International Review of Economics and Finance xxx (2017) 1–13

Contents lists available at ScienceDirect

International Review of Economics and Finance

journal homepage: www.elsevier.com/locate/iref

The role of investor sentiment in the long-term correlation between U.S. stock and bond markets

Libing Fang, Honghai Yu [*], Yingbo Huang

School of Management and Engineering, Nanjing University, Nanjing, China

A R T I C L E I N F O

Keywords:
DCC-MIDAS model
Investor sentiment
Long-term correlation
Structural change
Portfolio performance

A B S T R A C T

This paper investigates the influence of the composite index of investor sentiment on the time-varying long-term correlation of the U.S. stock and bond markets based on the DCC-MIDAS model. We modify the model by considering structural break points of the 1997 Asian financial crisis and the 2008 global financial crisis based on the Bai and Perron (2003) test to adjust the correlation during different periods. The results show that the composite index of investor sentiment has a significantly positive influence on the long-term stock-bond correlation, and the shock of crises significantly decrease the average correlation but the effect of sentiment does not change significantly. Finally, our out-of-sample analysis presents significant improvement for the performance of portfolio allocation after involving the effect of investor sentiment on the long-term stock-bond correlation.

1. Introduction

Stocks and bonds are most widely considered in investors' asset allocation and also the most prominent in positions held by investors. The correlation of the two assets substantially determines their weights in a portfolio, and thus, the performance of risk diversification. There have been some attempts to comprehend their fundamental relationship. Prior studies implicitly assume that the stock-bond correlation is time invariant and the observed levels cannot be justified by economic fundamentals (Campbell & Ammer, 1993). Recently several studies have shown that the co-movement between stock and bond returns exhibits considerable time variation (Cao, Galvani, & Gubellini, 2017; Gomes & Taamouti, 2016; Perego & Vermeulen, 2016).

The underlying factors of the long-term correlation between stock and bond returns have raised concern. A few variables that may affect the stock-bond correlation are macro-finance factors, which are expected to influence the future cash flows and discount rates of assets. Gomes and Taamouti (2016) use a DDC model to measure the covariances between returns and study the comovement of stock and sovereign bond markets of the Euro Area. Cao et al. (2017) find evidence of information flows streaming from the stock to the bond market. Further, bidirectional information flows are triggered by the 2007 financial crisis. The mean of the firm's value drives contemporaneous variation in stock and bond prices. On the other hand, Baele, Bekaert, and Inghelbrecht (2010) find that macroeconomic fundamentals contribute little to stock and bond return correlations but that other factors, especially liquidity proxies, play a more important role. Aslanidis and Christiansen (2014) provide fresh opinions on why macroeconomic factors have only little explanatory power when the correlation is largely positive.

In recent years, growing attention has been paid to the impact of investor sentiment on the correlation of stock and bond market returns (Abdelhédi-Zouch, Abbes, & Boujelbène, 2015). Investor sentiment, defined as the optimism or pessimism about stocks in

* Corresponding author. #22 Hankou Road, Gulou District, Nanjing, 210093, China.
E-mail address: hhyu@nju.edu.cn (H. Yu).

http://dx.doi.org/10.1016/j.iref.2018.03.005
Received 9 May 2017; Received in revised form 28 February 2018; Accepted 13 March 2018
Available online xxxx

general (Baker & Wurgler, 2006), can be transmitted to financial markets through investors' transactions and choices. Specifically, behavioral biases, such as loss aversion, pessimism, and herding, can have a considerable influence on the market during a crisis. This may have a significant impact on the long-term correlation between U.S. stock and bond markets, which can be explained by the flight-to-quality theory (Caballero & Krishnamurthy, 2008). Asgharian, Christiansen, and Hou (2016) focus their analysis of the impact of macro-finance factors on correlation, and also analyze the impact of individual indexes of investor sentiment, including PMI (the log-difference of the producer confidence index), CC (the log-difference of the consumer confidence index) and VXO (the log-difference of the volatility index), on the correlation of stock and bond markets.

In contrast to Asgharian et al. (2016), we focus on the impact of the composite index of investor sentiment on the long-term stock-bond correlation and further analyze the time-varying relationship reacts to financial crises. Specifically, we extend the DCC-MIDAS model proposed by Colacito, Engle, and Ghysels (2011) to allow long-term correlation driven by investor sentiment and consider structural breaks to adjust the correlation during different periods. Through the Bai and Perron (2003) test, we detect the multiple structural breakpoints during the time-varying correlation. Considering structural changes in July 1997 and April 2007, we divide the sample period into three sub-sample periods to test whether or not a financial crises impacts the long-term stock-bond correlations. The model can combine daily stock and bond returns with a monthly composite index of investor sentiment and take financial market turmoil into account. The results show that the composite index of investor sentiment has a significantly positive influence on the long-term stock-bond correlation, and the shock of crises significantly decrease the average correlation but the effect of sentiment does not change significantly. Furthermore, our out-of-sample analysis presents significant improvement for the performance of portfolio allocation after involving the effect of investor sentiment on the long-term stock-bond correlation.

This article contributes to the existing literature in several ways. First, we provide specific evidence on the driving effect of investor sentiment on the long-run correlation of stock and bond based on a composite sentiment index. Current literature (Asgharian et al., 2016; Lemmon & Portniaguina, 2006; Perego & Vermeulen, 2016) mainly focus on the macroeconomic determinants of the long-run correlation of stocks and bonds. Asgharian et al. (2016) analyze the effect of macro-finance factors related to inflation and interest rates, illiquidity, state of the economy, and market uncertainty, besides studying the impact of the individual sentiment proxies of PMI, CC, and VXO. Such individual sentiment proxies are likely to include a sentiment component as well as idiosyncratic, non-sentiment-related components (Baker & Wurgler, 2006). For example, the survey-based sentiment indices (including PMI and CC) are related to expected business conditions (Laborda & Muñoz, 2016; Yu, 2013). Furthermore, during the surveys, there is a potential gap between how people respond to a survey and their actual behave (Baker & Wurgler, 2007). In addition, it is important to emphasize that the proxy of VXO is forward-looking and measures the volatility that the investors expect to see (Whaley, 2000). VXO is used to measure investor fear gauge, while it also reflects the uncertainty of the future real economy, and is widely used to measure uncertainty in stock markets (see e.g. Ang, Hodrick, Xing, & Zhan, 2006; Connolly, Stivers, & Sun, 2005; Hilal, Poon, & Tawn, 2011; Li, 2012; Vahamaa & Aijo, 2011), which is a non-sentiment-related component.

Since these individual proxies of investor sentiment are likely to include a sentiment component as well as idiosyncratic, non-sentiment-related components, and there are no definitive or uncontroversial measures, Baker and Wurgler (2006) consider a more comprehensive set of sentiment proxies, and form their composite sentiment index by using a principal components analysis based on six individual sentiment proxies to isolate the common component. To purge the effects of macroeconomic conditions from their sentiment index, they first regress each of the individual proxies on six macroeconomic indicators. To further filter out idiosyncratic fluctuations in the six proxies and capture their common component, they take the first principal component of the six residual series from the regressions as their final composite index. For the first time we consider Baker and Wurgler (2006) composite index as an appropriate proxy for investor sentiment to analyze its impact on the long-run correlation of the stock and bond markets.

