The stock-bond correlation and macroeconomic conditions: One and a half centuries of evidence[☆]

Jian Yang [a]*, Yinggang Zhou[b], Zijun Wang[c]

[a] The Business School, University of Colorado Denver, Denver, CO 80217, USA
[b] Black Creek Global Advisors, Denver, CO 80202, USA
[c] Private Enterprise Research Center, Texas A&M University, College Station, TX 77843, USA

Abstract

Using monthly stock and bond return data in the past 150 years (1855-2001) for both the U.S. and the U.K., this study documents time-varying stock-bond correlation over macroeconomic conditions (the business cycle, the inflation environment and monetary policy stance). There are different patterns of time variation in stock-bond correlations over the business cycle between U.S. and U.K., which implies that bonds may be a better hedge against stock market risk and offer more diversification benefits to stock investors in the US than in the UK. Further, there is a general pattern across both the U.S. and the U.K. during the post-1923 subperiod and during the whole sample period: higher stock-bond correlations tend to follow higher short rates and (to a lesser extent) higher inflation rates.

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*Corresponding author. Tel: (303) 556-5852; Fax: (303) 556-5899
Email addresses: Jian.Yang@ucdenver.edu (J. Yang), zhou.yinggang@gmail.com (Y. Zhou), z-wang@tamu.edu (Z. Wang)

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1. Introduction

It is widely recognized that the correlation between stock and bond returns changes over time. Even after allowing for the changing correlation due to stock and bond market time-varying volatility, the conditional correlation between the US stock and bond returns has still varied considerably over the post-war period (Scruggs and Glabadanidis, 2003). Understanding the nature of the time variation in the stock-bond correlation carries crucial implications for asset allocation and risk management, as they are the two most important asset classes (Connolly et al., 2005; d'Addona and Kind, 2006; Kim et al., 2006).

Much recent effort has been made to explore various economic forces driving the time-varying stock-bond correlation. Specifically, Connolly et al. (2005, 2007) find that the future stock-bond correlation at higher daily frequency decreases with increasing stock market uncertainty in the US and several other major markets, arguably due to the flight-to-quality phenomenon. Kim et al. (2006) confirm the similar role of stock market uncertainty in this regard in many European markets.[1] Looking in more depth at economic forces driving the stock-bond correlation at lower (e.g., monthly) frequencies, Li (2002) argues that both the expected inflation uncertainty and the real interest rate uncertainty tend to increase the correlation between stock and bond returns.[2] By contrast, d'Addona and Kind (2006) show that although the volatility of real interest rates may increase the stock-bond correlation in G-7 countries, the inflation volatility tends to reduce the correlation.

[1] Kim et al. (2006) also consider a number of other economic variables in the context of the convergence to EMU, which may potentially drive international stock-bond correlation. In addition, Li and Zou (2008) qualitatively discuss how the policy change and the macroeconomic environment may cause the structural change in China's daily stock-bond correlation. Panchenko and Wu (2009) report that emerging stock market integration affects weekly stock-bond comovements in these markets.

[2] Guidolin and Timmermann (2005) document that the monthly correlations between the UK stock and bond returns are positive and significant in the normal and bull states, while they are negative in the bear state. In light of the stylized fact that stock market volatility increases in the bear state, their finding is generally in line with the above studies focusing on daily horizon. Nevertheless, unlike other cited studies here, bull and bear states in their study are exogenously determined rather than driven by some economic variables.

Boyd et al. (2005) and Andersen et al. (2007) also investigate the effects of macroeconomic news announcements on stock and bond markets in expansions and recessions. They argue that the cash flow effect may dominate during contractions, while the discount rate effect may be more important during expansions, thus resulting in positively correlated stock and bond returns in expansions and lower, perhaps even negative, correlations during recessions. Ilmanen (2003) also proposes a similar argument. By contrast, Jensen and Mercer (2003) document that the monthly correlation between stocks and bonds is lower during expansions than during recessions (though such difference is statistically significant for small cap stocks only, but not for large cap stocks), which is essentially inconsistent with the flight-to-quality argument. Also, as discussed above, it is still unsettled on whether the inflation volatility increases or decreases the stock-bond correlation. Hence, the debate remains open on how the time variation in the stock-bond correlation is driven by changing macroeconomic conditions, particularly at lower frequencies.

This study employs monthly data over the past 150 years (1855-2001) on both US and UK markets to examine whether the correlation between the stock and bond premiums is asymmetric over various macroeconomic condition indictors. The paper contributes to the literature in the following aspects. First, this study uses the longest historical data available that covers 32 expansions and 32 recessions for the US and 22 expansions and 21 recessions for the UK. By contrast, previous studies typically focus on a few cycles in recent decades.[3] Despite some data limitations, the use of very long financial data for more than one country is very important in testing the robustness of previous findings, and, in particular, in mitigating the "data snooping" biases associated with repeated attempts focusing on a single country (e.g., US) and a particular sample period (e.g., after World War II). Specifically, based on business cycle dating, we will

[3] For example, Boyd et al. (2005) study five expansions and four recessions from February 1957 to December 2000. Andersen et al. (2007) examine one expansion and one recession from July 1998 to December 2002.

demonstrate for the first time substantially different patterns of time varying stock-bond correlation for the US and the UK over the business cycle. Such different patterns across the countries, however, are not uncovered in the earlier studies focusing on a few business cycles (e.g., Andersen et al., 2007).[4]

Second, extending multivariate GARCH modeling widely used in the literature (e.g., Longin and Solnik, 1995; Kim et al., 2006; Li and Zou, 2008), we apply an innovative method that allows the conditional correlation to change across regimes directly as a nonlinear function of a macroeconomic variable and enables us to conduct a *one-step consistent* estimation.[5] Our methodology essentially extends the univariate smooth transition GARCH models used in the literature (e.g., Nam et al., 2002) to the bivariate context. Also noteworthy, compared with the popular two-state Markov-Switching model used in this line of the literature that dictates a rather abrupt change from one state to the other, our modeling flexibility can allow for a smooth transition in correlation from one regime to another (via numerous intermediate regimes in transition) and also the observation (albeit limited) that "there is also an indication that the correlation may evolve smoothly, shifting rather slowly from values typical of expansion to those typical of contraction" (Andersen et al., 2007, p.270).

Finally, similar to Longin and Solnik (1995) and Fama and French (1989) but different from two closely related studies (i.e., Li (2002) and d'Addona and Kind (2006)), we use (lagged) observable macroeconomic variables (at their levels) as the conditioning variables rather than unobservable macroeconomic volatilities. This might render our findings more straightforward to interpret and relatively free from potential volatility estimation errors, although the use of

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[4] Andersen et al. (2007, p. 270-271) report a similar pattern of the time variation in the stock-bond correlation across countries. As correctly pointed out by them (p. 257), the pattern revealed by the data for one expansion and one contraction cannot be claimed as a general pattern.

[5] At the minimum, compared to the one-step procedure, the two-step estimation procedure used in some previous studies would lose some efficiency, even though it may well be consistent.

macroeconomic volatilities may be theoretically motivated in their models. Also, in line with many previous studies (e.g., Li, 2002; d'Addona and Kind, 2006; Ilmanen, 2003; Jensen and Mercer, 2003), the macroeconomic condition indicators considered in this study include the business cycle, the inflation environment and monetary policy stance (or the short rate).[6] The rest of the paper is organized as follows. Section 2 describes the data. Section 3 discusses econometric methodology. Section 4 presents empirical results. Finally, Section 5 makes concluding remarks.

2. Data

For the purpose of comparison, the samples for the US and the UK both span from January 1855 to November 2001. The samples start from January 1855 because it is the earliest monthly reference by the NBER. November 2001 is the latest monthly reference for the US business cycle by the NBER.

2.1. Dependent and independent variables

The monthly stock and bond return data are compiled from a variety of sources. Monthly stock returns are calculated using composite indices. For the US, the early index prior to 1926 is from Schwert (1990) while the later data series (since 1926) is from the CRSP value-weighted index with dividends.[7] For the UK, the early index prior to 1970 is from the price index constructed by Tim Opler with dividend yield added while the later data series is the MSCI UK Total Return Index [MSUTDKL(RI)] from the Datastream.[8]

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[6] The dividend yield is not considered here, largely due to the unavailability of such long-term high quality data at the appropriate (e.g., monthly) frequency. For a similar reason, stock market volatility is not investigated here.

