strong evidence to support this postulate.

The Granger causality approach is used to test the above hypothesis using the Chicago Board Options Exchange Market Volatility Index (VIX) as a proxy for the information from the leading global market and the sovereign CDS spread as a measure of the sovereign credit risk. There are two main reasons for selecting VIX. First, VIX reflects global information. It is considered a key indicator of global investor sentiment and perception of volatility, and regarded as a “gauge of fear” by international market analysts (Remolona et al., 2008; Whaley, 2009). VIX is also used in Longstaff et al. (2011) to calculate the global risk premium. Second, it is calculated from S&P index option prices which contain information about the investors' expectation of US stock market risk in the near future.

In this paper, we provide a comprehensive study of the Granger causal relationship between VIX, sovereign bond yield (BYD), currency exchange rates (CUR), and the sovereign CDS spreads of 56 countries over the period 2001–2010. We use an error correction model (ECM) to test the Granger causality in mean between VIX, CDS spreads, BYD, and CUR for each country. BYD and CUR are used as control variables. We also employ the Hong (2001) and Hong, Liu, and Wang (2009) tests of Granger causality in mean, variance, and downside risk to investigate the Granger causality between changes in sovereign CDS spread, VIX, BYD, and CUR. These new tests complement the classical tests of Granger causality in mean by considering Granger causality in higher moments, for variance and value-at-risk (VaR), under conditional heteroskedasticity. The test results confirm the presence of a significant spillover effect from the S&P index option market to the sovereign CDS market in mean, variance, and VaR. The ECM model is also used for out-of-sample predictions of the sovereign CDS spread using VIX, especially during the subprime financial crisis period.[4] We also run the tests for three sub-periods, namely the pre-, during-, and post-subprime crisis periods. The results suggest a much stronger spillover effect during the recent financial crisis period, implying the existence of a contagion effect. We further decompose the VIX into the physical expected volatility and the variance risk premium and find that both components are useful in predicting the sovereign CDS spreads.[5]

Our paper contributes to the literature in several ways. First, most of the existing literature focusses on contemporaneous cause and effect or correlation-based relationships between CDS spreads and related variables.[6] Another strand of literature focusses on the causal relationship in mean using Granger (1969)-type VAR regressions or ECMs. The contemporaneous relationship is important to measure the effect of change in one market on another, while the causal relationship in variance and VaR are useful for testing the spillover or contagion effect of small risks and extreme downside risks, respectively, from one market to another. It is not possible to test such a distinction of spillover effects at different risk levels with sufficient accuracy using contemporary relationships or classical Granger causality tests. Since the main purpose of this study is to investigate the spillover effect between CDS and S&P 500 option markets, Granger causality tests in mean only may not capture such market risk co-movements. Therefore, we extend our analysis to causality tests in higher order moments, for variance and VaR, proposed by Hong (2001) and Hong et al. (2009). These tests introduce a new concept of Granger causality in risk – investigating small and extreme downside risk spillover effects – not previously addressed in the literature. Compared with alternative approaches, these tests are more powerful because they consider many possible spillover effects occurring at different lags of the time series. Such a comprehensive causal study is sparse in the literature. Several authors have pointed out the importance of using higher order Granger causality tests to investigate contagion effects between markets, as opposed to conventional correlation-based approaches. For example, Bekaert, Harvey, and Ng (2005) document that an increased correlation does not imply contagion. Forbes and Rigobon (2002) show that even a heteroskedasticity-adjusted correlation test finds little evidence of a contagion effect during a major financial crisis period. Furthermore, Longin and Solnik (2001) document that correlation is not related to market volatility per se and correlation could increase during bear markets, but not in bull markets.

Second, Blanco, Brennan, and Marsh (2005), Zhu (2006), Norden and Weber (2009), and Ammer and Cai (2011) test the lead–lag relationship in mean between the CDS spreads and the bond yield using an ECM, while our study focuses on the lead-lag relationship

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[2] According to the 2012 annual market statistics for the CBOE, the S&P index option is the most actively traded cash index option.

[3] For example, Anthony (1988) finds that options lead stocks. Sheikh and Ronn (1994) find the existence of information-based trading in options. Easley, O'Hara, and Srinivas (1998) develop a microstructure model and show that option trading volumes contain information about future stock prices. Hu (2013) shows that option trading conveys stock price information.

[4] There are two main reasons for running the out-of-sample test. First, a lot of literature on predictability shows the difference of in-sample results and out-of-sample results (see Bossaerts & Hillion, 1999; Goyal & Welch, 2003; Campbell & Thompson, 2008). In-sample significant results do not necessarily guarantee the significance of out-of-sample results. Second, the out-of-sample forecast is practically more appealing.

[5] The recent literature shows that variance risk premium is an important predictor of financial market returns. See Bollerslev, Marrone, Xu, and Zhou (2014); Wang, Zhou, and Zhou (2013).

[6] See for example, Duffie, Pedersen, and Singleton (2003), Carr and Wu (2007), Remolona et al. (2008), Pan and Singleton (2008), Hilscher and Nosbusch (2010) and Longstaff et al. (2011).

between VIX and the sovereign CDS spread using bond yield and currency as control variables. Third, we use both the ECM approach and the approaches proposed in Hong (2001) and Hong et al. (2009) to execute a comprehensive investigation of the Granger causality effect. That is, we run an ECM to test the Granger causality in mean between sovereign CDS and VIX, and we then employ Hong (2001) and Hong et al. (2009) to test the Granger causality in mean, variance, and VaR. These new tests are capable of investigating causal relationships of higher order moments, such as variance and VaR, that a conventional ECM cannot handle. In addition, we use a comprehensive sample of 56 countries with data spanning from 2001 to 2010, which is substantial compared with the samples used in other studies. For example, Carr and Wu (2007) use a sample of two countries from January 2002 to March 2005 and show that CDS spreads covary with currency option volatility. Norden and Weber (2009) use the data of 58 individual firms over the period 2000 to 2002 to investigate the lead–lag relationship between CDS, bond, and stock markets using a VAR model. Remolona et al. (2008) use a sample of 24 emerging markets from February 2002 to May 2006 to investigate how the investor's risk aversion, proxied by VIX, affects the CDS spreads. They use a dynamic panel regression model. Longstaff et al. (2011) use a regression model with a sample of 26 developed and less developed countries during the period 2000 to 2010 to find that sovereign credit risk is driven more by global factors, such as US stock and high-yield markets and a volatility risk premium embedded in the VIX index. Our dataset includes all the G20 countries (except Canada) and the most risky sovereign credits (CMA, 2012), and it also covers the recent financial crisis period, which enables us to study the sensitivity of the spillover effect due to extreme market conditions.

Our study is also relevant to investors from several different perspectives. First, the existence of a spillover effect from the S&P index option market to the CDS market suggests that the S&P index option market is a leading market that affects the CDS market. Second, evidence of a spillover effect from changes in VIX to changes in sovereign CDS spreads indicates that liquidity is an important factor for price efficiency. That is, a more liquid market tends to reflect the information more quickly and be more efficient. Third, evidence of a spillover effect suggests that past changes in VIX may improve the predictability of future changes in sovereign CDS spreads.

The remainder of the paper is organized as follows. Section 2 discusses the empirical methodology. Section 3 is devoted to a description of the variable selection and the data. Section 4 reports the empirical results. Section 5 summarizes the main findings and concludes the paper.

2. Empirical methodology

This section explains the models that will be used in Section 4. These models include Granger causality in mean using an ECM; Granger causality in mean, variance, and downside risk using tests developed by Hong (2001) and Hong et al. (2009); and the out-of-sample models used to forecast the sovereign CDS spreads using VIX as a global market factor and BYD and CUR to control for local factors.

2.1. Granger causality in mean using ECM

A cointegration-based ECM is used to investigate the Granger causality effects in mean of VIX, CUR, and BYD on the CDS market. VIX measures global risk, while CUR and BYD proxy for local factors. Since global risk may also affect CUR and BYD, we first run separate regressions of CUR and BYD on VIX and extract the residuals (RCUR and RBYD, respectively). Then, RCUR and RBYD are used in the ECM instead of CUR and BYD. By using residuals in this manner, we are able to clean the impact of global factors on CUR and BYD.[7] In order to formulate the ECM, each of the financial time series, CDS, VIX, RCUR, and RBYD, are first tested for the existence of a unit root using the Dickey and Fuller (1979, 1981) test.[8] Then, we use the following two-stage estimator (see Engle & Granger, 1987) to estimate the ECM, assuming that there exists a single cointegration vector.

First, we use OLS to estimate the three level regressions in Eq. (1) corresponding to each variable, VIX, RBYD, and RCUR, respectively.

$$CDS_t = \theta_0 + \theta_1 V_t + \xi_t, V_t \equiv \mathrm{VIX}_t, \mathrm{RBYD}_t, \mathrm{RCUR}_t \tag{1}$$

Using the residuals, $\hat{\xi}_t$ extracted from Eq. (1), we test for cointegration relationships between the pairs (CDS, VIX), (CDS, RBYD), and (CDS, RCUR) following the Dickey–Fuller regression,

$$\Delta \hat{\xi}_t = \psi^* \hat{\xi}_{t-1} + \sum_{i=1}^{p} \phi_i \Delta \hat{\xi}_{t-i} + \upsilon_t. \tag{2}$$

Since we have added a constant term in Eq. (1), we assume zero mean in Eq. (2). Furthermore, according to Hansen (1992), adding a trend term in Eq. (2) results in a loss of power of the Dickey and Fuller test, and therefore we exclude the trend term in Eq. (2). The best lag structure (p) in Eq. (2) is determined using the AIC criterion. For the countries that exhibit a cointegration

[7] We also used CUR and BYD instead of RCUR and RBYD in the analysis and found that the results are quite similar. They are available upon request.

[8] The results show that all series are integrated of order 1, that is, I(1). We also used the Phillips and Perron (1988) test and found the results are similar.

relationship,[9] we estimate the ECM in Eq. (3) to examine three types of Granger causality effects in mean of VIX, RBYD, and RCUR on the change in CDS spreads of each country[10]:

$$\Delta CDS_t = +\delta t + \sum_{i=1}^{5} \beta i \Delta CDS_{t-i} + \sum_{i=1}^{5} \gamma i \Delta_{t-i} + \lambda \hat{\xi}_{t-i} + \varepsilon_t, \tag{3}$$

where $\hat{\xi}_{t-1} = CDS_{t-1} - \hat{\theta}_1 V_{t-1}, V_{t-1} \equiv VIX_{t-1}, RBYD_{t-1}, RCUR_{t-1}$, and λ is the error correction term. The ECM regression in Eq. (3) is fitted for each variable by replacing V_{t-1} in Eq. (3) with VIX_{t-1}, $RBYD_{t-1}$ and $RCUR_{t-1}$, respectively. We then carry out the following three tests, each of which tests the null hypothesis of no Granger causality in mean:

Type 1 Granger causality test: $H_0: \lambda = 0$
Type 2 Granger causality test: $H_0: \gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = \gamma_5 = 0$
Type 3 Granger causality test: $H_0: \gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = \gamma_5 = \lambda = 0$.

The type 1 test examines the causality from the long-term equilibrium relationship. The type 2 test looks at the causality due to the recent changes, and the type 3 test is a joint check for causality from both the equilibrium relationship and the recent changes. To better understand the nature of the Granger causality relationship between the CDS spread and the VIX, we extend the ECM in Eq. (3) by controlling for the lagged effects of changes in country-specific local factors, such as RBYD and RCUR. That is, we fit

$$\Delta CDS_t = \alpha + \delta t + \sum_{i=1}^{5} \beta_i \Delta CDS_{t-i} + \sum_{i=1}^{5} \gamma_i \Delta VIX_{t-i} + \sum_{i=1}^{5} \phi_i \Delta RBYD_{t-i} + \sum_{i=1}^{5} \psi_i \Delta RCUR_{t-i} + \lambda\, \hat{\xi}_{t-1} + \eta_t \tag{4}$$

and repeat the same Granger causality tests in mean above using Eq. (4).

2.2. Granger causality in mean, variance, and downside risk

A classical Granger causality test, such as ECM, assumes conditional homoscedasticity, which may not be valid in most financial time series. Moreover, it tests the Granger causality effect in the conditional mean, which may not always capture small and extreme downside risk spillover effects between markets. Since the sovereign CDS is directly traded in the over-the-counter market, and there are VIX derivatives such as VIX futures and VIX options that use VIX as the underlying asset, it is also important to test the causal relationship of higher order moments, such as variance and VaR, between VIX and CDS spreads for risk management purposes. By employing Hong (2001) and Hong et al. (2009) tests of Granger causality in higher order moments, assuming conditional heteroskedasticity, our results are more robust compared with ECM results. Our analysis examines the unidirectional and bidirectional Granger causality in mean, variance, and downside risk of changes in BYD, CUR, and VIX on the sovereign CDS. The tests provide statistically more powerful evidence of small and extreme downside risk spillover effects between the S&P index option market and the sovereign CDS market.[11]

Hong (2001) proposes a general Granger causality test in mean that accounts for conditional heteroskedasticity and infinite unconditional variances. Following Granger (1969) and Granger (1980); Hong (2001) consider two stationary time series, $\{Y_{1t}, Y_{2t}\}$, such as $\{\Delta CDS_t, \Delta VIX_t\}$, and let $I_t = (I_{1t}, I_{2t})$ be the corresponding information set. Then, Y_{2t} is defined to be Granger-causing Y_{1t} given I_{t-1} if $P(Y_{1t} \mid I_{1t-1}) \neq P(Y_{1t} \mid I_{t-1})$. That is, this type of Granger causality test asks whether the past information on the movement of one market has the predictive ability for the future occurrence of similar movements in another market as opposed to the conventional cause-effect or co-movement type of tests on which most of the existing literature has focussed. A less general but more applicable definition of Granger causality in mean used in the Hong (2001) test is $E(Y_{1t} \mid I_{1t-1}) \neq E(Y_{1t} \mid I_{t-1})$.Using centred standardized residuals, $\hat{u}_t = \hat{\varepsilon}_{1t}/\hat{h}_{1t}^{1/2} - 1$, and $\hat{v}_t = \hat{\varepsilon}_{2t}/\hat{h}_{2t}^{1/2} - 1$, where $\hat{\varepsilon}_{1t}$ and $\hat{\varepsilon}_{2t}$ are extracted from univariate AR-GARCH(p,q) processes corresponding to the two time series, Hong (2001) suggests the following two test statistics, Q_1 and Q_2, to test the unidirectional and bidirectional Granger causality in mean between the two series:

$$Q_1 = \left[T \sum_{j=1}^{T-1} k^2 (j/M)\, \hat{\rho}_{uv}^2(j) - C_{1T} \right] / [2\, D_{1T}]^{1/2} \tag{5}$$

$$Q_2 = \left[T \sum_{j=1-T}^{T-1} k^2 (j/M)\, \hat{\rho}_{uv}^2(j) - C_{2T} \right] / [2\, D_{2T}]^{1/2}. \tag{6}$$

[9] According to Granger (1988), if two time series are both I(1) and are cointegrated, then there exists an ECM.
[10] We consider the lag order up to 5. We also tried other lag orders and found similar results.
[11] For example, Granger causality in variance provides evidence of small risk spillover, while Granger causality in VaR provides evidence of extreme downside risk spillover. This distinction of spillover effects is another great advantage of using Hong's tests.

