Economics Bulletin

Volume 36, Issue 4

Disaggregating the correlation under bearish and bullish markets: A Quantile-quantile approach

Syed jawad hussain Shahzad
Montpellier Business School, Montpellier, France

Saba Ameer
COMSATS Institute of Information and Technology, Virtual Campus Islamabad, Pakistan

Muhammad Shahbaz
Montpellier Business School, Montpellier, France

Abstract

We disaggregate the correlation between S&P 500, U.S. bond, oil, commodities and gold returns under bearish and bullish market states. In doing so, we apply a novel quantile-on-quantile (QQ) approach, on the monthly data from January 1982 to December 2015, to construct correlation estimates between the quantile of S&P 500 and quantile of other markets. This approach captures the dependence between the distributions of U.S. stock return and other markets and uncovers two nuance features. First, higher dependence of U.S. bond and Gold with U.S. stock market returns is found when the U.S. stock market is bullish (i.e. at upper U.S. return quantiles). Second, higher dependence of U.S. commodities and oil with U.S. stock market returns exists when the U.S. stock market is bearish (i.e. at lower U.S. return quantiles). Finally, the relationship between U.S equities and other investment markets is asymmetric.

We wish to thank the Editor Neil D. Pearson and anonymous reviewers for helpful comments and suggestions that have certainly improved the paper. Any remaining errors are solely ours.
Citation: Syed jawad hussain Shahzad and Saba Ameer and Muhammad Shahbaz, (2016) "Disaggregating the correlation under bearish and bullish markets: A Quantile-quantile approach", *Economics Bulletin*, Volume 36, Issue 4, pages 2465-2473
Contact: Syed jawad hussain Shahzad - jawad.kazmi5@gmail.com, Saba Ameer - sabaameer88@gmail.com, Muhammad Shahbaz - shahbazmohd@live.com.
Submitted: October 06, 2016. **Published:** December 21, 2016.

1. Introduction

The correlation between assets' returns is the key area of research with implications for portfolio decisions and risk diversification. The correlation between asset returns varies with time and significantly increases during bearish market conditions (Forbes and Rigobon, 2002). Susceptibility of financial markets to economic shocks has increased the investors and portfolio managers' attention towards commodities investments and financialization of commodities provides highly liquid financial asset that worked as a tool in diversifying, hedging and managing risk of investor's portfolios comprising of traditional (stocks and bonds) assets (see e.g., Silvennoinen and Thorp, 2013; Tang and Xiong, 2012; Vivian and Wohar, 2012). Investments in commodities have increased specially during global financial crises 2008-2009 (Cheng et al., 2014). This is due to the fact that commodities show equity like returns and low correlation with traditional assets (Gorton and Rouwenhorst, 2006) and the commodities have proven safe haven properties during periods of financial turmoil as commodities and stock move in opposite directions during turbulence market conditions (Silvennoninen and Thorp, 2013).

Portfolio management decisions require particular focus when the correlation (dependence) between various assets classes is known to be distribution specific (Basher and Sadorsky, 2016). Longin and Solnik (2001) suggest that stock markets have higher dependence during bearish times, and hence, the correlation structure depends on the performance of markets at a particular time i.e., the bearish and bullish markets. Guidolin and Timmermann (2005) highlighted that the relationship between stocks and bonds may drastically change during bearish markets as a result of ''flight to quality''. Chang et al. (2010) used eight different models (OLS, multivariate GARCH, error correction, and state space) to study the hedging ability of oil and gasoline futures during bull and bear markets and show that hedging effectiveness is higher in bull markets.

From a methodological perspective, the complexities such as asymmetry and heterogeneity in the assets relationships may render the standard econometric techniques (such as ordinary least squares and quantile regressions) insufficient. For instance, the dependence under large price shocks may differ compared to small price shocks, the so-called asymmetric price reactions. Similarly, it may also be heterogeneous, varying when market conditions may differ across markets i.e., when one market is bearish, the other market may be in bullish state.

