Decreasing Trends in Stock-Bond Correlations

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Abstract

Previous research documents the existence of long-run trends in comovements among the stock, bond, and commodities markets. Following these findings, this paper examines possible trends in stock-bond return correlations. To this end, we introduce a trend component into a smooth transition regression (STR) model including the multiple transition variables of Aslanidis and Christiansen (2012). The results indicate the existence of significant decreasing trends in stock-bond correlations. In addition, although stock market volatility continues to be an important factor in stock-bond correlations, the short rate and yield spread become only marginally significant once we introduce the trend component. Our out-of-sample analysis also demonstrates that the STR model including the VIX and time trend as the transition variables dominates other models. Our finding of decreasing trends in stock-bond correlations can be considered a consequence of the decreasing effects of diversification and more intensive flight-to-quality behavior that have taken place in recent years.

JEL classification: C22, G15, G17

Key Words: flight-to-quality; diversification effect; smooth transition regressions

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1 Introduction

Understanding time variations in stock-bond return correlations is one of the most important issues in finance because it has profound implications for asset allocation and risk management. Naturally, a number of studies examine the dynamics of stock-bond correlations and identify the economic factors driving their time series behavior. For instance, Li (2002) conducts a regression analysis to investigate the relationship between stock-bond correlations and macroeconomic variables, showing that unexpected inflation is the most important determinant of stock-bond correlations. Similarly, Ilmanen (2003) argues that stock-bond correlations are more likely to be negative when inflation is low and stock market volatility is high. Yang, Zhou, and Wang (2009) examine stock-bond correlations over the past 150 years using the smooth transition conditional correlation (STCC) model and find that higher stock-bond correlations tend to follow higher short rates and (to a lesser extent) higher inflation rates. In addition, Connolly, Stivers, and Sun (2005, 2007) identify the VIX stock market volatility index as an important determinant of stock-bond correlations. Furthermore, Aslanidis and Christiansen (2010, 2012) demonstrate that stock-bond correlations are explained mostly by short rates, yield spreads, and the VIX. On the other hand, Pastor and Stambaugh (2003) note that changes in stock-bond correlations depend on liquidity. Similarly, Baele, Bekaert, and Inghelbrecht (2010) find that macroeconomic fundamentals contribute little to explaining stock-bond correlations but that liquidity plays a more important role. Other related studies include Guidolin and Timmermann (2006); Bansal, Connolly, and Stivers (2010); and Viceira (2012).

A number of recent studies also investigate long-run trends in international financial markets. For instance, Christoffersen et al. (2012) examine copula correlations in international stock markets and find a significant increasing trend that can be explained by neither volatility nor other financial and macroeconomic variables. Similarly, Berben and Jansen (2005) and Okimoto (2011) report increasing dependence in major equity markets. In international bond markets, Kumar and Okimoto (2011) find an increasing trend in correlations among international long-term government bonds and a decreasing trend in correlations between short- and long-term government bonds within single countries. Existing trends in comovements are also documented in commodities markets. For example, Tang and Xiong (2012) show that the prices of non-energy commodity futures in the US have become increasingly correlated with oil prices. In addition, Ohashi and Okimoto (2013) find increasing trends in the excess comovements of commodities prices. Other related studies include Longin and Solnik (1995), Silvennoinen and Teräsvirta (2009), and Silvennoinen and Thorp (2013).

The main contribution of this paper is to provide new evidence of long-run decreasing trends in
stock-bond correlations by extending the smooth transition regression (STR) model of Aslanidis and Christiansen (2012). Although a growing number of studies exploring long-run trends in international financial markets suggest that it is of interest to analyze possible trends in stock-bond correlations, none of the previously mentioned studies consider these types of trends. Thus, it is very instructive to investigate long-run trends in stock-bond correlations. Indeed, our results indicate that there is a significant decreasing trend in realized stock-bond correlations. More importantly, although stock market volatility continues to be an important factor for stock-bond correlations, other important financial variables, namely the short rates and spreads between long- and short-term interest rates, become only marginally significant once we introduce the decreasing trend. Our out-of-sample analysis also indicates that the STR model including the VIX and time trend as the transition variables dominates other models. Our finding of a decreasing trend in stock-bond correlations can be considered a consequence of the decreasing effects of diversification and more intensive flight-to-quality behavior that have taken place in recent years.

The remainder of the paper is organized as follows: Section 2 presents the model, while Section 3 conducts the empirical analysis and Section 4 provides the conclusion.

2 Smooth Transition Regression Model

The main purpose of this paper is to examine possible long-run trends in realized stock-bond return correlations. To this end, we employ the smooth-transition model that was developed by Teräsvirta (1994) in the AR model framework and later used to analyze the determinants of stock-bond correlations by, among others, Yang, Zhou, and Wang (2009) and Aslanidis and Christiansen (2012). The former authors model correlations as latent variables and analyze them using the STCC model, whereas the latter authors investigate the realized correlation based on the smooth transition regression (STR) model with multiple transition variables. We employ the latter approach in this paper because it considerably facilitates the examination of the determinants of the time series behavior of stock-bond correlations, as emphasized by Aslanidis and Christiansen (2012). In addition, many other studies, including Ilmanen (2003) and Connolly et al. (2005, 2007), examine realized correlations. In particular, we apply the STR model with multiple transition variables to the realized correlations, following Aslanidis and Christiansen (2012).