Here, M is the lag function number under some specifications of the kernel function, $k(.)$ that assigns weights to the cross-correlation coefficients, $\hat{\rho}_{uv}(j)$. Both $Q_1$and Q_2 are N(0,1) under the null hypothesis of no Granger causality in mean. We apply the Hong (2001) test for the pairs $\{\Delta CDS_t, \Delta VIX_t\}$ to test for their Granger causality effect in mean.[12] See Appendix A for details of the test proposed in Hong (2001).

Information on the volatility spillover effect between financial markets is of vital interest to investors when hedging their investments against uncertainty (see Engle, Ito, & Lin, 1990; Hong et al., 2009; Baele, 2005). Evidence of volatility spillover implies that a market shock not only increases the volatility of its own assets, but also increases the volatility in other assets and other markets globally. Roll (1988) shows that the 1987 US stock market crash affected 19 out of 23 stock markets tested around the world. Causation in mean only is not sufficient to fully understand the nature of the spillover between two series, especially within financial time series such as VIX, BYD, CUR, and CDS spreads. We need to investigate the Granger causality effect due to higher order moments, such as variance and VaR, as well.

We use Hong's (2001) test to identify the Granger causality in variance between the CDS and VIX. Granger causality in variance is defined as $\text{var}(Y_{1t}|I_{1t-1}) \neq var(Y_{1t}|I_{t-1})$, and tests for risk spillover effects between markets. Hong's (2001) test for Granger causality in variance, considers the squares of the centred standard residuals, $\hat{u}_t = \hat{\varepsilon}_{1t}^2/\hat{h}_{1t} - 1$, $\hat{v}_t = \hat{\varepsilon}_{2t}^2/\hat{h}_{2t} - 1$. Hong (2001) shows that similar asymptotic theories that apply to the mean can also be applied to the Granger causality test of variance as well. As a result, this test calculates the test statistics, Q_1 and Q_2, under the null hypothesis of no Granger causality in variance using a similar approach.

Extreme downside market risk plays a pivotal role in financial risk management and portfolio selection. This topic has received increased attention from practitioners, portfolio managers, and academic researchers. Among various downside risk measures developed over the years, such as semi-variance and lower partial moment, the most commonly used is the VaR (see Duffie & Pan, 1997). VaR is used as a measure of extreme market risk in the test by Hong et al. (2009). Extreme market risk movements that occur occasionally in financial markets cannot be captured successfully by testing only for a volatility spillover effect, implying the necessity for an alternative test, such as VaR, to identify extreme downside risk spillover effect due to extreme losses.

We use the test devised by Hong et al. (2009) to identify the Granger causality in extreme downside risk between changes of CDS and VIX, CUR, and BYD, respectively. Hong et al. (2009) propose a class of kernel-based tests to detect extreme downside risk (measured by VaR) spillover between financial markets. The proposed tests have a convenient asymptotic standard normal distribution under the null hypothesis of no Granger causality in VaR. VaR is defined as $P\,(\,Y_t < -V_t \mid I_t\,) = \alpha$, where α is the pre-specified probability parameter. For example, V_t is the 95% VaR when $\alpha = 5\%$. Let Z_t be an indicating series that is defined as $Z_{it} = \ I\,(\,Y_{it} < -V_{it}\,), \quad i = 1, 2$. Using the indicator function, the Granger causality in VaR could be defined as $E\,(\,Z_{it} \mid I_{it-1}\,) \neq E\,(\,Z_{it} \mid I_{t-1}\,)$. Using the sample cross-correlation function between the two indicating series, Hong et al. (2009) propose a test statistic similar to Q_1 in Eq. (5) to test the unidirectional Granger causality in VaR, and a statistic similar to Q_2 in Eq. (6) to test bidirectional Granger causality. Under regular conditions, both Q_1 and Q_2 follow an asymptotic standard normal distribution. See Appendix B for details of the test proposed in Hong et al. (2009).

In this study, we model the ΔCDS *and* ΔVIX by AR(5)-GARCH(1,1), and use the residuals extracted from these regressions for the Hong (2001) and Hong et al. (2009) tests. The AR model is used to filter out any impact on the series by its own historical information, and, as a result, Granger causality can only come from the other explanatory factors in the model.

2.3. Out-of-sample prediction of sovereign CDS spreads

Our results show that the sovereign CDS spreads are Granger-caused in mean, variance, and VaR by the VIX, confirming that there exists a spillover from the option market to the sovereign CDS market. If this spillover is robust out-of-sample, we could expect the information content of the VIX to improve the out-of-sample forecast of sovereign CDS spreads. We use models (3) and (4) to forecast CDS spreads out-of-sample. We then compare the forecasted and observed CDS spreads.

The out-of-sample forecasts of CDS spreads are computed as follows. Suppose we have n daily data points in the sample and out-of-sample forecasts begin at $t + 1$, where $t < n$. We use the data up to time t to estimate models (3) and (4). The estimated parameters from the two models together with the information at time t are then used to forecast the expected change of sovereign CDS at time $t + 1$ (i.e., $\Delta\widehat{CDS}_{t+1}$). The forecasted CDS spread at time $t + 1$ is computed as $CDS_t + \Delta\widehat{CDS}_{t+1}$, where CDS_t is the observed CDS spread at time t. Similarly at time $t + 1$, we use all the data up to time $t + 1$ to re-estimate models (3) and (4) and re-calculate the forecasted change in the CDS spread for time $t + 2$, and so on. The process stops when n - t forecasted values are computed.

We compare the forecasted CDS spreads from the two models with the observed CDS spreads to determine the accuracy of the predictions by the two models out-of-sample. The root mean square error (RMSE) is computed to measure the accuracy of the out-of-sample predictions for the entire forecast period ($RMSE_{3W}$, $RMSE_{4W}$) and the financial crisis period ($RMSE_{3R}$, $RMSE_{4R}$), respectively.

[12] We also run the test for $\{\Delta CDS_t, \Delta BYD_t\}and\{\Delta CDS_t, \Delta CUR_t\}$, but do not report their results. We summarize the main results in footnote 16. The detailed results are available upon request.

Table 1
The sample of countries considered in the study. This table reports the list of countries and the corresponding dates for which the daily five-year sovereign credit default swap (CDS), daily foreign currency value quoted in US dollars, daily volatility index (VIX), and daily five-year sovereign bond yield data (if available) are used in the study.

Country	ID	Sample dates	Country	ID	Sample dates
Argentina	1	January 5, 2001–September 30, 2010	Lebanon	29	October 18, 2006–September 30, 2010
Australia	2	January 2, 2001–September 30, 2010	Lithuania	30	June 6, 2005–September 30, 2010
Austria	3	January 6, 2004–September 30, 2010	Malaysia	31	January 1, 2004–September 30, 2010
Bahrain	4	June 2, 2008–September 30, 2010	Mexico	32	October 15, 2001–September 30, 2010
Belgium	5	January 5, 2004–September 30, 2010	Morocco	33	January 1, 2003–September 30, 2010
Brazil	6	January 1, 2004–September 30, 2010	Netherlands	34	September 7, 2005–September 30, 2010
Bulgaria	7	October 24, 2000–September 30, 2010	New Zealand	35	April 24, 2006–September 30, 2010
Chile	8	January 1, 2004–September 30, 2010	Norway	36	August 11, 2003–September 30, 2010
China	9	January 1, 2004–September 30, 2010	Pakistan	37	October 12, 2004–September 30, 2010
Colombia	10	January 1, 2004–September 30, 2010	Peru	38	April 22, 2004–September 30, 2010
Croatia	11	January 6, 2004–September 30, 2010	Philippines	39	January 21, 2004–September 30, 2010
Czechoslovakia	12	January 6, 2004–September 30, 2010	Poland	40	January 1, 2004–September 30, 2010
Denmark	13	November 1, 2004–September 30, 2010	Portugal	41	January 26, 2004–September 30, 2010
Egypt	14	October 25, 2006–September 30, 2010	Romania	42	January 1, 2004–September 30, 2010
Finland	15	May 4, 2008–September 30, 2010	Russia	43	June 15, 2004–September 30, 2010
France	16	March 31, 2003–September 30, 2010	Saudi Arabia	44	July 2, 2008–September 30, 2010
Germany	17	January 8, 2004–September 30, 2010	South Africa	45	January 1, 2004–September 30, 2010
Greece	18	January 9, 2004–September 30, 2010	South Korea	46	January 5, 2004–September 30, 2010
Hong Kong	19	October 15, 2004–September 30, 2010	Spain	47	January 21, 2004–September 30, 2010
Hungary	20	January 1, 2004–September 30, 2010	Sweden	48	January 21, 2004–September 30, 2010
Iceland	21	January 6, 2004–September 30, 2010	Switzerland	49	January 16, 2009–September 30, 2010
India	22	January 1, 2003–September 30, 2010	Thailand	50	January 1, 2004–September 30, 2010
Indonesia	23	October 5, 2004–September 30, 2010	Turkey	51	May 17, 2004–September 30, 2010
Ireland	24	August 11, 2003–September 30, 2010	UK	52	November 13, 2007–September 30, 2010
Israel	25	May 11, 2004–September 30, 2010	Ukraine	53	August 19, 2004–September 30, 2010
Italy	26	January 20, 2004–September 30, 2010	US	54	December 11, 2007–September 30, 2010
Japan	27	January 1, 2004–September 30, 2010	Venezuela	55	May 10, 2004–September 30, 2010
Kazakhstan	28	November 12, 2004–September 30, 2010	Vietnam	56	May 9, 2006–September 30, 2010

3. Data and variable selection

This study uses daily data for 56 countries covering the period from October 15, 2001 to September 30, 2010. Our sample includes countries from Western Europe, the Middle East, North Africa, Oceania, and Asia. The sample includes all the G20 major economies (except Canada, for which we could not find data) and the most risky sovereign credits, such as Greece, Argentina, Portugal, Pakistan, Venezuela, Ukraine, Ireland, Spain, and Egypt, according to the CMA Global Sovereign Credit Risk Report, 2012. Sample details are reported in Table 1. Unlike previous studies, our sample also covers the subprime mortgage crisis (2007–2009) period, and it is more comprehensive.

The daily data include the five-year US dollar–denominated sovereign CDS spreads (in basis points), the sovereign currency exchange rate in terms of the US dollar (CUR), five-year sovereign bond yield (BYD), and the volatility index (VIX). The data are sourced from DataStream and Bloomberg. Most sovereign CDS contracts have maturities of one, five, or 10 years. Our study uses five-year CDS contracts, which is the most common maturity in our sample. Daily data for the MSCI and S&P 500 indexes used in robustness tests are also sourced from DataStream.

Table 2 reports the summary statistics of the data, including the sample mean and number of observations for each variable. The BYD data are available for 41 of the 56 countries. For those countries with no BYD data, only CUR is used as the local factor measure.[13] Table 2 shows that more risky countries tend to have a higher sovereign CDS spread level and a higher BYD level compared with other countries. In our sample, Argentina has the highest level of sovereign CDS spread, while Brazil has the highest level of BYD. Fig. 1 is a graph of the time series for the aggregate CDS index against the VIX index level from 2001 to 2010.[14] A brief scan of the figure indicates that both series seem to behave in a similar way. There is a marked increase in the CDS series during the 2008–2009 period due to uncertainty caused by the subprime mortgage crisis. In particular, Fig. 1 indicates that shocks are first absorbed by the more liquid options market as conveyed by the VIX, which is then transmitted to the CDS market, supporting our main postulate. The reaction and transfer of information between these two markets can be seen in Fig. 1, especially during mid-2002 and September 2008.

[13] Please note that due to different quoted numbers of currency used in the exchange rate, the mean exchange rate in Table 2 does not necessarily mean the amount of currency exchanged for 1 US dollar. For example, for Japan the quoted number of the exchange rate is 100. The mean exchange rate 0.952 means 1 US dollar is exchanged for 95.2 JPY on average during the sample period.

[14] The CDS index is constructed using data from October 15, 2001 to September 30, 2010. The index has an initial value of 418.75, which is the average of the CDS for Mexico and Bulgaria that have the available data. The index adjusts up and down by the average value of the change in the CDS for each country for which data are available each day.

Table 2
Summary statistics for each of the 56 countries in the sample. This table reports the summary statistics of daily five-year sovereign credit default swap (CDS), volatility index (VIX), five-year sovereign bond yield (BYD), and the value of each country's currency in US dollars (CUR). BYD was not available (NA) for Argentina, Bahrain, Bulgaria, Chile, Egypt, Iceland, Israel, Kazakhstan, Lebanon, Lithuania, Morocco, Russia, Saudi Arabia, Ukraine, and Venezuela. Mean is the sample mean of these variables, and n is the number of observations in each country.

