Anomaly in Stock-Bond Correlations
The Role of Monetary Policy

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Abstract

The paper estimates constant conditional correlation (CCC) GARCH models to test whether the dramatic changes in stock-bond market correlations can be explained by monetary policy variables such as OIS interest rate shocks or volatility regimes. We find that both specifications are empirically relevant: Correlations decrease after positive monetary shocks (decreasing rates) as well as in times with large central bank activity (high rate volatility regimes).

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1 Introduction

The correlation between aggregate stock and bond returns experienced a dramatic shift over the past two decades. Figure 1 illustrates (unconditional) stock-bond correlations using daily excess returns for five markets estimated over a moving one-year time interval between January 1987 to June 2014. The decline in correlations is obvious, in particular after the Asian and Russian crises in 1997/98. This shift is clearly observable in the US, the UK as well as Germany where the correlation was in a range between 0.2 and 0.6 before 1997/ 1998, and declined to a range between zero and -0.6 afterwards. A similar but less pronounced pattern can be observed in Switzerland, whereas the deterioration in correlations starts around five years earlier in Japan. The correlation breakdown is numerically documented in Table 1. Over the entire time period, stock-bond correlations are slightly below zero. A split of the sample into two essentially equal subperiods (before and after the turn of the millennium) reveals the described picture: The changes in correlation range between -0.37 (Switzerland) and -0.63 (Germany).

The overall pattern of negative correlations observed over the past fifteen years is particularly unusual in a longer perspective. Ilmanen (2003) shows that in case of the US markets, stock-bond correlations exhibit negative values only on a few occasions between 1926 and 2001, and over relatively short periods, namely from 1929 to 1932 and 1956 to 1965. Compared to these periods, the recent deterioration is (respectively, was) fairly long-lasting.

The consequences of this shift are far reaching: they affect asset allocation decisions as much as equilibrium risk premiums on bonds and equities. In this paper, we estimate various specifications of constant conditional correlation (CCC) GARCH models to analyze the role of monetary shocks and volatility regimes to explain the observed (i.e. unconditional) correlation pattern. These models assume that the variances and covariances of the analyzed variables conditionally change over time, or are subject to unexpected shocks, but the (conditional) correlation coefficient remains constant.[1] This reflects a widely maintained hypothesis in asset allocation models and the asset management industry.

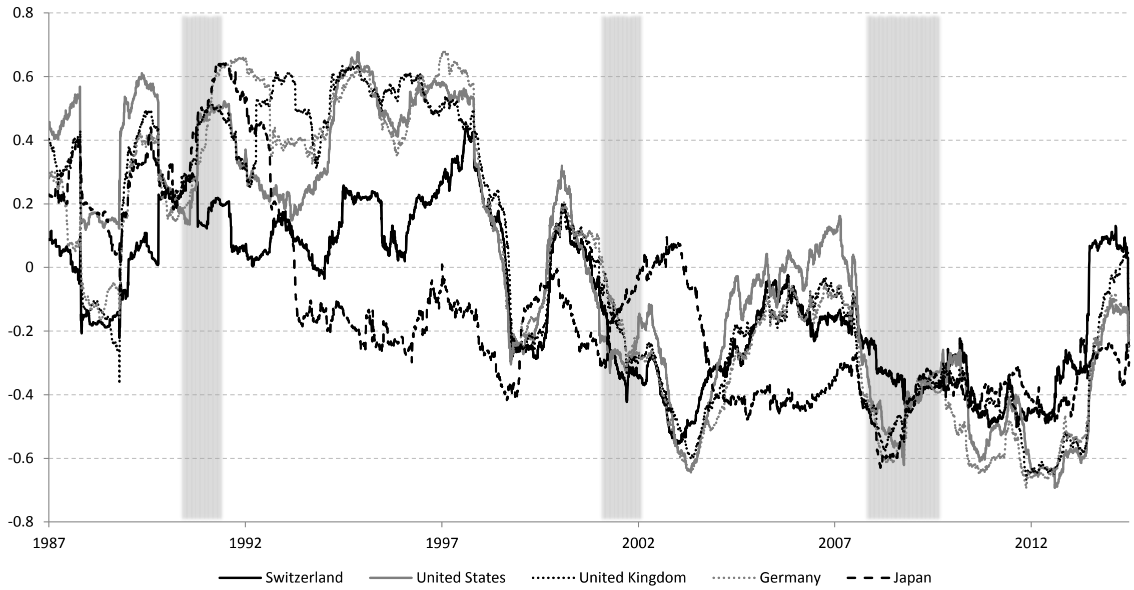
In this paper we argue that monetary interventions, particularly in times of financial crisis or stock market troughs, may well have caused the observed (unconditional) correlation pattern. Since the mid 90s, monetary authorities increasingly directed their monetary course to financial indicators, in particular, the state of the stock market. Enhancing the financial system by central bank liquidity in times of stress decreases short term interest rates and increases bond returns. This behavior potentially explains the negative correlation between stock and bond returns, and will be tested by conditioning stock-bond covariances upon monetary shocks and volatility regimes.

Due to data limitations, i.e. the availability of reliable monetary indicator rates (OIS

[1] This framework was developed by Bollerslev (1990) and was originally applied to analyze the changing behavior of stock market correlations by Longin and Solnik (1995).

Figure 1: Moving window of stock-bond correlations

This figure shows a one-year moving window of stock-bond correlations using daily data. Data run from January 1987 to June 2014. The gray bars denote periods of economic contraction according to NBER.



rates) since 2002 only, we are not able to empirically address the decline of (unconditional) correlations as documented in Figure 1 per se; however, our tests help to understand whether monetary policy effects play a role in "reversing" the (unconditional) correlation pattern of stock and bond returns.

A methodologically similar study, however covering a much longer time horizon (1855-2001) and using monthly data and different monetary indicators, is Yang et al. (2009). While their main focus is on the impact of business cycles on stock-bond correlation patterns (which is different between the UK and the US), their smooth transition conditional correlation (STCC) model reveals that higher stock-bond correlations tend to follow higher short rates in both countries, in particular in the period after 1923.

The role of a long-term trend, as opposed to cyclical variations, in stock-bond correlations is analyzed by Ohmi and Okimoto (2015). They extend a smooth transition regression (STR) model by a trend component and include multiple transition variables as suggested by Aslanidis and Christiansen (2012). They find that the short rate and yield spread become only marginally significant once the trend variable is included in the regression; the volatility remains significant.

Asgharian et al. (2015) also distinguish between long-run and short-run correlation components and use macro-finance variables to predict the long-run component. In order to combine daily return data with economic data available at lower frequency, they combine their dynamic conditional correlation (DCC) model with a mixed-data sampling (MIDAS)

Table 1: Descriptive statistics

This table shows the annualized mean (excess) returns in local currency and standard deviations of both stock and bond markets. Furthermore, the stock-bond correlations over the full as well as two subperiods are depicted. Data run from January 1987 to June 2014.

	SW	US	UK	Ger	JP
Mean stock	7.12%	7.59%	5.47%	4.07%	1.08%
Mean bond	3.04%	3.65%	3.88%	3.68%	3.14%
S.D. stock	16.68%	18.41%	16.90%	19.20%	20.60%
S.D. bond	4.63%	7.44%	6.69%	5.41%	5.11%
Stock-bond correlations					
full period	−0.14	−0.11	−0.07	−0.12	−0.08
before 2000	0.06	0.27	0.24	0.23	0.08
after 2000	−0.31	−0.35	−0.35	−0.40	−0.31

approach. They find that the behavior of the long-run stock-bond correlation is strongly affected by their macro-finance variables. Most important, their results confirm that long-run correlation tends to be small/negative when the economy is weak.

