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Identifying time variability in stock and interest rate dependence

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Abstract

The correlation between stock markets and interest rates has been discussed in numerous studies in the past, with differing results in terms of strength and direction of the relationship. This paper uses models of the multivariate GARCH type which allow for time-variability and regime changes in correlation. All estimated models allowing for time-varying correlation complement each other in identifying time-varying patterns found in the (co-)movement between the variables. Furthermore, we provide evidence for both large changes in correlation, as well as for the existence of regimes between which correlation may move. Our result of a dominant time factor indicates a transition in market structures over time, which is in line with observations in the markets and which may be seen as an explanation for previously differing results.

Keywords: Time-varying correlation; regime transition; multivariate GARCH; smooth transition; cross-asset correlation; non-linear estimation

JEL-Classification: *C32, C58*

Non-technical Summary

The interdependence between stock markets and interest rates (or bond markets) has been discussed in numerous studies in the past, with differing results in terms of the strength and direction of the relationship. While, in several studies in the past, reported correlations have been either negative or positive, recent studies have found strong and significant changes of correlation over time. This holds true for both direction and magnitude, and the explanations both on the theoretical side and in the empirical domain are large in number.

Although there appears to be a common understanding of time variability, there has not been a final answer to the question of when a possible major change in interdependence actually took place and how pronounced this possible change into a "new state of the world" was or is.

We investigate the very nature of the time variability and regime dependence in a framework that accounts for both the variability in dependence and the large swings in market variables prevalent in modern financial markets.

All estimated models allowing for time-varying correlation complement each other in identifying time-varying patterns found in the (co-)movement between the variables. Furthermore, we provide evidence for large changes in correlation, as well as for the existence of regimes between which the correlation may move. Our result of a dominant time factor indicates a transition in market structures over time, which is in line with observations in the markets and which may be seen as an explanation for previously differing results.

Nicht-technische Zusammenfassung

Die Abhängigkeiten zwischen Aktienmärkten und Zinsen (oder auch Anleihenmärkten) wurden in zahlreichen Studien diskutiert, wobei hier durchaus unterschiedliche Resultate hinsichtlich der Stärke und der Richtung des Zusammenhangs zu beobachten sind. Während frühere Studien entweder negative oder positive Korrelation als Ergebnis ausweisen, wurden in jüngeren Studien oftmals signifikante und starke Änderungen über die Zeit hinweg berichtet. Dies trifft sowohl für die Stärke als auch die Richtung zu; die Erklärungen sowohl theoretischer Art als auch im empirischen Bereich hierzu sind mannigfaltig.

Obgleich es eine anscheinend breite Zustimmung bezüglich eines zeitvariablen Zusammenhangs gibt, wurde noch nicht final geklärt, wann ein möglicher dominanter Wechsel in der Interdependenz stattfand und wann dieser zu einem neuen "Umweltzustand" geführt hat. Wir erforschen ebendiese Zeitvariabilität und Regime-Abhängigkeit und verwenden Methoden, welche sowohl der Variabilität in der Interdependenz als auch den starken Schwankungen von Finanzmarktvariablen an den modernen Märkten Rechnung tragen.

Alle verwendeten Modelle ergänzen sich gegenseitig, indem sie eine zeitvariable Korrelation identifizieren, obgleich es natürlicherweise Unterschiede basierend auf den Schätzmethoden gibt. Im Ergebnis der Schätzungen stehen sowohl starke Schwankungen in der Korrelation als auch eine Regime-Abhängigkeit der Interdependenz. Unser Ergebnis eines dominanten Zeitfaktors deutet an, dass sich Marktstrukturen über die Zeit hinweg geändert haben, was mit Marktbeobachtungen übereinstimmt und als Erklärung für unterschiedliche Resultate in der Vergangenheit dienen kann.

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1 Introduction

Correlations among the major asset classes take a central role in both theoretical and empirical research, as understanding, estimating and interpreting (co-)movements is crucial for market participants, institutions and policy makers. Considerable effort was spent on explanations and models, and work on identifying the behavior and determinants of correlations is still ongoing: Both the very nature of the financial markets that appear to be increasingly dynamic and the effects of time call for renewed and appropriate discussion of the topic. Not only is history prolonged with each additional trading day, the apparent structures are also shifting with more or less strong effects, making new insights and interpretations possible - and necessary.

While identifying the possible changes in structures and market behavior may be a challenge in itself, the expected interaction of asset classes is far from clear-cut: Considering the different asset classes, there exist many possible channels through which (co-)movements may be affected, and influences may have both time-varying magnitudes and directions. For the case of interest rates and stocks, negative correlation expectations have at least had to be relaxed in recent years.

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Li (2003) delivers a strong but interesting notion on the relation between stocks and interest rates, and ultimately bond markets:

”In the first version of The Intelligent Investor, published in the 1950s, the author, then investment guru Benjamin Graham, claims that the correlation between stock and bond returns is negative. His argument provides the basis for the asset allocation advice of 50-50 split in stocks and bonds. However, in the second version of this book published in the 1970s, the correlation structure has changed and the argument is dropped. Today, one can randomly search the term ’stock and bond correlation’ on the internet, and easily find sharply contradictory opinions among market participants. When it comes to story-telling, one man’s story is just as good as others. Most of these opinions are based on causal observations and lack the support of concrete evidence.”

However, there is evidence, even concrete evidence. The main problem nevertheless remains as evidence has been provided in either way in the past, and depending on the time span. With Shiller and Beltratti (1992) and Campbell and Ammer (1993) reporting positive correlation between long-term bond returns and stock returns,[2] the correlation is constant due to the construction of the analyses. It has been shown in the past however, that the correlation appears to be different between time periods, an observation found by Gulko (2002), Ilmanen (2003), Connolly, Stivers and Sun (2005), Andersson, Krylova and Vahamaa (2008), Aslanidis and Christiansen (2010) and Schopen and Missong (2012) among others. While the studies differ among each other, the most obviously identifiable pattern is a change from negative to positive correlation between stock returns and bond yields.

These findings have also been discussed in practice: The 2011 research paper ”Rise of Cross-Asset Correlations” by JP Morgan discusses an observable pattern of rising correlations among asset classes. Figure 1 shows the bond-stock correlation graphs of the

[2]Studies in the past differ regarding the correlation sign as some authors analyze stocks and bond yields, while others use stocks and bond prices.

study. JP Morgan identify the abandonment of the so-called Fed Model[3] in favor of a "risk-on/off" strategy as the driving factor behind the shift in correlation from negative to positive. The reasoning for this is that, nowadays, investors allocating away from risky assets move into riskless assets in the "flight to quality", thereby driving bond prices up and yields down. Furthermore, monetary policy with increasing rates during heated economic phases and low rates to accommodate growth and avoid recession in down-cycles further fuels the positive correlation according to the JP Morgan study. In contrast, the Fed Model would have provided an explanation of negative correlation: Interest rate yields are expected to be close to equity earning yields, inducing an inverse relationship between stock prices/returns and treasury yields through investors' comparison of expected gains.

While the Fed model has become popular among financial market practitioners, Salomons (2006) provides evidence against the model at least in the short-term domain of asset allocation. The arguments against the model on both empirical and theoretical grounds have also been raised in Asness (2003) and Estrada (2006) and Estrada (2009) among others, while Thomas and Zhang (2007) and Thomas and Zhang (2009) are proponents of the model. Abstaining from a discussion of the model and the critique, we can derive one common and important fact from studies in favor or in dismissal of the model: The observation of a negative correlation between interest rates and stocks and a change into positive dependency before the end of the 20^{th} century.