The STR model used by Aslanidis and Christiansen (2012) is given by

\[ FRC_t = \rho_1 \{1 - F(s_{t-1})\} + \rho_2 F(s_{t-1}) + \epsilon_t \]  

where \( FRC_t \) is the Fisher transformation of the realized correlation, \( RC_t \), namely

\[ FRC_t = \frac{1}{2} \log \left( \frac{1 + RC_t}{1 - RC_t} \right), \]
converting the realized correlation into a continuous variable not bounded between $-1$ and $1$.\(^1\) $F(s_{t-1})$ in (1) is the logistic transition function, taking values between 0 and 1. If $F(s_{t-1}) = 0$, the average value of $FRC$ would be $\rho_1$ and if $F(s_{t-1}) = 1$, the average value of $FRC$ would be $\rho_2$. In this sense, $\rho_1$ and $\rho_2$ in (1) can be considered the average correlations in regimes 1 and 2, respectively.\(^2\) Thus, the conditional mean of $FRC_t$ is modeled as the weighted average of the two correlation extremes; the weight is decided by $F(s_{t-1})$. $s_{t-1} = (s_{1,t-1} s_{2,t-1} \cdots s_{K,t-1})'$ is a $K \times 1$ vector of transition variables,\(^3\) governing the transition between regimes 1 and 2. Specifically, $F(s_{t-1})$ is expressed as

$$F(s_{t-1}) = \frac{1}{1 + \exp[-\gamma'(s_{t-1} - c)]} = \frac{1}{1 + \exp[-\gamma_1(s_{1,t-1} - c) + \cdots - \gamma_K(s_{K,t-1} - c)]}, \quad (3)$$

where $\gamma_k$ is assumed to be positive for at least one $k$ to identify the STR model with multiple transition variables. The location parameter $c$ decides the center of the transition, while the smoothness parameter vector $\gamma = (\gamma_1, \gamma_2, \ldots, \gamma_K)'$ specifies the speed of the transition. More precisely, the transition caused by the transition variable $s_{k,t-1}$ is abrupt for large values of $\gamma_k$ and gradual for small values of $\gamma_k$. One of the main advantages of the STR model is that it can detect detect, from the data, when and how any transitions occur in stock-bond correlations. In addition, the STR model can describe a wide variety of change patterns, depending on the parameters $c$ and $\gamma$, which can be estimated from the data. Thus, by estimating the STR model, we can estimate the best transition patterns in stock-bond correlations.

In contrast to Aslanidis and Christiansen (2012), we use time trends as one of the transition variables to capture long-run trends in stock-bond correlations, following Lin and Teräsvirta (1994). In this framework, the time-varying correlation $FRC_t$ changes smoothly from $\rho_1$ to $\rho_2$ with time, assuming that $\gamma_k$ for the time trend is positive. Thus, we can interpret $\rho_1$ as a correlation around the beginning of the sample and $\rho_2$ as correlation around the end of the sample. A similar model is applied to conditional correlations by, among others, Berben and Jansen (2005) and Kumar and Okimoto (2011), who examine trends in stock and bond markets, respectively. This paper differs from these studies by investigating possible trends in stock-bond return correlations.

One concern about STR model (1) is possible serial correlation in $FRC_t$. Aslanidis and Chris-
tiansen (2012) address the serial correlation of the error term by calculating the Newey-West standard errors. However, if $FRC_t$ itself has a serial correlation, this results in the inconsistent estimates of the correlation parameters. Indeed, a number of studies based on the dynamic conditional correlation (DCC) model of Engle (2002) suggest that the conditional correlations among financial returns are typically highly serially correlated. To address possible serial correlations in $FRC_t$, we modify STR model (1) by including the AR(1) term as follows:

$$FRC_t = \rho_1 \{1 - F(s_{t-1})\} + \rho_2 F(s_{t-1}) + \phi FRC_{t-1} + \varepsilon_t. \quad (4)$$

In this STR model, $FRC_t$ can be expressed as the weighted sum of the correlations expected by the economic variables and the previous correlation level. Theoretically, this model is also relevant because economic conditions may not be reflected immediately due, in part, to slow reactions by and imperfect information available to market participants. Therefore, the correlation may be adjusted slowly from the previous level, as in STR model (4).

We estimate STR model (4) using the maximum likelihood estimation (MLE) method, assuming that $\varepsilon_t$ follows independently and is identically normally distributed. If the normal distribution assumption is inappropriate, the estimation can be considered to follow the nonlinear least squares method.

## 3 Empirical Analysis

### 3.1 Data

Our empirical analysis is based on monthly data, with the sample period lasting from January 1991 to May 2012. All data used in the analysis are obtained from DataStream. The analyzed countries are the United States (US), Germany (GER), and the United Kingdom (UK). Initially, we obtain daily data on futures contracts in the stock and bond markets of these three countries. Using the daily data, we obtain the realized stock-bond return correlations in each country for each month. We use futures on the S&P 500 (US), DAX (GER), and FTSE (UK) stock indices to calculate stock returns and each country’s ten-year bond futures to calculate bond returns.

