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ORIGINAL RESEARCH

Dynamic stock–bond return correlations and financial market uncertainty

Thomas C. Chiang · Jiandong Li · Sheng-Yung Yang

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Abstract This paper investigates the dynamic correlations of stock–bond returns for six advanced markets. Statistics suggest that stock–bond relations are time-varying and display smooth transitional changes. The stock–bond correlations are negatively correlated with stock market uncertainty as measured by the conditional variance and the implied volatility of the S&P 500 index. However, stock–bond relations are positively related to bond market uncertainty as measured by the conditional variance of bond returns. The evidence also shows that stock–bond correlations are significantly influenced by default risk and the London interbank offered rate–T-bill rate spread in the crisis period.

Keywords Stock–bond correlation · Volatility · ADCC model · VIX · Default risk

JEL Classification C12 · C13 · G10 · G11

1 Introduction

The investigation of the correlation between returns on the stock and bond markets has long been an important topic in analyzing financial return series, since empirical

T. C. Chiang
Department of Finance, Drexel University, 3141 Chestnut Street, Philadelphia, PA 19104, USA
e-mail: chiangtc@drexel.edu

J. Li (✉)
Chinese Academy of Finance and Development (CAFD), Central University of Finance and Economics (CUFE), 39 South College Road, Beijing 100081, People's Republic of China
e-mail: jiandongli@cufe.edu.cn; jiandongli@hotmail.com

S.-Y. Yang
Department of Finance, National Chung Hsing University, 250 Kuo Kuang Road, Taichung 402, Taiwan, ROC
e-mail: shengyang@nchu.edu.tw

correlations between asset returns provide strategic information for guiding dynamic asset allocation, portfolio selection, and risk management. Since returns on bonds provide investors with fixed incomes, while returns on stocks are the reward for taking risks, holding combined assets in portfolios allows investors to diversify risk. In a dynamic environment, it is not desirable to hold a constant proportion of stocks and bonds in investors' portfolios. Strategically, investors are advised to continually assess market information and adjust their portfolios in response to emerging state variables/indicators. Thus, from the perspective of dynamic asset allocation, correlations between stock and bond returns are expected to vary, subject to the development of certain events or exogenous shocks.

Some early studies (Yardeni 1997; Abbott 2000) used a "Fed model" to investigate the relationship between the stock and bond markets. A premise of this model is that the P/E ratio derived from the stock market should be close to the reciprocal of the bond market's yield to maturity, implying a positive relationship between the stock market's E/P ratio and bond yields. The Fed model implies that whenever a return differential is created, investors tend to reallocate assets from lower return instruments to ones with higher returns through gross substitutes (Tobin 1969, 1982). A new equilibrium will be achieved as long as the parity relationship between earning yields (E/P) and bond yields is re-established. This model is clearly oversimplified owing to its restrictive assumption of using a common discount factor to project asset price movements. It ignores a main difference of asset characteristics between stocks and bonds: the relative risk associated with these two assets. Moreover, the traditional approach employs an unconditional procedure to calculate the correlation coefficient. The resulting constant coefficient property can be misleading, since it fails to incorporate the impact of changing market conditions arising from noise or unexpected shocks.

In light of the above observations, some recent studies have used a rolling regression method (Wainscott 1990; Andersson et al. 2008) or GARCH-type models (Engle and Kroner 1995; DeGoeij and Marquering 2004; Connolly et al. 2005) to derive time-varying stock–bond correlations. In particular, Connolly et al. (2005) find that the stock–bond relation is negatively related to stock market risk measured by implied volatility. Their argument is based on the flight-to-safety phenomenon—an increase in stock market risk induces investors to sell off stocks in favor of bonds. Since the stock–bond correlation involves both stock returns and bond returns, the determinant of the correlation should have a direct link to bond market risk as well. However, current research has not emphasized this channel. This paper provides empirical evidence to fill in this gap.

It can be hypothesized that stock–bond correlation is positively related to bond market risk. The rationale is as follows. A rise in bond market risk, which may be triggered by the illiquidity of a thin market or a lower credit rating (or default), means that bonds would have to pay a higher yield to induce investors to buy bonds. Since bond yields move in the same direction as the discounted rate of the equity market given that the stock risk premium is stable, a higher bond yield leads both bond and stock prices to go down, forming a positive relation.

However, when the bond yield falls, the discounted rate for stocks may not decline, since the stock risk premium is likely to work in the opposite direction. Thus, we may observe a negative stock–bond correlation, or a falling bond yield may moderate the positive correlation somewhat compared with the situation when bond yields rise.

To test the hypothesis, we carry out the following steps in this paper: First, we employ an asymmetric dynamic conditional correlation (ADCC) model (Cappiello et al. 2006) that helps us to derive dynamic correlation relations for stock–bond returns. This model captures not only a volatility clustering phenomenon but also the asymmetric effects on return volatility arising from a negative shock versus a positive shock. These features cannot be modeled in a rolling regression model, nor can it be done using a Cholesky decomposition (Tsay 2005; Chiang et al. 2007b). Second, having derived a dynamic conditional correlation series, we fit the conditional correlation series into a smooth transitional regression model. This procedure allows us to determine the timing of structural change if a series shifts from a higher correlation regime to a lower correlation regime. When a series undergoes this procedure, it is capable of achieving stationarity. Third, to explain the variations of dynamic correlation behavior over time, we conduct a direct test by regressing the residuals of the correlation series derived from the second step on bond market uncertainties, with stock market uncertainties being control variables.

Compared with existing studies in the literature, this study has several special features. First, to simplify the parametric complexity, we examine the correlation between returns of stocks and long-term government bonds using aggregate data for six advanced markets. One rationale for employing a multi-market investigation is that the evidence from most existing studies is mainly restricted to the U.S. market (Scruggs and Glabadanidis 2003; Connolly et al. 2005; Baele et al. 2010)[1]; there is no guarantee that other markets would share the same empirical regularities as those derived from the U.S. market. To facilitate comparisons, we employ a compatible set of data on stock market indices to calculate aggregate returns of stocks and we use data on 10-year government bonds to compute returns on bonds.

Second, unlike the extant literature, which assumes that the correlations between the stock and bond markets are either generated by a rolling window sample method (Wainscott 1990; Andersson et al. 2008) or derived from the BEKK model[2] (Engle and Kroner 1995; DeGoeij and Marquering 2004) and its equivalent model (Connolly et al. 2005), this study employs an asymmetric dynamic conditional correlation (ADCC) model (Engle 2002; Cappiello et al. 2006; Chou et al. 2009; Weiß 2013) that addresses the asymmetric shocks on conditional variances. The ADCC model is advantageous because it not only characterizes the time-varying nature of the correlation coefficients but also addresses the heteroskedasticity problem caused by abrupt changes in variances in the stock or bond market.[3]

Third, having derived the time-varying correlation coefficients, this paper examines structural change by using logistic smooth transition analysis. The resulting residual series of stock–bond correlations is then examined against a few key variables for proxies of financial market uncertainty, especially the bond market uncertainties. The uncertainties in the bond market are indicated by the conditional variance of the return on 10-year government bonds, default risk in long-term bonds (the yield difference between Aaa- and Baa-rated bonds), and short-term liquidity in the credit market as measured by the *TED* spread (Treasury-Bill Eurodollar Difference), which is the 3-month London interbank offered rate (LIBOR) minus 3-month Treasury bill rate. Connolly et al. (2005) highlight the significance of the *VIX* as a measure of stock market uncertainty on stock–bond

[1] An exception is d'Addona and Kind (2006). They test the G7 countries by using economic fundamentals to explain the correlation between stock and bond returns. Their study is based on monthly data. Our study, as discussed at a later point, includes daily and weekly observations. As a result, the state variables used to explain the stock–bond relation will be different.

[2] The BEKK method is a GARCH-type model developed by Baba et al. (1991), a paper that has been later published as Engle and Kroner (1995).

[3] Scruggs and Glabadanidis (2003) also propose a time-varying model to emphasize a similar issue.

correlation. This study takes both *VIX* and the conditional variances of stock returns as control variables in the regression. This advancement sheds some light on the spillover effect of bond market uncertainty on the dynamic stock–bond relation.

The test results suggest that the stock–bond relation is positively correlated with bond volatility (conditional variance of bond returns) and negatively correlated with stock market uncertainty (as measured by the conditional variance of stock returns and the *VIX*) and default risk. However, there are mixed signs for the *TED* in different markets.

Fourth, traditional tests of the stock–bond return relationship in the literature are mainly carried out using either quarterly or monthly time series data, since they focus on economic fundamentals. For instance, Baele et al. (2010) employ a semi-structural regime-switching model by using state variables such as interest rates, inflation, the output gap, and cash flow growth to explain stock and bond return correlations in the U.S. economy. Andersson et al. (2008) use monthly data from the U.S. and Germany to examine the impact of inflation and economic growth expectations on the time-varying correlation between stock and bond returns. Similarly, Yang et al. (2009) employ monthly data from the U.S. and the U.K. to explain stock–bond correlations in relation to the business cycle. Although these fundamental approaches provide significant contributions by using the inflation rate, economic growth (d'Addona and Kind 2006; Baele et al. 2010), the real interest rate (David and Veronesi 2008; d'Addona and Kind 2006), or the business cycle (Yang et al. 2009) to interpret the time-varying stock–bond return relation, the measures of these state variables are not generally available on a daily basis. Thus, the empirical information derived from these fundamental approaches cannot provide sufficiently precise information that reveals the stock–bond return variations in reacting to short-run shocks to financial markets.

With this understanding, this paper employs a set of short-run state variables pertinent to detecting the impact of financial market uncertainty on the stock–bond return relation. Moreover, in the empirical estimations, we test the same set of parametric models by using different time frequencies for the same sample period. Therefore, the empirical evidence derived from our tests will provide us with estimators across different time horizons, consistently reflecting the parametric impacts of financial market uncertainties on stock–bond return correlations. Thus, the test results serve to guide not only investors in making their portfolio allocations, but also policy makers in monitoring financial markets by observing changes in the state variables of uncertainty.

The remainder of the paper is structured as follows. Section 2 provides a literature review of studies on the correlation between stock and bond market returns. Section 3 describes the sample data. Section 4 describes a dynamic correlation model and reports the time-varying correlations. This section also describes structural changes in the dynamic correlations between stock and bond correlations. Section 5 provides preliminary estimates of the determinants of the dynamic correlation coefficient. Section 6 reports the estimates based on a general specification of financial market uncertainty on the dynamic stock–bond correlations. In Section 7, we conduct robustness tests by using sub-period observations. Section 8 concludes the paper.

2 Relation between stock returns and bond returns

It has been argued that stock and bond returns are positively correlated, since both the stock market and the bond market are exposed to similar macroeconomic conditions, such as the inflation rate, economic growth, and the real interest rate. When a country's economic prospects are good, bond prices appreciate and stock prices also soar, leading to a positive correlation. The experience in the late 1990s suggests that the wealth effect and optimistic prospects have become dominant factors that encourage investors to hold both types of assets simultaneously. Empirical studies by Keim and Stambaugh (1986), Campbell and Ammer (1993), Kwan (1996), and d'Addona and Kind (2006) provide some supportive evidence.

The literature also suggests a negative correlation between returns on the two assets. This is especially true when the stock market is in a downside period or during periods of high volatility. In the latter case, the stock risk premium and the bond risk premium diverge. In fact, when the stock market falls, investors may become more risk-averse. Under this circumstance, bonds become more attractive as investors move funds from the stock market to the bond market, creating a "flight-to-quality" phenomenon (Hartmann et al. 2001; Baur and Lucey 2009; Hakkio and Keeton 2009). On the other hand, when the stock market is rising, most investors become less risk-averse and opt to go back to those high returns, leading to the phenomenon of a "flight-from-quality." The correlation between stock returns and bond returns is, therefore, negative due to these two phenomena. Empirical supports are found in Gulko (2002), Connolly et al. (2005), Andersson et al. (2008), and Baur and Lucey (2009).

Some researchers, such as Alexander et al. (2000), have tried to reconcile the issue of the correlations' mixed signs. They find a significant positive correlation between daily stock returns and high-yield bond returns at the individual-firm level. They also detect a negative co-movement around wealth-transferring events. Putting the above-mentioned arguments together, there is no clear evidence on whether stock returns are positively or negatively correlated with bond returns or even if there is any correlation. In addition, d'Addona and Kind (2006) show that inflation shocks tend to reduce the correlation between stocks and bonds and that higher variability in dividend yields will raise the variability of stock returns and, in turn, decouple the correlation of stocks and bonds. Thus, the sign issue is unsettled.

