The Co-movement of Credit Default Swap Spreads, Stock Market Returns and Volatilities: Evidence from Asia-Pacific Markets *

José Da Fonseca† Katrin Gottschalk‡
October 17, 2015

Abstract

We study the co-movement of credit and equity markets in four Asia-Pacific countries at firm and index level. First, we establish realized volatility as an important determinant of credit default swap (CDS) spread levels and changes. Second, we examine lead-lag relationships between CDS spreads, volatility, and stock returns using a vector-autoregressive model. At the firm level stock returns lead the other variables. However, at the index level volatility and CDS spreads are equally important. Third, we analyze volatility spillovers using the measures proposed by Diebold and Yilmaz (2014). The results suggest that realized volatility is the main contributor to cross-market volatility spillovers.

Keywords: Credit Risk, Credit Default Swap, High-Frequency Data, Realized Volatility, Granger Causality, Volatility Spillover Effects

JEL Classification: G12, G13, C13

* A previous version of this paper was circulated under the name “The Dynamics of Credit Default Swap Spreads and Equity Volatility.” Comments from Offer-Moshe Shapir, Samer Saade, and participants at the 2011 Auckland Finance Meeting, the economic research seminar at the University of Auckland, the Asian Finance Association and Taiwan Finance Association 2012 Joint International Conference, and the 2013 World Finance Conference are gratefully acknowledged.

†Corresponding Author: Auckland University of Technology, Business School, Department of Finance, Private Bag 92006, 1142 Auckland, New Zealand. Phone: ++64 9 9219999 extn 5063. Email: jose.dafonseca@aut.ac.nz.

‡Auckland University of Technology, Business School, Department of Finance, Private Bag 92006, 1142 Auckland, New Zealand. Phone: ++64 9 9219999 extn 5707. Email: katrin.gottschalk@aut.ac.nz.
1 Introduction

The relationship between credit risk, stock volatility, and stock returns was underlined in the seminal work of Merton (1974) and initiated a large stream of research in subsequent decades. Nowadays, credit risk is conveniently extracted from the credit default swap (CDS) market, while stock volatility can be measured using high frequency data, which have become widely available. This enables researchers to overcome the lack of equity derivatives, a standard problem when dealing with less well developed financial markets. The aim of this study is to provide a robust assessment of the co-movement of CDS spreads, stock market returns, and volatilities in a sample of Asia-Pacific countries. In order to analyze the relationship between these three key quantities, we use three simple, yet powerful, statistical tools: regression analysis, a vector auto-regressive (VAR) model, and the spillover measure proposed by Diebold and Yilmaz (2009, 2012, 2014).

To start, we regress the dependent variable CDS spread on the explanatory variables equity volatility and equity returns plus a set of additional firm-level and macro-economic variables. This framework allows us to find the determinants of credit risk, and we expect stock volatility and stock returns to be important explanatory variables. A VAR system constitutes a natural extension of the regression model and is preferably applied to a small number of variables. Restricted to the three key quantities of interest, we can study the joint dynamic of these variables and find which asset class leads the others in the price discovery process through a classical Granger causality test. The spillover measure recently proposed in Diebold and Yilmaz (2009), which is based on the classical VAR model, enables us to quantify the contribution of each financial variable (and by extension of each asset class) to global market volatility. Combined together these three complementary measures provide an exhaustive examination of the fundamental relationship found by Merton (1974).

To the best of our knowledge, the VAR model and spillover measures have never been applied to the triplet of variables CDS spreads, stock returns, and return volatility for any market. While regression analysis has been applied extensively to U.S. data in order to explain credit spreads, both at the firm level and index level, surprisingly the studies focusing on the Asia-Pacific region are scarce. As a result, the Asia-Pacific markets are of interest because a thorough analysis of the relationship between CDS spreads, stock returns, and volatility can be performed by simultaneously applying the three methodologies for the first time. Furthermore, since for most of the Asia-Pacific firms no options are available, the use of realized volatility to quantify stock return volatility is extremely relevant. In addition to
the analysis at the firm level, we can study the relationship at the index level as for all these markets the key financial quantities are also available at the aggregate level. A comparison between market behavior at the firm level and the index level is pertinent to reveal liquidity as well as correlation issues.

The contribution of our work to the literature is threefold. First, we perform a study of the determinants of credit default swap spreads for the Australian, Japanese, Korean, and Hong Kong CDS markets. We analyze these markets both at the firm (individual) level and index (market) level. For these countries we obtain results that are qualitatively similar to results previously found for the U.S. market. Namely, realized volatility is an important determinant of the CDS spread, along with other firm-level variables (see, e.g., Zhang et al. (2009)).

Second, focusing only on credit default swap spreads, realized volatility, and equity returns we estimate a VAR model to determine Granger causality between this set of variables. We find that at the firm level stock returns lead changes in CDS spreads as well as changes in realized volatility. However, at the index level volatility changes and CDS spread changes lead stock returns, in contrast with what is observed at the firm level. This constitutes an interesting contribution of our work.

Third, our analysis of the volatility spillover effects among credit default swap spreads, realized volatility, and stock returns shows that realized volatility is the main contributor to aggregate market volatility, underlining the importance of this variable as a leading market activity indicator. Thus, we provide the first applications of Diebold and Yilmaz’ methodology to study cross-market linkages between these three markets.

The structure of the paper is as follows. In the first section we provide a literature review highlighting the main contributions to this research area. In the second section we describe our methodology and establish links with the existing literature. In the third section we present the data along with some descriptive statistics. The fourth section contains the empirical results for both the regression analysis and the dynamical analysis. The last section concludes the paper.

2 Literature Review

The fundamental relationship between credit risk, equity volatility, and stock returns found by Merton (1974) initiated a vast literature. The evolution of financial markets and more precisely the appearance
of new financial products led to a reexamination of this relationship. This partially explains why this
work has had and still has such an impact in finance. Indeed, earlier studies such as Collin-Dufresne
et al. (2001) and Campbell and Taksler (2003) define the credit spread as the difference between a
bond yield and the risk-free rate, whilst volatility is calculated as mean squared daily stock returns
or given by a volatility index. Their results show that equity volatility has strong explanatory power
for both levels and changes of credit spreads; however, the latter are more difficult to explain.

The rapid growth of the CDS\textsuperscript{1} market has provided an alternative to the bond market to extract
credit risk. Even though Blanco et al. (2005) confirm the theoretical equivalence of CDS spreads and
credit spreads extracted from bond yields for the U.S. and European markets, the emergence of these
new products led to a reexamination of the interaction between credit and equity markets. Using
CDS spreads instead of bond spreads, Ericsson et al. (2009) find similar results as Collin-Dufresne
et al. (2001). Other more recent papers that have examined the determinants of CDS spreads include
Avramov et al. (2007), Greatrex (2009), Annaert et al. (2013), and Galil et al. (2014).

With respect to equity volatility, the improvements of efficient pricing methodologies of vanilla options
as well as the further development of volatility indices have allowed to replace the traditionally used
average of squared returns with option volatilities as a way to measure volatility, see Benkert (2004)
and Cremers et al. (2008). This allows a more refined study of volatility as a determinant of credit
spreads, highlighting the importance of variance risk premia as in Wang et al. (2013) or the impact
of the slope of the volatility smile as in Cao et al. (2010) or Hui and Chung (2011).

More recent papers have extracted equity volatility from realized volatility, which is now feasible due
to the wide availability of high-frequency data, see for example Andersen et al. (2003). This strategy
is appealing because for many stocks either no options are available or their trading volume is so low
that illiquidity effects jeopardize the computation of volatility, a remark particularly relevant when
we focus on options markets that are less developed. For the Asia-Pacific markets, which are indeed
far less mature than the U.S. market, realized volatility is the best choice available to measure equity
volatility. As most of the individual stocks do not have options available, for a firm-level analysis

\textsuperscript{1}A credit default swap is a credit derivative contract between two counterparties that essentially provides insurance
against the default of an underlying entity. In a CDS, the protection buyer makes periodic payments to the protection
seller until the occurrence of a credit event or the maturity date of the contract, whichever is first. The premium paid by
the buyer is denoted as an annualized spread in basis points and referred to as CDS spread. If a credit event (default)
occurs on the underlying financial instrument, the buyer is compensated for the loss incurred as a result of the credit
event, i.e. the difference between the par value of the bond and its market value after default.
equity volatility can be computed using high-frequency data and the Two Scales Realized Volatility (TSRV) estimator proposed by Aït-Sahalia et al. (2011). At the index level all the major Asia-Pacific countries have liquid derivatives markets, so the conventional approach based on implied volatility can be used.

Understanding the determinants of credit spreads, either in levels or changes, allows to assess the importance of contemporaneous firm-level and macro-financial explanatory variables. For the U.S. and European countries, many papers have analyzed these relationships empirically; in addition to the above-mentioned papers, see also Byström (2008). The Asia-Pacific markets are far less well understood in this respect. However, we cannot expect surprising results, i.e. the conclusions should comply with Merton’s theoretical framework and, therefore, be consistent with the findings for the U.S. market.

In addition to analyzing the determinants of credit spreads, examining the joint dynamic of credit spreads with other financial variables is of crucial interest as it allows to measure the impact of credit risk on other variables. This extension is natural if the credit market is considered sufficiently developed, which is certainly the case for the CDS market nowadays. Merton’s model suggests to consider credit risk along with stock returns (in his work volatility is constant). However, the recent development of volatility products such as variance swaps, futures on volatility, and volatility options suggests the use of credit spreads, stock returns, and stock volatilities as more relevant state variables. Although this triplet of variables appears to be a natural choice, to the best of our knowledge, its joint dynamic has not been analyzed so far, not even for the U.S. market. Norden and Weber (2009) perform a VAR analysis with the triplet stock return, CDS spread, and bond yield spread on a sample of 58 entities from the U.S., Europe, and Asia (see their Table 4 and Table 5). The companies are large and among them only four are Asian. Hyun et al. (2012) analyze the volatility index (VKOSPI), the stock market index (KOSPI), and the sovereign CDS for the Korean market.