[7] The outbreak of WWI led to closure of the New York Stock Exchange from August 1914 to November 1914. The observations are missing only in the extended period that the NYSE was closed.

[8] There are some missing observations in Opler's price index because the market was closed in WWI and the data were not available for some months in 1920, 1921 and 1936. From 1924 to 1969, the Financial Times Actuaries

In the bond markets, government bonds are always dominant in these two countries. The longest available monthly data for government bond returns is from Global Financial Data (GFD). The US Bond returns are calculated using the USA 10-year government bond total return index. For the UK, bond returns are calculated using the UK consol total return index from the GFD. The UK consol is perpetually funded government debt. In terms of maturity risk, the UK consol is more risky than the US 10-year government bond.

Stock and bond premia are their excess returns over the short rates. As a proxy for the US short rate, bill returns are calculated using the USA Commercial/T-bill total return index from the GFD. The UK short rate comes from three sources: (1) the NBER provides the "open market rate of discount at London" from 1824 through 1939; (2) the Datastream provides the discount rate on 3-month Treasury bills from 1975; and (3) the gap between 1940 and 1975 is filled in using the discount rate on Treasury bills collected by Capie and Webber (1985). All monthly returns are compounded and annualized.

The business cycle is an important and deeply embedded feature present throughout the history of industrial economies. The National Bureau of Economic Research's (NBER) chronology of peaks and troughs is one of the simplest yet most common indictors for studying the US business cycle. The NBER reference chronology is also available for the UK through 1938. The Economic Cycle Research Institute (ECRI) applies the same methodology used by the NBER to the UK business cycle dating from 1952. The gap between 1938 and 1952 is filled in using the reference dates by Friedman and Schwartz (1982). We define a state of economy dummy ($STATE_t$) which is one for recessions and zero otherwise. Furthermore, wars may also exert influence on economies. Most of the wartime is also associated with expansions, except

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dividend yields are added to the return series. No dividend yield data was available through 1923. To fix this, we follow Dimson et al. (2001) and assume a yield of 5% per annum.

for the Gulf War. Consequently, we define a war dummy (WAR_t) which is one for war periods and zero otherwise.[9]

Certainly, over the last one and a half centuries the international economy might have been transformed in many aspects. A variety of historical data strongly supports the division of economic history into four segments,[10] which coincides with the usual division of this time frame into four distinct international monetary regimes: Classical Gold Standard, Interwar, Bretton Woods, and Floating Exchange Rates. Thus, we also define the following structural dummies to capture the potential impact of different monetary regimes: $GOLD_t$, $BRETTON_t$, and $FLOAT_t$. Also note that there is no need to define an additional dummy variable for the Interwar period other than WAR_t. The gold dummy, $GOLD_t$, is also slightly different for the US and the UK since they abandoned the gold standard in September 1931 and April 1933, respectively.

We further define several more dummy variables to capture other potentially significant events on the financial markets in both countries. The dummy variable $ACCORD_t$ attempts to model a potential structural break due to the event that the 1951 Treasury-Federal Reserve Accord formally relieved the Federal Reserve of the obligation to support the U.S. government bonds and allowed it to pursue an independent monetary policy. Similarly, for the UK, most of the wartime controls were eased or abandoned as the country turned politically conservative in 1951. The motivation for the dummy variable $RECENT_t$ is that Paul Volcker announced that the Fed would exercise controls over the money supply without regard to interest rate movement on October 6, 1979. For the UK, the conservative Thatcher government in the 1980s pursued policies similar to those of the Reagan administration in the US. The period from 1979 to 2001 was also a period of declining inflation and interest rates. Lastly, the dummies for the greenback

[9] Details on the starting and ending times and the durations of the business cycles and wars are available on request.
[10] Basu and Taylor (1999) use this division to study international business cycles.

period ($GREENBACK_t$) when the US Department of Treasury directly issued fiat paper money into circulation and the establishment of US Federal Reserve period (FED_t) are only applicable to the US (Table 1).

[Table 1 here]

We also collect monthly data on the two most popular macroeconomic condition indicators: the short rate and the inflation rate. The US bill return and the UK discount rate are used as the proxies of short rates. The inflation rates are measured as the log difference of the GFD producer's price index for the US and the UK.

Finally, we divide the whole sample into two subsamples, mainly due to concern for the data quality. Specifically, the US subsamples are divided based on the availability of the CRSP data, when high quality financial data are available since January 1926. The UK subsamples are divided based on the fact that the dividend data on the stock market index are only available since January 1924. Such divisions of the subsamples also serves the purpose of a robustness check quite well, as they still provide long enough time spans (particularly in terms of the number of business cycles) with sufficient numbers of observations for meaningful empirical analysis below.[11]

2.2 Summary statistics

Panel A of Table 2 reports that US stocks yielded a higher premium than US bonds while US stocks were more volatile than bonds. Skewness was negative for the US stock premium

[11] Following the suggestion of the referee, we also conducted the analysis with the sub-sample period 1972.01-1999.12 for the U.S. data considered by Jensen and Mercer (2003). The correlation statistics verify that our data is comparable to that of Jensen and Mercer (2003). In testing the constant conditional correlation versus the smooth transition conditional correlation model, we reject the null of constant correlation when the transition variable is either short rates or inflation rates. The results based on the 1972-1999 subsample show that while high correlations also tend to follow higher inflation rates during the period, lower correlations tend to follow higher short-term interest rates. The difference may be attributable to the fact that high short rates dominate the subsample of 1972-1999, compared to the longer post-1923 sample period. It again underscores the importance of using long data to mitigate the data snooping biases and reveal a general pattern (Andersen et al., 2007).

while it was positive for the US bond premium during the 150-year period. The comparison between the pre- and the post- CRSP periods (available on request) suggests that both the stock and bond premiums have increased and become more volatile. Inflation has increased while the short rate has decreased. Similarly, Panel B of Table 2 shows that much of what was said about the US applies to the UK. The UK equity premium dominated the bond premium and UK stocks were more volatile than bonds.

Panel C of Table 2 further shows that the US stock and bond premiums were more volatile in recessions than in expansions, based on the business cycle dating. The stock premium was on average positive in expansions and negative in recessions. Meanwhile, the stock premium was typically higher than the bond premium in expansions and lower than the bond premium in recessions. The average short rate was not significantly different between recessions and expansions during the whole period. The average US inflation rate was positive in expansions and significantly higher than in recessions. Panel D of Table 2 confirms that much of what was said about the US also applies to the UK.

[Table 2 here]

Table 3 shows the regime patterns of the stock-bond correlations. As shown in Panel A, the correlations tend to be stronger during expansions than during recessions, while the pattern is not clear for the second subperiod. Panel B shows the opposite regime pattern for the UK samples: the average correlations are stronger in recessions than in expansions.

[Table 3 here]

3. Econometric methodology

In this section, we choose a class of bivariate AR(1)-GARCH (1,1) models for conditional correlations between stock and bond premiums. In general, these models can be written as

$$
\begin{aligned}
r_t &= \mu_t + \varepsilon_t, \\
r_t &= (r_{st}, r_{bt})', \\
\mu_t &= E(r_t | F_{t-1}), \\
\varepsilon_t | F_{t-1} &\sim N(0, H_t),
\end{aligned}
\tag{1}
$$

where r_t is a 2×1 vector of stock and bond premia, μ_t is a 2×1 vector of means conditioned on the information set F_{t-1} and ε_t is a 2×1 vector of innovations. H_t is the conditional variance-covariance matrix of r_t since

$$
\operatorname{var}(r_t | F_{t-1}) = \operatorname{var}(\varepsilon_t | F_{t-1}) = H_t. \tag{2}
$$

For the conditional means, we consider the following AR(1) specification

$$
\begin{aligned}
&\mu_{it} = \mu_i + \lambda_i r_{i,t-1}, \\
&i = 1 \ \ for\ stock\ or\ 2\ for\ bond,
\end{aligned}
\tag{3}
$$

where μ_t is the constant mean and λ_i is the autoregressive coefficient of the first lag.