Connolly et al. (2005) demonstrate the significance of stock market uncertainty by using the *VIX* to explain variations in the stock–bond relation in the U.S. market. The *VIX* in their specification captures much information about the conditional variance of S&P index returns. As a result, no distinction is made between the domestic and external sources of stock market uncertainty. While Panchenko and Wu (2009) employ the *VIX* as an external influence to explain stock–bond relations, their study finds no statistical significance to support their argument. In this paper, we incorporate a broader information set in order to capture uncertainty from financial markets. In particular, we obtain a few key variables that are grouped into stock market uncertainty (conditional volatility of stock returns and the *VIX*), bond market uncertainty (conditional volatility of bond returns), and yield spreads (default risk and the *TED*). These variables can also be sorted into domestic components (conditional variances in stocks and bonds and the *TED*) and external components (the *VIX* and default risk from the U.S. market). Thus, the empirical estimations derived from this study will inform us of the magnitude and significance of each parameter as well as the source of the uncertainty in financial markets.

In a departure from the traditional approach of using a rolling window sample estimate of correlations or an unconditional correlation based on a specific sample period, recent advances in financial econometrics provide more rigorous approaches to describing time-varying behavior in time series. For instance, Scheicher (2003) uses a bivariate GARCH model to estimate the conditional correlation of stock returns and spread changes at the firm level. He finds a weak link between the stock market and the corporate bond market. DeGoeij and Marquering (2004) apply a multivariate GARCH model to examine the stock–bond relation by using a BEW estimation method (Bollerslev et al. 1988). Scruggs and Glabadanidis (2003) use an asymmetric dynamic covariance (ADC) model that nests the BEKK model and the constant correlation model of Bollerslev (1990) in the stock–bond relation (d'Addona and Kind 2006). Of course, non-GARCH-type models are used as well. For example, Pelletier (2006) adopts a regime-switching approach, in which the transitions between regimes are modeled by a Markov chain. This paper adopts an econometric technique featuring a dynamic conditional correlation proposed by Engle (2002) and Cappiello et al. (2006). Rather than generating a covariance series, these models directly estimate the correlation coefficients. This approach, of course, has its econometric appeal in modeling time-varying correlations, since it better specifies the dynamic process in facing a volatile environment through its use of standardized residuals of stock and bond returns to construct conditional correlation coefficients.

3 Data

To provide a consistent measure for stock market returns and bond market returns, this paper employs data with both daily and weekly frequencies. We use the closing observation of the day for the daily data and the Friday closing date for weekly data. The data cover six major advanced markets: Canada (CA), France (FR), Germany (GM), Italy (IT), the United Kingdom (UK), and the United States (US) for the sample period January 2, 1992 through April 20, 2011.[4] The bond indices are extracted from benchmark 10-year government bond price indices.[5] Following the literature (Connolly et al. 2005; Andersson et al. 2008), we use option-implied stock market volatility (*VIX*) to measure stock market uncertainty. A popular measure used to proxy for the credit risk in interbank lending is the *TED* spread. In addition, default spread (*DEFT*) is calculated as the difference in the annualized yields of Moody's Baa- and Aaa-rated bonds. All of the data are taken from Thomson Reuters' Datastream and returns are constructed by taking the log-difference of price indices times 100. The conditional variances of the stock returns and bond returns are generated by an asymmetric GARCH(1,1) process.

To investigate the overall impact of different state variables in relation to stock returns and bond returns, we conduct correlation analysis for each country and obtain four interesting observations. First, with the exception of Italy, correlations between stock returns and bond returns are negative and highly statistically significant.[6] Second, the bond return variable is positively correlated with other state variables. However, the significance levels for the correlations with bond returns are relatively low, implying that the main

[4] The starting date of the data is constrained by the first observation available for the measure of implied volatility of the DAX 30 index (*VDAX*). The selection of these countries is mainly restricted by the availability of similar well-defined data and trading time zone, although the European markets and the U.S. and Canada are separated by several hours. We do not include the Japanese market in our sample for a number of reasons. First, Japanese stocks are traded in a different time zone. Second, Japanese stock prices have been in a depressed state since 1994; the return on 10-year Japanese government bond has been steadily below 2 % since the end of 1997.

[5] Using the same maturity of each government bond index allows us to make comparisons across different markets. Yet, government bonds have very low default risk. The results could be quite different if the bonds were of lower credit quality.

[6] The unconditional stock–bond return correlations for CA, FR, GR, IT, the UK, and the US are: −0.08 (t = −5.90), −0.11 (t = −8.090), −0.12 (t = −8.63). 0.092 (6.59), −0.095 (−6.79), and −0.17 (−12.58), respectively. The correlation table for each country is available upon request.

impact of these state variables on the stock–bond correlations is likely on the stock-return side. Third, the conditional variances in stock and bond returns are all positively correlated with the *VIX,* with high statistical significance. The exception is the correlations of the Italian market, where bond volatility is negatively correlated with the *VIX*. Fourth, the *TED* variable in most markets shows a negative relation with the stock return and a positive relation with other state variables; an exception is the correlation coefficient of the *TED* in Germany. The opposite signs of the *TED* in the German market may reflect a relatively stronger lending position in the German market.[7]

4 Correlation coefficients between stock and bond markets

4.1 The dynamic correlation of stock and bond returns

On the econometric front, Engle's (2002) dynamic conditional correlation (DCC) model can be employed to estimate the conditional correlation coefficient for various countries.[8] In particular, Engle's procedure is divided into two steps. The first step is to estimate a series of univariate GARCH estimates, and the second step is to calculate correlation coefficients. Thus, parameters to be estimated in the correlation process are independent of the number of series to be correlated. It follows that very large correlation matrices can be estimated. In addition, the DCC method provides a mechanism to correct the heteroskedasticity problem, since the residuals of the returns are standardized by the conditional standard deviation based on a GARCH(1,1) process.

While Engle's (2002) DCC model has a computational advantage, however, it avoids the asymmetric effects of shocks on asset return volatility.[9] The subsequent article by Cappiello et al. (2006) addresses this issue. The research procedure in this paper will follow the spirit of Cappiello et al. (2006). The model, therefore, is labeled as an ADCC-GARCH(1,1) process. In particular, in the first stage, we specify two asset returns in a univariate asymmetric GARCH(1,1) process as follows:

$$\begin{gathered} R_{i,t} = \mu_i + \varepsilon_{i,t}, \quad \text{where } i = S \text{ and } B, \\ \eta_{i,t} = \max[0, -\varepsilon_{i,t}] \\ \varepsilon_{i,t} \sim N(0, h_{i,t}) \\ h_{i,t} = \omega_i + \nu_i \varepsilon_{i,t-1}^2 + \upsilon_i h_{i,t-1} + \delta_i \eta_{i,t-1}^2 \end{gathered} \tag{1}$$

where $R_{i,t}$ is the return for asset i, μ_i is the mean value of asset i, $h_{i,t}$ is the conditional variance, and $\varepsilon_{i,t}$ is an error term following a heteroskedastic normal distribution; subscripts, $i = S$ and B, stand for stocks and bonds, respectively.

[7] The statistic shows that the German market has the lowest percentage of the *TED* spread.

[8] DeGoeij and Marquering (2004) apply a GARCH-BEW model to examine the stock–bond relation. However, the BEW method cannot ensure the positive definiteness of the covariance matrix. D'Addona and Kind (2006) provide a comprehensive study of the stock–bond correlation by comparing rolling regression, BEKK-GARCH, and CCC-GARCH models using monthly data for the period January 1980 through March 1997. Yet, the BEKK method in modeling a multivariate GARCH approach often involves computational complexity, especially when the variables involved get larger. A main drawback of the BEKK and the constant correlation coefficient (CCC) GARCH (Bollerslev 1990) models is that the correlation coefficient in a multivariate setting is assumed to be invariant over time.

[9] Chiang et al. (2007a) and Yu et al. (2010) have applied Engle's (2002) model to analyze equity market correlations.

In the second stage, we model the correlation coefficients based on the residuals that have been normalized from the first stage as follows:

$$\begin{aligned} z_{i,t} &= \frac{\varepsilon_{i,t}}{\sqrt{h_{i,t}}}, \quad \text{where } i = S \text{ and } B, \\ z_{i,t} &\sim N(0, q_{i,t}) \\ \lambda_{i,t} &= \max[0, -z_{i,t}] \\ q_{SB,t} &= (1 - a - b - \kappa)\overline{\rho}_{SB} + a \cdot z_{S,t-1} z_{B,t-1} + b \cdot q_{SB,t-1} + \kappa \lambda_{S,t-1} \lambda_{B,t-1} \end{aligned} \tag{2}$$

where $z_{i,t}$ is the normalized residual; $q_{i,t}$ is the conditional variance for the normalized residual[10]; $q_{SB,t}$ is the conditional covariance for the two normalized residuals; and $\overline{\rho}_{SB}$ is the unconditional correlation coefficients between the two return series. Then, the dynamic conditional correlation coefficient between the stock and bond markets is defined as:

$$\rho_{SB,t} = \frac{q_{SB,t}}{\sqrt{q_{S,t}}\sqrt{q_{B,t}}} \tag{3}$$

4.2 Estimated stock–bond correlation coefficients

Table 1 contains parametric estimates of $\rho_{SB,t}$ using the ADCC-GARCH model as represented by the system of Eqs. (1) and (2). As may be seen from Table 1, the mean values of daily data in stock markets range from 0.0211 (Italy) to 0.0358 (Canada). Germany also has a high mean value of 0.0325. These figures are consistent with the high performance of the Canadian and German stock markets over the past two decades. Note that within each country the mean values of stock markets are higher than those of bond markets. The reported statistics on conditional variances indicate that the lagged conditional variance and the lagged shock squared term are mostly statistically significant, indicating that the GARCH-type model is relevant. Looking at the asymmetric impact of shocks on conditional variance, we find that all of the estimated coefficients in the stock and bond markets (δ_S and δ_B) are highly significant, except the bond coefficient in the German market. The evidence also shows the statistical significance of the estimates (parameters a and b) for the dynamics of conditional correlations, and these coefficients do not display significant differences across countries.[11]

While estimating the same model using weekly data (not reported), we obtain similar qualitative results, and no particular statistical discrepancy is found in the estimated parameters due to the use of different frequencies.[12] To visualize the movements of the estimated series and to make comparisons between the alternative estimated coefficients, we depict the dynamic conditional correlations for various countries. Figure 1

[10] The variances of the normalized residuals $z_{S,t}$ and $z_{B,t}$ equal $q_{S,t}$ and $q_{B,t}$, respectively. Both $q_{S,t}$ and $q_{B,t}$ have an expected value of 1.

[11] Taking the U.S. market in Table 1 as an example, although both $a = 0.0396$ and $b = 0.9556$ are statistically significant, the AR(1) term appears to play a dominant role in explaining the evolution of time-varying correlation. This phenomenon applies to all the markets under investigation. The parameter κ is insignificant except for the U.K., suggesting that there is no significant evidence in favor of the asymmetric hypothesis of having a positive shock vs. a negative shock. We then estimate the model by excluding this parameter from the insignificant countries.

[12] To save space, we do not report the statistics derived from weekly data. The estimates are available upon request.

