

Differences of Opinion and Stock Market Volatility: Evidence from a Nonparametric Causality-in-Quantiles Approach

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Abstract

This paper examines whether the differences of opinion across active money managers relates to stock market volatility via the recently proposed nonparametric causality-in-quantiles test. Using the dispersion in equity market exposures of active managers as a proxy for differences in opinion, we analyze the predictability of (realized) volatility of the S&P500 for the period July, 2006-August, 2016. Unlike the result of no predictability obtained under the misspecified linear set-up, our nonparametric causality-in-quantiles test indicates that dispersion in active managers' risk exposures to the stock market can predict volatility over the range of quantiles that correspond to moderately high levels of market volatility. Our findings are in line with the previous literature that relates divergent beliefs across investors to subsequent stock returns and suggest that the effect on subsequent returns is likely to be transmitted via the volatility channel. Our results highlight the importance of detecting and modeling nonlinearity when analyzing the information content of divergent beliefs across market participants.

Keywords: Realized Volatility; Differences of opinion, Quantile Causality.

JEL Codes: C22, C32, G1.

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1. Introduction

Numerous studies in the literature have examined the role played by active fund managers in determining stock prices (e.g. Gompers and Metrick, 2001; Chen *et al.*, 2002; Kacperczyk *et al.*, 2012; Kaniel and Kondor, 2013; and Vayanos and Woolley, 2013). One strand of this literature has specifically focused on the effect of divergent beliefs across active fund managers on stock market returns. Earlier studies including Diether *et al.* (2002) and Berkman *et al.* (2009) suggest a negative relationship between the level of dispersion in fund managers' beliefs and subsequent stock returns. More recently, Jiang and Sun (2014) show that both the level and the change in dispersion in fund managers' beliefs positively predict subsequent stock returns, even after adjusting for risk. Clearly, this issue is not only important regarding the informational efficiency of the stock market, but also allows one to make inferences regarding the value of active management and the information content reflected by active managers' trades.

A number of alternative proxies have been proposed in the literature to measure the divergent beliefs of market participants. These alternative proxies include the dispersion in analyst earnings forecasts (Diether *et al.*, 2002), the breadth of mutual fund ownership (Chen *et al.*, 2002), the dispersion in retail investor trading (Goetzmann and Massa, 2005), historical income volatility or stock return volatility (Berkman *et al.*, 2009), and more recently, mutual funds' active holdings, i.e. deviations from benchmarks (Jiang and Sun, 2014). In this study, we utilize data from the weekly surveys conducted by the National Association of Active Investment Managers (NAAIM) and use the dispersion in the equity market exposure of active managers as a proxy of divergent beliefs regarding the stock market. The proxy for divergent beliefs used in this study is similar in spirit to the proxies employed by Chen *et al.* (2002) and Jiang and Sun (2014) in that it provides a measure of the cross-sectional deviation in active managers' equity market positions so that the greater the level of heterogeneity in managers' beliefs, the more dispersed the equity market holdings would be across managers. However, an advantage of the proxy employed in this study

is the availability of the equity market exposure data at high frequency, in this case weekly. Equity market exposure data is obtained from the weekly surveys conducted by NAAIM in which active money managers are asked to provide a number that represents their overall equity positions, ranging between 0% (all cash/hedged/market neutral) and 200% (leveraged position). Hence, the first objective of this paper is to capture the dynamic relationship between differences in opinion and realized volatility of returns using the above mentioned proxy.

The second contribution of this study is that we employ the nonparametric causality-in-quantiles test of Jeong *et al.* (2012) to examine the predictability of weekly realized volatility of the S&P500 returns emanating from divergent beliefs of active managers. The causality-in-quantile approach has the following novelties: First, it is robust to misspecification errors as it detects the underlying dependence structure between the examined time series, which could prove to be particularly important as it is well known that equity market returns display nonlinear dynamics (see Bekiros *et al.*, forthcoming, for a detailed discussion in this regard). Second, via this methodology, we are able to test for causality over the entire conditional distribution of the dependent variable (realized volatility in our case), which is particularly important if the dependent variable has fat-tails – as is the case for financial return series. Consequently, the ability of our method to accommodate for nonlinearity and go beyond the causality at the conditional-mean, as is done in standard linear Granger causality tests and GARCH based models, makes the quantile based approach a more general one, and hence, enhances the possibility of detecting predictability by controlling for misspecification. To the best of our knowledge, this is the first paper that relates the divergent beliefs of active managers to the predictability of realized volatility of the S&P500 using a causality-in-quantile approach.