2The Australian bond market has been studied in Batten and Hogan (2003).

3Fung et al. (2008) examine U.S. stock market index returns and CDS index returns, while Chan et al. (2009) study the Asian sovereign CDS market jointly with equity indices. More precisely, they cover the following countries: China, Japan, Korea, Indonesia, Malaysia, Philippines, and Thailand. Nevertheless, it is useful to point out that for the Asia-Pacific region CDS indices are only available for few countries. Chan-Lau and Kim (2004) consider stock returns, CDS spreads, and bond spreads for a sample of emerging markets. Naifar (2012) uses a copula-based approach to study the Australian and Japanese iTraxx CDS indices jointly with the respective equity index volatilities (estimated with a GARCH(1,1) model). Individual CDS spreads jointly with option-implied volatilities were studied for the Korean market in Park and Kim (2012).
A complementary aspect to Granger causality is the concept of volatility spillover effects, which analyzes how shocks spread among a set of variables. Diebold and Yilmaz (2009, 2012, 2014) proposed a framework based on a generalized vector autoregressive representation for time series that enables the measurement of these effects. It has attracted a lot of interest amongst academics studying the recent crises, both the global financial crisis and the European debt crisis, as it naturally provides a measure for contagion. Their methodology is suitable to study credit default swap spreads, realized volatility, and stock returns and determine their respective contribution to global volatility. The use of their framework, which complements the standard VAR analysis, to determine cross-market linkages between the triplet CDS spread, stock return, and realized volatility has not been considered so far.

3 Methodology

Our aim is to study the relation between credit default swap (CDS), equity and volatility markets. As realized volatility is central to our study, in the first subsection below we explain which methodology, among the many available in the literature, we use to compute realized volatility.

In the second subsection, we present the main equations involved in our regression analysis. Following the existing literature, most notably Collin-Dufresne et al. (2001) and Zhang et al. (2009), we select explanatory variables that can be categorized into two groups. The first group contains firm-level variables (realized volatility, stock return, leverage ratio, return on equity, and dividend yield). The second group contains macro-financial variables (short-term interest rate and slope of the yield curve). The regression analysis, as described hereafter, allows identification of the factors that explain variation in CDS spreads.

Towards a better understanding of the link between CDS spreads, realized volatility, and stock returns (as established in the regression analysis), it is of interest to study the joint dynamics of these variables more thoroughly in order to determine the co-movements between the three markets. To this end we will perform both a Granger causality test (presented in the third subsection) and an analysis of volatility spillover effects (described in the last subsection), thereby providing a broader picture of the existing interactions.

\footnote{Volatility spillovers between the Chinese and U.S. equity markets are analyzed in Zhou et al. (2012), while Chevallier and Ielpo (2013) focus on cross-market linkages between commodity markets. The framework was applied to major Asian equity indices by Yilmaz (2010).}
3.1 Computing Realized Volatility

Our study heavily relies on realized volatility computed using high frequency data. The importance of realized volatility for forecasting and risk management purposes is now well established, among others we refer to Andersen et al. (2003). It is well known that microstructure noise effects can lead to unreliable estimation of realized volatility and this problem is likely to increase with higher sampling frequency. It is usually argued that the simplest way to avoid these effects is to sample the data at five-minute intervals. Thankfully, during the past decade many approaches were developed that allow to control for such effects and thus provide a convenient framework to handle data sampled at very high frequency (i.e., less than five-minute intervals). Among them is the TSRV (Two Scales Realized Volatility) estimator proposed by Aït-Sahalia et al. (2011) that will be used in this study. We briefly recall the definition of this estimator below and refer to Aït-Sahalia et al. (2011) for further details.

Suppose that \( \{s_{t,j}; j = 1 \ldots n_t\} \) is the set of quotes for a given day \( t \) and a given stock. The realized variance for this day, denoted by \( \overline{RV}_t \), is computed as:

\[
\overline{RV}_t = (1 - \frac{\bar{n}}{n})^{-1} \left\{ \frac{1}{K} \sum_{k=1}^{K} [Y,Y]^{(\text{sparse},k)} - \frac{\bar{n}}{n} [Y,Y]^{\text{all}} \right\}
\]

(1)

where

\[
[Y,Y]^{\text{all}} = \sum_{j=1}^{n_t-1} (\log s_{t,j+1} - \log s_{t,j})^2
\]

\[
[Y,Y]^{(\text{sparse},k)} = \sum_{j \in G_k} (\log s_{t,j+1} - \log s_{t,j})^2
\]

with \( G_k \subset \bar{G} = \{1 \ldots n_t\}, \bigcup_{k=1}^{K} G_k = \bar{G}, G_i \cap G_j = \emptyset \) and \( n_t = K\bar{n} \). We take \( K = 5 \) in our empirical study. To avoid closing and opening effects we only take quotes from 30 minutes after the opening hour until 30 minutes before the closing hour. The quotes are spaced at 1-minute intervals, which implies that market microstructure noise can affect the computation of realized volatility, but the TSRV estimator can cope with such problems. Finally, the realized variance given by (1) is annualized and we take the square root as in Zhang et al. (2009), thereby defining the realized volatility used henceforth as: \( RV_t = \sqrt{250\overline{RV}_t} \).
3.2 Regression Analysis

For the regression analysis we closely follow Zhang et al. (2009) and Wang et al. (2013). In order to ascertain the relationship between credit default swap spreads and equity volatility, we regress the logarithm of CDS quotes on the logarithm of realized volatility and a set of other firm-level explanatory variables that have been found to determine CDS spreads: the logarithm of realized volatility (logRV), the logarithm of stock returns (logRet), financial leverage (LEV), return on equity (ROE), and dividend yield (DIV). In addition, the following macro-financial variables are used to control for general economic conditions and the state of the business cycle: a short-term interest rate (ShortRate), and the slope of the yield curve (Slope).

We estimate coefficients and associated t-statistics by running pooled OLS regressions where all coefficients are restricted to be equal across reference entities. Standard errors clustered by firm are estimated using Petersen (2009)’s method. As a robustness check, we also run time-series regressions individually for each reference entity and tabulate average coefficients. t-statistics are calculated from the cross-sectional variation over the estimates for each coefficient as described in Collin-Dufresne et al. (2001). The regression for the logarithm of CDS spreads reads as follows:

$$\log \text{CDS}_{i,t} = \alpha_0 + \alpha_1 \log \text{RV}_{i,t-1} + \alpha_2 \log \text{Ret}_{i,t-1} + \alpha_3 \text{ShortRate}_{i,t-1} + \alpha_4 \text{Slope}_{i,t-1} + \alpha_5 \text{LEV}_{i,t-1} + \alpha_6 \text{ROE}_{i,t-1} + \alpha_7 \text{DIV}_{i,t-1} + \epsilon_{i,t}$$ (2)

As in Ericsson et al. (2009), in addition to regressions in levels we perform regressions in changes as this can also be motivated economically and statistically:

$$\Delta \log \text{CDS}_{i,t} = \beta_0 + \beta_1 \Delta \log \text{RV}_{i,t} + \beta_2 \Delta \log \text{Ret}_{i,t} + \beta_3 \Delta \text{ShortRate}_{i,t} + \beta_4 \Delta \text{Slope}_{i,t} + \beta_5 \Delta \text{LEV}_{i,t} + \beta_6 \Delta \text{ROE}_{i,t} + \beta_7 \Delta \text{DIV}_{i,t} + \epsilon_{i,t}$$ (3)

The expected effect of the explanatory variables on CDS spreads (+, −, ?) is given in parentheses below:

5The application of the log transformation to CDS spreads, stock returns, and realized volatility reduces the skewness of the underlying data and thereby leads to more reliable t-statistics. The log transformation is frequently used; see, for example, Forte and Pena (2009), Coudert and Gex (2010), or Alter and Schüler (2012).

6The results are not reported but available upon request.

7We do not take the changes of log returns (Δ log Ret_{i,t}) but continue to work with log returns (log Ret_{i,t}) as they already represent changes.
• Realized Volatility (+): Higher equity (and therefore asset) volatility makes firm value more likely to hit the default boundary (Zhang et al. (2009)).

• Stock Return (−): Higher growth in firm value reduces the probability of default (Zhang et al. (2009)).

• Short-term Rate (?): We use 3-month Treasury bill rates as a proxy for the level of short-term interest rates. The expected effect on CDS spreads is unclear a priori. While a higher spot rate increases the risk-neutral drift of the firm value process in structural models and thus reduces the probability of default (Collin-Dufresne et al. (2001)), it could also reflect a tightening of monetary policy and thus increase the probability of default (Zhang et al. (2009)).

• Slope of Yield Curve (?): The slope of the yield curve is approximated by the term spread between 10-year government bond yields and 3-month Treasury bill rates. Again, the implications for CDS premia from a steepening of the yield curve are unclear a priori. While a steeper slope of the term structure could indicate improving economic conditions with lower credit spreads, it could also foreshadow rising inflation and consequently a tightening of monetary policy with higher credit spreads (Zhang et al. (2009)).

• Financial Leverage (+): We calculate a firm’s leverage ratio as book value of total debt / (book value of total debt + market value of equity). Within the structural framework of Merton (1974), a firm defaults when its leverage ratio reaches one. Thus CDS spreads are expected to increase with leverage.