Table 1 Estimates of stock and bond returns using the ADCC model

	$R_{i,t,CA}$	$R_{i,t,FR}$	$R_{i,t,GM}$	$R_{i,t,IT}$	$R_{i,t,UK}$	$R_{i,t,US}$
μ_s	0.0358 (3.79)***	0.0212 (1.62)	0.0325 (2.44)**	0.0211 (1.39)	0.0252 (2.38)**	0.0282 (2.70)***
ω_s	0.0089 (5.69)***	0.0299 (6.87)***	0.0284 (5.91)***	0.0213 (5.40)***	0.0118 (6.30)***	0.0119 (6.60)***
ν_s	0.0401 (5.55)***	0.0129 (2.25)**	0.0255 (3.78)***	0.0457 (7.53)***	0.0213 (3.34)***	0.0025 (0.52)
υ_s	0.9163 (119.2)***	0.9071 (99.32)***	0.9072 (97.14)***	0.9046 (110.4)***	0.9172 (117.4)***	0.9275 (134.1)***
δ_s	0.0631 (6.04)***	0.1102 (9.69)***	0.0966 (8.03)***	0.0754 (7.68)***	0.0956 (9.71)***	0.1139 (10.38)***
μ_b	0.0072 (1.46)	0.0081 (2.00)**	0.0109 (2.97)***	0.0104 (2.49)**	0.0085 (1.81)*	0.0083 (1.49)
ω_b	0.0015 (3.63)***	0.0016 (4.96)***	9.46E−04 (4.59)***	0.0016 (4.85)***	0.0011 (3.75)***	0.0014 (3.47)***
ν_b	0.0358 (6.61)***	0.0333 (6.38)***	0.0525 (8.73)***	0.0490 (6.84)***	0.0299 (5.60)***	0.0412 (7.82)***
υ_b	0.9499 (160.87)***	0.9445 (157.2)***	0.9446 (188.3)***	0.9209 (108.63)***	0.9565 (198.74)***	0.9589 (184.67)***
δ_b	0.0122 (2.02)**	0.0175 (2.54)**	0.0094 (1.50)	0.0416 (4.70)***	0.01416 (2.16)**	−0.0125 (-2.18)**
a	0.0243 (6.13)***	0.0238 (7.12)***	0.0249 (7.04)***	0.0219 (4.70)***	0.0237 (314.4)***	0.0396 (7.27)***
b	0.9710 (187.52) ***	0.9748 (266.8)***	0.9732 (245.5)***	0.9749 (175.5)***	0.9745 (477.99)***	0.9556 (147.10)***
κ	−9.93E−04 (−0.57)	6.21E−04 (0.47)	0.0017 (0.92)	−0.0012 (−0.68)	9.49E−04 (3.07)***	0.0023 (1.01)

This table contains the parametric estimates of $\hat{\rho}_{SB,t}$ using the ADCC model as represented by the system of Eqs. (1) and (2). The sample is daily observations covering the period 1/02/1992–4/20/2011. The parameter μ_i is the mean value of return of asset *i,* in the estimated equation (subscripts, $i = S$ and *B,* stand for stock and bond, respectively); ω_i, ν_i, and υ_i are the parameters for the conditional variance equation; δ_i is an asymmetric parameter. The numbers in parentheses are values of t-statistics. ***,**, and * indicate 1, 5, and 10 % levels of significance, respectively

shows dynamic plots of conditional correlations for the daily data, and Fig. 2 for the weekly data.

The plotted correlation series for six markets in Figs. 1 and 2 display very similar patterns, positing some similar turning points and local trends. Correlations between the returns on the two assets display noticeable variations throughout the sample period. The plots clearly show that the correlations exhibit positive relationships, with a rising trend at the beginning of the sample period up to the end of 1997; in the subsequent period, late 1997 to late 2000, the correlations show substantial sign switching. After 2000, the correlations start to fall and eventually turn to negative territory. The paths of the time-varying correlations up to this point are very close to the trajectories depicted by Andersson et al. (2008) in their study of U.S. and German markets. From the beginning of April 2003, the correlations start rising and enter positive territory, although some negative correlations occur. This period coincided with the bull market in stocks spurred by the real estate

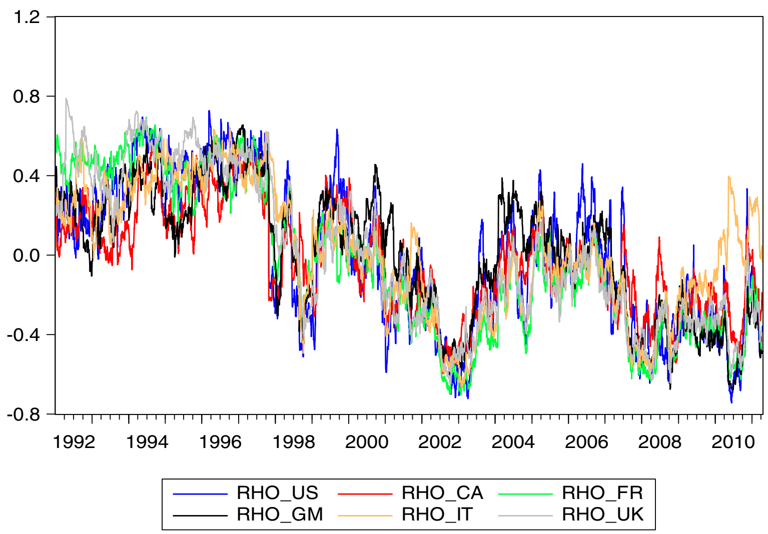

Fig. 1 Daily dynamic correlation coefficients for stock–bond index returns. This figure depicts dynamic correlation coefficients for six advanced markets: the US (*blue*), Canada (*red*), France (*green*), Germany (*black*), Italy (*orange*), and the UK (*grey*) (Color figure online)

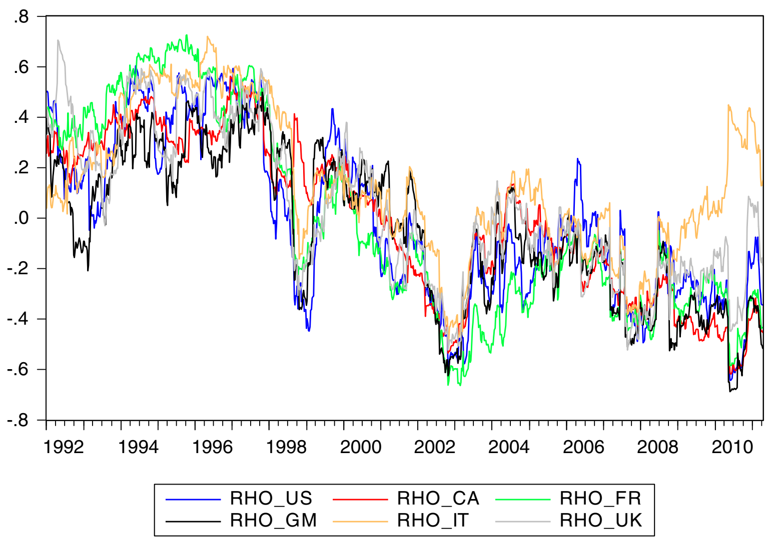

Fig. 2 Weekly dynamic correlation coefficients for stock–bond index returns. This figure depicts dynamic correlation coefficients for six advanced markets: the US (*blue*), Canada (*red*), France (*green*), Germany (*black*), Italy (*orange*), and the UK (*grey*) (Color figure online)

bubble. However, from February 28, 2007, to the end of the sample period,[13] the outbreak of the subprime loan crisis and the crisis in financial markets drags the correlations into negative territory for most of the period. The mixed behavior is consistent with the results of Connolly et al. (2005).

4.3 Statistics of conditional correlations at different time periods

The estimated conditional correlations on average show positive signs. However, in times of stock market uncertainty, the relation becomes negative. As may be seen from Table 2, Panel A, the average correlation coefficients of returns on the two assets for the entire sample period (1/02/1992–4/20/2011) could not produce a consistent sign for the six markets. However, as we checked special sub-periods, we found that in the early stage (1/02/1992–12/31/1998) of the sample, during which investors in the major advanced countries experienced a long period of a bull market, the correlations between stock returns and bond returns are positive (in Panel B).[14] However, in the following period, 1/04/1999–9/06/2008, the signs on the correlations become negative. This holds true for all of the markets under investigation. The statistics indicate that the correlation coefficients display greater absolute values of their negative signs, reflecting the more sizable portfolio shifts between stocks and bonds triggered by high market uncertainty.

Further negative correlations are shown in the sample period of 9/07/2008–4/20/2011, which covers the recent financial crisis.[15] The statistics indicate that the correlation coefficients display even greater absolute values of their negative signs than those of the previous period (Italy is an exception).

One interesting observation derived from Fig. 1 (daily data) and Fig. 2 (weekly data) as well as the statistics shown in Table 3 is that the correlations of stock–bond returns among these markets display a high degree of co-movement.[16] The pair-wise correlations of coefficients range from 0.71 (Germany and Italy) to 0.95 (U.K. and France), reflecting either a high degree of market integration and/or efficient dissemination and processing of financial information. The magnitude of the co-movements can also be seen by observing the variations in dispersions between the daily and weekly data as shown in Figs. 1 and 2. It can be seen that the daily time series distributions in Fig. 1 display a higher degree of

[13] On February 27, 2007, the Dow Jones industrial average in the U.S. market tumbled 416.02 points, to 12,216.24, the biggest point loss (−3.3 %) since September 17, 2001, when the 30-share index was down nearly 685 points. The S&P 500 index fell 50.33 points (−3.5 %) to 1,399.04. It was the worst one-day percentage loss since March 2003. In Canada, the Toronto composite index was down 2.7 %. In Europe, the FTSE100 dropped 2.3 %, the DAX30 slipped 2.96 %, and the CAC40 lost 3 %. In Asia, China's Shanghai stock index plunged 8.8 %, Japan's market fell 2.9 %, and Hong Kong fell 2.5 % on February 27, 2007, its biggest one-day drop in a decade. This outbreak of investor gloom was due to weak corporate profits and expectations of reversals in market spreads worldwide. On the other hand, Treasury prices rallied as investors sought safety.

[14] As we shall show in the next section (in Table 4), the end of the first sample period is mainly determined by a logistic smooth transition model that shows the structural change. We find that the transition mid-points for most countries are detected at the start of 1999. We use the U.S. market as a benchmark because of the relatively large size of its capital market.

[15] There is no clear-cut beginning for the crisis period. We choose September 7, 2008, because on that date, the Federal Housing Finance Agency (FHFA) placed Fannie Mae and Freddie Mac in conservatorship. As conservator, the FHFA has full powers to control the assets and operations of the firms (Jickling 2008).

[16] To save space, we report only the statistics for daily data. Both weekly and monthly data show similar results. The statistics are available upon request.

Table 2 Summary statistics of coefficients between stock and bond returns: daily data

	$\rho_{SB,US}$	$\rho_{SB,CA}$	$\rho_{SB,FR}$	$\rho_{SB,GM}$	$\rho_{SB,IT}$	$\rho_{SB,UK}$
Panel A. Sample period: 1/02/1992–4/20/2011						
Mean	0.001074	−0.023218	−0.030416	0.015500	0.024356	0.004871
Median	−0.006010	−0.030595	−0.080930	0.073123	0.008823	−0.069049
Maximum	0.727352	0.559098	0.694154	0.656069	0.636955	0.789266
Minimum	−0.744113	−0.597140	−0.704951	−0.678977	−0.664970	−0.649355
SD	0.364999	0.259782	0.383515	0.319276	0.314182	0.371411
Observations	5,035	5,035	5,035	5,035	5,035	5,035
Panel B. Sample period: 1/02/1992–12/31/1998						
Mean	0.300838	0.189534	0.377205	0.259583	0.323420	0.016962
Median	0.373102	0.189396	0.441739	0.287076	0.367131	0.011094
Maximum	0.727352	0.559098	0.694154	0.656069	0.636955	3.597452
Minimum	−0.512459	−0.311198	−0.402320	−0.454297	−0.493546	−2.364859
SD	0.280342	0.196637	0.213153	0.218225	0.192845	0.449403
Observations	1,872	1,872	1,872	1,872	1,872	1,872
Panel C. Sample period: 1/02/1999–9/06/2008						
Mean	−0.126453	−0.115053	−0.234817	−0.048864	−0.182549	−0.187313
Median	−0.111599	−0.110365	−0.199625	−0.008703	−0.134066	−0.194753
Maximum	0.632918	0.401838	0.277529	0.455778	0.283878	0.322326
Minimum	−0.722344	−0.597140	−0.704951	−0.599191	−0.664970	−0.649355
SD	0.287533	0.207339	0.234187	0.256053	0.222277	0.211921
Observations	2,480	2,480	2,480	2,480	2,480	2,480
Panel D. Sample period: 9/07/2008–4/20/2011						
Mean	−0.357480	−0.272882	−0.405453	−0.419788	−0.044054	−0.356599
Median	−0.362249	−0.272281	−0.397521	−0.418746	−0.079999	−0.341072
Maximum	0.333769	0.146161	−0.103363	−0.122844	0.397467	0.048533
Minimum	−0.744113	−0.556447	−0.632896	−0.678977	−0.526066	−0.643864
SD	0.180822	0.135875	0.113167	0.122934	0.202816	0.119359
Observations	683	683	683	683	683	683

This table presents a summary of statistics of the stock–bond return correlations ($\rho_{SB,t}$) for six advanced markets using daily data. $\rho_{SB,t}$ is time-varying and derived from the asymmetric dynamic correlation coefficient model. The sample period in Panel B is determined by the sample break, especially by the U.S., suggested by the logistic smooth transition method (LSTM). The starting point of the crisis period is September 7, 2008, the date on which the Federal Housing Finance Agency placed Fannie Mae and Freddie Mac in conservatorship. As conservator, the FHFA has full powers to control the assets and operations of the firms (Jickling 2008)

clustering among different countries compared to the co-movements measured by the weekly data shown in Fig. 2.