Our tests suggest that dispersion in active managers' risk exposures to the stock market can predict volatility over the range of quantiles that correspond to moderately high levels of market volatility. This is in fact in line with the previous literature that relates divergent beliefs across

investors to subsequent stock returns. However, unlike the previous studies, our tests imply that the effect on subsequent returns is likely to be transmitted via the volatility channel which is consistent with the suggestion by Johnson (2004) that the effect of divergent beliefs on returns can be explained away by financial leverage. Furthermore, given the short-sale constraints that prevent active managers from taking full advantage of negative information, we argue that the effect of divergent beliefs on realized volatility is primarily driven by the large, positive bets placed by informed traders which drives the dispersion in risk exposures across active managers. Overall, our results enhance our understanding of the channels through which divergent beliefs among active managers relate to financial returns and also highlight the importance of detecting and modeling nonlinearity when analyzing the information content of divergent beliefs across market participants. From an investment perspective, the findings underscore the asymmetry in the forecasting power of the dispersion in beliefs with respect to good and bad news and suggest that differentially informed investors can indeed influence return dynamics in financial markets. The rest of the paper is organized as follows: Section 2 presents the methodology, while Section 3 discusses the data and the results. Finally, Section 4 concludes.

2. Methodology

In this section we briefly discuss the basics of the causality-in-quantiles test proposed by Jeong *et al.*, (2012). Our dependent variable is the weekly realized volatility, which is obtained from the daily sum of squared log-returns of the S&P500 over a specific week (see, Andersen and Bollerslev (1998) for more details). The realized volatility of the S&P500 is designated as y_t while the proxy for divergent beliefs is designated as x_t . Based on Jeong *et al.*, (2012), we define

the quantile-based causality as follow¹: x_t does not cause y_t in the θ -quantile with regards to the lag-vector of $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$ if

$$Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}) = Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}) \quad (1)$$

x_t is presumably cause of y_t in the θ -th quantile with regards to $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$ if

$$Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}) \neq Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}) \quad (2)$$

Here, $Q_\theta(y_t | \cdot)$ is the θ -th quantile of y_t . The conditional quantiles of y_t , $Q_\theta(y_t | \cdot)$, depends on t and the quantiles are restricted between zero and one, i.e., $0 < \theta < 1$.

For a compact presentation of the causality-in-quantiles tests, we define the following vectors $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, and $Z_t = (X_t, Y_t)$. Following this specification, the conditional distribution functions $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ signify the distribution functions of y_t conditioned on vectors Z_{t-1} and Y_{t-1} , respectively. Moreover, the conditional distribution $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ is presumed to be completely continuous in y_t for nearly all Z_{t-1} . By defining $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we can see that $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$, which holds with a probability equal to one. As a result, the hypotheses to be evaluated for the causality-in-quantiles based on the equations (1) and (2) can be represented as:

$$H_0: P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} = 1 \quad (3)$$

$$H_1: P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} < 1 \quad (4)$$

In order to define a measurable metric for the practical implementation of the causality-in-quantiles tests, Jeong *et al.*, (2012) make use of the distance measure $J = \{\varepsilon_t E(\varepsilon_t | Z_{t-1}) f_Z(Z_{t-1})\}$, where ε_t denotes the regression error and $f_Z(Z_{t-1})$ denotes the marginal density function of Z_{t-1} . Consequently, the causality-in-quantiles test is based on the regression error ε_t . The

¹ The exposition in this section closely follows Jeong *et al.*, (2012).