Second, we reveal the structural changes caused by the financial crises on the relation between investor sentiment and correlation of stock and bond. We find that the deviations between the long-term and short-term components of the stock-bond correlation fluctuate, and the goodness of fit of the DCC-MIDAS-sentiment model is poor if we do not consider the structural changes. By considering structural changes caused by the financial crises, the goodness of fit of the DCC-MIDAS-sentiment model is improved significantly. Our results with structural changes show that the average correlation between stock and bond decreased significantly. It is intuitive since the demand for bonds increases and demand for stocks decreases, resulting in a decrease in their correlation after the financial crisis event. It has been widely demonstrated that the financial crises have a significant influence on the investor sentiment (e.g., Canbaş & Kandõr, 2009; Duchin, Ozbas, & Sensoy, 2010; Fisher & Statman, 2000; Zouaoui, Nouyrigat, & Beer, 2011). Furthermore, Tsai (2017) find that bad news can easily induce a rapid diffusion of pessimistic investor sentiment. Therefore, our work goes beyond these literature by revealing how financial crises affect the long-term correlation on stocks and bonds through investor sentiment.

Third, we contribute to the literature by presenting the out-of-sample performance of portfolio allocation between stocks and bonds in long-run by considering the effect of investor sentiment based on composite index. Even though the existing literature, such as Asgharian et al. (2016), has investigated the performance of portfolio allocation with the effect of PMI, CC, and VXO, these proxies are noisy, and include a sentiment component as well as idiosyncratic, non-sentiment-related components. Our work presents portfolio performance based on the composite index of investor sentiment to overcome the shortcomings of individual sentiment proxies. Furthermore, we provide more comprehensive performance evaluation of portfolio allocation. We use minimum variance method proposed by Engle and Colacit (2006), which is similar to Asgharian et al. (2016). Besides, we have further considered the criterion of Ederington (1979) variance reduction and the criterion of certainty equivalent (CE) by Alexander and Barbosa (2008).

The remainder of the article is organized as follows. First, we introduce the data in Section 2. In Section 3, we discuss the empirical findings. We conclude in Section 4.

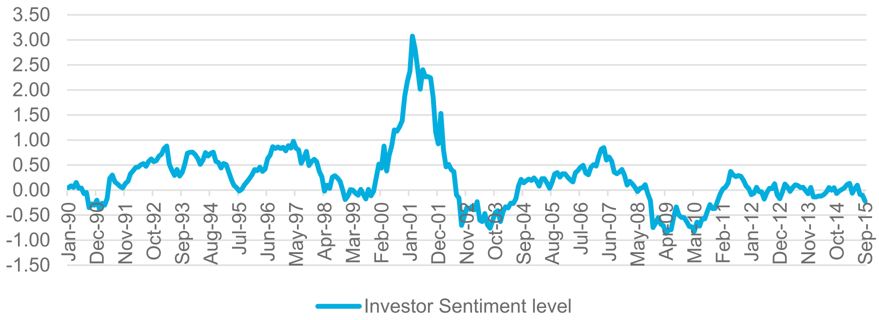

Fig. 1. Investor sentiment.

2. Data and methodology

In this study, we combine daily U.S. stock and bond market returns with monthly U.S. investor sentiment index. Stock and bond market returns in the U.S. are calculated from the S&P 500 index and the 10-year Treasury constant maturity yield from the Bloomberg database, and the total return indices take dividends and yield into account. As for the investor sentiment, we consider the sentiment index measured by Baker and Wurgler (2006).[1] They form their composite sentiment index based on six individual sentiment proxies: the number of initial public offerings (IPOs); the average first-day returns of IPOs; the dividend premium; the closed-end fund discount; the New York Stock Exchange (NYSE) turnover; and the equity share in new issues. To purge the effects of macroeconomic conditions from their sentiment index, they first regress each of the individual proxies on six macroeconomic indicators: growth in industrial production; real growth in durable, nondurable, and services consumption; growth in employment; and a National Bureau of Economic Research (NBER) recession indicator. To further filter out idiosyncratic fluctuations in the six proxies and capture their comment component, they take the first principal component of the six residual series from the regressions as their final composite index.

The sample period ranges from January 3, 1986 to September 30, 2015. The period covers many extreme events, such as the 1997 Asian financial crisis, 2000 dot-com crisis, 2007 global financial crisis and 2009 European sovereign debt crisis. Fig. 1 depicts the monthly evolution of the investor sentiment index. Obviously, investor sentiment reflects turbulent economic events such as the global financial crisis during 2007–2009, when the index hits historic lows.

We begin with the univariate GARCH-MIDAS framework of Engle, Ghysels, and Sohn (2013) to model stock and bond market returns and then apply the DCC-MIDAS model (Colacito et al., 2011) based on the standardized residuals calculated in the first step to investigate the long-term correlation between the stock and bond markets.

Consider that a bivariate vector of returns $\mathbf{r_t} = [r_{stock,t}, r_{bond,t}]'$ on day t and $r_{i,t}$ (i denotes stock and bond markets respectively) follows the process:

$$r_{i,t} = \mu_i + \sqrt{m_{i,\tau} \cdot g_{i,t}}\xi_{i,t} \tag{1}$$

where $\xi_{i,t}|\Omega_{t-1} \sim N(0,1)$ with Ω_{t-1} is the information set up till day $t-1$; $g_{i,t}$ is the short-term variance component; and $m_{i,\tau}$ the long-term component. Specially, the short-run variance component $g_{i,t}$ changes with the daily frequency t, and follows a GARCH(1,1) model, while the long-run variance component $m_{i,\tau}$ is held fixed at the monthly frequency τ. The GARCH(1,1) model for short-run variance is specified as follows:

$$g_{i,t} = (1 - \alpha_i - \beta_i) + \alpha_i \frac{(r_{i-1,t} - \mu)^2}{m_{i,\tau}} + \beta_i g_{i-1,t} \tag{2}$$

with $\alpha_i > 0, \beta_i > 0$; and $\alpha_i + \beta_i < 1$. The long-run component $m_{i,\tau}$ is modeled as a slowly varying function of the lagged sentiment using the MIDAS specification

$$\log(m_{i,\tau}) = m_v + \theta_v \sum_{k=1}^{K_v} \varphi_k(w_v)\mathrm{SENTIMENT}_{\tau-k} \tag{3}$$

The weighting scheme in above specification is the so-called beta weights, which is defined as:

$$\varphi_k\left(w_v^i\right) = \frac{\left(1 - \frac{k}{K_1}\right)^{w_v^i - 1}}{\sum_{j=1}^{K_v}\left(1 - \frac{j}{K_v}\right)^{w_v^i - 1}}, \forall k = 1, \ldots, K_v \tag{4}$$

We choose the beta weights scheme because it is flexible and performs better than exponential polynomial with regard to statistical

[1] The data of the investor sentiment index is available at the homepage of Wurgler and the website is http://pages.stern.nyu.edu/~jwurgler/.

significance (Ghysels et al., 2006, 2007).

The DCC-MIDAS model (Colacito et al., 2011) naturally extends the GARCH-MIDAS model to dynamic correlations. As in Conrad, Loch, and Rittler (2014), we extend the specification by allowing the long-run correlation to depend directly on the lagged sentiment. In this paper, the conditional correlation between stock and bond market returns is given as $R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2}$, where Q_t is the short-run correlation component. Further, we define $q_{ij,t}$ as the elements in Q_t:

$$q_{ij,t} = (1 - a - b)\overline{\rho}_{ij,\tau} + a\xi_{i,t-1}\xi_{j,t-1} + bq_{ij,t-1} \tag{5}$$

where $\xi_{i,t-1}$ and $\xi_{j,t-1}$ are the standardized residuals from GARCH-MIDAS models, and $\overline{\rho}_{ij,\tau}$ is the slowly moving long-run correlation defined by a Fisher-z transformation of the correlation coefficient as follows:

$$\overline{\rho}_{ij,\tau} = \frac{\exp(2z_{ij,\tau}) - 1}{\exp(2z_{ij,\tau}) + 1} \tag{6}$$

$\overline{\rho}_{ij,\tau}$ remains locally constant during the long-term period τ, whereas $z_{ij,\tau}$ is directly dependent on the lagged sentiment:

$$z_{ij,\tau} = m_c + \theta_c \sum_{k=1}^{K_c} \delta_k(w_c)\mathrm{SENTIMENT}_{t-k} \tag{7}$$

The correlation ρ_t is obtained by the specification $\rho_t = \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}}$, which is the correlation between the standardized residuals. The weighting scheme $\delta_k(w_c)$ is defined in a manner similar to $\varphi_k(w_v^i)$ and the parameter θ_c denotes the effect of the sentiment on the long-term correlation.