4.4 Structural changes

Eyeballing the dynamic correlations in the graphs and checking the statistical evidence with different sample periods suggest that some sort of transitional changes might take place over time. Following the literature (Teräsvirta and Anderson 1992; Leybourne et al.

Table 3 Analysis of correlations of stock–bond returns across different countries

Correlation (t-ratio)	$\rho_{SB,US}$	$\rho_{SB,CA}$	$\rho_{SB,FR}$	$\rho_{SB,GM}$	$\rho_{SB,IT}$	$\rho_{SB,UK}$
$\rho_{SB,US}$	1.0000 —					
$\rho_{SB,CA}$	0.8962 (143.30)***	1.0000 —				
$\rho_{SB,FR}$	0.8758 (128.72)***	0.8558 (117.38)***	1.0000 —			
$\rho_{SB,GM}$	0.8645 (122.01)***	0.8367 (108.40)***	0.8625 (120.95)***	1.0000 —		
$\rho_{SB,IT}$	0.7794 (88.25)***	0.7604 (83.06)***	0.8521 (115.53) ***	0.7154 (72.65)***	1.0000 —	
$\rho_{SB,UK}$	0.8761 (128.93)***	0.8579 (118.49) ***	0.9510 (217.52) ***	0.8454 (112.28)***	0.8461 (112.64)***	1.0000 —

This table presents the correlation matrix for stock–bond return correlations among six advanced markets. The numbers in parentheses are values of *t*-statistics. ***, **, and *denote statistical significance at the 1, 5, and 10 % levels, respectively

1998; Berben and Jansen 2005; Chelly-Steely 2005; Lahrech and Sylwester 2011), we fit a conditional correlation series into a smooth transition regression model as:

$$\hat{\rho}_{SB,t} = \alpha + \beta \cdot G_t(\gamma, \tau) + u_t \tag{4}$$

$$G_t(\gamma, \tau) = \frac{1}{1 + e^{-\gamma(t - \tau T)}}, \tau > 0 \tag{5}$$

where $\hat{\rho}_{SB,t}$ is the conditional correlations of stock and bond returns derived from the ADCC model (Engle 2002; Cappiello et al. 2006), u_t is a zero mean stationary series; G_t is the logistic function; T is the sample size; α, β, γ, and τ are estimated parameters. The parameter γ determines the speed of the transition between two correlation regimes. The timing of the transition midpoint, which is the halfway point moving from regime one to two, is determined by the parameter τ. Estimates of Eqs. (4) and (5) are reported in Table 4 and the fitted values are depicted in Fig. 3a–f. It can be seen from these figures that all the countries exhibit regime changes, shifting from a higher correlation regime to a lower correlation regime. The statistics in Table 4 indicate that structural transition occurs around the turn of 1998–1999 (Germany's and Canada's occur at a later time) as evidenced by the parameter τ ranging from 0.3567 (U.K.) to 0.4096 (Canada). It is worth noting that if we did not fit the conditional correlation series into a smooth transitional regression model, these correlation series could be mistakenly interpreted as a simple time trend relation. As a result, it is important to test whether a smooth transition model is applicable to the data against a unit root process. One way to test is to examine whether the residuals from a smooth transition model are stationary around the trend. Following the procedure by Leybourne et al. (1998), we apply the augmented Dickey–Fuller test to the residual series after fitting a smooth transition regression model. The ADF statistics in Table 4 indicate that all of the countries are significant at least at the 10 % level, supporting the use of a smooth transition model. The evidence of structural change is consistent with the changing market behavior of return correlations between stocks and bonds moving from positive to negative as investors continually evaluate market uncertainty and reallocate their portfolio combinations between stocks and bonds.

Table 4 Estimates of the logistic smooth transition regression model

Country	α	β	γ	τ	Transition midpoint	ADF statistic	Adjusted R^2
CA	0.2231 (16.63)***	0.4171 (71.78)***	−0.0047 (−4.09)***	0.4096 (34.52)***	11/26/1999	−5.00***	0.51
FR	−0.3308 (−24.04)***	0.8297 (42,67)***	−0.0034 (−10.26)***	0.3619 (50.35)***	12/28/1998	−4.55**	0.82
GM	−0.3368 (−72.64)***	0.8152 (89.63)***	−0.0032 (−11.01)***	0.3816 (138.79)***	5/14/1999	−4.23**	0.73
IT	−0.2352 (−15.35)***	0.6119 (28.79)***	−0.0046 (−6.59)***	0.3638 (169.45)***	1/07/1999	−3.91*	0.69
UK	−0.2796 (−23.36)***	0.7974 (33.06)***	−0.0033 (−9.96)***	0.3567 (39.20)***	11/20/1998	−4.74***	0.78
US	−0.2231 (−12.52)***	0.6182 (21.70)***	−0.0039 (−4.91)***	0.3625 (24.14)***	1/04/1999	−5.31***	0.55

This table presents the estimates of the logistic smooth transition regression model for the conditional correlation time series $\hat{\rho}_{SB,t}$. The model is given by $\hat{\rho}_{SB,t} = \alpha + \beta \cdot G_t(\gamma, \tau) + u_t$ $G_t(\gamma,\ \tau) = (1 + \exp(-\gamma(t - \tau \mathrm{T})))^{-1}$, $\tau > 0$. where u_t is a zero mean stationary series; G_t is the logistic function; T is the sample size; and α, β, γ, and τ are estimated parameters. t-statistics are given in parentheses. The critical values for the ADF statistic at the 1, 5, and 10 % levels of significance are −4.685, −4.103, and −3.797, respectively (source: Leybourne et al. 1998). ***, **, and * denote statistical significance at the 1, 5, and 10 % levels, respectively

5 Dynamic correlations of stock–bond relationships and uncertainty

5.1 The source of uncertainty

The advantage of fitting the model with a smooth transition regression procedure helps to achieve the stationary condition. Figure 4 shows a collection of the residual series after fitting a smooth transition model for each country. However, the procedure does not provide any arguments pertinent to explaining variations in stock–bond return relations over time, nor can it explain the nature of the co-movements of the conditional correlations across different countries.

An empirical question to answer now is: What factors contribute to making the correlation coefficients time-varying? On the basis of quarterly data, Baele et al. (2010) suggest that economic state variables such as interest rates, the inflation rate, real output, and uncertainty measures derived from macroeconomics/finance should be included. Using monthly data, David and Veronesi (2008) and d'Addona and Kind (2006) suggest that state variables, such as real interest rates, the inflation rate, and earnings growth, should be employed. Using monthly data, Ghosh and Clayton (2006) find that employment information has an influence on the stock–bond correlations. Using daily data, Connolly et al. (2005) find evidence that co-movements of daily stock and Treasury bond returns are linked to measures of stock market uncertainty. Since our analysis focuses on the daily and weekly market behavior of stock–bond relationships, the absence of high-frequency data prevents us from including the longer-run economic variables, such as the inflation rate, the real interest rate, and real output.[17] Instead, we shall follow the approach of Connolly et al.

[17] Favero (2009) reports that the Baa–Aaa spread and the volatility in the *VIX* strongly co-move and have the same cyclical properties during NBER-dated recessions. As discussed below, we include both the Baa–Aaa spread and *VIX* volatility in our explanatory variables.

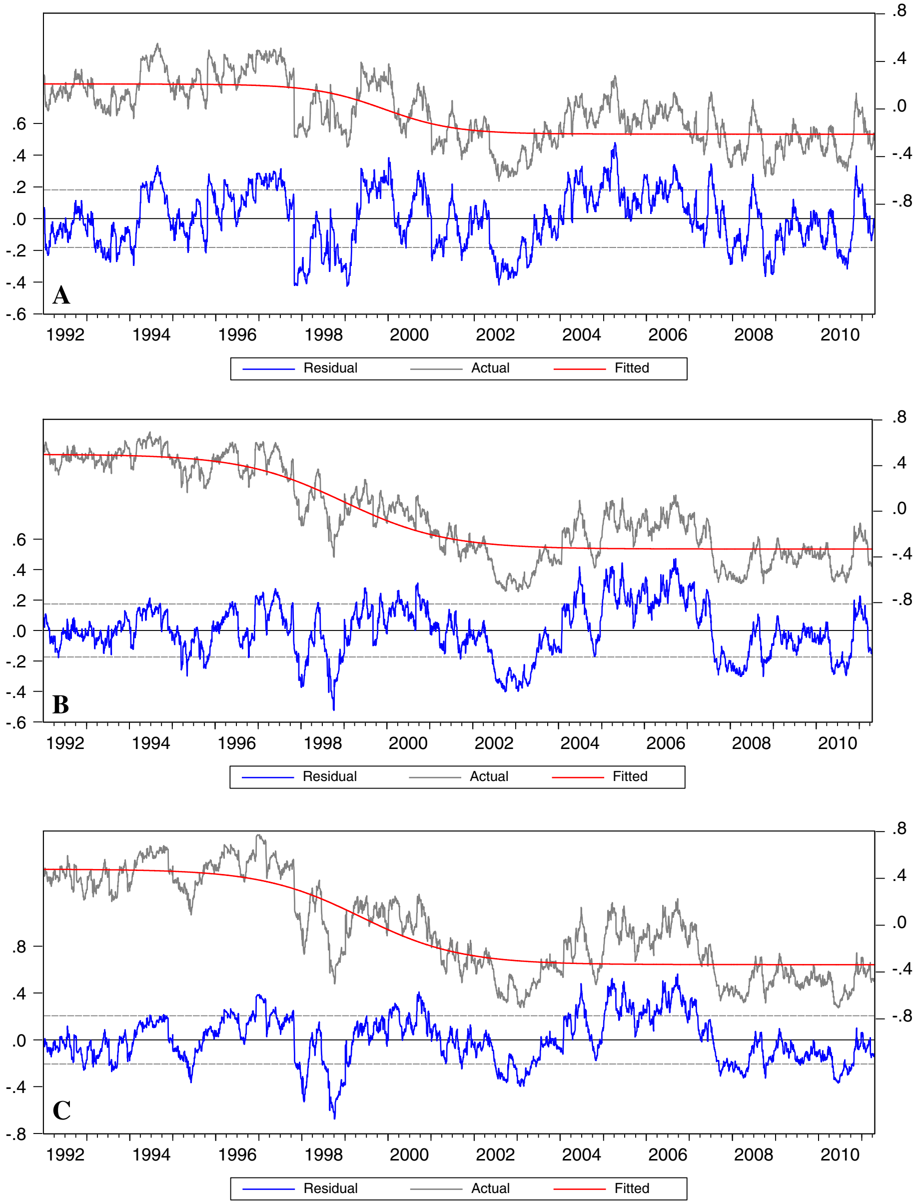

Fig. 3 **a** Actual, fitted values and residuals of stock–bond return correlations for Canada. **b** Actual, fitted values and residuals of stock–bond return correlations for France. **c** Actual, fitted values and residuals of stock–bond return correlations for Germany. **d** Actual, fitted values and residuals of stock–bond return correlations for Italy. **e** Actual, fitted values and residuals of stock–bond return correlations for UK. **f** Actual, fitted values and residuals of stock–bond return correlations for US