Based on the seminal work of Ma and Koenker (2006) which requires a triangular system of equations, Sim and Zhou (2015) proposed a non-parametric Quantile-on-Quantile (QQ) regression approach to express the dependence between quantiles. They examined the relationship between oil prices and U.S equities and find that negative oil price shocks (i.e. lower oil price shock quantiles) can affect U.S equities positively when the U.S stock market is performing well (i.e. at higher U.S stock return quantiles). In another study, Sim (2016) proposed the copula quantile-on-quantile regression (C-QQR) approach to study the conditional correlation of U.S stock market with the stock markets of Australia, Hong Kong, Japan, and Singapore. In the similar vein, Reboredo and Ugolini (2016), examine the impact of quantile and inter-quantile oil price movements on different stock return quantiles using a copula based quantile-on-quantile model.

We extend this recent strand of knowledge, mainly concentrated on the impact of oil shocks on stock returns, in two ways. First, instead of only focusing on stock-oil relationship, we examine the quantile-on-quantile relationship of U.S stock with bond, oil, commodities and gold returns under bearish and bullish market conditions. This would help in identifying best risk diversifying options for portfolios during bearish and bullish market conditions. Second, we model the relationships in a two steps procedure; i). a quantile regressor identification equation that identifies the quantile of the U.S. stock market return and ii). a quantile dependence equation that expresses how one return is dependent on the second return. In the second equation, instead of regression framework (used in previous work), we use quantile correlations measure proposed by Li et al. (2015).

Rest of the paper is organized as follows. Section 2 discusses the empirical model. Section 3 describes the data and analyzes the empirical results. Section 4 gives some concluding comments.

2. Empirical model

To model the dependence between the quantile of U.S. stock market returns and returns of U.S. bond, commodities, oil and gold, a two-step approach is utilized: a quantile regressor identification equation that identifies the quantile of the U.S. stock market return and a quantile dependence equation that expresses how the returns of a market are correlated with returns of another market under different market conditions. This two-step procedure resembles the instrumental variable technique for quantile-regression as proposed by Kim and Muller (2004) - a straight forward extension of the two-stage least square. We assume that the U.S fundamentals are sufficient to determine the U.S stock market returns. Thus, this analytical framework provides information on how the relationships between the markets change at different points of their distribution functions.

Balvers et al. (1990) considered a logarithmic utility function and full capital depreciation to derive an econometric model where stock return depends linearly on the output and other control variables. Therefore, let the stock returns (r_t) depend on the macroeconomic aggregates through:

$$Q_{r_t}(\tau|X_t) = \beta_0^\tau + \beta_1^\tau IPI_t + \beta_2^\tau INF_t + \beta_3^\tau IR_t + \beta_4^\tau SLOPE_t + \beta_5^\tau PREM_t + \nu_t^\tau \tag{1}$$

In equation (1), *IPI* is the monthly industrial production index, *INF* stands for consumer price inflation, *IR* is the 10 years Treasury bond rate, *SLOPE* is the difference between 10 year and 3 month Treasury rates and *PREM* is the default premium measured as the difference between Baa and Aaa rated bonds. Q_{r_t} represents the τth quantile of the conditional distribution of the dependent variable (r_t), assumed to be linearly dependent on the set of explanatory variables (X_t). A key feature of the quantile regression approach is that the estimator vector β^τ may change across quantiles. Varying the value of τ from 0 to 1 reveals the entire distribution of the dependent variable conditional on the independent variables.