This is in line with the above mentioned studies identifying time variability mentioned above, and we argue later that the divergence of results and interpretations of these studies may be best understood by considering this very fact. Moreover, we will relate to specific earlier studies in the empirical section, thereby providing insight into how the relation of interest rates and stocks changes over time.

[3]The name derives from the a Federal Reserve Policy Report of July 1997, although many sources cite Yardeni (1997) and Yardeni (1999), as the first reference to it was made therein. See Lander, Orphanides and Douvogiannis (1997a) and Lander, Orphanides and Douvogiannis (1997b) for the Fed report and a related publication.

From the perspective of financial stability, changes in the correlation between the returns of relatively safe assets, like US government bonds, and of risky financial assets, such as stocks, are of special interest due to the implications for risk management of financial market participants. Another important question is how changes in correlation depend on risk appetite, which in this paper is proxied by implied volatility of stock returns. Moreover, changes in correlation might be an indicator of herding of financial market participants, particularly in times of crisis.

As our focus is on identifying whether there is time dependency and how it is structured, it is crucial to know if this is due to underlying driving factors, or whether structural changes or a shift in structures are the cause. Moreover, we focus on whether the time variability is identified through regimes, between which there may be transitioning or switching. Regarding earlier work, regime-dependent modeling of the correlation between interest rates and stock markets with smooth transition methods and observable transition parameters is limited to the study of Aslanidis and Christiansen (2010). However, their approach contains an estimation of the correlation in the first step, on order to model it using a smooth transition regression model thereafter, rather than having the correlation as an integral part of a multivariate estimation. Accordingly, we add to the literature by providing an analysis that allows the correlation to vary over time and to be regime-dependent, while the correlation itself is controlled by observable transition variables.

The structure of the study is as follows: We discuss the methodology in Section 2, and present the empirical results in Section 3. Implications derived from the results are discussed in Section 4, followed by a summary in Section 5.

2 Correlation Estimation in Multivariate GARCH Models

We employ the class of multivariate models with generalized autoregressive conditional heteroscedasticity (GARCH). As has become common when analyzing financial data exhibiting time-varying variance and clustering of periods of large movements, GARCH models are capable of accounting for these effects and, depending on the type of specification, allow for several modifications.

Consider first the standard notation of the GARCH(p,q) process following Bollerslev (1986), where the variance of a series is modeled with lagged observations of the squared residuals and lags of the conditional variance itself:

$$\varepsilon_t \mid \psi_{t-1} \sim N(0, h_t)$$
$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \cdot \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \cdot h_{t-j} = \alpha_0 + A(L)\varepsilon_t^2 + B(L)h_t$$

The most widely used model for financial market indices like stock market indices is the GARCH(1,1) specification with $p = 1$ and $q = 1$, where the volatility estimates are done on data coming from a de-meaning filtration in the first step.[4]

Extending the univariate modeling of the volatility process to a multivariate setup may be done by specifying the variance-covariance matrix accordingly:

$$\epsilon_t = H_t^{1/2} z_t; \quad E[z_t] = 0; \quad E[z_t z_t'] = I_N; \quad z_t \sim G(0, I_N)$$
$$E_{t-1}[\epsilon_t] = 0$$
$$E_{t-1}[\epsilon_t \epsilon_t'] = H_t$$

Accordingly, the conditional variance vector for the univariate specification is extended with the cross-influences between the included variables, such that each element depends

[4]This may be accomplished by regressing on a constant which is the most commonly used procedure. However, adding a lag of the explained variable and/or a moving average term leading to the ARMA(1,1)-GARCH(1,1) specification may be possible as well. We did not find an effect arising from different mean equation specifications in our analysis, however.

on the q lags of squared residuals and the cross-terms, as well as on the p lags of the variance-covariance matrix itself. As all elements in the variance-covariance matrix follow a vector of autoregressive moving average (ARMA) processes in the squared residuals and the cross-terms, the following specification by Bollerslev, Engle and Wooldridge (1988) displays the multivariate GARCH (MGARCH) process in its most general form, the vech (half-vec) representation:

$$vech(H_t) = W + \sum_{i=1}^{q} A_i^* \cdot vech(\epsilon_{t-i}\epsilon_{t-i}') + \sum_{j=1}^{p} B_j^* \cdot vech(H_{t-j})$$
$$vech(H_t) = W + A^*(L) \cdot vech(\epsilon_t\epsilon_t') + B^*(L) \cdot vech(H_t)$$

The half-vec operator vech() stacks the columns of the upper half of the symmetric matrix. Due to the fact that the estimation of such processes is exorbitantly demanding, and in many cases simply impossible, different models with restrictions emerged in order to make the MGARCH models usable. We briefly review the ones that are used in this study, focusing in particular on how the interaction between the variables is modeled.

Bollerslev (1990) decomposed the variance-covariance matrix to separate the conditional correlations from the conditional variances, leading to a parameterization of the conditional covariance and proportionality to the conditional standard deviation:

$$E_{t-1}[\epsilon_t\epsilon_t'] = H_t$$
$$\{H_t\}_{ii} = h_{ii}; \quad i = 1, ..., N$$
$$\{H_t\}_{ij} = h_{ijt} = \rho_{ij} * h_{it}^{1/2} \cdot h_{jt}^{1/2}; \quad i \neq j; \quad i, j = 1, ..., N$$
$$D_t = diag\{h_{1t}, ..., h_{Nt}\}$$
$$H_t = D_t^{1/2} \cdot R \cdot D_t^{1/2}$$

This results in the matrix of variances and covariances being defined as follows:

$$H_t = \begin{pmatrix} h_{1t}^{1/2} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & h_{Nt}^{1/2} \end{pmatrix} \cdot \begin{pmatrix} 1 & \rho_{12} & \cdots & \rho_{1N} \\ \rho_{21} & 1 & \cdots & \vdots \\ \vdots & \cdots & \ddots & \rho_{N-1N} \\ \rho_{N1} & \cdots & \rho_{NN-1} & 1 \end{pmatrix} \cdot \begin{pmatrix} h_{1t}^{1/2} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & h_{Nt}^{1/2} \end{pmatrix}$$

While the decomposition is favorable with respect to dimensionality and estimation, this constant conditional correlation model lacks the possibility of modeling spillover effects, and correlations may not change during the course of time. ENGLE (2002) on the other hand extended the CCC model to allow for time-varying correlation, thereby decomposing the GARCH modeling from the correlation specification. With the correlation matrix linking the univariate GARCH processes, the dynamic conditional correlation (DCC) model takes on the following form:

$$\rho_{XY,t} = \frac{Cov_{t-1}(X_t \cdot Y_t)}{\sqrt{E_{t-1}(X_t - \mu_{X,t})^2 \cdot E_{t-1}(Y_t - \mu_{Y,t})^2}}$$

$$Y_t|\psi_{t-1} \sim N(0, H_t)$$

$$H_t = D_t^{1/2} \cdot R_t \cdot D_t^{1/2}$$

$$D_t = diag(Var_{t-1}(y_{1t}), ..., Var(y_{Nt}))$$

$$\eta_t = D_t^{-1/2} \cdot Y_t$$

$$E_{t-1}(\eta_t \eta_t') = D_t^{-1/2} \cdot H_t \cdot D_t^{-1/2} = R_t = \{\rho_{ij,t}\}$$

While the models discussed above have become pretty much standard approaches along with, for example, the BEKK model[5], the class of GARCH models allowing for smooth transition in the variance or correlation have extended the groups of available multivariate volatility models. With respect to the model selection, we are in line with ASLANIDIS, OSBORN and SENSIER (2009) who favor the smooth transition volatility models over Markov-type approaches as used for example in ANG and BEKAERT (2002) and PELLETIER (2006), as the smooth transition property allows the process to be continuously modeled and observed.