ID	CDS		VIX		BYD		CUR		ID	CDS		VIX		BYD		CUR	
	Mean (bps)	n	Mean (%)	n	Mean (%)	n	Mean (US$)	n		Mean (bps)	n	Mean (%)	n	Mean (%)	n	Mean (US$)	n
1	755.715	1759	20.800	1759	NA	NA	0.312	1759	29	396.534	816	25.584	816	NA	NA	0.001	816
2	29.372	2021	20.946	2021	5.410	2021	0.783	2021	30	177.682	1389	22.397	1389	NA	NA	0.390	1389
3	30.919	1758	20.801	1758	3.371	1758	1.329	1758	31	70.031	1761	20.796	1761	3.737	1761	0.282	1761
4	264.963	591	31.142	591	NA	NA	2.653	591	32	141.870	2233	21.607	2233	8.460	2233	0.090	2233
5	26.595	1759	20.799	1759	3.374	1759	1.329	1759	33	146.101	2022	20.949	2022	NA	NA	0.117	2022
6	235.220	1761	20.796	1761	11.028	880	0.476	1761	34	23.629	1322	22.921	1322	3.326	1322	1.354	1322
7	207.946	2531	22.114	2531	NA	NA	0.625	2531	35	37.461	1159	24.408	1159	5.815	1159	0.690	1159
8	58.786	1761	20.796	1761	NA	NA	0.184	1761	36	11.683	1864	20.642	1864	3.776	1864	0.161	1864
9	53.479	1761	20.796	1761	2.992	1386	0.133	1761	37	750.935	1558	21.420	1558	10.760	1558	1.488	1558
10	229.547	1761	20.796	1761	7.432	235	0.046	1761	38	186.581	1681	21.001	1681	5.655	783	0.322	1681
11	122.862	1758	20.801	1758	5.449	551	0.133	1758	39	272.158	1747	20.830	1747	8.331	1747	0.020	1747
12	45.610	1758	20.801	1758	3.608	1758	0.048	1758	40	67.525	1761	20.796	1761	5.741	1761	0.335	1761
13	45.190	598	28.989	598	2.987	598	0.182	598	41	50.173	1744	20.841	1744	3.611	1744	1.330	1744
14	239.763	1027	25.753	1027	NA	NA	0.130	1027	42	167.658	1761	20.796	1761	5.048	842	0.000	1761
15	31.262	622	30.601	622	2.847	622	1.383	622	43	173.723	1643	21.099	1643	NA	NA	0.036	1643
16	17.003	1849	20.754	1849	3.257	1849	1.309	1849	44	122.189	587	31.193	587	NA	NA	0.267	587
17	13.729	1756	20.806	1756	3.200	1756	1.329	1756	45	125.200	1761	20.796	1761	9.017	1761	0.140	1761
18	111.983	1755	20.809	1755	4.376	1755	1.329	1755	46	85.168	1759	20.799	1759	4.814	1759	10.394	1759
19	34.871	1555	21.431	1555	2.992	1555	0.129	1555	47	52.979	1417	22.229	1417	3.518	1417	1.346	1417
20	124.525	1761	20.796	1761	8.006	1761	0.513	1761	48	20.597	1524	21.089	1524	3.246	1524	0.138	1524
21	209.718	1758	20.801	1758	NA	NA	1.278	1758	49	62.327	445	27.772	445	1.150	445	0.931	445
22	143.919	2022	20.949	2022	6.815	2022	0.022	2022	50	80.700	1761	20.796	1761	3.888	1761	0.021	1761
23	250.073	1563	21.397	1563	10.553	1563	0.000	1563	51	248.104	1664	21.043	1664	6.095	1664	0.713	1664
24	63.651	1864	20.642	1864	3.614	1864	1.320	1864	52	60.109	753	29.458	753	3.244	753	1.680	753
25	71.990	1668	21.037	1668	NA	NA	0.245	1668	53	661.402	1547	21.215	1547	NA	NA	0.176	1547
26	47.949	1748	20.827	1748	3.518	1748	1.329	1748	54	33.943	733	29.591	733	2.399	733	1.000	733
27	24.475	1761	20.796	1761	0.852	1761	0.952	1761	55	703.769	1669	21.036	1669	NA	NA	0.001	1669
28	234.833	1382	22.209	1382	NA	NA	0.008	1759	56	213.762	1076	24.359	1076	10.158	1038	0.000	1076

4. Empirical results

4.1. Granger causality in mean by ECM

The cointegration test results using the Dickey and Fuller (1979, 1981) test in Table 3 show that the cointegration between CDS spread and VIX is highly significant for all the countries except five (i.e., 91% of the sample).[15] CDS is cointegrated with RBYD for 35 countries out of the 41 that have the available BYD data (i.e., 85% of the countries) and cointegrated with RCUR for 43 countries out of 56 countries (i.e., 77%). The results suggest that there is a very strong long-term equilibrium relationship between CDS spread and VIX, which is more evident compared with the local factors RBYD and RCUR.

For those countries that exhibit a cointegration relationship between CDS and VIX, RBYD, and RCUR, we estimate models (3) and (4), respectively. Table 4 reports the corresponding estimated values of the error correction term, λ, and the corresponding results for the type 1 Granger causality test. According to Table 4, the coefficient of the error correction term between CDS and VIX without control factors is negative and very highly significant for 98% of the countries. The result remains almost the same (98%) when local variables (RBYD, RCUR) are introduced in model (4) as control factors. Out of the 52 countries that have a significant cointegration relationship between the sovereign CDS spreads and VIX, Switzerland (country number 49) is the only country that does not support this hypothesis. This implies that VIX Granger-causes the sovereign CDS spread in mean significantly from the equilibrium relationship. Furthermore, 83% of the countries show evidence of type 1 Granger causality in mean from the RBYD to the CDS spreads. This finding is contrary to Blanco et al. (2005) who report the evidence of reverse Granger causality based on corporate bonds data. That is, the CDS market contributes significantly to the price discovery of credit risk. The proposed ECM also suggests that 85% of the countries show a type 1 Granger causality in mean from RCUR to CDS, which is consistent with the findings of Carr and Wu (2007). The results confirm that the deviation from the long-run relationship between the sovereign

[15] Although our paper reports results for tests of cointegration based on the well-known Dickey and Fuller (1979, 1981) method, we also tried the Phillips and Perron (1988) test and the Zivot and Andrews (1992) procedure. The Zivot and Andrews (1992) test is both robust to breaks in the deterministic trend function and more powerful than the ADF and PP tests. Zivot and Andrews (1992) search for a break point and test for the presence of a unit root when the process has a shift in trend (see Chaudhuri & Wu, 2003). The results using the Zivot and Andrews (1992) and Phillips and Perron (1988) tests are almost the same as those reported for the Dickey–Fuller tests.

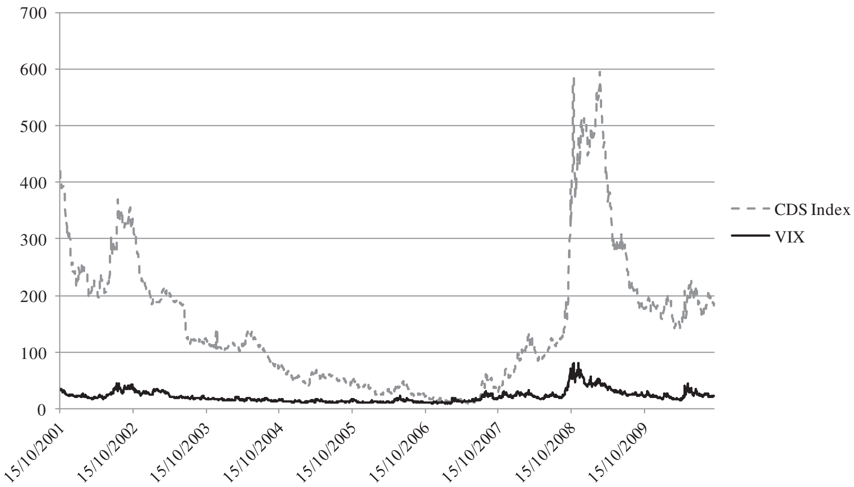

Fig. 1. The sovereign CDS index and the VIX series from October 15, 2001 to September 30, 2010. A CDS index is constructed using a base level of 418.75, which is the average of the starting CDS values for Mexico and Bulgaria (the first two countries to have data in our sample). As the data for other countries become available in the sample, the index is adjusted by the average value of the change in the CDS measure for each country, each day.

CDS spreads and VIX, RBYD, and RCUR affect the future change of sovereign CDS spreads; however, the impact from VIX is more promising compared with RBYD and RCUR.

Table 5 reports the type 2 and type 3 Granger causality results between the sovereign CDS spreads and VIX, RBYD, and RCUR, respectively, using model (3). Only for the VIX, which is the main focus in this study, do we consider model (4) as well, which controls for RBYD and RCUR. Without controlling for local factors (model (3)), the type 2 Granger causality in mean from VIX to the sovereign CDS spread is significant for 87% of the countries, while the type 3 Granger causality in mean from VIX to the sovereign CDS

Table 3

Cointegration test results between sovereign CDS spread and VIX, RBYD, and RCUR. This table reports the results for the cointegration test between sovereign CDS spread and VIX, RBYD, and RCUR, respectively. Using the Dickey–Fuller unit root test, Eq. (2), with up to 10 lags (i.e., p = 10), the null hypothesis $H_0: \psi^* = 0$ (pair is not cointegrated) is tested using the critical values taken from Davidson and MacKinnon (1993). The corresponding test statistic values for each country and their significance are reported. The residuals ξ_t in Eq. (2) are extracted from Eq. (1) for each of $V_t \equiv VIX_t, RBYD_t, RCUR_t$, respectively. *, ** and *** means significance at the 10%, 5%, and 1% levels, respectively. The %Sig. reports the percentage of the countries that have significant results at the 10% level or below.

ID	VIX	RBYD	RCUR	ID	VIX	RBYD	RCUR
1	−6.37***	NA	Not CI	29	−2.69***	NA	−4.38***
2	−5.62***	−2.96***	−2.45**	30	−4.44***	NA	Not CI
3	−3.94***	−2.17**	−1.83*	31	−8.68***	−3.07***	−3.05***
4	−2.53**	NA	−1.76*	32	−5.90***	−2.65***	−2.91***
5	−2.45**	Not CI	Not CI	33	−4.16***	NA	−2.79***
6	−6.96***	−2.61***	−2.89***	34	−6.37***	−3.60***	−3.08***
7	−4.81***	NA	−1.93*	35	−2.68***	−2.66***	−2.21**
8	−8.02***	NA	−2.06**	36	−5.50***	−2.33**	−2.13**
9	−5.96***	−2.42**	−2.50**	37	−6.71***	−2.31**	−2.33**
10	Not CI	−2.86***	−2.88***	38	−5.87***	−2.34**	−2.95***
11	−2.96***	−3.02***	−2.31**	39	−2.02**	−5.07***	−3.00***
12	−5.15***	−1.76*	−1.75*	40	−4.98***	−1.71*	Not CI
13	−3.01***	Not CI	−1.66*	41	Not CI	Not CI	Not CI
14	−6.00***	NA	Not CI	42	−3.78***	−2.08**	−2.04**
15	−2.72***	−1.76*	−1.90*	43	−5.93***	NA	−2.64***
16	−2.71***	−1.73*	Not CI	44	−3.10***	NA	Not CI
17	−3.67***	−2.19**	Not CI	45	−8.35***	−2.29**	−2.48**
18	Not CI	−2.83***	Not CI	46	−8.19***	−2.84***	−2.92***
19	−5.55***	−2.05**	−1.73*	47	Not CI	Not CI	Not CI
20	−4.79***	Not CI	Not CI	48	−4.25***	−2.25**	−2.00**
21	−7.03***	NA	−2.22**	49	−4.89***	−2.09**	−2.29**
22	−8.46***	−2.39**	−2.39**	50	−8.75***	−3.30***	−3.26***
23	−4.94***	−3.15***	−3.00***	51	−4.41***	−3.04***	−3.68***
24	Not CI	Not CI	Not CI	52	−2.13**	−1.80*	−2.49**
25	−5.02***	NA	Not CI	53	−4.59***	NA	−1.98**
26	−2.70***	−1.66*	Not CI	54	−2.37**	−2.05**	−2.18**
27	−3.16***	−2.00**	−2.94***	55	−5.47***	NA	Not CI
28	−4.60***	NA	−1.79*	56	−5.65***	−2.01**	−1.98**
% Sig.	91.07	85.37	76.79				

Table 4

The error correction estimates of the ECM and type 1 Granger causality results. This table reports the error correction terms (λ) of the ECM models between sovereign CDS spreads and VIX, RBYD, and RCUR, respectively, for the countries that demonstrate a CI(1,1) relationship and also the results of the type 1 Granger causality test, that is $H_0: \lambda = 0$. The results are calculated from models (3) or (4), respectively. Model (4) is only estimated for VIX, which is our main focus. NA means the results are not available due to either no available data or no cointegration relationship. *, ** and *** means significance at the 10%, 5%, and 1% levels, respectively. The %Sig. reports the percentage of the countries that have significant results at the 10% level or below.