Since both the GARCH-MIDAS and DCC-MIDAS models require additional lags of the explanatory variables at the beginning of the sample, we include three MIDAS lag years in the filter, which means that $K_v = K_c = 36$; the three-year MIDAS lag corresponds to Conrad et al. (2014).

Baker and Wurgler (2006) form a composite index of sentiment that is based on the common variation in six underlying proxies for sentiment:

$$SENTIMENT_t = -0.241CEFD_t + 0.242TURN_{t-1} + 0.253NIPO_t + 0.257RIPO_{t-1} + 0.112S_t - 0.283P_{t-1}^{D-ND} \tag{8}$$

where *SENTIMENT* is defined as the first principal component of the correlation matrix of the six variables—each proxy's lead or lag. *CEFD* is the average difference between the net asset values (NAV) of closed-end stock fund shares and their market prices. *TURN* is the natural log of the raw turnover ratio, detrended by the 5-year moving average. *NIPO* is the number of IPOs, and *RIPO* represents the average first-day returns. S is the share of equity issues in total equity and debt issues. P_{t-1}^{D-ND} is the dividend premium.

They also construct a second index that explicitly removes business cycle variation from each of the proxies prior to the principal components analysis. The residuals from these regressions, labeled with a superscript $\perp$ give:

$$SENTIMENT_t^{\perp} = -0.198CEFD_t^{\perp} + 0.225TURN_{t-1} + 0.234NIPO_t^{\perp} + 0.263RIPO_{t-1}^{\perp} + 0.211S_t^{\perp} - 0.243P_{t-1}^{D-ND,\perp} \tag{9}$$

Since the first measure cannot separate a business cycle component and a sentiment component, we use a second index in order to address the concern about the effect of business cycle on the sentiment component; the second index removes business cycle variation as the measure of investor sentiment in the following empirical estimation.

3. Empirical results

In this section, we first apply the DCC-MIDAS model (Colacito et al., 2011) without exogenous variables to describe the long-term correlation of stock and bond returns. Subsequently, we extend the model by allowing long-term volatility and correlation to be affected by investor sentiment.

3.1. DCC-MIDAS model

Without exogenous variables, we first examine the long-term correlation between the stock and bond markets affected by the realized correlation (RC). Table 1 shows the results of estimating the DCC-GARCH model for the stock and bond market returns. Obviously, θ is significant for the realized volatility (RV) and realized correlation (RC). This is a baseline model which does not incorporate investor's sentiment.

From Table 1, we can find that the results in the table show that almost all parameters are significant. The estimates of α and β take typical values. The sign of θ_v indicates the response of long-run volatility to RVs. Another feature of the GARCH–MIDAS model in Table 1 is that the sums of α and β are 0.9808 and 0.9915 for the GARCH–MIDAS of stock and bond markets volatility. These numbers are noticeably less than but close to 1, which implies high persistence of financial volatility. As DCC-MIDAS is concerned, the estimated parameters of a and b are 0.0653 and 0.8522, whose sum is also less than 1. The results of the DCC-MIDAS dynamic correlation estimation, ω_c reflects how the stock-bond correlation responds to RC shocks. We find a statistically insignificant but positive ω_c, suggesting that the impact of RC may be misspecified. Different results can be found in Table 2 where investor's sentiment is involved.

Table 1
GARCH-MIDAS and DCC-MIDAS parameter estimates of realized correlation (RC).

GARCH-MIDAS	μ	α	β	θ_v	ω_v	m_v
Stock	0.0505***	0.0865***	0.8943***	0.0128***	1.3777***	−0.3058***
	(0.0106)	(0.0051)	(0.0067)	(0.0021)	(0.4216)	(0.1074)
Bond	0.0331**	0.0474***	0.9441***	0.0139***	1.3818***	−0.0762
	(0.0130)	(0.0034)	(0.0040)	(0.0016)	(0.3997)	(0.1268)
DCC-MIDAS	a		b		ω_c	
	0.0653***		0.8522***		12.8245	
	(0.0131)		(0.0419)		(8.7321)	

Note: The top panel reports the estimates of the GARCH-MIDAS coefficients for the considered assets. The bottom panel reports the estimates of the DCC-MIDAS parameters of RC. The number of MIDAS lags is 36 for the GARCH process and 36 for the DCC process. The sample covers the period from January 03, 1986 to September 30, 2015.
***, **, and * indicate significance at the 1% level, 5% level, and 10% level, respectively.

3.2. DCC-MIDAS-sentiment model

The preceding empirical results fundamentally exhibit the long-term correlation between stock and bond markets. Based on the framework, we extend the specification by allowing long-term volatility and correlation to be affected by the sentiment index. The model combines daily stock and bond returns with the monthly sentiment index and decomposes the total dynamic correlation into long- and short-term components.

We subsequently estimate the DCC-MIDAS-sentiment parameters by incorporating monthly investor sentiment into the long-term volatility and correlation component. Table 2 presents the DCC-MIDAS estimation results of dynamic correlation influenced by investor sentiment.

Panel A of Table 2 shows the results from estimating the GARCH-MIDAS model for stock returns and bond returns when we incorporate investor sentiment in the MIDAS equation. Then, we discuss the estimated θ parameters individually for the two markets. The sign of θ indicates the response of long-run volatility to investor sentiment. The coefficient θ_v is negative and significant at the 5% level for bond returns, indicating that sentiment has a significantly negative influence on long-term bond market volatility. Our finding confirms the negative relationship between sentiment and bond market volatility proposed by Asgharian et al. (2016). However, the estimated coefficient θ of stock market is insignificantly negative, which means that the effect of sentiment on the long-term stock volatility is rather ambiguous. The DCC estimation results are shown in Panel B of Table 2. The estimated parameter θ_c reflects how stock-bond correlation responds to sentiment shocks. Here, the coefficient θ_c is positive and statistically significant at the 5% level.

As a further illustration, we depict the estimated stock-bond correlation in Fig. 2. We notice that deviations between the long-term and short-term components of the stock-bond correlation fluctuate during different periods. As seen in Fig. 2, the long-term correlation is below the short-term trend line before 1997, but is significantly above the short-term correlation after 2007. A key explanation is that there are structural break points around 1997 and 2009, which lead to the goodness of fit of DCC-MIDAS-sentiment model being poor; further, we find that sentiment index is not the only factor that drives the changes in correlation.

Furthermore, we find that the relationship between stock and bond is influenced by the past information, where RC contains the information of the past 3 years. In contrast, the investor sentiment index cannot represent all the information during the past, and it is not the only factor that drives the changes in correlation. It is clear that m in DCC-MIDAS model represents the correlation that cannot be explained by investor sentiment. So, we extend DCC-GARCH model by adjusting dynamic change of m.

For the validation of model specification, we use the test of normality, stationarity, and ARCH effect for the residuals estimated by QMLE. All of the results can be found in Appendix A1.

3.3. Modified model

The sample period covers a few economic crises, which resulted in downturns in stock market returns and had a significant impact on the demand for bonds. These economic crises may cause structural changes in the long-term stock-bond correlation trends. From Fig. 2, we can see that the long-term correlation is below the short-term correlation before 1997, but the long-term component is significantly above the short-term correlation after 2007, which means here are structural changes in m.