Before we outline the smooth transition volatility models, consider first the standard specification of a smooth transition (autoregressive) regression, ST(A)R model as defined

[5]The model defined in KRONER and ENGLE (1995) can be seen as a restricted and parameterized version of the general model, and was previously introduced by BABA et al. (1991), leading to the name 'Baba-Engle-Kraft-Kroner'.

by Teräsvirta (1994) and Teräsvirta (2004):

$$
\begin{aligned}
y_t = & \alpha^0 + \sum_{i=1}^{p} \beta_t^0 y_{t-i} + \sum_{k=1}^{K} \sum_{j=0}^{q} y_{jk}^0 x_{k,t-j} \\
& + G(\Box)(\alpha^1 + \sum_{i=1}^{p} \beta_t^1 y_{t-i} + \sum_{k=1}^{K} \sum_{j=0}^{q} y_{jk}^1 x_{k,t-j}) \qquad \text{for } t = 1, ..., T
\end{aligned}
$$

In the most general form, both lagged and contemporaneous values of the exogenous variables as well as lags of the endogenous variable can enter the equation. Superscript 0 refers to the coefficients of the linear part of the model and superscript 1 to the non-linear part, with the transition function $G(\Box)$ being bounded between 0 and 1. The most common specification of the transition function is the logistic form with one linear and one non-linear regime:

$$G(\gamma, c, s_t) = (1 + \exp\{-\gamma(s_t - c)\})^{-1} \qquad \text{with } \gamma > 0$$

In this specification, the transition between the regimes is determined by the transition parameter γ, based on the values of the transition variable s_t which is responsible for the process to change to the other regime when the threshold value for c, s_t, is crossed.[6]

As the speed of transition is determined by the transition parameter, for large values of γ the transition becomes rather abrupt and the ST(A)R model approximates the self-exciting threshold autoregressive model, SETAR.[7] According to Teräsvirta (2004), a large value for the standardized transition parameter is above 10, with the standardized value of γ being the γ divided by the sample standard deviation of the transition variable s. Numerical problems may arise with respect to estimating γ when transition is rather quick, as in this case the amount of observations surrounding the threshold value is scarce, resulting in a large standard deviation of of γ and a low t-ratio.

The general ST(A)R approach was specified in general as an extension to the single-equation autoregressive distributed lag (ADL) model, which includes both lagged endogenous and exogenous variables. Extensions include vector autoregression with smooth

[6]See Teräsvirta (1994) and Teräsvirta (2004).

[7]See Franses and van Dijk (2000) for a discussion of the relation between the models and reasoning of approximation with the instantaneous model.

transitions (STVAR) like in Weise (1999), van Dijk (2001), and Camacho (2004); panel smooth transition regression (PSTR) as in Gonzalez, Teraesvirta and van Dijk (2005) and Fok, van Dijk and Franses (2005a) and Fok, van Dijk and Franses (2005b); smooth transition models with long memory in Hillebrand and Medeiros (2009), and weighted smooth transition regression in Medeiros and Veiga (2003), Medeiros and Veiga (2005) and Becker and Osborn (2007).

Whereas the STR model and the various extensions above relate to estimations of the mean of time series, financial market research has prompted the ongoing development of smooth transition regression models in the area of volatility models. Lundbergh and Teräsvirta (1999) propose the STAR-STGARCH model with smooth transition in both the mean and the variance equation within a univariate GARCH framework.[8] Lanne and Saikkonen (2005) also model the variance of a univariate GARCH process with smooth transitions, thereby altering the inclusion of the lagged volatility. Extensions exist as well, with Dueker et al. (2011), for example, introducing the contemporaneous-threshold autoregressive conditionally heteroscedastic model (C-STGARCH), allowing for the transition function to be dependent on more parameters and the data itself.

Extension of the STAR framework in the variance domain was not limited to the univariate type, however, with a class of models focusing on the interaction between the variables under consideration: Silvennoinen and Teräsvirta (2005) and Berben and Jansen (2005) introduce time-varying conditional correlation of the smooth transition type, and Silvennoinen and Teräsvirta (2009) extend their model to allow for two transition variables. The common characteristic of the multivariate GARCH models with smooth transition is the specification of regime-dependent correlations for the variables in the link of the volatility estimations, where the decomposition of variance and correlation is a feature known from multivariate GARCH models discussed above.

[8]Generally, this follows from Hagerud (1996) and Gonzalez-Rivera (1998), with the STAR-STGARCH model being a generalization of the GJR-GARCH model of Glosten, Jagannathan and Runkle (1993).

We considered it especially useful to employ multivariate GARCH (MGARCH) models with smooth transitions as the interaction of the variables under investigation can be assessed on a time-varying basis, thereby accounting for changes in volatility and correlation. While this desirable property is shared with the DCC model, the possibility of a continuously modeled shift between regimes and the identification of the drivers behind the transitions is advantageous in the presence of major changes in the system and for interpretation of economic structures.

Silvennoinen and Teräsvirta (2005) introduce the smooth transition in the correlation by defining the conditional correlation matrix to be a result of the transition function and two extreme states for the correlation matrices R_1 and R_2. The transition function G is defined as a logistic transition function and the general MGARCH specification is as in the conditional correlation models discussed earlier, leading to the smooth transition conditional correlation GARCH (STCC-GARCH) model:

$$
\begin{aligned}
H_t &= D_t^{1/2} \cdot R_t \cdot D_t^{1/2} \\
R_t &= (1 - G_t) \cdot R_1 + G_t \cdot R_2
\end{aligned}
$$

One prominent feature apart from the continuously modeled transition between correlation states is the selection possibility for the transition variable. While Berben and Jansen (2005), in their independently introduced approach, have a time transition, one may select transition variables according to aspects of the respective study's aim.[9]

Silvennoinen and Teräsvirta (2009) extended the STCC-GARCH model to allow for two transition variables. Accordingly, the specification below leads to the double smooth transition conditional correlation GARCH (DSTCC-GARCH) model with four

[9] Any (D)STCC model that includes a time transition may therefore be seen as a type of time-varying STCC (TV-STCC) model. We adhere to the naming as (D)STCC with time transition for the sake of brevity, however.

correlation matrices and two transition functions and transition variables:

$$R_t = (1 - G_{1t}) \cdot R_{1t} + G_{1t} \cdot R_{2t}$$
$$R_{it} = (1 - G_{2t}) \cdot R_{i1} + G_{2t} \cdot R_{i2} \qquad \text{with } i = 1, 2$$

$$G_{it} = (1 + e^{-\gamma_i (s_{it} - c_i)})^{-1}, \quad \gamma_i > 0, \quad i = 1, 2$$

The DSTCC-GARCH model makes it possible to combine effects of two variables for the conditional correlation, and Silvennoinen and Terï¿½svirta (2009) note the possibility of using both a variable influence and a time transition, what makes the models highly suitable for our study.

3 Empirical Results for Identification of Correlation Changes

3.1 Data and Setup

We use standard data in the area of analyzing interactions between interest rates and stock markets. Interest rates are measured by the 10 Year Treasury Yield, obtained from the U.S. Department of the Treasury, and the US stock market is best represented by the Standard and Poors 500 Composite Index (S&P 500).