Other papers have recently analyzed the time-variation of stock-bond correlations using high-frequency data: Christiansen and Ranaldo (2007) investigate the effects of macroeconomic announcements by estimating simple "news" regressions. They find that in economic expansions (recessions) announcements increase (decrease) realized correlations. Aslanidis and Christiansen (2012) estimate smooth transition regression (STR) models for high frequency data and find that positive and negative correlation regimes are primarily related to financial transition variables (such as the short rate, yield spread, and the VIX volatility index), and to a lesser extent to macroeconomic variables. Aslanidis and Christiansen (2014) extend this analysis by estimating quantile regressions which allows to investigate the entire distribution of stock–bond correlations; they moreover include a larger set of predictive variables. They find that macro-finance predictors are most useful for explaining correlations if these are strongly negative. Schopen and Missong (2011), also using high-frequency data, estimate a generalized DCC model and separate correlations effects from volatility effects. They find that most macroeconomic news lead to falling conditional correlations, while the contrary is observed for the publication of news concerning future interest rates or inflation figures.

None of these papers addresses monetary effects explicitly, which we measure by OIS (overnight index swap) rates in this paper and which are widely regarded as adequate monetary indicators. We use the standard CCC-GARCH framework to test the impact of monetary shocks and volatility regimes on conditional correlations. This is not only a parsimonious estimation approach, but also reflects the hypothesis – and widely maintained assumption in portfolio and asset pricing models – that the conditional correlation between stocks and bonds exhibits a "natural" level which is only affected by abnormal economic conditions.

The rest of the paper is structured as follows: Section 2 presents the CCC model, and Section 3 describes the data used in this study and presents basic CCC model estimates. Section 4 discusses the results of our main model which specifies the CCC model with monetary shocks. Section 5 summarizes our findings.

2 Methodology

The evolution of correlations across stock and bond markets can be measured with the procedure used in Longin and Solnik (1995). They employ the standard constant conditional correlation (CCC) GARCH model originally proposed by Bollerslev (1990). Estimating the correlation between two assets, the corresponding model consists of a mean as well as a covariance part, where in case of the latter both the two variances and the covariance are modeled to vary over time. However, the correlation coefficient within the covariance part is constant and, hence, can be extended to explicitly model deviations. Moreover, lagged information variables are incorporated as exogenous variables in both the mean and variance equation assumed to predict future returns and variances. In what follows, the methodology to estimate the CCC model using a simple, parsimonious GARCH(1,1) process is described briefly.

2.1 Constant conditional correlation

Following Longin and Solnik (1995), we start with a simple GARCH(1,1) model to estimate constant conditional correlation. The corresponding mean equation looks as follows:

$$R_t^i = b^{i\prime} Z_{t-1}^i + \epsilon_t^i, \tag{1}$$

where R_t^i denotes the excess return of asset i, i.e. the return of stock or bond markets less the risk-free rate of the particular country.[2] Z_{t-1}^i represents the vector of predetermined information variables at time $t-1$ including a constant.[3] The unexpected return of asset i is characterized by ϵ_t^i. This vector of individual innovations is assumed to be conditionally normal with conditional variance-covariance matrix H_t. H_t contains diagonal elements h_t^i (variances) and off-diagonal terms h_t^{ij} (covariances). For reasons of simplicity, the applied set of information variables is equivalent in both mean and both variance equations, i.e. stock and bond returns as well as variances are assumed to be predicted using the same information basis.

The conditional variance of each asset is defined to be a function of the past squared innovation, the past conditional variance and the same set of information variables used

[2] The risk-free security in each country is defined as the one-month LIBOR.

[3] Following previous studies, e.g. Harvey (1991) for equity portfolios and Silva et al. (2003) for bond portfolios, it is assumed that excess returns are a linear function of past information.

in the mean equation. Furthermore, the conditional covariance is defined as the product of the constant correlation parameter and the time varying standard deviations of each asset. Therefore, variance and covariance equations in the bivariate CCC GARCH(1,1) specification look as follows:

$$\begin{aligned} h_t^i &= \omega^i + \alpha^i \epsilon_{t-1}^{2i} + \beta^i h_{t-1}^i + b^{i\prime} Z_{t-1}^i \\ h_t^{ij} &= \rho^{ij} \sqrt{h_t^i} \sqrt{h_t^j}, \end{aligned} \tag{2}$$

where h_t^i denotes the conditional variance of asset i, and h_t^{ij} represents the conditional covariance between assets i and j (stocks and bonds) in a particular country, with ρ being the corresponding constant correlation parameter. As in Longin and Solnik (1995), the GARCH system defined by Equations (1) and (2) is used as the base model. After estimating the base model, various alterations of it can be tested and employed for comparison concerning the assumption of constant conditional correlation. Using this setup, the conditional variance-covariance matrix, H_t, is defined as:

$$H_t = D_t R D_t \tag{3}$$

where D_t is a $N \times N$ diagonal matrix with elements $\sqrt{h_t^i}$, and R denotes a time-invariant $N \times N$ matrix of conditional correlations with N representing the dimension of the model, i.e. the number of assets.

The base model described in Equations (1) and (2) is estimated by maximizing the following log-likelihood, $l_t(\theta)$, at each point in time:

$$l_t(\theta) = -\frac{1}{2} \left(N \log(2\pi) + \log |H_t| + \epsilon_t' H_t^{-1} \epsilon_t \right), \tag{4}$$

where θ denotes the vector of model parameters. Accordingly, the log-likelihood for the whole sample, i.e. from time 1 to T, is equal to:

$$L(\theta) = \sum_{t=1}^{T} l_t(\theta). \tag{5}$$

The log-likelihood is estimated for each country individually, implying the estimation of a bivariate GARCH model with 21 parameters. Eight of those are allotted to the mean equations, i.e. a constant and three coefficients belonging to the information variables for both stock and bond returns. On the other hand, the variance part contains twelve parameters, three for the GARCH terms as well as three concerning the information variables (again for each asset). At last, the remaining parameter denotes the constant correlation coefficient.

3 Data and structural characteristics

The first part (3.1) of this section briefly describes the data set employed in the CCC model estimation. Based on the definition of all incorporated variables, Section 3.2 proceeds with investigating the results obtained from estimating the base model. Section 3.3 then introduces two standard tests to check whether and how correlation changed over time.

3.1 Variables

The data set used in modeling the evolution of stock-bond correlations via a simple CCC model consists of three different parts. First, the returns of all markets examined, i.e. data on those stock and bond markets for which the correlations are analyzed. Second, a set of variables representing the information basis assumed to predict stock and bond returns and variances. Third, to measure the impact of monetary policy on correlations, a short-term interest rate is required as proxy for monetary policy. The examined period ranges from March 2002 to June 2014 employing daily data (3203 observations).

Stock and bond returns: Return series are generated for the following countries: Switzerland, the US, the UK, Germany, Japan. All data are collected from Thomson Reuters datastream. For stock returns, the datastream market indices of each country are used to calculate daily excess returns employing the one-month LIBOR as the risk-free security. The excess returns on bond markets are derived analogously. Both stock and bond returns are applied in local currency.