ID	VIX		RBYD	RCUR	ID	VIX		RBYD	RCUR
	(3)	(4)	(3)	(3)		(3)	(4)	(3)	(3)
1	−0.022***	−0.022***	NA	NA	29	−0.027***	−0.027***	NA	−0.017***
2	−0.025***	−0.022***	−0.010***	−0.008**	30	−0.014***	−0.014***	NA	NA
3	−0.013***	−0.013***	−0.006***	−0.006***	31	−0.037***	−0.037***	−0.010***	−0.010***
4	−0.016***	−0.015***	NA	−0.008*	32	−0.023***	−0.020***	−0.006***	−0.008***
5	−0.005**	−0.005*	NA	NA	33	−0.014***	−0.014***	NA	−0.009***
6	−0.044***	−0.040***	−0.010**	−0.012**	34	−0.049***	−0.048***	−0.024***	−0.031***
7	−0.005***	−0.005***	NA	−0.002**	35	−0.013***	−0.010**	−0.013***	−0.014***
8	−0.025***	−0.026***	NA	−0.006**	36	−0.026***	−0.024***	−0.009**	−0.010***
9	−0.029***	−0.029***	−0.009**	−0.007**	37	−0.025***	−0.026***	−0.006*	−0.005
10	NA	NA	−0.069***	−0.069***	38	−0.037***	−0.035***	−0.010**	−0.012**
11	−0.032***	−0.032***	−0.017***	−0.019***	39	−0.009***	−0.009***	−0.019***	−0.006*
12	−0.015***	−0.015***	−0.007***	−0.006**	40	−0.015***	−0.015***	−0.005**	NA
13	−0.022***	−0.023***	NA	−0.007*	41	NA	NA	NA	NA
14	−0.018***	−0.019***	NA	NA	42	−0.022***	−0.022***	−0.005	−0.005*
15	−0.018***	−0.017***	−0.010**	−0.010**	43	−0.024***	−0.027***	NA	−0.007***
16	−0.007***	−0.007***	−0.005*	NA	44	−0.021***	−0.021***	NA	NA
17	−0.009***	−0.009***	−0.005**	NA	45	−0.032***	−0.030***	−0.007**	−0.008***
18	NA	NA	0.003	NA	46	−0.035***	−0.038***	−0.008***	−0.007**
19	−0.020***	−0.020***	−0.003	−0.005*	47	NA	NA	NA	NA
20	−0.015***	−0.014***	NA	NA	48	−0.018***	−0.017***	−0.005	−0.009**
21	−0.015***	−0.013***	NA	−0.003	49	−0.013	−0.014	−0.008	−0.009
22	−0.020***	−0.021***	−0.007***	−0.007***	50	−0.045***	−0.044***	−0.011***	−0.012***
23	−0.028***	−0.027***	−0.011***	−0.007**	51	−0.018***	−0.018***	−0.011***	−0.012***
24	NA	NA	NA	NA	52	−0.013***	−0.013**	−0.005	−0.006
25	−0.013***	−0.012***	NA	NA	53	−0.012***	−0.012***	NA	0.001
26	−0.009***	−0.008***	−0.010***	NA	54	−0.018***	−0.016**	−0.009*	−0.008
27	−0.010***	−0.010***	−0.015***	−0.009**	55	−0.015***	−0.015***	NA	NA
28	−0.011***	−0.013***	NA	−0.007***	56	−0.032***	−0.032***	−0.011**	−0.007*
% Sig.	98.04	98.04	82.86	85.00					

spread is significant for 98% of the countries. We get similar results for model (4) as well. This shows that the recent changes in the investment risk of the S&P index option market reflected in VIX on average contain useful information about the future change in sovereign CDS spreads. Combining the results in Table 4 and Table 5, we find that both the equilibrium relationship and recent changes in VIX significantly affect future changes in sovereign CDS spreads. This is a novel and significant contribution to the CDS literature.

There is a considerable amount of type 2 and type 3 Granger causality in mean between the sovereign CDS spread and RBYD and RCUR as well, but they are weaker than the type 1 Granger causality in mean shown in Table 4. Overall, 58% and 83% of the countries show significant type 2 and type 3 Granger causality in mean from RBYD to sovereign CDS spread, and 81% and 93% of the countries show significant type 2 and type 3 Granger causality in mean from RCUR to the sovereign CDS spread.

4.2. Granger causality in mean, variance, and VaR

We extend our analysis by testing for the Granger causality in mean, variance, and VaR between changes in the CDS spread and changes of VIX under conditional heteroskedasticity using the methodology developed by Hong (2001) and Hong et al. (2009). The conditional heteroskedasticity assumption in Hong (2001) and Hong et al.'s (2009) tests is very important in financial time series, but the conventional ECMs do not take this into account, arguing the robustness of the results from ECMs. In this study, the Granger causality test is performed under two scenarios, namely, with and without control factors. In the case of no control factors, an AR(5)-GARCH(1,1) model (hereinafter referred to as model M1) is fitted for the two time series {ΔCDSt} and {ΔVIXt}, respectively. The residuals are extracted and used to calculate the test statistics proposed by Hong (2001) and Hong et al. (2009). The residuals for the case with control factors are extracted by including the first five daily lags of the change in government bond yield ($\sum_{i=1}^{5}\varnothing_i \Delta BYD_{t-i}$) and currency exchange rate ($\sum_{i=1}^{5}\varphi_i \Delta CUR_{t-i}$) in the AR(5)-GARCH(1,1) model (hereinafter referred to as model M2). The test statistics follow a standard normal distribution under the null hypothesis of no Granger causality.

The results for Granger causality in mean, variance, and VAR using Hong (2001) and Hong et al. (2009) tests are reported in Panels A, B, and C, respectively, in Table 6. In Panel A, if no local factors are used, 96% of the countries in the sample show strong evidence of a unidirectional spillover effect in mean from the VIX to the CDS markets, confirming the robustness of our findings from the ECM model above. The results provide little evidence for the reverse Granger causality in mean from CDS to

Table 5

Results of type-2 and -3 Granger causality in mean using the ECM. This table reports the F-test statistics corresponding to the type 2 and type 3 Granger causality tests in mean between sovereign CDS spreads and VIX, RBYD, RCUR, respectively, calculated from the error correction models in Eqs. (3) and (4). Type 2 Granger causality test is $H_0: \gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = \gamma_5 = 0$ and type 3 Granger causality test is $H_0: \gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = \gamma_5 = \lambda = 0$. NA means the results are not available due to either no available data or no cointegration relationship. Model (4) is only estimated for VIX, which is our main focus. *, ** and *** means significance at the 10%, 5%, and 1% levels, respectively. % Sig. reports the percentage of the countries that have significant results at the 10% level or below.

ID	VIX				RBYD		RCUR		ID	VIX				RBYD		RCUR	
	Model (3)		Model (4)		Model (3)		Model (3)			Model (3)		Model (4)		Model (3)		Model (3)	
	Type 2	Type 3	Type 2	Type 3	Type 2	Type 3	Type 2	Type 3		Type 2	Type 3	Type 2	Type 3	Type 2	Type 3	Type 2	Type 3
1	7.81***	17.98***	1.39	10.90***	NA	NA	NA	NA	29	8.94***	11.06***	8.77***	10.80***	NA	NA	0.16	1.61
2	13.97***	20.30***	8.94***	13.88***	7.72***	7.63***	8.31***	8.26***	30	7.28***	10.17***	3.69***	6.29***	NA	NA	NA	NA
3	4.96***	9.37***	0.86	4.49***	1.16	2.31**	12.76***	12.26***	31	42.78***	41.26***	27.81***	28.16***	2.53**	3.66***	15.04***	14.15***
4	12.74***	13.41***	12.42***	13.01***	NA	NA	2.03*	2.26**	32	14.00***	15.42***	14.67***	17.42***	4.60***	5.22***	25.54***	22.69***
5	7.24***	7.30***	1.11	1.49	NA	NA	NA	NA	33	1.87*	4.93***	1.25	4.36***	NA	NA	1.03	2.69**
6	13.50***	14.18***	8.67***	10.72***	2.74**	3.04***	9.77***	8.94***	34	0.37	5.47***	0.36	4.46***	0.15	1.77	3.70***	5.76***
7	15.79***	15.72***	15.59***	15.65***	NA	NA	2.45**	2.77**	35	4.50***	6.15***	5.01***	6.30***	1.81	3.04***	6.39***	7.24***
8	21.52***	28.54***	21.22***	28.69***	NA	NA	3.15***	3.61***	36	1.54	8.30***	1.41	6.57***	0.77	1.69	4.21***	5.02***
9	30.29***	29.44***	1.14	4.84***	0.68	1.5	30.53***	26.52***	37	14.22***	15.87***	2.61**	5.20***	14.51***	12.77***	11.65***	10.18***
10	NA	NA	NA	NA	1.2	2.44**	0.61	1.6	38	10.39***	11.12***	7.71***	8.89***	2.63**	2.93***	6.41***	6.31***
11	6.92***	8.33***	1.53	3.83***	5.56***	5.69***	0.84	2.36**	39	31.83***	28.15***	11.12***	10.88***	24.86***	22.52***	14.29***	12.46***
12	24.54***	24.70***	8.24***	9.48***	5.60***	6.05***	29.58***	25.94***	40	19.47***	21.24***	8.02***	10.10***	6.85***	6.61***	NA	NA
13	1.74	5.37***	1.34	4.54***	NA	NA	1.15	1.54	41	NA	NA	NA	NA	NA	NA	NA	NA
14	6.50***	8.67***	7.45***	9.67***	NA	NA	NA	NA	42	9.38***	10.15***	7.69***	8.85***	0.83	1.12	2.17*	2.28**
15	1.53	3.76***	2.35**	3.97***	2.38**	2.93***	2.11*	2.62**	43	28.22***	29.58***	22.26***	25.29***	NA	NA	9.75***	9.18***
16	7.49***	8.02***	4.04***	4.54***	0.63	1.13	NA	NA	44	6.53***	9.87***	5.53***	9.00***	NA	NA	NA	NA
17	4.22***	6.26***	0.95	2.89***	0.99	1.48	NA	NA	45	20.30***	22.81***	10.36***	14.99***	5.56***	5.72***	19.03***	16.99***
18	NA	NA	NA	NA	6.92***	5.94***	NA	NA	46	42.18***	41.75***	19.64***	21.25***	4.58***	5.07***	30.25***	26.50***
19	9.92***	16.26***	2.53**	7.88***	11.11***	9.52***	2.67**	2.72**	47	NA	NA	NA	NA	NA	NA	NA	NA
20	11.89***	12.49***	8.27***	8.83***	NA	NA	NA	NA	48	5.33***	10.11***	5.88***	9.66***	2.26**	2.25**	6.07***	6.18***
21	10.51***	13.84***	18.22***	18.57***	NA	NA	16.86***	14.34***	49	0.45	0.62	0.86	1.04	3.56***	3.30***	0.76	1.03
22	13.71***	16.78***	14.58***	17.63***	3.11***	3.86***	2.54**	3.38***	50	46.16***	44.41***	19.39***	20.97***	25.21***	23.01***	6.33***	7.25***
23	37.92***	36.39***	9.06***	10.11***	31.19***	27.62***	37.80***	33.15***	51	20.51***	20.50***	20.95***	21.74***	14.87***	14.24***	14.46***	14.22***
24	NA	NA	NA	NA	NA	NA	NA	NA	52	1.77	3.29***	4.11***	5.27***	2.19*	2.03*	0.82	0.92
25	28.38***	28.58***	11.85***	12.22***	NA	NA	NA	NA	53	20.10***	25.23***	4.35***	8.28***	NA	NA	23.66***	19.78***
26	1.09	2.56**	2.13*	2.72**	4.26***	5.18***	NA	NA	54	2.17*	3.80***	2.92**	4.31***	3.55***	3.60***	0.95	1.24
27	18.18***	18.60***	15.90***	16.44***	2.55**	3.84***	5.52***	5.37***	55	17.51***	23.49***	16.38***	22.64***	NA	NA	NA	NA
28	20.40***	19.38***	20.35***	20.12***	NA	NA	3.43***	3.97***	56	13.78***	15.12***	6.56***	8.74***	10.62***	9.69***	10.45***	9.12***
% Sig.	86.53	98.07	80.77	96.15	58.33	83.33	81.40	93.02									

VIX. According to Panel B, when no control factors are used, 25% of the countries, including five G20 economies (Germany, Italy, Japan, Turkey, and the UK), have experienced the small risk spillover effects from the S&P 500 option market to the CDS market over the sample period, while 52% (see Panel B) of the countries, including 11 of the G20 economies (Australia, France, Germany, India, Indonesia, Italy, South Korea, the UK, the US, Argentina, and Russia), have experienced extreme downside risk spillover effects from the S&P 500 option market to the CDS market. Overall, the extreme downside risk spillover effect from the S&P 500 option market to the CDS market is much stronger than the volatility spillover effect,[16] which is a new and interesting finding in the CDS literature. It is also interesting to observe from Table 6 that some sovereigns, such as Bulgaria, Israel, Japan, Kazakhstan, and Saudi Arabia, are subjected to only small risk spillovers, but they are susceptible to extreme downside risk spillovers. This shows the power of Hong (2001) and Hong et al. (2009) in detecting different kinds of spillover effect. On the other hand, the reverse Granger causality in variance and VaR from the sovereign CDS to VIX is much weaker. That is, after controlling for local factors, only 4% of the countries have significant Granger causality in variance from sovereign CDS spreads to VIX, and only 9% of the countries have significant Granger causality in VaR from sovereign CDS spreads to VIX. Overall, even under the conditional heteroskedasticity conditions in the Hong (2001) and Hong et al. (2009) tests, the empirical results suggest a strong unidirectional information spillover from the S&P index option market to the sovereign CDS markets with respect to both small and extreme downside risk. For those countries in Table 6 that have significant unidirectional Granger causality from VIX to the sovereign CDS after controlling for the local variables (M2), we also report their rankings using Hong et al.'s statistics. These rankings represent the sensitivity of the countries to the spillover effect. For example, Kazakhstan (country number 28), Ukraine (country number 53), and Bahrain (country number 4) have the most significant small risk spillover effect. Bahrain, France, and the US have the most significant spillover effect in extreme downside risk. This documents another interesting result from our study.

4.3. Sub-period analysis

Table 7 reports the results of spillover from VIX to CDS during different sub-periods, namely, the pre-crisis period (before July 1, 2007), the crisis period (between July 1, 2007 and September 30, 2009) and the post-crisis period (after September 30, 2009). The financial crisis period is defined following Dick-Nielsen, Feldhutter, and Lando (2012) and Friewald, Jankowitsch, and Subrahmanyam (2012). Table 7 reports the percentage of countries that have significant results at the 10% level or below. The results confirm a significant increase in the spillover effect during the crisis period. Using the ECM model after controlling for local variables (model (4)), the significant rate of type 1, type 2, and type 3 Granger causality in mean from VIX to CDS is 84%, 38%, and 78%, respectively, before the crisis. These percentages increase markedly to 93%, 75%, and 95% during the crisis. After the crisis, they drop again to the normal levels. Using the Hong (2001) and Hong et al. (2009) tests, the significant spillover effects in mean, variance, and VaR from VIX to CDS after controlling for local factors are only 42%, 14%, and 22%, respectively, before the crisis. During the crisis, these rates increase notably to 93%, 45%, and 43%. These results support the existence of a contagion effect from the S&P 500 option market to the CDS market.

4.4. Decomposition of VIX and spillover

VIX, which measures the expected volatility under a risk-neutral measure, can be further decomposed into physical expected volatility (EVOL) and the variance risk premium (VRP). We examine whether both components support price discovery in the sovereign CDS market. In order to test this, on each date we run a GARCH (1,1) model for the monthly S&P 500 index returns of the last 10 years and then use the estimated parameters to calculate the EVOL of the next month. The difference between the EVOL and the VIX is VRP. We then use the EVOL and VRP, respectively, as the predictors in model (4) in place of VIX. For simplicity, we only report the results corresponding to the models with control variables.