• Return on Equity (−): Return on equity is as calculated by Datastream (net income / shareholders’ equity). Higher profitability of a firm results in lower probability of default (Zhang et al. (2009)). Hence, we expect a negative relation between CDS spreads and return on equity.

• Dividend Yield (+): Dividend yields are also obtained directly from Datastream. CDS spreads are expected to increase with dividend yields for two reasons. First, a higher dividend payout ratio results in decreasing asset value, which in turn increases the probability of default (Zhang et al. (2009)). Second, eroding equity prices of a firm in financial difficulties also imply higher dividend yields.
3.3 Lead-lag Relationships between CDS Spreads, Realized Volatility and Stock Returns

The previous subsection has presented a framework to analyze the relation between credit default swap spreads (both levels and changes) and several contemporaneous firm-level and macro-financial variables. Now, we restrict our attention to the triplet credit default swap spread, realized volatility, and stock return in order to perform a more thorough analysis of the interaction between these variables. Following Norden and Weber (2009), we focus on lead-lag relationships between the variables by estimating the following VAR model:

\[
\log \text{Ret}_t = \alpha_1 + \sum_{i=1}^{p} \beta_{1i} \log \text{Ret}_{t-i} + \sum_{i=1}^{p} \gamma_{1i} \Delta \log \text{RV}_{t-i} + \sum_{i=1}^{p} \nu_{1i} \Delta \log \text{CDS}_{t-i} + \epsilon_{1t} \tag{4}
\]

\[
\Delta \log \text{RV}_t = \alpha_2 + \sum_{i=1}^{p} \beta_{2i} \log \text{Ret}_{t-i} + \sum_{i=1}^{p} \gamma_{2i} \Delta \log \text{RV}_{t-i} + \sum_{i=1}^{p} \nu_{2i} \Delta \log \text{CDS}_{t-i} + \epsilon_{2t} \tag{5}
\]

\[
\Delta \log \text{CDS}_t = \alpha_3 + \sum_{i=1}^{p} \beta_{3i} \log \text{Ret}_{t-i} + \sum_{i=1}^{p} \gamma_{3i} \Delta \log \text{RV}_{t-i} + \sum_{i=1}^{p} \nu_{3i} \Delta \log \text{CDS}_{t-i} + \epsilon_{3t} \tag{6}
\]

This system of equations serves to determine the impact of lagged equity returns, realized volatility, and CDS spreads on each of the other two variables. A Wald test for \(\{\nu_{1i}; i = 1 \ldots p\}\) of equation (4) allows us to determine if changes in CDS spreads Granger cause stock returns. Similarly, a Wald test for \(\{\nu_{2i}; i = 1 \ldots p\}\) of equation (5) allows us to determine if changes in CDS spreads Granger cause changes in realized volatility. For each set of lagged explanatory variables, the set of coefficients and corresponding Wald tests lead to a conclusion about Granger causality from a given market to another market. This model allows us to quantify the co-movements and interactions between the different markets in a very simple way. We work with a specification without gaps and with lag order \(p = 2\), which is greater or equal to the lag order given by the Akaike information criterion applied to each individual regression. We perform this analysis for both firms and indices.

The VAR model applied to quantify the co-movements or interactions between the credit default swap market, the volatility market, and the stock market is based on the Granger causality concept, as defined in Granger (1969). More recently, other measures have emerged that quantify the interaction between financial variables, and the recent financial crisis has raised a keen interest in this research area. Of particular interest is the methodology proposed by Diebold and Yilmaz (2009, 2012, 2014),

---

8We only consider autoregressive models. For a copula-based approach to the interaction between equity volatility and CDS spreads see Naifar (2012).

9Other criteria considered, the Hannan-Quinn information criterion and the Schwarz information criterion, suggest the same lag order.
which allows to study volatility spillover effects among different markets.

3.4 Volatility Spillover Effects between CDS Spreads, Realized Volatility, and Stock Returns

In order to better understand how the different markets are interrelated, a novel measure has been proposed in a series of papers by Diebold and Yilmaz (2009, 2012, 2014). More precisely, based on a generalized vector autoregressive framework for which the forecast-error variance decomposition is invariant to variable ordering, they develop measures for both total and directional volatility spillover effects. As mentioned by these authors, their work relies heavily on the results of Koop et al. (1996) and is therefore related to impulse response function analysis.\(^\text{10}\) However, compared with the standard use of impulse response functions, the measures proposed have the advantage that they can be easily aggregated. We briefly present the main results and refer to the original papers for further details.

Suppose an \(N\)-variable VAR model, 
\[
x_t = \sum_{k=1}^{p} \Phi_k x_{t-k} + \epsilon_t,
\]
where \(\epsilon \sim N(0, \Sigma)\) is a vector of independently and identically distributed disturbances, and its moving average representation 
\[
x_t = \sum_{k=1}^{p} \Theta_k \epsilon_{t-k}\]
with \(\Theta_k = \sum_{l=1}^{p} \Phi_l \Theta_{k-l}; \Theta_k = 0\) for \(k < 0\). Define the \(H\)-step forecast variance decomposition between the elements \(i\) and \(j\) (with \(i \in \{1 \ldots N\}\) and \(j \in \{1 \ldots N\}\)) as
\[
d_{ij}^H = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i^\top \Theta_h \Sigma \Theta_h e_j)^2}{\sum_{h=0}^{H-1} e_i^\top \Theta_h \Sigma \Theta_h^\top e_i},
\]
where \(e_i\) is a vector of size \(N\) with the \(i^{th}\) element equal to 1 and zero elsewhere, and \(\sigma_{jj}\) is the square root of the \(j^{th}\) diagonal term of \(\Sigma\). As the sum along a row is not equal to 1, the authors propose to define the normalized quantity 
\[
\tilde{d}_{ij}^H = \frac{d_{ij}^H}{\sum_{j=1}^{N} d_{ij}^H}
\]
so that by construction we have \(\sum_{j=1}^{N} \tilde{d}_{ij}^H = 1\) and \(\sum_{i,j=1}^{N} \tilde{d}_{ij}^H = N\).

Given the above quantities, the authors define a set of different volatility spillover measures. The first one is the total volatility spillover index, which measures the contribution of spillovers of volatility shocks across \(N\) asset classes to the total forecast error variance. It is defined by
\[
S = \frac{1}{N} \sum_{i,j=1}^{N} \tilde{d}_{ij}^H \times 100.
\]
The second measure is the directional volatility spillovers received by the \(i^{th}\) asset from all other assets, given by

\(^\text{10}\)See also Hammoudeh and Sari (2011) and Hammoudeh et al. (2013) for other approaches based on generalized variance decomposition for generalized vector autoregressive models.
The third measure is the directional volatility spillovers transmitted by the \( j^{th} \) asset to all other assets and is defined as

\[
S_{i\rightarrow j} = \frac{1}{N} \sum_{j=1, j \neq i}^{N} \tilde{d}_{ij}^H \times 100.
\] (9)

The net volatility spillover for the \( i^{th} \) asset is given by \( S_{i\rightarrow i} - S_{i\leftarrow i} \) and quantifies the contribution of this asset to the global volatility spillover effects.

These measures are appealing because they are numerically simple to implement and can also be used to define the network relating the different assets, thereby allowing us to quantify the degree of connectedness between the different asset classes, see Diebold and Yilmaz (2014). This way to consider volatility spillover effects has attracted much interest recently, mainly because of the global financial crisis.\(^{11}\) Alternative measures exist, but they involve more sophisticated mathematics, see Billio et al. (2012).

4 Data

We focus on the Australian, Japanese, Korean, and Hong Kong CDS markets as these prove to be the largest and most liquid in the Asia-Pacific region. Our sample comprises data from 14/09/2007 to 31/12/2010, sampled weekly on every Wednesday.\(^{12}\)

The credit default swap data used in this paper are provided by Markit. Markit collects CDS data from market makers and applies a cleaning process where stale, flat curves, outliers, and inconsistent data are discarded. CDS spreads for different maturities and recovery rates are available by entity, tier, currency, and restructuring clause. We focus on the 5-year maturity as this is the most liquid

\(^{11}\)Alter and Beyer (2014) quantify spillovers between sovereign credit markets and banks in the euro area. They consider only CDS spreads as endogenous variables while control variables such as a stock market index and volatility index are assumed to be exogenous.

\(^{12}\)As the studied entities are required to have a CDS quote for the entire sample period, by construction we exclude companies that defaulted during these years. Analyzing CDS spreads during or near a default event is of interest, but it seems to us that this should not be done through a panel regression as performed here because the specific behavior of CDS spreads and volatility of defaulted companies might be lost during the aggregation process inherent in panel techniques.
point on the CDS curve. Moreover, we restrict our analysis to CDS contracts that meet the following requirements: (1) non-sovereign entities from all sectors except the financial,\(^{13}\) (2) senior unsecured debt (RED tier code: SNRFOR), and (3) denominated in U.S. dollars. For Japan, Korea, and Hong Kong we use contracts with full restructuring clause (CR) and for Australia contracts with modified restructuring clause (MR) as, again, these are the most liquid contracts.

Stock market data for individual entities are obtained from SIRCA using the Thomson Reuters Tick History.\(^{14}\) Realized volatility is calculated from intra-day data as outlined in the methodology section. As the other variables are computed on a weekly basis, we average daily realized volatilities over one week. We also calculate weekly log stock returns. All macro-financial variables (short-term rate and slope of yield curve) and firm-specific variables (leverage ratio, return on equity, and dividend yield) were obtained from Datastream.