Equation (1) shows that holding the conditioning variables fixed, any extrinsic variation in the U.S returns (r_t) must be attributed to ν_t^τ. In other words, the conditional quantile of the U.S returns is linked to the quantile of ν_t^τ. Hence, we extract the residual $\hat{\nu}_t(\tau_r)$ to present the conditional quantile of the U.S stock market returns by standard quantile regression as:

$$\min_{b} \sum_{t=1}^{T} \rho_\tau(r_t - \mathrm{b}^{\mathrm{T}} x_t) \tag{2}$$

Next, Li et al. (2015) proposed the quantile correlation between any two variables x_t and y_t as follows: Let $Q_{\tau,x}$ be the τth unconditional quantile of y_t and $Q_{\tau,y}(x)$ be the τth quantile of y_t conditioned on x_t. Now, the $Q_{\tau,Y}(x)$ is independent of x_t, i.e. $Q_{\tau,y}(x) = Q_{\tau,y}$ with probability one, if and only if the random variables $I(y - Q_{\tau,y} > 0)$ and x_t are independent, where $I(\cdot)$ is the indicator function. Li et al. (2015), for $0 < \tau < 1$, define quantile covariance as:

$$\mathrm{qcov}_\tau\{y, x\} = \mathrm{cov}\{I(y - Q_{\tau,y} > 0), x\} = E\{\psi_\tau(y - Q_{\tau,y})(x - Ex)\} \tag{3}$$

where the function $\psi_\tau(w) = \tau - I(w < 0)$. Subsequently, the quantile correlation is calculated as:

$$\mathrm{qcor}_\tau\{y, x\} = \frac{\mathrm{qcov}_\tau\{y,x\}}{\sqrt{\mathrm{var}\{\psi_\tau(y - Q_{\tau,y})\}\mathrm{var}(x)}} = \frac{E\{\psi_\tau(Y - Q_{\tau,y})(x - Ex)\}}{\sqrt{(\tau - \tau^2)\sigma_x^2}} \tag{4}$$

where $\sigma_x^2 = \mathrm{var}(x)$. Equations (1) and (4) are utilized to obtain the quantiles of U.S stock market returns and its quantile-on-quantile correlation (QQCOR) with U.S bond, oil, commodities and gold returns. The QQCOR enables to model the correlation in a highly flexible manner. To examine the dependence between bear markets, the quantile of returns may be set between 0.05 and 0.10. This captures the dependence between the 5$^{\text{th}}$-10$^{\text{th}}$ percentiles of returns, observed when markets are bearish. Pertaining to normal events, one possibility is the return quantiles may be set to 0.50 and look at the dependence between the median returns. For correlation during bull markets, quantiles can be set to 0.90 and 0.95. This illustrates the range of possible correlations under (4). We calculate the QQCOR for the quantile ranging from 0.05 to 0.95 with equal intervals of 0.05.

Next, the dynamic correlation can be constructed by matching the QQCOR correlations to the quantiles of returns for each period. Let's denote the empirical distributions of returns of x_t and y_t as $\tilde{F}_X(x_t)$ and $\tilde{F}_Y(y_t)$, respectively. If $\tilde{F}_X(x_t)$ and /or$\tilde{F}_Y(y_t)$ is less than 0.05 then replaced with 0.05. On the other hand, if $\tilde{F}_X(x_t)$ and/or $\tilde{F}_Y(y_t)$ is more than 0.95 then replaced with 0.95. The new series may be called $\tilde{F}_X^1(x_t)$ and $\tilde{F}_Y^1(y_t)$ and round them to the nearest first decimal point and result will be on the grid [0.05,…, 0.95]. Recall that QQCOR correlation is a 19 x 19 matrix, where each point on the matrix corresponds to a combination of points on two grids, each representing the percentiles of two market returns, respectively. The time t correlation is obtained by matching the quantiles of returns to the QQCOR correlation matrix.

3. Data and findings

We first obtain the quantiles of U.S stock market returns using the auxiliary regression as defined in Equation-1. Our monthly data spans over the period January 1982 to December 2015. Data of auxiliary regression predictors i.e., industrial production index (IPI), 10 years U.S Treasury yield, slope of the yield curve (difference between 10 year and 3 month treasury rates), default premium (difference between Baa and Aaa rated bonds yields) is obtained from St. Louis Federal

Reserve (FRED) and data of U.S consumer price index is obtained through U.S Bureau of Labor Statistics. The data of S&P 500 composite index, U.S benchmark 10 year government bond index, Brent crude oil prices, S&P GSCI commodity total return index and Gold Bullion LBM U$/Troy Ounce (ICE Benchmark Administration Ltd.) is obtained through Thomson Reuters Datastream (Thomson International). Time trends of the investments markets are shown in Figure-1. The price indices are standardized (subtracting the price at time t from the average and dividing by standard deviation) to show a better comparative picture.