For the conditional variance-covariance matrix, H_t can be further decomposed into the conditional standard deviation matrix D_t and the conditional correlation matrix R_t

$$
H_t = S_t R_t S_t, \tag{4}
$$

where

$$
\begin{aligned}
&S_t = diag(h_{it}^{1/2}), \\
&h_{it} = \omega_i + \alpha_i \varepsilon_{t-1}^2 + \beta_i h_{i,t-1}, \\
&R_t = (\rho_{ijt}), \ with \ \ \rho_{iit} = 1, \\
&i, j = 1 \ \ for \ \ stock, \ or \ \ 2 \ \ for \ \ bond.
\end{aligned}
\tag{5}
$$

Note that the conditional volatility h_{it} is assumed to follow a univariate GARCH(1,1) process. $\rho_{12,t}$ is the conditional correlation of the stock and bond premiums.

Assuming normality, the conditional log-likelihood of the observation r_t is given by

(6) $$l_t = -\frac{1}{2}\ln\left|S_t R_t S_t\right| - \frac{1}{2}\varepsilon_t^{'} S_t^{-1} R_t^{-1} S_t^{-1} \varepsilon_t ,$$

from which we can obtain the log-likelihood function of the sample as $l = \sum_{t=1}^{T} l_t$. Even without the normality assumption, the quasi-maximum likelihood estimates (QMLEs) can be obtained by maximizing *l* with respect to the parameters.

3.1. The base model: Constant conditional correlation

The full model would require the estimation of a large number of coefficients. To simplify the exposition, we start with a base model in which the conditional correlation is constant as follows

(7) $$R_t = (\rho_{ij}), \ with \ \rho_{ii} = 1.$$

This is the Constant Conditional Correlation (CCC) GARCH model. The parameters for the benchmark model are ($\mu_i, \lambda_i, \omega_i, \alpha_i, \beta_i, \rho_{12}$). The estimation of these parameters is relatively simple, so the model has become popular among practitioners. The computed values of the likelihood function are referred to as Lik1s.

In the literature, the assumption of constant conditional correlation has often been found to be too restrictive, especially in the context of asset returns.[12] Thus, the main purpose of laying out this base model is to provide a benchmark for setting the augmented models below and for testing asymmetric correlation.

3.2. The augmented model I: Dummies in the conditional correlation

There is evidence that the correlations are not only dependent on time but also on the state of the economies. To see whether conditional correlations change across business cycles, we

[12] For example, Longin and Solnik (1995) reject the hypothesis of a constant conditional correlation in international equity returns.

augment the model to include the state of the economy dummy and other dummy variables in the conditional correlation matrix.

(8) $$\rho_{12t} = \rho_{12}^{0} \cdot (1 - STATE_t) + \rho_{12}^{1} \cdot STATE_t + K \cdot D_t ,$$

where $STATE_t$ is the state of the economy dummy which is zero for expansions and one for recessions, D_t is a column vector of other dummies defined in Section 2, ρ_{12}^{0} and ρ_{12}^{1} are the conditional correlations in an expansion and a recession, respectively, and K is a row vector of coefficients.

The computed values of the likelihood function are referred to as Lik2s. Needless to say, this specification is still a simplistic modeling of the time-variation in correlation. The purpose is to see whether the correlations in expansions and recessions are still significantly different after controlling for structural breaks. This leads to the following null hypothesis (*Symmetric Correlation Hypothesis*).

(9) $$H_0\text{:}\ \rho_{12}^{0} = \rho_{12}^{1} .$$

We can perform a likelihood-ratio test (LR test hereafter) on the null hypothesis, and the likelihood-ratio statistics are referred to as LR12s.

3.3. The augmented model II: Smooth transition in the conditional correlation

A further extension is to see how conditional correlations change dynamically. A number of multivariate GARCH models have been developed to improve the dynamic correlation estimators. In this section, we follow Silvennoinen and Terasvirta (2005) and allow conditional correlations to change smoothly across two regimes depending on a transition variable, which extends the earlier literature (e.g., Li, 2002) in the following ways. First, this specification allows two different constant correlation coefficients within each of two regimes, while the correlation also changes continuously due to the gradual transition from one regime to the other.

Our choice is motivated by business cycle asymmetry. Second, this model is conditional on the (first) lag of observable macroeconomic variables rather than the volatility measures, which enable us to test the asymmetric correlation in a more straightforward fashion. Instead of using several variables all together, we use one particular transition variable each time, which will be easier to estimate and more importantly easier to interpret for results. On the other hand, we can also see how predictive power might vary from one indicator to another.

Specifically, the correlation equation in (8) is replaced by:

(10) $$\rho_{ijt} = \rho_{12}^{l}(1-G_t) + \rho_{12}^{h}G_t \,,$$

where ρ_{12}^{l} and ρ_{12}^{h} are two constant conditional correlations in two states when the transition variable takes low and high values respectively. G_t is a transition function whose values are bounded between 0 and 1. The transition function is chosen to be the logistic function

(11) $$G_t = \frac{1}{1+\exp[-\gamma(s_t - \delta)]}, \quad \gamma > 0 \,,$$

where $s_t \in \{SHORT_{t-1}, INF_{t-1}\}$ is the transition variable, which is chosen to be the first lag of one instrument defined in section 3. The slope of the function, γ >0, is the velocity of transition. If γ =0, the model collapses into the base model since G_t=1/2. If $\gamma \rightarrow \infty$, G_t=1 is a dummy and the transition becomes abrupt. δ is the threshold of the transition.

Earlier empirical experience shows that γ and δ are difficult to estimate in general and that the estimate of γ often converges toward a very large value in particular. As a solution to the estimation problem encountered, the value of γ is constrained to a particular positive value.[13]

The symmetric correlation hypothesis can be tested as follows,

[13] Silvennoinen and Terasvirta (2005) constrain γ to be 100 in the context of correlations among five stocks in the S&P 500 index. We follow this practice, but also vary the constraint to test the robustness.

(12) $$H_0\text{: } \rho_{12}^{l} = \rho_{12}^{h}.$$

Meanwhile, the estimate for the threshold of transition parameter δ may tell us the location in which the transition takes place. The computed values of the likelihood function are referred to as Lik3s. The likelihood-ratio statistics against the base model are referred to as LR13s.

In short, rather than modeling time-variation in stock-bond correlations as in the previous literature, we explicitly model the asymmetry in conditional correlations as a function of macroeconomic variables and test for the existence of predictable asymmetry in these correlations.

Before turning to the presentation of the empirical results, it is important to note that asymptotic properties of the maximum likelihood estimators in the present case are not known (Silvennoinen and Terasvirta, 2005). Some caution should be exercised in interpreting the estimation results below.

4. Empirical results

4.1. Asymmetric stock-bond correlations over macroeconomic conditions

Table 4 shows the parameter estimates of the base model. Panels A and B show that for the US, the assumption of AR(1)-GARCH(1,1) is supported by the estimation results, as parameters λ, α and β are significant for most samples. The estimates of ρ_{12} are positive and significant at least at 10% for all of the cases. Panels C and D report the results for the UK. It is notable that the correlations for the UK are significantly positive and bigger than those for the US. Moreover, the correlations increase in the recent sample for the UK.

[Table 4 here]

Table 5 reports (the most relevant part of) the estimation results of the augmented model I with dummies in the conditional correlation. The estimates of the conditional mean and conditional variance equations are not reported since they are quite similar to their counterparts in Table 4. In the case of the US, the evidence of asymmetric correlation is not very strong. The symmetric correlation hypothesis is rejected for the whole sample period and the earlier subperiod, but not in the more recent subperiod. In the case of the UK, symmetric correlation is not rejected for the whole sample period but for two subperiods. The evidence strongly suggests that the use of dummy variables that aim to capture abrupt structural changes may not be adequate to address potentially more gradual structural changes during the long sample period, motivating our further use of smooth transition models in the augmented model II.

It should also be noted that the conditional correlations across business cycles show different patterns between the US and the UK. For the US, the conditional correlations in recessions are lower than those in expansions. By comparison, for the UK, correlations in recessions are higher than those in expansions. The presence of asymmetric correlations carries implications for stock-bond portfolio diversification benefits. A lower stock-bond correlation indicates better diversification. In recessions, asset returns tend to be more volatile. The evidence here implies the better diversification potential between stocks and bonds in the US than in the UK.