After matching all firm-level data, we are left with a final sample of 85 entities (14 from Australia, 58 from Japan, 7 from South Korea, and 6 from Hong Kong). Their sector distribution as well as median rating by country are shown in Table 1.

\[\text{[Insert Table 1 here]}\]

In addition, we perform an analysis at index level in order to determine whether similar results can be observed at the aggregate level. The CDS index series used are the iTraxx Australia, iTraxx Japan, and iTraxx Korea (there is no iTraxx index for Hong Kong). Stock market returns are calculated from each country’s headline index, and for volatility we take the corresponding equity volatility index. The S&P/ASX 200 VIX measures the 30-day implied volatility in the Australian stock market, using settlement prices for S&P/ASX 200 put and call options to calculate a weighted average of the implied volatility of the options. The Nikkei Stock Average Volatility Index is its Japanese counterpart, calculated using the option prices on the Nikkei 225 listed on the Osaka Securities Exchange. For Korea the VKOSPI, the volatility index of the KOSPI 200, is used. CDS spreads are expected to increase with an increase in general market volatility.

\(^{13}\)We exclude financial companies because the accounting variables for this sector require special treatment, which is why financial companies are commonly excluded from empirical studies. However, Hammoudeh and Sari (2011) and Hammoudeh et al. (2013) specifically analyze this sector for the US market.

4.1 Descriptive Statistics

Summary statistics for all dependent and independent variables are reported in Table 2. 5-year CDS spreads have a sample mean of 140 basis points (bps), with Korean CDS spreads (163 bps) being slightly higher on average than Hong Kong CDS spreads (159 bps), Australian CDS spreads (147 bps), and Japanese CDS spreads (133 bps). Standard deviations are, however, substantial at 216 bps for the whole sample (141 bps for Korea, 173 bps for Hong Kong, 157 bps for Australia, and 239 bps for Japan). iTraxx CDS indices show comparable average levels for all three countries, ranging from 141 bps (Korea) to 159 bps (Japan).

[Insert Table 2 here]

Average weekly realized volatility of individual equities (annualized) stands at 27.6% (28.7% for Australia, 26.8% for Japan, 29.6% for Korea, and 30.5% for Hong Kong). Average annualized weekly returns show a mean of −14.8% for the whole sample. Again, market-level variables are fairly close to firm-level averages, except for Korea. The mean value for the implied volatility index is 27.1% for Australia, 32.1% for Japan, and 28.5% for Korea. Average market returns are between −21.0% (Japan) and −4.8% (Korea).

Short-term interest rates as measured by 3-month Treasury bill rates have a sample mean of 5.2% for Australia, 0.6% for Japan, 3.7% for Korea, and 0.5% for Hong Kong. The slope of the yield curve has been comparatively flat for all three countries in the period under consideration with an average term spread between 10-year government bond yields and 3-month Treasury bill rates of 0.3% for Australia, 0.7% for Japan, 1.5% for Korea, and 2.1% for Hong Kong.

The average firm in our sample has a leverage ratio of 33.4%. Japanese firms seem to have carried higher levels of debt with a leverage ratio of 38.2% versus 20.1% for Australian firms, 26.4% for Korean firms, and 26.8% for Hong Kong firms. The mean return on equity (ROE) is 7.2%. Australian, Korean, and Hong Kong entities show signs of higher profitability with an average ROE of 15.1%, 12.6% and 22.5%, respectively, whereas this figure stands at 3.1% for Japan. The average dividend yield has been 2.5% for the sample. Australian equities lead their Japanese, Korean, and Hong Kong counterparts with 4.7% against 1.9%, 2.7% and 3.2%, respectively.
5 Empirical Results

5.1 Regression Analysis

In order to determine the relation between CDS spreads, equity volatility and several other variables that have been proposed as determinants of credit spreads by structural models and in the existing literature, we start with the regression analysis outlined in the methodology section. This closely follows Zhang et al. (2009) and Wang et al. (2013). Other papers that analyze the determinants of CDS spreads in a similar spirit include Blanco et al. (2005) and Ericsson et al. (2009). Most existing papers have, however, concentrated on bond markets when assessing credit spreads, e.g. Collin-Dufresne et al. (2001), Campbell and Taksler (2003), Cremers et al. (2008), and Hibbert et al. (2011). We regress weekly CDS spreads on the individual firm’s realized equity volatility and equity return as well as macro-financial variables (short-term interest rate, slope of the yield curve) and firm-level financial information (leverage ratio, return on equity, dividend yield).

We report pooled coefficient estimates as well as average coefficient estimates for the whole sample and for each of the four countries studied separately. First, regression results from regressions in levels are summarized in Tables 3 and 4. All proposed variables show significant explanatory power for CDS spreads. Altogether we are able to explain 30% of the variation in CDS spreads in the pooled model and on average 72% in individual firm-level regressions. This proportion is even higher for individual countries.

Using the logarithm of the CDS spread as dependent variable allows us to interpret the regression coefficient as an elasticity parameter whenever the independent variable is also expressed as a logarithm. This is the case for realized volatility. From Table 3 we deduce that the percentage change for the CDS spread will be around half of the percentage change for the realized volatility for Australia and Hong Kong while it will around par for Korea and Japan. Table 4 carries similar information albeit with different numbers (one third for Australia and Japan, 65% for Korea and one fifth for Hong Kong). This is consistent with the results in literature although in our case we use the realized volatility, computed using high frequency data, that is readily available for these stocks and get around the problem of lack of option data. Higher CDS spreads in our sample are also accompanied
by higher individual stock returns, a result that looks puzzling at first sight but we need to keep in mind that Merton’s framework relates stock return with CDS changes, and we should also add the fact this relation stands for contemporaneous variables, thus lagging the explanatory variables can have an undetermined impact (unless a variable is strongly auto-correlated as it is the case for the level of the realized volatility). In other other words Merton (1974) provides no guidance regarding the sign for this regression coefficient as stock return are weakly auto-correlated. The coefficients are positive and significant for Australia and Japan for both regressions, for Hong Kong it is positive and significant for the pooled regression only while for Korea it is never significant.

As for interest rates, the majority of the regressions indicate that higher short-term rates and a steeper yield curve result in lower levels of credit spreads, which is in line with findings by Campbell and Taksler (2003), Cremers et al. (2008), and Ericsson et al. (2009).

When statistically significant, the coefficients of firm-level financial variables all show the correct sign as predicted by theory. Increased leverage, reduced profitability (as measured by ROE) and higher dividend yields all result in higher CDS spreads on average.

Looking more closely at the values, we can carry out a thorough comparison with the existing literature. As a reference we chose Zhang et al. (2009), and mainly their Table 2 and Table 4-column 4, because when it comes to computing the volatility, both papers use high-frequency data. Needless to say, we cannot expect to have exactly the same results as our markets are different—they focus on the U.S. market while we cover the Asian market—and the sample periods are different. Nevertheless, despite these differences, all the results should comply with Merton’s framework. Regarding the realized volatility, these authors find an elasticity of 0.358 that is in line with what we obtain for Australia and Hong Kong, but it is one third of the results for Japan and Korea.\[15\] The value 0.358 is equal to \(1.47 \times \frac{42.1}{172.4}\), that is, the regression coefficient for RV(C) (i.e. 1.47) times the 1-week RV(C) (42.1 in Table 2 of Zhang et al. (2009)) divided by 172.4, the CDS in basis points for the whole sample also reported in that Table 2. In Zhang et al. (2009), RV(C) represents the continuous part of the realized volatility, it excludes stock jumps and is given by the Bipower variation estimator of Barndorff-Nielsen and Shephard (2004). We cannot perform a better comparison as they do not provide the regression coefficient for RV in their Table 4, which aggregates a continuous component given by RV(C) and a

\[15\] Notice that in Zhang et al. (2009) the authors regress on both RV(C) and the 1-year historical volatility. Had they regressed only on RV(C), certainly the coefficient would have been larger.
pure jump component, the very good reason being that their objective is to assess the importance of stock jump components as explanatory variable for CDS spreads. Regarding stock returns, these authors obtain a non-significant parameter with a t-stat of 0.9. For the short rate’s impact on the CDS spread they obtain an elasticity of -0.205 (−16.62 × 2.13/172.4 with 2.13 being the average short rate and 172.4 the average CDS spread) while we get -0.402 for Australia, -0.227 for Korea, -0.447 for Hong Kong and −1.793 for Japan. The results are roughly comparable for all but Japan, which is known for having very specific properties when it comes to interest rates. Notice that on average the CDS spread in Zhang et al. (2009) is 172.40, slightly higher than the 139.85 we have when we aggregate all entities; this may explain the differences. For the slope of the yield curve for each country we obtain a negative significant coefficient, while in Zhang et al. (2009) a positive but insignificant value is found, this preventing a comparison. What is more, for this parameter there is no consensus on the sign this coefficient should have. Regarding the ROE, leverage ratio and the dividend yield, our regression leads to -1.153, 1.39 and 10.069 at the aggregate level, which is representative as for all countries similar results are obtained. They are very much in line with those of Zhang et al. (2009) as they find -1.44, 0.78 and 28.46. The discrepancies may be explained by differences in the variable values (e.g. the leverage ratio for the Asian market is 33.42, while for the U.S. it is 48.84, thus the lower coefficient found in the regression). Overall, the results are consistent with the findings for the U.S. market.

Next, we report regression results from regressions of changes in Tables 5 and 6. Both Ericsson et al. (2009) and Zhang et al. (2009), following Collin-Dufresne et al. (2001), provide economic and statistical arguments for analysing spread changes in addition to levels. As expected, adjusted $R^2$ measures are lower, but we are still able to explain 10% of the variation in CDS spreads in the pooled model and on average 18% in individual firm-level regressions. This proportion is higher for individual countries.