As the STCC and DSTCC models are estimated using transition variables, we need to specify which variables should be used as expected driving factors regarding the correlation. Besides the time as a transition variable, we decided to include the stock market volatility, measured by the Chicago Board Options Exchange Market Volatility Index (VIX) as a second transition variable. By doing so, we are able to see whether there is indeed a risk-on/off structure that shows up in the correlation between interest rates and stock markets. Furthermore, the DSTCC study of stock market correlations by Aslanidis, Osborn and Sensier (2009) finds correlation dependence on the VIX, and Silvennoinen and Teräsvirta (2009), in their bond-stock example, identify the VIX as most significant in a test of constant correlation versus alternatives including the STCC and DSTCC models.

As the VIX measures the implied volatility of S&P 500 index options, it therefore serves as a natural measure of volatility which is observable and prevailing at the market. One favorable feature is that the VIX by construction can be interpreted as a forward-looking measure. This is especially suitable when aiming at the identification of regimes that are expected to be driven by a risk-on/off structure.

Data is available at a daily frequency, although we had to use weekly data for the sake of estimation. While many GARCH applications, even in the multivariate area, have been done on daily data, we are in line with studies employing the smooth transition method to data at lower frequency when long time horizons are considered and where data is heterogeneous. This stems from the fact that although the computational burden could be tractable with respect to dimensionality, the large differences in the possible parameter estimates over time hamper algorithm convergence. Fortunately, a switch to weekly frequency was a sufficient reduction in frequency, thereby preserving more data information as compared to monthly frequency.

The time period from the first week of 1990 (the date when the VIX was introduced) until the last week of February 2012 is covered by the sample, resulting in 1156 observations of level data and 1155 observations of return data.

Descriptive statistics of the series are presented in Table 1 and all series in levels and returns are depicted in Figure 2. Following initial unit-root tests which show non-stationarity for all series, we conducted the analysis of the correlation with treasury yield changes and stock market returns. This leaves the aim of the investigation intact, however.

3.2 CCC GARCH Model and Rolling Correlations

As a first step in the analysis of interaction between the series, we ran the CCC GARCH model on the change in the treasury rate and the log-returns of the stock market data.

Estimated parameters of the CCC-GARCH and test statistics enter Panels 1 and 2 of Table 2. The GARCH estimation for the two series indicates that both the ARCH and GARCH parameters are highly significant and within the necessary restrictions that ensure a non-explosive process. The sum of the GARCH coefficients for the S&P 500 is around 0.98 what displays the common result of considerably high persistence of volatility shocks, although the values do not give rise to concerns regarding the model stability.

By construction, the correlation for the CCC GARCH model remains the same over the whole estimation period. The estimated value of 0.04 corresponds to a conditional correlation of treasury yield changes and stock market returns that is near zero. While the CCC GARCH estimation mainly serves as an entry point to the analysis and to compare the models, we check whether the constant correlation of the CCC model holds against alternatives. As discussed above, we use the alternatives of STCC-GARCH with time and with volatility respectively, and DSTCC-GARCH with both variables as transition variables. The test statistics for all three alternatives are included in Panel 2 of Table 2 and indicate a rejection of the null of constant correlation when testing conditioned on the presence of the transition variables time, volatility or both.

As an intermediate step before estimating the various MGARCH models that allow for time-varying and/or regime-dependent conditional correlation, we contrast the CCC estimation with rolling correlations. Using a window length of 52 to obtain estimates of the correlation on an annual horizon, we obtain the pattern over time as plotted in Figure 3, with correlations ranging from -0.79 to 0.72. Interestingly, there is an apparently strong tendency to positive correlations over the course of time. Notably, the average of the rolling correlations with about 0.005 is very near to zero and to the CCC estimate. Accordingly, the large differences in the correlation appear to be averaged out in the estimation process of the CCC model, leaving the variation to the covariances based on the volatility processes and omitting the change in interdependency.

Increasing correlations over time as seen in the rolling window analysis may stem from either a trend in the correlation or from one or more structural breaks/ regime shifts in the interaction between the two series. Furthermore, this finding is in line with the JP Morgan study mentioned above and - comparing Figures 1 and 3 - roughly resembles the pattern observed in their study. This result of large differences in correlations over time is a well-documented fact for the last 30 years and is found in many studies and with differing approaches and aims, as found by Gulko (2002), Ilmanen (2003), Jones and Wilson (2004), Connolly, Stivers and Sun (2005) and Connolly, Stivers and Sun (2007), Cappiello, Engle and Sheppard (2006), Engle and Colacito (2006), Christiansen and Ranaldo (2007), Andersson, Krylova and Vahamaa (2008), Aslanidis and Christiansen (2010) and Schopen and Missong (2012).

3.3 Comparison of Time Varying Conditional Correlation GARCH Models

Although DCC-GARCH model applications and extensions to it are numerous, regime-dependent modeling of the correlation between interest rates and stock markets with smooth transition methods and observable transition parameters only recently gained attention: Apart from the examples in Silvennoinen and Teräsvirta (2009), we are not aware of studies employing the DSTCC framework to the rate-stock correlation question yet. Below, the results of this approach are therefore discussed and compared to the DCC model estimations.

DCC model estimation is done to see how the correlation changes over time and to have a comparison for the STCC and DSTCC estimations. STCC-GARCH and DSTCC-GARCH models were fitted using the transition variables time and the log-change in the VIX. We test the two transition variables in two separate STCC-GARCH models and include both simultaneously in the DSTCC model allowing for two transition variables. All results are presented in Panels 1 and 2 of Table 2.

As in the CCC-GARCH model, the estimated volatility models show highly significant parameters which satisfy the restrictions with all sums of ARCH and GARCH parameters being between 0.974 and 0.983. Furthermore, the additional conditional correlation parameters of the DCC model are highly significant as well and sum up to less than unity.

The dynamic conditional correlation over time is similar to the rolling correlation and to patterns reported in most other recent studies[10]: An increase in the correlation between interest rates and the stock market is revealed, with sustained positive correlation following earlier periods of negative interaction. Ranging from -0.793 to 0.748, the dynamic conditional correlation estimate moves within a large span as the rolling correlations do. In addition, the average of the DCC correlations with a value of 0.012 is approximately zero, as is the CCC estimate and the average of the rolling correlations.

The results from the DCC-GARCH strengthen the notion that estimation of correlations should be done within a time-varying framework, allowing for a correlation that is not fixed to be constant over time. In addition, the results of negative correlations in the beginning and positive correlation in the second half of the estimation period raise the question of whether there is a trend or break in the correlation, and whether it is possible to detect this with regime-dependent analyses.

Estimating the separate STCC-GARCH models with time and volatility change, we obtain different results regarding the significance of the location parameters and the estimated correlations. While the conditional correlation estimate for both regimes and the location parameter is highly significant for the STCC model with time as the transition variable, conditional correlation in the STCC model with volatility change as the transition variable is insignificant. The location parameter, however, is significant in the STCC model with volatility as well.

In the model with time as the transition parameter, conditional correlation is negative with a value of -0.509 at the beginning of the sample period and is positive during the

[10]Naturally, studies analyzing bond returns rather than treasury yields show the respective inverse picture of falling correlations over time, as shown in Andersson, Krylova and Vahamaa (2008), for example, where both rolling windows as well as DCC-GARCH estimation was used.

estimation sample with a value of 0.399. This increase from clearly negative to clearly positive is in line with previous findings both in our analysis and in related studies. The fact that both correlation values - which can be seen as extreme regimes of correlation between which the process moves smoothly- are highly significant indicates that there is indeed regime-dependence. The transition location is 0.414 (or 41.4% of the sample size), which corresponds to the beginning of March 1999. At this point, the estimated conditional correlation is -0.0538, which is approximately zero what was observed earlier in the CCC model and in the averages of the CCC and rolling correlation approach.