Information variables: According to Ferson and Harvey (1999), several different variables come into consideration as information basis for predicting stock returns. Due to lack of availability of some variables in some countries, the information set used in this study is restricted to the lagged dividend yield (e.g. Fama and French (1989)), the lagged short-term interest rate (e.g. Fama and Schwert (1977) and Ferson (1989)) and the lagged term spread. The dividend yield is calculated as the log of the total value of dividends paid of all constituent parts of the index at time t minus the log of the total market value of the index at time t.[4] The short-term interest rate is the one-month LIBOR in each country. At last, the term spread is defined as the difference between the 10-year and the three-month interest rate.

These three variables are supposed to also predict bond returns. This selection can be justified in two ways. First, Keim and Stambaugh (1986), for instance, detect that both US stock and bond markets are subject to common predictability. Second, both the short-term interest rate as well as the term spread are applied as information variables in studies where only bond returns are predicted, e.g. Silva et al. (2003).

Accordingly, stock and bond returns are subsequently assumed to be predicted by the same set of variables. All instruments are available on a daily basis and enter the CCC

[4] Logarithms are taken because of superior time series properties (Lewellen (2004)).

model as lagged variables, i.e. their values at time $t - 1$ are supposed to predict asset returns at time t. Data on all information variables are taken from Thomson Reuters datastream.

Monetary policy: To analyze the effect of monetary policy shocks as well as monetary policy regimes on correlations, a suitable proxy for monetary policy is required. The short-term interest rate thereby denotes the most obvious proxy as the central bank's main instrument. One possible and convenient method would be to simply employ the three-month LIBOR as a proxy for monetary policy due to its availability in all countries over a long period of time. However, in periods of financial distress, e.g. the recent financial crisis, the LIBOR tends to be a rather bad proxy as the spread to the true key policy rates, e.g. the Federal funds rate in case of the US, largely increases.

A viable alternative is to use the overnight indexed swap (OIS), depicting a rather good proxy also in stressed market conditions. Moreover, the OIS rates represent a variable that is available in all countries, making a consistent comparison of results possible. Accordingly, daily OIS data are used to proxy for monetary policy, the corresponding data are taken from Bloomberg. The usage of OIS rates, however, comprises one drawback in the from of rather short time series available, implying an analysis period that starts between 2000 and 2002 depending on the country.

3.2 Base model

This section discusses the findings of the base model defined in Equations (1) and (2). Table 2 provides the corresponding results. Panel A shows the estimated coefficients of the mean equations for stock and bond returns as well as the correlation coefficient, ρ, and the log likelihood, *Lik*, for each country. Panel B illustrates the results of the variance equations.

Looking at Panel A reveals that the coefficient of the dividend yield is positive in all stock markets except for Switzerland. This positive relationship intuitively makes sense as a high dividend yield should lead to higher future returns, indicating that the particular company is financially sound. In cases of the US and the UK, the coefficient is statistically significant at the 1% level. For bond markets the dividend yield also tends to exhibit a positive impact with a significant coefficient observed only in case of Switzerland. Short-term interest rates tend to have a negative effect on stock markets (except for the US) with significant effects in Switzerland and Japan. This finding is in line with the literature as higher interest rates raise the cost of financing of companies. On the other hand, the impact on bond returns is somehow counterintuitive. Recall that the bond returns are generated using 10-year bond indices, and, hence, the difference in time to maturity is quite large. Moreover, long-term interest rates tend to be determined by what impact the market believes short-term interest rates will have on long-term interest rates. Accordingly, a possible explanation of the positive effect is derived via expectations of future inflation.

Table 2: Constant conditional correlations between stock and bond markets

This table shows the GARCH coefficients of the following system of equations:

$$\begin{aligned} R_t^i &= b_{0i} + b_{1i} DY_{t-1}^i + b_{2i} sIR_{t-1}^i + b_{3i} TS_{t-1}^i + \epsilon_t^i \\ h_t^i &= \omega^i + \alpha^i \epsilon_{t-1}^{2i} + \beta^i h_{t-1}^i + b_{1i} DY_{t-1}^i + b_{2i} sIR_{t-1}^i + b_{3i} TS_{t-1}^i \\ h_t^{ij} &= \rho^{ij} \sqrt{h_t^i} \sqrt{h_t^j}, \end{aligned}$$

where R_t^i denotes the return on either stock or bond markets. DY, sIR and TS represent, respectively, the lagged dividend yield, the lagged short-term interest rate and the lagged term spread. h_t^i is the variance of either stock or bond markets, and h_t^{ij} denotes the corresponding covariance with ρ^{ij} being the constant correlation coefficient. Standard errors are shown in parentheses. Data run from March 2002 to June 2014.

Panel A: Mean equation, correlation and log likelihood

		b_0	DY $\cdot 10^3$	sIR	TS	ρ	Lik
SW	Stocks	0.003^{***}	-1.653^{**}	-0.071^{**}	-0.079^{**}	-0.290^{***}	25085
		(0.001)	(0.805)	(0.029)	(0.033)	(0.015)	
	Bonds	-0.001^{**}	0.652^{**}	0.013	0.038^{***}		
		(0.000)	(0.274)	(0.009)	(0.011)		
US	Stocks	-0.007^{***}	8.690^{***}	0.055^{**}	0.067^{*}	-0.356^{***}	23272
		(0.003)	(2.519)	(0.028)	(0.036)	(0.013)	
	Bonds	-0.002^{**}	1.680	0.030^{**}	0.048^{***}		
		(0.001)	(1.034)	(0.013)	(0.017)		
UK	Stocks	-0.003^{*}	3.707^{***}	-0.014	-0.026	-0.355^{***}	24136
		(0.002)	(1.381)	(0.015)	(0.025)	(0.014)	
	Bonds	-0.001	0.306	0.011	0.025^{**}		
		(0.001)	(0.484)	(0.008)	(0.012)		
Ger	Stocks	0.001	0.384	-0.018	-0.018	-0.412^{***}	24212
		(0.001)	(0.976)	(0.020)	(0.030)	(0.013)	
	Bonds	0.000	0.225	0.004	0.020^{**}		
		(0.000)	(0.315)	(0.007)	(0.010)		
JP	Stocks	0.001	0.370	-0.246^{**}	-0.016	-0.380^{***}	25231
		(0.001)	(0.715)	(0.100)	(0.076)	(0.014)	
	Bonds	0.000	0.044	0.003	0.006		
		(0.000)	(0.110)	(0.017)	(0.012)		

For instance, if short-term interest rates are (believed to be too) low, expected inflation increases implying long-term interest rates to increase as well due to decreasing purchasing power of future bond cash flows. The estimated coefficients of the term spread are negative for stock markets (except for the US) but mostly insignificant. In case of bond markets, the impact is unambiguously positive and mostly significant. Overall, roughly half of the coefficients with respect to the information set are significant (at least at the 10% level). In addition, it seems that predicting returns works comparatively well in Switzerland and the US.