[Insert Table 5 here]

[Insert Table 6 here]

For both regressions the analysis of changes confirms that an increase in CDS spreads is accompanied by significant increases in equity volatility and lower individual stock returns, thus these results are consistent with Merton (1974)’s theoretical framework. For the remaining macro-financial and firm-level accounting variables, our results are largely in line with theoretical predictions and empirical evidence. Overall, our results confirm existing results for the Asian market.
As for the previous regression in level we can compare the numerical values for the pooled regression for changes with those reported in Table 5 Regression 3 of Zhang et al. (2009). As we work with the logarithm of the CDS spread we will transform the coefficients, mainly through an exponentiation, for a comparison to be meaningful. For the stock return for the U.S. market a coefficient of -0.01 is found while we get for the sample using all the entities a coefficient of -0.00615, so roughly half. For the realized volatility they find a significant coefficient of 0.13 while our data lead to 0.259, but as for the regression in level these authors also include as explanatory variable the changes in the 1-year historical volatility that leads to a positive but non significant coefficient. Notice also that the average value and standard deviation for that variable are 49.19 and 22.18 for the U.S. market (see the descriptive statistics Table 2 in Zhang et al. (2009)) while for the Asian market we obtain 14.44, respectively, while it is 27.57 and 14.44. These two aspects may explain the differences in the coefficients. For the short rate and the slope of the yield curve the obtain -25.32 and -14.38, both significant, while we get -23.15 and -29.95. Again, the results are quite similar. Note that the average and standard deviation values for the short are rather similar for the two markets whereas for the slope of the yield curve the Asian market exhibits smaller numbers. With respect to the ROE, leverage ratio and dividend yield variables only the second is significant for the U.S. market with a coefficient of 0.11 close to the 0.139 for the Asian market although for this latter it is not significant. Allowing for a t-statistic of 1.9 enables the comparison of the coefficient for the dividend yield that is equal to 1.08 for the U.S. market while the Asian market leads to a strongly significant value of 4.54. The changes in the ROE appear to be insignificant for both markets. It is worth noticing that whether U.S. or Asian the importance of stock return and realized volatility is unambiguous, as attested by the strongly significant coefficients, it underlines that in Merton’s model these are the key variables. The others are of secondary importance and translates into a lack of robustness (i.e. change of coefficient sign, coefficient becoming significant or not) to a change of input data.

Lastly, in order to ensure the robustness of our results at an aggregate level we perform a regression analysis using CDS indices, namely the iTraxx Australia, iTraxx Japan, and iTraxx Korea. Log returns are computed from the corresponding headline stock market index (S&P/ASX 200 for Australia, Nikkei 225 for Japan, and KOSPI for Korea), whilst for volatility we use a market-wide volatility index. The results are summarized in Table 7 and are also consistent with those obtained for individual CDSs. As expected the $R^2$ are much higher. The regression in levels shows that the CDS market overreacts to a change in the volatility as the elasticities are all greater than one. A similar conclusion can be drown from the regression in changes as the coefficients are much larger to their counterpart at the
firm level, a given change in the volatility will have a greater impact on the CDS market if it occurs at the index level. Interestingly, at the index level similar conclusion applies to the relationship between CDS spread changes and index return as the coefficients are larger in absolute value terms but are, as expected, all negative. For the short rate and the slope of the yield curve the results are in line with those at the firm level with Japan displaying a specific behaviour. The discrepancies between the regressions performed at the firm level and index level suggest a tighter relationship between the CDS, stock and volatility at the index level possibly due to trading activity that can be carried out much more easily at the market level (the availability of futures is one of the reasons).

[Insert Table 7 here]

5.2 Lead-lag Relationships between CDS Spreads, Realized Volatility and Stock Returns

In the previous section we analyzed the determinants of credit default swap spreads (both levels and changes) in terms of firm-level and macro-financial variables. We now turn our attention to lead-lag relationships between log CDS spread changes, log realized volatility changes, and log stock returns, as described in the methodology section.\textsuperscript{16} We estimate the VAR model given by equations (4), (5), and (6) for \( p = 2 \). We first focus on Table 8, which contains firm-level estimates. To build this table we proceed as in Norden and Weber (2009). We run firm-specific regressions and report median coefficients as well as the percentage of firms for which the coefficients of the explanatory variables are significantly different from zero at the 1% level. We also provide the percentage of firms for which the null hypothesis that lags 1 to 2 have no joint explanatory power can be rejected at the 1% level (this Wald test for \( p = 2 \) corresponds to a Granger causality test). The following conclusions can be drawn: Stock returns lead credit default swap spreads and realized volatility as in both cases for at least 20% of the sample the coefficient of the first lag of the stock return is significant and negative, which is consistent with economic intuition and the contemporaneous co-movement analysis (a decrease of the stock price is associated with an increase of the CDS spread). Moreover, lags 1 to 2 of stock returns Granger cause changes in CDS spreads (realized volatility) in 19% (15%) of the cases. These findings become much stronger if a 5% significance level is adopted. The results are in line with Norden and Weber (2009), who find that stock returns lead CDS as well as bond spread changes. Our results extend their conclusions to the Asia-Pacific CDS markets, which have not been studied previously, but also underline the Granger causality relation that exists between stock returns and realized volatility.

\textsuperscript{16}As previously mentioned, we work with log CDS spread changes and log realized volatility changes, but we will simply refer to CDS spread and realized volatility in the text.
at the firm level (notice that in Norden and Weber (2009) the authors do not consider any volatility variable).

[Insert Table 8 here]

In Table 9 we report the estimates for the indices. As there are three CDS indices, we perform a pooled regression for each equation and show t-statistics together with the estimated coefficients. Following Norden and Weber (2009), we conclude there is Granger causality running from one market to another market if one of the coefficients is statistically significant. Here, the conclusions contrast with those obtained for individual firms. Volatility leads both CDS spreads and stock returns. The coefficient of $\Delta \log RV_{t-2}$ ($\Delta \log RV_{t-1}$ and $\Delta \log RV_{t-2}$) is significant for the equation with $\Delta \log CDS_t$ ($\log \text{Ret}_t$) as dependent variable. Also, credit default swap spreads Granger cause stock returns because the coefficient of $\Delta \log CDS_{t-1}$ is significant in the last column of Table 9, which reports the regression results for equation (4) with $\log \text{Ret}_t$ as dependent variable. Moreover, all the significant coefficients have the predicted sign, with the exception of $\log \text{Ret}_{t-1}$ in the volatility equation. We still find that stock returns lead volatility because the coefficient of $\log \text{Ret}_{t-1}$ is significant in the column titled $\Delta \log RV_t$.

[Insert Table 9 here]

In conclusion, the results at the index level and firm level differ. In the latter case stock returns lead the other markets, which is consistent with previous results if we restrict the analysis to the pair credit default swap spread and stock return. At the index level the lead-lag effects are shared between the three asset classes, although volatility seems the most important.

The discrepancy between the results at firm level and index level could be explained by the fact that for the index the volatility is given by a volatility index, hence option volatility, whereas for individual stocks we use realized volatility. In that case the difference is related to a variance risk premium, which is the difference between implied volatility and expected (realized) volatility. As our results suggest that implied volatility has more explanatory power than realized volatility, this implies that the variance risk premium contains relevant information for the CDS and equity markets. This is consistent with the results obtained by Cao et al. (2010) and Wang et al. (2013) for the U.S. market. There could also be another explanation for this difference that is associated with systemic risk. For instance, it is well known that index options exhibit a smile which is steeper than the one observed for individual options and this is related to correlation risk embedded in index products (see Branger
and Schlag (2004) and Driessen et al. (2009)). We might be faced with a similar effect here, although further study is needed to understand this problem.

5.3 Volatility Spillover Effects between CDS Spreads, Realized Volatility and Stock Returns

The concept of Granger causality underlines the interaction between variables; it allows us to quantify to which extent the dynamics of the variables are linked. There are alternative measures to describe cross-effects between variables that provide a complementary point of view to the Granger causality concept.

Recently, Diebold and Yilmaz (2009, 2012, 2014) have proposed a measure of volatility spillover effects between financial variables that can also be interpreted as a degree of connectedness. We apply their approach, as presented in the methodology section, to the triplet credit default swap spread, realized volatility and stock return ($\Delta \text{Log CDS}_t, \Delta \text{Log RV}_t, \text{LogRet}_t$). For the VAR model we choose the parameter values $p = 4$ and $H = 10$ as suggested in Diebold and Yilmaz (2014). The results are robust to a change of these parameter values. Table 10 and Table 11 contain the results for firms and indices, respectively.

For individual firms, the net spillover effect for CDS spreads is close to zero ($21.16 - 19.82$), hence a nil contribution of the CDS asset class to cross-market volatility contagion. For realized volatility the net volatility spillover effect is positive and large ($30.76 - 4.91$); it emphasizes the importance of this variable as a major contributor to volatility spillover effects between the three asset classes. Lastly, for stock returns the net value is negative ($8.19 - 35.39$). According to this criterion, realized volatility is a major contributor to overall market volatility.