Figure 1: Time trend of U.S markets – standardized prices

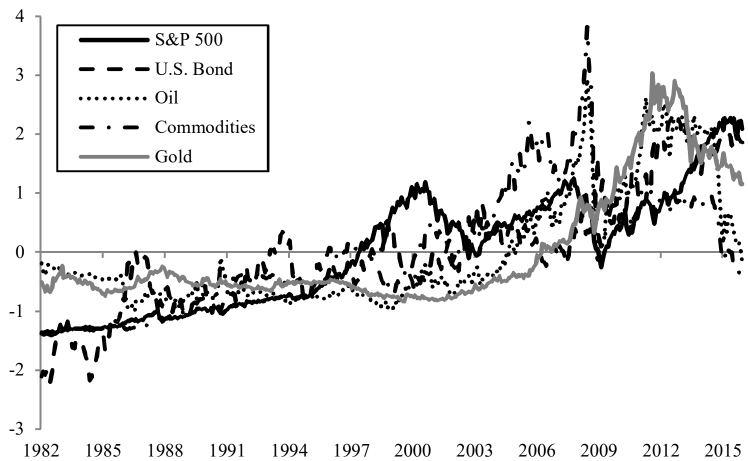


Table 1 reports the descriptive statistics of the data. The returns are calculated using the natural logarithmic difference between the month-end closing prices whereas the auxiliary regression variables enter the equation in first difference from. Monthly average returns are highest (0.69%) for the stock market index whereas these are lowest (0.01%) for the oil. The volatility is highest (10.52%) in case of oil returns, as measured through standard deviations. The returns series are leptokurtic with fat tails and the null hypothesis of normality (through Jarque-Bera test) is rejected at usual levels of significance. The unit root (the augmented Dickey and Fuller (ADF; 1979)) tests show that all the time series are stationary processes at the conventional levels.

Table 1: Statistical properties of the variables

	Mean	Min.	Max.	Std. Dev.	Skew.	Kurt.	J-B Stats	ADF
Panel A: Investment markets (% returns)								
S&P 500	0.691	-24.54	12.37	4.398	-0.941	6.421	258.6***	-19.09***
U.S Bond	0.156	-6.423	8.493	2.231	0.043	3.717	8.860**	-19.04***
Oil	0.007	-44.14	47.13	10.51	-0.076	5.889	141.9***	-19.20***
Commodities	0.298	-33.12	20.65	5.748	-0.589	6.155	192.3***	-16.51***
Gold	0.248	-19.11	18.83	4.704	-0.003	4.788	54.24***	-22.97***
Panel B: Auxiliary regression variables (Δ)								
IPI	0.136	-4.301	1.788	0.537	-2.065	16.67	3458.6***	-5.202***
Interest Rate	-0.030	-1.430	0.780	0.271	-0.432	5.377	108.8***	-13.17***
Slope	0.001	-1.520	1.970	0.288	0.373	10.63	997.1***	-14.13***
Default Premium	-0.001	-0.630	0.940	0.112	1.042	19.55	4723.2***	-12.48***

Inflation	0.352	-3.842	2.700	0.485	-1.736	20.08	5154.4***	-13.18***

Note: Min., Max., Std. Dev., Skew., Kurt. JB and ADF stand for minimum, maximum, standard deviations, Skewness, Kurtosis, Jarque-Bera test and Augmented Dickey Fuller test, respectively. *** and ** indicate rejection of normality and unit root at 1% and 5% level, respectively.