We use the well-known test of Bai and Perron (2003) to detect multiple structural breakpoints in the stock-bond correlation. First, we estimate the following model for the long-run correlation:

$$Correlation_T = \mu_l + \mu_T \tag{10}$$

where $l = 1, ..., m+1$, μ_l are regime-dependent levels of long-run correlations within break dates $T = (T_1, ..., T_m)$, and m is the optimal number of breakpoints. We estimate the between-break levels and the break dates by minimizing the sum of squared residuals $\sum_{l=1}^{m+1}\sum_{T=T_{l-1}+1}^{T_l}[Cor_T - \mu_l]^2$. Finally, we obtain the optimal number of breakpoints m, using the sequential method proposed by Bai and

[2] Fig. 2 depict the estimated stock-bond correlation influenced by the investor sentiment index using the original DCC-MIDAS model.

Table 2
GARCH-MIDAS and DCC-MIDAS parameter estimate of investor sentiment.

GARCH-MIDAS	$Short_{i,t-1}$	$Crash_{i,t-1}$	$Size_{i,t-1}$	$BM_{i,t-1}$	$Lev_{i,t-1}$	$ROE_{i,t-1}$		
Stock	0.0498***	0.0841***	0.9032***	−0.2153	4.9859	0.1669		
	(0.0101)	(0.0130)	(0.0145)	(0.4094)	(4.0708)	(0.2052)		
Bond	−0.0124	0.0726***	0.9274***	−2.0251**	4.9944**	−1.9459*		
	(0.0175)	(0.0148)	(0.0139)	(0.9051)	(1.9915)	(1.0632)		
	AIC	**BIC**	**LLF**					
Stock	16958	16999	−8473					
Bond	20722	20763	−10355					
DCC-MIDAS	$Ret_{i,t-1}$	$Ret_{i,t-2}$	$Ret_{i,t-3}$	$Ret_{i,t-4}$	$Ret_{i,t-5}$	**AIC**	**BIC**	**LLF**
	0.0425***	0.9502***	0.4489**	49.9539***	0.0062	34954	34954	−17472
	(0.0096)	(0.0122)	(0.4651)	(19.0673)	(0.0799)			

Note: The top panel reports the estimates of the GARCH-MIDAS coefficients for the considered assets. The bottom panel reports the estimates of the DCC-MIDAS parameters of the investor sentiment index. AIC is the Akaike information criterion and BIC the Bayesian information criterion. LLF is the log-likelihood function. The number of MIDAS lags is 36 for the GARCH process and 36 for the DCC process. The sample covers 3 Jan 1986 until 30 September 2015.
***, **, and * indicate significance at the 1% level, 5% level, and 10% level, respectively.

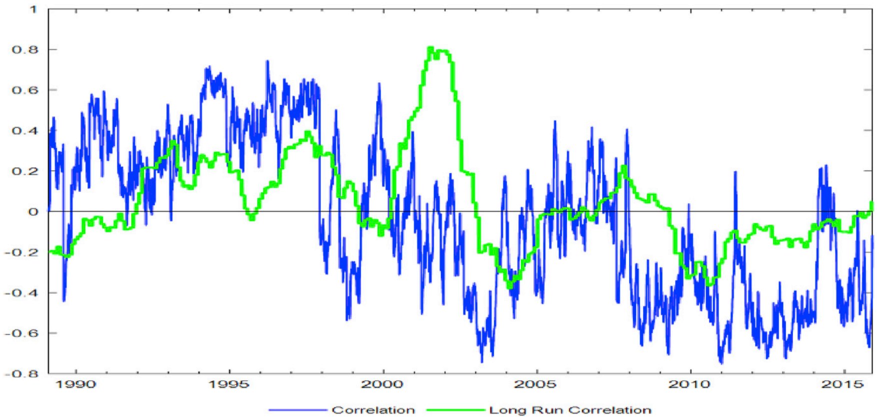

Fig. 2. Dynamic correlation and long-run component between bond and stock markets affected by investor sentiment[2].

Perron (2003). The idea behind this method is to sequentially identify the statistical relevance of including an additional breakpoint. We assess this relevance by comparing the minimal value of the sum of squared residuals over all segments, including the additional breakpoints.

Table 3
Structural breakpoints for long-term stock-bond correlation.

	Correlation
Number of break points	2
Break point1	July 1997
Break point2	April 2007
F-statistic	82.93**
Scaled F-statistic	82.93**
Weighted F-statistic	98.55**

Note: This table reports the number of the structural breakpoints and the break dates for long-run stock-bond correlation. The table shows that the F-statistic, scaled F-statistic, and weighted F-statistic of break points exceed their critical value, which is 7.22, thus, we reject the null hypothesis of no breaks in the 95% confidence interval. However, when the number of break points equals three, the F-statistic, scaled F-statistic, and weighted F-statistic of break points are less than their critical value. In addition, the UDmax and WDmax statistics value of 93.64 and 162.08, respectively, both indicate the presence of structural breakpoints in the 95% confidence interval. As such, in the 95% confidence interval, the break dates for long-run stock-bond correlation are around 1997 and 2007.

Table 4
Modified GARCH-MIDAS and DCC-MIDAS parameter estimate of investor sentiment.

GARCH-MIDAS	$Ret_{i,t-6}$	*CrashDays*	*CrashDays*	$Long_{t-1}$	Long_{t-2}	Long_{t-3}	$Short_{t-1}$	$Short_{t-1}$	$Short_{t-2}$	$Short_{t-3}$
Stock	0.0524***	0.0874***	0.8903***	−1.4183**	2.1393***	1.3196	2.6533*	0.0751	−0.0365	−0.0872
	(0.0100)	(0.0129)	(0.0153)	(0.5817)	(0.4916)	(1.0061)	(1.5344)	(0.2573)	(0.2489)	(0.3922)
Bond	0.1067***	0.0669***	0.9331***	−3.4917*	0.5707	0.1567	4.8263***	−1.7045**	−0.0910	−0.1459
	(0.0178)	(0.0127)	(0.0125)	(2.0146)	(1.4387)	(1.5645)	(1.2275)	(0.7478)	(0.8009)	(0.5373)
	AIC	**BIC**	**LLF**							
Stock	16920	16989	−8450							
Bond	20920	20989	−10450							
DCC-MIDAS	Ret_{t-1}	Ret_{t-2}	Ret_{t-3}	*Asy*2	Asy1 = *Longact* − *Shortact*	Asy2 = ln(*Shortact*)/ln(*Longact*)	*Shortact*	*ln*(*Shortact*)	Asy1 = *Longact* − *Shortact*	
	0.0490***	0.9222***	0.4620*	−0.4279	−0.1848	49.9255***	0.3137***	−0.4865***	−0.6386*	
	(0.0155)	(0.0318)	(0.2451)	(0.3213)	(1.3740)	(14.5247)	(0.0838)	(0.0991)	(0.3380)	
	AIC	**BIC**	**LLF**							
	34921	34983	−17451							

Note: The panel reports the estimates of the modified DCC-MIDAS parameters of investor sentiment index. AIC is the Akaike information criterion and BIC the Bayesian information criterion. LLF is the log-likelihood function. The number of MIDAS lags is 36 for the GARCH process and 36 for the DCC process. The sample covers 3 Jan 1986 until 30 September 2015.
***, **, and * indicate significance at the 1% level, 5% level, and 10% level, respectively.

We present the results of the structural break test in Table 3, which shows that structural changes occur around 1997 and 2007, both of which are the beginning of important financial crisis events. It should be noted that there are two crisis event after July 1997, that is, the Asian crisis and the dot-com crisis. Both of them are typical crisis events that have significant impacts on the stock market. The first break point in July 1997 shown by the BP test implies that these two crisis events can be viewed together and start from July 1997, in a statistical sense. After April 2007, the global financial crisis began and it was also followed by the European sovereign debt crisis.