The results of the index analysis (reported in Table 11) are slightly different but carry the same message. The net volatility spillover effect for the CDS spread is now positive ($49.00 - 34.89$), suggesting a contribution to global market volatility from the CDS asset class. For realized volatility the net volatility spillover effect is still positive and large ($74.92 - 32.53$). For the last variable, stock return, the net spillover effect is negative ($17.02 - 73.51$). Here realized volatility also appears to be a major contributor to overall market volatility. However, the credit default swap market plays a much more important role at the index level. It is interesting to note that the total volatility spillover index is
equal to 46.98 at the index level, whereas it drops to 20.04 at the firm level. This implies a stronger interaction between the three asset classes at the index level, a fact already mentioned in the regression analysis part, and illustrates, once again, a different behavior at the firm level and index level. Several possible explanations for this difference. First, the availability of derivatives on the indexes, like index futures or even futures on volatility indexes, allows for a stronger trading activity. Second, portfolio positions are often hedged against market risk by trading on index derivatives. Third, correlation risk/systemic risk put forward in the previous subsection is likely to also explain the difference between what is observed at the index level and firm level. Lastly, liquidity considerations are likely to be responsible for this difference, see Junge and Trolle (2015) for an analysis of CDS market liquidity issues. All this aspects are related and deserves further study.

In conclusion, both tables underline the importance of realized volatility as a main contributor to volatility spillover effects between credit default swap spreads, realized volatility, and stock returns. In fact, in both cases the net volatility spillover effect for this variable is large and positive, whilst for the CDS spread the net effect is close to zero (at individual level) or positive (at market level). As the sum of the net volatility spillover effects over all three asset classes is equal to zero, the net effect for stock returns has to be negative.

6 Conclusion

The link between equity volatility and credit spreads has attracted much research interest since the seminal work of Merton (1974). In this paper, we analyze Australian, Korean, Japanese, and Hong Kong credit default swap markets and their relation with equity market volatility. As a proxy for volatility we use realized volatility, computed using high-frequency data. This provides a simple alternative to the use of options to extract information on equity volatility.\footnote{Obviously, when options are available they offer a much more subtle analysis of the interaction between volatility and CDS markets, see Da Fonseca and Gottschalk (2013).}

We contribute to the literature in several ways. First, we perform a regression analysis in order to investigate the determinants of CDS spreads where we consider other firm-level variables apart from realized volatility as well as macro-financial variables. By focusing on four Asia-Pacific countries, we extend the empirical evidence beyond the U.S. market, which has been the focus of most prior
studies. We find that realized volatility is an important determinant of CDS spreads, along with other firm-level variables. This reinforces findings from more mature credit and equity markets.

Next, towards a finer understanding of the interaction between credit and equity markets, we perform an analysis of lead-lag relationships as well as volatility spillover effects between CDS spreads, realized volatility, and stock returns. The findings are as follows: At firm level stock returns lead the CDS and volatility markets, whereas at index level the lead-lag relationships are shared among all asset classes. The volatility spillover effects between the asset classes confirm the importance of equity volatility (either realized or implied) as a major contributor to global market volatility. Our study also underlines the advantage of using realized volatility, computed from high frequency data with an estimator such as the TSRV (which can cope with microstructure noise), to study cross-market linkages when no options or only illiquid options are available.

The fact that we work at the firm level with realized volatility whilst we use a volatility index at the market level does not explain the difference observed in our results. Our conclusions, namely the discrepancy between what is obtained at the firm level and at the market level, remain even if we restrict our analysis to the pair CDS spread and stock return. Although surprising, such a discrepancy has already been observed in other markets. For example, Driessen et al. (2009) find that index options have a large negative variance risk premium whereas individual options on all index components do not exhibit such a negative variance risk premium. As a consequence, a strategy that sells index options and buys individual options will lead to a large Sharpe ratio. Our study points towards an analysis of correlation risk embedded in CDS indices as this might explain our results.

To study volatility spillover effects we use the framework proposed by Diebold and Yilmaz (2009, 2012, 2014), but other measures could be used to quantify the interactions between the volatility and CDS markets, a regime-switching model as in Billio et al. (2012) being one of them. Notice also that for the U.S. market a cross-market spillover analysis using the measure of Diebold and Yilmaz (2009) has not been performed so far for the set of variables studied here. The tight relation between stock volatility and CDS spreads underlined in our study calls for a more thorough analysis of the relation between stock options and credit derivatives such as CDOs. So far, only a few studies deal with this important but highly technical problem. The notable exceptions are Collin-Dufresne et al. (2012) and Carverhill and Luo (2013), but the subject certainly deserves further attention.
References


## Appendix

<table>
<thead>
<tr>
<th>Sector</th>
<th>Australia</th>
<th>Japan</th>
<th>Korea</th>
<th>Hong Kong</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic Materials</td>
<td>2</td>
<td>5</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Consumer Goods</td>
<td>2</td>
<td>14</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>Consumer Services</td>
<td>4</td>
<td>9</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Industrials</td>
<td>3</td>
<td>21</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Oil &amp; Gas</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Technology</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Telecommunications</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Utilities</td>
<td>0</td>
<td>4</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td><strong>Total Number</strong></td>
<td><strong>14</strong></td>
<td><strong>58</strong></td>
<td><strong>7</strong></td>
<td><strong>6</strong></td>
</tr>
<tr>
<td><strong>Median Rating</strong></td>
<td>AA</td>
<td>BBB</td>
<td>AA</td>
<td>AA</td>
</tr>
</tbody>
</table>

Table 1: Total number of entities per country and sector distribution. The table also reports the median rating.
Table 2: Descriptive statistics for the sample period 14/09/2007 to 31/12/2010. CDS spreads are expressed in basis points, all other variables as percentages. Means are reported, with standard deviations in parentheses. Volatility is measured as realized volatility for individual firms (left-hand side panel) and as a volatility index for whole markets (right-hand side panel). Log return refers to individual equity returns for the left-hand side panel and a market return for the right-hand side panel. Since there is no iTraxx index for Hong Kong, we cannot perform analyses at the CDS index level and therefore do not report summary statistics for market volatility and returns either.
Table 3: Regression results from pooled OLS regressions of the CDS spread with 5-year maturity on a set of explanatory variables. The sample period is 14/09/2007 to 31/12/2010. Standard errors clustered by firm are estimated using Petersen (2009)'s method. Absolute values of t-statistics are given in parentheses.

<table>
<thead>
<tr>
<th>Variable</th>
<th>All</th>
<th>Australia</th>
<th>Japan</th>
<th>Korea</th>
<th>Hong Kong</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.283</td>
<td>5.124</td>
<td>2.177</td>
<td>2.453</td>
<td>3.901</td>
</tr>
<tr>
<td></td>
<td>(5.58)</td>
<td>(10.10)</td>
<td>(5.14)</td>
<td>(7.57)</td>
<td>(6.42)</td>
</tr>
<tr>
<td>Log Realized Volatility</td>
<td>0.722</td>
<td>0.491</td>
<td>1.053</td>
<td>0.959</td>
<td>0.433</td>
</tr>
<tr>
<td></td>
<td>(10.28)</td>
<td>(4.80)</td>
<td>(6.70)</td>
<td>(12.30)</td>
<td>(3.67)</td>
</tr>
<tr>
<td>Log Return $\times 10^3$</td>
<td>0.150</td>
<td>0.168</td>
<td>0.143</td>
<td>0.019</td>
<td>0.131</td>
</tr>
<tr>
<td></td>
<td>(3.33)</td>
<td>(5.58)</td>
<td>(2.93)</td>
<td>(0.32)</td>
<td>(2.01)</td>
</tr>
<tr>
<td>Short-term Rate</td>
<td>0.106</td>
<td>-0.402</td>
<td>-1.793</td>
<td>-0.227</td>
<td>-0.447</td>
</tr>
<tr>
<td></td>
<td>(3.85)</td>
<td>(6.83)</td>
<td>(7.21)</td>
<td>(4.58)</td>
<td>(5.82)</td>
</tr>
<tr>
<td>Slope of Yield Curve</td>
<td>0.247</td>
<td>-0.418</td>
<td>-0.769</td>
<td>-0.107</td>
<td>-0.423</td>
</tr>
<tr>
<td></td>
<td>(5.82)</td>
<td>(5.78)</td>
<td>(5.50)</td>
<td>(2.26)</td>
<td>(4.64)</td>
</tr>
<tr>
<td>Leverage Ratio</td>
<td>0.010</td>
<td>0.009</td>
<td>0.011</td>
<td>0.006</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>(4.96)</td>
<td>(1.04)</td>
<td>(4.36)</td>
<td>(1.39)</td>
<td>(2.72)</td>
</tr>
<tr>
<td>ROE</td>
<td>-0.011</td>
<td>-0.007</td>
<td>-0.010</td>
<td>-0.010</td>
<td>-0.004</td>
</tr>
<tr>
<td></td>
<td>(2.97)</td>
<td>(1.07)</td>
<td>(2.18)</td>
<td>(0.49)</td>
<td>(1.11)</td>
</tr>
<tr>
<td>Dividend Yield</td>
<td>0.072</td>
<td>0.022</td>
<td>0.031</td>
<td>0.077</td>
<td>0.105</td>
</tr>
<tr>
<td></td>
<td>(2.47)</td>
<td>(0.82)</td>
<td>(0.39)</td>
<td>(2.54)</td>
<td>(2.96)</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.30</td>
<td>0.46</td>
<td>0.36</td>
<td>0.39</td>
<td>0.54</td>
</tr>
</tbody>
</table>

Table 4: Regression results (average estimates) from individual regressions of a firm’s CDS spread with 5-year maturity on a set of explanatory variables. The sample period is 14/09/2007 to 31/12/2010. Absolute values of t-statistics are given in parentheses and computed as in Collin-Dufresne et al. (2001).