[Table 5 here]

The estimation results for the augmented model II are reported in Table 6, with the first lagged short rate as the transition variable. The LR tests, based on the asymptotic values, reject the symmetric correlation hypothesis for both the whole sample period and the two subperiods all at the 5% significance level for the US. Nevertheless, as pointed out earlier, the asymptotic properties of the (quasi-) MLE are unknown and the critical values of the χ^2-distribution might not be reliable for the above LR tests. As a robustness check, we also simulate the distribution of the computed LR test statistics in testing CCC-GARCH (the null model) versus STCC-AGRCH. Briefly speaking, we generate artificial data from the null model, with the sample sizes equivalent to those of the actual data, by using the parameter values and drawing errors with replacement from the null model (see, for example, Kim et al. (1998) for details on the implementation of the simulation). The number of replications is 200. Based upon the simulated critical values, the constant conditional correlation model is again rejected, although the evidence now becomes insignificant at the 10 percent level for the US in the first subperiod.[14]

Panels A and B of Table 6 show that the correlations are typically predicted to increase in the regime of higher short rates. It is also evident that the transitions take place around 0.053 to 0.069, which is above the means of short rates. The evidence for the UK is similar, as we can reject the symmetric correlation hypothesis for both the whole sample period and the more recent second subperiod, but not for the first subperiod. Again, the correlations tend to increase with higher short rates for the whole sample and the second subperiod.

[Table 6 here]

Table 7 presents the estimated smooth transition conditional correlations with the first lagged inflation rate as the transition variable. For the whole sample in Panel A, the correlation is predicted to increase in the regime of a higher inflation rate, which, however, is not significant at the 10 percent level based on the simulated critical values. There is strong evidence for a rejection of the symmetric correlation hypothesis in the case of the US during the post-1926

[14] We also implemented the LM test discussed in Silvenninen and Terasvirta (2005). We find that the null hypothesis of constant conditional correlation can be strongly rejected for the US data in most cases. The evidence is less strong for the UK data, a similar pattern found with the LR test. The result is not surprising since, in finite samples, LM tests are more conservative than LR tests.

period, and the correlations tend to increase in the regime of a higher inflation rate during the subperiod. By contrast, as shown in Panel B, in the regime of a higher inflation rate, the correlations tend to decrease during the first subperiod, although it is not significant at any conventional significance levels based on the simulated critical values. This implies that other factors such as monetary regimes might play additional roles in affecting the information content of inflation. Specifically, the paper-based monetary regime applies only during the most of the second subperiod but not in the first subperiod. We will discuss the issue in more detail below. We also find mixed evidence for asymmetric correlation for the whole sample period and the first subperiod for the UK. Nevertheless, the correlation is still higher in the regime of a higher inflation rate in the UK for the second subperiod (although it is only marginally significant at the 10% level even based on the asymptotic critical value). In sum, as in the case of the US, we still find similarly different patterns across the two subperiods in the UK.

[Table 7 here]

As a further illustration, we plot in Figure 1 the estimated transition functions over the range of the corresponding transition variables for the recent sample periods for both the US and UK. It is clear from the graphs that since the transition parameter, γ, is large, the transition functions generally are not smooth, especially in the bottom two panels that use the inflation as the transition variables. Nevertheless, some interesting results can still be read from the graphs. For example, when the short rate ranges in the U.S. market are lower than 0.044, the transition function G_t is essentially 0 (< 0.01). The conditional correlation between stock and bond in Equation (10) is dominated by ρ_{12}^{l}. On the other hand, when the short rate is larger than 0.062, G_t is essentially 1 (> 0.99) and the conditional correlation is dominated by ρ_{12}^{h}. The correlation moves relatively smoothly over the short rate in the range of 0.044 and 0.062 (more than 22% of the sample observations fall in this range).

[Figure 1 about here]

To provide additional graphical evidence on how the evolution of the stock-bond conditional correlation can be affected by business cycles, we plot in Figure 2 the estimated conditional correlation over time and superimpose business cycle dates as indicated by shaded areas in the graphs. In the case of the US, we can see from the graphs that lower correlations generally followed recessions. The exceptions occurred in the two brief recessions in the early 1980s. Similar patterns can also be found in the two panels for UK. Examining the four panels of graphs in Figure 2, we also note that there might be a few instances when the conditional correlation reached the extreme regimes and remained there for extended periods of time. These include the UK prior to the 1970s when short rates are used as the transition variable, and mid- to late 1990s for both transition variables. One possible reason is, as many studies have found, that both short rates and inflation variables are persistent (see, for example, Baillie et al. (2002)). Using a variable that contains a near unit root or is close to being nonstationary may cause some technical difficulties for the estimation of the STCC-GARCH model. In particular, if the transition variable is nonstationary, then there is a positive probability the conditional correlations may stay in one of the extreme regimes indefinitely. Fortunately, as shown in Figure 1, such a problem does not exist in this study.[15]

[Figure 2 about here]

4.2. Possible explanations on the predictive patterns of short rates and inflation rates

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[15] We are thankful to an anonymous referee for bringing this issue to our attention. As pointed by the referee, in general, little is known about the ergodicity and stationarity of the STCC-GARCH model when the transition variable is nonstationary. Finding a general solution to this problem would be an interesting topic for future research.

We first provide a preliminary investigation on why the US stock-bond correlations are predicted to increase when the short rate is higher than a threshold between 0.053 and 0.069. There may be more than one plausible story, but we are particularly interested in one possible explanation: contagion. More generally, the explanation points to the strengthened stock-bond comovement due to the increased importance of interest rates in driving both stock and bond returns during the regime of higher interest rates (which is bad news). Noting that higher interest rates typically coincide with expansions, the explanation to be tested below essentially provides another direct test on the argument of Boyd et al. (2005) and Andersen et al. (2007).

To investigate this possibility, we include the first lagged short rate in the conditional means as follows

$$\begin{aligned} &\mu_{it} = \mu_i + \lambda_i r_{i,t-1} + \theta_i SHORT_{t-1}, \\ &i = 1 \ \textit{for stock or}\ 2 \ \textit{for bond}, \end{aligned} \tag{13}$$

where μ_i and λ_i are defined above in equation (3). θ_i is the regression coefficient of the first lagged short rate. If contagion exists, both premia will decrease and the correlation will go up as the short rate increases. That is, θ_i<0 and $\rho_{12}^{l} < \rho_{12}^{h}$. The computed values of the likelihood function are referred to as Lik4s. The likelihood-ratio statistics against the base model (augmented with short rates in the mean equations) are referred to as LR14s.

Table 8 shows some evidence supporting the contagion hypothesis. However, the evidence is a bit weaker in the second subperiod. In particular, although the bond market did go down when the short rate went up, it is not statistically significant. The evidence carries the asset allocation implication that investors should increase the shorting of both stocks and bonds when the interest rate goes beyond the range of 0.061 to 0.070, and in this case the more important hedge for risk is the risk-free asset.

[Table 8 here]

Further, we offer some tentative explanations why inflation predicts the stock-bond correlation quite differently in the earlier and later subperiods. Fiscal and monetary policies could explain the opposite patterns predicted by inflation. In particular, the opposite patterns predicted by inflation seem to coincide with the switch from the gold-based standard to the paper-based standard. One explanation for this is the proxy hypothesis. The proxy hypothesis was proposed by Fama (1981) to explain the negative stock return-inflation relation. He argues that the negative relation is induced by a negative relation between inflation and real activity, which in turn is explained by money demand. Geske and Roll (1983) extend Fama's argument to include counter-cyclical fiscal policy. Kaul (1987) takes a step further to show that there is a positive relation under the gold standard due to pro-cyclical movements in money, inflation, and stock prices. Simply put, under a gold-based monetary standard, recessions are typically associated with falling commodity prices. Under a paper-based monetary standard, recessions are more likely to be associated with inflation rather than deflation, because the government often attempts to offset economic downturns with expansionary fiscal and monetary policies.