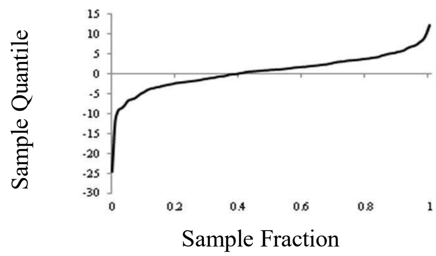
The QQ approach used in this study focuses on the correlation between U.S stock return and returns of different investable assets at their various quantiles. To provide a sense of how these quantiles look like, the quantiles of asset returns are plotted in Figure 2 and show that the return below the 40th percentiles are negative; hence, the lower quantiles of the returns are indicative of a bearish market conditions and vice versa.

Figure 3 shows the estimates of quantile correlations and provides several interesting results. First, there is a considerable heterogeneity in relationship for all four pairs. Two, a marked variation in the correlation coefficients is observed across the different quantiles of the stock market returns and asset returns. This suggests that the link between any two markets is not uniform (but asymmetric) across the quantiles and that this link depends on both the sign and size of the market shocks i.e., whether there are bullish, normal or bearish conditions in the markets.

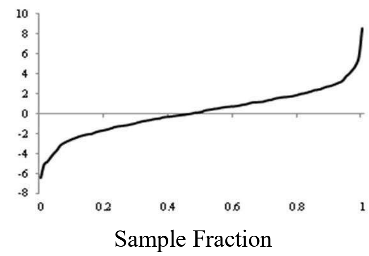
The correlation between stock and bond pair is higher when the bond (stock) market is in bearish (bullish) state. The returns in these markets are negatively correlated for lower and upper quantiles of stock and bond markets, respectively. There is an average dependence between the stock and bond markets when both markets are in similar states i.e., when both are either bearish or bullish. Similar pattern of dependence is evident for the stock and gold pair, with difference in magnitude. The correlation of stock market returns is also alike with both oil and commodities index returns. However, this dependence structure is opposite to what we show for stock-bond and stock-gold pairs. The stock market returns have a higher correlation with oil and commodities when the stock market is bearish (lower quantile i.e., 0.10-0.30) and other markets are bullish (upper quantiles i.e., 0.70-0.90). It is noted that correlation of stock market may further increase (decrease) from its average level during crisis periods where we associate the lower stock market quantiles with the bad or crisis situations in the markets. Hence, the portfolio weights of the portfolios or the speculative bets may be adjusted during the changing market conditions.