Therefore, we extend the model by adjusting the dynamic changes in parameter m and θ to measure the impact of the investor sentiment index during different periods. Specifically, considering the structural changes occurred in July 1997 and April 2007, we incorporate dummy variables for both "intercept" and "slope" to adjust the structural changes. The inclusion of "intercept" and "slope" dummies allows us to investigate the influence of investor sentiment on the long-run correlation more comprehensively. For this purpose, we incorporate dummy variables to adjust the structural changes of parameter m and θ. In regard to formulae (11) and (12), we set D_1 equal to 1 when t is in the period between July 1, 1997, to April 2, 2007, and 0 otherwise. In addition, we set $D_2 = 1$ when t is later than April 2, 2007, and 0 otherwise. To consider possible structural changes in both of the GARCH-MIDAS and DCC-MIDAS models the models are modified as

$$\log(m_{i,\tau}) = m_{v0} + \sum m_{vi}D_t + \left(\theta_{vi} + \sum \theta_{vi}D_t\right)\sum_{k=1}^{K_{vi}} \varphi_k(w_{vi})\mathrm{SENTIMENT}_{\tau-k} \tag{11}$$

$$z_{ij,\tau} = m_{c0} + \sum m_{ci}D_t + \left(\theta_{c0} + \sum \theta_{ci}D_t\right)\sum_{k=1}^{K_{ci}} \varphi_k(w_{ci})\mathrm{SENTIMENT}_{\tau-k} \tag{12}$$

Coefficient m_{ci} is considered as the increment in the intercept m during sub-sample period i. Here, we use i to indicate the subsample periods after crises shocks, and i can equals to 1 and 2. By considering the structural changes in the relationship between the stock-bond correlation and sentiment index in the period around the financial crisis, the modified model fits more accurately.

Table 4 presents the estimation results for the modified model. The sums of α and β are appreciably less than 1, indicating that in all specifications the short-run volatility component mean-reverts to the long-run trend. The signs of the effects from the investor sentiment variable imply that the long-run stock or bond market volatility is smaller during times when investor sentiment is high, which is consistent with Asgharian et al. (2016). In line with our intuition, we can note a positive and significant θ_c, which means investor sentiment has a significantly positive impact on the long-term stock-bond correlation. When sentiment is low, investors, being risk averse, tend to sell in the relatively riskier stock market and buy in the relatively safer bond market, known as flight to quality, leading to a decline in the correlations. Moreover, we notice that the coefficients θ_{c1} and θ_{c2} are insignificant, which suggests that there are no significant changes in the impact of investor sentiment during the subsample periods. However, ω_c is very large, which means that the effect of sentiment decays very quickly. Fig. 3 plots the correlation estimated by modified model. Considering the dynamic change of m, the long- and short-term components follow a similar trend, which indicates that the modified model is more efficient than the original

[3] Fig. 3 depict the estimated stock-bond correlation influenced by the investor sentiment index by using the modified DCC-MIDAS model, where we added dummy variables both for the "intercept" and "slope" part.

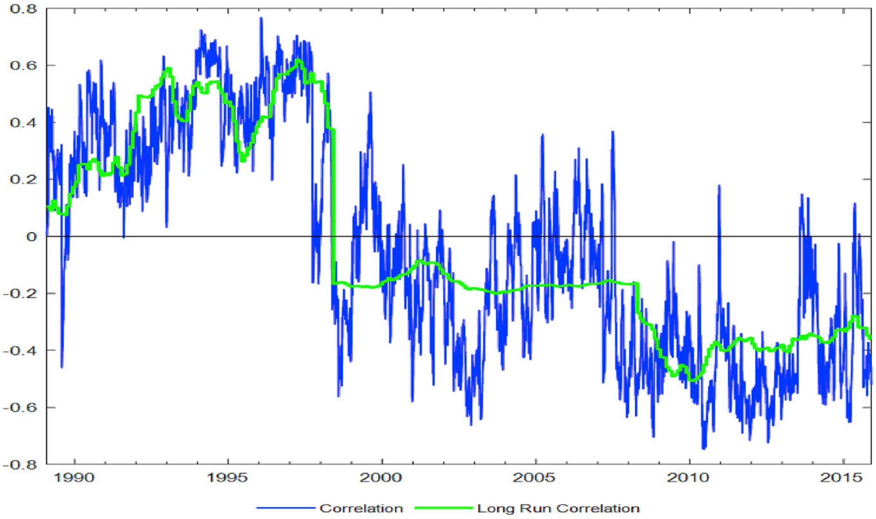

Fig. 3. Dynamic correlation and long-run component between bond and stock markets affected by investor sentiment in the modified model[3].

model. Although the coefficients of dummy variables are not significant, we keep the specification with dummy variables for the integrity of the economic implication of the model. The AIC, BIC, and loglikelihood in Tables 2 and 4 show that the fit of the modified model is improved, which means that incorporating the dummy variables can be helpful in capturing the structural changes.

In addition, we also perform an alternative study by using the first investor sentiment index proposed by Baker and Wurgler (2006). The results justify the robustness of the above findings. All the results can be found in Appendix A2.

3.4. *Out-of-sample performance*

Compared with in-sample performance, people are more concerned about out-of-sample model performance, because the latter can be used to infer how well the model will perform in the practice. Therefore, we test for the out-of-sample performance of stock-bond portfolio constructed by our modified DCC-MIDAS model and compare it with other popular portfolio strategies such as DCC-MIDAS+RC and DCC-MIDAS + Investment Sentiment models. We divide the whole sample period into two subperiods: the in-sample period for modeling and parameter estimating, which extends from January 3, 1986 to December 31, 2009 (5744 data points) and the out-of-sample period for evaluating portfolio performance, which is from January 1, 2010 to September 30, 2015 (1376 data points). We estimate the model parameters using the in-sample data and then use the parameter estimates to forecast the future stock-bond ratio.

Next we consider the optimal portfolio of stocks and bonds, that is, test for the out-of-sample performance of different strategies and compare them. The return on a stock-bond portfolio can be denoted as:

$$R_{P,t} = R_{S,t} + \gamma_t R_{B,t} \tag{13}$$

where $R_{S,t}$ is the return on the stock position; $R_{B,t}$ is the return on the bond position; and γ_t is the stock-bond ratio in the portfolio. The variance of the portfolio conditional on the information set at time t −1 is:

$$\mathrm{var}(R_{P,t}|I_{t-1}) = \mathrm{var}(R_{S,t}|I_{t-1}) + 2\gamma_t \mathrm{cov}(R_{B,t}, R_{S,t}|I_{t-1}) + \gamma_t^2 \mathrm{var}(R_{B,t}|I_{t-1}) \tag{14}$$

The optimal stock-bond ratio ($OSBR_t$) is defined as the value of γ_t, that minimizes the conditional variance of the stock-bond portfolio.

For comparing the portfolio performances of different models, we use the following two popular criteria. The first criterion is Ederington (1979) variance reduction, a variance reduction ratio that can be written as follows:

$$VR = \frac{\mathrm{var}_S - \mathrm{var}_{SB}}{\mathrm{var}_S} \tag{15}$$

where var_{SB} is the variance of the stock-bond portfolio return, and var_S is the variance of the portfolio return when it only contains stocks. A higher VR indicates a larger risk reduction, so a portfolio strategy with a higher VR is regarded as a superior strategy.

Following Alexander and Barbosa (2008), our second criterion for measuring the performance of a portfolio is the certainty equivalent (CE), which can be derived from following the exponential utility function:

$$U(R_{P,t}) = -\lambda exp(-R_{P,t}/\lambda) \tag{16}$$

where λ is the risk tolerance coefficient. Then, the CE is approximated as:

$$CE \approx \overline{R}_{P,t} - \frac{\mathrm{var}(R_{P,t})}{2\lambda} + \frac{\varphi}{6\lambda^2} - \frac{\kappa}{24\lambda^3} \tag{17}$$

where $\overline{R}_{P,t}$ is the mean of the returns of the stock-bond portfolio, $\varphi = E[(R_{P,t} - \overline{R}_{P,t})^3]$ and $\kappa = E[(R_{P,t} - \overline{R}_{P,t})^4]$. The CE is positively related to the mean of the return but has a negative relation with the variance.