Finally, the constant conditional correlation coefficients, ρ, in Panel A are considerably below zero and clearly significant in all countries. This is, of course, due to the chosen period starting in March 2002. The corresponding correlation coefficients range between -0.29 (Switzerland) and -0.41 (Germany). This finding of negative correlations is now subject to further tests conducted in Section 3.3 and Section 4 by adding either simple extensions

Table 2 (continued)

		Panel B: Variance equation					
		$\omega \cdot 10^3$	α	β	DY $\cdot 10^3$	sIR $\cdot 10^3$	TS $\cdot 10^3$
SW	Stocks	-0.002	0.090^{***}	0.881^{***}	0.003^{***}	0.122^{***}	0.094^{**}
		(0.001)	(0.008)	(0.010)	(0.001)	(0.038)	(0.038)
	Bonds	0.000^{***}	0.046^{***}	0.938^{***}	0.000	0.003^{*}	-0.001
		(0.000)	(0.004)	(0.005)	(0.000)	(0.002)	(0.002)
US	Stocks	-0.003	0.078^{***}	0.901^{***}	0.004	0.062^{*}	0.080^{*}
		(0.003)	(0.007)	(0.008)	(0.004)	(0.035)	(0.045)
	Bonds	0.000	0.036^{***}	0.956^{***}	0.000	0.003	0.004
		(0.000)	(0.004)	(0.006)	(0.000)	(0.003)	(0.005)
UK	Stocks	0.002	0.088^{***}	0.898^{***}	0.000	-0.001	0.008
		(0.002)	(0.008)	(0.008)	(0.002)	(0.014)	(0.025)
	Bonds	0.000	0.028^{***}	0.954^{***}	0.000^{**}	-0.006^{***}	-0.006^{**}
		(0.000)	(0.004)	(0.009)	(0.000)	(0.002)	(0.003)
Ger	Stocks	-0.008^{***}	0.091^{***}	0.863^{***}	0.010^{***}	0.157^{***}	0.099^{**}
		(0.003)	(0.008)	(0.012)	(0.002)	(0.038)	(0.046)
	Bonds	0.000	0.029^{***}	0.952^{***}	0.000^{*}	0.000	-0.003
		(0.000)	(0.005)	(0.007)	(0.000)	(0.001)	(0.002)
JP	Stocks	0.010^{***}	0.110^{***}	0.861^{***}	-0.003^{**}	0.411^{**}	-0.439^{***}
		(0.002)	(0.008)	(0.011)	(0.001)	(0.193)	(0.154)
	Bonds	0.000^{***}	0.076^{***}	0.905^{***}	0.000^{***}	0.017^{***}	0.003
		(0.000)	(0.005)	(0.006)	(0.000)	(0.005)	(0.002)

based on stock market volatility and through the incorporation of monetary policy effects, respectively. Both approaches help identifying and measuring possible deviations from the constant correlation base model.

Panel B illustrates that conditional variances are primarily driven by the GARCH parameters. All α's and β's are highly significant in each country for both stock and bond returns. Moreover, they take on the usual values, and the condition for (weak) stationarity, $\alpha + \beta < 1$, holds in all cases. On the other hand, the set of information variables exhibits rather small effects on conditional variances as their coefficient values are all close to zero. However, there is quite some statistical significance with more than half of the coefficients being statistically significant (at least at the 10% level).

For reasons of comparison, two bivariate homoskedastic model specifications are estimated in addition to the heteroskedastic base model. Doing so enables one to test the hypothesis of constant means and variances using likelihood ratio tests. The first of the two homoskedastic models contains no information variables at all, and, hence, only one parameter in each mean equation (two constants) as well as seven covariance terms have to be estimated (three GARCH parameters for each asset as well as the correlation coefficient). The second model, on the other hand, adds the vector of information variables to the mean equation only, implying a total of 15 parameters. The log likelihood is then estimated for both specifications.

Results not shown here indicate that both mean and variance exhibit variability over time. Likelihood ratio tests comparing the base model with the homoskedastic model with no information variables at all yield test statistics significant at the 1% level in all countries. Concerning the homoskedastic model with information variables included only in the mean equation, the null hypothesis of constant variances can be rejected at the 5% significance level in all countries except for the US. As a consequence, the chosen set of information variables and its incorporation into the mean and variance equations seem to be appropriate.

To see whether the GARCH(1,1) specification of the base model does well in capturing the existing heteroskedasticity, two simple tests following Bollerslev (1990) are conducted. First, the standard Ljung-Box portmanteau misspecification test on standardized residuals is applied. The test can be performed on squared standardized residuals, $\hat{\epsilon}_t^{i2}/\hat{h}_t^i$, of asset i in each country separately, yielding a total number of ten tests. The maximum lag, h, is set to nine, i.e. the log of the number of observations.[5] Nine of ten test statistics range between 4.05 (Swiss bonds) and 16.64 (Japanese bonds) when nine lags are included and, hence, lie below the critical value (16.92) of the chi square distribution, $\chi^2_{0.95,9}$. However, in one case (US stocks) the test statistic is slightly above the critical value, suggesting that the corresponding residuals are not independently distributed.

The validity of the GARCH specification in Equations (1) and (2) can also be tested by implementing the regression based approach suggested by Bollerslev (1990). As noted before, using the GARCH parametrization it is assumed that $E(e_t^i e_t^j \mid Z_{t-1}) = h_t^{ij}$. Setting $i = j$ the test is conducted by regressing $(\hat{\epsilon}_t^{i2}/\hat{h}_t^i - 1)$ on $1/\hat{h}_t^i$ and $\hat{\epsilon}_{t-1}^{i2}/\hat{h}_t^i, \ldots, \hat{\epsilon}_{t-5}^{i2}/\hat{h}_t^i$. To check whether the estimated coefficients are jointly equal to zero one then has to perform a conventional F-test. The corresponding 95% critical value for the $F_{6,3192}$ distribution is 2.1. Results not shown here confirm the findings of the Ljung-Box test, meaning that the F-test values are statistically insignificant at the 5% level in nine of ten cases. Again, only for US stocks the F-test yields a value of 4.47, and, hence, the null hypothesis of all coefficients being jointly equal to zero is rejected at the 1% level.

To sum up, both tests indicate that the parsimonious multivariate GARCH(1,1) model with constant conditional correlation is specified well enough. Only in case of US stocks the null hypothesis of no serial correlation in the residuals is rejected in both test specifications.

3.3 Simple extensions

In this section, two simple approaches to model deviations from the constant correlation base model are employed. Both are applied using a set of dummy variables constructed with respect to the stock market volatility. As volatility tends to increase when stock markets fall, one would expect correlation to be smaller in recessions and vice versa. On the other hand, increasing volatility can be decomposed into positive and negative shocks to stock market returns, enabling the researcher to identify asymmetric effects on correlation due to

[5] Note that the incorporation of 20 lags in the Ljung-Box test leads to similar results.

shocks in the stock market. From theory, some amount of asymmetry would be expected in the form of lower correlations following a negative stock market shock compared to a positive one.

To investigate the influence of high stock market volatility, the base model in Equations (1) and (2) is augmented with a dummy variable, S_{t-1}, implying the following covariance equation:

$$h_t^{ij} = (\rho_0 + \rho_1 S_{t-1})\sqrt{h_t^i}\sqrt{h_t^j}, \tag{6}$$

where S_{t-1} takes on the value one if the conditional stock market volatility of the base model at time t is larger than the unconditional stock market volatility and zero otherwise. Incorporating the so constructed time series as a lagged variable describes the impact of high stock market volatility at time $t-1$ on correlation at time t.

As Panel A of Table 3 displays, the impact of high stock market volatility on stock-bond correlations is obvious as the correlation considerably deteriorates in all countries. In Japan the reduction is the lowest and statistically insignificant. The remaining countries, on the other hand, exhibit highly significant and negative effects with ρ_1 ranging between -0.11 (Switzerland) and -0.21 (US). The negative impact turns out as expected and underlines the benefit of diversification in turbulent times using bonds. As the augmented model is nested with the base model, standard likelihood ratio tests are employed. The corresponding test statistics are shown in the last row and clearly indicate a rejection of the null hypothesis of the base model except for Japan.

