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Abstract

This paper examines the conditions under which investors flee from stocks to bonds or vice versa. Daily and weekly stock and bond returns are analyzed to determine when investors start to flee from a market and rebalance their portfolios. We use a theoretical model that demonstrates why rational investors deviate from the optimal portfolio weights and under which conditions they rebalance their portfolios. Quantile Regression is employed to analyze empirically when investors flee from certain asset classes. The results demonstrate significant advantages of this approach compared to commonly employed (dynamic) correlation estimates. The approach can quasi-endogenously identify different regimes of stock-bond co-movements and directly distinguish between flight-to-quality and flight-from-quality. Our empirical results for eight major stock and bond markets show that there are three distinct regimes of stock-bond co-movements. Time-varying quantile estimates further show that there is a positive trend in the likelihood and severity of flights. The findings show that diversification between stocks and bonds is effective especially in times when it is needed most.

JEL classification: C32; E44; F3; G14; G15
Keywords: quantile regression, flight-to-quality, stock-bond co-movements

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Introduction

When do investors start to become nervous and rebalance their portfolios? This is the question we attempt to answer. The answer is potentially interesting for a variety of reasons. First, if an investor knows when other investors will start to rebalance their portfolios, the investor can act ahead of the majority and thus make a profit relative to the others. Second, if central banks know when investors flee from certain types of assets, they might be better able to forecast drops in liquidity and act in time. Finally, a relatively abrupt and extreme change in the weights allocated to risky and risk-free assets may have severe consequences for the stability of the financial system. Hence, it might be fundamental to know for both investors and policy makers under which conditions such extreme changes happen and what the consequences of such changes are.

When portfolio managers rebalance and change their asset holdings, asset prices will be affected. Some prices will fall and others might increase, e.g. stock prices fall and the price for gold increases. Such rebalancing has not only an influence on prices and returns but also on the co-movement between assets. In times when the average (representative) investor does not change the weights of the portfolio, the co-movement (correlation) is stable. Only if investors change their portfolio structure, the co-movement between assets might change. For example, let us assume that the average investor holds seventy percent of his wealth in stocks and thirty percent in government bonds and the co-movement is positive but close to zero. If the average investor decreases the weight in stocks to sixty percent and increases the weight in government bonds to forty percent, the co-movement between the two asset classes will become negative. This example becomes more interesting when it is related to stock-bond co-movements and cross-country stock-stock and bond-bond co-movements. Cross-country stock or bond market co-movements are usually positive (clearly above zero), showed an upward trend in recent years and vary within relatively small bands. In contrast, stock-bond co-movements are not clearly positive, did not show an upward trend in recent years and vary considerably between relatively large negative correlation levels and relatively large positive correlation levels (e.g. see Baur and Lucey, 2006). One major reason for these differences can be macroeconomic factors such as common business cycles, inflation expectations and interest rate changes among others (e.g. see Li, 2002). However, large changes in the level of co-movements (from positive regimes to negative regimes or vice versa) in a relatively short time period, e.g. less than one week, suggest that investors play a major role as well. Moreover, since correlations are an essential ingredient in the determination of an asset's weight in a portfolio, it is perhaps not surprising that these weights also determine or influence the correlations. One prominent example is financial contagion (e.g. see Baig and Goldfajn, 1999). Investors sell certain assets simultaneously across countries causing stock markets to fall jointly and causing correlations to increase. This lowers the benefits of diversification in a situation when this diversification is needed most. In contrast, decreasing correlations as found for stock-bond correlations in crisis periods (see e.g. Hartmann, Straetmann and De Vries, 2001) increases the benefits of diversification (ceteris paribus) potentially compensating investors for losses incurred with other investments.

The literature on stocks and bonds dates back to Keim and Stambaugh (1986) who were the first to investigate this relationship. A more recent study is Ilmanen (2003) who finds a positive correlation on average but several sub-periods with a negative stock-bond correlation. He attributes negative correlations to deflationary recessions, equity weaknesses and high-volatility stock market regimes. This is in line with the study by Stivers, Sun and Connolly (2005) who find stock market uncertainty to be a major determinant of significant stock-bond correlation changes.[2]

There are different theoretical arguments that help to determine the level of stock-bond correlations. A positive correlation can be expected due to common macroeconomic variables that drive both stocks and bonds in the same direction. A negative correlation can be caused by inflation expectations that lower bond prices and have an ambiguous effect on stock prices. Negative correlations can also be caused by (i) flight-to-quality from stocks to bonds[3] or (ii) flight-from-quality from bonds to stocks. Interestingly, the literature does still not provide a model to forecast or explain the level of stock-bond correlations.

This paper is motivated by the observation that stock-bond co-movements exhibit relatively large and abrupt fluctuations that can not be explained with macroeconomic variables. Therefore, we attempt to give an alternative explanation for these fluctuations and present a model that

[2] Other studies analyze the relation of stock and bond market liquidity (Chordia, Sarkar and Subrahmanyam, 2005), the link between corporate bonds and stocks (e.g. Baker and Wurgler, 2005), momentum spillover effects (Gebhardt, Hvidkjaer and Swaminathan, 2005), asymmetric dynamics of stock and bond correlations (Capiello, Engle and Sheppard, 2003) and the transmission of volatility between stock and bond markets (Steeley, 2005) among others. Dopfel (2003) and Li (2002) analyze stock-bond correlations and additionally study the welfare effects of correlation changes for investors.

[3] See De Goeij and Marquering, 2004, Gulko, 2002, Hartmann, Straetmann and De Vries, 2001, Li, 2002 and Stivers, Sun and Connolly, 2005 among others.

demonstrates when investors start to rebalance their portfolios and cause co-movements to change significantly. The main contribution of the paper is a new econometric approach (Quantile Regression) to estimate the co-movement of stocks and bonds with the distinguishing feature that different regimes can be modelled without an a priori definition of the number or the type of regimes. The regimes are quasi endogenously determined by the econometric model. This feature is important since it can also show in which conditions (when) investors start to flee form a certain asset class. The paper is, to the best of our knowledge, the first to apply quantile regression to stock-bond co-movements.

The remainder of the paper is structured as follows: section I presents the model that demonstrates under which conditions investors start to rebalance their portfolios. Section II outlines the econometric framework and associated hypothesis tests. Section III describes the data and section IV presents the empirical results. Finally, section V summarizes the main results and concludes.

I. A Basic Framework of Stock-Bond Portfolio Diversification

The aim of this section is to provide a theoretical basis for the empirical analysis in the next section. It is well known that investors choose the proportion invested in risky assets and the proportion invested in a risk-free asset according to their risk preference. This can be shown with the following utility function

$$U= X\ E(R_P) – (1-X)R_F - AX^2\sigma_P^2$$

where U is the utility of a representative investor determined by the expected return of the risky portfolio P, the risk-free asset F and the variance of the risky portfolio. A is a parameter representing the investor's risk aversion and X is the weight invested in the risky portfolio P. Maximizing this function with respect to X and solving for X yields

$$X^* = [E(R_P)-R_F] / [2A\sigma_P^2]$$

where X* denotes the optimal amount of wealth allocated to the risky portfolio P and the risk-free asset F given by (1-X*). The solution to the utility maximization problem shows that X* depends on the difference of the expected return of the risky portfolio and the risk-free asset, the investor's risk aversion and the risk (variance) of the risky portfolio.

Given that all these variables might vary, it is clear that X* will vary as well. Note that even if just one variable varies through time (e.g. the volatility of the risky portfolio), X* will vary. It is however also clear that the typical investor will not change the weights assigned to the risky portfolio and the risk-free asset continuously in time. It is more likely that investors react to changes in X* only with a lag or if the actual portfolio weights deviate significantly from the optimal weights X*. One major explanation for one of these cases is transaction costs. Since it is costly to rebalance a portfolio, investors will only change the weights of their portfolios if changes are justified by the incurred transaction costs. Another explanation might be that portfolio managers only adjust their portfolios if other managers adjust theirs as well due to compensation schemes that are based on the average portfolio managers' performance.

The above can be summarized and formalized as follows. The representative investor changes her portfolio weights if the difference between the current or actual weights (X_{actual}) and the optimal weights (X*) exceed a certain threshold q*:

$$| X_{actual} - X^* | > q^*$$

This decision rule can be integrated in an augmented utility function as proposed by Calvo and Mendoza (2000) as follows:

$$U(X) = X\, E(R_P) + (1-X)\, R_F - A\sigma_X^2 - \lambda\, (\mu(X^*) - \mu(X))$$

where $\mu(X^*)$ and $\mu(X)$ are the expected returns of a portfolio comprising a risky portfolio and a risk-free asset given the portfolio weights X* and X, respectively and λ is a (non-negative) parameter governing the costs or benefits associated with a deviation from the optimal portfolio X*.

If $\mu(X^*) = \mu(X)$, there is no additional benefit or cost. However, if $\mu(X^*) > \mu(X)$, there is a cost of not holding the optimal portfolio. In contrast, if $\mu(X^*) < \mu(X)$, there is a benefit of deviating from the optimal portfolio structure. If the cost exceeds a certain threshold, investors will rebalance their portfolios leading to X*=X and a flight from risky assets (e.g. stocks) to bonds or vice versa. This flight will be associated with lower prices for one asset class and higher prices for the other asset class.

< Insert figure 1 about here >

Figure 1 aims to show graphically what happens if investors simultaneously rebalance their portfolios. The figure shows how a simultaneous rebalancing can lead to flight to quality from stocks to bonds or to a flight from quality from bonds to stocks.

It is possible that benefits and costs are not symmetric and that a portfolio manager suffers more if she underperforms than she gains when she outperforms the benchmark. To account for this, the last term (λ ($\mu(X^*)$ – $\mu(X)$)) could be separated into a component for under- and out-performance with two different parameters λ_1 and λ_2.

II. The Econometric Framework

A. Quantile Regression

The main question this paper tries to answer is when investors begin to change their portfolio weights and flee from a certain market in the sense that they significantly decrease the exposure in that market. Such a flight from stocks to bonds (flight to quality) or from bonds to stocks (flight from quality) might occur in certain market conditions. However, it is not clear in which market conditions these phenomena occur and when exactly investors start to rebalance their portfolios.

We propose a new approach that shows in which market conditions investors start to rebalance their portfolios. Our new approach is based on Quantile Regression (QR) which can assess the differential linkage between markets conditional on certain market conditions or returns.[4]

The advantage of QR compared to a regime-switching model is that an a priori unspecified number of regimes can be detected or implicitly modelled.

Therefore, in order to circumvent a priori definitions of regimes (e.g. normal and extreme market regimes), we employ a quantile regression model that provides estimates of the linkage between stocks and bonds in any market condition represented by the conditional quantiles of the return of the market under investigation. The model can be written as follows:

$$r_{s,it} = a_i + b_i\, r_{b,it} + v_{it}, \qquad Q_r(\tau|r_{b,it}) = a_i(\tau) + b_i(\tau)\, r_{b,it} \qquad (1)$$

[4] For an introduction to Quantile Regression see Koenker and Basset (1978) and Koenker and Hallock (2001).

where $r_{s,t}$ is the stock market return at time t in country i, $r_{b,t}$ is the bond market return in country i and v_{it} represents the idiosyncratic shock of market i at time t. $Q_r(\tau|r_{b,it})$ denotes the τ-th conditional quantile of $r_{s,t}$, assumed to be linearly dependent on $r_{b,t}$. The model is estimated with the quantile regression method and can thus assess the impact of $r_{b,t}$ on different conditional quantiles of $r_{s,t,}$ that is, different market conditions (see Koenker and Bassett, 1978).

If $b_i(\tau)$ in equation 1 is stable, that is, constant over all quantiles, the linkage or co-movement between stocks and bonds is constant. On the contrary, if $b_i(\tau)$ varies across quantiles, this linkage varies as well. Flights to either stocks or bonds imply that the linkage is significantly different in certain market conditions. Flights can be associated with volatile and extreme market conditions. Hence, one can hypothesize that the linkage is significantly different in lower and upper quantiles. If flight to quality occurs in extreme adverse stock market conditions (lower quantiles, e.g. 1% or 5% quantile), $b_i(\tau)$ is expected to be negative. If on the other hand, a flight from quality occurs, the hypothesis is that stocks exhibit relatively large returns associated with relatively low (negative) bond returns implying that $b_i(\tau)$ is negative in the upper quantiles (e.g. 99% or 95% quantile). In order to distinguish flights from normal or average linkages we analyze changes of b_i estimates across quantiles. If there is no significant difference between average and extreme linkages, there is no evidence of a flight from one market to the other irrespective of the estimate for b_i.

Thus, we formulate the following hypotheses:

Hypothesis 1: *Flight to quality*

H_0: $b_i(1) \geq 0$ & $b_i(1) \geq b_i(50)$

The null hypothesis tests whether the coefficient estimates in the 1% quantile (extreme negative stock returns) are negative and smaller than the median. Only if the coefficient estimate is negative and different from the normal (median) coefficient, there is evidence for a change in stock-bond co-movements indicating a negative correlation between stocks and bonds. If the null hypothesis is rejected, there is flight to quality from stocks to bonds.

Hypothesis 2: *Flight from quality*

H_0: $b_i(99) \geq 0$ & $b_i(99) \geq b_i(50)$

This hypothesis is similar to the previous one with the only difference that it focuses on the upper extreme quantile. The null hypothesis tests whether there is a negative relationship of stocks and bonds if stocks exhibit large positive returns and that this relationship is significantly different from normal (median) relationships. If the null hypothesis is rejected, there is evidence for a flight from quality from bonds to stocks.

Hypothesis 3 : *Contagion*

H_0: $b_i(1) \leq 0$ & $b_i(1) \leq b_i(50)$

This hypothesis tests whether there is an increased co-movement between stocks and bonds in times when stock markets exhibit extreme negative returns. The hypothesis is similar to tests applied for cross-country stock market co-movements (e.g. see Forbes and Rigobon, 2002). If the null hypothesis is rejected, there is evidence for contagion between stock and bond markets.

B. When do Investors flee ?

The title of the paper asks the question how bad conditions must be to make investors flee. To answer this question we analyze the coefficient estimates for all quantiles and determine at which quantiles the linkages become negative representing a negative correlation between stocks and bonds and indicating that investors flee from one market, that is, sell one asset class and buy another asset class.

Plots of the coefficient estimate for each quantile will show under which conditions investors start to engage in flights. The plots also show whether there is an asymmetry between flights in extreme negative stock market conditions and in extreme positive stock market conditions.

In order to link the quantile coefficient estimates with events in time, we estimate the quantile coefficients recursively with increasing window lengths and obtain a time-series of coefficient estimates for different quantiles. This analysis will provide additional information regarding the time-varying behaviour of stock-bond co-movements. In contrast to dynamic correlation estimators, this approach will yield dynamic coefficient estimates for different stock market conditions.

III. The Data

A. Daily Data

The data consists of daily continuously compounded MSCI stock and bond index returns of the US, the UK, Germany, France, Italy, Australia, Canada and Japan. The MSCI bond indices are sovereign total return indices with maturities longer than 10 years (10year+). All indices are in local currencies. The data cover a time-period of more than 12 years from January 1994 until September 2006 leading to a sample size of $T=3291$ observations. The descriptive statistics are shown in table 1. It is noteworthy to mention that the empirical analysis only focuses on relationships within a country. Thus, commonly encountered problems in cross-country studies with non-synchronous trading or exchange rate effects do not apply to this study.