Figure 2: Quantile Plots

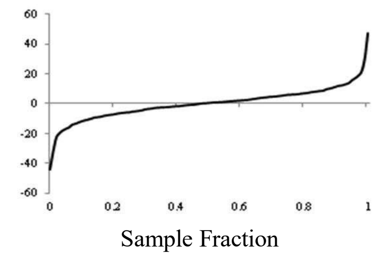
a). Quantile of S&P 500 Returns



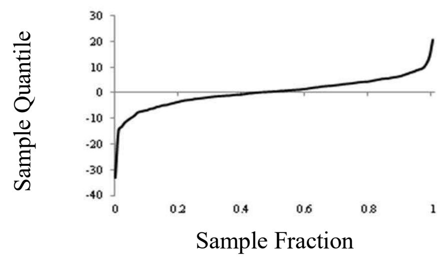
b). Quantile of U.S. Bond Returns



c). Quantile of Oil Returns



d). Quantile of Commodities Returns



e). Quantile of Gold Returns

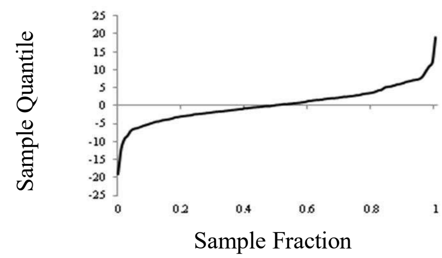
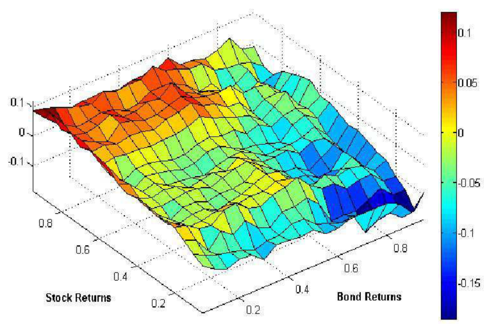
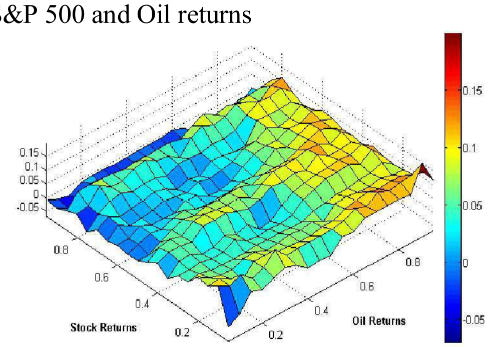


Figure 3: Quantile-quantile correlation

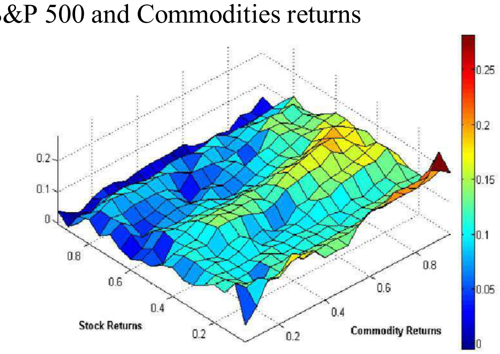
a). S&P 500 and U.S. Bond returns



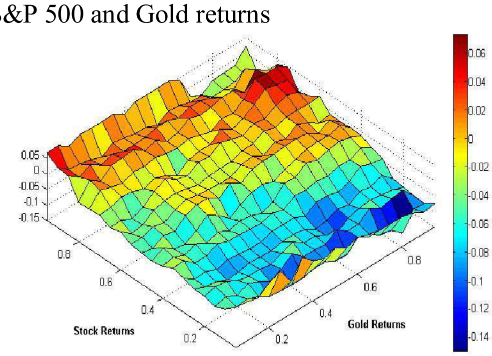
b). S&P 500 and Oil returns



c). S&P 500 and Commodities returns



d). S&P 500 and Gold returns



Note: The graphs depict the correlations estimates placed on the *z*-axis. The colors in the colors bar measure the degree of the association or the comovement between the two assets. The red color corresponds to a positive and growing value of correlation coefficient while the blue color corresponds to low or negative coefficients.

Next, we utilize two risk management measures to compare the performance of each of the alternate asset available to equity investors. The risk reduction effectiveness of an equally weighted portfolio (composed of stock and bond/oil/commodities or gold) is examined by comparing the % reduction in the variance with the benchmark portfolio i.e., comprised of stock market only through:

$$RE_{Var} = 1 - \frac{Var(P_j)}{Var(P_{\mathrm{I}})} \tag{5}$$

Where, $Var(P_j)$ and $Var(P_{\mathrm{I}})$ shows the variance of equally weighted portfolio and the benchmark stock portfolio, respectively. The higher values indicate higher risk reduction effectiveness and vice versa. The results reported in Table 2 show that risk reduction performance of assets also differ across quantiles and bond and gold investments provide relatively better risk reduction when added to stock markets portfolio.

The risk reduction measure is a standalone measure and does not capture the additional portfolio returns obtained by adding an asset to equity portfolio. Thus, we calculate the Sharpe ratios for both the portfolio of equity returns and the equally weighted portfolio comprising of equity and other assets. Table 3 reports the quantile-quantile growth in Sharpe ratio when an asset is added to stock market portfolio. The results show that all four assets result in better portfolio performance when their respective returns are in lower quantiles (the bearish conditions) and the magnitude of benefits are relatively higher when the stock market is in bullish state.