Following the methods of Kroner and Ng (1998), the third criterion is the optimal portfolio weighting of stock/bond holdings, given by:

$$w_{SB,t} = \frac{\mathrm{var}(R_{B,t}|I_{t-1}) - \mathrm{cov}(R_{S,t}, R_{B,t}|I_{t-1})}{\mathrm{var}(R_{S,t}|I_{t-1}) - 2\mathrm{cov}(R_{S,t}, R_{B,t}|I_{t-1}) + \mathrm{var}(R_{B,t}|I_{t-1})} \tag{18}$$

$$w_{SB,t} = \begin{cases} 0, & \text{if} \quad w_{SB,t} < 0 \\ w_{SB,t}, & \text{if} \quad 0 \le w_{SB,t} \le 1 \\ 1, & \text{if} \quad w_{SB,t} > 1 \end{cases} \tag{19}$$

where $w_{SB,t}(1 - w_{SB,t})$ is the weight of the stock (bond) in a one-dollar stock/bond portfolio at time t. In addition, we compute the Sharpe ratio of different strategies.

In Table 5, we can see that the modified DCC-MIDAS model has the highest variance reduction. Moreover, based on the criterion of the CE, our modified DCC-MIDAS model is the optimal model for constructing portfolios with stocks and bonds. More importantly, the relative performance of these models does not depend on the values of λ, implying the robustness of our results based on the criterion of the CE. Moreover, considering the Sharpe ratio, the modified DCC-MIDAS model has the largest value. Thus, under all three criteria, our modified DCC-MIDAS model has a better performance than the conventional DCC-MIDAS+RC and DCC-MIDAS + Investment Sentiment models.

The average values of $w_{SB,t}$ are reported in the third column of Table 5. For instance, the average value of $w_{SB,t}$ of a portfolio comprising of stocks and bonds is 0.7585. This suggests that the optimal holding of stocks in a one-dollar stock/bond portfolio is 76 cents, with the remaining 24 cents in bonds. Furthermore, the modified DCC-MIDAS model has the lowest average value of $w_{SB,t}$. These optimal portfolio weights suggest that investors should have more stocks than bonds in their portfolios to minimize risk without lowering expected return. Thus, our modified DCC-MIDAS model has the best performance not only for in-sample estimation, but also for the out-of-sample analysis.

4. Conclusion

Investor sentiment measures the optimism or pessimism of investors' expectations about the financial market in the future. It transmits among variant financial markets along with investors trading activities. We are interested in how the composite index of investor sentiment based on Baker and Wurgler (2006) impacts the long-term correlation of the stock and bond markets since these two assets are most widely considered in investors' asset allocation. Their time-varying correlation substantially determines their weight in portfolio selection, and thus, the portfolio performance.

We use the DCC-MIDAS to quantify the long-term stock-bond correlation and thereby explore the impact of the composite index of investor sentiment on the long-term stock-bond correlation. Then, we evaluate the portfolio performance with the time-varying weight based on the forecasted correlations and volatilities after considering the impact of investor sentiment. We decompose the total stock-bond correlation into its short-run and long-run components and focus on the effect of investor sentiment on the long-run component. Our results show that crisis shock occurred in July 1997 and April 2007, the investor sentiment on average still has a significant positive impact on the long-term stock-bond correlations. However, both of the crises shocks significantly decreased the magnitude of such effect. It is intuitive since the demand for the safer bonds increases and the demand for stock decreases, resulting in a decrease in the

Table 5
The out-of-sample performance of stock-bond portfolio.

Variable	Optimal Portfolio					
	VR	CE			w_{SB}	Sharpe-ratio
		$\lambda = 0.3$	$\lambda = 0.5$	$\lambda = 0.7$		
Panel A: DCC-MIDAS model						
RC	0.0004	−14.5563	−3.9081	1.8101	0.8466	−0.0112
RC+Sentiment	0.0043	−14.4620	−3.8821	−1.7979	0.8340	−0.0107
Panel B: modified DCC-MIDAS model						
RC+Sentiment	0.2944	−14.4439	−3.4102	−1.4111	0.7585	0.0209

Note: The results are the out-of-sample performance of stock-bond portfolio. Panel A reports the portfolio performance estimated by the DCC-MIDAS model. Panel B reports the portfolio performance estimated by our modified DCC-MIDAS model. VR denotes variance reduction. CE measures the utility of the stock-bond portfolio, where λ is the risk tolerance coefficient. w_{SB} is the optimal portfolio weighting of stock/bond holdings. Sharpe ratio measures the excess return (or risk premium) per unit of deviation in an investment asset or a trading strategy, typically referred to as risk.

correlation after the financial crisis event.

Since including the investor sentiment index could improve the investment portfolio performance, it is of great significance for the investors' portfolio optimization and risk management. For example, our results of financial crisis decreasing stock-bond correlation significantly imply that investors are more likely to avoid risky asset, whatever stock or bond market. However, this does not change the effect of investor sentiment. Therefore, it has further implication for the policy makers. Our results imply that policy makers should take the investor sentiment into account when framing financial policy. That is to say, as far as the policy concerning investor's sentiment, the policy makers need not either to make more strong regulation after financial crisis or ease policy before it. Our results also provide an interesting future direction for the study of stock and bond correlation from the perspective of other investor behavioral biases such as gambling (see e.g. Li et al., 2018).

Acknowledgements

The authors acknowledge financial support from the National Natural Science Foundation of China (71472085, 71401071, 71672081, 71771117 and 71720107001).

Appendix B. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.iref.2018.03.005.

Appendix A1. statistical analysis for the estimated residuals

A1.1 The normality of the residuals of the stock and bond markets

We perform some statistical analysis for normal properties of the estimated residuals. First, to test the normality of the stock and bond markets' residuals, we conduct the Jarque-Bera (JB) test and the Q-Q (quantile-quantile) plots for the residuals of stock and bond.

Table A1
The descriptive statistics for the residuals of stock and bond market returns

Market	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	P value	Q(5)	Q(10)
Stock	−0.0290	1.0434	−1.7087	31.0931	237601.30	0.0000	1.8385	7.9456
Bond	0.0040	0.9773	0.0303	4.6034	763.81	0.0000	6.1938	9.1278

Note: Q(5) and Q(10) report the Ljung-Box statistics for the autocorrelation of the residuals.

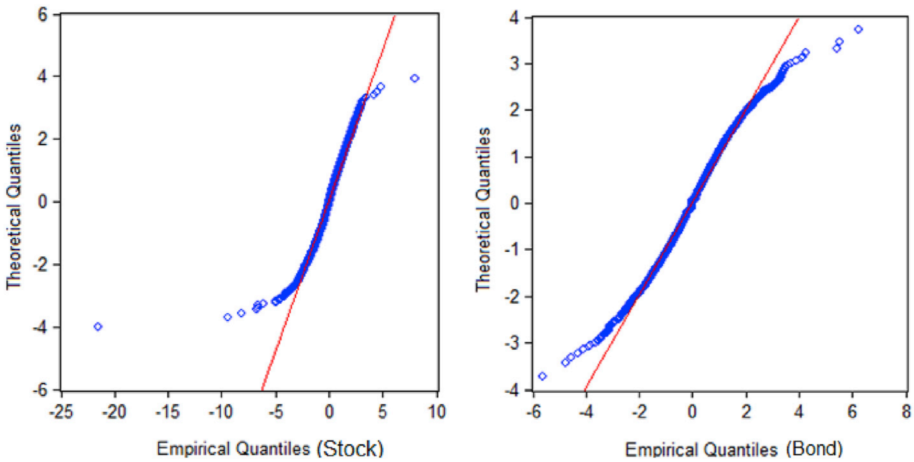

Fig. A1. the Q-Q plot for the residual series

From the results in Table A1, we can see that the mean value of the residuals is close to zero and standard deviation is close to 1. The Ljung-Box statistics implies there is no significant autocorrelation in the residuals. All of the results imply that the residuals are similar to white noise. Although the results of Jarque-Bera test and QQ plot imply deviation from the assumption of normal distribution, the properly normalized sum of the residuals tends toward a normal distribution according to the central limit theorem. The theorem of QMLE also implies asymptotic consistency of the estimated parameters.