When discussing the location parameter of the time transition variable in context of a smooth transition model, we need to take into account that the transition, of course, begins earlier. How early depends on the speed of transition as measured by the transition parameter. Due to the fact that intuition is hard to extract from the estimated value of 19.218, we depict the transition function in Figure 4: About 80% of the transition to the regime with positive correlations takes place during August 1996 and September 2001, which is only about 23% of the sample size. Moreover, half of the transition (from 25% to 75%) happens between December 1997 and June 2000, corresponding to about 11.4% of the analyzed time period.

Regarding the correlation changes during the mentioned periods, -0.417 to 0.308 is obtained during the August 1996 and September 2001 span and -0.281 to 0.173 during the December 1997 and June 2000 period. Correlation crossing the line between negative and positive values occurs in June 1999. To compare the results with the DCC-GARCH, we calculate the average of the dynamic conditional correlation for the corresponding time periods. At the point where the transition according to the STCC-GARCH with time is at 10% or -0.417 correlation, the average of the DCC correlation from the sample beginning up to that point in time is -0.347 and at the 25% point the comparison yields -0.281 versus -0.375. Estimated conditional correlations during the phase where we are still in the old regime are therefore in the same area. Averaging the dynamic condition correlation from the 75% point and 90% point forward until the estimation's end, we obtain 0.283 and

0.309 compared to 0.173 and 0.308 in the STCC. We conclude that despite the swings in conditional correlation that are possible in the DCC model, the STCC with only time as the transition variable is near the average of those dynamic conditional correlations when the sub-periods are considered. This can be seen from Figure 3 as well, with the DCC correlation roughly swinging around the correlation as estimated using the STCC with time transition.

As for the CCC model, we ran the test on whether the conditional correlation should be modeled with an alternative; here, we remain with a possible extension to the DSTCC model with both time and volatility change transition. The test statistic as shown in Panel 2 of Table 2 indicates clearly that the specification with only time as the transition variable should be forfeited in favor of the richer model with both transition variables.

Before we discuss the DSTCC model, however, we need to focus on the STCC with volatility change as transition variable. As mentioned above, the estimation of this model yields a significant location parameter but insignificant correlation estimates for both regimes. Both estimated conditional correlations which are separated by a location parameter of -0.007 (regimes are separated depending on rising or falling volatility approximately[11]) are near zero and very close to each other with values of 0.033 and 0.038. While we should abstain from interpreting too much into insignificant parameters, correlation estimates here correspond to the zero averages seen before. The insignificance comes as a surprise, especially in context of the significant location parameter indicating different regimes for rising and falling volatility.

Our approach of using the change in volatility rather than the level deviates from usage within smooth transition analyses in Cai, Chou and Li (2009) and Silvennoinen and Teräsvirta (2009) but is in line with Aslanidis, Osborn and Sensier (2009) and Aslanidis and Christiansen (2010). Accordingly, we estimate the effects of changes in the volatility, rather than the level of volatility. To see whether the results

[11]Given the high dispersion in the VIX itself, the value of 0.7% should be interpreted as zero.

would change when using the level of the VIX, we ran that estimation as well, keeping in mind that the unit-root tests indicated that the VIX was not stationary. This is not reported in detail here but available upon request and there is no improvement. We therefore remain unconvinced whether the volatility alone may be responsible for causing regime shifts and/or changes in correlation between rates and stock market returns.

Having analyzed the STCC models with time and volatility change separately, the next step was to estimate the DSTCC-GARCH with two transitions; the results again are reported in Panels 1 and 2 of Table 2. All four correlations are highly significant, as are the location parameters for both transition functions. The location of 0.429 (July 1999) for the time transition function takes on a value that is approximately the same as in the STCC with time transition (0.414 or March 1999) as the single transition variable. In the transition function dependent on the volatility change, the location parameter is 0.040, meaning that the regime is changing at an increase of about 4% of the implied market volatility.

DSTCC correlation over time is depicted in Figure 3 and is similar to the STCC with time transition, only that now the correlation can vary not only over time, but within a range over time - due to the second transition variable. At the beginning of the sample when the time transition has not yet taken effect, correlation varies between -0.573 and -0.376, depending on the value of the change in stock market volatility as the second transition variable. Accordingly, now not only are the parameters of the volatility transition function significant, but the volatility change effect is observable and significant for the correlation values as well. Transitions are considerably fast, as indicated by the speed of transition parameter value of 231.31 and as seen from the graph of the value of the transition function in Figure 4. At the end of the sample period, when time transition is completed and the conditional correlation of this transition function is fully in its new regime, the correlation remains within a tighter range from 0.425 to 0.389. This implies that the influence of the volatility change does not increase correlation but decreases the absolute value of correlation. Thus, regimes of increasing volatility would be associated with less dependence between the assets. At first, this may come as a surprise when considering the possibility that, especially after the 1997/1998 period, there is a regime that is marked by risk-on/off behavior. But within the framework using a time trend, this is not contradictory when considering the influence *given the rise in correlation driven by a structural shift and captured by the time transition.* Accordingly, a risk-on/off behavior may indeed be identified by these results, only that it is a structure that now prevails in the market and does not immediately switch back, resulting in large changes in correlation driven by volatility change. Furthermore, the fact that volatility changes the correlation even at the beginning of the sample already implies a risk-on/off behavior in contrast to the disputed Fed Model.

One striking result of the DSTCC estimation is that the time transition part is almost the same as in the STCC with time as the single transition variable. This underpins the results in terms of robustness. Additionally, with volatility change entering the model significantly and all correlation estimates being significant, we conclude that the variable itself indeed belongs into the estimation - only that without taking the time transition into account its effects are less visible. In addition, the strong time trend may be responsible for the slim band in which the correlation remains in the second half of the sample, with volatility being still significant, but having a smaller impact on the correlation itself.

4 Implications

From the estimations, one can clearly see that the correlation is highly time-varying and regime-dependent. From both the STCC models and the DSTCC model it is evident that there is a strong effect of time, whereas the volatility influence is less clear-cut at first glance. But considering the results from the DSTCC and the apparently strong time effect, these results have a natural interpretation: The insignificance of some parameters and the conditional correlation of about zero in the STCC model with volatility change transition may be due to an averaging out of the correlation, as the correlation normally could be clearly negative or positive, *depending on the period of time*. Therefore, without the possibility of moving from negative to positive in the course of time, there may be no distinction of the regimes due to volatility change.

The above interpretation is crucial in light of the discussion of a change from a Fed Model structure to a risk-on/off world. The fact that volatility is not the driving factor of a major change is by no means evidence against this possible structural development. It simply states that the effect of stock market volatility had a stronger impact before the transition to a new regime - as indicated by the time transition - took effect, and the possibility that the main effects are captured through the time factor. This implies a risk-on/off behavior that is marked by volatility considerations in earlier periods but becomes a structural factor in later time periods.

Moreover, as the recent years with the unfolding of the sub-prime crisis and what followed were marked by numerous phases of market turmoil, extreme changes and financial market deteriorations, correlation's relation to several otherwise identifiable drivers may have changed or simply been in disproportion and buried in the noise of the markets. Meanwhile, the time transition was in full effect with over 90% of the transition already being completed some years before the stock markets peaked in 2007 - and the estimated correlation sufficiently captures the nowadays positive relation between interest rates and stock markets.