To analyze possible asymmetries in the effect of shocks in stock market returns on correlation, a set of four dummy variables is defined following Longin and Solnik (1995). The dummies are constructed using ϵ_{t-1}^i, i.e. the resulting residuals in the mean equation for stocks in the base model, and take on the following values:

- $S_{1,t-1} = 1$ if ϵ_{t-1}^i is greater than σ^i,
- $S_{2,t-1} = 1$ if ϵ_{t-1}^i is greater than 0 and less than σ^i,
- $S_{3,t-1} = 1$ if ϵ_{t-1}^i is less than 0 and greater than $-\sigma^i$,
- $S_{4,t-1} = 1$ if ϵ_{t-1}^i is less than $-\sigma^i$,

and zero otherwise. Note that σ^i denotes the standard deviation of the residuals generated with the mean equation for stocks in the base model.

Including these four dummies in the GARCH specification results in the following covariance equation:

$$h_t^{ij} = (\rho_1 S_{1,t-1} + \rho_2 S_{2,t-1} + \rho_3 S_{3,t-1} + \rho_4 S_{4,t-1})\sqrt{h_t^i}\sqrt{h_t^j}, \tag{7}$$

where the constant correlation parameter, ρ_0, is dropped. Assuming that the negative

Table 3: Simple extensions to constant conditional correlation

This table shows the results of two simple extensions of the base model. First, in Panel A the base model is augmented with a dummy variable representing high stock market volatility, i.e. times of financial distress. The coefficient ρ_1 measures the change in correlation in volatile markets compared to the constant correlation, ρ_0. Second, Panel B shows the results of a model extension where the covariance equation is a function of four stock market shock dummies. Thereby, ρ_1, ρ_2, ρ_3 and ρ_4 denote strong positive, weak positive, weak negative and strong negative stock market shocks, respectively. If $\rho_1 = \rho_4$ and $\rho_2 = \rho_3$, there is no asymmetry. Standard errors are given in brackets. As the model in Panel A is nested with the base model, the likelihood ratio test statistic, LR, and the corresponding p-value are shown in addition to the coefficients. Data run from March 2002 to June 2014.

	SW	US	UK	Ger	JP
			Panel A: Volatility shock		
ρ_0	-0.256^{***}	-0.299^{***}	-0.296^{***}	-0.354^{***}	-0.373^{***}
	(0.018)	(0.016)	(0.017)	(0.016)	(0.017)
ρ_1	-0.110^{***}	-0.206^{***}	-0.190^{***}	-0.192^{***}	-0.028
	(0.029)	(0.027)	(0.027)	(0.025)	(0.026)
LR	10.371	37.681	35.775	39.910	0.727
(p-value)	(0.001)	(0.000)	(0.000)	(0.000)	(0.394)
			Panel B: Volatility thresholds		
ρ_1	-0.362^{***}	-0.408^{***}	-0.454^{***}	-0.506^{***}	-0.239^{***}
	(0.053)	(0.042)	(0.045)	(0.034)	(0.036)
ρ_2	-0.271^{***}	-0.317^{***}	-0.351^{***}	-0.373^{***}	-0.396^{***}
	(0.023)	(0.021)	(0.022)	(0.021)	(0.023)
ρ_3	-0.278^{***}	-0.362^{***}	-0.314^{***}	-0.407^{***}	-0.413^{***}
	(0.022)	(0.019)	(0.020)	(0.018)	(0.019)
ρ_4	-0.330^{***}	-0.419^{***}	-0.434^{***}	-0.476^{***}	-0.367^{***}
	(0.040)	(0.033)	(0.033)	(0.027)	(0.040)

effect of high stock market volatility in Panel A of Table 3 is mainly due to negative shocks, coefficients should be asymmetric when ρ_1 and ρ_4 or ρ_2 and ρ_3 are compared.

Panel B of Table 3 presents the estimated coefficients using the augmented model incorporating volatility thresholds. The four coefficients show two interesting results that appear to a similar extent in all countries except for Japan. First, correlations are considerably lower after strong stock market shocks, independent of the shock's sign. Second, large negative and large positive shocks seem to be symmetric. Only in case of Japan, there is a distinct asymmetry in terms of stock market shocks, implying lower correlations upon large negative shocks compared to large positive shocks. Overall, a rather symmetric pattern is observed concerning the reaction of stock-bond correlations to stock market shocks. Differences in the correlation coefficients between (large) positive and (large) negative shocks are small and only for Japan an asymmetry is unambiguously detected.

To conclude, results above reveal that increasing stock market volatility leads to a lower stock-bond correlation. However, over this period of overall negative correlations the impact of stock market shocks seems to be independent of its sign.

4 Empirical Results

This section investigates the impact of monetary policy on correlation between stocks and bonds. Thereby, monetary policy is proxied by OIS rates representing the central bank's primary instrument. According to standard valuation models, one would expect that both stock and bond prices fall in response to a higher interest rate and vice versa since interest rates determine the risk-free part of discount rates.

In what follows the impact of monetary policy is measured in two different ways. First, monetary policy shocks are estimated using a simple autoregressive-moving average model. Second, monetary policy regimes are specified based on a standard Markov regime switching model.

4.1 Monetary policy shocks

The first approach to measure the impact of interest rates on stock-bond correlations uses monetary policy shocks. The corresponding time series of interest rate shocks is constructed with a simple autoregressive-moving average (ARMA) model. A parsimonious ARMA(1,1) specification is estimated using first differences of the raw interest rate data:

$$y_t = \phi_i y_{t-i} + \theta_j \epsilon_{t-j} + \epsilon_t, \text{[6]} \tag{8}$$

where y_t denotes the vector of interest rate differences. Interest rate shocks, i.e. the resulting residuals, ϵ_t, are obtained by applying this model to the differenced interest rate series of each country individually. Using the generated time series of interest rate shocks, two dummy variables can be defined according to the following thresholds:

- $S_{1,t-1} = 1$ if ϵ^i_{t-1} is greater than σ^i,
- $S_{2,t-1} = 1$ if ϵ^i_{t-1} is less than $-\sigma^i$.[7]

Incorporating these dummy variables leads to the below covariance equation of the GARCH specification:

$$h^{ij}_t = (\rho^{ij}_0 + \rho^{ij}_1 S_{1,t-1} + \rho^{ij}_2 S_{2,t-1})\sqrt{h^i_t}\sqrt{h^j_t}. \tag{9}$$

Accordingly, dummy variables $S_{1,t-1}$ and $S_{2,t-1}$ represent negative (increasing rates) and positive (decreasing rates) monetary policy shocks, respectively, at time $t-1$.

The covariance specified in Equation (9) now enables the researcher to directly investigate the impact of monetary policy shocks on stock-bond correlations. In order to have consistent and comparable data among countries, OIS series are employed to proxy monetary policy and generate the corresponding shocks. As mentioned earlier, the availability

[6] For reasons of simplicity and comparability, a lag of one is chosen for both the AR and MA part, implying the estimation of a simple ARMA(1,1) for all countries.

[7] Note that the definition of a one standard deviation threshold is highly arbitrary. For robustness checks using alternative threshold specifications see Section 4.3.

and length of OIS data series depend on the chosen country, and, hence, the definition of the investigated period is not unambiguous. One way of specifying the period is to use a common sample by simply employing the period of the shortest available time series, i.e. the Japanese OIS series. Thus, Panel A of Table 4 displays the results concerning the impact of monetary policy shocks on stock-bond correlations generated with daily OIS data according to Equation (8) over the period from March 2002 to June 2014. The three coefficients are defined in Equation (9), where ρ_1 denotes the impact of negative and ρ_2 represents the influence of positive monetary policy shocks.