< Insert table 1 about here >

Table 1 shows that the mean of the bond index returns is similar or larger than the average stock index returns, the standard deviation of bonds is lower than that of stocks and the minimum and maximum values are lower in absolute terms for bonds than for stocks. All return series are negatively skewed and leptokurtic.

Table 2 presents the unconditional stock-stock, bond-bond and stock-bond correlations for all countries.

< Insert table 2 about here >

The upper triangular matrix contains the correlation coefficient between the bond indices and the lower triangular matrix presents the correlation coefficient between the stock indices. The main diagonal contains the unconditional stock-bond correlations. Stock-stock and bond-bond correlations have a comparable magnitude for the same pairs of markets. For example, the bond-bond correlation of the US and the UK is 0.4617 and the stock-stock correlation for the same markets is 0.4117. The similarity is even more pronounced for the stock-stock and bond-bond correlations of Germany and the UK. It is 0.7355 for bonds and 0.7094 for stocks. Finally, the correlations of the US and German markets for stocks (0.4725) and bonds (0.4617) are lower than for the UK-German pairs and even more similar. Cross-country stock and bond correlations are relatively low for Australia and Japan which can be explained with the different time zone. Note also that the sample contains stock and bond market returns in local currencies. This yields intra-country stock-bond correlations that are independent of exchange rate changes. In contrast, cross-country stock and bond market return correlations are affected by exchange rate changes. Stock-bond co-movements are tabulated on the main diagonal of the matrix and are close to zero (in most cases negative) for many countries except Italy, Australia and Japan. Italy and Australia have positive stock-bond correlations of 0.1852 and 0.1132 and Japan exhibits a negative correlation of -0.2056.

< Insert table 3 about here >

Table 3 presents the unconditional stock-bond correlations for four sub samples, namely 1994-1997, 1997-2001, 2001-2005 and 2005-2006. There are two main features. First, there is significant variation of the correlations through time and second, there is less variation in the cross-section of the sample for each sub period. The standard deviation among all countries averaged over the four sub periods is 0.1324. On the other hand, the standard deviation among all sub sample periods averaged over the eight countries is 0.2918. Obviously, Japan exhibits a very different stock-bond correlation level than the other countries. The main insight from this table is the relatively strong co-movement of stock-bond linkages among most countries. High correlations are a common feature in the first sub sample, low (around zero) and negative correlations are a common feature in the second and third sub sample period and the fourth sub sample exhibits low correlations around zero for all markets except Japan.

B. Weekly Data

In order to assess whether flights and portfolio rebalancing primarily occur within a week or rather on a weekly basis, we transform the daily data to weekly data to analyze differences in stock-bond linkages for daily and weekly data. Descriptive statistics are not provided due to space considerations. Differences between daily and weekly returns are analyzed as a part of robustness checks.

IV. Empirical Results

A. Daily Data

This section presents the estimation results of the quantile regressions. Figures 4 and 5 present the coefficient estimates of the co-movement between US stocks and US bonds for 99 quantiles (e.g. 1%-99% quantile) for daily and weekly data, respectively. The same information is contained in figures 6 and 7 for the UK, figures 8 and 9 for Germany, figures 10 and 11 for France, figures 12 and 13 for Italy, figures 14 and 15 for Australia, figures 16 and 17 for Canada and figures 18 and 19 for Japan.

< Insert figure 4 about here >

We first describe and discuss the results based on daily data. The common feature for all coefficient estimates is an inverted u-shape pattern. The coefficients are clearly lower in the extreme quantiles (e.g. 1% and 99%) than in the intermediate quantiles (e.g. 50%). This inverted u-shape is more pronounced for the US, the UK, Germany, France and Canada and less so for the remaining countries, that is, Italy, Australia and Japan. For these latter countries, the difference between intermediate quantiles and extreme quantiles is smaller compared to the other countries rendering the inverted u-shape form less pronounced or non-existent as is the case for Japan. There is another important difference. The level of the coefficient estimates differs across countries. All countries that exhibit the 'pronounced' inverted u-shape pattern have significantly negative coefficient estimates in the extreme quantiles and positive coefficient estimates in the intermediate quantiles. For Italy and Australia almost all coefficient estimates are positive and the Japanese coefficient plot shows that all estimates are negative.

< Insert figure 6 about here >

The figures include a 95% confidence band with which the significance of the estimates can be assessed.[5] However, these coefficient plots do not show whether the estimate for the 1% quantile is significantly different from any other coefficient estimate, e.g. for the 50% quantile. This

[5] The standard errors are computed with a bootstrap using 100 repetitions. Alternative numbers of repetitions (50, 200) are considered but do not yield qualitatively significant different standard error estimates.

information is important in order to determine whether flights from stocks to bonds or from bonds to stocks occurred or not. Assessing differences in coefficient estimates also provides information on asymmetries between extreme lower and extreme upper quantiles. If there are significant differences in the coefficient estimates in extreme quantiles, it would indicate that investors behave differently in bull markets than in bear markets. Such a finding would not be surprising but has not been reported in a stock-bond co-movement context so far. Table 4 provides the test results for flight to quality (FTQ), flight from quality (FFQ) and for asymmetries between the extreme lower and upper quantiles.

< Insert table 4 and about here >

Table 4 illustrates that only the countries with the pronounced inverted u-shape pattern of the coefficient estimates exhibit flights. Italy, Australia and Japan do not exhibit such investor behaviour. It is noteworthy to stress that it is possible that these countries exhibit typical flight scenarios for other assets not analyzed here. The focus is only on flights from stocks to bonds or vice versa within a country. If Australian investors flee from Australian stocks and buy US government bonds, there is a flight to quality but it involves cross-country flights which are excluded from the analysis. One reason for the exclusion is the non-synchronicity of trading hours for the countries under study.

To summarize, investors in the US, UK, Germany, France and Canada flee in certain market conditions form stocks to bonds or vice versa.

The important question to answer now is, under which conditions investors rebalance their portfolios. The question can be answered by analyzing (given the inverted u-shape pattern) when the coefficient estimates turn negative (starting from intermediate quantiles and moving towards the extreme lower quantiles or the extreme upper quantiles). For the US, stock-bond co-movements become negative for quantiles below the 13% or above the 92% quantile. For the UK, the quantiles are the 8% and the 91% quantile, for Germany the 15% and the 90% quantile, for France the 6% and the 96% quantile and for Canada it is the 99% quantile only. Italy, Australia exhibit positive values across all quantiles and Japan exhibits negative values across all quantiles.

It is obvious that there is some heterogeneity in the results. According to these obtained quantiles, US investors start to flee earlier from an asset class (13% and 92%) than French investors (6% and 96%) for example.

B. Weekly Data

The coefficient estimate plots are presented in figures 5, 7, 9, 11, 13, 15, 17 and 19 for the US, the UK, Germany, France, Italy, Australia, Canada and Japan, respectively. The plots illustrate several common features in relation to the findings for daily data. First, the coefficient estimates fluctuate more across quantiles, second the standard errors of the estimates are larger leading to wider confidence bands and third, the inverted u-shape disappears. The coefficients are relatively stable within a relatively large band. However, some countries still exhibit negative values for lower quantiles (e.g. 5%) but constant (compared to intermediate quantiles) or positive values for upper quantiles (e.g. 95%). The only countries that exhibit an inverted u-shape form of the coefficients are the UK and Japan (all values negative).

< Insert figure 5 about here >

< Insert figure 7 about here >

By analyzing the coefficient plots, we can conclude that there is no clear evidence for flights from stocks to bonds or bonds to stocks based on weekly data. Moreover, the results also indicate that flights occur relatively fast within days and not on a weekly basis. The findings suggest that investors rebalance their portfolios simultaneously and within a couple of days.

C. Dynamic Quantile Coefficient Estimates

The previous sections analyzed whether flights exist and under which market conditions they occur. However, the results did not show in which periods or on which days these flights occur. The aim of this section is to illustrate the dynamics of the coefficient estimates for several quantiles. We compute time-varying estimates by recursively estimating the model with quantile regression. The initial window comprises 100 observations and is augmented by ten observations until the maximum number of observations (N=3291) is reached. Figures 20-27 show the dynamic coefficient estimates for all eight countries in the sample. The figures contain the 1% quantile across time (denoted as qx1), the 50% quantile (denoted as qx2) and the 99% quantile (denoted as qx3). The common feature for all countries (except Japan) is the downward trend of the coefficient estimates for the 1% and the 99% quantile. This implies that the likelihood and the severity of flights have increased from the beginning of the sample (1994) until the end of the sample period (2006).

The reasons for this trend shall not be discussed here since they are probably beyond the scope of this paper. However, the implication of this trend is very clear. Lower co-movements between stocks and bonds in extreme market conditions means that diversification is effective in these extreme market conditions. In other words, it works when it is needed most.

< Insert figure 20 about here >

< Insert figure 21 about here >

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D. Robustness Analysis

This section examines the robustness of our results with respect to different specifications. First, the model is re-estimated with lags of the dependent and the independent variable:

$r_{s,it} = a_i + b_i\, r_{b,it} + c_i\, r_{b,it-1} + v_{it}$, $\quad Q_r(\tau|r_{b,it}) = a_i(\tau) + b_i(\tau)\, r_{b,it} + c_i(\tau)\, r_{b,it-1}$

The inverted u-shape pattern is preserved but the coefficient estimates in the extreme quantiles are slightly lower due to the lagged variables. The estimations reveal an interesting feature. Lagged stock returns are significant and positive in the lower extreme quantiles and significantly negative in the extreme upper quantiles indicating some persistence in bear markets and reversals in bull markets. The lagged bond return is generally not significant across the quantiles. Results are not reported due to space considerations.

Another specification analysis concerns the choice of the dependent and the independent variable. The focus of this paper is on certain stock market conditions, which justifies the choice of this variable as the dependent variable in a quantile regression framework. However, it is interesting to examine how the results change if the dependent and independent variables were swapped implying the following model

$r_{b,it} = a_i + b_i\, r_{s,it} + v_{it}$, $\quad Q_r(\tau|r_{s,it}) = a_i(\tau) + b_i(\tau)\, r_{s,it} + c_i(\tau)\, r_{b,it-1}$

Interestingly, the coefficients are generally not significantly different from zero across all quantiles and for all countries. Results are not reported due to space considerations.

V. Conclusions

This paper analyzed the co-movement of stock and bond markets for eight developed countries for a sample of more than ten years. The paper focuses on the question under which conditions and when investors flee from certain asset classes, here stocks or bonds. We use a novel approach in the context of stock-bond co-movements and flight to quality and show that this new quantile regression approach has several advantages compared to previously employed methods. The empirical results show that there are three distinct regimes of stock-bond co-movements, a flight to quality regime, a flight from quality regime and a tranquil regime in which stock-bond co-movements are relatively stable. A comparison of daily and weekly data shows that investors rebalance their portfolios simultaneously and relatively fast, within less than five days. The evidence of flight to quality and negative stock-bond correlations in extreme market conditions is good news for investors and the stability of the financial system since it implies that diversification is effective when it is needed most. Interestingly, it is the action of investors who provide this effectiveness.

Future research could extend the sample and analyze differences between developed countries and emerging countries. Moreover, it could be examined how liquidity concerns affect investors' decisions to flee from one market to another.

References

Bae, K.-H., Karolyi, G. A. and R. M. Stulz, 2003, A New Approach to Measuring Financial Contagion, *Review of Financial Studies*, 16(3), 717–763.

Baele, L., Ferrando, A., Hordahl, P., Krylova, E., Monnet, C., 2004. Measuring Financial Integration in the Euro Area. *Occasional Paper 14, European Central Bank.*

Baig, T. and I. Goldfajn, 1999, Financial market contagion in the Asian crisis, *IMF Staff Papers*, IMF 46, 2

Barr, D.G. and R. Priestley, 2004, Expected returns, risk and the integration of international bond markets, *Journal of International Money and Finance*, 23, 2004, 71-97

Baur, D. and B. M. Lucey, 2006, Flight-to-quality or contagion? An empirical analysis of stock-bond correlations. *IIIS Discussion Paper Series, University of Dublin - Trinity College*

Bekaert, G., Harvey, C.R., 1995. Time-varying world market integration. *Journal of Finance* 50, 403-444.

Bekaert, Geert, Campbell Harvey and Robin Lumsdaine, 2002, Dating the Integration of World Equity Markets, *Journal of Financial Economics*, 65, 203-247.

Bekaert, Geert, Campbell Harvey and Angela Ng, 2005, Market Integration and Contagion, *Journal of Business*, 78 (1), 39-70

Bekaert, G. and S. Grenadier, 2001, Stock and bond pricing in an affine economy, *Working Paper*

Bracker, K., Docking, D., Koch, P., 1999. Economic determinants of evolution in international stock market integration. *Journal of Empirical Finance,* 6, 1-27.

Calvo, G. A. and E.G. Mendoza, 2000, Rational Contagion and the Globalization of Securities Markets, *Journal of International Economics*, Vol. 51, 1, 79-113

Campbell, J.Y. and J. Ammer, 1993, What Moves the Stock and Bond Markets? A Variance Decomposition for Long-Term Asset Returns, *The Journal of Finance*, 48, 1, 3-37

Capiello, L., Engle, R.F. and K. Sheppard, 2003, Asymmetric Dynamics in the Correlations Of Global Equity and Bond Returns, *ECB Working Paper*

Connolly, R. A., Stivers, C. and L. Sun, 2005, Stock Market Uncertainty and the Stock-Bond Return Relation, *Journal of Financial and Quantitative Analysis*, 40, 1.

Connolly, R. A., Stivers, C. and L. Sun, 2007, Commonality in the time-variation of stock-stock and stock-bond return co-movements, *Journal of Financial Markets,* 10, 192-218

Dungey, M, Fry, R.A., Gonzalez-Hermosillo, B. and V.L. Martin, 2006, Contagion in International Bond Markets During the Russian and LTCM Crises, *Journal of Financial Stability*, 2, 1, 1-27

Forbes, K. and R. Rigobon, 2002, No Contagion, Only Interdependence, *Journal of Finance* 57, 5, 2223-2261

Giles, J.A., 2000, Testing for Two-step Granger Noncausality in Trivariate VAR Models, *Econometrics Working Paper EWP0008, University of Victoria, British Columbia, Canada*

Gonzalo, J. and J. Olmo, 2005, Contagion versus flight-to-quality in financial markets, *Working Paper 05-18, Universidad Carlos III Madrid*

Keim, D.B. and E.B. Stambaugh, 1986, Predicting returns in the stock and bond markets, *Journal of Financial Economics*, 17, 357-390

Kim, S. J., F. Moshirian and E. Wu, 2006, Dynamic stock-bond market integration driven by the European Monetary Union: An empirical analysis, *Journal of Banking and Finance*, 30 (5), 1507-1534.

Koenker, R. and G. Bassett, 1978, Regression Quantiles, *Econometrica*, 46 (1), 33–50.