We also obtain the VIX, short rate, and yield spread as transition variables, following Aslanidis and Christiansen (2012), who demonstrate that these three variables are the most important transition variables for determining stock-bond correlation regimes. These three variables are also documented as important determinants of stock-bond correlations by many previous studies. For instance, Aslanidis and Christiansen (2010) find that these three variables are by far the most critical predictors of stock-bond correlations at their low and high quantiles. In addition, Connolly,
Stivers, and Sun (2005, 2007) identify the VIX stock market volatility index a factor that influences stock-bond correlations, while Baele, Bekaert, and Inghelbrecht (2010) use the short rate as an important explanatory variable for stock-bond correlations. Furthermore, Viceira (2012) finds that short rates and yield spreads are the two most important predictors of the realized bond CAPM beta and the bond C-CAPM beta.

The VIX ($VIX$) is the volatility index for the Chicago Board of Options Exchange (CBOE) and is based on the volatility of options on the S&P 500 index. We use the US VIX for all countries due to the limited availability of VIX data for the two other examined countries. The short rate ($R$) is the three-month Treasury bill rate from the secondary market for the US and the three-month LIBOR rate for Germany and UK, while the yield spread ($SPR$) is defined as the ten-year constant maturity Treasury bond yield minus the short-rate for each country.

### 3.2 Benchmark Model Results

Our benchmark model is Aslanidis and Christiansen’s (2012) preferred model, namely STR model (4), with $s_{t-1} = (VIX_{t-1}, R_{t-1}, SPR_{t-1})'$. We refer to this model Model 1 and its estimation results are presented in Table 1, in which several items are worth noting. First, the last two rows of the table report the results of a version of Teräsvirta’s (1994) linearity test and Eitrheim and Teräsvirta’s (1996) additive nonlinearity test. As can be seen, the linearity test rejects the null of linearity in favor of the STR alternative at the 1% significance level for all countries. In contrast, the additive nonlinearity test is not significant, meaning that the proposed model adequately captures all smooth transition regime-switching behavior in the data without additional regimes for all countries.

Second, the AR parameters $\phi$ are highly significant, with estimated values of 0.38, 0.34, and 0.25 for the US, GER, and the UK, respectively. In other words, our results indicate that stock-bond correlations change from the previous level toward the correlation level expected by economic variables with some serial correlation, which is not captured by Aslanidis and Christiansen’s (2012) original model.

Third, the correlation parameters for regime 1 are significantly positive, with estimated values of 0.30, 0.38, and 0.44 for the US, GER, and the UK, respectively, while those for regime 2 are significantly negative, with respective values of $-0.32$, $-0.40$, and $-0.36$. In other words, there are two distinct regimes, one with positive average correlations and the other with negative average correlations. Thus, correlations change smoothly or rapidly from positive to negative or negative

\footnote{We confirm that the German and UK VIX indices are highly correlated with the US VIX, with a correlation that is greater than 0.8. We also confirm that we can obtain quantitatively similar results even if we use each country’s VIX data with a shorter sample period.}
Finally, all three transition variables, the VIX, short rate, and yield spread, have statistically significant effects on the regime transition at the 5% significance level for all countries. These results are fairly consistent with those of Aslanidis and Christiansen (2012), who demonstrate that stock-bond correlations are explained mostly by these three variables using STR model (1) without the AR term. These three variables are also reported to be important determinants of stock-bond correlations by other studies. For instance, the VIX is identified as a predominant factor for stock-bond correlations by Connoly et al. (2005, 2007) and Bansal et al. (2010). In addition, Baele et al. (2010) use the short rate as an important explanatory variable for stock-bond correlations, while Yang, Zhou, and Wang (2009) find that higher stock-bond correlations tend to follow higher short rates. Furthermore, Viceira (2012) finds that the yield spread and the short rate are important predictors for the realized bond CAPM beta and bond C-CAPM beta, which can be regarded as a transformation of the stock-bond correlation.

To see more detailed information on the regime transitions for each variable, the transition functions of each variable are plotted in Figure 1, holding the other variables constant at their mean values of zero. As can be seen, there is little difference across countries in terms of short rates and yield spreads and the correlation regime changes rather rapidly from the negative regime to the positive regime as these variables get larger. For instance, if the short rate is lower than the average by one standard deviation, the transition function takes a value greater than 0.97, meaning that the weight of the negative correlation regime is greater than 97%. More specifically, if the short rate is lower than the average value by one standard deviation, the average correlation is less than $-0.30$, $-0.39$, and $-0.35$ for the US, GER, and the UK, respectively. On the other hand, if the short rate is higher than the average value plus one standard deviation, the weight of negative regime becomes less than 0.04, making the average correlation more than 0.28 for all countries. Similarly, if the yield spread is lower (larger) than the average value by one standard deviation, the transition function is greater (less) than 0.90 (0.11), with an average correlation of less than $-0.26$ (greater than 0.18) for all countries. Since larger yield spreads and short rates are usually associated with better macroeconomic conditions, the results indicate that stock-bond correlations tend to be positive when the economy is booming. In other words, when the economy is in recession, stock-bond correlations have a tendency to be negative. This is arguably consistent with flight-to-quality behavior because investors do not want to take many risks when economic conditions are not good.