The estimates clearly suggest that some sort of anomaly exists when negative and positive shocks are compared. The anomaly arises from the significantly negative value of the coefficient ρ_2. Standard valuation models indicate that lower interest rates imply higher stock as well as higher bond prices. However, ρ_2 reveals that positive monetary policy shocks decrease stock-bond correlations in all countries except for Japan. The negative effects range between -0.078 in Switzerland and -0.163 in Germany. Moreover, negative effects are statistically significant to the 10%, 5% and 1% significance level in Switzerland, the US and both the UK and Germany, respectively. On the other hand, coefficients estimated with negative monetary policy shocks tend to be close to zero and statistically insignificant. Thus, it seems that the causality is reversed, implying that deteriorating stock markets induce monetary policy to lower interest rates which, in turn, leads to increasing bond prices. As the base model in Section 3.2 is also estimated using the common sample, Panel A of Table 4 furthermore displays the test statistics as well as the corresponding p-values of simple likelihood ratio tests. In case of the UK and Germany, these clearly indicate a rejection of the null hypothesis of the base model. For the remaining three countries there is no significant improvement. However, dropping the negative monetary policy shock from the covariance equation since ρ_1 is always insignificant, yields likelihood ratio tests that reject the null hypothesis in case of the US at the 10% level and only closely fail to reject the null hypothesis in case of Switzerland.

For comparative purposes, Panel B of Table 4 shows the results of the same model with a set of slightly different data. It presents the outcome using the complete OIS data series in each country, and, hence, the investigated period now differs between countries. Accordingly, the sample starts in August 2000, December 2001, January 2001, January 2000, and March 2002 in Switzerland, the US, the UK, Germany and Japan, respectively. A mere look clearly indicates that the negative effect is still present when individual sample periods are analyzed. Interestingly, the impact is even stronger, i.e. more negative, and significant at the 1% level in Switzerland. On the other hand, positive monetary policy shocks exhibit a weaker and less significant effect in the US, the UK and Germany, where the latter is only inconsiderably below zero. The influence of negative shocks tends to be positive but remains insignificant. Due to different sample periods, the model is no longer nested with the base model and, hence, no likelihood ratio tests are performed.

Table 4: Monetary policy shocks

This table shows the results of the base model augmented with two dummy variables accounting for negative and positive monetary policy shocks, given by ρ_1 and ρ_2, respectively. Note that a positive monetary policy shock denotes decreasing interest rates and vice versa. Standard errors are given in brackets. Data range from March 2002 to June 2014 in Panel A whereas Panel B employs country-specific samples.

	SW	US	UK	Ger	JP
			Panel A: Common sample (03:2002 - 06:2014)		
ρ_0	-0.282^{***}	-0.345^{***}	-0.343^{***}	-0.396^{***}	-0.386^{***}
	(0.016)	(0.014)	(0.015)	(0.015)	(0.015)
ρ_1	-0.017	-0.068	-0.027	-0.002	0.022
	(0.067)	(0.058)	(0.063)	(0.051)	(0.051)
ρ_2	-0.078^{*}	-0.112^{**}	-0.158^{***}	-0.163^{***}	0.075
	(0.045)	(0.051)	(0.047)	(0.031)	(0.054)
LR	2.033	4.228	7.932	13.328	1.559
	(0.362)	(0.121)	(0.019)	(0.001)	(0.459)
			Panel B: Individual sample (... - 06:2014)		
	08:2000...	*12:2001...*	*01:2001...*	*01:2000...*	*03:2002...*
ρ_0	-0.284^{***}	-0.352^{***}	-0.337^{***}	-0.365^{***}	-0.386^{***}
	(0.015)	(0.014)	(0.014)	(0.013)	(0.015)
ρ_1	0.042	0.096	-0.023	0.024	0.022
	(0.064)	(0.063)	(0.057)	(0.055)	(0.051)
ρ_2	-0.150^{***}	-0.089^{*}	-0.106^{**}	-0.026	0.075
	(0.037)	(0.048)	(0.044)	(0.032)	(0.054)

Overall, findings discussed here clearly show that stock-bond correlation decreases at time t when there is a positive monetary policy shock at time $t-1$. This depicts some sort of anomaly as central banks possibly react to falling stock markets by lowering interest rates, leading to higher bond prices. However, this insight cannot explain why the overall negative correlation during the 21$^{\text{st}}$ century exists as the negative effect only reduces the negativity further, i.e. ρ_0 is already clearly and significantly negative throughout all countries as can be seen in Table 4.

4.2 Monetary policy regimes

The second approach to measure the influence of interest rates on stock-bond correlations is based on the existence of monetary policy regimes. In contrast to the case of shocks as explained before, one could expect regimes to be more persistent, i.e. switches from low to high interest rate regimes and vice versa do not occur very often. Due to this fact, the differentiation between the impact of shocks and the one of regimes makes sense.

To define a regime dummy, a simple Markov regime switching model is applied to short-term interest rates in differenced form. Again, the OIS rate serves as a proxy for monetary policy actions. The model is estimated using the following specification:

$$\begin{aligned} y_t &= \mu_{S_t} + \epsilon_t, \\ \epsilon_t &\sim (0, \sigma^2_{S_t}) \end{aligned} \tag{10}$$

where y_t denotes, again, the differenced interest rate series, and S_t represents the state of the process. The constant, μ_{S_t}, and the variance of the residual, $\sigma^2_{S_t}$, are either high or low depending on the state. Assuming the existence of only two states, the transition probability matrix, P, is defined as follows:

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}, \tag{11}$$

where p_{ij} denotes the probability of being in regime j at time t switching to regime i at time $t+1$. Hamilton's (1994) filter is then employed in the maximum likelihood estimation. Based on that optimization, the vector of interest including the smoothed probabilities used to define the regimes is generated according to Kim (1994).

Figure 2 shows the estimated smoothed probabilities for the high volatility regime for Switzerland and the US using OIS data. The two graphs look similar and indicate some periods of high volatility, one of which clearly took place during the financial crisis.[8] Moreover, the aftermath of the dotcom bubble also seems to be more volatile in terms of monetary policy. All in all, periods of high probability for high volatility occur only seldom and primarily around business crises, and, thus, the specification of monetary policy regimes in addition to monetary policy shocks makes sense.

To implement the Markov regime switching probabilities into the CCC model, let $\tilde{p}_t$ be the vector of smoothed probabilities for state two, i.e. the high volatility regime. The dummy variable to measure the influence of high volatility regimes in monetary policy on stock-bond correlations is then defined as:

- $S_{1,t-1} = 1$ if $\tilde{p}_{t-1}$ is greater than or equal to 0.95,[9]

and, hence, the covariance equation looks as follows:

$$h_t^{ij} = (\rho_0 + \rho_1 S_{1,t-1})\sqrt{h_t^i}\sqrt{h_t^j}. \tag{12}$$

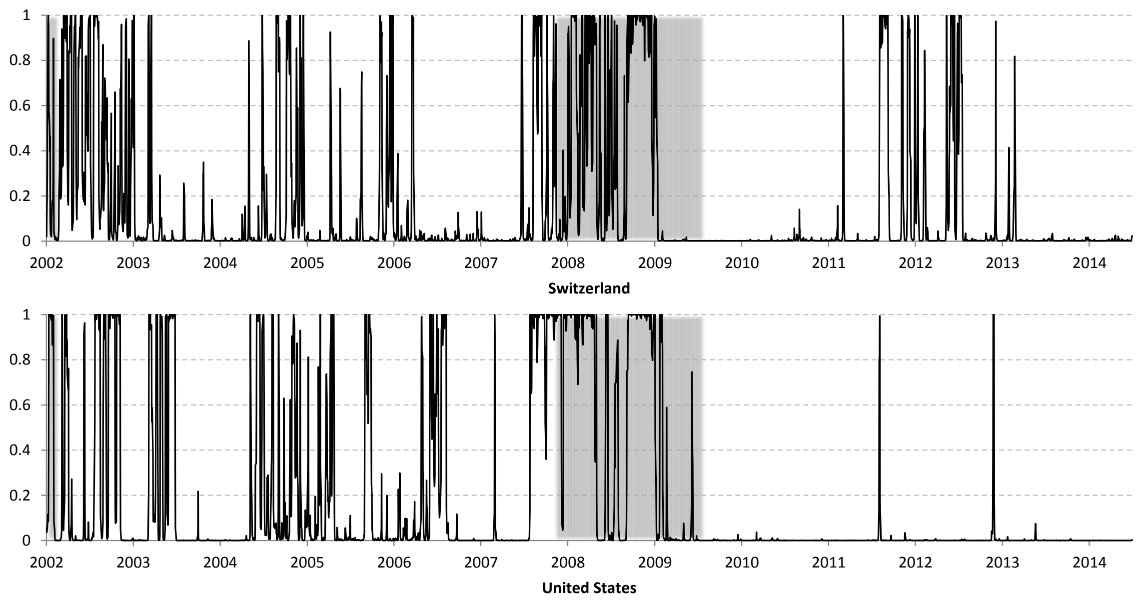
Table 5 presents the corresponding coefficients. Panel A shows the results using OIS data as a proxy for monetary policy and a common sample that ranges from March 2002

[8] The variation of the smoothed probabilities for the UK, Germany and Japan is not shown here but looks similar.

[9] Using this simple rule, the dummy variable is equal to one for about 9.6% and 12.5% of all observations in Switzerland and the US, respectively. Note that, however, defining a threshold of 0.95 is highly arbitrary. Accordingly, Section 4.3 provides an overview on several tests of robustness employing alternative threshold specifications.

Figure 2: Smoothed probability of the high volatility regime

This figure shows the estimated smoothed probabilities of high volatility regimes using OIS series in Switzerland and the US. The gray bars denote periods of economic contraction according to NBER.



to June 2014, i.e. the sample equals the length of the Japanese OIS series. Interestingly, stock-bond correlations at time t are lower when monetary policy is in the high volatility regime at time $t-1$ for each country except for Japan. Moreover, this negative impact is statistically significant at least at the 5% significance level in all countries. This finding suggests, again, that some sort of anomaly is present when central banks are particularly active, i.e. when the volatility in policy rate changes is comparatively large. Finally, likelihood ratio tests indicate a rejection of the null hypothesis of the base model at least at the 10% level. As in the previous section for monetary policy shocks, Panel B of Table 5 displays the estimates of country-specific samples, each equal to the total length of the OIS series. The corresponding results confirm the insight of deteriorating stock-bond correlations even though the effect is smaller and not significant in case of the UK and Germany. Again, keep in mind that the effect cannot be held responsible for the overall negativity of stock-bond correlations in the 21^{st} century as the constant correlation, ρ_0, is clearly negative and significant as well.

Overall, results using monetary policy regimes confirm the findings generated with monetary policy shocks. A negative shift in stock-bond correlations is revealed in times when monetary policy exhibits high volatility, i.e. during periods of large central bank activity, and, hence, the OIS rate is subject to rather large changes. Therefore, the anomaly of reversed causality is also present using a simple Markov regime switching model to identify volatile periods of monetary policy.

Table 5: Monetary policy regimes

This table presents the results of the bivariate GARCH(1,1) model augmented with an additional dummy variable representing monetary policy regimes. The standard correlation coefficient is denoted by ρ_0, whereas ρ_1 represents the change of the constant correlation at time t when the Markov process is in the high volatility regime at time $t-1$. Standard errors are given in brackets. Data range from March 2002 to June 2014 in Panel A whereas Panel B employs country-specific samples.

	SW	US	UK	Ger	JP
			Panel A: Common sample (03:2002 - 06:2014)		
ρ_1	-0.279^{***}	-0.340^{***}	-0.340^{***}	-0.382^{***}	-0.391^{***}
	(0.016)	(0.014)	(0.015)	(0.015)	(0.020)
ρ_2	-0.096^{**}	-0.086^{**}	-0.068^{**}	-0.139^{***}	0.022
	(0.042)	(0.034)	(0.033)	(0.027)	(0.025)
LR	3.658	4.999	3.649	17.522	0.592
	(0.056)	(0.025)	(0.056)	(0.000)	(0.442)
			Panel B: Individual sample (... - 06:2014)		
	08:2000...	*12:2001...*	*01:2001...*	*01:2000...*	*03:2002...*
ρ_0	-0.284^{***}	-0.338^{***}	-0.339^{***}	-0.360^{***}	-0.391^{***}
	(0.015)	(0.014)	(0.015)	(0.014)	(0.020)
ρ_1	-0.094^{***}	-0.084^{**}	-0.031	-0.024	0.022
	(0.035)	(0.033)	(0.029)	(0.026)	(0.025)

4.3 Robustness tests

This section serves to check whether the results concerning the effect of monetary policy shocks and regimes on stock-bond correlations are robust. Using daily OIS data reveals an anomaly in terms of the sign, i.e. positive shocks significantly decrease the observed correlation. This finding is interesting as it suggests a reversed causality, meaning that monetary policy possibly reacts to deteriorating stock prices by lowering interest rates which, in turn, increases bond prices, and, thus, lowers the correlation between stocks and bonds.

The specification of those monetary policy shocks and regimes is, however, highly arbitrary. In order to check whether the findings are robust, Table 6 now displays the results of the bivariate GARCH model when either the thresholds - defining monetary policy shocks and regimes in the covariance equation - are slightly altered or a different set of data is employed. Thus, Panel A shows the estimates using a common sample when the threshold defining the shock dummy variable is set equal to $\frac{1}{2}\sigma$ instead of σ. The corresponding coefficients are very similar to those in the standard specification, implying that the positive shock decreases stock-bond correlations at the 5% significance level in Switzerland, the UK and Germany and at least at the 10% level in the US. On the other hand, negative shocks exhibit positive coefficients that are, again, insignificant. Panel B displays the coefficients of monetary policy regimes with a common sample employing a threshold of 0.9 instead of 0.95, i.e. the dummy variable is set equal to one if the probability of the Markov regime switching process is larger than 0.9. Again, the results seem to be

Table 6: Robustness tests

This table shows the results of several robustness tests. Panel A lists the coefficients of monetary policy shocks when the corresponding dummy variable is defined according to a threshold of $\frac{1}{2}\sigma$ instead of σ. Panel B presents the estimates of monetary policy regimes, where the dummy variable is set equal to one if the smoothed probability of the high volatility regime is larger than 0.9 rather than 0.95. Panels C and D display the coefficients for both monetary policy shocks and regimes when the 10year bond market data are replaced with 1-3year bond series. The average correlation is denoted by ρ_0. In Panels A and C, ρ_1 and ρ_2 represent positive and negative policy shocks, respectively. In Panels B and D, ρ_1 denotes the effect of the high volatility regime. A common sample is employed that ranges from March 2002 to June 2014. Standard errors are given in brackets.