Another more technical consideration is one that focuses on the sensitivity of correlation estimates. As Füss and Glück (2012) point out, DCC models tend to exhibit highly unstable conditional correlation patterns and erratic behaviour. They propose confidence intervals to identify fundamental changes in the conditional correlation process. This can be interpreted as a technical correspondence to a theoretical notion of a more stable and medium- to long-term consideration of correlation, i.e. an expectation that correlation structures in an economically meaningful way do not change at high frequency - and are therefore not due to quick changes in a possible transition variable either.

Apart from the discussion regarding impacts of time and volatility transition, the economic perspective that is related to the differing assumptions of yield comparisons in the Fed Model and the risk-on/off approach is interesting regarding the fact that there might indeed be a change and that the change took place at the end of the 20^{th} century. While several studies have identified various factors that may be driving the correlation, our study does not provide evidence against these, but is complementing others, for to the following reasons. Given the assumption that there is interplay between variables that changed over the course of time, the effects of those may be non-identifiable when a strong structural effect emerges from that interplay. Furthermore, the analysis identified a strong change from 1997 to 2001, and while other studies that focus on explaining the correlation may find that the correlation is driven by factors that changed during that time, the time effect itself can be seen as the dominant driver that captures the effects in the shift towards a new regime with positive correlations.

We compared our results to findings in the respective studies mentioned above, and ran the analyses, selecting as transition variables what could be driving correlation or what was identified in models that do not allow for time-variation. This included inflation, differences in bond and stock volatility and bond risk premia among others. Both for single STCC models and in combination with time in the DSTCC model, there was a common result: While some models worked and others did not, it was the time factor that was estimated as the dominant and significant driver, with other variables having a declining impact over time. Interestingly, the shape and strength of time transition was mostly the same for other combinations. We conclude that the differing results on direction in early studies and several approaches that have found similar results of a rise in correlation may both be explained by the time factor capturing the market structure changes in the shift to a new regime.

These implications and the fact that the time transition is far from being linear but steepest around the expected time period at the end of the 20th century, leads us to the conclusion that the (D)STCC model with time transition correctly identifies a structural shift into a new regime of positive correlation in the estimated time period.

5 Summary

We identify a strong and significant time transition in the correlation between interest rates and the stock market using both STCC models with time transition and DSTCC models where the change in market volatility is added as a second transition variable. The time where the transition occurs is in line with both anecdotal evidence in the markets and earlier research. Most crucial from our point of view is the existence of a regime change, indicating that the positive correlation between rates and stocks in recent years is indeed an effect of a changed structure prevalent in financial markets.

Apparently, the time effect is so strong and robust that, in the STCC model with time as a single transition variable as well as accompanied by the volatility change, the transition function is almost the same. While the volatility change influences the estimation and all estimated correlation regimes are significant, the role of changing volatility as a transition variable is less strong than that of time regarding the correlation. This may be either due to the fact of the dominating influence of structural change that is identified through the time factor, or it may arise from the fact that the volatility itself has been influenced heavily by the forces that drove the structural change at hand - because the time effect already captured much of the effects otherwise associated with volatility.

Regarding further research, it will be interesting to identify whether the structural change that apparently occurred may be disentangled using different market factors and how sustainable the new regime is.

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Appendix

Table 1: Descriptive Statistics

	VIX	S&P 500	10 Year Treasury Bill
Mean	0.699	0.190	-0.005
Median	0.299	0.263	-0.010
Maximum	102.874	13.866	0.610
Minimum	-33.604	-13.828	-0.630
Std. Dev.	12.367	2.537	0.139
Skewness	1.388	-0.139	0.246
Kurtosis	9.839	6.944	3.823
Jarque-Bera	2621.547	752.104	44.271
Prob.-Value	0	0	0
Observations	1155	1155	1155

***Notes*: The sample starts in the second week of January 1990 and ends in the last week of February 2012. Descriptive statistics are for the (log) changes of the CBOE Volatility Index, the S&P 500, and the 10 Year US Treasury Yield. All values reported in percent.**

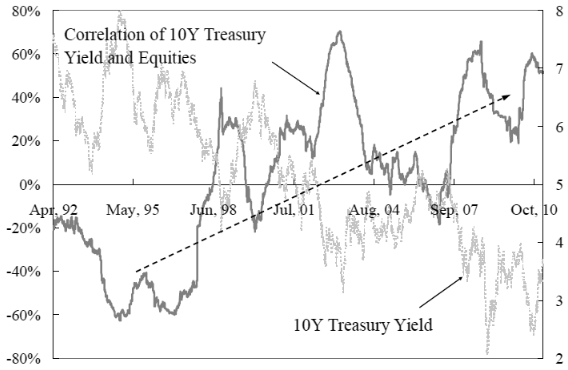
Table 2: Estimates of CCC-, DCC-, STCC-, and DSTCC-GARCH models

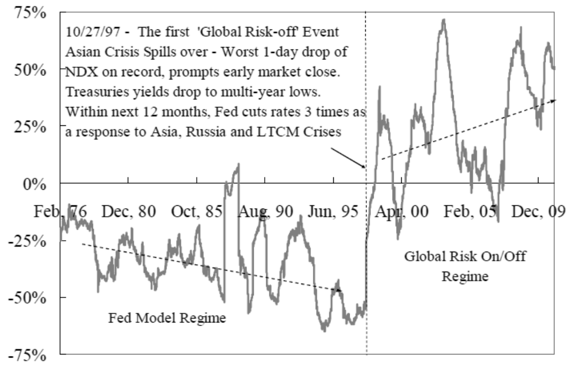
Model	CCC	DCC	STCC with time transiton	STCC with volatility transition	DSTCC with time and volatility transition
Constant rate series	0.00148 (0.00081)	0.00152 (0.00001)	0.00205 (0.00097)	0.00148 (0.00081)	0.00206 (0.00092)
Constant stock series	0.16078 (0.05323)	0.15268 (0.00417)	0.16956 (0.05540)	0.16046 (0.05329)	0.17753 (0.05705)
ARCH (1) rate series	0.06289 (0.01878)	0.06298 (0.00057)	0.06056 (0.01851)	0.06284 (0.01877)	0.06352 (0.01880)
ARCH (1) stock series	0.14982 (0.02529)	0.15029 (0.00133)	0.13671 (0.02358)	0.14972 (0.02532)	0.13963 (0.02412)
GARCH(1) rate series	0.86000 (0.05369)	0.85818 (0.00435)	0.83369 (0.06123)	0.86016 (0.05382)	0.83280 (0.05808)
GARCH(1) stock series	0.83076 (0.02672)	0.83238 (0.00127)	0.83903 (0.02701)	0.83091 (0.02677)	0.83504 (0.02763)
DCC p		0.07351 (0.00024)			
DCC q		0.91443 (0.00037)			
Correlation R	0.03612 (0.02968)	Average: 0.0124			
Correlation R 11			-0.50859 (0.04082)	0.03317 (0.04900)	-0.57320 (0.04202)
Correlation R 12			0.39857 (0.03646)	0.03781 (0.03712)	-0.37566 (0.07086)
Correlation R 21					0.42484 (0.05061)
Correlation R 22					0.38887 (0.04788)

Location Transition Variable Time		0.41358 (0.01778) [March 99]		0.42972 (0.02012) [July 99]
Speed of Transition 1		19.218		19.955
Location Transition Variable Volatility			-0.00724 (0.00001)	0.04074 (0.00001)
Speed of Transition 2			345.50	231.31
Test Statistics: Estimated Models vs Alternatives				
CCC vs STCC with time transition	148.74 (0.00000)			
CCC vs STCC with volatility change transition	12.532 (0.00040)			
CCC vs DSTCC with time and volatility change transition	236.56 (0.00000)			
STCC with time transition vs DSTCC with time and volatility change transition		9.0949 (0.00256)		
STCC with volatility transition vs DSTCC with time and volatility change transition			148.84 (0.00000)	

***Notes*: This table reports the coefficients and test statistics of the different MGARCH models; standard errors for the coefficients are in parentheses if not indicated otherwise.**

Figure 1: JP Morgan's Plot of the Correlation between Treasury Yields and Stocks.