The VIX transition function also demonstrates flight-to-quality behavior. For the US and GER, the VIX transition function indicates that the correlation regime changes relatively smoothly from
the negative regime to the positive regime as the standardized VIX changes from $-3$ to $3$. The UK VIX transition function indicates slower changes in the correlation regime but still suggests that a higher VIX tends to be associated with negative stock-bond correlations. Thus, the results demonstrate that when the VIX is high or there is much uncertainty in the market, investors try to escape from risks, making stock-bond correlations negative.

Finally, the time series of the estimated correlations for Model 1 together with the actual realized correlations for each country are plotted in Panel (a) of Figures 2-4 to indicate goodness of fit. As can be seen, the estimated correlation fits the actual correlation quite well for all countries. More specifically, Model 1 successfully captures the tendency for there to be positive correlations before 2000 and negative correlations after 2000 because the correlation regimes tend to be identified as the positive regime before 2000 and the negative regime after 2000.

In sum, the results of Model 1 indicate that the VIX, short rate, and yield spread are important determinants of stock-bond correlation regimes for all countries, which is consistent with previous studies such as Aslanidis and Christiansen (2012), who estimated a similar model for the US. In addition, we demonstrate the significance of including the AR(1) to allow for smooth adjustments in correlation regimes, in contrast with Aslanidis and Christiansen (2012). Although the performance of Model 1 is quite satisfactory, it is possible to improve Model 1 by including other variables. In particular, recent studies find long-run correlation trends in international financial markets, suggesting that we can modify Model 1 by introducing a time trend component; this is examined in next subsection.

### 3.3 Introduction of Time Trend Component

The results of Model 1 are fairly consistent with previous studies examining the dynamics of stock-bond correlations. On the other hand, the another previous studies suggest the existence of long-run correlation trends in international financial markets. For instance, Christoffersen et al. (2012) examine copula correlations in international stock markets and find a significant increasing trend in the comovements of international stock returns that can be explained by neither volatility nor other financial and macroeconomic variables. In addition, Kumar and Okimoto (2011) find an increasing trend in correlations between international long-term government bonds and decreasing trends in correlations between the short- and long-term government bonds within single countries. Furthermore, Tang and Xiong (2012) document increasing correlations of commodities returns with crude oil after 2004. It is therefore of interest to analyze possible trends in stock-bond correlations by estimating STR model (4) including time $(T)$ as well the VIX, short-rate, and spread as transition variables (Model 2). Thus, the vector of transition variables for Model 2 is
defined as \( s_{t-1} = (VIX_{t-1}, R_{t-1}, SPR_{t-1}, T_t)' \).\(^5\)

Table 2 reports the estimation results for Model 2. As can be seen, the results suggest that the basic structure of Model 2 is reasonably similar to that of Model 1. Specifically, the linearity and additive nonlinearity tests documented in the last two rows of Table 2 show that the two-state STR model is preferred to the linear model without regime changes and the three-state STR model with an additional correlation regime. In addition, Model 2 indicates the existence of two distinct correlation regimes, with a negative average correlation for one regime and a positive average correlation for the other, as in Model 1. Furthermore, the AR term is significant at least at the 10% significance level for the US and GER, suggesting smooth adjustments in stock-bond correlations in these countries.

Although the basic structures of Models 1 and 2 are quite similar, there are important differences in the determinants of their stock-bond correlation regimes. In particular, the estimation results of Model 2 indicate that the time trend component is highly significant for all countries, suggesting that Model 1 omits an important factor of stock-bond correlations. More specifically, the time trend component coefficient estimates are significantly positive for all countries, meaning that there is a decreasing trend in stock-bond correlations. To see this more clearly, we plot the time trend for the correlations estimated through Model 2 in Panel (a) of Figure 5. As can be seen, the stock-bond correlations for all countries have clear decreasing trends, with a rapid decrease between the late 1990s and the early 2000s, reaching an average of \(-0.42\) by the end of sample period in May 2012. Our finding of the existence of a time trend in correlations between financial assets is completely in line with recent studies. For instance, Berben and Jansen (2005) and Christoffersen (2012) document increasing correlations in the major equity markets. Similarly, Kumar and Okimoto (2011) find an increasing trend in correlations between international long-term government bonds and decreasing trends in correlations between a single country’s short- and long-term government bonds.

Another important difference between Models 1 and 2 is the significance of the short rate and yield spread in determining the stock-bond correlation regime. Although the VIX remains an important factor in determining stock-bond correlations, the short rate and yield spread become less important in Model 2. Specifically, neither of these measures are significant for the US, while only one of them is significant for GER and the UK. In addition, the the short rate coefficient for GER is significantly positive instead of negative, making interpretation of the result rather difficult. The results are in contrast with the findings of the previously mentioned studies examining the determinants of stock-bond correlations without a time trend component. Thus, our results

\(^5\)Since \( T \) is a non-random predetermined variable, we use \( T_t \) instead of \( T_{t-1} \) as a transition variable.
demonstrate that some of the important factors suggested by previous studies are not as relevant once we consider possible decreasing trends in stock-bond correlations.