Table 8 reports the percentage of countries that have significant results at the 10% level or below. The results show that both EVOL and RVP Granger-cause the sovereign CDS spreads for a large number of countries. When the ECM model is used, EVOL is significant for about 76% of the countries on average, while VRP is significant for about 89% of the countries on average. When the approach proposed in Hong (2001) and Hong et al. (2009) is used, EVOL is significant for about 22% of the countries on average, while VRP is significant for about 21% of the countries on average.

4.5. Out-of-sample forecast of sovereign CDS spreads

Another important consequence of the Granger causality tests that we use in this study is the prediction of CDS spreads. Table 9 reports the results of out-of-sample one-day-ahead forecasts of the sovereign CDS spreads using models (3) and (4). For each country, except Colombia and Switzerland (due to insufficient data), the first 500 observations are used to estimate the parameters of models (3) and (4) initially. Out-of-sample forecasts of CDS are then made starting from the 501st day. In the case of Colombia and Switzerland, only the first 200 observations are used to estimate the parameters due to insufficient

[16] We also test the Granger causality in mean, variance, and VaR between sovereign CDS spreads and the local factors BYD and CUR using the Hong (2001) and Hong et al. (2009) tests. The results show evidence of a bidirectional significant causality effect between the sovereign CDS and BYD for 50% of the countries, and between CDS and CUR for 59% of the countries, respectively, but the unidirectional causality effect is not that strong. That is, 24% and 57% of the countries in the sample demonstrated a unidirectional causality effect in mean from BYD and CUR to the CDS market. The results are not reported here; however, they are available upon request from the authors.

Table 6

Granger causality in mean, variance, and value-at-risk between sovereign CDS and VIX. This table reports the Hong (2001) and Hong et al. (2009) unidirectional and bidirectional Granger causality test statistics under conditional heteroskedasticity between the change of sovereign CDS spreads and the change of VIX with and without controlling for the change of domestic factors. Panels A, B, and C report the Granger causality results in mean, variance, and 99% value-at-risk (VaR), respectively.*, ** and *** mean significance at the 10%, 5%, and 1% levels, respectively. M1 means the model that does not control for the local factors, while M2 means the model that controls for the local factors. The last column reports the ranks of statistical value for those countries that have significant Hong (2001) and Hong et al.'s (2009) test statistics of unidirectional Granger causality from VIX to the sovereign CDS using M2. The %Sig. reports the percentage of the countries that have significant results at 10% or below.

ID	ΔVIX ↔ ΔCDS (Q2)		ΔCDS → ΔVIX(Q1)		ΔVIX → ΔCDS(Q1)		Rank	ID	ΔVIX ↔ ΔCDS (Q2)		ΔCDS → ΔVIX(Q1)		ΔVIX → ΔCDS(Q1)		Rank
	M1	M2	M1	M2	M1	M2			M1	M2	M1	M2	M1	M2	
Panel A. Granger causality in mean															
1	2.42***	2.29**	−0.42	−0.38	3.84***	3.62***	42	29	3.30***	3.31***	−0.59	−0.50	5.25***	5.18***	36
2	4.88***	1.79**	0.45	0.03	6.45***	2.50***	47	30	3.07***	3.29***	- 0.27	−0.04	4.61***	4.70***	38
3	8.99***	9.55***	−0.56	−0.82	13.28***	14.33***	18	31	38.89***	37.92***	0.85	0.51	54.15***	53.12***	1
4	5.43***	5.31***	−0.61	−0.54	8.29***	8.04***	31	32	10.13***	9.33***	0.05	−0.04	14.27***	13.24***	19
5	6.12***	5.93***	−0.53	−0.44	9.19***	8.83***	29	33	2.29**	1.23	0.86	1.02	2.38***	0.71	
6	8.21***	5.14***	1.24	0.64	10.37***	6.62***	32	34	1.54*	1.43*	0.14	0.17	2.03**	1.85**	48
7	17.04***	17.23***	−0.43	−0.40	24.54***	24.77***	8	35	−1.54	−1.58	−1.08	−1.04	−1.09	−1.20	
8	15.25***	13.53***	−1.12	−1.11	22.69***	20.25***	12	36	5.35***	3.18***	0.22	−0.31	7.35***	4.80***	37
9	28.48***	28.56***	0.04	0.15	40.23***	40.24***	5	37	1.44*	0.24	−0.75	−0.76	2.79***	1.10	
10	7.20***	7.25***	0.74	0.78	9.43***	9.48***	28	38	2.69***	2.84***	2.15**	2.35**	1.66**	1.67**	50
11	12.05***	11.12***	−1.36	−1.25	18.40***	16.98***	15	39	3.72***	3.70***	0.62	0.65	4.63***	4.58***	39
12	7.47***	7.64***	−0.24	−0.03	10.80***	10.84***	25	40	33.10***	32.75***	0.32	−0.66	46.49***	46.97***	3
13	2.17**	0.61	1.14	0.84	1.93**	0.02		41	13.29***	11.78***	−0.53	−0.22	19.32***	16.88***	16
14	1.53*	1.10	−0.04	−0.15	2.21**	1.71**	49	42	8.58***	7.35***	0.27	−0.65	11.86***	11.05***	24
15	2.35***	1.33*	−0.21	−0.78	3.54***	2.66***	46	43	15.08***	14.69***	−0.20	−0.81	21.52***	21.58***	11
16	0.00	1.91**	−1.03	−0.83	1.03	3.53***	44	44	22.23***	21.43***	1.56*	0.69	29.88***	29.62***	7
17	5.68***	3.88***	0.35	0.28	7.68***	5.21***	35	45	2.16**	2.91***	0.04	0.31	3.01***	3.81***	41
18	6.20***	5.35***	1.39*	1.18	7.38***	6.39***	33	46	10.43***	7.32***	0.07	−0.03	14.68***	10.38***	26
19	9.55***	7.58***	−0.33	−0.65	13.83***	11.37***	23	47	37.72***	35.95***	−0.44	−0.39	53.78***	51.23***	2
20	10.28***	10.27***	−0.99	−1.16	15.53***	15.68***	17	48	2.31**	1.83**	−0.55	−0.60	3.81***	3.20***	45
21	5.48***	4.95***	0.67	0.92	7.08***	6.08***	34	49	1.91**	2.46***	−1.25	−0.66	3.95***	4.13***	40
22	9.40***	7.71***	−0.95	−0.74	14.25***	11.64***	21	50	2.19**	1.08	0.53	0.62	2.57***	0.91	
23	26.62***	27.11***	0.43	0.54	37.21***	37.79***	6	51	32.86***	32.23***	1.83**	2.08**	44.65***	43.50***	4
24	3.77***	3.58***	1.44*	1.48*	3.89***	3.58***	43	52	18.56***	7.95***	1.01	−0.22	25.24***	11.45***	22
25	12.46***	12.16***	−0.48	−0.57	18.10***	17.77***	14	53	15.53***	15.43***	−0.42	−0.66	22.38***	22.49***	10
26	8.78***	8.21***	−0.33	−0.34	12.75***	11.96***	20	54	5.63***	6.45***	0.23	0.51	7.73***	8.61***	30
27	14.39***	13.86***	0.93	0.64	19.42***	18.96***	13	55	2.49***	−0.13	−1.07	−1.34	4.60***	1.16	
28	16.38***	16.68***	−0.83	−0.73	23.99***	24.33***	9	56	7.54***	7.63***	0.82	0.92	9.84***	9.87***	27
% Sig.	96.43	87.50	8.93	5.36	96.43	89.29									
Panel B. Granger causality in variance															
1	−2.56	−2.54	−1.68	−1.64	−1.94	−1.94		29	−2.25	−2.23	−1.42	−1.39	−1.77	−1.76	
2	−2.38	−2.37	−1.75	−1.76	−1.62	−1.59		30	−2.12	−2.01	−1.41	−1.25	−1.59	−1.60	
3	−1.24	−1.33	−1.62	−1.60	−0.13	−0.29		31	0.74	0.16	−0.54	−0.31	1.59*	0.54	
4	8.32***	7.20***	0.28	0.40	11.49***	9.79***	3	32	−1.39	−1.49	−0.98	−1.12	−0.98	−0.99	
5	−1.54	−1.71	−1.70	−1.71	−0.48	−0.71		33	−2.45	−2.45	−1.71	−1.71	−1.75	−1.76	
6	−1.71	−1.66	−1.53	−1.52	−0.89	−0.83		34	−2.41	−2.40	−1.80	−1.80	−1.61	−1.60	
7	1.91**	2.74***	0.48	0.32	2.21**	3.55***	7	35	1.40*	1.61*	1.51*	1.93**	0.47	0.34	
8	0.30	−0.06	−0.70	−0.90	1.13	0.81		36	−1.00	−0.91	0.08	0.19	−1.49	−1.48	
9	−0.72	−0.89	−1.01	−1.06	−0.01	−0.19		37	−0.80	−0.73	0.79	0.89	−1.92	−1.92	

10	−1.79	−1.81	−1.41	−1.36	−1.12	−1.20		38	−1.98	−1.99	−1.50	−1.53	−1.30	−1.28	
11	−1.71	−1.76	−1.20	−1.23	−1.22	−1.26		39	0.64	0.82	−0.81	−0.84	1.71**	2.00**	11
12	−1.63	−1.68	−0.97	−1.06	−1.34	−1.31		40	−1.24	−1.32	−1.59	−1.56	−0.15	−0.31	
13	−0.06	0.30	−0.99	−0.44	0.91	0.86		41	0.73	0.62	−1.50	−1.48	2.53***	2.37***	9
14	−1.73	−1.80	−0.96	−1.03	−1.48	−1.51		42	−1.09	−0.11	−0.90	−0.38	−0.64	0.23	
15	0.67	0.45	0.00	−0.20	0.96	0.84		43	−1.06	−1.07	−1.28	−1.26	−0.21	−0.26	
16	−2.41	−2.45	−1.90	−1.91	−1.50	−1.55		44	4.04***	5.02***	4.62***	4.71***	1.09	2.38***	8
17	0.62	−0.74	−1.47	−1.42	2.35***	0.36		45	−2.09	−2.18	−1.78	−1.80	−1.17	−1.28	
18	1.36*	0.63	−0.24	−0.60	2.16**	1.49*	12	46	0.06	0.15	−0.78	−0.57	0.86	0.78	
19	−1.71	−1.73	−0.88	−0.97	−1.54	−1.47		47	−2.60	−2.61	−1.83	−1.83	−1.85	−1.87	
20	−1.93	−1.99	−1.72	−1.71	−1.02	−1.10		48	−2.13	−1.70	−1.77	−1.61	−1.25	−0.79	
21	0.73	0.30	−0.44	−0.45	1.47	0.87		49	−1.33	0.90	−0.92	0.19	−0.96	1.08	
22	−2.47	−2.46	−1.78	−1.76	−1.71	−1.73		50	−1.79	−1.88	−1.49	−1.50	−1.04	−1.16	
23	−2.30	−2.29	−1.64	−1.63	−1.61	−1.60		51	2.67***	2.40**	0.46	1.23	3.31***	2.17**	10
24	−2.11	−1.82	−1.52	−1.20	−1.46	−1.38		52	−1.11	−1.12	−0.67	−0.74	−0.90	−0.84	
25	2.87***	3.30***	0.23	0.10	3.84***	4.57***	5	53	12.63***	10.43***	−0.21	−0.10	18.07***	14.84***	2
26	3.93***	3.08***	−1.61	−1.52	7.16***	5.87***	4	54	−0.66	−0.86	−0.89	−0.93	−0.05	−0.28	
27	1.37*	1.57*	−1.58	−1.52	3.52***	3.74***	6	55	−2.32	−2.31	−1.67	−1.67	−1.60	−1.60	
28	23.52***	20.37***	−0.78	−0.74	34.05***	29.55***	1	56	0.09	−0.20	−1.73	−1.70	1.85**	1.42*	13
% Sig.	19.64	17.86	3.57	3.57	25.00	23.21									

Panel C. Granger causality in VaR

1	0.61	0.11	−1.79	−1.77	2.66***	1.92**	23	29	−0.59	−0.6	−1.79	−1.79	0.95	0.93	
2	2.56***	−0.46	1.79**	−1.83	1.82**	1.18		30	−0.29	−2.62	−1.89	−1.85	1.48*	−1.86	
3	1.81**	1.08	−1.26	−1.33	3.82***	2.86***	18	31	1.36*	2.39***	−1.07	−1.04	2.99***	4.43***	10
4	13.52***	15.42***	−1.95	−1.96	21.07***	23.77***	1	32	0.18	−0.14	−0.44	−0.58	0.69	0.39	
5	10.64***	5.14***	11.34***	7.37***	3.70***	−0.09		33	0.68	0.67	−1.83	−1.82	2.79***	2.78***	20
6	−2.66	−2.63	−1.88	−1.86	−1.89	−1.87		34	−2.78	−2.76	−1.97	−1.95	−1.97	−1.95	
7	0.13	0.23	−0.79	−0.85	0.97	1.18		35	−2.70	0.81	−1.91	1.31*	−1.90	−0.17	
8	1.18	1.29*	−1.75	−1.76	3.42***	3.57***	15	36	−2.69	−2.66	−1.93	−1.91	−1.87	−1.86	
9	0.22	−0.64	1.71**	0.59	−1.39	−1.49		37	−0.95	−1.26	−1.95	−1.94	0.60	0.16	
10	−0.44	−0.69	0.88	0.53	−1.50	−1.51		38	−1.66	−1.70	−0.91	−0.96	−1.44	−1.45	
11	−2.12	−2.17	−1.82	−1.78	−1.18	−1.28		39	−2.30	−2.30	−1.81	−1.80	−1.44	−1.45	
12	0.68	1.53*	−1.46	0.26	2.42***	1.90**	24	40	0.17	0.61	−1.82	−1.84	2.06**	2.71***	21
13	−2.70	0.00	−1.91	0.00	−1.91	0.00		41	1.74**	3.00***	−1.80	1.44*	4.27***	2.80***	19
14	−2.41	−2.66	−1.57	−1.9	−1.84	−1.85		42	2.00**	0.72	−0.24	−0.66	3.06***	1.67**	25
15	−2.64	−2.64	−1.78	−1.78	−1.96	−1.96		43	3.28***	3.19***	−1.76	−1.82	6.40***	6.33***	5
16	17.69***	5.00***	−1.95	−1.92	26.97***	8.99***	2	44	2.75***	11.19***	5.73***	11.19***	−1.85	−1.95	
17	3.60***	3.33***	0.98	0.84	4.11***	3.87***	12	45	−2.28	−2.28	−1.81	−1.81	−1.40	−1.41	
18	4.01***	0.92	2.33**	−1.78	3.34***	3.08***	17	46	1.13	1.30*	−1.81	−1.82	3.40***	3.66***	13
19	−1.52	1.22	−1.86	−1.89	−0.29	3.62***	14	47	4.02***	1.92**	−1.92	−1.89	7.61***	4.60***	9
20	1.03	0.82	−1.78	−1.77	3.23***	2.93***	6	48	−1.57	−0.73	−0.41	0.86	−1.81	−1.90	
21	0.00	0.75	−1.38	−1.35	1.38*	2.41***	8	49	−2.69	−2.72	−1.90	−1.93	−1.91	−1.91	
22	3.06***	3.04***	−1.79	−1.79	6.12***	6.09***	11	50	−1.83	−1.59	−0.70	−0.34	−1.89	−1.92	
23	4.06***	2.20**	−1.87	−1.83	7.62***	4.94***		51	−2.21	−2.69	−1.88	−1.89	−1.25	−1.91	
24	1.60*	1.58*	−1.88	−1.88	4.14***	4.12***	7	52	1.14	1.29*	1.12	1.24	0.49	0.59	
25	0.75	−2.39	−1.80	−1.76	2.87***	−1.61		53	2.18**	3.95***	−1.91	−1.93	5.00***	7.52***	4
26	3.27***	2.98***	−1.26	−1.35	5.89***	5.56***		54	5.70***	4.57***	−1.94	−1.93	9.81***	8.40***	3
27	−1.78	−1.76	−1.02	−0.99	−1.51	−1.50	23	55	2.40***	2.38***	1.26	1.25	2.14**	2.13**	22
28	1.21	1.19	3.61***	3.59***	−1.90	−1.90		56	−1.60	1.39*	−1.14	−1.12	−1.11	3.09***	16
% Sig.	35.71	37.50	10.71	8.93	51.78	48.21									