An alternative explanation might be the Fisher effect versus the Gibson effect. The Fisher hypothesis states that nominal interest rates rise point-for-point with expected inflation, leaving the real rate unaffected. However, under the classical gold standard, interest rates exhibited an essentially zero correlation with the inflation rate. This puzzling relation is referred to as the Gibson's paradox.[16] The evidence of the Gibson correlation is weaker for the wartimes and the interwar years than for the classical gold standard period. The complete disappearance of Gibson's paradox by the early 1970s coincides with the final break with gold at that time. A resulting implication is that inflation under the gold standard was largely unexpected while it has

[16] See Barsky (1989) for reference.

become more likely to be expected under the paper-based standard. Thus, a plausible explanation for the opposite predictive patterns might go as follows: the expected inflation increases the stock-bond correlation while the unexpected inflation decreases the correlation. This is consistent with the finding of Li (2002), where inflation is decomposed into an expected component and an unexpected component. Further research may be needed to look at this issue in more depth.

5. Conclusions

This study explores time-varying patterns of stock-bond correlations over macroeconomic conditions in the US and the UK in the past 150 years (1855-2001). Similar to Ilmanen (2003) and many other studies, we consider several dimensions of macroeconomic conditions: the business cycle, inflation environment, and monetary policy stance (short rate). Based on business cycle dating, we document for the first time evidence for different patterns in stock-bond correlations over recessions versus expansions between the US and the UK. In the US, the stock-bond correlations during recessions are lower than those during expansions, which is consistent with many previous studies (e.g., Boyd et al., 2005; Andersen et al., 2007). By contrast, the higher correlations occur during recessions than during expansions in the UK. An important implication of the finding is that bonds may be to some extent a better hedge against stock market risk and offer more diversification benefits to stock investors in the US than in the UK.

Furthermore, we demonstrate (statistically) significant time-varying stock-bond correlations *predictable* by two key macroeconomic condition indicators (i.e., the short rate and inflation rate). Although evidence for the UK is weaker, there is a general pattern across both the US and the UK during the post-1923 subperiod and (particularly in the U.S.) during the whole sample period: higher stock-bond correlations tend to follow higher short rates or (to a lesser extent) higher inflation rates in the previous period. While our overall finding is well in line with intuitive observations of Ilmanen (2003), to our knowledge, such empirical evidence is not yet reported in the literature. Also noteworthy, as the short rate typically rises during expansions and falls during contractions (Fama and French, 1989)[17], our finding on the short rate may be consistent with Boyd et al. (2005) and Andersen et al. (2007), but not Jensen and Mercer (2003), who document that correlations between large cap stocks and bonds are lower during the restrictive monetary policy environment (or economic expansions) than during the expansive monetary policy environment (or economic recessions). Furthermore, in light of the observation that higher inflation rate typically coincides with higher inflation uncertainty, our finding on the inflation rate during the more recent subperiod is also generally supportive of Li (2002) but less so for d'Addona and Kind (2006).

Finally, note that the correlation is a linear measure of dependence or a canonical measure of co-movement, which only applies in the case of the mean-variance preference of investors or the multivariate normal distribution of returns. Future research may go beyond these restrictive assumptions on investor preferences and return distributions to explore how the higher order co-movement between stocks and bonds may vary over macroeconomic conditions. It would also be interesting to examine how time-varying comovements among stocks, bonds and other asset classes both in a single country and a multi-country context may be driven by domestic and international macroeconomic conditions. Finally, the econometric methodology used in this study should be useful to provide more insights on many other topics that often employ rather standard multivariate GARCH models (e.g., Lien and Yang, 2008).

[17] Ang et al. (2006) recently also show that the short rate has more predictive power than any term spread in forecasting GDP out-of-sample.

References

Andersen, T.G., Bollerslev, T., Diebold, F.X., Vega, C., 2007. Real-time price discovery in stock, bond and foreign exchange markets. Journal of International Economics 73, 251-277.

Ang, A., Piazzesi, M., Wei, M., 2006. What does the yield curve tell us about GDP growth? Journal of Econometrics 131, 359-403.

Baillie, R.T., Han, Y.-W., Kwon, T., 2002. Further long memory properties of inflationary shocks. Southern Economic Journal 68, 496-510.

Barsky, R.B., 1989. Why don't the prices of stocks and bonds move together? American Economic Review 79, 1132-1145.

Basu, S., Taylor, A.M., 1999. Business cycles in international historical perspective. Journal of Economic Perspective 13(2), 45-68.

Boyd, J. H., Jagannathan, R., Hu, J., 2005. The stock market's reaction to unemployment news: Why bad news is usually good for stocks. Journal of Finance 60, 649-672.

Capie, F., Webber, A., 1985. *A* Monetary History of the United Kingdom, 1870-1982. George Allen & Unwin (Publishers) Ltd.

Connolly, R., Stivers, C., Sun, L., 2005. Stock market uncertainty and the stock-bond return relation. Journal of Financial and Quantitative Analysis 40, 161-194.

Connolly, R., Stivers, C., Sun, L., 2007. Commonality in the time variation of stock–bond and stock–stock return comovements. Journal of Financial Markets 10, 192–218.

d'Addona, S., Kind, A.H., 2006. International stock–bond correlations in a simple affine asset pricing model. Journal of Banking & Finance 30, 2747-2765

Dimson, E., Marsh, P., Staunton, M., 2001. Triumph of the Optimists: 101 Years of Global Investment Returns. Princeton University Press.

Fama, E.F., 1981. Stock returns, real activity, inflation and money. American Economic Review 71(4), 545-565.

Fama, E.F., French, K., 1989. Business conditions and expected returns on stocks and bonds. Journal of Financial Economics 25, 23-49.

Friedman, M., Schwartz, A.J., 1982. Monetary Trends in the United States and the United Kingdom. The University of Chicago Press.

Geske, R., Roll, R., 1983. The fiscal and monetary linkage between stock returns and inflation. Journal of Finance 38, 1-33.

Guidolin, M., Timmermann, A., 2005. Economic implications of bull and bear regimes in UK stock and bond returns. Economic Journal 115, 111-143.

Ilmanen, A., 2003. Stock–bond correlations. Journal of Fixed Income 12, 55-66.

Jensen, G. R., Mercer, J.M., 2003. New evidence on optimal asset allocation. Financial Review 38, 435-454.

Kaul, G., 1987. Stock returns and inflation: The role of the monetary sector. Journal of Financial Economics 18, 253-276.

Kim, S., Moshirian, F., Wu, E., 2006. Evolution of international stock and bond market integration: Influence of the European Monetary Union. Journal of Banking & Finance 30, 1507-1534

Kim, S., Shephard, N., Chib, S., 1998, Stochastic volatility: Likelihood inference and comparison with ARCH models. Review of Economic Studies 65, 361-393.

Li, L., 2002. Macroeconomic factors and the correlation of stock and bond returns. Working paper, Yale University.

Li, X., Zou, L., 2008. How do policy and information shocks impact co-movements of China's T-bond and stock markets? Journal of Banking & Finance 32, 347-359.

Lien, D., Yang, L., 2008. Asymmetric effect of basis on dynamic futures hedging: Empirical evidence from commodity markets, Journal of Banking & Finance 32, 187-198.

Longin, F., Solnik, B., 1995. Is the correlation in international equity returns constant: 1960-1990? Journal of International Money and Finance 14, 3-26.

Nam, K., Pyun, C. S., Arize, A. C., 2002. Asymmetric return reversals and contrarian profits: ANST-GARCH approach. Journal of Empirical Finance 9, 475-608.

Panchenko, V., Wu, E., 2009. Time-varying market integration and stock and bond return concordance in emerging markets, Journal of Banking & Finance, forthcoming.

Schwert, W.G., 1990. Indexes of United States stock prices from 1802 to 1987. Journal of Business 63, 399-426.

Scruggs, J.T., Glabadanidis, P., 2003. Risk premia and the dynamic covariance between stock and bond returns. Journal of Financial and Quantitative Analysis 38, 295-316.

Silvennoinen, A., Teräsvirta, T., 2005. Multivariate autoregressive conditional heteroskedasiticy with smooth transitions in conditional correlation. Working Paper, Stockholm School of Economics.