To compare the goodness of fit of Models 1 and 2, we plot the time series of the correlations estimated through Model 2 together with the actual realized correlations for each country in Panel (b) of Figures 2-4. As can be seen, the correlations estimated through Models 1 and 2 are similar to each other and do not differ much over the sample. Thus, they qualitatively have the same power in illustrating the time series behavior of stock-bond correlations.

We can compare the goodness of fit of Models 1 and 2 more formally using the information criteria reported in Table 3, namely the Schwartz information criterion (SIC) and Akaike information criterion (AIC). Although the AIC favors Model 2 for GER and the UK, the SIC prefers Model 1 to Model 2 for all countries. Thus, in terms of the in-sample fit, our results are somewhat inconclusive.

To make a more comprehensive comparison between Models 1 and 2, we conduct an out-of-sample forecast evaluation as follows. First, we estimate both Models 1 and 2 using data from February 1991 to January 2001 and evaluate the terminal one-month-ahead forecast error based on the estimation results. The data are then updated by one month, and the terminal one-month-ahead forecast error is re-calculated from the updated sample (specifically, from March 1991 to February 2001). This procedure is repeated until reaching one month before the end of the sample period, namely April 2012. Finally, we calculate the root-mean-squared forecast errors (RMSE) and mean absolute error (MAE) using the obtained time series of one-month-ahead forecast errors. The third and fourth rows of Table 4 report the RMSE and MAE values for Models 1 and 2. As can be seen, the RMSE and MAE values of Model 2 are smaller than those of Model 1 for GER, while Model 1 exhibits better out-of-sample performance than Model 2 for other two countries.

Overall, our model comparison results show that Model 2 is not necessarily a better model than Model 1, although the time trend component is highly significant. One possible explanation for this result is the weak significance of the short rate and yield spread in Model 2, as mentioned. Indeed, neither of these factors are significant for US, while only one of them is significant for GER and UK. Thus, we might be able to improve the model by excluding these variables. To examine this possibility, we will consider a more parsimonious model in next subsection.

3.4 Results with Selected Transition Variables

Our results for Model 2 indicate that the short rate and yield spread become less important determinants of stock-bond correlations if decreasing trends in stock-bond correlations are taken into consideration. To illustrate this point more clearly, we estimate a more parsimonious STR
model (4) that includes only VIX and time as the transition variables (Model 3).

The estimation results for Model 3 are shown in Table 3. As can be seen, the estimation results are essentially same as those of Model 2. The two-state STR model with a negative average correlation for one regime and a positive average correlation for the other regime is preferred to the linear model without regime changes and the three-state STR model. In addition, the AR term is highly significant for the US and GER, suggesting that the stock-bond correlations of these countries change slowly from the previous level toward the correlation level expected by economic variables. Furthermore, the VIX is significantly positive for all countries. Thus, the correlation regime changes from a positive to a negative regime when the VIX is high. Finally, the estimated time trend component is also significantly positive for all countries, meaning that stock-bond correlations tend to be in the negative regime in more recent periods. The decreasing trend can be confirmed visually from the estimated time trend component of stock-bond correlation depicted in Panel (b) of Figure 5. As can be seen from the figure, stock-bond correlations in all countries exhibit clear decreasing trends, with a rapid decrease from an average correlation of over 0.2 in the beginning of 1999 to an average correlation lower than $-0.2$ at the end of 2003, reaching an average of $-0.42$ around the end of the sample period in May 2012.

We also plot the time series of the estimated correlation for Model 3 together with the actual realized correlation for each country in Panel (c) of Figures 2-4 to graphically illustrate the performance of Model 3. As can be seen, the estimated correlations of Model 3 are quite similar to those of other models and do not differ much over the sample, suggesting that all models have the same qualitative explanatory power over stock-bond correlation behavior. Given that Model 3 has only two transition variables, this arguably indicates the superiority of Model 3 over the other two models. We can confirm this point more formally using the SIC and AIC reported in Table 3. As can be seen, Model 3 has the smallest SIC and AIC values for all countries, meaning that Model 3 is the best among the three models in terms of in-sample fit.

We additionally compare the out-of-sample performance of Model 3 and the other two models by conducting the same out-of-sample forecast evaluation as before. The results reported in Table 4 indicate that Model 3 exhibits the best out-of-sample performance for all countries, regardless of the employed performance measure.

In sum, our results are clear: Model 3 is the best among the three models, meaning that transitions between correlation regimes can be described sufficiently well by the VIX and time trend components. In other words, we demonstrate the possibility that the short rate and yield spread are not important factors in relation to stock-bond correlation regimes, in great contrast to previous studies such as Aslanidis and Christiansen (2012). Thus, flight-to-quality behavior is
not strongly related with economic conditions, measured by short rates and yield spreads, but is associated with market uncertainty, as captured by the VIX. In addition, flight-to-quality behavior has become stronger in more recent years, resulting in decreasing trends in stock-bond correlations.