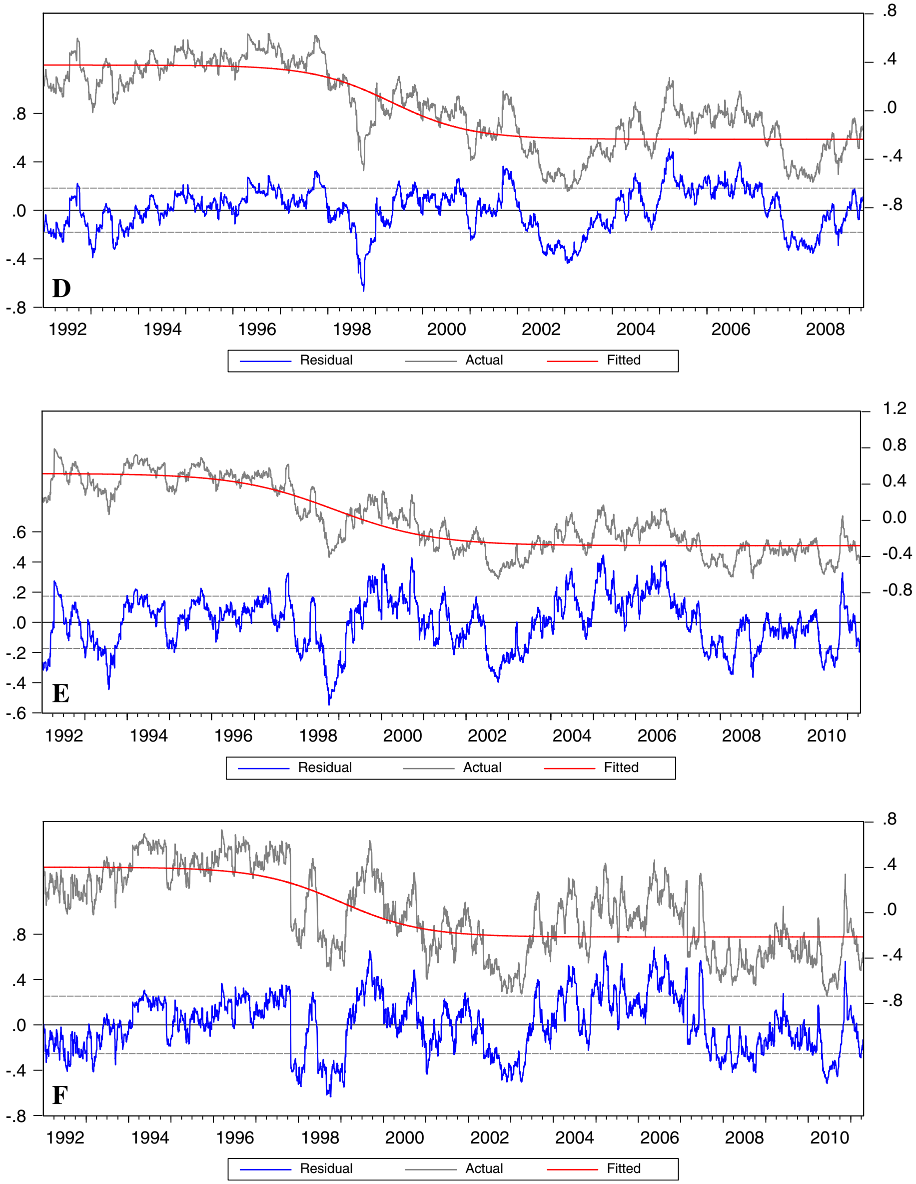

Fig. 3 continued

(2005) and extend the information coverage beyond uncertainty in the stock market. In particular, in this paper, information used to specify financial market uncertainty includes the following variables: bond market uncertainty—the conditional variance of 10-year government bond returns, default risk spread (*DEFT*), and the *TED* spread; and stock market uncertainty—conditional volatility of stock index returns and the implied volatility of stocks (*VIX*).

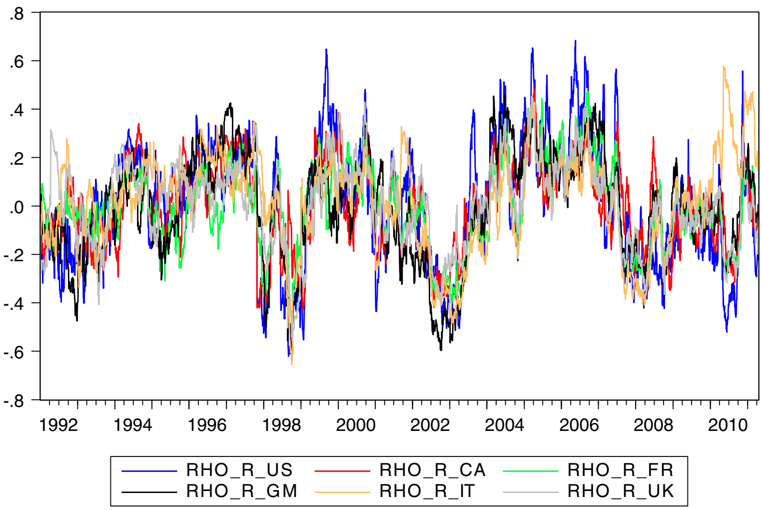

Fig. 4 Daily dynamic correlation coefficients for stock–bond index returns after removing the smooth transition. This figure depicts dynamic correlation coefficients for six advanced markets: the US (*blue*), Canada (*red*), France (*green*), Germany (*black*), Italy (*orange*), and the UK (*grey*) (Color figure online)

5.2 Conditional variances of stock returns and bond returns

To start with, it is convenient to follow the GARCH-type model by using conditional variance to measure asset return uncertainty. In the equation below, we specify that the stock–bond return relation is a linear function of the domestic conditional variance of stock returns and the domestic conditional variance of bond returns:

$$\hat{\hat{\rho}}^*_{SB,t} = \varphi_0 + \varphi_1 \hat{\sigma}^2_{S,t} + \varphi_2 \hat{\sigma}^2_{B,t} + \varepsilon_t \tag{6}$$

where $\hat{\hat{\rho}}^*_{SB,t}$ *is* a stock–bond correlation coefficient series obtained from a smooth transition regression model[18]; $\hat{\sigma}^2_{s,t}$and $\hat{\sigma}^2_{B,t}$are conditional variances of the stock index return and 10-year government bond index return, respectively. Both conditional variance variables are independently generated from an asymmetric GARCH(1,1) process.

Table 5 presents the consistent estimates (Newey and West 1987) of Eq. (6). The evidence shows that the sign for the domestic conditional variance of stock returns is negative for all of the markets and statistically significant at the 1 % level. The negative sign of the conditional variance of stock returns is consistent with market behavior: a rise in uncertainty in the stock market spawns fear of further deterioration. To hedge risk, investors move funds out of the stock market and purchase long-term government bonds, generating a "flight-to-quality" phenomenon (Fleming et al. 1995; Andersson et al. 2008).

With respect to the coefficient of the conditional variance of bond returns, we find that all of the countries show positive signs and statistical significance. The positive effect of bond market uncertainty on the stock–bond correlation might stem from the fact that when the equity risk premium is relatively stable, an increase in uncertainty in the bond market

[18] Since the dependent variable is bound to interval [−1, +1], we apply a Fisher transformation $\left(\hat{\hat{\rho}}^*_{SB,t} = \frac{1}{2}\ln\left[\frac{1+\hat{\rho}^*_{SB,t}}{1-\hat{\rho}^*_{SB,t}}\right]\right)$ on the correlation coefficient first and then conduct the regression estimation.

Table 5 Estimates of stock–bond return correlations regressed on financial market volatilities: 1/02/1992–4/20/2011

	Dependent variables					
	$\hat{\hat{\rho}}^*_{SB,CA}$	$\hat{\hat{\rho}}^*_{SB,FR}$	$\hat{\hat{\rho}}^*_{SB,GM}$	$\hat{\hat{\rho}}^*_{SB,IT}$	$\hat{\hat{\rho}}^*_{SB,UK}$	$\hat{\hat{\rho}}^*_{SB,US}$
ϕ_0	−0.0111	0.0322	0.0294	0.0223	0.0179	0.0463
	(−0.73)	(2.08)**	(1.62)	(1.84)*	(1.33)	(23.46)***
ϕ_1	−0.0232	−0.0440	−0.0383	−0.0195	−0.0388	−0.0358
	(−7.99)***	(−5.91)***	(−5.38)***	(−3.54)***	(−4.82)***	(−45.04)***
ϕ_2	0.2217	0.2380	0.2353	0.1684	0.2106	0.1270
	(3.20)***	(3.07)***	(1.91)*	(4.61)***	(4.06)***	(10.82)***
$\bar{R}^2$	0.0750	0.1662	0.1018	0.0528	0.1467	0.0536

This table presents the estimates of the stock–bond return correlations in relation to a set of state variables for measuring stock and bond market uncertainties. The dependent variables are the residuals of applying the logistic smooth transition regression (LSTR) model suggested by Granger and Teräsvirta (1993) and Lin and Teräsvirta (1994) to remove structural changes in the conditional correlation series. The sample covers daily observations for the full sample 1/02/1992–4/20/2011. The Newey and West (1987) consistent estimator is used to estimate the following equation: $\hat{\hat{\rho}}^*_{SB,t} = \varphi_0 + \varphi_1\hat{\sigma}^2_{S,t} + \varphi_2\hat{\sigma}^2_{B,t} + \varepsilon_t$. where $\hat{\hat{\rho}}^*_{SB,t}$is a residual series of correlation coefficients between stock returns and bond returns based on the LSTR model and then taking a Fisher transformation; $\hat{\sigma}^2_{s,t}$ is the conditional variance of the ith national stock index return; and $\hat{\sigma}^2_{B,t}$ is the conditional variance of the ith national 10-year government bond index return; both are derived from an asymmetric GARCH(1,1) model. Estimations include markets of CA, FR, GM, IT, UK, and US. $\bar{R}^2$ is the adjusted R^2. The numbers in parentheses are values of t-statistics. ***, **, and * denote statistical significance at the 1, 5, and 10 % levels, respectively

affects the expected future discount rates for both stocks and bonds in the same direction. This leads to a positive correlation between returns on outstanding stocks and long-term bonds. A decrease in uncertainty in the bond market is likely to moderate the bond yield, pushing up bond prices. However, the decline in bond yields may not drive up stock prices because the equity risk premium works in the opposite direction.

6 A general specification of financial market uncertainty

6.1 Incremental variables

In the empirical literature, the *VIX* is commonly used as a measure of stock market uncertainty. The *VIX* is the Chicago Board Options Exchange (CBOE) volatility index, a forward-looking index of the expected return volatility of the S&P 500 index over the next 30 days (Whaley 1993). Whaley (2009) observes that the *VIX* spikes during periods of market turmoil, reflecting a market phenomenon that if expected market volatility increases (decreases), stock prices fall (rise), since investors require a higher (lower) rate of return to compensate for bearing risk. Banerjee et al. (2007) find that the *VIX* variable has a significant power to predict stock returns and consider it as a priced factor. Hakkio and Keeton (2009) even argue that the *VIX* can capture uncertainty arising from asset fundamentals or unexpected shifts in investor behavior. Empirically, it is of interest to examine whether the implied volatility of the stock market (*VIX*) would drive stock returns and bond returns in different directions and shed some light on the benefits of stock–bond diversification (Connolly et al. 2005; Hobbes et al. 2007).[19]

Although both the conditional variance of stock returns and the *VIX* are commonly used as proxies for stock market uncertainty, these two variables in fact may represent different information about market uncertainty.[20] Specifically, Kanas (2012) shows that *VIX* should be an exogenous variable in the conditional variance equation. The conditional variance can be viewed as an unbiased forecast of volatility derived from the historical time series pattern based on a GARCH-type model, while the *VIX* reflects market expectations of volatility extracted from options pricing. The literature suggests that the contagion effect, cross-market herding, and volatility spillover may contribute to the co-movements of the *VIX* and the domestic conditional variance of stock returns. Because of their respective information content, it is relevant to incorporate both sets of information into the model.

In assessing the risk in bond markets, in addition to the conditional variance of bond returns, investors often look at the default risk spread (hereafter *DEFT*), calculated as the difference in the annualized yields of Moody's Baa- and Aaa-rated bonds.[21] This spread directly measures the premium that uncertainty commands in the bond market. This variable has been used in the literature to capture systematic default risk (Chen et al. 1986; Fama and French 1993).[22] Evidence shows that the S&P 500 index moves inversely with this yield spread, since a lower spread reflects better market sentiment, contributing to an increase in stock prices (Dichev 1998; Campbell et al. 2008). In contrast, a widening of the default spread may reflect either deterioration in the financial health of the borrowing firms or signify a rise in compensation for liquidity risk (Avramov 2002; Houweling et al. 2005). As the spread increases and market participants perceive that economic prospects are becoming less promising, risk-averse investors tend to short their stocks, causing stock prices to fall. For this reason, the *DEFT* is expected to have a negative effect on the stock–bond relation.