regression error ε_t arises based on the null hypothesis specified in equation (3), which would be true, if and only if $E[\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})|Z_{t-1}\}] = \theta$. In order to make the regression error explicit, we rewrite this last statement as $\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is an indicator function. Now, following Jeong *et al.*, (2012), based on the regression error, the distance metric can be defined as:

$$J = E \left[\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} - \theta\}^2 f_Z(Z_{t-1}) \right] \quad (5)$$

In relation to equations (3) and (4), it is crucial to understand that $J \geq 0$. The statement will hold with an equality, i.e., $J = 0$, if and only if the null H_0 in equation (3) is true, while $J > 0$ holds under the alternative H_1 in equation (4). The feasible counterpart of the distance measure J in equation (5) gives us a kernel-based causality-in-quantiles test statistics for the fixed quantile θ and defined as:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^T \sum_{s=p+1, s \neq t}^T K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \quad (6)$$

where $K(\cdot)$ denotes a known kernel function, h is the bandwidth for the kernel estimation, T denotes the sample size, and p represents the lag-order used for defining vector Z_t . Jeong *et al.* (2012) establish that the re-scaled statistics $Th^p \hat{J}_T / \hat{\sigma}_0$ is asymptotically distributed as standard normal, where $\hat{\sigma}_0 = \sqrt{2\theta(1-\theta)} \sqrt{1/(T(T-1)h^{2p})} \sqrt{\sum_{t \neq s} K^2((Z_{t-1} - Z_{s-1})/h)}$. The most crucial element of the test statistics \hat{J}_T is the regression error $\hat{\varepsilon}_t$. In our particular case, the estimator of the unknown regression error is defined as:

$$\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq \hat{Q}_\theta(Y_{t-1})\} - \theta \quad (7)$$

In equation (7), the quantile estimator $\hat{Q}_\theta(Y_{t-1})$ yields an estimate of the θ -th conditional quantile of y_t given Y_{t-1} . We estimate $\hat{Q}_\theta(Y_{t-1})$ by employing the nonparametric kernel approach as:

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}_{y_t|Y_{t-1}}^{-1}(\theta|Y_{t-1}) \quad (8)$$

where $\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ denote the *Nadarya-Watson* kernel estimator given by:

$$\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1}) = \frac{\sum_{s=p+1, s \neq t}^T L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right) \mathbf{1}_{\{y_s \leq y_t\}}}{\sum_{s=p+1, s \neq t}^T L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)} \quad (9)$$

with $L(\cdot)$ denote a known kernel function and h is the bandwidth used in the kernel estimation.

The empirical application of causality testing through quantiles require identifying three crucial choices: the lag order p , the bandwidth h , and the kernel type for $K(\cdot)$ and $L(\cdot)$ in equations (6) and (9), respectively. In this study, we make use of lag order of 2 based on the Schwarz Information Criterion (SIC) under a VAR involving realized volatility and the divergent beliefs proxy series. Moreover, when it comes to choosing lags, the SIC is considered being parsimonious compared to other lag-length selection criteria. The SIC helps overcome the issue of overparametrization usually arising with nonparametric frameworks.² The bandwidth value is chosen by employing the least squares cross-validation techniques.³ Finally, for $K(\cdot)$ and $L(\cdot)$ Gaussian-type kernels was employed.

4. Data and Empirical Findings

4.1 Data

Our analysis is based on two variables, namely, the weekly realized volatility of the S&P500 (RV) and the proxy for dispersion in beliefs (DIB). Since the data on the equity market exposure of active managers is available only weekly, our analysis covers the first week of July, 2006 till the

² Hurvich and Tsai (1989) examine the Akaike Information Criterion (AIC) and show that it is biased towards selecting an overparameterized model, while the SIC is asymptotically consistent.

³ For each quantile, we determine the bandwidth h sing the leave-one-out least-squares cross validation method of Racine and Li (2004) and Li and Racine (2004).

second week of August, 2016, i.e., 528 observations. Note that the start and end dates are purely driven by data availability of the equity market exposure data.