	SW	US	UK	Ger	JP
			Panel A: Policy shocks - $\frac{1}{2}\sigma$ threshold		
ρ_0	-0.285^{***}	-0.353^{***}	-0.336^{***}	-0.402^{***}	-0.381^{***}
	(0.018)	(0.015)	(0.016)	(0.015)	(0.016)
ρ_1	0.064	0.032	-0.042	0.023	-0.004
	(0.047)	(0.036)	(0.042)	(0.037)	(0.040)
ρ_2	-0.077^{**}	-0.068^{*}	-0.088^{**}	-0.073^{**}	0.018
	(0.035)	(0.039)	(0.038)	(0.029)	(0.041)
			Panel B: Policy regimes - 0.9 probability threshold		
ρ_0	-0.278^{***}	-0.341^{***}	-0.343^{***}	-0.376^{***}	-0.391^{***}
	(0.016)	(0.014)	(0.016)	(0.015)	(0.020)
ρ_1	-0.103^{**}	-0.079^{**}	-0.047	-0.145^{***}	0.022
	(0.040)	(0.033)	(0.032)	(0.026)	(0.025)
			Panel C: Policy shocks - 1-3year bond data		
ρ_0	-0.159^{***}	-0.280^{***}	-0.329^{***}	-0.300^{***}	-0.220^{***}
	(0.019)	(0.015)	(0.015)	(0.017)	(0.017)
ρ_1	0.046	-0.235^{***}	-0.071	-0.044	0.000
	(0.080)	(0.048)	(0.067)	(0.057)	(0.038)
ρ_2	-0.143^{***}	-0.139^{***}	-0.194^{***}	-0.127^{***}	0.000
	(0.049)	(0.052)	(0.044)	(0.044)	(0.050)
			Panel D: Policy regimes - 1-3year bond data		
ρ_0	-0.143^{***}	-0.267^{***}	-0.315^{***}	-0.293^{***}	-0.253^{***}
	(0.019)	(0.016)	(0.016)	(0.018)	(0.021)
ρ_1	-0.143^{***}	-0.142^{***}	-0.092^{***}	-0.071^{**}	0.005
	(0.042)	(0.029)	(0.028)	(0.031)	(0.027)

robust. The negative effect remains when a slightly altered threshold is applied. The only difference is the fact that the effect is not significant anymore in case of the UK.

A second approach to test the robustness of the findings is presented in Panels C and D. In both cases the standard model is estimated for a common sample without altering the thresholds. What changes, however, is the underlying bond market data. Now, the datastream 1-3year bond market indices are employed to calculate stock-bond correlations rather than the 10year indices. The idea is to check whether the previously discussed anomaly is also present at a shorter duration. Panels C and D thus display the coefficients of monetary policy shocks and regimes, respectively, in the standard model specification. First, it is interesting to note that all countries exhibit considerably larger overall stock-bond correlations, i.e. the coefficient ρ_0 is less negative when the duration is reduced. Second, however, the coefficients measuring the sensitivity with respect to monetary policy shocks and regimes are still negative and highly significant (except for Japan). Thus, the anomaly of reversed causality also exists at shorter duration. Moreover, from a statistical point of view the effect is even more pronounced as the coefficients are significant at the 1% level in most cases. Note that the effect of a negative monetary policy shock in the US is also significantly negative and even larger compared to the positive impact. We do not have an obvious explanation for this observation.

Instead of altering the thresholds or interchanging the employed data series, one can also estimate the model at a different frequency in order to see whether the anomaly is still present. Results not shown here suggest that the insight of reversed causality is, however, not robust when we switch from daily to weekly data. Using weekly data yields stock-bond correlations, ρ_0, that are slightly lower compared to the daily coefficients and, more importantly, effects with respect to positive monetary policy shocks that are now highly ambiguous exhibiting mixed signs across countries. Furthermore, none of the coefficients measuring the response of stock-bond correlations to monetary policy is statistically significant. Therefore, the anomaly of reversed causality strongly depends on the usage of daily data.

Overall, the robustness tests indicate that the findings are indeed robust to alternative thresholds. Moreover, the negative impact of monetary policy shocks and regimes on stock-bond correlations appears to a very similar extent at a shorter bond duration. The anomaly, however, is strongly reliant on the usage of daily data as the effect completely vanishes if the frequency is lowered.

5 Conclusion

As shown by Ilmanen (2003), stock-bond correlation strongly varied over time in the US with only a few cycles where it remained negative for a longer period of time. Figure 1 shows that one of these periods with negative correlation occurred around the first decade of the 21^{st} century, starting with the Asian/Russian crises after a period of normal, i.e. positive, correlations. This study analyzes stock-bond correlations in five major economies during this period of ongoing negativity in correlations using a constant conditional correlation model. This model is used to test whether monetary interventions may have caused the observed correlation pattern. The examined countries are Switzerland, the US, the UK, Germany and Japan.

The basic constant conditional correlation model first shows average correlation coefficients considerably below zero during the 2002-2014 sample period. Section 3.3 revealed that high stock market volatility at time $t-1$ reduces stock bond correlations at time t by a minimum of 0.11 (Switzerland) and a maximum of 0.21 (US). Interestingly, there seem to be symmetric effects concerning stock market shocks, i.e. negative and positive shocks tend to exhibit similar negative effects on correlation. More importantly, using OIS rates as a proxy for monetary policy reveals a statistically significant, negative reaction of stock-bond correlations to positive monetary policy shocks. The same is observed when monetary policy is in the high volatility state according to a simple Markov regime switching model. A potential explanation is that central banks possibly react to deteriorating stock markets by lowering their policy rates. This, in turn, increases bond prices leading to lower stock-bond correlations. Due to data availability, this finding covers only the period ranging from roughly 2002 until 2014. Accordingly, it does not explain the overall negative correlation but rather opens up the possibility of an anomaly concerning the causality between the policy rate and asset prices.

Overall, the findings suggest several reasons that possibly explain the low or even negative correlation between stock and bond markets. Thereby, market volatility probably represents the most reasonable and obvious one. Moreover, positive monetary policy shocks and regimes of high central bank activity tend to reduce stock-bond-correlations. However, this negative effect occurs in a period where correlations are already at negative levels. Accordingly, none of these findings suffice to explain the general shift from positive to negative correlation and the rather long period or persistence of negative correlation. The simple fact that this period of negative correlations started with the Asian/Russian crises and went on with two more major crises, i.e. the dotcom bubble as well as the financial crisis, may comprise another key source due to the rather high percentage of time spent in turbulent economic and financial conditions. In terms of asset allocation, the recent period of negative stock-bond correlations clearly helped to build a well diversified portfolio. From this perspective, one question that remains is whether this positive characteristic continues when interest rates start to increase again.

Although none of the previous studies uses OIS rates as monetary indicators, our results do at least not contradict those papers who have used TBill and longer rates as conditioning variables of latent or realized stock-bond correlations. Interest rate effects are reported for monthly and high frequency data in the literature discussed in the Introduction of this paper. For monthly data, Yang et al. (2009) and Ohmi and Okimoto (2015) find that higher (lower) stock-bond correlations follow higher (lower) short rates, and the seconds study reveals that this partly explains the negative time trend observed over the recent decades. Using the same methodology (smooth transition regression) but high frequency data, Aslanidis and Christiansen (2012) find that among the financial transition variables the short rate plays a prominent role: high short rates imply a positive stock-bond correlation. This is consistent with Schopen and Missong (2011) using a generalized DCC (dynamic conditional correlation) model; they find that positive (negative) interest rate news imply a positive (negative) effect on correlation between stock and bond returns.[10] However, these announcement effects capture a different aspect of monetary policy than we address in our paper.

[10] See their Table 4, second last column.

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