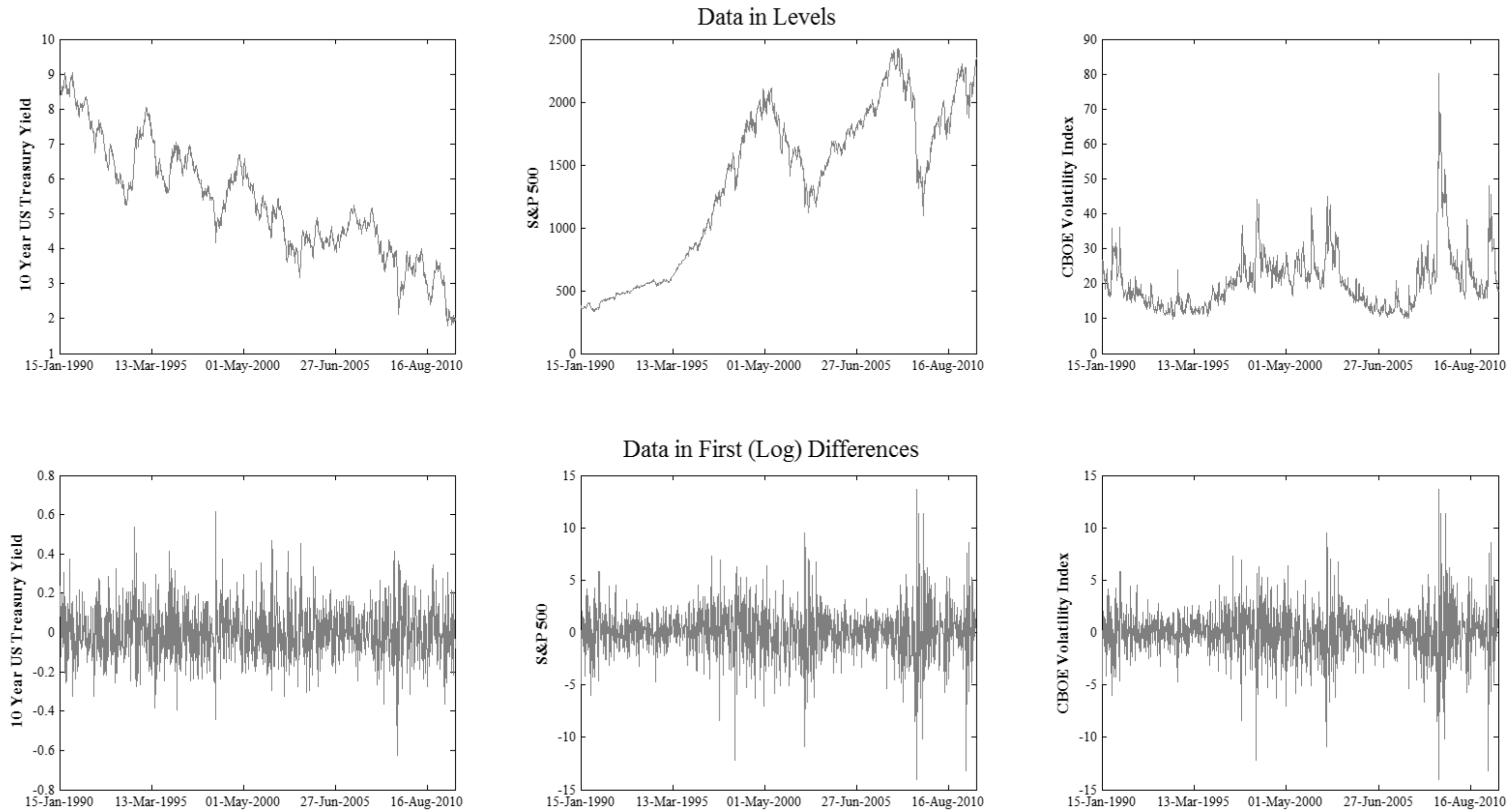


Asset Class	Correlation Between	1990-1995*	Past 5Y	Change
Equity	DM Country Indices	31%	47%	**17%**
Equity	EM Country Indices	23%	45%	**23%**
Equity	DM and EM Indices	38%	74%	**36%**
Equity	Economic Sectors	57%	69%	**12%**
Equity	Individual Stocks	25%	41%	**16%**
Credit	High Yield and Equities	46%	64%	**19%**
Credit	High Yield and VIX	37%	60%	**24%**
Foreign Exch.	DM Currencies and Equities	-1%	28%	**29%**
Foreign Exch.	EM Currencies and Equities	6%	42%	**36%**
Interest Rates	10Y Rate and Equities	-38%	29%	**67%**
Commodity	All Commodities	5%	25%	**21%**
Commodity	Commodities and Equities	-5%	12%	**17%**
Average		19%	45%	**26%**

* For Credit 2002-2005. All Currencies vs. USD

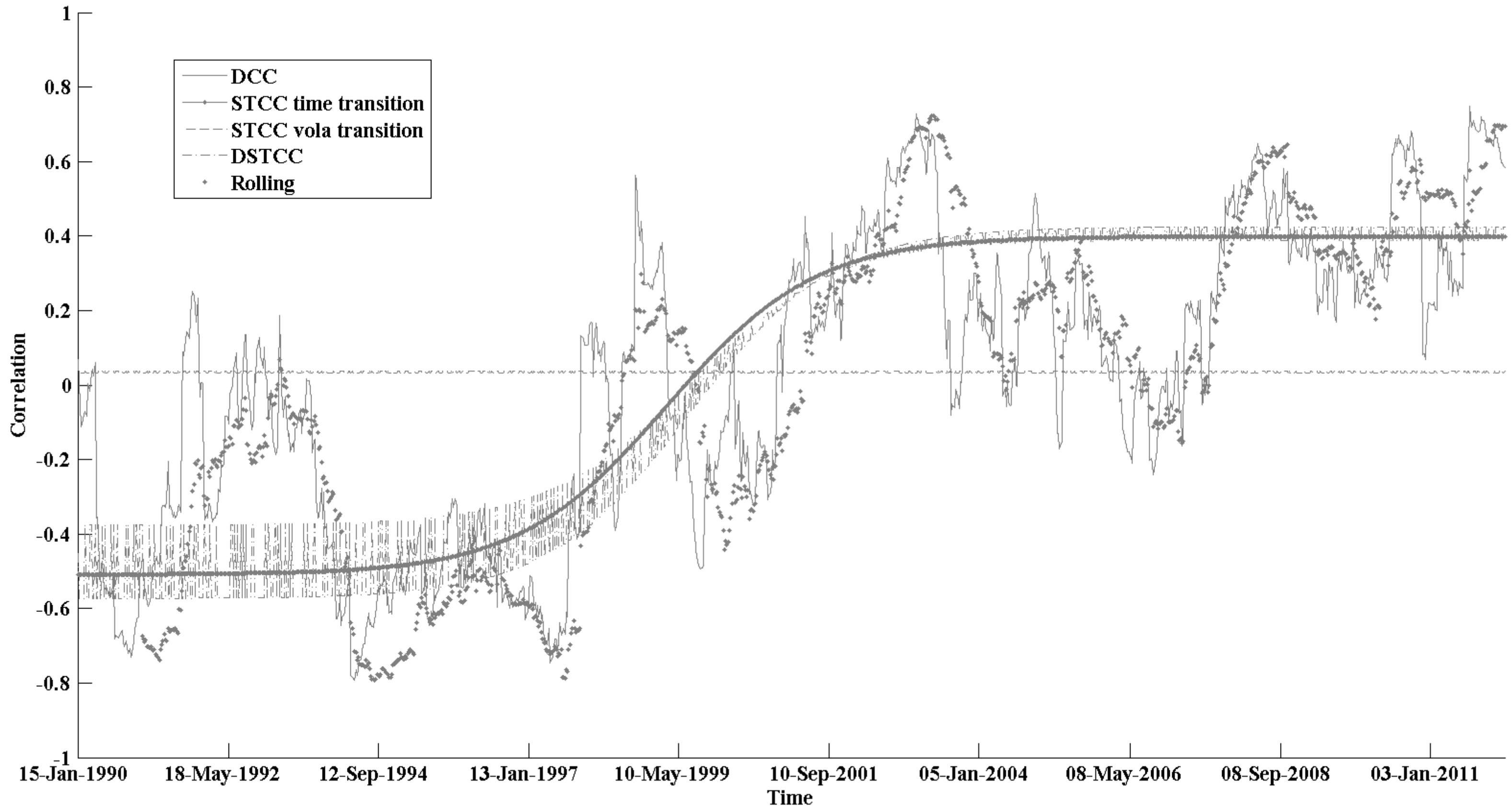
Notes: **The plot shows the 10 Year Treasury Yield, the S&P 500 and the CBOE Volatility Index over the entire sample period between January 1990 and February 2012. Data is weekly, differences were taken for the interest rate series, log differences for the stock market and volatility index series. Source: JP Morgan via Chicago Board Options Exchange (http://www.cboe.com/Institutional/JPMCrossAssetCorrelations.pdf)**