Table 7
Pre-, during, and post-crisis spillover effect. This table reports the results of spillover from VIX to CDS during three sub-periods, namely, pre-crisis period (before 1 July, 2007), crisis period (between 1 July, 2007 and 30 September, 2009), and post-crisis period (after 30 September, 2009). It is to be noted that the pre- and post- crisis periods may vary depending on the availability of data, but the crisis period is the same for all countries. This table reports the percentage of countries that have significant results at the 10% level or below. Model (3) does not use the local variables as the controlling variables, while Model (4) uses them as controlling variables. The results of Granger causality in mean, variance, and VaR are calculated by the approach proposed in Hong (2001) and Hong et al. (2009). M1 and M2 refer to the model without and with controlling variables, respectively. NA implies that we do not calculate the results of Granger causality in VaR for the post-crisis periods due to insufficient observations to calculate the indicator series of extreme value that give the results of one.

Model	Test	% of sig.		
		Pre-crisis (%)	Crisis (%)	Post-crisis (%)
ECM	Type 1 (Model (3))	85.71	96.43	81.13
	Type 1 (Model (4))	84.44	92.73	86.54
	Type 2 (Model (3))	40.81	87.50	33.96
	Type 2 (Model (4))	37.78	74.55	30.77
	Type 3 (Model (3))	77.55	98.21	71.69
	Type 3 (Model (4))	77.78	94.55	75.00
Granger causality	In mean (M1): $\Delta VIX \rightarrow \Delta CDS$	40.00	92.86	39.29
(Hong, 2001; Hong et al., 2009)	In mean (M2): $\Delta VIX \rightarrow \Delta CDS$	42.00	92.86	32.14
	In variance (M1): $\Delta VIX \rightarrow \Delta CDS$	14.00	44.64	33.93
	In variance (M2): $\Delta VIX \rightarrow \Delta CDS$	14.00	44.64	33.93
	In VaR (M1): $\Delta VIX \rightarrow \Delta CDS$	23.91	45.28	NA
	in VaR (M2): $\Delta \mathrm{VIX} \rightarrow \Delta \mathrm{CDS}$	21.74	43.40	NA

data, and their forecasts begin on the 201st day. Forecasting accuracy is determined using the RMSE between the observed and predicted sovereign CDS spreads. Table 9 reports the RSME corresponding to models (3) and (4) for the whole forecast period (RMSE3W, RMSE4W) and for the recent financial crisis period (RMSE3R, RMSE4R), respectively. Table 9 also reports the corresponding percentage RMSE values, which are calculated by taking the RMSE as a percentage of the mean observed CDS value, a benchmark, over the forecast period for each country.

As shown in Table 9, all the countries have percentage root mean square values that are less than 14% corresponding to $RMSE_{3W}$ and $RMSE_{4W}$, implying that the out-of-sample forecasted CDS spreads using models with and without local control factors are very close to the observed ones. The spillover from the VIX to the CDS market during the financial crisis is also evident from the results in Table 9. During the financial crisis period, 96% of the countries with available data have percentage root mean square values less than 14% corresponding to $RMSE_{3R}$ and $RMSE_{4R}$. These findings imply that regardless of the business cycle, even in the out-of-sample, VIX provides useful information for predicting sovereign CDS spreads. More recently, the research examining the predictability of models over the business cycle indicate stronger results during periods of low economic growth (Rapach, Strauss, & Zhou, 2010; Henkel, Martin, & Nardari, 2011). Evidence from Longstaff (2010) indicates forecasting ability from cross-market linkages dissipated as the subprime crisis shifted to the broader global financial crisis. However, our results show strong forecasting ability from the VIX to the sovereign CDS markets before, during, and after the crisis. This finding provides evidence for the transmission of information from a leading market independently of the business cycle.

As an illustration of the prediction accuracy contained within the RMSE values, we plot the observed and forecasted CDS spreads for Norway, Pakistan, and the US in Figs. 2, 3, and 4, respectively. Norway and Pakistan have the lowest and highest RMSE values, respectively. Figs. 2, 3, and 4 confirm the results reported in Table 9. That is, VIX helps to produce very accurate predictions of the future CDS spreads before, during, and after the crisis period using both model (3) and model (4).

Table 8
Decomposition of VIX and the spillover. This table reports the results of Granger causality of sovereign CDS by physical expected volatility (EVOL) and variance risk premium (VRP). On each date, we run GARCH (1,1) model for the monthly S&P 500 index returns of the last 10 years and then use the estimated parameters to calculate the physical expected volatility of the next month. The difference between the EVOL and the VIX is variance risk premium. This table reports the percentage of countries that have significant results at the 10% level or below. The results of Granger causality in mean, variance, and VaR are calculated by the approach proposed in Hong (2001) and Hong et al. (2009). For simplicity, we report the results corresponding to model (4), which uses the local variables as the controlling factors.

Model	Test	% of sig.	
		With EVOL (%)	With VRP (%)
ECM	Type 1	73.21	92.86
	Type 2	67.86	80.36
	Type 3	85.71	92.31
	Average	75.59	88.51
Granger causality: $\Delta VIX \rightarrow \Delta CDS$ (Hong, 2001; Hong et al., 2009)	In mean	42.86	19.64
	In variance	12.50	17.86
	In VaR	10.71	25.00
	Average	22.02	20.83

Table 9

Out-of-sample forecast of sovereign CDS spreads. This table reports the results of out-of-sample root mean square error (RMSE) for the one-day-ahead forecast of the sovereign CDS spreads. $RMSE_{3W}$ refers to the results for Eq. (3) over the whole forecast period, while $RMSE_{3R}$ refers to the results for Eq. (3) during the financial crisis period. $RMSE_{4W}$ and $RMSE_{4R}$ refer to the corresponding measures based on Eq. (4). The % is the percentage of RMSE with respect to the mean of the sovereign CDS spreads calculated over the whole forecast period and the financial crisis period, respectively. The recent financial crisis period is considered as July 2007 to September 2009 following Dick-Nielsen et al. (2012), and Friewald et al. (2012). In nine countries where the sovereign CDS have started recently, the crisis period is contained within the first 500 observations used to estimate models (3) and (4). As a result, the RMSE values are not available (NA) for those countries.

ID	$RMSE_{3W}$	%	$RMSE_{4W}$	%	$RMSE_{3R}$	%	$RMSE_{4R}$	%	ID	$RMSE_{3W}$	%	$RMSE_{4W}$	%	$RMSE_{3R}$	%	$RMSE_{4R}$	%
1	66.57	6.59	66.86	6.61	95.16	6.11	95.58	6.14	29	2.99	9.42	3.00	9.45	3.60	11.36	3.62	11.43
2	3.83	11.61	3.83	11.59	5.24	10.64	5.23	10.62	30	33.26	10.01	33.34	10.03	40.64	9.87	40.73	9.89
3	4.04	9.55	4.01	9.50	5.27	9.48	5.23	9.41	31	5.94	2.06	6.96	2.41	6.47	2.04	9.55	3.02
4	3.70	2.17	3.88	2.27	NA	NA	NA	NA	32	14.09	5.21	14.14	5.23	16.26	5.71	16.32	5.73
5	2.90	8.07	2.88	8.02	3.16	7.93	3.15	7.93	33	9.99	11.88	10.07	11.97	14.25	11.58	14.36	11.67
6	6.24	4.42	7.09	5.02	7.45	4.31	9.24	5.34	34	10.32	8.62	10.10	8.43	17.06	9.71	16.62	9.46
7	8.53	5.60	8.58	5.63	13.60	5.54	13.66	5.56	35	11.19	9.36	11.27	9.43	10.67	6.64	10.79	6.71
8	5.68	8.08	5.67	8.07	7.93	7.76	7.92	7.75	36	4.70	13.33	4.81	13.65	5.52	16.53	5.65	16.90
9	7.16	8.72	7.19	8.76	8.45	9.51	8.49	9.56	37	7.45	12.82	7.36	12.65	9.34	15.35	9.20	15.12
10	3.34	2.68	3.49	2.80	NA	NA	NA	NA	38	1.47	10.11	1.46	10.10	1.69	8.25	1.68	8.22
11	4.88	1.91	5.02	1.96	NA	NA	NA	NA	39	134.51	13.50	134.59	13.51	171.49	12.76	171.64	12.77
12	5.84	9.80	5.91	9.91	8.06	9.59	8.16	9.71	40	5.45	4.34	10.29	8.18	4.41	3.45	5.04	3.94
13	1.09	2.78	1.14	2.92	NA	NA	NA	NA	41	14.86	7.14	14.85	7.14	20.67	8.06	20.65	8.05
14	22.81	6.60	23.07	6.67	31.35	6.76	31.67	6.83	42	6.98	8.11	6.86	7.97	9.16	7.86	8.99	7.71
15	1.57	5.29	1.54	5.18	NA	NA	NA	NA	43	9.51	13.95	9.52	13.96	3.36	6.52	3.35	6.51
16	1.95	8.98	1.95	9.00	2.42	9.53	2.43	9.58	44	11.00	3.79	11.16	3.85	10.42	3.48	10.43	3.48
17	1.41	7.87	1.41	7.86	1.63	7.64	1.63	7.64	45	19.98	10.12	20.10	10.19	27.06	9.62	27.19	9.67
18	18.74	12.30	20.20	13.26	4.93	5.27	4.90	5.24	46	1.89	2.57	2.14	2.91	NA	NA	NA	NA
19	3.41	7.43	3.42	7.45	4.30	7.40	4.30	7.42	47	12.89	9.06	12.81	9.00	17.66	8.49	17.31	8.32
20	12.01	7.25	12.00	7.25	15.51	7.04	15.52	7.05	48	13.31	12.98	13.73	13.39	18.89	11.89	19.52	12.28
21	31.59	10.85	31.52	10.83	44.78	10.12	44.70	10.10	49	6.44	8.03	6.43	8.02	3.85	6.97	3.86	6.98
22	11.06	7.49	11.06	7.49	16.18	7.39	16.20	7.40	50	3.84	12.94	3.82	12.88	5.61	13.74	5.58	13.66
23	24.78	9.75	25.75	10.12	32.53	9.67	33.90	10.07	51	2.25	4.86	2.37	5.12	NA	NA	NA	NA
24	7.64	9.09	7.65	9.10	7.22	7.30	7.21	7.30	52	10.19	10.38	10.21	10.41	14.36	10.76	14.38	10.77
25	5.08	5.86	5.06	5.84	6.78	6.39	6.74	6.35	53	13.62	5.81	14.08	6.01	17.91	6.28	18.58	6.51
26	5.10	8.04	5.08	8.00	3.83	5.66	3.81	5.63	54	3.15	4.28	3.15	4.29	NA	NA	NA	NA
27	66.57	6.59	66.86	6.61	95.16	6.11	95.58	6.14	55	77.86	8.91	78.79	9.02	103.13	8.87	104.39	8.98
28	3.83	11.61	3.83	11.59	5.24	10.64	5.23	10.62	56	1.95	4.85	1.93	4.81	NA	NA	NA	NA

4.6. Robustness test

In order to test the robustness of our empirical findings, we repeat the analysis under two scenarios. First, we replace VIX with two other stock market indices, the MSCI world index and the S&P 500 index, and repeat the Granger causality tests to investigate whether our findings still hold. Second, we repeat the out-of-sample forecasting with monthly data to examine whether our findings are still valid on a longer prediction horizon.[17]

Table 10 reports the results of the robustness test.[18] Panel A reports the Granger causality test results, while Panel B reports the results for the out-of-sample forecast. In order to conserve space, we only report the results of Granger causality test from the leading market (MSCI and S&P 500) to sovereign CDS in Panel A.[19] The results reported in Table 10 clearly show that when we replace VIX with the MSCI index or the S&P 500 index, strong Granger causality results from the MSCI and S&P 500 indexes to CDS continue to hold. For example, the type 3 Granger causality test is significant for 100% (97.92%) of the countries under model (4) for the MSCI (S&P 500) index. They are very close or stronger than the corresponding percentages when VIX is used. This suggests that our findings are robust with respect to the choice of leading market proxy. When the data frequency changes to monthly data, we still observe quite significant causality results, although they are not as strong as for daily data.[20] The results of out-of-sample forecasts in Panel B reveal similar findings. For example, when the MSCI (S&P 500) index is used, 80% of the countries have RMSE in percentage below 10.70% (10.24%) during the whole period, and below 10.24% (10.68%) during the crisis period.

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[17] Thank you to an anonymous referee for proposing these suggestions.