Koenker, R. and K.F. Hallock, 2001, Quantile Regression, *Journal of Economic Perspectives*, 15 (4), 143-156

Li, L., 2002, Macroeconomic Factors and the Correlation of Stock and Bond Returns, *Yale University Working Paper*

Table 1: Summary Statistics

This table shows the number of observations, the mean, the standard deviation and the minimum and maximum values of all stock market index returns and government bond returns.

	Variable	*Obs*	*Mean*	*Std. Dev.*	*Min.*	*Max.*
stocks	US	3291	0.0003	0.0105	-0.0697	0.0561
	UK	3291	0.0002	0.0103	-0.0601	0.0559
	GER	3291	0.0002	0.0143	-0.0867	0.0745
	FR	3291	0.0003	0.0130	-0.0723	0.0657
	ITA	3291	0.0003	0.0131	-0.0742	0.0704
	AUS	3291	0.0002	0.0083	-0.0676	0.0522
	CAN	3291	0.0003	0.0103	-0.0926	0.0532
	JAP	3291	0.0000	0.0120	-0.0651	0.0681
bonds	US	3291	0.0003	0.0055	-0.0312	0.0203
	UK	3291	0.0003	0.0049	-0.0351	0.0323
	GER	3291	0.0003	0.0052	-0.0343	0.0253
	FR	3291	0.0003	0.0046	-0.0233	0.0212
	ITA	3291	0.0004	0.0057	-0.0418	0.0296
	AUS	3291	0.0003	0.0054	-0.0328	0.0282
	CAN	3291	0.0003	0.0049	-0.0299	0.0247
	JAP	3291	0.0002	0.0043	-0.0320	0.0247

Table 2: Stock-bond cross-county and within-country correlations

This table shows the unconditional correlation coefficients of cross-country and cross-asset stock and bond market returns. The upper triangular matrix contains cross-country bond market returns, the lower triangular matrix contains cross-country stock market returns and the main diagonal of the matrix contains (cross-asset) stock-bond correlations for each country.

	US	*UK*	*GER*	*FRA*	*ITA*	*AUS*	*CAN*	*JAP*
US	**-0.0149**	0.4617	0.4753	0.4400	0.3670	0.0907	0.7806	0.0558
UK	0.4117	**-0.0321**	0.7355	0.7236	0.6038	0.1642	0.4320	0.0797
GER	0.4725	0.7094	**-0.0564**	0.8986	0.7257	0.1870	0.4521	0.0849
FRA	0.4336	0.7967	0.7868	**0.0102**	0.7467	0.1957	0.4220	0.0846
ITA	0.3648	0.6727	0.6750	0.7427	**0.1852**	0.1664	0.3743	0.0507
AUS	0.0834	0.2484	0.2593	0.2407	0.2162	**0.1132**	0.1695	0.1472
CAN	0.6651	0.4070	0.4505	0.4311	0.3597	0.1577	**0.0348**	0.0375
JAP	0.1003	0.2292	0.2177	0.2349	0.1872	0.4078	0.1505	**-0.2056**

Table 3: Unconditional stock-bond correlations for four sub-samples

The table shows the unconditional correlation coefficients of cross-asset stock and bond market returns.

	1994-1997	*1997-2001*	*2001-2005*	*2005-2006*
US	0.4843	-0.0691	-0.2898	0.0532
UK	0.5020	-0.0932	-0.3577	-0.0809
GER	0.3029	0.0194	-0.3678	-0.0536
FRA	0.5676	-0.0022	-0.4083	-0.0728
ITA	0.5893	0.0805	-0.3486	0.0023
AUS	0.3788	0.0431	-0.2003	-0.0336
CAN	0.3788	-0.0121	-0.2217	-0.0070
JAP	-0.1942	-0.1602	-0.2407	-0.3531

Table 4: Hypotheses tests

This table contains the test statistics of hypothesis tests assessing the existence of flight to quality (FTQ), flight from quality (FFQ) and asymmetries between extreme lower and extreme upper quantiles.

	FTQ				*FTQ?*	*FFQ*				*FFQ?*	*Asymmetry*			*Asymmetry?*
US	q1=q5=q10=q50	q1=q50	q5=q50	q10=q50		q99=q95=q90=q50	q99=q50	q95=q50	q90=q50		q1=q99	q5=q95	q10=q90	
	9.66	18.16	26.62	17.27		11.90	15.55	33.99	23.68		1.00	0.39	0.25	
	0.00	0.00	0.00	0.00	**YES**	0.00	0.00	0.00	0.00	**YES**	0.32	0.53	0.62	**NO**
UK	q1=q5=q10=q50	q1=q50	q5=q50	q10=q50		q99=q95=q90=q50	q99=q50	q95=q50	q90=q50		q1=q99	q5=q95	q10=q90	
	5.71	6.31	16.69	6.45		8.43	12.64	24.82	11.80		0.84	0.85	0.39	
	0.00	0.01	0.00	0.01	**YES**	0.00	0.00	0.00	0.00	**YES**	0.36	0.36	0.53	**NO**
GER	q1=q5=q10=q50	q1=q50	q5=q50	q10=q50		q99=q95=q90=q50	q99=q50	q95=q50	q90=q50		q1=q99	q5=q95	q10=q90	
	9.59	8.10	14.33	27.76		4.31	6.27	9.07	9.92		0.07	1.21	1.49	
	0.00	0.00	0.00	0.00	**YES**	0.00	0.01	0.00	0.00	**YES**	0.79	0.27	0.22	**NO**
FR	q1=q5=q10=q50	q1=q50	q5=q50	q10=q50		q99=q95=q90=q50	q99=q50	q95=q50	q90=q50		q1=q99	q5=q95	q10=q90	
	13.11	30.20	28.18	17.77		8.83	23.99	18.01	11.11		0.02	1.01	0.58	
	0.00	0.00	0.00	0.00	**YES**	0.00	0.00	0.00	0.00	**YES**	0.89	0.31	0.45	**NO**
ITA	q1=q5=q10=q50	q1=q50	q5=q50	q10=q50		q99=q95=q90=q50	q99=q50	q95=q50	q90=q50		q1=q99	q5=q95	q10=q90	
	1.84	3.79	3.67	0.97		0.24	0.16	0.43	0.00		0.59	0.72	0.37	
	0.14	0.05	0.06	0.33	**NO**	0.87	0.69	0.51	0.95	**NO**	0.44	0.40	0.54	**NO**
AUS	q1=q5=q10=q50	q1=q50	q5=q50	q10=q50		q99=q95=q90=q50	q99=q50	q95=q50	q90=q50		q1=q99	q5=q95	q10=q90	
	0.20	0.53	0.42	0.28		1.01	1.43	0.10	0.14		0.05	0.45	0.38	
	0.89	0.47	0.52	0.60	**NO**	0.39	0.23	0.75	0.71	**NO**	0.82	0.50	0.54	**NO**
CAN	q1=q5=q10=q50	q1=q50	q5=q50	q10=q50		q99=q95=q90=q50	q99=q50	q95=q50	q90=q50		q1=q99	q5=q95	q10=q90	
	2.14	5.07	3.97	3.57		6.88	11.71	15.64	2.49		2.26	0.95	0.35	
	0.09	0.02	0.05	0.06	**YES**	0.00	0.00	0.00	0.11	**YES**	0.13	0.33	0.55	**NO**
JAP	q1=q5=q10=q50	q1=q50	q5=q50	q10=q50		q99=q95=q90=q50	q99=q50	q95=q50	q90=q50		q1=q99	q5=q95	q10=q90	
	1.37	0.10	2.44	0.98		1.31	0.49	0.22	2.56		0.62	0.45	0.46	
	0.25	0.75	0.12	0.32	**NO**	0.27	0.48	0.64	0.11	**NO**	0.43	0.50	0.50	**NO**

Figure 1: Capital Allocation Line

This graph shows under which conditions flight to quality (FTQ) and flight from quality (FFQ) can occur. If investors are over-invested in the risk-free asset, there is a risk of a flight from quality if a threshold q* is exceeded. Similarly, if investors are over-invested in the risky portfolio, there is a risk of a flight to quality if a threshold q* is exceeded. Note that μ(X*) and the associated band is time-varying.

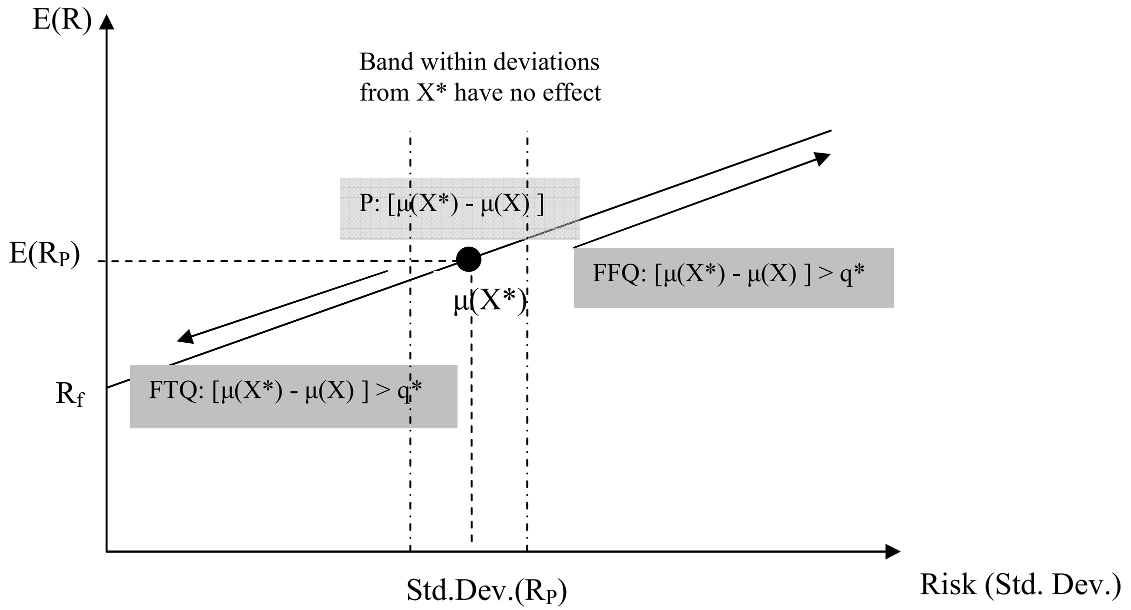


Figure 2: Stock market indices

This figure shows the evolution of the stock market indices of the eight countries in the sample through time. The sample period is 1994 to 2006.

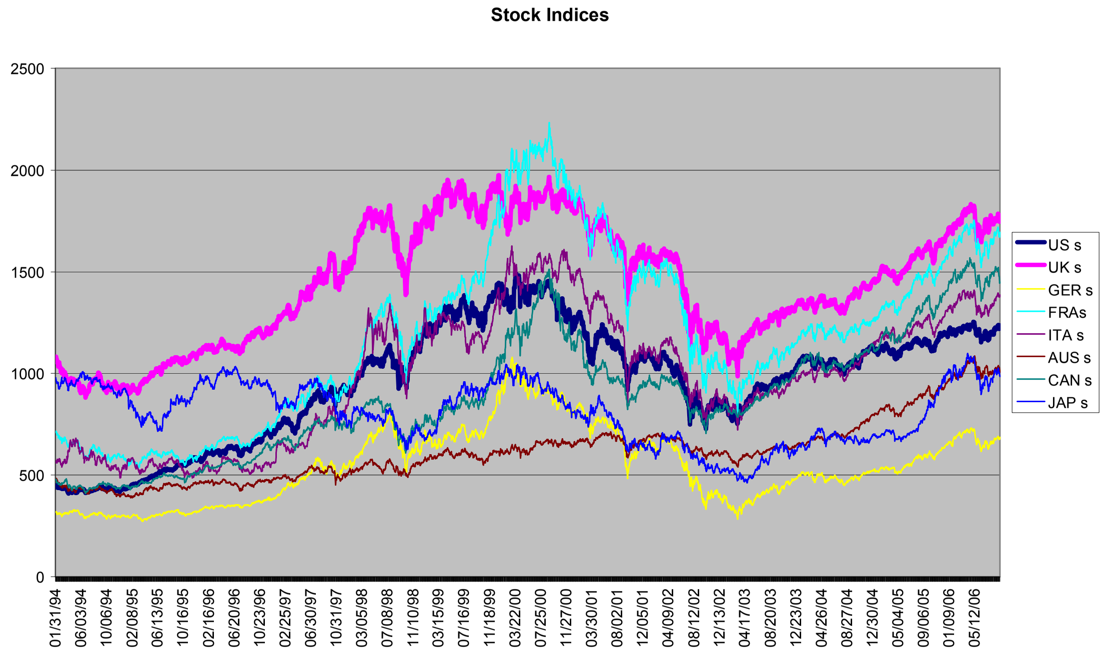


Figure 3: Bond market indices

This figure shows the evolution of the bond market indices of the eight countries in the sample through time. The sample period is 1994 to 2006.

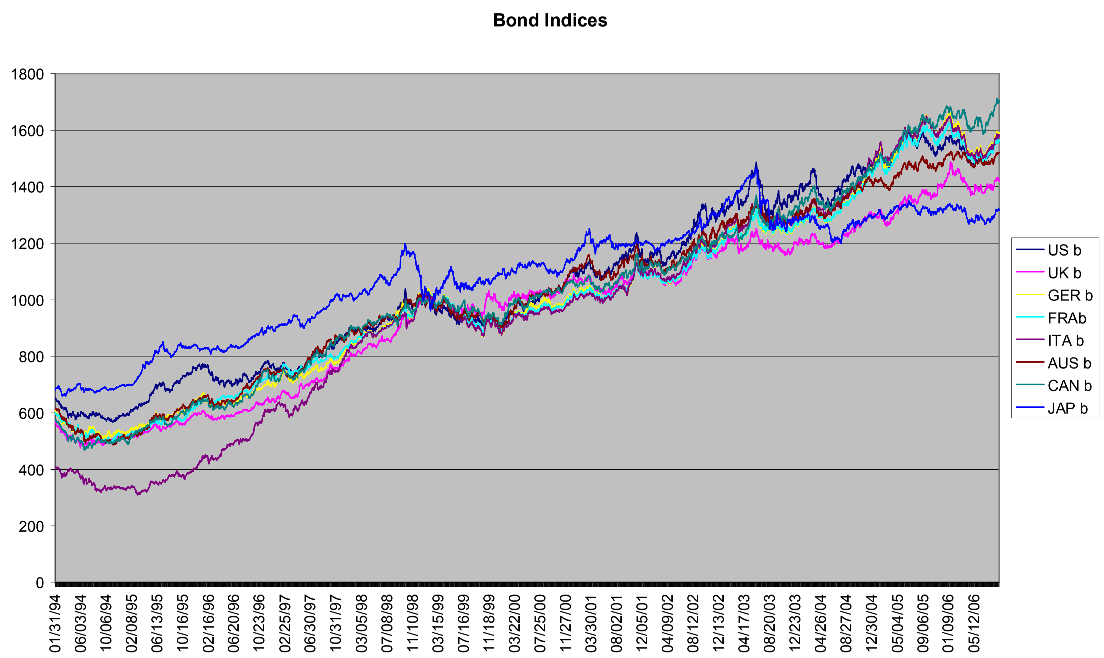


Figure 4: QR estimates (daily data, US stocks on US bonds)

Model: $r_{s,it} = a_i + b_i\ r_{b,it} + v_{it}$, $Q_r(\tau|r_{b,it}) = a_i(\tau) + b_i(\tau)\ r_{b,it}$

This figure shows the coefficient estimates of the co-movement between stocks and bonds conditional on different stock market conditions (bad conditions (low quantiles), tranquil conditions (intermediate quantiles) and good conditions (high quantiles)). The horizontal axis shows the quantiles and the vertical axis shows the coefficient estimates (b_i).