As mentioned earlier, we utilize data from the weekly surveys conducted by the National Association of Active Investment Managers (NAAIM) on its member fund managers. NAAIM member firms who are active money managers are asked each week to provide a number which represents their overall equity exposure at the market close on a specific day of the week, currently Wednesdays.⁴ As the responses can vary widely, we use the standard deviation of the equity market exposures across active managers as a proxy for divergent beliefs regarding the stock market. To that end, our measure is similar to the dispersion proxies employed by Chen *et al.* (2002) and Jiang and Sun (2014) in that it provides a measure of the dispersion in asset positions across managers; however, an advantage of the proxy employed in this study is the availability of the risk exposure data at high frequency, in this case weekly, which allows us to capture the dynamic relationship between differences in opinion and realized volatility of returns. Furthermore, the members who participate in the survey are called NAAIM Trend Setters and it can be argued that the survey data on equity market exposures reflects the positions held by the most active fund managers who are relatively more informed.

Since the equity market exposure data is available weekly, we compute the weekly realized volatility of the S&P500 using daily data. The measure that we consider is the classical estimator of realized volatility, i.e. the sum of squared daily returns (Andersen and Bollerslev, 1998), expressed as

$$RV_t = \sum_{i=1}^M r_{t,i}^2$$

where $r_{t,i}$ is the daily $M \times 1$ return vector and $i = 1, \dots, M$ the number of daily returns over a week. The daily data on the S&P500 closing prices in US dollars have been sourced from the Global Financial Database. With both RV and DIB variables being stationary, based on standard

⁴ The data is available for download from: <http://www.naaim.org/programs/naaim-exposure-index/>.

unit root tests⁵, these two variables do not require any further transformations to be analysed based on our causality-in-quantiles methodology, which in turn, does require stationary data.

Table 1 presents the summary statistics for the realized volatility of the S&P500 and the weekly dispersion in equity market exposures. We observe that, for our context of causality-in-quantiles, our dependent variable, i.e., realized volatility has a non-normal distribution, as indicated by the strong rejection of Jarque-Bera statistic (which has a null of normality) at 1 percent level of significance. However, the normality of DIB cannot be rejected. The heavy-tail of the distribution of realized volatility provides us with a preliminary justification for the causality-in-quantiles test used in this paper. The plots for RV and DIB are presented in Figure 1.

[INSERT TABLE 1 and FIGURE 1]

Despite the notable spikes observed for realized volatility in Figure 1a during the global financial crisis period and later in 2011 around the Greek bailout discussions, dispersion in equity market exposures in Figure 1b do not suggest obvious trends that can be related to market volatility.⁶

4.2 Empirical Findings

As mentioned earlier, the main focus of this study is the causality-in-quantiles running from the proxy for divergent beliefs (DIB) to realized volatility (RV) of the S&P500. Nevertheless, for the sake of completeness and comparability, we also conducted the standard linear Granger causality test based on a VAR(2) model. The resulting $\chi^2(2)$ statistic for the null that DIB does not *Granger* cause RV is 1.2797 with a p -value of 0.5274. In other words, the standard, linear test of causality

⁵ Complete details of the unit root tests are available upon request from the authors.

⁶ However, a preliminary examination of the quantile process based on estimates from parametric quantile regressions revealed strong correlations between lagged DIB and RV variables; particularly during quantiles that correspond to moderately high market volatility. Complete details of these results are available upon request from the authors.

indicates no evidence of predictability emanating from DIB to RV even at the ten percent level of significance.

Next, in order to motivate the use of the nonparametric quantile-in-causality approach, we statistically investigate the possibility of nonlinearity in the relationship between RV and DIB. To this end, we apply the Brock *et al.*, (1996, BDS) test on the residuals of an AR(2) model of RV, and the RV equation in the VAR(2) model involving DIB. As shown in Table 2, we find strong evidence, at the highest level of significance, for the rejection of the null of *i.i.d.* residuals at various embedded dimensions (m). These results provide strong evidence of nonlinearity in not only the evolution of RV, but also in its relationship with DIB, further suggesting that the finding on causality based on the linear Granger causality test cannot be deemed robust and reliable.