A1.2 The stationarity test

Second, we test the stationarity by the Augment Dickey-Fuller (ADF) and Phillips-Perron (PP) statistics.

Table A2
the results of ADF and PP tests for the residuals of stock and bond

Residual series	ADF test		PP test	
	t-Statistic	P value	t-Statistic	P value
Stock	−84.3818	0.0001	−81.5619	0.0001
Bond	−81.5982	0.0001	−81.5661	0.0001

The results in Table A2 show that both of ADF and PP statistics for the residual series of stocks and bonds are much less than their critical values, indicating that the residuals have stationarity.

A1.3 The heteroscedasticity of the residuals

Third, autoregressive conditional heteroskedasticity (ARCH) test is applied to identify the heteroscedasticity of the residual.

Table A3
the results of ARCH test for the residuals of stock and bond

Residual series	ARCH effect test			
	ARCH(1)		ARCH(5)	
	F-Statistic	P Value	F-Statistic	P Value
Stock	0.9733	0.3305	1.3716	0.1703
Bond	0.0309	0.8604	0.0309	0.8604

As we can see, for the residual series of the bond and stock market returns, the testing results imply that the raw bond series has removed the heteroscedasticity. These results imply that we can follow the widely used specification of GARCH (1, 1).

To sum, our residuals are deviated from normal distribution. However, in the limited case, the QMLE makes the estimated parameter asymptotically consistent in statistical sense. Both of the residuals of the two market returns are stationary which confirm further the validation of our model specification. The insignificant heteroscedasticity confirms the choice of GARCH(1, 1).

A2. Robustness check

For robustness, we use the first investor sentiment index proposed by Baker and Wurgler (2006) as alternative one. The first measure is the first principal component of the correlation matrix of six proxies. However, this construction method cannot separate a common sentiment component and a common business cycle component. Considering the effect of business cycle on the sentiment component, we employ the second index in the main document. We use the first one for a robustness here. The empirical results are as follows.

Table A4
GARCH-MIDAS and DCC-MIDAS parameter estimates of the first investor sentiment index (including business cycle)

GARCH-MIDAS	*Size*	*BM*	*Turnover*	σ	R_{pt}	*Longact* − *Shortact*
stock	0.0497***	0.0842***	0.9030***	−0.2150	3.6967	0.1910
	(0.0102)	(0.0127)	(0.0142)	(0.3349)	(4.2769)	(0.2104)
bond	−0.0010	0.0728***	0.9272***	−2.0802***	4.9884***	−1.0076***
	(0.0174)	(0.0136)	(0.0136)	(0.7057)	(1.4127)	(0.3649)
DCC-MIDAS	*Longact*	*b*	*Asy*1	*Asy*2	R_t	
	0.0425***	0.9538***	0.2317**	49.99484***	−0.1786***	
	(0.0081)	(0.0106)	(0.0907)	(15.6486)	(0.0598)	

Note: The top panel reports the estimates of the GARCH-MIDAS coefficients for the considered assets. The bottom panel reports the estimates of the DCC-MIDAS parameters of the first investor sentiment index. The number of MIDAS lags is 36 for the GARCH process and 36 for the DCC process. The sample covers3 Jan 1986 until 30 Sep 2015.
*** Indicate significance at the 1%, level.
** Indicate significance at the 5% level.
* Indicate significance at the 10% level.

Table A5
Modified GARCH-MIDAS and DCC-MIDAS parameter estimates of the first investor sentiment index (including business cycle)

GARCH-MIDAS	R_t	*Size*	*BM*	*Turnover*	σ	R_{pt}	*Asy*1 = *Longact* − *Shortact*	*Longact*	*Asy*1	*Asy*2
stock	0.0524***	0.0874***	0.8903***	−1.4183***	2.1393***	1.3198	2.6532*	0.0750	−0.0365	−0.0871
	(0.0100)	(0.0129)	(0.0153)	(0.5436)	(0.4778)	(0.9852)	(1.5888)	(0.2518)	(0.2435)	(0.4156)
bond	0.0331**	0.0455***	0.9467***	0.4056	0.3606	−3.6993**	1.0010***	0.0537	0.2596	0.4293
	(0.0129)	(0.0057)	(0.0083)	(0.5417)	(0.6746)	(1.5786)	(0.1085)	(0.3384)	(0.3025)	(0.6545)

(*continued on next page*)

Table A5 (*continued*)

GARCH-MIDAS	R_t	*Size*	*BM*	*Turnover*	σ	R_{pt}	$Asy1 = Longact - Shortact$	*Longact*	$Asy1$	$Asy2$
DCC-MIDAS	$Asy1$	b	*Size*	*BM*	*BM*	*Turnover*	σ	R_{pt}	R_{pt}	
	0.0423***	0.9333***	0.3764	−0.2813	−0.3845	49.9252*	0.1257	−0.3609***	−0.5132*	
	(0.0145)	(0.0326)	(0.3475)	(0.4166)	(0.8283)	(32.0823)	(0.1493)	(0.1679)	(0.1621)	

Note: The panel reports the estimates of the modified DCC-MIDAS parameters of the first investor sentiment index. The number of MIDAS lags is 36 for the GARCH process and 36 for the DCC process. The sample covers 3 Jan 1986 until 30 Sep 2015.
*** Indicate significance at the 1%, level.
** Indicate significance at the 5% level.
* Indicate significance at the 10% level.

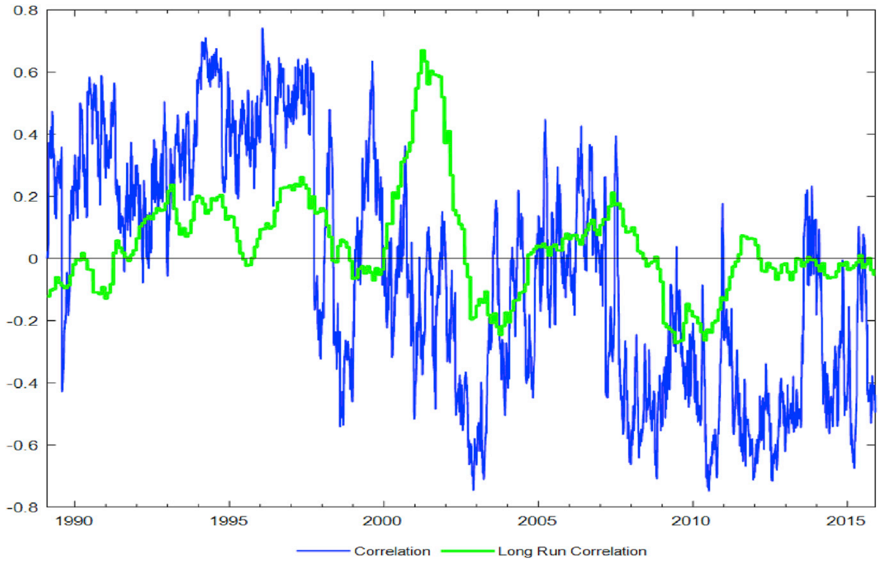

Fig. A2. Dynamic correlation and long-run component between bond and stock markets affected by the first investor sentiment index (including business cycle)