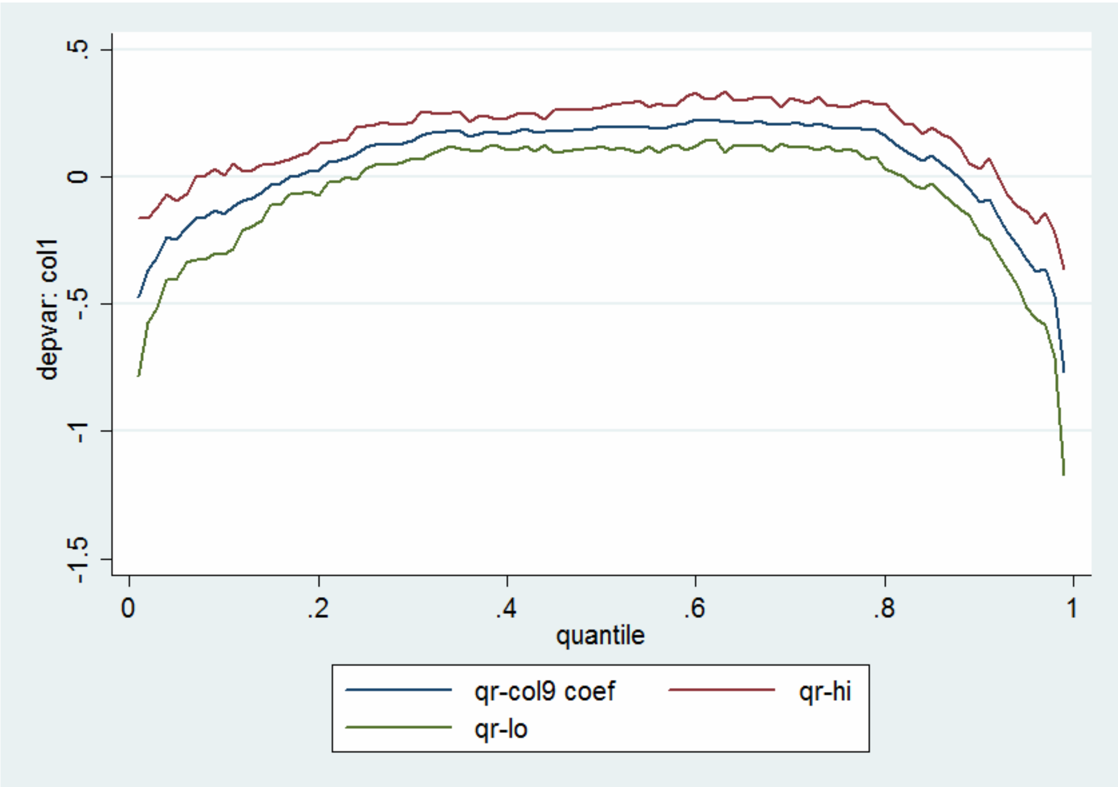


Figure 5: QR estimates (weekly data, US stocks on US bonds)

Model: $r_{s,it} = a_i + b_i\, r_{b,it} + v_{it}$, $Q_r(\tau|r_{b,it}) = a_i(\tau) + b_i(\tau)\, r_{b,it}$

This figure shows the coefficient estimates of the co-movement between stocks and bonds conditional on different stock market conditions (bad conditions (low quantiles), tranquil conditions (intermediate quantiles) and good conditions (high quantiles)). The horizontal axis shows the quantiles and the vertical axis shows the coefficient estimates (b_i).

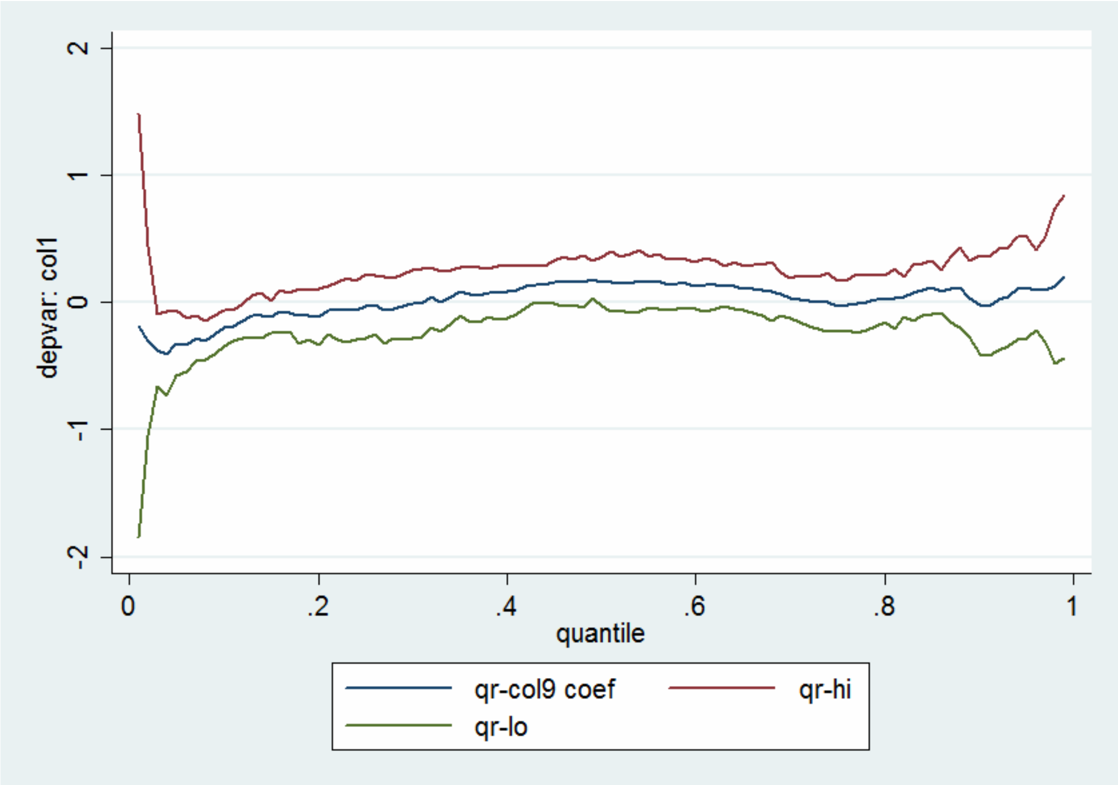


Figure 6: QR estimates (daily data, UK stocks on UK bonds)

Model: $r_{s,it} = a_i + b_i\, r_{b,it} + v_{it}$, $Q_r(\tau|r_{b,it}) = a_i(\tau) + b_i(\tau)\, r_{b,it}$

This figure shows the coefficient estimates of the co-movement between stocks and bonds conditional on different stock market conditions (bad conditions (low quantiles), tranquil conditions (intermediate quantiles) and good conditions (high quantiles)). The horizontal axis shows the quantiles and the vertical axis shows the coefficient estimates (b_i).

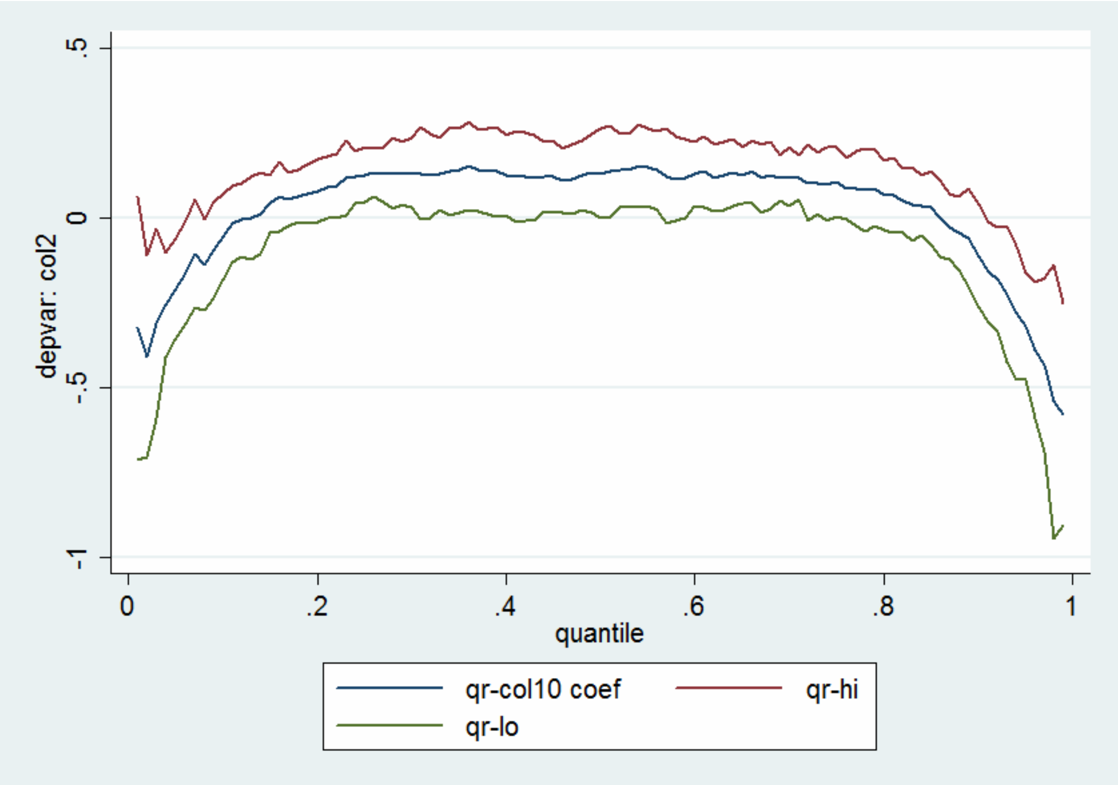


Figure 7: QR estimates (weekly data, UK stocks on UK bonds)

Model: $r_{s,it} = a_i + b_i\ r_{b,it} + v_{it}$, $Q_r(\tau|r_{b,it}) = a_i(\tau) + b_i(\tau)\ r_{b,it}$

This figure shows the coefficient estimates of the co-movement between stocks and bonds conditional on different stock market conditions (bad conditions (low quantiles), tranquil conditions (intermediate quantiles) and good conditions (high quantiles)). The horizontal axis shows the quantiles and the vertical axis shows the coefficient estimates (b_i).

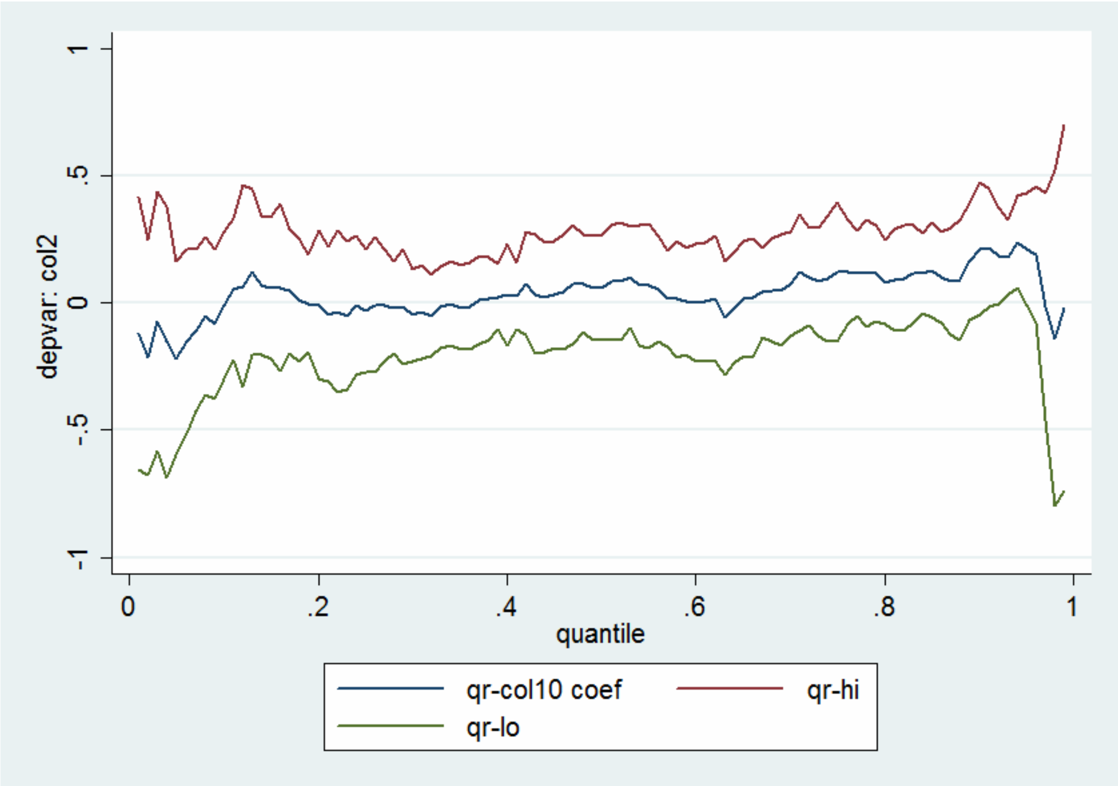


Figure 8: QR estimates (daily data, GER stocks on GER bonds)

Model: $r_{s,it} = a_i + b_i\, r_{b,it} + v_{it}$, $Q_r(\tau|r_{b,it}) = a_i(\tau) + b_i(\tau)\, r_{b,it}$

This figure shows the coefficient estimates of the co-movement between stocks and bonds conditional on different stock market conditions (bad conditions (low quantiles), tranquil conditions (intermediate quantiles) and good conditions (high quantiles)). The horizontal axis shows the quantiles and the vertical axis shows the coefficient estimates (b_i).