Over a shorter time horizon, market participants might pay more attention to the movements of the *TED* spread, which is one of the short-term indicators of perceived credit risk in financial markets. From a lender's perspective, T-bills are considered to be risk-free, while *LIBOR* contains the credit risk of lending to commercial banks. When the *TED* spread widens, it sends a signal to the market that lenders perceive that the risk of default on interbank loans is rising. Interbank lenders, therefore, either demand a higher rate of interest or make a flight to quality, purchasing safe instruments that have lower returns, such as Treasury bills. In addition, this type of credit risk reflected in a rising *TED* spread is likely to generate liquidity risk, causing widespread uncertainty that impinges on financial markets, leading to the collapse of both stock and bond prices.[23] A general message

[19] Connolly et al. (2005) find that bond returns tend to be high (low) relative to stock returns during the time period when implied stock market volatility is high (low).

[20] The *VIX* is positively correlated with the conditional variances of stock returns (0.70–0.8).

[21] Tang and Yan (2010) use the credit risk spread, which is the difference between the yield on a corporate bond and a government bond, to measure the risk of investing in bonds. In practice, the *credit spread* can be measured by the difference between the yield on Moody's Aaa seasoned corporate bonds and the 10-year Treasury bond; an increase in the credit spread will impair the bondholder by causing a higher yield to maturity and a lower bond price. Because we have used a few proxy variables in the measure of bond risk, to avoid the multi-collinearity problem, we do not include this measure of credit risk in our estimations.

[22] Fama and French (1993) define default risk as the difference between the return on a market portfolio of long-term composite corporate bonds (Ibbotson Associates) and the return on long-term government bonds.

[23] The *TED* spread exceeded 300 basis points in September and early October 2008, after the bankruptcies of several big banks and investment companies in the U.S. market that constituted part of the global financial crisis. On October 10, 2008, the *TED* spread hit a record high of 458 basis points (the U.S. 3-month Treasury

emerging from market participants is that the *TED* spread can be viewed as an indicator of confidence in the banking system. As the *TED* spread narrows, it stimulates both stock and bond prices.[24] In a period of low inflation and stable availability of liquidity, the correlation of stock–bond returns and the *TED* is more likely to be positive. However, in a period of dramatic shifts in bank credit risk, the impact of credit risk on liquidity will be severe, putting downward pressure on stock prices. From this perspective, the sign of the *TED* will be negative, as witnessed by market behavior in the financial crisis of 2007–2009.

It is conceivable that market participants' decisions to reallocate their portfolios between stocks and bonds are not mainly determined by information contained in a particular variable per se. In a general equilibrium framework, the decision to hedge risk may result from a complex interaction across markets. Suppose there is bad news about a credit crunch that heightens the risk of future borrowing, which would lead to an increase in the default risk spread. The increasing default risk spread may reinforce stock market volatility spontaneously.[25] With this consideration, we incorporate the interactive terms of (*VIX**-*DEFT*) into the test equation. Finally, we add the prevailing level of the stock market index (*TOTM*) to the test equation to capture the wealth effect or market sentiment; a rise in market-wide stock prices tends to increase demand for both stocks and bonds (Tobin 1969), creating a positive correlation reflecting in $\hat{\rho}^*_{SB,t}$.

6.2 Empirical evidence

Collecting the arguments we presented above, we write a test equation as[26]:

$$\begin{aligned}\hat{\hat{\rho}}^*_{SB_{,t}} = \varphi_0 + \varphi_1\hat{\sigma}^2_{S,t} + \varphi_2\hat{\sigma}^2_{B,t} + \varphi_3 VIX_t + \varphi_4 DEFT_t + \varphi_5 TED_t + \varphi_6(VIX_t \cdot DEFT_t) \\ + \varphi_7 TOTM_t + \varphi_8\varepsilon_{t-1} + \varepsilon_t.\end{aligned} \tag{7}$$

This equation represents a general specification of stock–bond return correlation coefficient, $\hat{\hat{\rho}}^*_{sb,t}$, in relation to a set of information about financial market uncertainty as measured by domestic conditional variances of stock returns and bond returns ($\hat{\sigma}^2_{s,t}$and $\hat{\sigma}^2_{B,t}$),

Footnote 23 continued
bill was 0.24 % and the corresponding LIBOR was 4.818 %; the difference was 4.58 %), signifying a severe default risk and credit crunch in interbank lending.

[24] Krugman (2009) notes that the "*TED* was a good indicator of fear in the banking system." This view is consistent with an earlier report by de Aenlle (1992), who noted that "as the *TED* spread continues to narrow, confidence grows. That, in turn, means lower interest rates and, much of the time, a higher stock market."

[25] The interaction between the *VIX* and bond market news can be seen in an episode on August 8, 2011. As Standard & Poor's announced that it had downgraded the U.S. credit rating from AAA to AA+, the Dow Jones industrial average sank 634.76 points, or 5.6 %, falling to 10,810. The S&P 500 lost 79.92 points, or 6.7 %, falling to 1,120. And the Nasdaq Composite dropped 174.72 points, or 6.9 %, falling to 2,358. In London, the FTSE closed at 5,068.95, off 178.04 points, while the German *DAX* lost 312.89, to close at 5,923.27. The *VIX* "fear" index jumped 44 %, to 45.98. Ironically, bond prices rose, and the yield on the benchmark 10-year U.S. Treasury bill fell to 2.34 % from 2.56 %. (see Sweet 2011. http://money.cnn.com/2011/08/08/markets/markets_newyork/index.htm, August 30, 2011).

[26] Although the literature has suggested including uncertainty among the macroeconomic fundamentals such as the variability of GDP and inflation, we did not employ these variables because of their inappropriateness in measuring daily observations. Recent studies find very little evidence to support including these variables (Baele et al. 2010).

implied volatility of stock indices (*VIX*), long-term bond default risk (*DEFT*), and short-term credit/liquidity risk (*TED*). To capture the wealth effect, we add the level of the stock index ($TOTM_t$) to the test equation, since a higher level of the stock market index creates a wealth effect in demand for both stocks and bonds. An MA(1) in error term captures long lags of the AR effect. Table 6 contains the regression estimates using the GARCH(1,1) method.[27] In general, the statistics produce consistent signs across different countries and the adjusted R^2 ranges from 0.69 (Italy) to 0.79 (France). The evidence on each explanatory variable is summarized as follows.[28]

First, the effect of stock market uncertainty on the stock–bond relationship is quite outstanding. The evidence shows that ϕ_3 uniformly presents a negative sign and high significance in the contemporaneous period.[29] The inclusion of the *VIX* variable does not affect the qualitative direction and the significance of the $\hat{\sigma}^2_{s,t}$; the domestic conditional variance of the stock returns still shows a negative impact on $\hat{\hat{\rho}}^*_{sb,t}$ This finding is consistent with the market behavior that a rise in uncertainty in the stock market shown as a rise in the *VIX* or $\hat{\sigma}^2_{s,t}$ creates fear, resulting in a fall in stock prices as investors are prompted to move funds out of the stock market and into the bond market, such as long-term government bonds (Fleming et al. 1995; Andersson et al. 2008). Moreover, higher volatility in stock markets can cause a demand for liquidity, since leveraged investors/fund managers will have to liquidate some of their assets to meet margin calls (Brunnermeier and Pedersen 2009). This “flight to liquidity” also leads to depressed stock prices. The negative effect of stock uncertainty on the stock–bond return correlations is consistent with results in the literature, for example, Fleming et al. (1995), Connolly et al. (2005), d’Addona and Kind (2006), and Andersson et al. (2008).[30] However, the evidence on the influence of the *VIX* on the advanced markets is quite different from the results reported by Panchenko and Wu (2009); they do not find any external influence of the *VIX* on stock–bond relations in their study of 18 emerging markets.

Second, the estimated coefficient ϕ_2 is positive and highly significant for all of the markets, indicating that the effect of bond market uncertainty is somehow different from that of stock market uncertainty. As we mentioned earlier, a rise in stock market

[27] Footnote 34 presents a possible explanation for the endogenous behavior of the coefficient of the *VIX*. The prevailing stock index, *TOTM*, is used as a wealth effect, serving as a control variable.

[28] Since the independent variables in Eq. (7) contain various measures of uncertainty from the stock market (or the bond market), some degree of muticollinearity may be present. Econometric theory suggests that if two variables contain a similar information set (near muticollinearity is present), the estimated standard errors become large. As a result, the usual *t*-tests will lead to the conclusion that parameter values are not significant. Taking the U.S. market as an example, if the *VIX* and the conditional variance are highly correlated, either or both coefficients will be insignificant. The evidence from Tables 6–9 in most cases indicates that both coefficients are statistically significant. This indicates that the muticollinearity problem is not serious, should it exist. An econometric treatment for dealing with the muticollinearity problem is to drop an insignificant variable. In our analysis, we don’t think this is necessary. Moreover, dropping a relevant variable may cause estimates of the parameters of the remaining variables to be biased (Kennedy 2008, 197).

[29] When replacing the *VIX* by the *VDAX*, the implied volatility from the German DAX, we obtain a comparable result (not reported to save space). The estimations using the *VDAX* are available upon request.

[30] Our finding is slightly different from the result documented by Connolly et al. (2005), since in their study of the U.S. market, the *VIX* is used to measure stock market volatility; the conditional variance was left out of their model. In our model, the *VIX* is considered as an external influence on the non-U.S. markets. The foreign influence on the U.S. market using the *VDAX* yields a similar result. The coefficient of the *VDAX* on the stock–bond correlation is −0.0305 (t = −15.31).

Table 6 Estimates of stock–bond return correlations regressed on financial market uncertainty: 1/02/1992–4/20/2011 (Daily data)

	Dependent variables					
	$\hat{\hat{\rho}}^{*}_{SB,CA}$	$\hat{\hat{\rho}}^{*}_{SB,FR}$	$\hat{\hat{\rho}}^{*}_{SB,GM}$	$\hat{\hat{\rho}}^{*}_{SB,IT}$	$\hat{\hat{\rho}}^{*}_{SB,UK}$	$\hat{\hat{\rho}}^{*}_{SB,US}$
ϕ_0	0.1607	0.1421	0.4222	0.1444	0.1761	0.7333
	(16.97)***	(24.89)***	(50.26)***	(20.60)***	(25.77)***	(56.53)***
ϕ_1	−0.0150	−0.0269	−0.0268	−0.0107	−0.0248	−0.0379
	(−12.26)***	(−45.64)***	(−21.47)***	(−14.45)***	(−36.06)***	(−18.58)***
ϕ_2	0.5276	0.4068	0.2480	0.0176	0.4011	0.0955
	(38.60)***	(35. 80)***	(17.84)***	(2.75)***	(53.86)***	(4.31)***
ϕ_3	−0.0149	−0.0110	−0.0171	−0.0029	−0.0127	−0.0314
	(−51.04)***	(−43.71)***	(−61.56)***	(−11.03)***	(−52.32)***	(−57.40)***
ϕ_4	−0.3237	−0.2517	−0.5584	−0.0512	−0.2800	−0.9078
	(−32.04)***	(−36.01)***	(−56.81)***	(−8.94)***	(−46.83)***	(−53.93)***
ϕ_5	−0.0367	0.0049	−0.0340	0.0144	−0.0876	−0.1036
	(−8.27)***	(1.78)*	(−1.08)	(9.03)***	(−25.13)***	(−19.71)***
ϕ_6	0.0080	0.0064	0.0115	0.0008	0.0071	0.0242
	(29.94)***	(38.15)***	(47.67)***	(5.93)***	(39.97)***	(47.58)***
ϕ_7	0.00003	0.0001	0.0002	0.00001	0.00006	0.0004
	(52.95)***	(74.59)***	(49.96)***	(7.79)***	(64.42)***	(58.23)***
ϕ_8	0.8731	0.7845	0.8018	0.8174	0.7767	0.7857
	(435.95)***	(82.21)***	(81.24)***	(83.97)***	(64.32)***	(78.03)***
$\bar{R}^2$	0.7757	0.7946	0.7676	0.6915	0.7830	0.7543

The estimated equation is given as follows: $\hat{\hat{\rho}}^{*}_{SB,t} = \varphi_0 + \varphi_1\hat{\sigma}^2_{S,t} + \varphi_2\hat{\sigma}^2_{B,t} + \varphi_3 VIX_t + \varphi_4 DEFT_t + \varphi_5 TED_t + \varphi_6(VIX_t \cdot DEFT_t) + \varphi_7(TOTM_t) + \varphi_8\varepsilon_{t-1} + \varepsilon_t$. where $\hat{\hat{\rho}}^{*}_{SB,t}$is a residual series of correlation coefficients between stock returns and bond returns derived from the logistic smooth transition regression (LSTR) model and then taking a Fisher transformation; $\hat{\sigma}^2_{s,t}$is the conditional variance of national stock index return; $\hat{\sigma}^2_{B,t}$ is the conditional variance of national 10-year government bond index return; both are based on an asymmetric GARCH(1,1) model. The markets include CA, FR, GM, IT, UK, and US. The *VIX* is the CBOE implied volatility index used as an external influence on stock volatility in the markets of Canada, France, Germany, Italy, and the UK; the DEFT is the default risk spread = Moody (Baa–Aaa); the *TED* = (the 3-month London interbank offered rate (LIBOR) − the 3-month T-bill interest rate); the *TOTM* is the total market stock price index for each market. $\bar{R}^2$ is the adjusted R^2. The numbers in parentheses are values of z-statistics. ***, **, and * denote statistical significance at the 1, 5, and 10 % levels, respectively

uncertainty will induce investors to shift their funds from stocks to bonds, depressing stock prices and bidding up bond prices. However, an escalation in bond market uncertainty will immediately increase the bond market's risk premium, which spills over to the stock market and increases equity risk premium as well. Consequently, both the stock and the bond market returns are moving in the same direction. Our finding is consistent with that of the earlier study by Campbell and Ammer (1993), who found that co-movements are present when expected future risk premiums for holding stocks and bonds change.