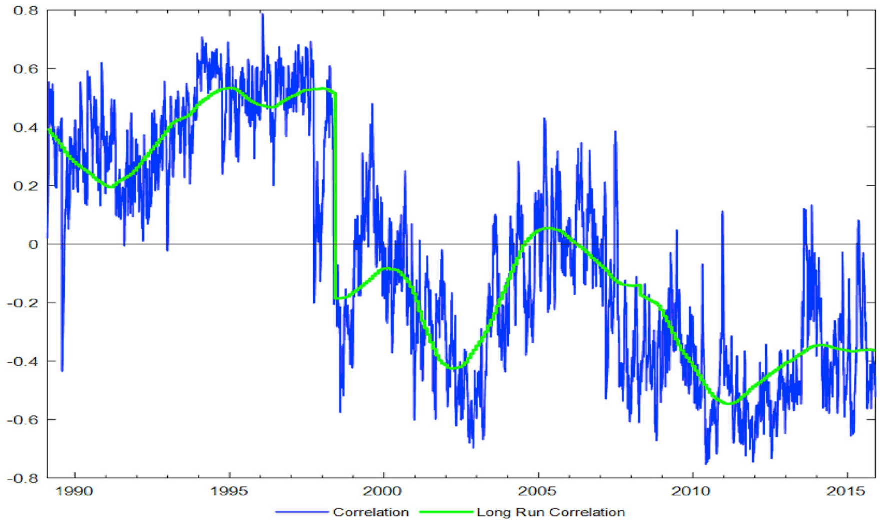

Fig. A3. Modified correlation and long-run component between bond and stock markets affected by the first investor sentiment index (including business cycle)

The empirical results using the first investor sentiment index shows that the modified model is more efficient than the original model, which is similar to the results in the manuscript and proves the robustness of our result.

References

Abdelhédi-Zouch, M., Abbes, M. B., & Boujelbène, Y. (2015). Volatility spillover and investor sentiment: Subprime crisis. *Asian Academy of Management Journal of Accounting and Finance, 11*(2), 83–101.
Alexander, C., & Barbosa, A. (2008). Hedging index exchange traded funds. *Journal of Banking & Finance, 32*(2), 326–337.
Ang, A., Hodrick, R. J., Xing, Y., & Zhan, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance, 61*(1), 259–299.

Asgharian, H., Christiansen, C., & Hou, A. J. (2016). Macro-finance determinants of the long-run stock-bond correlation: The DCC-MIDAS Specification. *Journal of Financial Econometrics, 14*(3), 617–642.

Aslanidis, N., & Christiansen, C. (2014). Quantiles of the realized stock-bond correlation and links to the macroeconomy. *Journal of Empirical Finance, 28*, 321–331.

Baele, L., Bekaert, G., & Inghelbrecht, K. (2010). The determinants of stock and bond return comovements. *Review of Financial Studies, 23*(6), 2374–2428.

Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural-change models. *Journal of Applied Economics, 18*(1), 1–22.

Baker, M. P., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance, 61*(4), 1645–1680.

Baker, M. P., & Wurgler, J. (2007). Investor sentiment in the stock market. *The Journal of Economic Perspectives, 21*(2), 129–151.

Caballero, R. J., & Krishnamurthy, A. (2008). Collective risk management in a flight to quality episode. *The Journal of Finance, 63*(5), 2195–2230.

Campbell, J. Y., & Ammer, J. (1993). What moves the stock and bond markets? A variance decomposition for long term asset returns. *The Journal of Finance, 48*(1), 3–37.

Canbaş, S., & Kandõr, S. Y. (2009). Investor sentiment and stock returns: Evidence from Turkey. *Emerging Markets Finance and Trade, 45*(4), 36–52.

Cao, N., Galvani, V., & Gubellini, S. (2017). Firm-specific stock and bond predictability: New evidence from Canada. *International Review of Economics & Finance, 51*, 174–192.

Colacito, R., Engle, R. F., & Ghysels, E. (2011). A component model for dynamic correlations. *Journal of Econometrics, 164*, 45–59.

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.

Conrad, C., Loch, K., & Rittler, D. (2014). On the macroeconomic determinants of long-term volatilities and correlations in U.S. stock and crude oil markets. *Journal of Empirical Finance, 29*, 26–40.

Duchin, R., Ozbas, O., & Sensoy, B. A. (2010). Costly external finance, corporate investment, and the subprime mortgage credit crisis. *Journal of Financial Economics, 97*(3), 418–435.

Ederington, L. H. (1979). The hedging performance of the new futures markets. *The Journal of Finance, 34*(1), 157–170.

Engle, R., & Colacito, R. (2006). Testing and valuing dynamic correlations for asset allocation. *Journal of Business & Economic Statistics, 24*(2), 238–253.

Engle, R. F., Ghysels, E., & Sohn, B. (2013). On the economic sources of stock market volatility. *The Review of Economics and Statistics, 93*, 776–797.

Fisher, K. L., & Statman, M. (2000). Investor sentiment and stock returns. *Financial Analysts Journal, 56*(2), 16–23.

Ghysels, E., Santa-Clara, P., & Valkanov, R. (2006). Predicting volatility: Getting the most out of return data sampled at different frequencies. *Journal of Econometrics, 131*(1), 59–95.

Ghysels, E., Sinko, A., & Valkanov, R. (2007). MIDAS regressions: Further results and new directions. *Econometric Reviews, 26*(1), 53–90.

Gomes, P., & Taamouti, A. (2016). In search of the determinants of European asset market comovements. *International Review of Economics & Finance, 44*, 103–117.

Hilal, S., Poon, S.-H., & Tawn, J. (2011). Hedging the black swan: Conditional heteroskedasticity and tail dependence in S&P500 and VIX. *Journal of Banking & Finance, 35*(9), 2374–2387.

Kroner, K. F., & Ng, V. K. (1998). Modeling asymmetric comovements of asset returns. *Review of Financial Studies, 11*(4), 817–844.

Laborda, R., & Muñoz, F. (2016). Optimal allocation of government bond funds through the business cycle. Is money smart? *International Review of Economics & Finance, 45*, 46–67.

Lemmon, M., & Portniaguina, E. (2006). Consumer confidence and asset prices: Some empirical evidence. *Review of Financial Studies, 19*(4), 1499–1529.

Li, J. (2012). Option-implied volatility factors and the cross-section of market risk premia. *Journal of Banking & Finance, 36*(1), 249–260.

Li, X. D., Subrahmanyam, A., & Yang, X. W. (2018). Can financial innovation succeed by catering to behavioral preferences? Evidence from a callable options market. *Journal of Financial Economics, 128*(1), 38–65.

Perego, E. R., & Vermeulen, W. N. (2016). Macro-economic determinants of European stock and government bond correlations: A tale of two regions. *Journal of Empirical Finance, 37*, 139–140.

Tsai, I. C. (2017). Diffusion of optimistic and pessimistic investor sentiment: An empirical study of an emerging market. *International Review of Economics & Finance, 47*, 22–34.

Vahamaa, S., & Aijo, J. (2011). The Fed's policy decisions and implied volatility. *Journal of Futures Markets, 31*(10), 995–1010.

Whaley, R. E. (2000). The investor fear gauge. *Journal of Portfolio Management, 26*(3), 12–17.

Yu, J. F. (2013). A sentiment-based explanation of the forward premium puzzle. *Journal of Monetary Economics, 60*(4), 474–491.

Zouaoui, M., Nouyrigat, G., & Beer, F. (2011). How does investor sentiment affect stock market crises? Evidence from panel data. *Financial Review, 46*(4), 723–747.