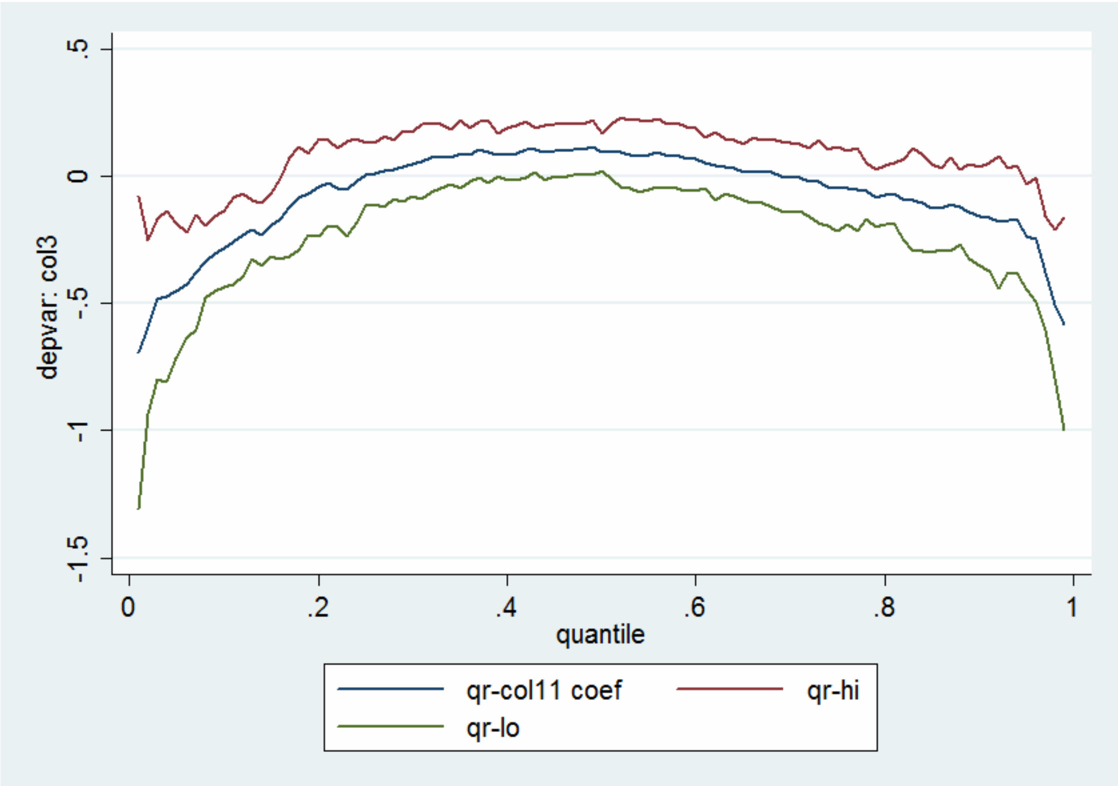


Figure 9: QR estimates (weekly data, GER stocks on GER bonds)

Model: $r_{s,it} = a_i + b_i\, r_{b,it} + v_{it}$, $Q_r(\tau|r_{b,it}) = a_i(\tau) + b_i(\tau)\, r_{b,it}$

This figure shows the coefficient estimates of the co-movement between stocks and bonds conditional on different stock market conditions (bad conditions (low quantiles), tranquil conditions (intermediate quantiles) and good conditions (high quantiles)). The horizontal axis shows the quantiles and the vertical axis shows the coefficient estimates (b_i).

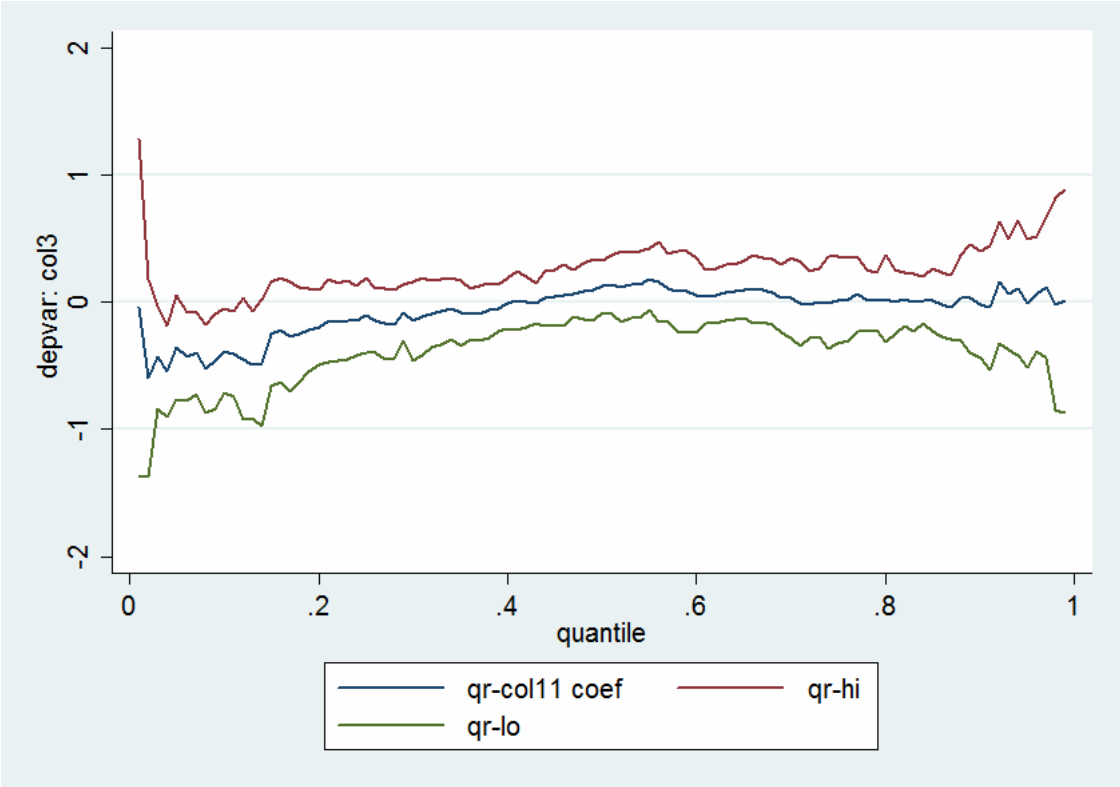


Figure 10: QR estimates (daily data, FR stocks on FR bonds)

Model: $r_{s,it} = a_i + b_i\, r_{b,it} + v_{it}$, $Q_r(\tau|r_{b,it}) = a_i(\tau) + b_i(\tau)\, r_{b,it}$

This figure shows the coefficient estimates of the co-movement between stocks and bonds conditional on different stock market conditions (bad conditions (low quantiles), tranquil conditions (intermediate quantiles) and good conditions (high quantiles)). The horizontal axis shows the quantiles and the vertical axis shows the coefficient estimates (b_i).

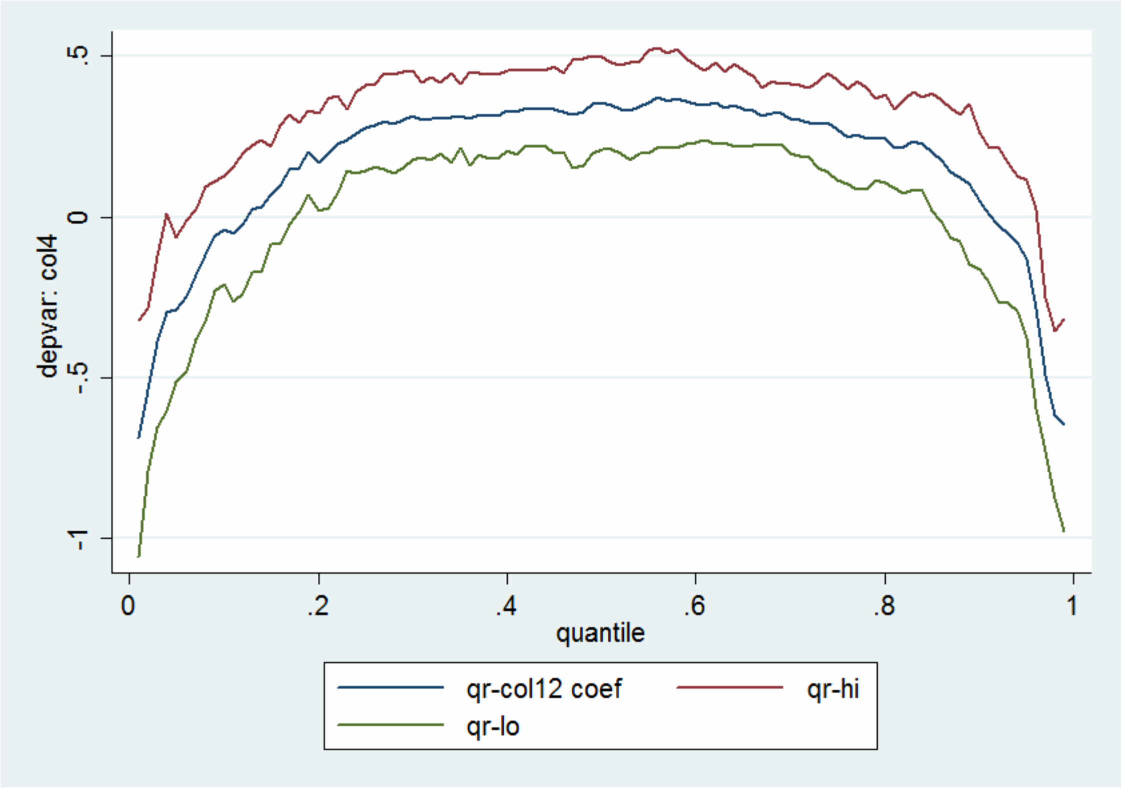


Figure 11: QR estimates (weekly data, FR stocks on FR bonds)

Model: $r_{s,it} = a_i + b_i\ r_{b,it} + v_{it}$, $Q_r(\tau|r_{b,it}) = a_i(\tau) + b_i(\tau)\ r_{b,it}$

This figure shows the coefficient estimates of the co-movement between stocks and bonds conditional on different stock market conditions (bad conditions (low quantiles), tranquil conditions (intermediate quantiles) and good conditions (high quantiles)). The horizontal axis shows the quantiles and the vertical axis shows the coefficient estimates (b_i).

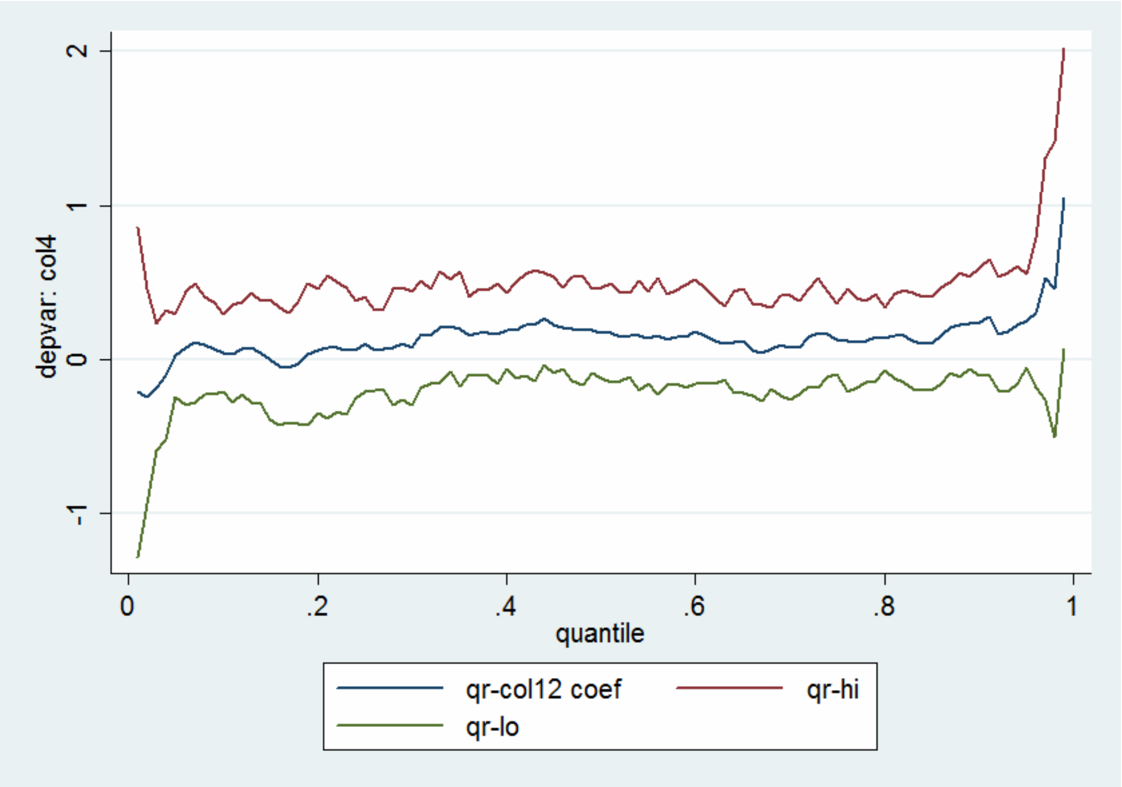


Figure 12: QR estimates (daily data, ITA stocks on ITA bonds)

Model: $r_{s,it} = a_i + b_i\, r_{b,it} + v_{it}$, $Q_r(\tau|r_{b,it}) = a_i(\tau) + b_i(\tau)\, r_{b,it}$

This figure shows the coefficient estimates of the co-movement between stocks and bonds conditional on different stock market conditions (bad conditions (low quantiles), tranquil conditions (intermediate quantiles) and good conditions (high quantiles)). The horizontal axis shows the quantiles and the vertical axis shows the coefficient estimates (b_i).

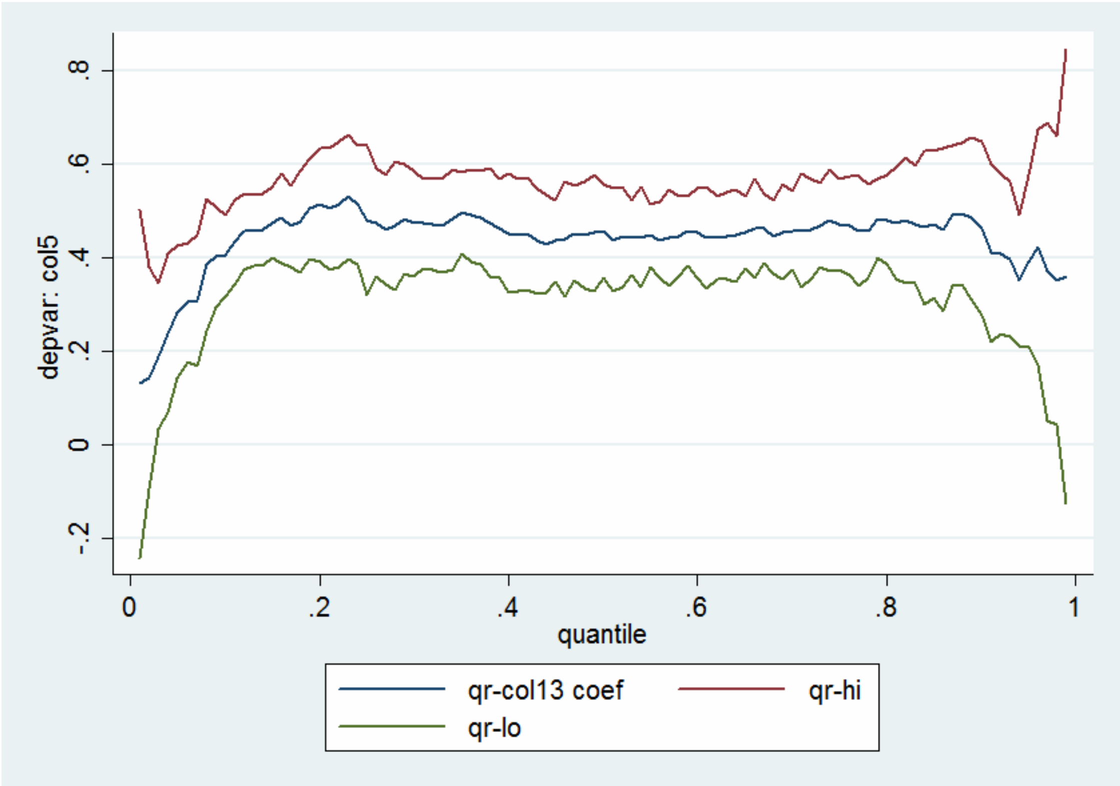


Figure 13: QR estimates (weekly data, ITA stocks on ITA bonds)

Model: $r_{s,it} = a_i + b_i\, r_{b,it} + v_{it}$, $Q_r(\tau|r_{b,it}) = a_i(\tau) + b_i(\tau)\, r_{b,it}$

This figure shows the coefficient estimates of the co-movement between stocks and bonds conditional on different stock market conditions (bad conditions (low quantiles), tranquil conditions (intermediate quantiles) and good conditions (high quantiles)). The horizontal axis shows the quantiles and the vertical axis shows the coefficient estimates (b_i).