Table 2: The Quantile-quantile risk reduction

S&P 500	**a).** U.S. Bond returns						**b).** Oil returns				
Quantiles	*Q(0.05)*	*Q(0.10)*	*Q(0.50)*	*Q(0.90)*	*Q(0.95)*		*Q(0.05)*	*Q(0.10)*	*Q(0.50)*	*Q(0.90)*	*Q(0.95)*
Q(0.05)	0.7444	0.2777	0.0424	0.2401	0.3786		-0.0730	0.1954	0.0435	0.1484	-1.8102
Q(0.10)	0.9547	0.7160	0.1898	0.6403	0.5193		-1.4763	-0.4746	0.1409	-1.4840	-17.289
Q(0.50)	0.9681	0.8573	0.2748	0.5485	0.0420		-2.2629	-3.0641	-1.1028	-8.8169	-40.917
Q(0.90)	0.9562	0.7372	0.1791	0.6112	0.4155		-1.6890	-0.9015	0.0531	-2.4701	-21.238
Q(0.95)	0.9245	0.5793	0.1108	0.4775	0.4837		-1.1422	-0.1462	0.0790	-0.7803	-11.209
	c). Commodities returns						**d).** Gold returns				
Q(0.05)	0.4503	0.2587	0.0428	0.2408	0.1565		0.5890	0.2758	0.0430	0.2397	0.2318
Q(0.10)	0.0674	0.3802	0.1834	0.4909	-1.4383		0.4801	0.6624	0.1784	0.4327	-0.7982
Q(0.50)	-0.2129	-0.2672	0.0747	-0.2130	-4.6159		0.3357	0.6729	-0.0706	-0.4902	-3.1154
Q(0.90)	-0.0183	0.2519	0.1591	0.3624	-2.0280		0.4311	0.6536	0.1452	0.2715	-1.2382
Q(0.95)	0.1595	0.3652	0.1057	0.3752	-0.8407		0.5107	0.5426	0.1022	0.3380	-0.4133

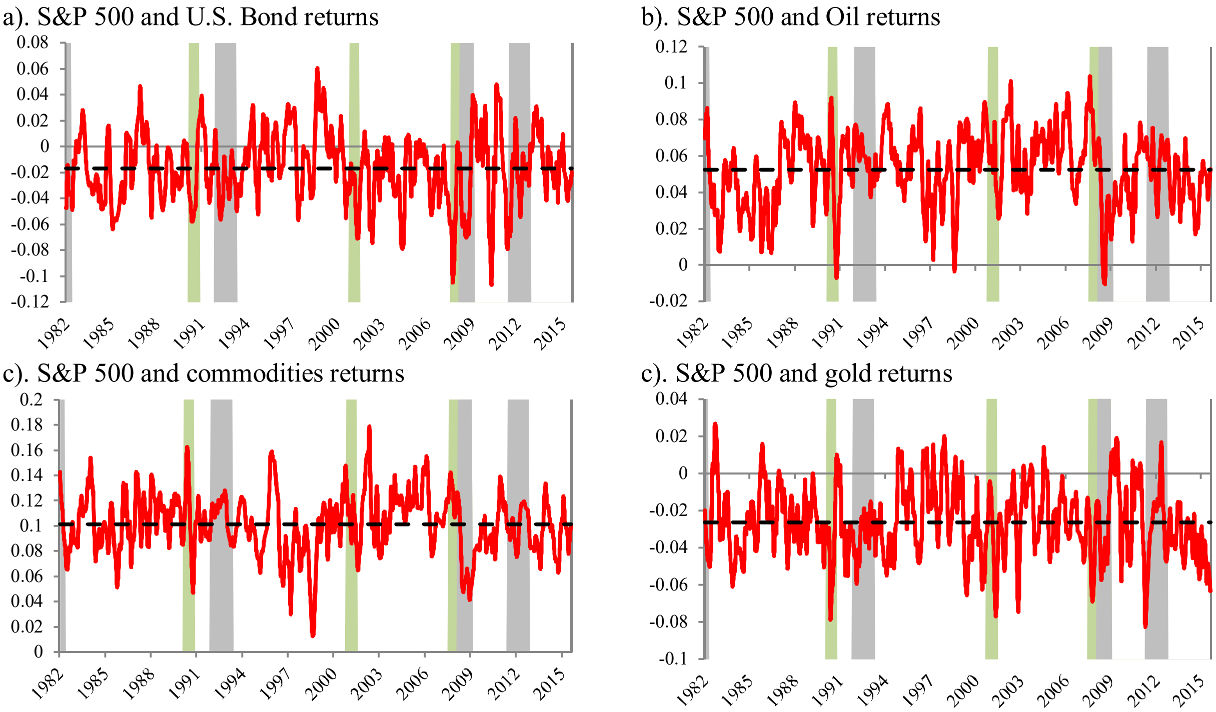
Table 3: The Quantile-quantile growth in Sharpe ratio