Table 1
Definition of dummy variables

This table provides the definition of the dummies to capture potential structural changes. The state dummy ($STATE_t$) is defined according to Table A1 in the appendix (available on request). The war dummy (WAR_t) is defined according to Table A2 in the appendix (available on request). The other structural dummies are based on the historical background in Section 2. Note that the gold dummy, $GOLD_t$, is slightly different for the US and the UK since they abandoned the gold standard in September 1931 and April 1933 respectively. Also, the dummies for the greenback and Federal Reserve periods are only valid for the US.

Panel A: The US

	one	zero
$STATE_t$	recessions	expansions
WAR_t	war periods	peace periods
$GOLD_t$	since Apr.1933	otherwise
$BRETTON_t$	Oct.1945 ~ Jul.1971	otherwise
$FLOAT_t$	Aug.1971 ~ Nov.2001	otherwise
$ACCORD_t$	Jan.1952 ~Nov. 2001	otherwise
$RECENT_t$	Oct. 1979 ~Jan. 2001	otherwise
FED_t	since Jan.1914	otherwise
$GREENBACK_t$	Apr.1861 ~ Dec.1878	otherwise

Panel B: The UK

	One	zero
$STATE_t$	recessions	expansions
WAR_t	war periods	peace periods
$GOLD_t$	since Sep. 1931	otherwise
$BRETTON_t$	Oct.1945 ~ Jul.1971	otherwise
$FLOAT_t$	Aug.1971 ~ Nov.2001	otherwise
$ACCORD_t$	Jan.1952 ~Nov. 2001	otherwise
$RECENT_t$	Oct. 1979 ~Jan. 2001	otherwise

Table 2
Summary statistics of the data

The stock and bond premia are their returns in excess of short rate. Short rate, labeled SHORT, is the log difference of the USA Commerical/T-bill total return. Inflation, labeled INF, is the log difference of the US producer's price index. "E" and "R" denote expansion and recession periods. "Nobs" is the numbers of monthly observations for the series.

Panel A: US data (the whole sample)

Period	Stat	Stock premium	Bond premium	SHORT	INF
Jan.1855 - Nov.2001	Nobs	1759	1763	1763	1763
	Mean	0.043	0.003	0.045	0.018
	Std	0.607	0.173	0.030	0.205
	Skew	-0.568	0.715	2.901	0.464
	Kurt	6.321	13.620	31.129	11.132

Panel B: UK data (the whole sample)

Period	Stat	Stock premium	Bond premium	SHORT	INF
Jan.1855 - Nov.2001	Nobs	1727	1763	1763	1764
	Mean	0.039	0.002	0.044	0.026
	Std	0.438	0.259	0.033	0.202
	Skew	0.219	0.296	1.251	0.276
	Kurt	19.386	3.421	1.298	42.840

Panel C: US data (regime patterns)

Period		Stat.	Stock premium	Bond premium	SHORT	INF
Jan.1855 - Nov.2001	E	Nobs	1205	1205	1205	1205
		Mean	0.092	-0.000	0.043	0.050
		Std.	0.526	0.167	0.030	0.192
	R	Nobs	554	558	558	558
		Mean	-0.065	0.009	0.048	-0.053
		Std.	0.742	0.186	0.031	0.217

Panel D: UK data (regime patterns)

Period		Stat.	Stock premium	Bond premium	SHORT	INF
Jan.1855 - Nov.2001	E	Nobs	1247	1278	1278	1279
		Mean	0.056	0.000	0.045	0.051
		Std.	0.438	0.268	0.032	0.184
	R	Nobs	480	485	485	485
		Mean	-0.001	0.006	0.042	-0.042
		Std.	0.435	0.233	0.035	0.229

Table 3
Regime patterns of the stock-bond correlations

The table shows the unconditional correlations of various samples, their expansion and recession periods between the stock and bond premiums. Panel A is for the US and Panel B is for the UK. * denotes significance at 10%, ** denotes significance at 5%, and *** denotes significance at 1%.

Panel A: The US

	Period		On average	Expansion	Recession
Whole sample	Jan.1855	Nov.2001	0.154***	0.162***	0.155***
Sub-samples	Jan.1855	Dec.1925	0.188***	0.211***	0.165***
	Jan.1926	Nov.2001	0.149***	0.162***	0.161***

Panel B: The UK

	Period		On average	Expansion	Recession
Whole sample	Jan.1855	Nov.2001	0.255***	0.247***	0.287***
Sub-samples	Jan.1855	Dec.1923	0.204***	0.184***	0.288***
	Jan.1924	Nov.2001	0.265***	0.260***	0.288***

Table 4
Estimation results of the base model

The base model is as follows:

$$r_{it} = \mu_i + \lambda_i r_{it-1} + \varepsilon_{it},\ \varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})' \sim N(0, H_t),\ H_t = D_t R_t D_t,$$
$$D_t = diag(h_{it}^{1/2}),\ h_{it} = \omega_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i h_{i,t-1},\ R_t = (\rho_{ij}),\ with\ \ \rho_{ii} = 1,$$

where subscripts i, j $\in \{1,2\}$ with 1 and 2 denoting the US (or UK) stock and bond respectively. The t-statistics of ρ_{12} are reported with *, **, and *** denoting significance at 10%, 5%, and 1% respectively. The log-likelihood values, denoted by Lik1, are also reported.

Panel A: The whole sample - US

Period		μ	λ	ω	α	β	ρ_{12}	Lik1
Jan.1855 - Nov.2001	Stock	0.048	0.078	0.015	0.119	0.842	0.162***	-127.094
	t-value	5.033	3.978	4.617	7.310	43.134	8.164	
	Bond	0.000	0.225	0.000	0.107	0.891		
	t-value	0.130	7.371	5.884	7.568	71.355		

Panel B: The subsamples - US

Period		μ	λ	ω	α	β	ρ_{12}	Lik1
Jan.1855 - Dec.1925	Stock	0.021	0.044	0.033	0.147	0.744	0.176***	214.211
	t-value	1.245	1.159	3.752	4.750	16.866	5.212	
	Bond	-0.008	0.164	0.000	0.026	0.962		
	t-value	-2.901	3.271	2.878	2.584	86.059		
Jan.1926 - Nov.2001	Stock	0.074	0.091	0.009	0.122	0.864	0.151***	-317.832
	t-value	4.080	2.473	2.854	6.090	47.649	4.816	
	Bond	0.008	0.163	0.000	0.125	0.803		
	t-value	2.219	4.368	3.478	6.763	34.754		

Panel C: The whole sample - UK

Period		μ	λ	ω	α	β	ρ_{12}	Lik1
Jan.1855 - Nov.2001	stock	-0.003	0.131	0.002	0.267	0.786	0.238***	-206.757
	t-value	-0.590	5.866	4.244	9.683	45.274	11.047	
	bond	0.004	0.105	0.000	0.071	0.925		
	t-value	1.018	4.106	3.994	6.999	92.288		

Panel D: The subsamples - UK

Period		μ	λ	ω	α	β	ρ_{12}	Lik1
Jan.1855 - Dec.1923	stock	-0.008	0.201	0.002	0.350	0.717	0.204***	495.001
	t-value	-1.243	4.619	1.932	7.032	18.952	6.375	
	bond	0.002	-0.043	0.000	0.028	0.969		
	t-value	0.481	-1.058	1.738	3.879	125.348		
Jan.1924 - Nov.2001	stock	0.009	0.091	0.002	0.188	0.807	0.278***	-673.097
	t-value	0.902	2.479	2.628	6.520	41.195	8.837	
	bond	0.006	0.201	0.001	0.096	0.895		
	t-value	0.680	6.465	2.641	6.035	56.035		

Table 5
Estimation results of the dummies in correlation

The model with dummies in conditional correlation is as follows:

$$\rho_{12t} = \rho_{12}^{0} \cdot (1 - STATE_t) + \rho_{12}^{1} \cdot STATE_t + K \cdot D_t .$$

The log-likelihood values (Lik2s) and likelihood ratio statistics (LR12s) are also reported with * denoting significance at 10%, ** denoting significance at 5%, and *** denoting significance at 1%.