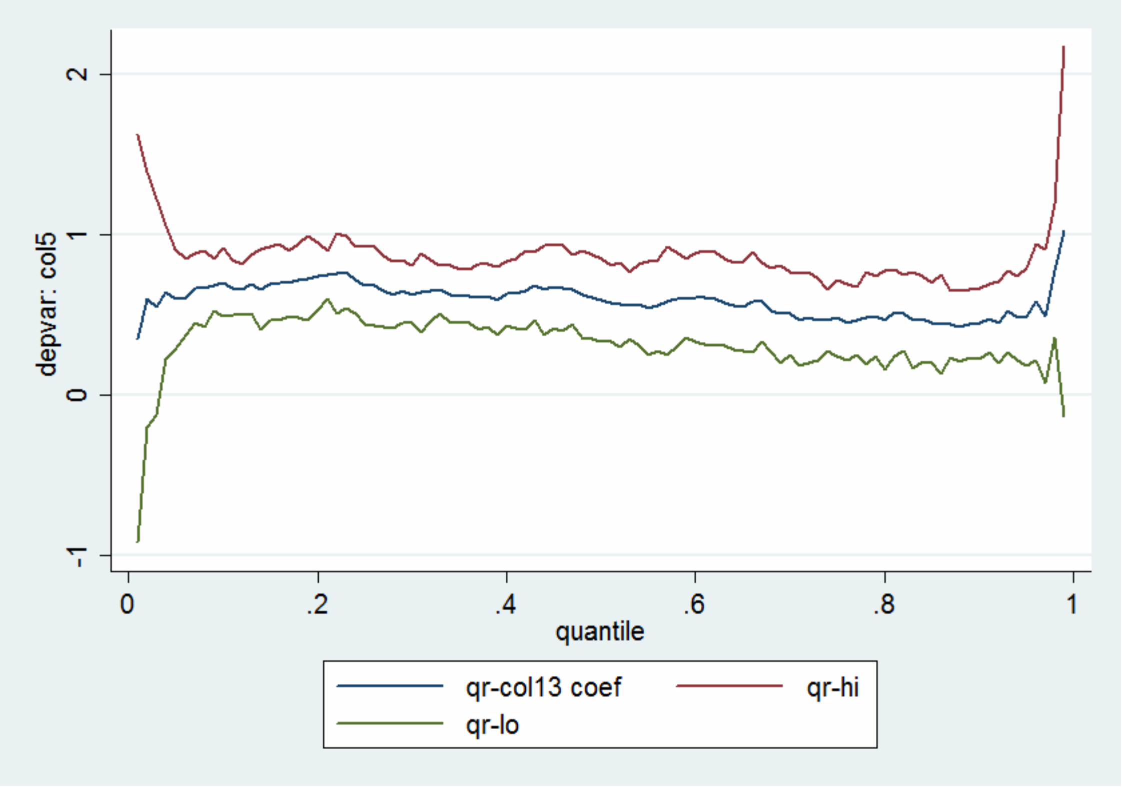


Figure 14: QR estimates (daily data, AUS stocks on AUS bonds)

Model: $r_{s,it} = a_i + b_i\, r_{b,it} + v_{it}$, $Q_r(\tau|r_{b,it}) = a_i(\tau) + b_i(\tau)\, r_{b,it}$

This figure shows the coefficient estimates of the co-movement between stocks and bonds conditional on different stock market conditions (bad conditions (low quantiles), tranquil conditions (intermediate quantiles) and good conditions (high quantiles)). The horizontal axis shows the quantiles and the vertical axis shows the coefficient estimates (b_i).

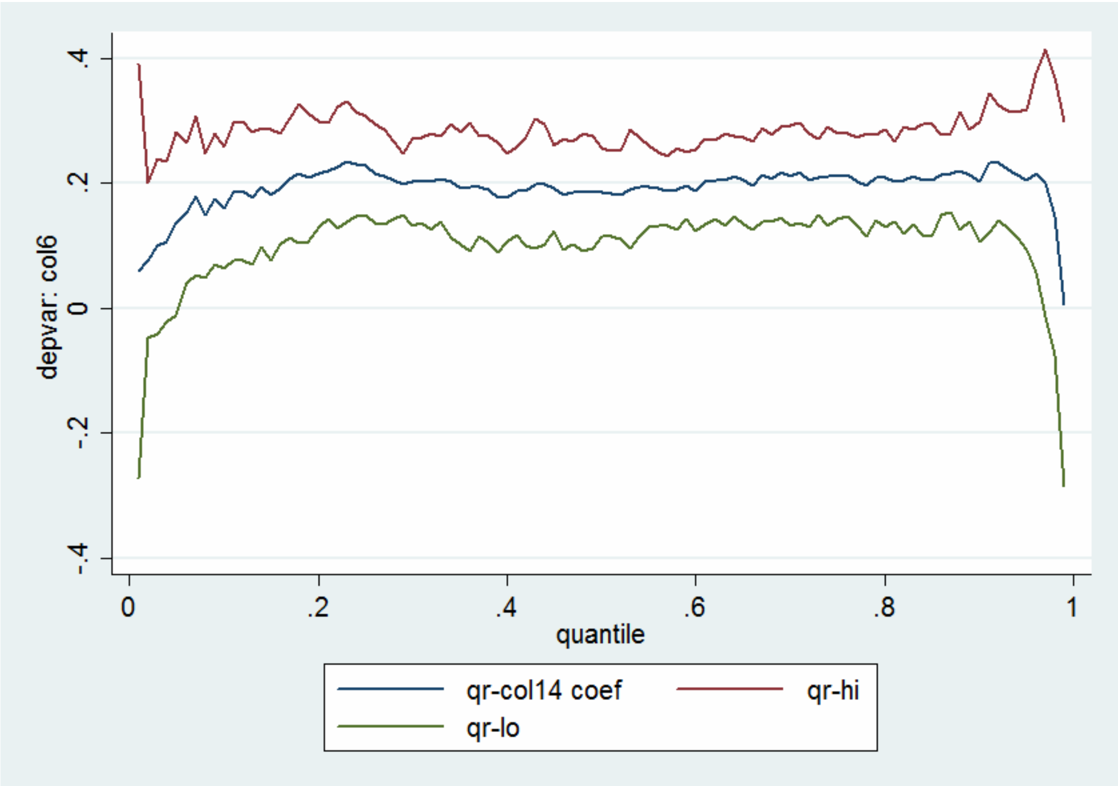


Figure 15: QR estimates (weekly data, AUS stocks on AUS bonds)

Model: $r_{s,it} = a_i + b_i\, r_{b,it} + v_{it}$, $Q_r(\tau|r_{b,it}) = a_i(\tau) + b_i(\tau)\, r_{b,it}$

This figure shows the coefficient estimates of the co-movement between stocks and bonds conditional on different stock market conditions (bad conditions (low quantiles), tranquil conditions (intermediate quantiles) and good conditions (high quantiles)). The horizontal axis shows the quantiles and the vertical axis shows the coefficient estimates (b_i).

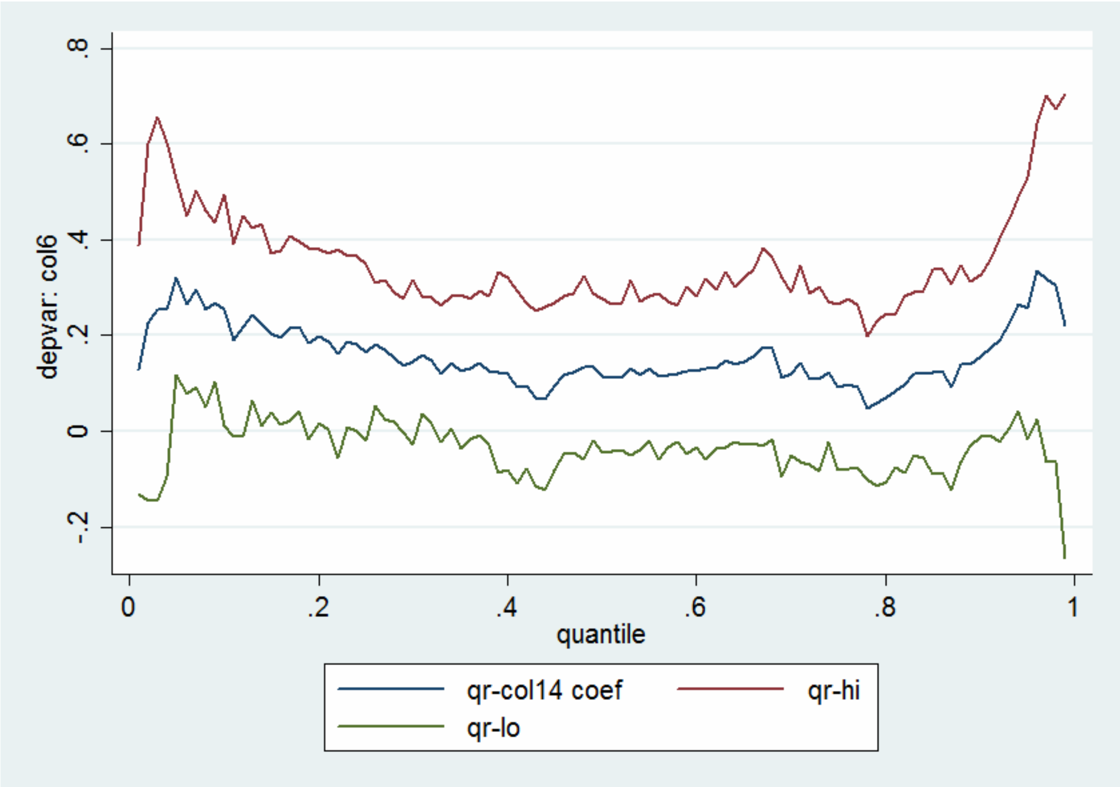


Figure 16: QR estimates (daily data, CAN stocks on CAN bonds)

Model: $r_{s,it} = a_i + b_i\, r_{b,it} + v_{it}$, $Q_r(\tau|r_{b,it}) = a_i(\tau) + b_i(\tau)\, r_{b,it}$

This figure shows the coefficient estimates of the co-movement between stocks and bonds conditional on different stock market conditions (bad conditions (low quantiles), tranquil conditions (intermediate quantiles) and good conditions (high quantiles)). The horizontal axis shows the quantiles and the vertical axis shows the coefficient estimates (b_i).

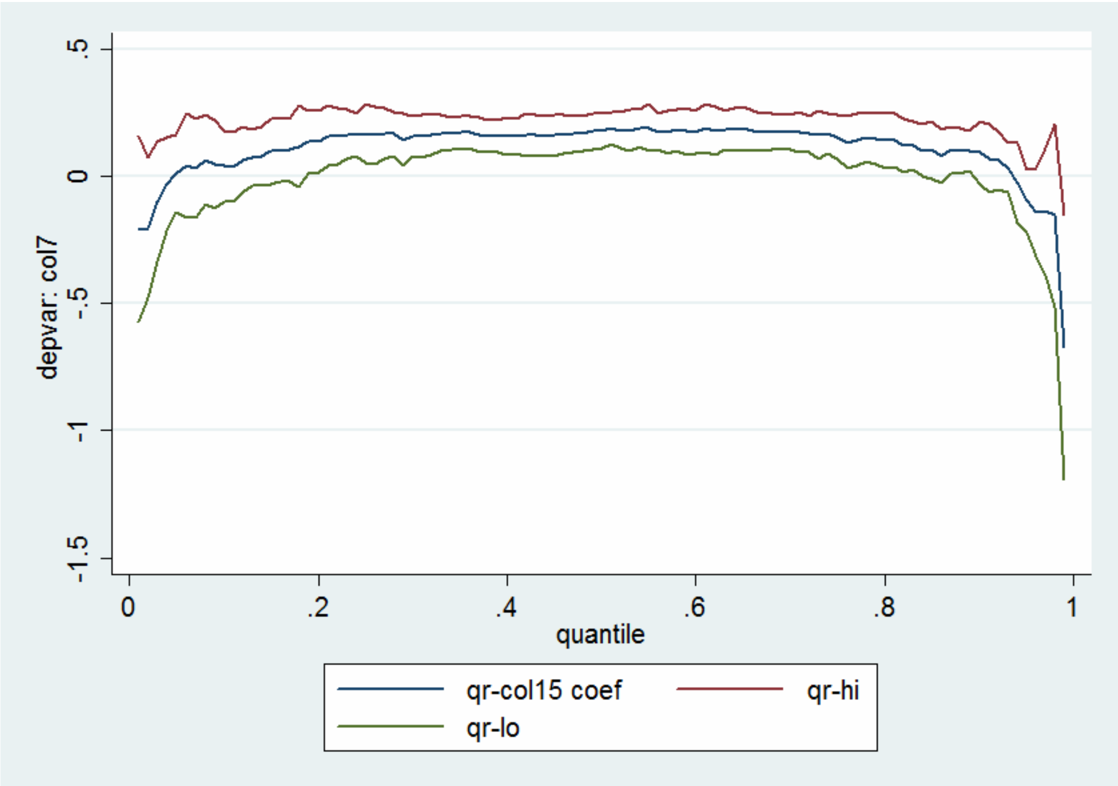


Figure 17: QR estimates (weekly data, CAN stocks on CAN bonds)

Model: $r_{s,it} = a_i + b_i\, r_{b,it} + v_{it}$, $Q_r(\tau|r_{b,it}) = a_i(\tau) + b_i(\tau)\, r_{b,it}$

This figure shows the coefficient estimates of the co-movement between stocks and bonds conditional on different stock market conditions (bad conditions (low quantiles), tranquil conditions (intermediate quantiles) and good conditions (high quantiles)). The horizontal axis shows the quantiles and the vertical axis shows the coefficient estimates (b_i).