[18] When running the Granger causality test following Hong (2001) and Hong et al. (2009), we use the log-changes of stock index, since they are commonly used in the literature as the measure of stock market return.

[19] The other results are available upon request.

[20] The procedure used was exactly the same as with the daily data, but applied to monthly average CDS spreads series and VIX series. In out-of-sample forecasting, the initial period used for estimating the model parameters was the first 40 months (due to insufficient data points) and the rest of the period was used for the out-of-sample predictions. Considering the number of parameters to be estimated in the ECM in the case of monthly data, we had to restrict the sample to only those countries which had data for at least 70 months. As a result, the sample size was dropped from 56 (with daily data) to 35 (with monthly data).

Table 10

Robustness tests. This table reports the results of robustness tests. We consider two different types of robustness check. One is to replace VIX with the MSCI world index or S&P 500 index. The other is to test the causality and out-of-sample forecast at monthly frequency. Panel A reports the results of the causality test from leading market to sovereign CDS, while Panel B reports the results of the out-of-sample forecast. Under the Granger causality test framework, M1 means the model that does not control for the local factors, while M2 means the model that controls for local factors. $RMSE_{3W}\%$ is the percentage of out-of-sample root mean square error (RMSE) with respect to the mean of the sovereign CDS spreads calculated over the whole forecast period for Eq. (3). $RMSE_{3R}\%$ is the percentage of RMSE with respect to the mean of the sovereign CDS spreads calculated over the financial crisis period for Eq. (3). $RMSE_{4W}\%$ and $RMSE_{4R}\%$ refer to the corresponding measures based on Eq. (4). The recent financial crisis period is considered as July 2007 to September 2009 following Dick-Nielsen et al. (2012), and Friewald et al. (2012). We do not calculate the results of Granger causality in VaR for monthly data since the number of observations is not enough.

Panel A. Granger causality test from leading market to sovereign CDS

Model	Test	% of sig.		
		Daily		Monthly
		MSCI	S&P500	VIX
ECM	Type 1 (Model (3))	89.36	79.17	51.43
	Type 1 (Model (4))	85.11	79.17	42.86
	Type 2 (Model (3))	100.00	100.00	48.57
	Type 2 (Model (4))	97.87	97.92	60.00
	Type 3 (Model (3))	100.00	100.00	71.43
	Type 3 (Model (4))	100.00	97.92	77.14
Granger causality (Hong, 2001; Hong et al., 2009)	In mean (M1)	89.29	96.43	73.21
	In mean (M2)	89.29	94.64	62.50
	In variance (M1)	51.79	53.57	17.86
	In variance (M2)	53.57	57.14	16.07
	In VaR (M1)	39.29	32.14	NA
	In VaR (M2)	37.50	37.50	NA

Panel B. Out-of-sample forecast of sovereign CDS

Horizon	Data	RMSE	Mean	Percentile			
				20%	40%	60%	80%
Daily	MSCI	$RMSE_{3W}\%$	7.90	4.76	7.32	8.86	10.71
		$RMSE_{4W}\%$	8.04	5.06	7.46	8.94	10.70
		$RMSE_{3R}\%$	8.25	6.11	7.20	8.81	9.95
		$RMSE_{4R}\%$	8.31	6.13	7.21	8.86	10.27
	S&P500	$RMSE_{3W}\%$	7.87	4.90	7.47	8.90	10.24
		$RMSE_{4W}\%$	8.02	4.92	7.54	8.97	10.34
		$RMSE_{3R}\%$	8.68	6.25	7.56	9.47	10.68
		$RMSE_{4R}\%$	8.68	6.25	7.56	9.47	10.68
Monthly	VIX	$RMSE_{3W}\%$	55.61	34.86	42.44	50.77	72.26
		$RMSE_{4W}\%$	55.61	37.40	42.31	54.70	72.09

5. Conclusion

This paper studies the Granger causal relationship between the sovereign CDS spread and a leading market indicator, VIX, and local factors, BYD and CUR, in 56 countries over the period 2001–2010. VIX is found to be the most dominant and significant factor. Using an ECM, we document a very strong unidirectional spillover effect from the S&P index options market to the sovereign CDS market. The Granger causality in mean from VIX to the sovereign CDS spread is significant for 98% of the countries. The results do not change much even if the local factors, BYD and CUR, are used as the controlling factors. Our findings are consistent with the spillover literature, which suggests that information gradually spills from a leading market to other markets. The Granger causality from VIX to the sovereign CDS market provides evidence of how information is transmitted between markets. Our findings are also consistent with the view that global shocks first affect the more liquid markets, such as the S&P index options market, before spilling over to other less liquid markets. This study provides evidence of the importance of liquidity and how it affects the price efficiency of financial markets. We also find a Granger causality effect in mean from the BYD and CUR to the sovereign CDS spreads, but it is not as strong as VIX. The ECM results suggest that both local and global factors contribute to the price discovery of the sovereign CDS spreads.

We further investigate the effect of the VIX on sovereign CDS spreads using the Granger causality tests proposed by Hong (2001) and Hong et al. (2009). These tests are robust to conditional heteroskedasticity and are used to test for Granger causality in mean, variance, and downside risk. We find evidence for a strong unidirectional Granger causality in mean, variance, and downside risk from the S&P index option market to the sovereign CDS market. These findings further confirm the Granger causality in mean results from VIX to the sovereign CDS spreads produced by the ECM. Furthermore, Hong (2001) and Hong et al.'s (2009) tests identify the sovereigns that are subjected to small risk spillovers and extreme downside risk spillovers. On the other hand, we find little evidence of reverse Granger causality from sovereign CDS to VIX. Taken together, these results show that the nature of the Granger causality is unidirectional, flowing from the S&P index option market to the sovereign CDS markets.

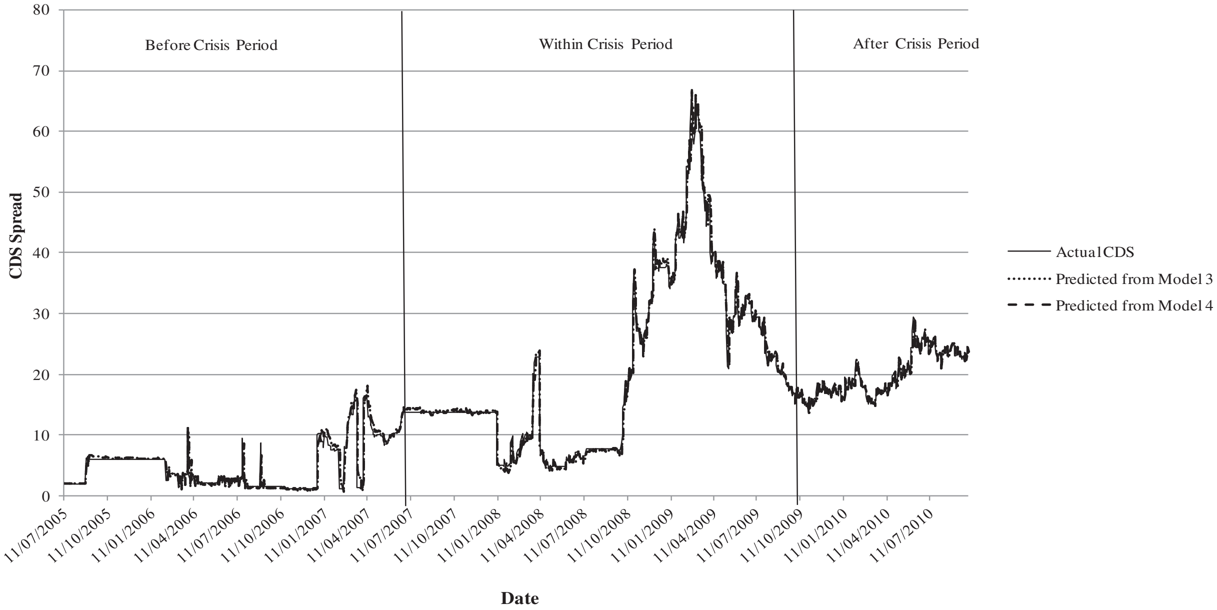

Fig. 2. The actual versus out-of-sample predicted CDS spreads for Norway from July 11, 2005 to September 30, 2010. Models (3) and (4) are fitted using the first 500 observations of actual CDS spread data of Norway initially. The out-of-sample forecasts are made starting from the 501st day. This graph illustrates the observed CDS spread of Norway (country with the lowest RMSE value in Table 7) and the one-day-ahead predicted values from models (3) and (4) before, during, and after the crisis period.

The sub-period analysis documents a significant increase of spillover during the crisis period. The results of all the tests show a higher percentage of significance during the crisis. This provides robust evidence of a contagion effect on the sovereign CDS market. The results using physical expected volatility and variance risk premium show that both components are helpful in price discovery of the sovereign CDS spreads.

Evidence of a spillover effect suggests that past changes in VIX may improve the predictability of future changes in sovereign CDS spreads. The out-of-sample forecast results show that introducing the VIX could help reduce the forecast errors of the daily

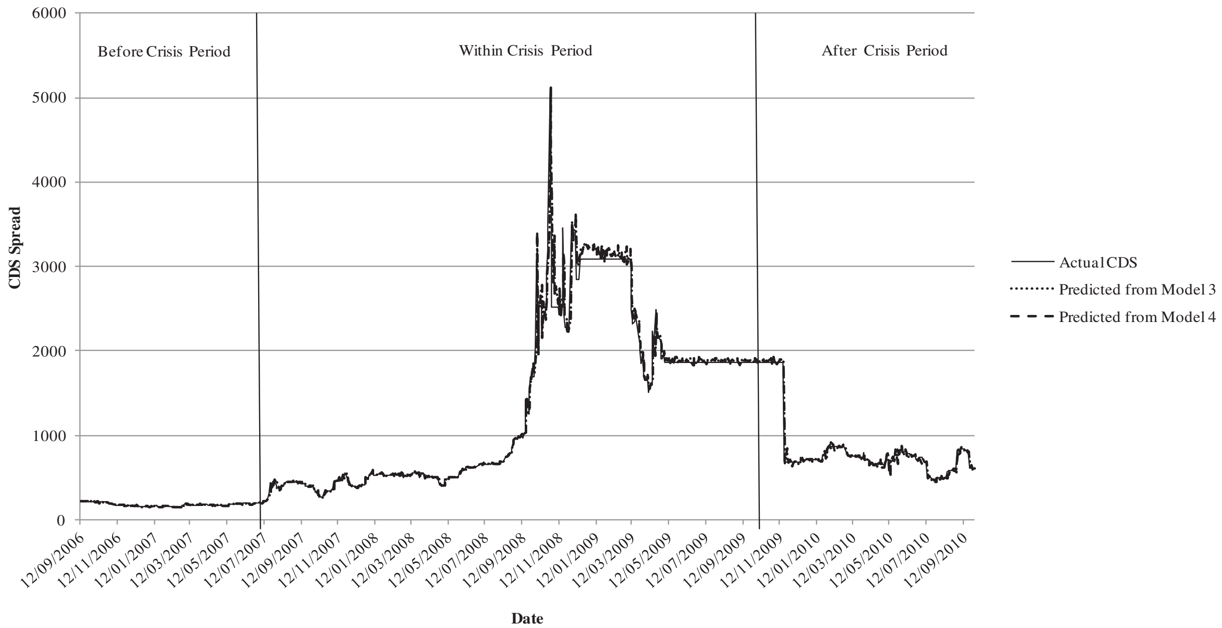

Fig. 3. The actual versus out-of-sample predicted CDS spreads for Pakistan from September 12, 2006 to September 30, 2010. Models (3) and (4) are fitted using the first 500 observations of actual CDS spread data of Pakistan initially. The out-of-sample forecasts are made starting from the 501st day. This graph illustrates the observed CDS spread of Pakistan (country with the highest RMSE value in Table 7) and the one-day-ahead predicted values from models (3) and (4) before, during, and after the crisis period.

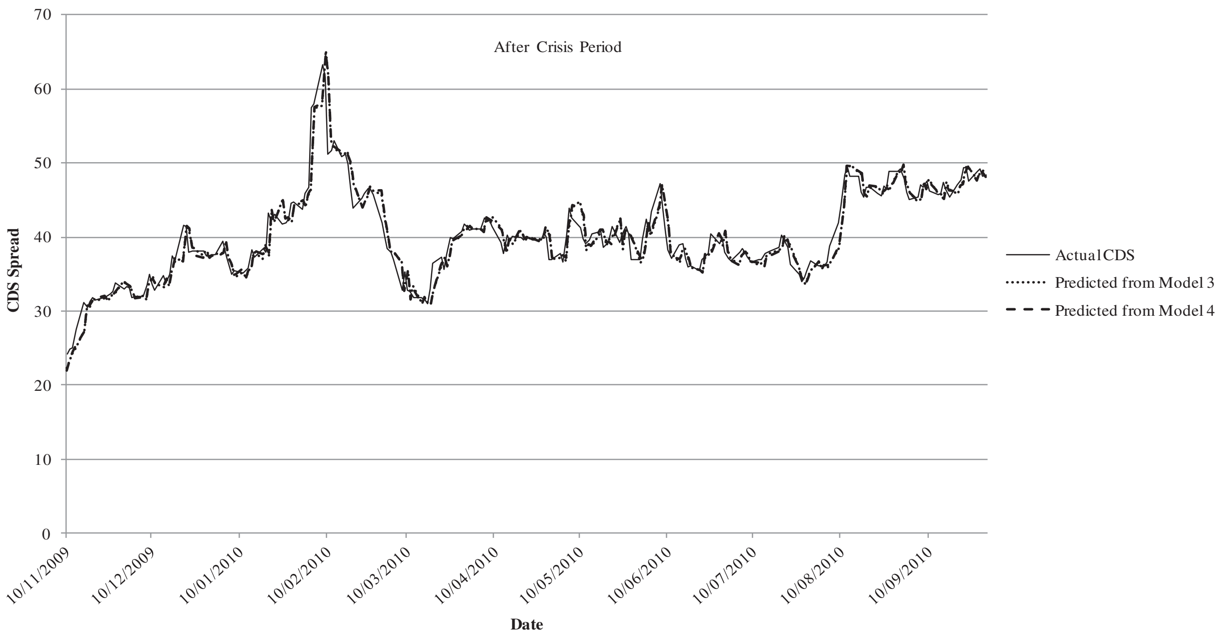

Fig. 4. The actual versus out-of-sample predicted CDS spreads for US from November 10, 2009 to September 30, 2010. Models (3) and (4) are fitted using the first 500 observations of actual CDS spread data for the US initially. The out-of-sample forecasts are made starting from the 501st day. This graph illustrates the observed CDS spread for the US and the one-day-ahead predicted values from models (3) and (4) after the crisis period from November 10, 2009 to September 30, 2010. Note that no prediction is made before or during the crisis, as these data are used to estimate models (3) and (4) initially.

sovereign CDS spreads to below 14% in 98% of the countries if both long-run relationship information and short-run change information are used. During the financial crisis period, VIX reduces the forecast error to below 14% in 93% of the countries in the sample. The contribution of VIX in the transmission of information to the sovereign CDS market is still very significant during the recent financial crisis period. Our results show that the sovereign CDS spreads are Granger-caused by the VIX, confirming the presence of a spillover effect from the leading market to the sovereign CDS market. An important insight of this study is that VIX provides useful information for forecasting the future change in sovereign CDS spreads before, during, and after the financial crisis.