<table>
<thead>
<tr>
<th>Variable</th>
<th>All</th>
<th>Australia</th>
<th>Japan</th>
<th>Korea</th>
<th>Hong Kong</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.999</td>
<td>3.557</td>
<td>1.134</td>
<td>4.020</td>
<td>4.372</td>
</tr>
<tr>
<td></td>
<td>(5.15)</td>
<td>(6.40)</td>
<td>(2.79)</td>
<td>(1.56)</td>
<td>(3.32)</td>
</tr>
<tr>
<td>Log Realized Volatility</td>
<td>0.340</td>
<td>0.300</td>
<td>0.329</td>
<td>0.659</td>
<td>0.179</td>
</tr>
<tr>
<td></td>
<td>(11.81)</td>
<td>(8.54)</td>
<td>(9.42)</td>
<td>(5.32)</td>
<td>(2.56)</td>
</tr>
<tr>
<td>Log Return $\times 10^3$</td>
<td>0.104</td>
<td>0.108</td>
<td>0.129</td>
<td>0.008</td>
<td>-0.036</td>
</tr>
<tr>
<td></td>
<td>(7.27)</td>
<td>(4.65)</td>
<td>(8.76)</td>
<td>(0.08)</td>
<td>(0.81)</td>
</tr>
<tr>
<td>Short-term Rate</td>
<td>-0.412</td>
<td>-0.299</td>
<td>-0.478</td>
<td>-0.127</td>
<td>-0.364</td>
</tr>
<tr>
<td></td>
<td>(2.92)</td>
<td>(5.61)</td>
<td>(2.33)</td>
<td>(0.76)</td>
<td>(8.59)</td>
</tr>
<tr>
<td>Slope of Yield Curve</td>
<td>-0.467</td>
<td>-0.344</td>
<td>-0.561</td>
<td>-0.066</td>
<td>-0.319</td>
</tr>
<tr>
<td></td>
<td>(7.96)</td>
<td>(6.27)</td>
<td>(6.95)</td>
<td>(0.64)</td>
<td>(5.68)</td>
</tr>
<tr>
<td>Leverage Ratio</td>
<td>0.042</td>
<td>0.002</td>
<td>0.050</td>
<td>0.074</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td>(4.66)</td>
<td>(0.17)</td>
<td>(5.85)</td>
<td>(0.98)</td>
<td>(0.54)</td>
</tr>
<tr>
<td>ROE</td>
<td>-0.009</td>
<td>0.023</td>
<td>0.000</td>
<td>-0.164</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>(0.85)</td>
<td>(1.41)</td>
<td>(0.07)</td>
<td>(1.86)</td>
<td>(0.87)</td>
</tr>
<tr>
<td>Dividend Yield</td>
<td>0.081</td>
<td>0.215</td>
<td>0.043</td>
<td>0.245</td>
<td>-0.059</td>
</tr>
<tr>
<td></td>
<td>(0.63)</td>
<td>(2.56)</td>
<td>(0.24)</td>
<td>(0.90)</td>
<td>(0.40)</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.72</td>
<td>0.76</td>
<td>0.71</td>
<td>0.70</td>
<td>0.79</td>
</tr>
</tbody>
</table>
### Table 5: Regression results from pooled OLS regressions of changes of the CDS spread with 5-year maturity on a set of explanatory variables (also expressed as a change). The sample period is 14/09/2007 to 31/12/2010. Standard errors clustered by firm are estimated using Petersen (2009)’s method. Absolute values of t-statistics are given in parentheses.

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Australia</th>
<th>Japan</th>
<th>Korea</th>
<th>Hong Kong</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.006</td>
<td>0.005</td>
<td>0.009</td>
<td>0.006</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(18.03)</td>
<td>(8.72)</td>
<td>(19.08)</td>
<td>(5.16)</td>
<td>(2.43)</td>
</tr>
<tr>
<td>$\Delta$ Log Realized Volatility</td>
<td>0.052</td>
<td>0.016</td>
<td>0.057</td>
<td>0.109</td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td>(9.71)</td>
<td>(2.81)</td>
<td>(11.26)</td>
<td>(6.57)</td>
<td>(0.84)</td>
</tr>
<tr>
<td>Log Return $\times 10^3$</td>
<td>$-0.044$</td>
<td>$-0.098$</td>
<td>$-0.025$</td>
<td>$-0.122$</td>
<td>$-0.119$</td>
</tr>
<tr>
<td></td>
<td>(3.35)</td>
<td>(7.26)</td>
<td>(2.83)</td>
<td>(2.50)</td>
<td>(3.37)</td>
</tr>
<tr>
<td>$\Delta$ Short-term Rate</td>
<td>$-0.181$</td>
<td>$-0.170$</td>
<td>0.642</td>
<td>$-0.033$</td>
<td>$-0.142$</td>
</tr>
<tr>
<td></td>
<td>(12.10)</td>
<td>(13.44)</td>
<td>(11.73)</td>
<td>(3.38)</td>
<td>(15.92)</td>
</tr>
<tr>
<td>$\Delta$ Slope of Yield Curve</td>
<td>$-0.241$</td>
<td>$-0.285$</td>
<td>$-0.453$</td>
<td>$-0.031$</td>
<td>$-0.111$</td>
</tr>
<tr>
<td></td>
<td>(11.10)</td>
<td>(15.89)</td>
<td>(27.30)</td>
<td>(2.48)</td>
<td>(7.93)</td>
</tr>
<tr>
<td>$\Delta$ Leverage Ratio</td>
<td>0.001</td>
<td>0.000</td>
<td>0.000</td>
<td>$-0.007$</td>
<td>$-0.001$</td>
</tr>
<tr>
<td></td>
<td>(1.42)</td>
<td>(3.08)</td>
<td>(1.28)</td>
<td>(2.03)</td>
<td>(0.91)</td>
</tr>
<tr>
<td>$\Delta$ ROE</td>
<td>$-0.001$</td>
<td>$-0.001$</td>
<td>$-0.001$</td>
<td>$-0.001$</td>
<td>$-0.001$</td>
</tr>
<tr>
<td></td>
<td>(1.42)</td>
<td>(0.32)</td>
<td>(2.45)</td>
<td>(1.18)</td>
<td>(1.32)</td>
</tr>
<tr>
<td>$\Delta$ Dividend Yield</td>
<td>0.032</td>
<td>$-0.003$</td>
<td>0.051</td>
<td>0.074</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(4.87)</td>
<td>(3.22)</td>
<td>(6.06)</td>
<td>(2.40)</td>
<td>(1.89)</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.10</td>
<td>0.22</td>
<td>0.11</td>
<td>0.13</td>
<td>0.18</td>
</tr>
</tbody>
</table>

### Table 6: Regression results (average estimates) from individual regressions of changes of a firm’s CDS spread with 5-year maturity on a set of explanatory variables (also expressed as a change). The sample period is 14/09/2007 to 31/12/2010. Absolute values of t-statistics are given in parentheses and computed as in Collin-Dufresne et al. (2001).

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Australia</th>
<th>Japan</th>
<th>Korea</th>
<th>Hong Kong</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.007</td>
<td>0.005</td>
<td>0.009</td>
<td>0.006</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(18.38)</td>
<td>(8.14)</td>
<td>(17.80)</td>
<td>(5.62)</td>
<td>(2.69)</td>
</tr>
<tr>
<td>$\Delta$ Log Realized Volatility</td>
<td>0.051</td>
<td>0.018</td>
<td>0.055</td>
<td>0.109</td>
<td>0.033</td>
</tr>
<tr>
<td></td>
<td>(11.74)</td>
<td>(2.69)</td>
<td>(12.11)</td>
<td>(6.87)</td>
<td>(1.79)</td>
</tr>
<tr>
<td>Log Return $\times 10^3$</td>
<td>$-0.118$</td>
<td>$-0.084$</td>
<td>$-1.349$</td>
<td>$-0.096$</td>
<td>$-0.066$</td>
</tr>
<tr>
<td></td>
<td>(6.96)</td>
<td>(3.17)</td>
<td>(6.13)</td>
<td>(1.37)</td>
<td>(1.25)</td>
</tr>
<tr>
<td>$\Delta$ Short-term Rate</td>
<td>0.385</td>
<td>$-0.160$</td>
<td>0.619</td>
<td>$-0.020$</td>
<td>$-0.124$</td>
</tr>
<tr>
<td></td>
<td>(7.40)</td>
<td>(9.64)</td>
<td>(11.75)</td>
<td>(0.82)</td>
<td>(7.38)</td>
</tr>
<tr>
<td>$\Delta$ Slope of Yield Curve</td>
<td>$-0.291$</td>
<td>$-0.276$</td>
<td>$-0.347$</td>
<td>$-0.026$</td>
<td>$-0.092$</td>
</tr>
<tr>
<td></td>
<td>(17.17)</td>
<td>(14.11)</td>
<td>(19.39)</td>
<td>(1.81)</td>
<td>(7.34)</td>
</tr>
<tr>
<td>$\Delta$ Leverage Ratio</td>
<td>0.001</td>
<td>$-0.000$</td>
<td>$-0.001$</td>
<td>0.018</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>(0.38)</td>
<td>(0.19)</td>
<td>(0.56)</td>
<td>(0.93)</td>
<td>(1.74)</td>
</tr>
<tr>
<td>$\Delta$ ROE</td>
<td>$-0.002$</td>
<td>0.006</td>
<td>$-0.003$</td>
<td>$-0.007$</td>
<td>$-0.003$</td>
</tr>
<tr>
<td></td>
<td>(1.37)</td>
<td>(2.25)</td>
<td>(2.36)</td>
<td>(0.93)</td>
<td>(0.74)</td>
</tr>
<tr>
<td>$\Delta$ Dividend Yield</td>
<td>$-0.018$</td>
<td>0.020</td>
<td>$-0.005$</td>
<td>0.170</td>
<td>0.121</td>
</tr>
<tr>
<td></td>
<td>(0.41)</td>
<td>(0.96)</td>
<td>(1.04)</td>
<td>(1.75)</td>
<td>(1.57)</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.18</td>
<td>0.24</td>
<td>0.16</td>
<td>0.17</td>
<td>0.25</td>
</tr>
<tr>
<td>Intercept</td>
<td>Levels</td>
<td>Increments</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-----------</td>
<td>--------</td>
<td>------------</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Australia</td>
<td>Japan</td>
<td>Korea</td>
<td>Australia</td>
<td>Japan</td>
</tr>
<tr>
<td></td>
<td>3.092</td>
<td>−1.457</td>
<td>−0.495</td>
<td>0.003</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(5.43)</td>
<td>(2.73)</td>
<td>(1.05)</td>
<td>(0.53)</td>
<td>(0.67)</td>
</tr>
<tr>
<td>Log Volatility Index</td>
<td>1.149</td>
<td>1.996</td>
<td>1.784</td>
<td>0.151</td>
<td>0.149</td>
</tr>
<tr>
<td></td>
<td>(10.74)</td>
<td>(15.90)</td>
<td>(18.51)</td>
<td>(2.40)</td>
<td>(1.88)</td>
</tr>
<tr>
<td>Log Return $\times 10^3$</td>
<td>0.368</td>
<td>0.791</td>
<td>0.231</td>
<td>−0.231</td>
<td>−0.190</td>
</tr>
<tr>
<td></td>
<td>(2.34)</td>
<td>(5.09)</td>
<td>(1.49)</td>
<td>(4.80)</td>
<td>(4.13)</td>
</tr>
<tr>
<td>Short-term Rate</td>
<td>−0.356</td>
<td>−1.354</td>
<td>−0.165</td>
<td>−0.137</td>
<td>1.117</td>
</tr>
<tr>
<td></td>
<td>(6.90)</td>
<td>(7.40)</td>
<td>(2.41)</td>
<td>(2.39)</td>
<td>(2.18)</td>
</tr>
<tr>
<td>Slope of Yield Curve</td>
<td>−0.339</td>
<td>0.511</td>
<td>−0.042</td>
<td>−0.186</td>
<td>−0.125</td>
</tr>
<tr>
<td></td>
<td>(4.93)</td>
<td>(1.89)</td>
<td>(0.51)</td>
<td>(3.78)</td>
<td>(0.86)</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.72</td>
<td>0.63</td>
<td>0.69</td>
<td>0.42</td>
<td>0.50</td>
</tr>
</tbody>
</table>