Panel A: The whole sample - US

Period	Jan.1855-Nov.2001	
	Coeff.	t-value
ρ_{12}^{0}	0.363***	3.436
ρ_{12}^{1}	0.236**	2.014
WAR	-0.022	-0.394
GREEN	-0.126*	-1.789
FED	-0.155**	-1.992
GOLD	-0.006	-0.061
BRETTON	0.031	0.191
FLOAT	0.218	1.152
ACCORD	-0.112	-0.723
RECENT	-0.079	-0.839
Lik2	-119.007	
Lik1	-127.094	
LR12	16.173*	

Panel B: The subsamples - US

Period	Jan.1855-Dec.1925		Jan.1926-Nov.2001	
	Coeff.	t-value	Co-eff.	t-value
ρ_{12}^{0}	0.284***	5.796	0.166*	1.869
ρ_{12}^{1}	0.063**	1.374	0.136	1.341
WAR	-0.224***	-2.776	-0.010	-0.132
GREEN	-0.015	-0.209		
FED	0.160	1.742		
GOLD			-0.178	-1.356
BRETTON			0.033	0.217
FLOAT			0.223	1.326
ACCORD			-0.097	-0.672
RECENT			-0.071	-0.939
Lik2	221.554		-313.505	
Lik1	214.171		-317.832	
LR12	14.766***		8.654	

Table 5 (Continued)

Panel C: The whole sample - UK

Period	Jan.1855-Nov.2001	
	Coeff.	t-value
ρ_{12}^{0}	0.229***	2.934
ρ_{12}^{1}	0.306***	4.182
WAR	-0.016	-0.230
GOLD	-0.060	-0.768
BRETTON	0.126	1.163
FLOAT	0.295**	2.148
ACCORD	-0.158	-1.610
RECENT	-0.071	-0.871
Lik2	-200.877	
Lik1	-206.757	
LR12	11.760	

Panel D: The subsamples - UK

Period	Jan.1855-Dec.1923		Jan.1924-Nov.2001	
	Coeff.	t-value	Coeff.	t-value
ρ_{12}^{0}	0.180***	4.212	0.245***	3.206
ρ_{12}^{1}	0.364***	6.665	0.275***	3.770
WAR	-0.078	-1.080	0.292***	3.333
GOLD			-0.183	-1.403
BRETTON			0.145**	2.214
FLOAT			0.332***	6.848
ACCORD			-0.190***	2.754
RECENT			-0.110	-1.520
Lik2	499.384		-666.116	
Lik1	495.001		-673.097	
LR12	8.766**		13.961*	

Table 6
Estimation results of the smooth transition in correlation: the first lagged short rate as the transition variable

The model with the transition variable of the first lagged short rate is as follows:

$$\rho_{ijt} = \rho_{12}^{l}(1-G_t) + \rho_{12}^{h}G_t \text{, and } G_t = \frac{1}{1+\exp[-\gamma(SHORT_{t-1}-\delta)]}, \ \gamma > 0.$$

γ is constrained to be 500. The log-likelihood values (Lik3s) and the likelihood ratio statistics against the base model (LR13s) are reported with * denoting significance at 10%, ** denoting significance at 5%, and *** denoting significance at 1%, based on the asymptotic critical values. The numbers in the parentheses are the *p*-values based on the simulated critical values.

Panel A: The whole sample - US

Period	Jan.1855-Nov.2001	
	Coeff.	t-value
ρ_{12}^{l}	0.108***	4.188
ρ_{12}^{h}	0.335***	7.431
δ	0.069***	27.988
γ	500	
Lik3	-118.781	
Lik1	-127.094	
LR13	16.626*** (.055)	

Panel B: The subsamples – US

Period	Jan.1855-Dec.1925		Jan.1926-Nov.2001	
	Coeff.	t-value	Coeff.	t-value
ρ_{12}^{l}	0.097**	2.261	0.078*	1.869
ρ_{12}^{h}	0.335***	6.223	0.276***	5.609
δ	0.060***	20.305	0.053***	18.644
γ	500		500	
Lik3	218.976		-313.906	
Lik1	214.211		-317.832	
LR13	9.531*** (.115)		7.851*** (0.025)	

Panel C: The whole sample - UK

Period	Jan.1855-Nov.2001	
	Coeff.	t-value
ρ_{12}^{l}	0.219***	13.980
ρ_{12}^{h}	0.395***	6.029
δ	0.104***	10.472
γ	500	
Lik3	-203.636	
Lik1	-206.757	
LR13	6.243** (0.080)	

Panel D: The subsamples – UK

Period	Jan.1855-Dec.1923		Jan.1924-Nov.2001	
	Coeff.	t-value	Coeff.	t-value
ρ_{12}^{l}	0.221***	6.398	0.245***	7.081
ρ_{12}^{h}	0.065	0.568	0.406***	7.383
δ	0.058***	11.781	0.104***	25.581
γ	500		500	
Lik3	495.808		-670.782	
Lik1	495.001		-673.097	
LR13	1.615 (0.210)		4.629** (0.060)	

Table 7
Estimation results of the smooth transition in correlation: the first lagged inflation as the transition variable

The model with the transition variable of the first lagged inflation rate is as follows:

$$\rho_{12t} = \rho_{12}^{l}(1-G_t) + \rho_{12}^{h}G_t \text{, and } G_t = \frac{1}{1+\exp[-\gamma(INF_{t-1}-\delta)]}, \quad \gamma > 0.$$

γ is constrained to be 100. The log-likelihood values (Lik3) and the likelihood ratio statistics against the base model (LR13) are reported with * denoting significance at 10%, ** denoting significance at 5%, and *** denoting significance at 1%, based on the asymptotic critical values. The numbers in the parentheses are the *p*-values based on the simulated critical values.

Panel A: The whole sample - US

Period	Jan.1855-Nov.2001	
	Coeff.	t-value
ρ_{12}^{l}	0.129***	4.560
ρ_{12}^{h}	0.240***	6.883
δ	0.028	1.401
γ	100	
Lik3	-125.086	
Lik1	-127.094	
LR13	4.015** (0.155)	

Panel B: The subsamples – US

Period	Jan.1855-Dec.1925		Jan.1926-Nov.2001	
	Coeff.	t-value	Coeff.	t-value
ρ_{12}^{l}	0.297***	4.789	-0.170*	-1.745
ρ_{12}^{h}	0.141***	4.156	0.202***	5.699
δ	-0.045	-1.325	-0.099***	5.225
γ	100		100	
Lik3	216.205		-311.645	
Lik1	214.171		-317.832	
LR13	4.067** (0.340)		12.373*** (0.010)	

Panel C: The whole sample - UK

Period	Jan.1855-Nov.2001	
	Coeff.	t-value
ρ_{12}^{l}	0.443***	8.421
ρ_{12}^{h}	0.217***	9.552
δ	-0.057***	-3.210
γ	100	
Lik3	-201.889	
Lik1	-206.757	
LR13	9.737*** (0.055)	

Panel D: The subsamples – UK

Period	Jan.1855-Dec.1923		Jan.1924-Nov.2001	
	Coeff.	t-value	Coeff.	t-value
ρ_{12}^{l}	0.467***	8.198	0.253***	7.992
ρ_{12}^{h}	0.094**	2.230	0.379***	7.549
δ	-0.002	-.253	0.164***	4.962
γ	100		100	
Lik3	503.573		-671.783	
Lik1	495.001		-673.097	
LR13	17.145*** (0.010)		2.628 (0.230)	

Table 8
Estimation results of the contagion hypothesis for the US

This table presents estimates of the following model for the US

$$\mu_{it} = \mu_i + \lambda_i r_{i,t-1} + \theta_i SHORT_{t-1},\ i = 1 \textit{ for stock or } 2 \textit{ for bond},$$

$$\rho_{12t} = \rho_{12}^l (1 - G_t) + \rho_{12}^h G_t \text{, and } G_t = \frac{1}{1 + \exp[-\gamma(SHORT_{t-1} - \delta)]},\ \gamma > 0.$$

The log-likelihood values (Lik4s) and the likelihood ratio statistics against the base model (augmented with $SHORT_{t-1}$ in the mean equations) (LR14s) are reported with * denoting significance at 10%, ** denoting significance at 5%, and *** denoting significance at 1%, based on the asymptotic critical values. The numbers in the parentheses are the *p*-values based on the simulated critical values. Panel A is for the whole sample, Panel B is for the two subsamples.