There are several open questions for future research. This paper finds evidence of spillover with a large sample using a long time period. The variables that affect the magnitude of spillover in individual countries could be an interesting research question. In addition to BYD and CUR, more local macroeconomic variables could be used as the controlling variables in future research. It may also be possible to combine the spillover effect into the pricing of CDS.

Appendix A. Granger causality test in mean

Consider the following process:

$$\varepsilon_{it} = Y_{it} - E(Y_{it}|I_{1t-1}), i = 1, 2, \tag{A1}$$

where $\varepsilon_{it} = h_{it}^{1/2}\xi_{it}$, and ξ_{it} satisfies

$$E(\xi_{it} \mid I_{it-1}) = 0 \quad a.s., \quad E\left(\xi_{it}^2 \mid I_{it-1}\right) = 1\ a.s. \tag{A2}$$

Assuming it follows a *GARCH* (p,q) process, the centred standardized residuals can be calculated from $\hat{u}_t = \hat{\varepsilon}_{1t}/\hat{h}_{1t}^{1/2}$, and $\hat{v}_t = \hat{\varepsilon}_{2t}/\hat{h}_{2t}^{1/2}$. The sample cross-correlation function is obtained as $\hat{\rho}_{uv}(j) = [\hat{C}_{uu}(0)\hat{C}_{vv}(0)]^{-1/2}\hat{C}_{uv}(j)$, where j is the number of lag orders, and $\hat{C}_{uv}(j)$ denotes the sample cross-covariance function which is in the following form:

$$\hat{C}_{uv}(j) = \begin{Bmatrix} T^{-1}\sum_{t=j+1}^{T}\hat{u}_t\,\hat{v}_{t-j}, & j \geq 0 \\ T^{-1}\sum_{t=j+1}^{T}\hat{u}_t\,\hat{v}_t\,, & j < 0 \end{Bmatrix} \tag{A3}$$

and $\hat{C}_{uu}(0) = T^{-1}\sum_{t=1}^{T}\hat{u}_t^2, \quad \hat{C}_{vv}(0) = T^{-1}\sum_{t=1}^{T}\hat{v}_t^2.$

Hong (2001) proposes the following test statistic to test unidirectional Granger causality in mean:

$$Q_1 = \left[T\sum_{j=1}^{T-1}k^2(j/M)\,\hat{\rho}_{uv}^2(j) - C_{1T}\right]/[2\,D_{1T}]^{1/2}, \tag{A4}$$

where $k(\cdot)$ is the kernel function that gives weights to cross-correlation coefficients, M is a lag truncation number under some specifications of k, and C_{1T} and D_{1T} are functions of k as follows:

$$C_{1T} = \sum_{j=1}^{T-1} (1-j/T)\ k^2\ (j/M), \tag{A5}$$

$$D_{1T} = \sum_{j=1}^{T-1} (1-j/T)\ [\,1-(j+1)/T\,]\ k^4\ (j/M). \tag{A6}$$

Under regular conditions, Hong (2001) shows that $Q_1 \to N(0,1)$ in distribution under the null hypothesis of no Granger causality in mean. Hong (2001) also proposes the following test statistic to test bidirectional Granger causality:

$$Q_2 = \left[T \sum_{j=1-T}^{T-1} k^2 (j/M)\ \hat{\rho}^2_{uv}(j) - C_{2T} \right] / [2\ D_{2T}]^{1/2}, \tag{A7}$$

where

$$C_{2T} = \sum_{j=1-T}^{T-1} (1-|j|/T)\ k^2\ (j/M), \tag{A8}$$

$$D_{2T} = \sum_{j=1}^{T-1} (1-|j|/T)\ [\,1-(|j|+1)/T\,] k^4\ (j/M). \tag{A9}$$

Hong (2001) shows that Q_2 also follows N (0,1) under the null hypothesis.

Appendix B. Granger causality test in downside risk

The sample cross-covariance function of the indicator series $\{Z_{1t}, Z_{2t}\}$ is defined as

$$\hat{C}(j) = \begin{Bmatrix} T^{-1} \sum_{t=1+j}^{T} \left(\hat{Z}_{1t} - \hat{\alpha}_1 \right) \left(\hat{Z}_{2(t-j)} - \hat{\alpha}_2 \right), 0 \le j \le T-1 \\ T^{-1} \sum_{t=1+j}^{T} \left(\hat{Z}_{1(t+j)} - \hat{\alpha}_1 \right) \left(\hat{Z}_{2t} - \hat{\alpha}_2 \right), 1-T \le j \le 0 \end{Bmatrix}, \tag{B1}$$

where $\hat{Z}_{it} = I\ (Y_{it} < -V_{it})$ and $\hat{\alpha}_i = T^{-1} \sum_{i=1}^{T} \hat{Z}_{it}$. Thus, the sample cross-correlation function between $\{Z_{1t}\}$ and $\{Z_{2t}\}$ is calculated as

$$\hat{\rho}\ (j) = \hat{C}\ (j)/\hat{S}_1 \hat{S}_2, \quad j = 0, \pm 1, \pm 2, \ldots, \pm T-1, \tag{B2}$$

where $\hat{S}_i^2 = \hat{\alpha}_i\ (1-\hat{\alpha}_i)$ denotes the sample variance. Hong et al. (2009) propose a test statistic similar to Q_1 to test the unidirectional Granger causality in VaR, and the Q_2 statistic to test bidirectional Granger causality. Under regulatory conditions, both Q_1 and Q_2 follow an asymptotic standard normal distribution with zero mean and variance one.

References

Ammer, J., & Cai, F. (2011). Sovereign CDS and bond pricing dynamics in emerging markets: Does the cheapest-to-deliver option matter? *Journal of International Financial Markets Institutions and Money*, *21*, 369–387.

Anthony, J. H. (1988). The interrelation of stock and options market trading-volume data. *Journal of Finance*, *43*, 949–964.

Baele, L. (2005). Volatility spillover effects in European equity markets. *Journal of Financial and Quantitative Analysis*, *40*, 373–400.

Bekaert, G., Harvey, C. R., & Ng, A. (2005). Market integration and contagion. *Journal of Business*, *78*, 39–69.

Blanco, R., Brennan, S., & Marsh, I. W. (2005). An empirical analysis of the dynamic relationship between investment grade bonds and credit default swaps. *Journal of Finance*, *60*, 2255–2281.

Bollerslev, T., Marrone, J., Xu, L., & Zhou, H. (2014). Stock return predictability and variance risk premia: Statistical inference and international evidence. *Journal of Financial and Quantitative Analysis*, *49*, 633–661.

Bossaerts, P., & Hillion, P. (1999). Implementing statistical criteria to select return forecasting models: What do we learn? *Review of Financial Studies*, *12*, 405–428.

Campbell, J. Y., & Thompson, S. B. (2008). Predicting the equity premium out of sample: Can anything beat the historical average? *Review of Financial Studies*, *21*, 1509–1531.

Carr, P., & Wu, L. (2007). Theory and evidence on the dynamic interactions between sovereign credit default swaps and currency options. *Journal of Banking & Finance*, *31*, 2383–2403.

Chaudhuri, K., & Wu, Y. (2003). Random walk versus breaking trend in stock prices: Evidence from emerging markets. *Journal of Banking & Finance*, *27*, 575–592.

CMA (2012). *CMA Sovereign Credit Risk Report*.

Davidson, R., & MacKinnon, J. G. (1993). *Estimation and inference in econometrics*. Oxford University Press.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators in autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*, 427–431.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, *49*, 1057–1082.

Dick-Nielsen, J., Feldhutter, P., & Lando, D. (2012). Corporate bond liquidity before and after the onset of the subprime crisis. *Journal of Financial Economics*, *103*, 471–492.

Duffie, D., & Pan, J. (1997). An overview of the value at risk. *Journal of Derivatives*, *4*, 7–49.

Duffie, D., Pedersen, L. H., & Singleton, K. J. (2003). Modeling sovereign yield spreads: A case study of Russian debt. *Journal of Finance*, *58*, 119–159.
Easley, D., O'Hara, M., & Srinivas, P. S. (1998). Option volume and stock prices: Evidence on where informed traders trade. *Journal of Finance*, *53*, 431–465.
Engle, R. F., & Granger, C. W. J. (1987). Co-integration and error correction: Representation, estimation and testing. *Econometrica*, *55*, 251–276.
Engle, R. F., Ito, T., & Lin, W. (1990). Meteor shower or heat wave? Heteroskedastic intra-daily volatility in the foreign exchange market. *Econometrica*, *58*, 525–542.
Forbes, K., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market co-movements. *Journal of Finance*, *57*, 2223–2261.
Friewald, N., Jankowitsch, R., & Subrahmanyam, M. G. (2012). Illiquidity or credit deterioration: A study of liquidity in the US corporate bond market during financial crises. *Journal of Financial Economics*, *105*, 18–36.
Gande, A., & Parsley, D. C. (2005). News spillovers in the sovereign debt markets. *Journal of Financial Economics*, *75*, 691–734.
Gorea, D., & Radev, D. (2014). The Euro area sovereign debt crisis: Can contagion spread from the periphery to the core? *International Review of Economics and Finance*, *30*, 78–100.
Goyal, A., & Welch, I. (2003). Predicting the equity premium with dividend ratios. *Management Science*, *49*, 639–654.
Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, *37*, 424–438.
Granger, C. W. J. (1980). Testing for causality: A personal view. *Journal of Economic Dynamics and Control*, *2*, 239–252.
Granger, C. W. J. (1988). Some recent developments in a concept of causality. *Journal of Econometrics*, *39*, 199–211.
Guo, F., Chen, C. R., & Huang, Y. S. (2011). Markets contagion during financial crisis: A regime-switching approach. *International Review of Economics and Finance*, *20*, 95–109.
Hansen, B. E. (1992). Efficient estimation and testing of cointegration vectors in the presence of deterministic trends. *Journal of Econometrics*, *53*, 87–121.
Henkel, S. J., Martin, J. S., & Nardari, F. (2011). Time-varying short-horizon predictability. *Journal of Financial Economics*, *99*, 560–580.
Hilscher, J., & Nosbusch, Y. (2010). Determinants of sovereign risk: Macroeconomic fundamentals and the pricing of sovereign debt. *Review of Finance*, *14*, 235–262.
Hong, Y. (2001). A test for volatility spillover with application to exchange rates. *Journal of Econometrics*, *103*, 183–224.
Hong, Y., Liu, Y., & Wang, S. (2009). Granger causality in risk and detection of extreme risk spillover between financial markets. *Journal of Econometrics*, *150*, 271–287.
Hu, J. (2013). Does option trading convey stock price information? *Journal of Financial Economics*, *111*, 625–645.
Longin, F., & Solnik, B. (2001). Extreme correlation of international equity markets. *Journal of Finance*, *56*, 649–676.
Longstaff, F. A. (2010). The subprime credit crisis and contagion in financial markets. *Journal of Financial Economics*, *97*, 436–450.
Longstaff, F. A., Pan, J., Pedersen, L. H., & Singleton, K. J. (2011). How sovereign is sovereign credit risk? *American Economic Journal: Macroeconomics*, *3*, 75–103.
Morales, L., & Andreosso-O'Callaghan, B. (2014). The global financial crisis: World market or regional contagion effects? *International Review of Economics and Finance*, *29*, 108–131.
Norden, L., & Weber, M. (2009). The co-movement of credit default swap, bond and stock markets: An empirical analysis. *European Financial Management*, *15*, 529–562.
Pan, J., & Singleton, K. J. (2008). Default and recovery implicit in the term structure of sovereign CDS spreads. *Journal of Finance*, *63*, 2345–2384.
Phillips, P. C. B., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, *75*, 335–346.
Rapach, D. E., Strauss, J. K., & Zhou, G. (2010). Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. *Review of Financial Studies*, *23*, 821–862.
Rapach, D. E., Strauss, J. K., & Zhou, G. (2013). International stock return predictability: What is the role of the United States? *Journal of Finance*, *68*, 1633–1662.
Remolona, E., Scatigna, M., & Wu, E. (2008). The dynamic pricing of sovereign risk in emerging markets: Fundamentals of risk aversion. *Journal of Fixed Income*, *17*, 57–71.
Roll, R. (1988). The international crash of October 1987. *Financial Analysts Journal*, *44*, 19–35.
Sheikh, A. M., & Ronn, E. I. (1994). A characterization of the daily and intra-day behaviour of returns on options. *Journal of Finance*, *49*, 557–580.
Suh, S. (2015). Measuring sovereign risk contagion in the Eurozone. *International Review of Economics and Finance*, *35*, 45–65.
Syllignakis, M. N., & Kouretas, G. P. (2011). Dynamic correlation analysis of financial contagion: Evidence from the central and eastern European markets. *International Review of Economics and Finance*, *20*, 717–732.
Wang, H., Zhou, H., & Zhou, Y. (2013). Credit default swap spreads and variance risk premia. *Journal of Banking & Finance*, *37*, 3733–3746.
Whaley, R. E. (2009). Understanding the VIX. *Journal of Portfolio Management*, *35*, 98–105.
Zhu, H. (2006). An empirical comparison of credit spreads between the bond market and the credit default swap market. *Journal of Financial Services Research*, *29*, 211–235.
Zivot, E., & Andrews, D. W. K. (1992). Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *Journal of Business and Economic Statistics*, *10*, 251–270.