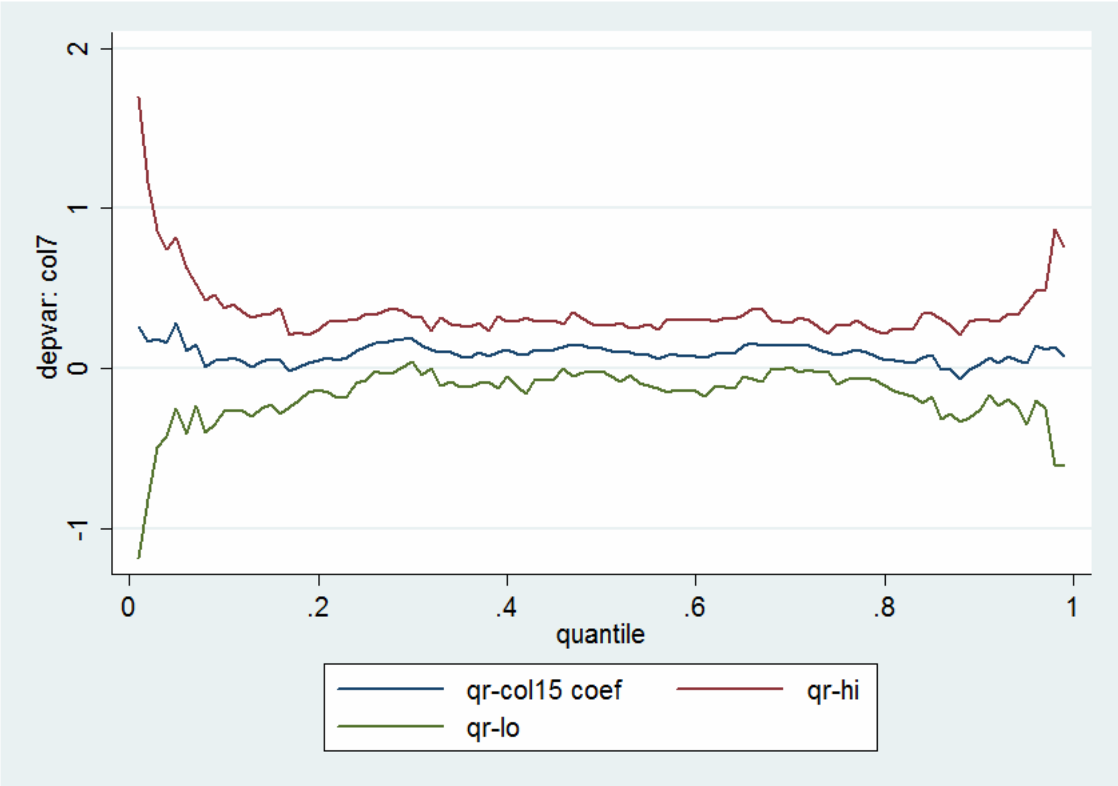


Figure 18: QR estimates (daily data, JAP stocks on JAP bonds)

Model: $r_{s,it} = a_i + b_i\, r_{b,it} + v_{it}$, $Q_r(\tau|r_{b,it}) = a_i(\tau) + b_i(\tau)\, r_{b,it}$

This figure shows the coefficient estimates of the co-movement between stocks and bonds conditional on different stock market conditions (bad conditions (low quantiles), tranquil conditions (intermediate quantiles) and good conditions (high quantiles)). The horizontal axis shows the quantiles and the vertical axis shows the coefficient estimates (b_i).

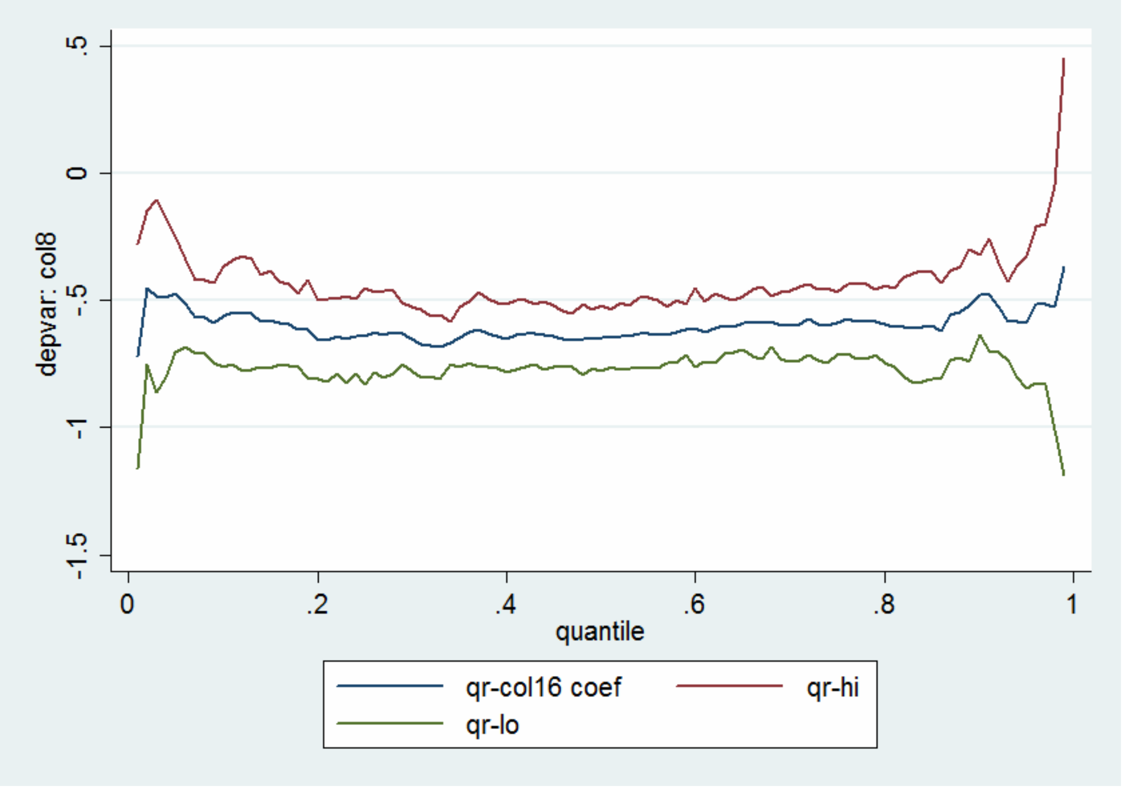


Figure 19: QR estimates (weekly data, JAP stocks on JAP bonds)

Model: $r_{s,it} = a_i + b_i\, r_{b,it} + v_{it}$, $Q_r(\tau|r_{b,it}) = a_i(\tau) + b_i(\tau)\, r_{b,it}$

This figure shows the coefficient estimates of the co-movement between stocks and bonds conditional on different stock market conditions (bad conditions (low quantiles), tranquil conditions (intermediate quantiles) and good conditions (high quantiles)). The horizontal axis shows the quantiles and the vertical axis shows the coefficient estimates (b_i).

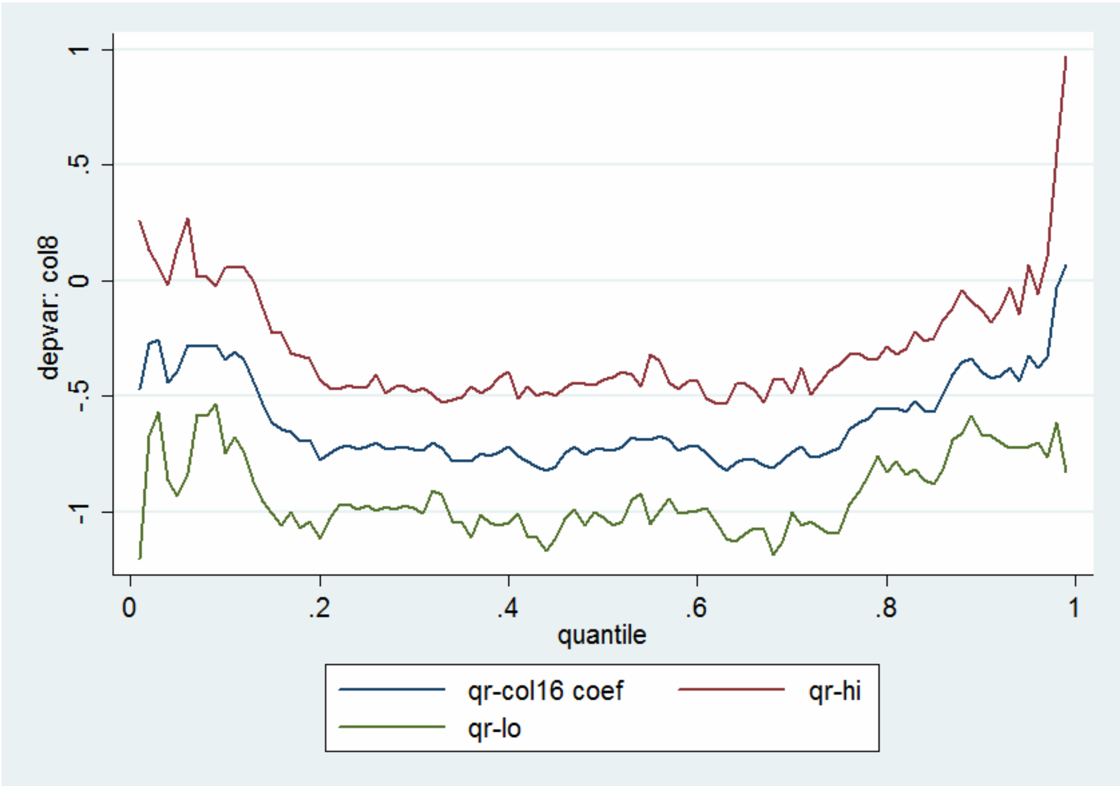


Figure 20: Time-varying coefficient estimates (US)

This figure shows the dynamic (recursively estimated) coefficient estimates of the co-movement between stocks and bonds for the 1%, 50% and 99% quantile.

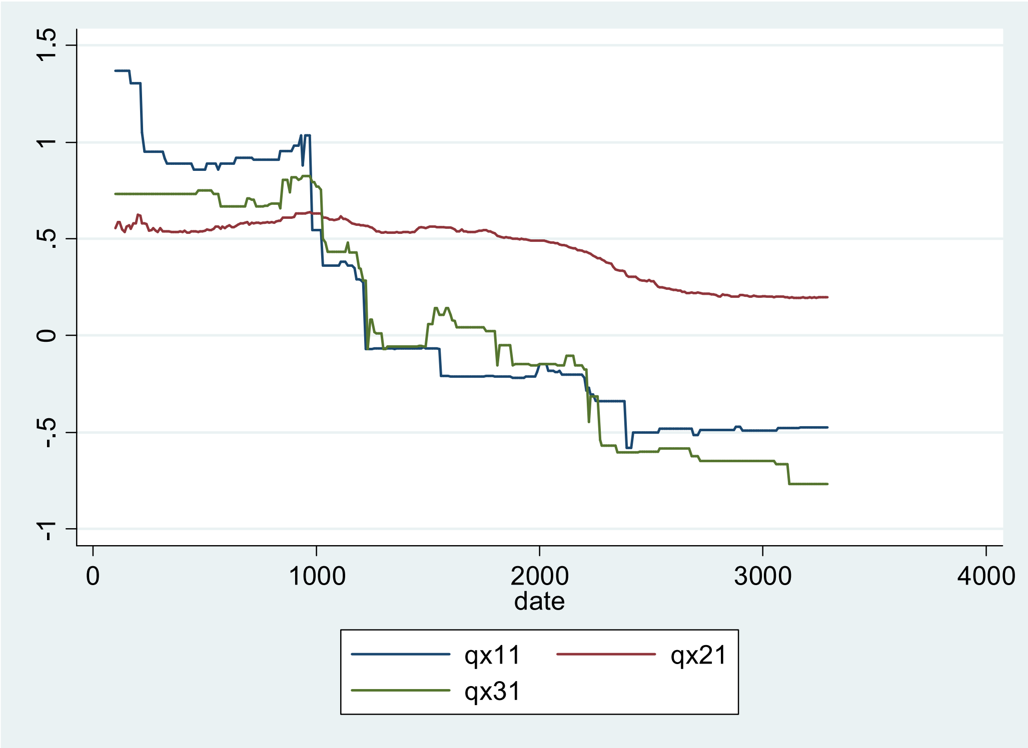


Figure 21: Time-varying coefficient estimates (UK)

This figure shows the dynamic (recursively estimated) coefficient estimates of the co-movement between stocks and bonds for the 1%, 50% and 99% quantile.

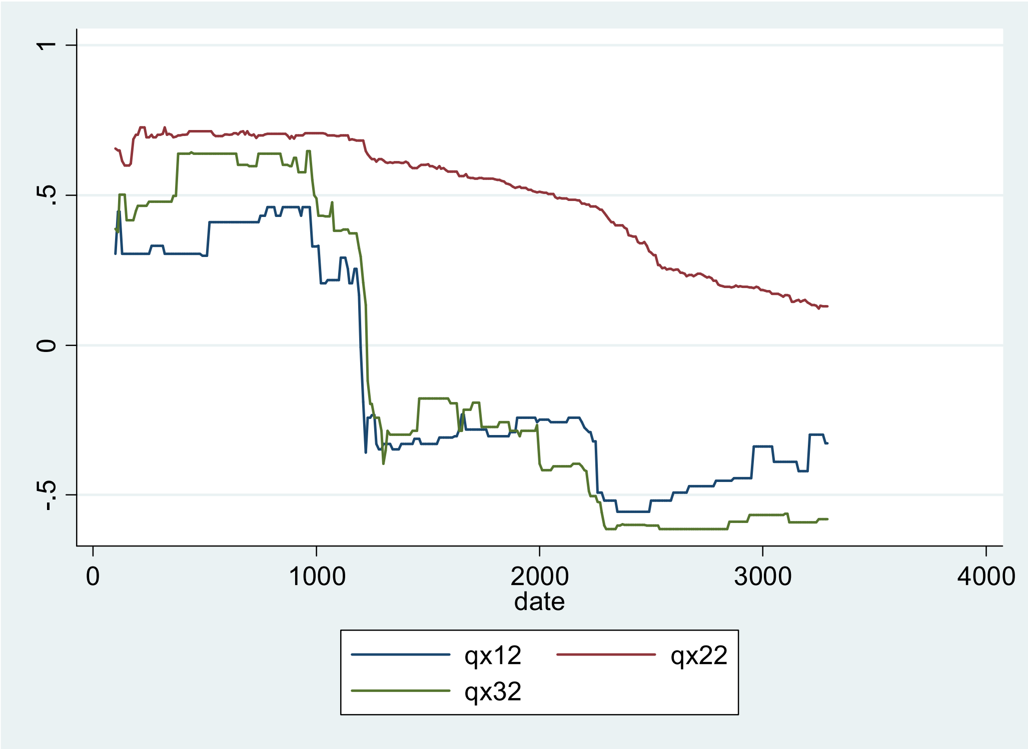


Figure 22: Time-varying coefficient estimates (GER)

This figure shows the dynamic (recursively estimated) coefficient estimates of the co-movement between stocks and bonds for the 1%, 50% and 99% quantile.