A possible explanation for this trend in flight-to-quality behavior is the recent increasing trend in correlations in international equity markets, which is documented by Christoffersen, et al. (2012), among others. Specifically, they emphasize that benefits from international diversification have decreased over time and this decrease has been especially drastic among developed markets, such as those examined in this study. In addition, Berben and Jansen (2005) show that correlations among the GER, UK, and US stock markets have doubled between 1980 and 2000. Similarly, Silvennoinen and Teräsvirta (2009) show that stock returns within and across European and Asian markets exhibit a clear upward shift in the level of correlations between 1998 and 2003, which corresponds to the timing of the rapid decrease in the estimated time trend of stock-bond correlations from our models. Thus, benefits from international diversification seem to begin disappearing after 2000. In this case, the investors who allocated their money into the equity markets of those countries have been exposed to higher risks of simultaneous drops in stock prices in recent years. As a consequence, they have more recently needed to make greater use of bond markets to control their risk exposure, producing the decreasing trend in stock-bond correlations. Indeed, the beginning of the integration of international equity markets and the beginning of decreases in stock-bond correlations appear to occur around the same time.

In addition to integration in equity markets, increasing correlations are observed in other markets as well. For instance, Kumar and Okimoto (2011) show that long-term government bond markets have become more integrated since the late 1990s, while Silvennoinen and Thorp (2013) find that correlations among stock, bond, and commodity future returns greatly increased around the early 2000s. Similarly, Tang and Xiong (2012) document increasing correlations of non-energy commodity with crude oil after 2004. These phenomena further diminish the effects of diversification in international financial markets, making investors diversify risks through bond markets. This phenomenon induces a rebalancing, particularly with from stocks to bonds.

Fleming, Kirby, and Ostdiek (1998) and Kodres and Pritsker (2002) study how cross-market hedging theoretically influences asset pricing. Specifically, Fleming, Kirby, and Ostdiek (1998) demonstrate that information linkages in stock and bond markets may be greater if cross-market hedging effects are considered within daily returns. In addition, Kodres and Pritsker (2002) show that a shock in one asset market may generate cross-market rebalancing, which influences prices in non-shocked asset markets. Since the disappearance of diversification effects produces investment behavior involving rebalancing from stocks to bonds, correlations between stocks and bonds tend
to be negative, which can be captured by a trend variable, as indicated by our results.

4 Conclusion

In this paper, we investigated the existence of long-run trends in realized stock-bond return correlations. To this end, we introduce a trend component into the smooth transition regression (STR) model with the multiple transition variables of Aslanidis and Christiansen (2012). In addition, we analyzed not only the US, but also Germany and the UK, to conduct a more comprehensive examination. The results indicated the existence of a significant decreasing trend in stock-bond correlations for all countries.

Since a number of studies based on the dynamic conditional correlation (DCC) model of Engle (2002) suggest that conditional correlations between financial returns are typically highly serially correlated, we extended the STR model of Aslanidis and Christiansen (2012) by including the AR(1) term. The AR parameter estimates are highly significant for all countries. Thus, our results demonstrated that stock-bond correlations change slowly from the previous level toward the correlation level expected by economic variables, which is not captured by the original model of Aslanidis and Christiansen (2012).

In the case of transition variables, we examined three variables, namely the VIX, short rate, and yield spread, which have been identified by previous studies as arguably three of the most important factors. All three transition variables have statistically significant effects on regime transitions for all countries in our extended model. The results are fairly consistent with those of previous studies, particularly Aslanidis and Christiansen (2012). However, once we introduce the trend component, although the VIX remains an important factor for stock-bond correlations, the short rate and yield spread become only marginally significant. Indeed, our in-sample analysis suggested that the STR model including the VIX and time trend as the transition variables is the best model based on the SIC and AIC, meaning that the transition of stock-bond correlation regimes can be described sufficiently well by the VIX and time trend components. In addition, our out-of-sample analysis also demonstrated that the STR model with the VIX and time trend as the transition variables dominates other models.

Previous studies document the existence of long-run trends in comovements in the stock, bond, and commodities markets, suggesting that benefits from international diversification have recently been disappearing. Therefore, investors have been exposed to higher risks of simultaneous drops in stock prices in recent years. As a consequence, they have needed to make greater use of bond markets to control their risk exposure, producing the decreasing trend in stock-bond correlations. Interestingly, the beginning of the integration of international equity markets suggested by several
previous studies and the beginning of decreases in stock-bond correlations appear to occur around the same time. Thus, our finding of a decreasing trend in stock-bond correlations can be considered a consequence of decreasing diversification effects and more intensive flight-to-quality behavior in recent years.