Both the bond price and the stock price depend on the discount rate. However, besides the discount rate, stock price depends on future dividends and dividend growth expectations. As a result, bond market uncertainty relates to bond risk premium and may lead to equity risk premium change. However, the stock market uncertainty does not necessarily relate to equity risk premium, which then may not cause bond risk premium change.

Third, the estimated coefficients on the default risk spread (*DEFT*) ϕ_4 are negative and highly significant across different markets. This evidence is very much in line with the existing literature. For instance, Dichev (1998) finds a negative relationship between default risk and equity returns during the period 1981–1995. Campbell et al. (2008) show that stocks with a high risk of default turn out to have anomalously low stock returns. Our finding is consistent with the scenario that a widening of the default risk spread at the aggregate level signifies a deterioration in the financial health of firms. As a result, market participants sense that economic prospects are becoming less promising, and risk-averse investors tend to sell off their stocks, causing stock prices to fall, leading to a "flight to quality": higher default risk leads investors to increase their share of securities with a safer class of assets. [31,32]

Fourth, the evidence in Table 6 suggests that the coefficient of the *TED* spread ϕ_5 is negative for four of the six markets: Canada, Germany, the UK, and the U.S.; however, the signs are positive for France and Italy. The diverse signs may be linked to different financing strengths and market conditions for each country. Although the *TED* is observed to be correlated with default risk, the difference is that the *TED* variable captures financial institutions' credit and liquidity risk in the short run. Its variation is certainly related to the central bank's interventions to deal with the easiness of short-term credit or financial crisis.[33] At any rate, a widening of this spread signifies a rise in default on interbank loans, which creates liquidity risk, giving rise to more uncertainty in financial markets, leading to a plunge in stock prices and in the pricing of instruments related to financial institutions.

Fifth, the coefficient ϕ_6 of the interactive term of (*VIX*DEFT*) is positive. One way to interpret the interactive term is that the *DEFT* will affect ϕ_3, the coefficient of the *VIX* in the test equation.[34] The evidence from Table 6 suggests that a nonlinear specification is relevant, since all of the nonlinear components are highly significant. However, it is well recognized that a nonlinear specification is rather complex. One challenge we face is that it is not feasible to sort out all of the different specifications of nonlinearity and at the same time come up with a meaningful interpretation of the underlying economics, since some market behavior is not directly observable (Granger and Teräsvirta 1993). Here we choose to treat ϕ_3 endogenously, to explore a possible reaction function for investors in response to variations in *DEFT* in making stock–bond portfolio decisions.[35]

[31] Kwan (1996) establishes a micro-level linkage with a firm's valuation in that an increase in the default spread is interpreted as a threat to the expected future cash flows of the issuing firm, which also affects the firm's stock price. His study assumes that stocks and bonds are issued by the same firm. Hence, specific information about the firm should have an impact on both the firm's outstanding stocks and its outstanding bonds, leading to a co-movement between individual stock and bond prices. This study is different from Kwan's, since we conduct a macro-level investigation and examine the relationship of returns between 10-year government bonds and a stock index in response to default risk.

[32] On December 3, 2008, the default risk spread hit a record high of a 3.5 % annual rate against an average level of 0.94 % for the whole sample period.

[33] As we shall see in the estimation of the crisis period.

[34] If we have a linear function that $\hat{\rho}^*_{SB,t} = \varphi_0 + \varphi_1\sigma^2_{S,t} + \varphi_2\sigma^2_{B,t} + \varphi_3 VIX_t + \varphi_4(DEFT)_t + \varphi_5(TED)_t + \varphi_6 TOTM_t + \varepsilon_t$, (A1) and assume $\varphi_3 = v_0 + v_1 DEFT_t + e_t$, (A2). Substituting A(2) into A(1) will yield a nonlinear component in Eq. (7).

[35] The reason for selecting the coefficient of the implied volatility of stock returns (*VIX*), rather than that of the domestic conditional variance ($\sigma^2_{s,t}$), is that the *VIX* appears to be an external force that is consistently interacting with the *DEFT* in the same time zone.

Table 7 Estimates of stock–bond return correlations regressed on financial market uncertainty: 1/02/1992–12/31/1998 (daily data)

	Dependent variables					
	$\hat{\hat{\rho}}^*_{SB,CA}$	$\hat{\hat{\rho}}^*_{SB,FR}$	$\hat{\hat{\rho}}^*_{SB,GM}$	$\hat{\hat{\rho}}^*_{SB,IT}$	$\hat{\hat{\rho}}^*_{SB,UK}$	$\hat{\hat{\rho}}^*_{SB,US}$
ϕ_0	−1.3088 (−34.80)***	0.1074 (4.05)***	0.0063 (0.39)	0.5862 (15.26)***	0.0639 (1.52)	−0.0810 (−1.43)
ϕ_1	−0.0936 (−20.26)***	−0.0288 (−10.73)***	−0.0202 (−15.31)***	0.0113 (8.10)***	−0.0441 (−8.74)***	0.0704 (9.92)***
ϕ_2	0.6718 (46.86)***	0.5561 (45.15)***	0.3718 (27.02)***	0.0184 (2.74)***	0.3247 (29.09)***	0.6970 (29.46)***
ϕ_3	0.0654 (33.86)***	−0.0024 (−1.97)**	0.0053 (7.00)***	−0.0054 (−3.53)***	0.0473 (26.44)***	0.0571 (21.17)***
ϕ_4	1.1014 (21.67)***	−0.2540 (−7.28)***	−0.1858 (−8.21)***	−0.7744 (−13.81)***	1.0664 (17.84)***	0.6088 (7.73)***
ϕ_5	0.0072 (1.23)	0.0112 (2.85)***	0.1006 (3.40)***	0.0055 (3.59)***	−0.0734 (−10.28)***	−0.0279 (−2.10)**
ϕ_6	−0.0849 (−32.89)***	0.0043 (2.70)***	−0.0100 (−11.70)***	0.0169 (6.86)***	−0.0779 (−29.54)***	−0.0832 (−20.91)***
ϕ_7	0.00008 (33.56)***	−0.000009 (−1.48)	0.0002 (20.69)***	−0.0001 (−21.69)***	−0.00009 (−22.67)***	−0.0001 (−5.93)***
ϕ_8	0.7692 (39.50)***	0.7919 (57.59)***	0.8003 (60.66)***	0.7678 (40.91)***	0.8003 (58.53)***	0.7833 (52.12)***
$\bar{R}^2$	0.6411	0.7095	0.7753	0.6819	0.8702	0.6139

The estimated equation is given as follows: $\hat{\hat{\rho}}^*_{SB,t} = \varphi_0 + \varphi_1\hat{\sigma}^2_{S,t} + \varphi_2\hat{\sigma}^2_{B,t} + \varphi_3 VIX_t + \varphi_4 DEFT_t + \varphi_5 TED_t + \varphi_6(VIX_t \cdot DEFT_t) + \varphi_7(TOTM_t) + \varphi_8\varepsilon_{t-1} + \varepsilon_t$. where $\hat{\hat{\rho}}^*_{SB,t}$is a residual series of correlation coefficients between stock returns and bond returns derived from the logistic smooth transition regression (LSTR) model and then taking a Fisher transformation; $\hat{\sigma}^2_{s,t}$is the conditional variance of a national stock index return; $\hat{\sigma}^2_{B,t}$ is the conditional variance of a national 10-year government bond index return; both are based on an asymmetric GARCH(1,1) model. The markets include CA, FR, GM, IT, UK, and US. The *VIX* is the CBOE implied volatility index; the DEFT is the default risk spread = Moody (Baa–Aaa); the *TED* = (the 3-month London interbank offered rate (LIBOR) − the 3-month T-bill interest rate); the *TOTM* is the total market stock price index for each market. $\bar{R}^2$ is the adjusted R^2. The numbers in parentheses are values of z-statistics. ***, **, and * denote statistical significance at the 1, 5, and 10 % levels, respectively

Finally, the sign of ϕ_7 is positive and highly significant despite the small magnitudes of the estimated coefficients. This finding confirms that the wealth effect, as shown in a higher current level of a stock index, tends to drive both stock and bond prices in the same direction. This effect holds true for all the countries under investigation.[36,37]

[36] We also estimate the regression model that replaces the *VIX* index with the *VDAX* index. Evidence form Äijö (2008) shows that a large proportion of the forecast variance of the *SMI* (Swiss market index) and the STOXX (Euro STOXX 50 index) can be explained by the *DAX*. The *VDAX* can be viewed as a proxy for the *VSTOXX*, European volatility. Our test indicates (not reported) that all of the statistics using the *VDAX* produce very similar results in terms of signs and significance levels. This is not surprising, since we find that the correlation between the *VIX* and the *VDAX* for the sample period is as high as 0.87.

[37] We re-estimate the regression model by employing weekly data. The evidence shows that both daily and weekly data produce very comparable statistical outcomes. The estimates of variables, in general, maintain similar qualitative results as we check the sign, significance level, and explanatory power. To save space, we do not report the results. However, the table is available upon request.

Table 8 Estimates of stock–bond return correlations regressed on financial market uncertainty: 1/02/1999–9/06/2008 (daily data)

	Dependent variables					
	$\hat{\hat{\rho}}^*_{SB,CA}$	$\hat{\hat{\rho}}^*_{SB,FR}$	$\hat{\hat{\rho}}^*_{SB,GM}$	$\hat{\hat{\rho}}^*_{SB,IT}$	$\hat{\hat{\rho}}^*_{SB,UK}$	$\hat{\hat{\rho}}^*_{SB,US}$
ϕ_0	0.5977 (23.33)***	0.3747 (13.72)***	0.7185 (29.43)***	0.0955 (3.49)***	0.3011 (9.56)***	0.3033 (8.15)***
ϕ_1	−0.0305 (−14.22)***	−0.0076 (−4.91)***	−0.0072 (−4.61)***	−0.0088 (−5.24)***	−0.0387 (−17.39)***	−0.0399 (−15.06)***
ϕ_2	−0.1211 (−3.48)***	0.4024 (13.05)***	0.0829 (2.50)**	0.0029 (1.04)	1.1427 (31.94)***	−0.3905 (−12.96)***
ϕ_3	−0.01633 (−15.43)***	−0.0162 (−13.25)***	−0.0133 (−11.97)***	−0.0057 (−4.95)***	−0.0079 (−5.91)***	−0.0008 (−0.60)
ϕ_4	−0.5980 (−24.16)***	−0.3103 (−11.18)***	−0.5686 (−21.29)***	−0.3007 (−10.67)***	−0.7699 (−24.12)***	−0.4893 (−16.02)***
ϕ_5	−0.0301 (−4.03)***	0.2664 (29.66)***	0.0308 (0.21)	0.0066 (0.57)	−0.1864 (−17.22)***	−0.1216 (−12.82)**
ϕ_6	0.0089 (8.7104)***	0.0025 (1.96)**	0.0005 (0.42)	−0.0006 (−0.44)	0.0070 (5.03)***	−0.00005 (−0.43)
ϕ_7	0.0001 (17.70)***	0.0001 (21.36)***	0.0001 (11.69)***	0.0001 (29.24)***	0.0005 (15.37)***	0.0002 (9.88)***
ϕ_8	0.7709 (44.29)***	0.9138 (492.81)***	0.7559 (48.34)***	0.7661 (33.49)***	0.7821 (53.49)***	0.7860 (57.43)***
$\bar{R}^2$	0.8053	0.8511	0.8788	0.7979	0.8492	0.6139