Figure 2: The Data from 1990 to 2012



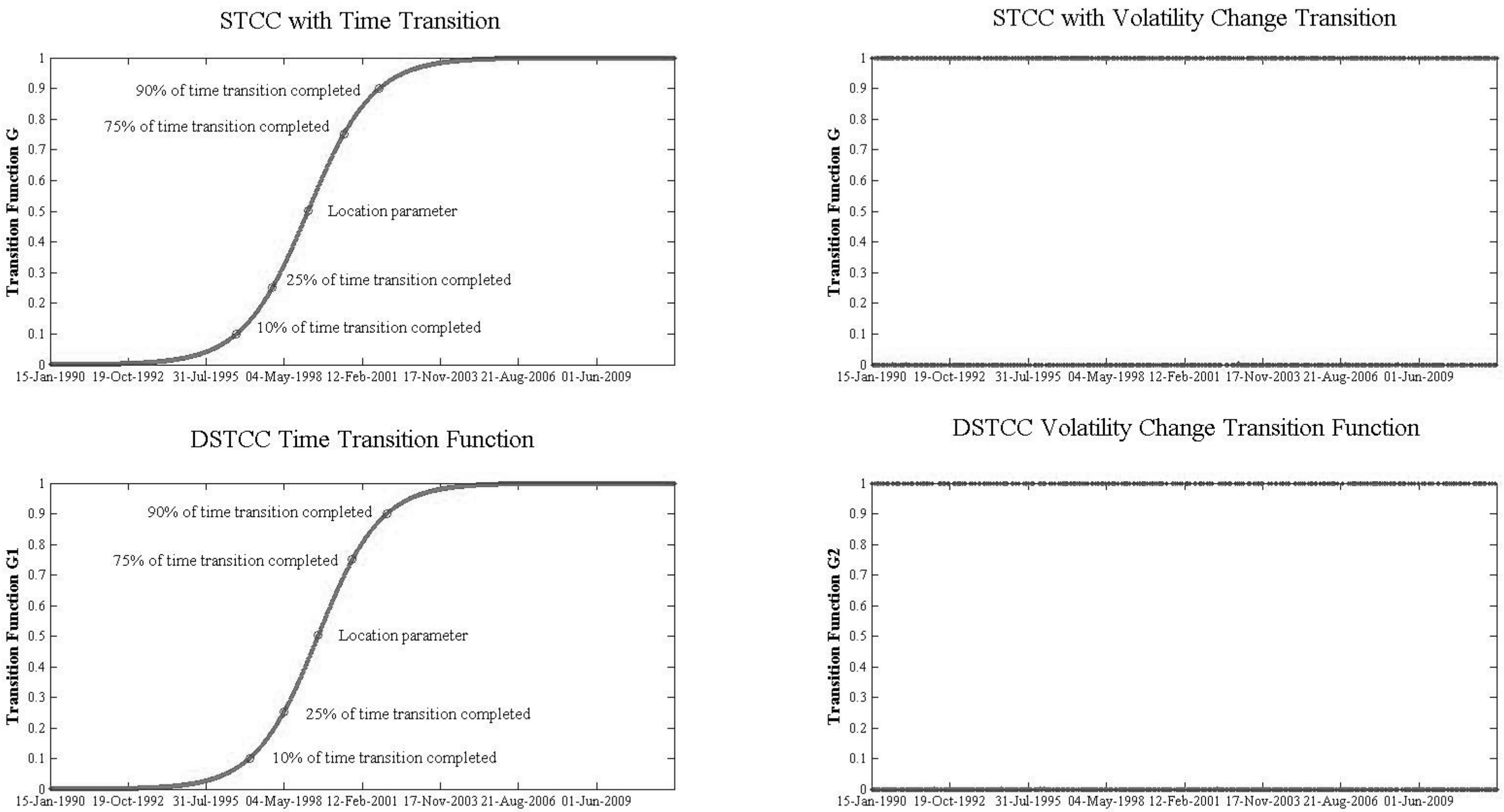
Notes: **The plot shows the 10 Year Treasury Yield, the S&P 500 and the CBOE Volatility Index over the entire sample period between January 1990 and February 2012. Data is weekly, differences were taken for the interest rate series, log differences for the stock market and volatility index series.**

Figure 3: Comparison of Time-Varying Correlations



Notes: The plot shows the various estimated conditional and rolling correlations from the time-varying MGARCH models. Correlations from the STCC-GARCH with time transition move from -0.509 to 0.399, for the STCC-GARCH with volatility change transition the "extreme" regime correlations are about zero with 0.033 and 0.037. DSTCC-GARCH correlations begin with the range of -0.573 and -0.376 and end with the range of 0.425 and 0.389. DCC-GARCH correlation dynamically moves over time with minimum -0.793 and maximum 0.784, mean about zero wit 0.012. For the rolling correlation estimates for preceding 52 weeks, the minimum is -0.792 and the maximum is 0.722, mean about zero with 0.037. Constant conditional correlation estimate from CCC-GARCH is about zero with 0.036.

Figure 4: Comparison of Transition Functions



Notes: **The plots show the estimated transition functions over time for the STCC-GARCH with time as transition variable, STCC-GARCH with volatility change as transition variable and the DSTCC-GARCH with both as transition variables. Time transition and volatility transition functions of the DSTCC-GARCH are close to those obtained when estimating the respective STCC-GARCH models. In STCC-GARCH with time, 80% of transition to the new regime between August 1996 and September 2001 and 50% between December 1997 and June 2000. In DTSCC-GARCH, 80% of transition to the new regime between February 1997 and December 2001 and 50% between April 1998 and October 2000.**

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