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Table 1: Estimation results of the benchmark model (Model 1)

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<th></th>
<th>US</th>
<th></th>
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<th></th>
<th>UK</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Coef</td>
<td>St. err</td>
<td>Coef</td>
<td>St. err</td>
<td>Coef</td>
<td>St. err</td>
</tr>
<tr>
<td>$\rho_1$</td>
<td>0.298***</td>
<td>0.101</td>
<td>0.378**</td>
<td>0.164</td>
<td>0.437***</td>
<td>0.055</td>
</tr>
<tr>
<td>$\rho_2$</td>
<td>-0.321***</td>
<td>0.129</td>
<td>-0.404***</td>
<td>0.147</td>
<td>-0.360***</td>
<td>0.038</td>
</tr>
<tr>
<td>$\phi$</td>
<td>0.380***</td>
<td>0.090</td>
<td>0.342**</td>
<td>0.134</td>
<td>0.249***</td>
<td>0.080</td>
</tr>
<tr>
<td>VIX</td>
<td>1.370***</td>
<td>0.206</td>
<td>1.308***</td>
<td>0.099</td>
<td>0.537***</td>
<td>0.103</td>
</tr>
<tr>
<td>R</td>
<td>-3.414***</td>
<td>1.018</td>
<td>-3.968***</td>
<td>0.528</td>
<td>-3.824***</td>
<td>0.097</td>
</tr>
<tr>
<td>SPR</td>
<td>-2.201***</td>
<td>0.673</td>
<td>-2.839***</td>
<td>0.610</td>
<td>-2.476***</td>
<td>0.219</td>
</tr>
<tr>
<td>c</td>
<td>0.046</td>
<td>0.095</td>
<td>0.062</td>
<td>0.208</td>
<td>-0.007</td>
<td>0.077</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-248.86</td>
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<td>-250.95</td>
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<td>-248.34</td>
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</tr>
<tr>
<td>Linearity test</td>
<td>12.3***</td>
<td></td>
<td>24.44***</td>
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<td>16.55***</td>
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</tr>
<tr>
<td>Additive nonlinearity test</td>
<td>0.22</td>
<td></td>
<td>0.73</td>
<td></td>
<td>0.20</td>
<td></td>
</tr>
</tbody>
</table>

Note: the table shows the estimation results of the STR Model 1 with transition variables; VIX index (VIX), short rate (R), yield spread (SPR). */**/*** indicates that the variable is significant at the 10%/5%/1% level of significance, respectively. Linearity test reports the LM-type statistic of null of no STR-type nonlinearity. Additive non-linearity shows the LM-Type statistic of null on no remaining STR-type nonlinearity.
Table 2: Estimation results of the model with time trend component (Model 2)

<table>
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<tr>
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<tbody>
<tr>
<td></td>
<td>Coef</td>
<td>St. err</td>
<td>Coef</td>
<td>St. err</td>
<td>Coef</td>
<td>St. err</td>
</tr>
<tr>
<td>ρ₁</td>
<td>0.297**</td>
<td>0.140</td>
<td>0.630***</td>
<td>0.052</td>
<td>0.502***</td>
<td>0.117</td>
</tr>
<tr>
<td>ρ₂</td>
<td>-0.368***</td>
<td>0.099</td>
<td>-0.580***</td>
<td>0.027</td>
<td>-0.440***</td>
<td>0.075</td>
</tr>
<tr>
<td>ϕ</td>
<td>0.346*</td>
<td>0.192</td>
<td>0.140***</td>
<td>0.028</td>
<td>0.156</td>
<td>0.105</td>
</tr>
<tr>
<td>VIX</td>
<td>1.925***</td>
<td>0.616</td>
<td>1.142***</td>
<td>0.083</td>
<td>1.163***</td>
<td>0.354</td>
</tr>
<tr>
<td>R</td>
<td>-0.576</td>
<td>0.461</td>
<td>1.323***</td>
<td>0.039</td>
<td>0.159</td>
<td>0.140</td>
</tr>
<tr>
<td>SPR</td>
<td>-0.294</td>
<td>0.672</td>
<td>0.051</td>
<td>0.049</td>
<td>-0.450***</td>
<td>0.161</td>
</tr>
<tr>
<td>T</td>
<td>2.571***</td>
<td>0.943</td>
<td>2.804***</td>
<td>0.010</td>
<td>2.725***</td>
<td>0.311</td>
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<tr>
<td>c</td>
<td>0.071</td>
<td>0.165</td>
<td>-0.144***</td>
<td>0.054</td>
<td>-0.065</td>
<td>0.158</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-248.23</td>
<td></td>
<td>-248.25</td>
<td></td>
<td>-247.29</td>
<td></td>
</tr>
<tr>
<td>Linearity test</td>
<td>10.95***</td>
<td></td>
<td>24.26***</td>
<td></td>
<td>21.54***</td>
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</tr>
</tbody>
</table>

Additive nonlinearity test: 1.28  2.55  0.09

Note: the table shows the estimation results of the STR Model 1 with transition variables; VIX index (VIX), short rate (R), yield spread (SPR), time trend (T). */**/*** indicates that the variable is significant at the 10%/5%/1% level of significance, respectively. Linearity test reports the LM-type statistic of null of no STR-type nonlinearity. Additive non-linearity shows the LM-Type statistic of null on no remaining STR-type nonlinearity.
Table 3: Results of in-sample comparison

<table>
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<tbody>
<tr>
<td></td>
<td>AIC</td>
<td>SIC</td>
<td>AIC</td>
<td>SIC</td>
<td>AIC</td>
<td>SIC</td>
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<tr>
<td>Model 1</td>
<td>511.72</td>
<td>536.54</td>
<td>515.90</td>
<td>540.71</td>
<td>510.68</td>
<td>535.50</td>
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<tr>
<td>Model 2</td>
<td>512.46</td>
<td>540.82</td>
<td>512.51</td>
<td>540.87</td>
<td>510.58</td>
<td>538.95</td>
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<tr>
<td>Model 3</td>
<td>508.54</td>
<td>529.81</td>
<td>509.30</td>
<td>530.58</td>
<td>507.01</td>
<td>528.28</td>
</tr>
</tbody>
</table>

Note: the table reports the AIC and SIC for STR Models 1-3 to compare in-sample performance.