The estimated equation is given as follows: $\hat{\hat{\rho}}^*_{SB,t} = \varphi_0 + \varphi_1\hat{\sigma}^2_{S,t} + \varphi_2\hat{\sigma}^2_{B,t} + \varphi_3 VIX_t + \varphi_4 DEFT_t + \varphi_5 TED_t + \varphi_6(VIX_t \cdot DEFT_t) + \varphi_7(TOTM_t) + \varphi_8\varepsilon_{t-1} + \varepsilon_t$. where $\hat{\hat{\rho}}^*_{SB,t}$ is a residual series of correlation coefficients between stock returns and bond returns derived from the logistic smooth transition regression (LSTR) model and then taking a Fisher transformation; $\hat{\sigma}^2_{s,t}$ is the conditional variance of a national stock index return; $\hat{\sigma}^2_{B,t}$ is the conditional variance of a national 10-year government bond index return; both are based on an asymmetric GARCH(1,1) model. The markets include CA, FR, GM, IT, UK, and US. The *VIX* is the CBOE implied volatility index; the DEFT is the default risk spread = Moody (Baa–Aaa); the *TED* = (the 3-month London interbank offered rate (LIBOR) − the 3-month T-bill interest rate); the *TOTM* is the total market stock price index for each market. $\bar{R}^2$ is the adjusted R^2. The numbers in parentheses are values of z-statistics. ***, **, and * denote statistical significance at the 1, 5, and 10 % levels, respectively

7 Estimations based on sub-periods

Empirical evidence based on long-term data is useful, since it provides an average long-term, and stable parametric relationship for a test equation. However, from a time series perspective, using long-term data tends to stretch out weights over the entire period, which helps to smooth out the variations in the series. As a result, the impact of the short-run market phenomenon may be moderate. To highlight the characteristics of the behavioral reaction associated with a shorter time horizon, in this section we further investigate the model based on three sub-periods: January 2, 1992–December 31, 1998, January 2, 1999–September 6, 2008, and September 7, 2008–April 20, 2011. The sub-sample selections are based on market conditions present in each period. Specifically, the first period covers a time during which both stock and bond returns were rising and positively correlated; in the second period, the market underwent a substantial stock-return reversal and the stock–bond correlation shifted from a negative to a positive regime; the last period covers the time during which the U.S. experienced credit/liquidity crises, which were followed by the European sovereign debt crisis.

Table 9 Estimates of stock–bond return correlations regressed on financial market uncertainty: 9/07/2008–4/20/2011 (daily data)

	Dependent variables					
	$\hat{\hat{\rho}}^*_{SB,CA}$	$\hat{\hat{\rho}}^*_{SB,FR}$	$\hat{\hat{\rho}}^*_{SB,GM}$	$\hat{\hat{\rho}}^*_{SB,IT}$	$\hat{\hat{\rho}}^*_{SB,UK}$	$\hat{\hat{\rho}}^*_{SB,US}$
ϕ_0	−0.4080 (−6.76)***	−0.1869 (−4.44)***	−0.6166 (−14.41)***	0.5736 (13.36)***	−0.2323 (−4.21)***	−0.6396 (−5.81)***
ϕ_1	−0.0093 (−11.85)***	−0.0136 (−11.63)***	−0.0187 (−21.22)***	−0.0154 (−17.11)***	−0.0082 (−7.22)***	−0.0188 (−9.34)***
ϕ_2	0.5639 (9.62)***	0.2795 (3.60)***	0.1162 (2.25)**	0.8153 (14.20)***	0.2129 (9.54)***	0.4002 (13.87)***
ϕ_3	−0.0018 (−1.82)*	−0.0019 (−3.20)***	−0.0054 (−6.17)***	−0.0094 (−11.11)***	−0.0044 (−4.87)***	−0.0065 (−3.41)***
ϕ_4	0.0397 (2.49)***	0.0054 (0.61)	0.0567 (5.14)***	−0.1457 (−13.90)***	−0.0730 (−6.31)***	0.0473 (1.71)*
ϕ_5	−0.0799 (−12.66)***	−0.0563 (−5.59)***	−0.4220 (−5.71)***	−0.0578 (−8.14)***	−0.0154 (−1.26)	−0.0554 (−4.38)***
ϕ_6	0.0003 (0.78)	0.0007 (3.43)***	0.002 (6.52)***	0.0024 (7.97)***	0.0017 (6.22)***	0.0019 (2.896)***
ϕ_7	0.00002 (7.09)***	0.00009 (5.00)***	0.0002 (7.31)***	−0.0002 (−12.26)***	0.000005 (0.510)	0.0002 (3. 30)***
ϕ_8	0.7488 (24.81)***	0.7497 (21.39)***	0.7224 (25.94)***	0.7020 (14.57)***	0.7599 (25.58)***	0.7421 (22.69)***
$\bar{R}^2$	0.7520	0.7291	0.7618	0.8269	0.7336	0.7149

The estimated equation is given as follows: $\hat{\hat{\rho}}^*_{SB,t} = \varphi_0 + \varphi_1\hat{\sigma}^2_{S,t} + \varphi_2\hat{\sigma}^2_{B,t} + \varphi_3 VIX_t + \varphi_4 DEFT_t + \varphi_5 TED_t + \varphi_6(VIX_t \cdot DEFT_t) + \varphi_7(TOTM_t) + \varphi_8\varepsilon_{t-1} + \varepsilon_t$. where $\hat{\hat{\rho}}^*_{SB,t}$ is a residual series of correlation coefficients between stock returns and bond returns derived from the logistic smooth transition regression (LSTR) mode and then taking a Fisher transformation l; $\hat{\sigma}^2_{s,t}$is the conditional variance of a national stock index return; $\hat{\sigma}^2_{B,t}$ is the conditional variance of a national 10-year government bond index return; both are based on an asymmetric GARCH(1,1) model. The markets include CA, FR, GM, IT, UK, and US. The *VIX* is the CBOE implied volatility index used as an external influence on volatility in the stock markets of Canada, France, Germany, Italy, and the UK; the DEFT is the default risk spread = Moody (Baa–Aaa); the *TED* = (the 3-month London interbank offered rate (LIBOR) − the 3-month T-bill interest rate); the *TOTM* is the total market stock price index for each market. $\bar{R}^2$ is the adjusted R^2. The numbers in parentheses are values of z-statistics. ***, **, and * denote statistical significance at the 1, 5, and 10 % levels, respectively

Tables 7, 8, 9 report the regression estimates of the model for each period. It is more convenient to compare the estimates of the three sub-period statistics (Tables 7, 8, 9) with those we derived from the full sample case (Table 6). Consistent with previous findings, the estimated coefficients of the $\sigma^2_{s,t}$ and the $\sigma^2_{B,t}$ consistently show the expected sign with high statistical significance. That is, a rise of uncertainty in the stock market tends to move stock–bond correlations in opposite directions; high uncertainty in the bond market moves stock–bond correlations in the same direction. With some minor exceptions (Italy in period one, the U.S. and Canada in period two), these statistical results hold true for all of the countries under investigation.[38]

[38] An exception in the stock market is the estimated coefficient of $\sigma^2_{s,t}$ for Italy, which exhibits a positive sign in the first period. A negative sign is found in the bond market in the second period for the U.S. and Canada. During this period (1/02/1999–9/06/2008), the *VIX* was relatively low and so were interest rates. The volatility of the bond market appears to play a significant role in explaining the stock–bond correlations.

For the *VIX* variable, we find that the sign of ϕ_3 during the period January 2, 1992–December 31, 1998 is positive and statistically significant for Canada, German, the U.K., and the U.S. This may be attributable to the fact that the perceived risk implied by the *VIX* was curbed, since rising asset prices tend to be driven by market sentiments in the boom period.[39] However, as we examine ϕ_3 in the following two periods, the sign consistently turns negative for all of the countries, reflecting the fear of holding stocks as the *VIX* rises.

We now turn to the external force of bond market variables, ϕ_4, which consistently shows a negative sign during the second period. However, the sign turns positive in the Canadian, U.K., German, and U.S. markets in the crisis periods. This suggests that short-run market behavior is sensitive to ongoing market conditions or shocks that frequently deviate from the long-run relationship.

A most important result is the evidence of ϕ_5 in Table 9, which consistently shows a negative sign in the period of liquidity shortfalls and low confidence in credit markets. This outcome is not surprising, since, during this period, especially in the second half of 2008, world financial institutions suffered from a severe credit crunch, and the global demand for liquidity widened the spreads in the *TED,* reflecting the short-run liquidity crisis. The evidence of the negative effect on the stock–bond relation reveals a "fight-to-liquidity" phenomenon: the higher *TED* spread trigged by a short-run liquidity crisis moves stock and bond prices in opposite directions. In sum, consistent with the findings in Gulko (2002), the international data suggest that stocks and bonds tend to decouple during periods of financial crisis, while the relationship between stocks and bonds is positive when economic conditions are perceived to be optimistic.

8 Conclusion

This paper examines the impact of financial market uncertainty on the correlation between stock returns and bond returns. Analyzing the financial data of six advanced markets for the period 1992–2011, we derive several important empirical conclusions. First, empirical estimations based on an asymmetric dynamic correlation coefficient model (ADCC) indicate that stock–bond correlations are time-varying and the conditional correlations display structural changes over time. The statistics demonstrate that in the period with good economic prospects, stock–bond correlations show a positive relationship, while in crisis periods, the correlations turn negative. Interestingly, the time-varying stock–bond correlation coefficients are highly correlated across different countries.

Second, evidence confirms that the stock–bond relationship is negatively correlated with stock market uncertainty as measured by the conditional variance and/or the implied volatility (*VIX*), since a rise in uncertainty creates fear, leading to a "flight-to-safety." Our study shows that, in the long run, this variable maintains a stable and consistently significant impact on movements in stock–bond correlations. However, during the boom period, the sign on the *VIX* for some countries is positive because market sentiment is overwhelmingly dominated by the momentum of speculative profits.

Third, although both conditional variance and implied volatility are commonly used to proxy for market uncertainty, our study shows that both variables have their respective information content in explaining the stock–bond comovement. The conditional variance derives its informational content by extrapolating from time series regularity and represents domestic market volatility, while the implied volatility abstracts from options pricing

[39] This period coincides with the high-tech bubble.

and represents the expected market volatility from an external influence.[40] Both sets of variables, to some extent, reflect different market information and complementarily contribute to explaining movements in stock and bond return correlations.

Fourth, our findings suggest that estimated coefficients of the conditional variances of bond returns are positive and highly significant for all of the markets, indicating that the uncertainty in the bond market drives stock and bond returns in the same direction. The spillover of uncertainty in the bond market to the stock market is different from the uncertainty that originates in the stock market, since investors in the former case do not necessarily move funds from the bond market to the stock market. Instead, a rise in bond market uncertainty will immediately be reflected in the bond market's risk premium, which, in turn, dampens stock prices. Consequently, the risk premium effects on both the stock and the bond markets drive stock–bond returns in the same direction.

Fifth, this study finds evidence that stock–bond correlations are negatively correlated with default risk in the long run and the *TED* spread in the crisis period. An increase in these spreads tends to signify deterioration in financial markets, causing stock prices to fall. This empirical finding is consistent with a "flight to quality": higher default/credit risk leads investors to increase the demand for high-quality investment instruments in their portfolios. A systematic negative relationship between the *TED* and stock–bond return correlations across different markets is exhibited during the credit crunch period.

Sixth, in addition to the linear component of the uncertainty measures of stock and bond markets, our findings suggest that the inclusion of the interactive term of nonlinear components is statistically significant. This is consistent with the market phenomenon that investors' reaction to stock market uncertainty is also influenced by uncertainty in the bond market.

In conclusion, this paper provides significant empirical evidence to support the impact of financial uncertainty on stock–bond correlations. In addition to the bond return variance, we find significant evidence in favor of the uncoupling of the stock–bond relationship as bond spreads increase or as financial uncertainty rises in the stock market. This is consistent with the flight-to-quality hypothesis (Gulko 2002; Connolly et al. 2005; Andersson et al. 2008).

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[40] It is referred to as the *VIX* variable in markets outside the U.S. and the *VDAX* in the U.S. market.

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