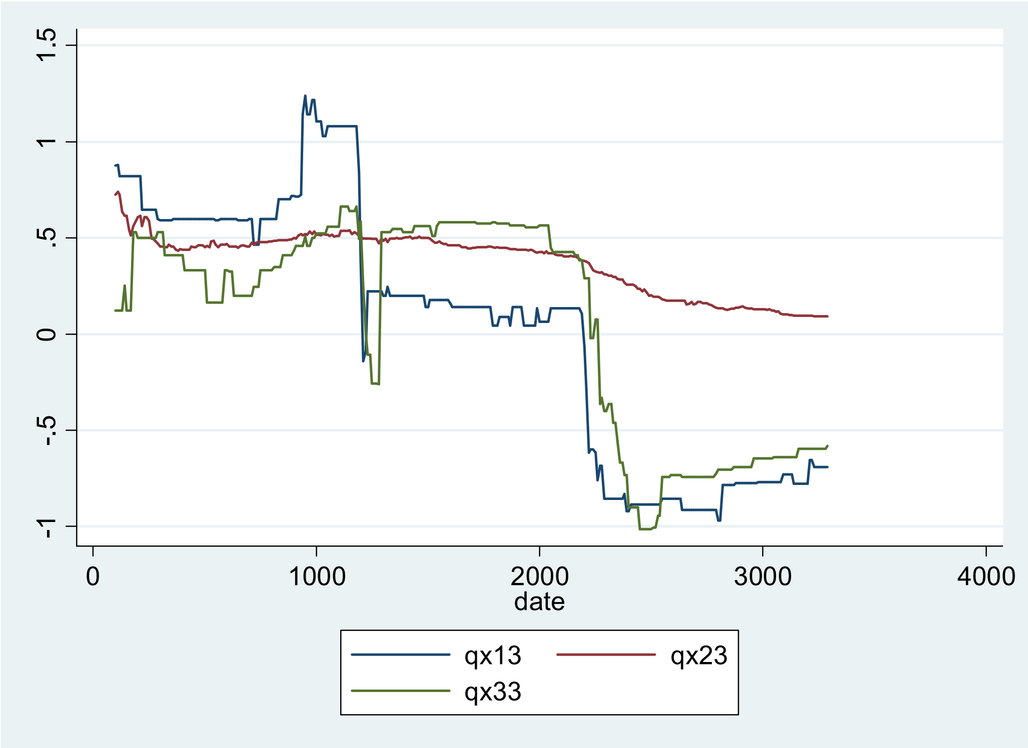


Figure 23: Time-varying coefficient estimates (FRA)

This figure shows the dynamic (recursively estimated) coefficient estimates of the co-movement between stocks and bonds for the 1%, 50% and 99% quantile.

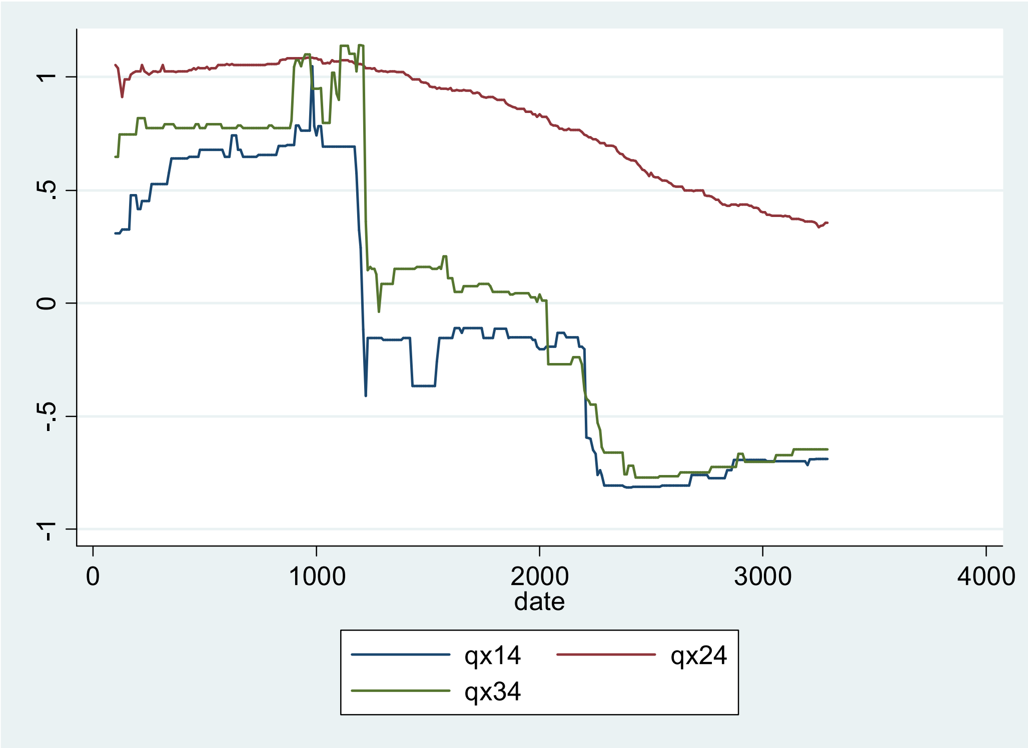


Figure 24: Time-varying coefficient estimates (ITA)

This figure shows the dynamic (recursively estimated) coefficient estimates of the co-movement between stocks and bonds for the 1%, 50% and 99% quantile.

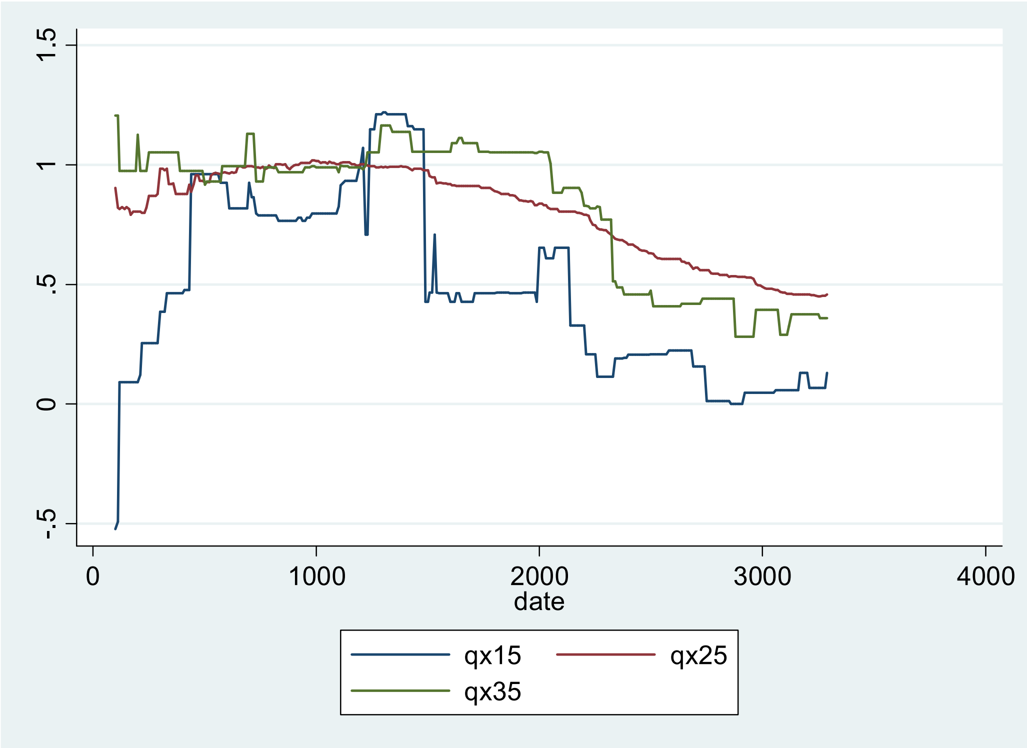


Figure 25: Time-varying coefficient estimates (AUS)

This figure shows the dynamic (recursively estimated) coefficient estimates of the co-movement between stocks and bonds for the 1%, 50% and 99% quantile.

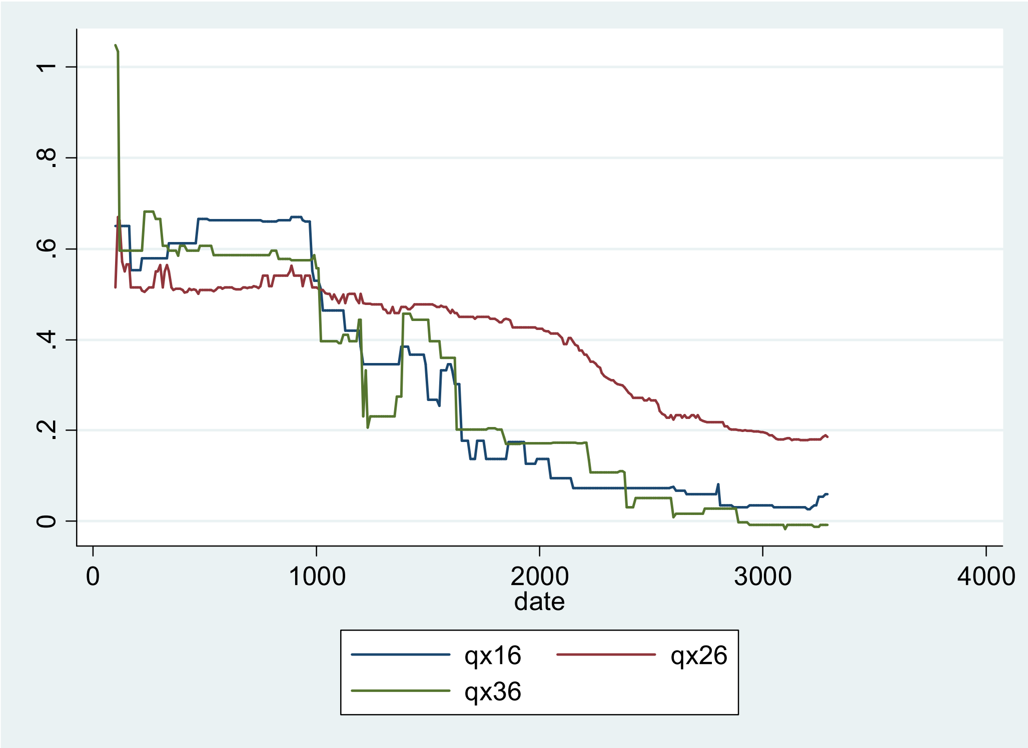


Figure 26: Time-varying coefficient estimates (CAN)

This figure shows the dynamic (recursively estimated) coefficient estimates of the co-movement between stocks and bonds for the 1%, 50% and 99% quantile.

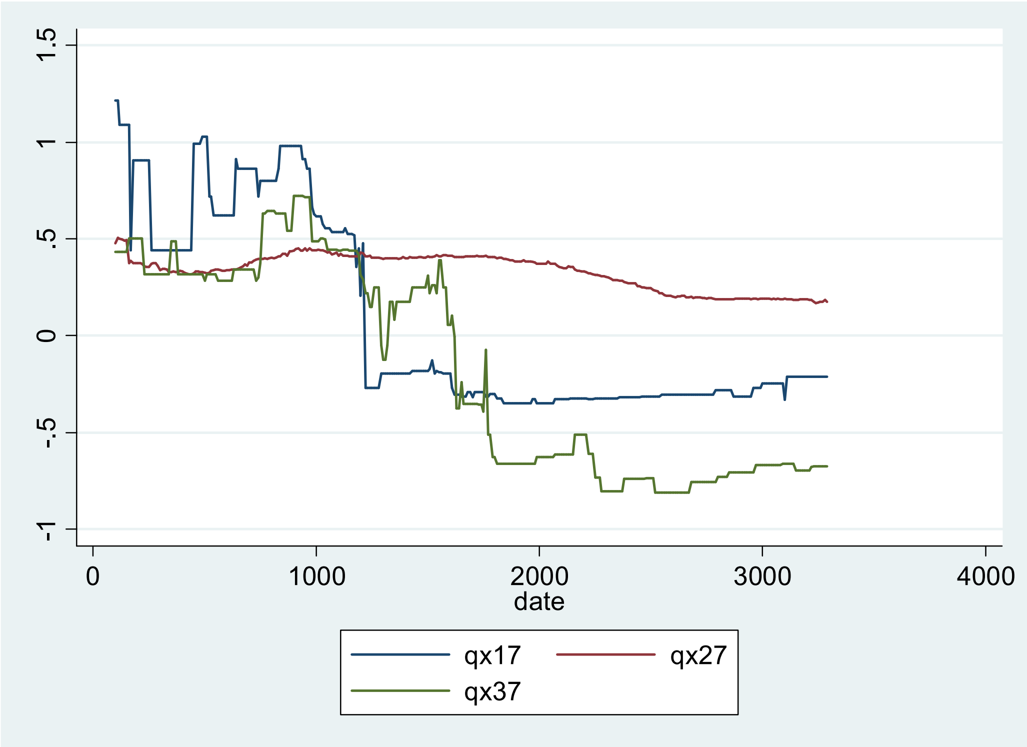
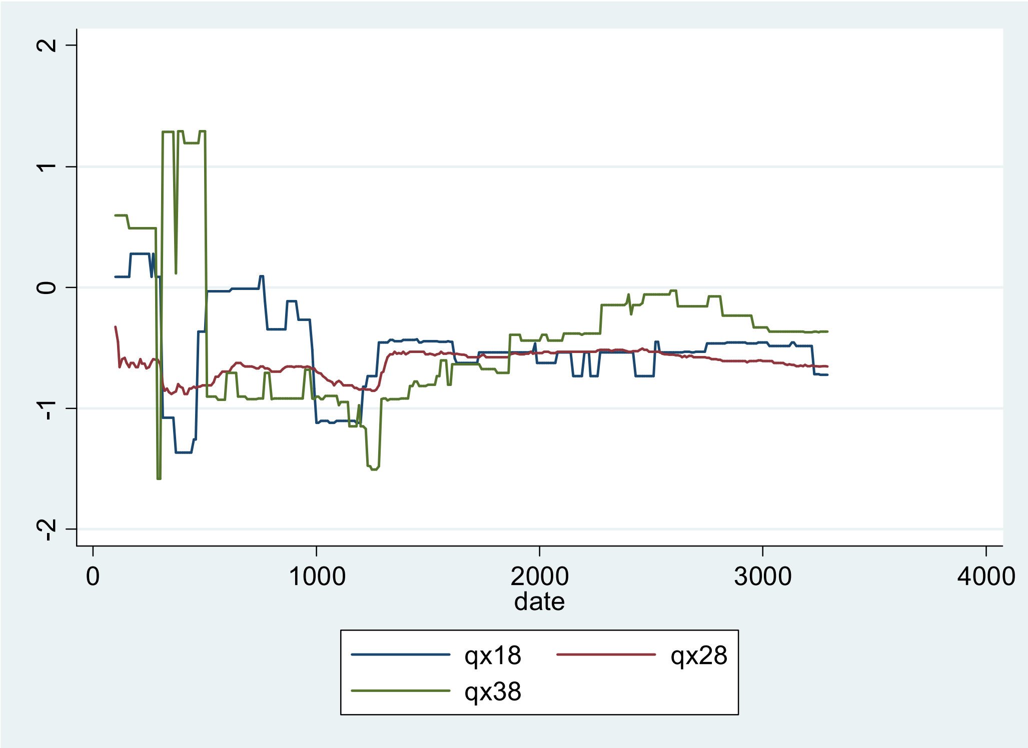


Figure 27: Time-varying coefficient estimates (JAP)

This figure shows the dynamic (recursively estimated) coefficient estimates of the co-movement between stocks and bonds for the 1%, 50% and 99% quantile.



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