Table 4: Results of out-of-sample comparison

<table>
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<tr>
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<tbody>
<tr>
<td></td>
<td>RMSE</td>
<td>MAE</td>
<td>RMSE</td>
<td>MAE</td>
<td>RMSE</td>
<td>MAE</td>
</tr>
<tr>
<td>Model 1</td>
<td>0.201</td>
<td>0.155</td>
<td>0.322</td>
<td>0.257</td>
<td>0.259</td>
<td>0.212</td>
</tr>
<tr>
<td>Model 2</td>
<td>0.203</td>
<td>0.161</td>
<td>0.297</td>
<td>0.231</td>
<td>0.274</td>
<td>0.221</td>
</tr>
<tr>
<td>Model 3</td>
<td>0.174</td>
<td>0.136</td>
<td>0.296</td>
<td>0.231</td>
<td>0.241</td>
<td>0.199</td>
</tr>
</tbody>
</table>

Notes: the table reports the out-of-sample RMSE and MAE for STR Models 1-3. The forecast horizon is 1 month and the forecast period is 2000/12-2012/05.
Table 5: Estimation results of the parsimonious model (Model 3)

<table>
<thead>
<tr>
<th></th>
<th>US</th>
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<th>GER</th>
<th></th>
<th>UK</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef</td>
<td>St. err</td>
<td>Coef</td>
<td>St. err</td>
<td>Coef</td>
<td>St. err</td>
</tr>
<tr>
<td>$\rho_1$</td>
<td>0.289***</td>
<td>0.001</td>
<td>0.459***</td>
<td>0.002</td>
<td>0.483***</td>
<td>0.185</td>
</tr>
<tr>
<td>$\rho_2$</td>
<td>-0.363***</td>
<td>0.002</td>
<td>-0.570***</td>
<td>0.006</td>
<td>-0.419**</td>
<td>0.173</td>
</tr>
<tr>
<td>$\phi$</td>
<td>0.359***</td>
<td>0.001</td>
<td>0.136***</td>
<td>0.005</td>
<td>0.173</td>
<td>0.192</td>
</tr>
<tr>
<td>VIX</td>
<td>1.983***</td>
<td>0.003</td>
<td>1.901***</td>
<td>0.009</td>
<td>1.373***</td>
<td>0.345</td>
</tr>
<tr>
<td>T</td>
<td>2.959***</td>
<td>0.003</td>
<td>3.315***</td>
<td>0.095</td>
<td>2.808***</td>
<td>0.675</td>
</tr>
<tr>
<td>c</td>
<td>0.068*</td>
<td>0.041</td>
<td>0.005</td>
<td>0.067</td>
<td>-0.106</td>
<td>0.192</td>
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<tr>
<td>LLF</td>
<td>-248.27</td>
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<td>-248.65</td>
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<td>-247.51</td>
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</tr>
<tr>
<td>Linearity test</td>
<td>21.33***</td>
<td></td>
<td>36.88***</td>
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<td>38.87***</td>
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</tr>
<tr>
<td>Additive nonlinearity test</td>
<td>1.25</td>
<td></td>
<td>0.02</td>
<td></td>
<td>0.61</td>
<td></td>
</tr>
</tbody>
</table>

Note: the table shows STR Model 3 with transition variables; VIX index (VIX), Time Trend (T). */**/*** indicates that the variable is significant at the 10%/5%/1% level of significance, respectively. Linearity test reports the LM-type statistic of null of no STR-type nonlinearity. Additive non-linearity shows the LM-Type statistic of null on no remaining STR-type nonlinearity.
Notes: the graph shows the estimated transition function of model1 against each of the transition variables holding the other transition variables constant at their sample mean. The transition variables are VIX index (VIX), short rate (R), and yield spread (SPR).
Figure 2: Estimated stock-bond correlation for US

(a) Model 1

(b) Model 2

(c) Model 3

Notes: the graph shows the time series of the actual and estimated stock-bond correlation for Models 1-3 for US.
Figure 3: Estimated stock-bond correlation for GER

(a) Model 1

(b) Model 2

(c) Model 3

Notes: the graph shows the time series of the actual and estimated stock-bond correlation for Models 1-3 for GER.
Figure 4: Estimated stock-bond correlation for UK

(a) Model 1

(b) Model 2

(c) Model 3

Notes: the graph shows the time series of the actual and estimated stock-bond correlation for Models 1-3 for UK.
Figure 5: Estimated time trend component in the stock-bond correlation

(a) Model 2

(b) Model 3

Note: the graph shows the time series of the estimated time trend component in the stock-bond correlation for Models 2 and 3.