S&P 500	**a).** U.S. Bond returns						**b).** Oil returns				
Quantiles	*Q(0.05)*	*Q(0.10)*	*Q(0.50)*	*Q(0.90)*	*Q(0.95)*		*Q(0.05)*	*Q(0.10)*	*Q(0.50)*	*Q(0.90)*	*Q(0.95)*
Q(0.05)	0.3492	-0.0327	0.1636	0.7788	1.1400		0.4156	0.4582	0.1188	1.1916	0.9038
Q(0.10)	0.7102	0.3177	0.2951	1.3912	3.3594		0.1807	0.3295	0.2138	0.7378	-0.0166
Q(0.50)	0.6158	0.1010	-0.4875	-0.1810	-0.6763		0.3667	0.3595	-1.0035	-0.6914	-2.1872
Q(0.90)	1.1049	0.8113	-0.0529	0.1602	-0.0449		0.8558	1.2574	-0.0694	-0.2343	-1.8322
Q(0.95)	0.9591	0.6277	-0.0643	0.0646	0.0545		1.0779	1.6122	-0.0360	0.0794	-1.1907
	c). Commodities returns						**d).** Gold returns				
Q(0.05)	0.3998	0.2867	0.1236	-7.9225	0.7798		0.3536	0.1960	0.1728	-1.1772	0.3532
Q(0.10)	0.2458	0.3734	0.2403	0.5985	0.0354		0.2718	0.4582	0.3014	0.5033	-0.2541
Q(0.50)	0.2959	0.3294	-0.3599	0.0273	-0.9765		0.1685	0.5201	-0.9135	-0.1222	-0.9844

Q(0.90)	0.7573	1.8570	-0.0138	0.2600	-0.5422		0.1520	-0.3613	-0.0875	0.1891	-0.4749
Q(0.95)	1.1824	-5.0748	-0.0257	0.2611	-0.2170		0.4223	0.1037	-0.0797	0.2224	-0.1737

Figure 4 shows the dynamic QQ correlation coefficients which suggest that the correlations between stock and other markets' returns are indeed time varying. Bond and gold returns (oil and commodities returns) have a low to negative (positive) correlation with stock market returns. Substantial drop in correlation values is evident during crises episodes.

Figure 4: Quantile-quantile correlation (four months moving average)



Note: The green area indicates 1990/91, 2001 and 2007/09 US recessions dated by National Bureau of Economic Research (NBER). The gray area indicates 1992/93, 2008/09 and 2011/12 Euro Area recessions dated by Centre for Economic Policy Research (CEPR).

4. Conclusion

We examine the correlation and thereafter portfolio implications of stock, bond, oil, commodities and gold investments using monthly data from January 1982 to December 2015. The data covers significant markets events like global financial crises of 2007-08 and Eurozone debt crises of 2011-12. Using a novel quantile-on-quantile (QQ) approach, we show that dependence structure between investable assets change under bullish and bearish conditions in a particular market and the relationship is asymmetric.

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