Panel A: The whole sample

Period	Jan.1855-Nov.2001	
	Coeff.	t-value
θ_1	-2.178***	-5.217
θ_2	-0.500***	-4.985
ρ_{12}^l	0.102***	3.898
ρ_{12}^h	0.317***	9.101
δ	0.069***	28.782
γ	500	
Lik4	-98.545	
Lik1	-106.058	
LR14	15.026*** (0.000)	

Panel B: The sub-samples

Period	Jan.1855-Dec.1925		Jan.1926-Nov.2001	
	Coeff.	t-value	Coeff.	t-value
θ_1	-2.317***	-3.341	-1.720***	-3.607
θ_2	-0.511***	-3.901	-0.256	-1.485
ρ_{12}^l	0.089*	1.920	0.098***	2.698
ρ_{12}^h	0.318***	5.631	0.343***	5.716
δ	0.061***	20.304	0.070***	20.282
γ	500		500	
Lik4	227.589		-308.192	
Lik1	223.116		-312.638	
LR14	8.947*** (0.055)		8.892*** (0.045)	

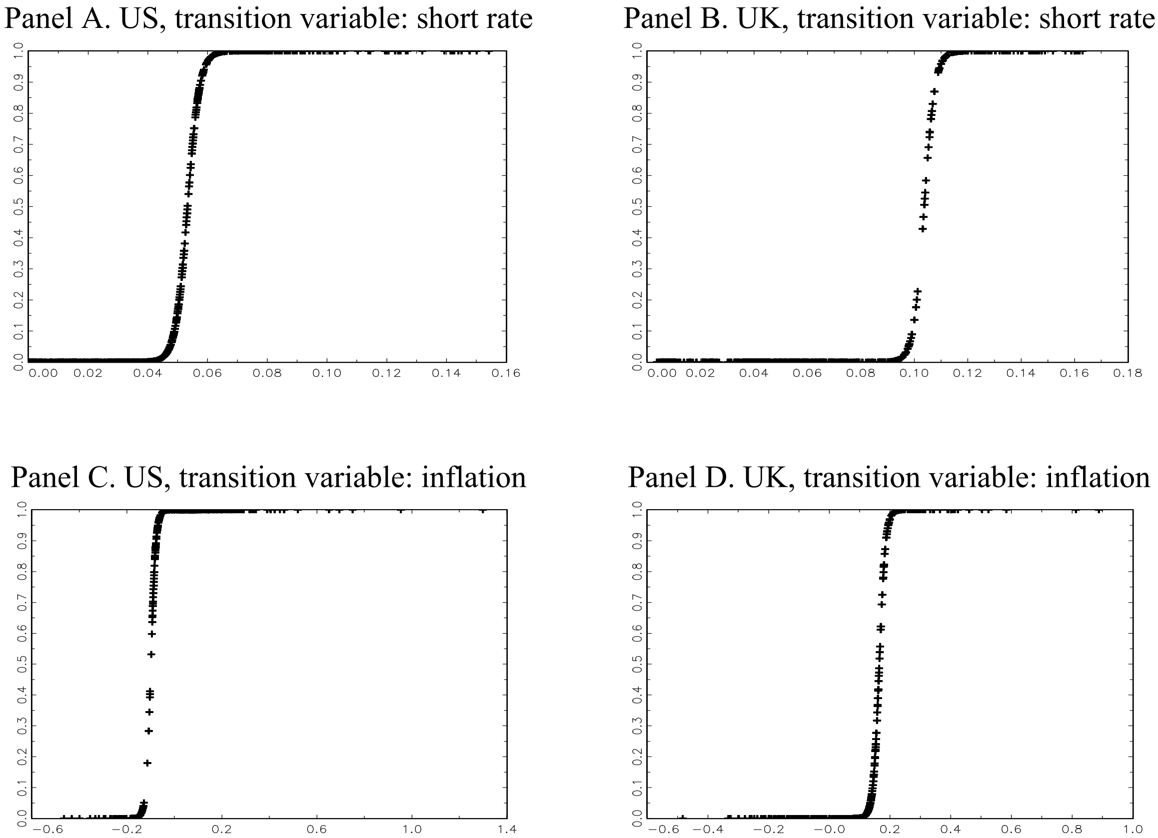

Fig. 1. The estimated transition functions

Note: The graphs are based on the STCC-GARCH model estimates for the sample period and the level axis is the transition variable.

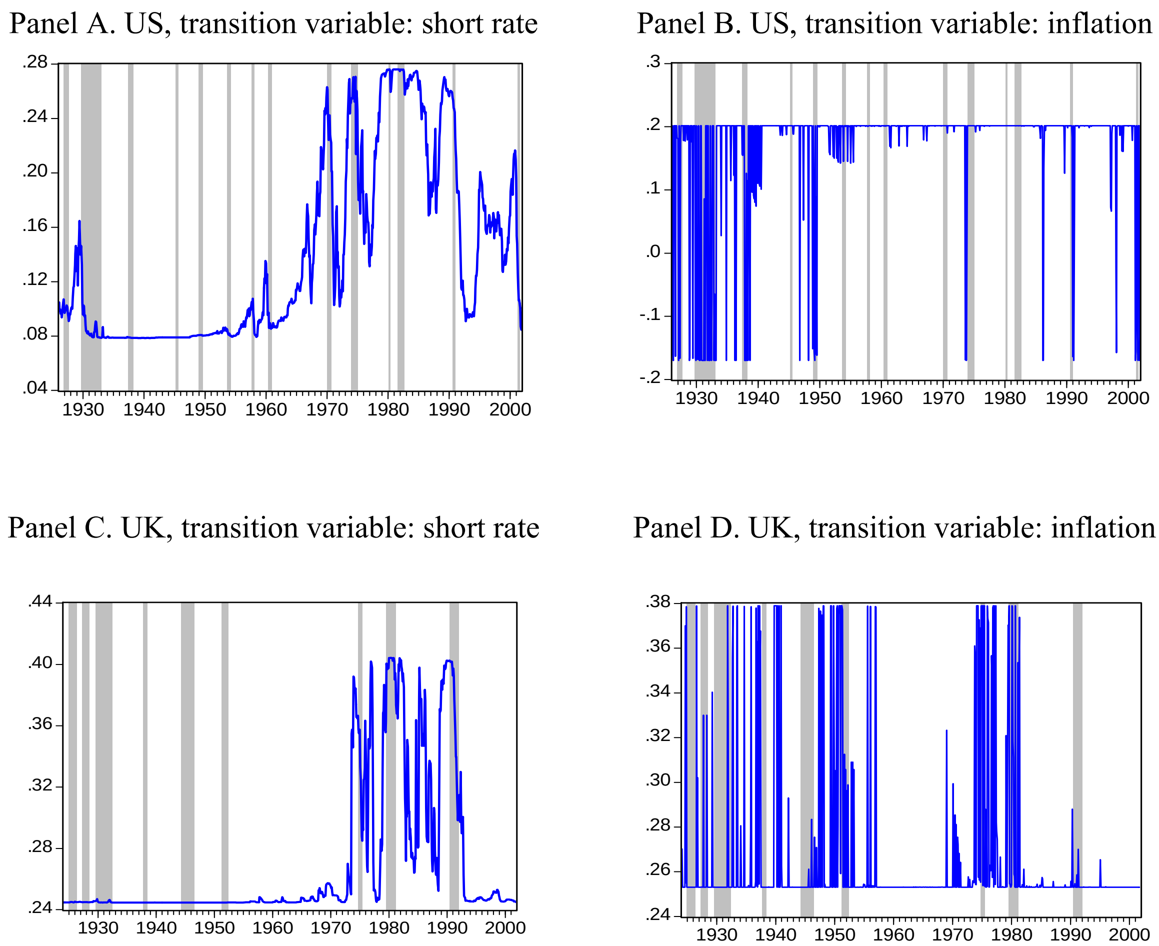

Fig. 2. The estimated conditional correlations

Note: The graphs are based on the STCC-GARCH model estimates for the sample period and the level axis is the transition variable. The shaded areas indicate business recessions dated by NBER.