Table 7: Regression analysis for the 5-year CDS index (iTraxx Australia, iTraxx Japan and iTraxx Korea) in levels and increments. Absolute values of t-statistics are given in parentheses.

<table>
<thead>
<tr>
<th>ΔLog CDS$_t$</th>
<th>$t$-test (%)</th>
<th>Wald (%)</th>
<th>ΔLog RV$_t$</th>
<th>$t$-test (%)</th>
<th>Wald (%)</th>
<th>LogRet$_t$</th>
<th>$t$-test (%)</th>
<th>Wald (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔLog CDS$_{t-1}$</td>
<td>0.135</td>
<td>16.47</td>
<td>0.148</td>
<td>5.88</td>
<td>−28.950</td>
<td>3.53</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔLog CDS$_{t-2}$</td>
<td>0.050</td>
<td>2.35</td>
<td>22.35</td>
<td>−0.044</td>
<td>1.18</td>
<td>4.71</td>
<td>−63.090</td>
<td>4.71</td>
</tr>
<tr>
<td>ΔLog RV$_{t-1}$</td>
<td>0.032</td>
<td>1.18</td>
<td>−0.375</td>
<td>97.65</td>
<td>−48.183</td>
<td>5.88</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔLog RV$_{t-2}$</td>
<td>0.054</td>
<td>9.41</td>
<td>5.88</td>
<td>−0.173</td>
<td>31.76</td>
<td>96.47</td>
<td>−78.108</td>
<td>2.35</td>
</tr>
<tr>
<td>LogRet$_{t-1} \times 10^3$</td>
<td>−0.041</td>
<td>21.18</td>
<td>−0.073</td>
<td>1.12</td>
<td>−201.710</td>
<td>1.94</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LogRet$_{t-2} \times 10^3$</td>
<td>0.004</td>
<td>1.18</td>
<td>18.82</td>
<td>−0.017</td>
<td>1.18</td>
<td>15.29</td>
<td>−81.326</td>
<td>9.41</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.10</td>
<td>0.16</td>
<td>0.06</td>
<td>0.06</td>
<td>0.10</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 8: Lead-lag analysis with a VAR model for individual firms using 5-year CDS spreads. The variables are the change in log CDS spreads (ΔLog CDS$_t$), the change in log realized volatility (ΔLog RV$_t$) and the log stock return (LogRet$_t$). The table reports the median coefficients (column “Coeff.”) and the percentage of entities for which these coefficients are significantly different from zero at the 1% level (column “$t$-test (%)”). The column “Wald (%)” contains the percentage of firms for which we can reject the null hypotheses at a 1% level that lags 1 to 2 have no joint explanatory power. (This Wald test for $p = 2$ corresponds to a Granger causality test.)

<table>
<thead>
<tr>
<th>ΔLog CDS$_t$</th>
<th>$t$-stat.</th>
<th>ΔLog RV$_t$</th>
<th>$t$-stat.</th>
<th>LogRet$_t$</th>
<th>$t$-stat.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔLog CDS$_{t-1}$</td>
<td>0.145</td>
<td>2.60</td>
<td>0.019</td>
<td>0.32</td>
<td>−214.249</td>
</tr>
<tr>
<td>ΔLog CDS$_{t-2}$</td>
<td>0.067</td>
<td>1.20</td>
<td>0.021</td>
<td>0.36</td>
<td>16.362</td>
</tr>
<tr>
<td>ΔLog RV$_{t-1}$</td>
<td>0.041</td>
<td>0.68</td>
<td>−0.073</td>
<td>1.12</td>
<td>−201.710</td>
</tr>
<tr>
<td>ΔLog RV$_{t-2}$</td>
<td>0.122</td>
<td>2.20</td>
<td>0.113</td>
<td>1.91</td>
<td>−287.976</td>
</tr>
<tr>
<td>LogRet$_{t-1} \times 10^3$</td>
<td>0.039</td>
<td>1.06</td>
<td>0.103</td>
<td>2.66</td>
<td>87.379</td>
</tr>
<tr>
<td>LogRet$_{t-2} \times 10^3$</td>
<td>−0.038</td>
<td>1.12</td>
<td>−0.016</td>
<td>0.46</td>
<td>−28.297</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.06</td>
<td>0.06</td>
<td>0.10</td>
<td>0.10</td>
<td></td>
</tr>
</tbody>
</table>
Table 10: Volatility spillover measures for the three asset classes using firm-level data. Average values of the spillover measures computed for each entity are reported. The variables are the change in log CDS spreads ($\Delta \text{Log CDS}_t$), the change in log realized volatility ($\Delta \text{Log RV}_t$) and the log stock return ($\text{LogRet}_t$). The rightmost column gives the directional spillover to an asset class from the other asset classes. The bottom row gives the directional spillover from an asset class to the other asset classes. The lower right value is the total spillover index. All values are in percent.

<table>
<thead>
<tr>
<th></th>
<th>$\Delta \text{Log CDS}_t$</th>
<th>$\Delta \text{Log RV}_t$</th>
<th>$\text{LogRet}_t$</th>
<th>Directional FROM others</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \text{Log CDS}_t$</td>
<td>80.17</td>
<td>13.46</td>
<td>6.36</td>
<td>19.82</td>
</tr>
<tr>
<td>$\Delta \text{Log RV}_t$</td>
<td>3.08</td>
<td>95.08</td>
<td>1.82</td>
<td>4.91</td>
</tr>
<tr>
<td>$\text{LogRet}_t$</td>
<td>18.08</td>
<td>17.30</td>
<td>64.60</td>
<td>35.39</td>
</tr>
<tr>
<td>Directional</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TO others</td>
<td>21.16</td>
<td>30.76</td>
<td>8.19</td>
<td>20.04</td>
</tr>
</tbody>
</table>

Table 11: Volatility spillover measures for the three asset classes using index-level data (iTraxx Australia, iTraxx Japan and iTraxx Korea). Average values of the spillover measures computed for each index are reported. The variables are the change in log CDS spreads ($\Delta \text{Log CDS}_t$), the change in log volatility ($\Delta \text{Log RV}_t$) and the log stock market return ($\text{LogRet}_t$). The rightmost column gives the directional spillover to an asset class from the other asset classes. The bottom row gives the directional spillover from an asset class to the other asset classes. The lower right value is the total spillover index. All values are in percent.

<table>
<thead>
<tr>
<th></th>
<th>$\Delta \text{Log CDS}_t$</th>
<th>$\Delta \text{Log RV}_t$</th>
<th>$\text{LogRet}_t$</th>
<th>Directional FROM others</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \text{Log CDS}_t$</td>
<td>65.10</td>
<td>28.36</td>
<td>6.53</td>
<td>34.89</td>
</tr>
<tr>
<td>$\Delta \text{Log RV}_t$</td>
<td>22.04</td>
<td>67.46</td>
<td>10.49</td>
<td>32.53</td>
</tr>
<tr>
<td>$\text{LogRet}_t$</td>
<td>18.08</td>
<td>46.55</td>
<td>26.48</td>
<td>73.51</td>
</tr>
<tr>
<td>Directional</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TO others</td>
<td>49.00</td>
<td>74.92</td>
<td>17.02</td>
<td>46.98</td>
</tr>
</tbody>
</table>