[INSERT TABLE 2]

In the next step, we turn to the powerful sequential and repartition tests of Bai and Perron (2003) and apply it again to the AR(2) model for RV as well as to the RV equation in the VAR(2) model that includes DIB. In both cases, we detect two breaks in the third week of October, 2008, and third week of June, 2010. Existence of structural breaks indicate that a parametric linear specification is not appropriate for testing Granger causality from DIB to RV. In other words, the breaks seem to be during the peak of the recent global financial crisis and thereafter. Having detected nonlinearity, existence of structural breaks in realized volatility, and in its relationship with the dispersion in equity market exposures based on the BDS test, we conclude that the Granger causality tests based on a linear framework is likely to suffer from misspecification. Given the strong evidence of nonlinearity and regime changes in the relationship between RV and DIB, we now turn our attention to the causality-in-quantiles test, which is robust to linear misspecification due to its nonparametric (i.e., data-driven) approach.

Figure 2 presents the results obtained from the quantile causality tests for the realized volatility of the S&P500 due to the dispersion in equity market exposures across active managers. As can be seen, the null that DIB does not *Granger* cause RV is rejected at the five percent level of significance (critical value of 1.96) over the quantile range (τ) of 0.50 to 0.80 of the conditional distribution of the realized volatility. In other words, the divergent beliefs proxy can predict realized volatility when the latter falls between the normal to moderately high phases, but not when volatility is below the median or exceptionally high.⁷ The observed effect on realized volatility, particularly at quantiles that corresponds to relatively higher level of volatility, suggests that the effect of divergent beliefs on subsequent returns is likely to be transmitted via the volatility channel which is consistent with the suggestion by Johnson (2004) that the effect of divergent beliefs on returns can be explained away by financial leverage. It also explains the finding by Berkman *et al.* (2009) that stocks that are subject to high differences of opinion earn significantly lower returns.

In our case, the financial leverage argument by Johnson (2004) is particularly supported by the insignificant causality results obtained for lower quantiles of RV, suggesting that divergent beliefs drive a ‘volatility effect’ in stock returns. Furthermore, given the short-sale constraints that prevent active managers from taking full advantage of negative information (e.g. Jiang and Sun, 2014), it can be argued that the effect of divergent beliefs on realized volatility is primarily driven by positive signals about stocks, either privately available to informed traders or as a result of superior skills that the manager has in interpreting those signals. Consequently, as Jiang and Sun (2014) argue, positive signals received by informed managers lead them to place large bets relative to their peers, thus driving the dispersion in equity market exposures across active managers and hence the volatility effect that is evidenced in our tests.

⁷ Though there is also evidence of causality at the ten percent level of significance (critical value of 1.645) at lower quantiles of 0.25 to 0.45 barring 0.35, and the upper quantile of 0.85. This suggest weak evidence of predictability of realized volatility due to divergent beliefs even at certain lower quantiles.

As a result, it can be argued that the causality effect that we observe at relatively higher quantiles of RV reflects the presence of differential information when informed managers receive private, positive signals that are not available to their peers and thus take advantage of this information by placing large, positive bets on stocks. This is in fact consistent with prior evidence that the effect of divergent beliefs is particularly strong in small stocks (Diether *et al.*, 2002) and for stocks with high information asymmetry (Jiang and Sun, 2014), i.e. assets that would be more subject to such market imperfections. Interestingly, however, the insignificant causality results observed at exceptionally high quantiles of RV can be explained by possible herding among fund managers who would have a greater tendency to follow each other's trades during crisis periods characterized by extreme market volatility. It can be argued that extreme market uncertainty drives investors not to fall far from other traders' bets, thus driving the dispersion in equity market exposures lower and leading to insignificant causality results that we observe at exceptionally high quantile of market volatility.

Overall, the findings presented in this paper enhance our understanding of the channels through which divergent beliefs among active managers relate to financial returns and the role of differential information in driving market volatility. They also highlight the importance of detecting and modeling nonlinearity when analyzing the information content of divergent beliefs across market participants.

5. Conclusion

This paper contributes to the literature that relates divergent beliefs among investors to stock returns by analyzing whether differences in opinion across active managers can predict the (realized) volatility of the S&P500. For this purpose, we utilize data from the weekly surveys conducted by the National Association of Active Investment Managers (NAAIM) and use the dispersion in the equity market exposure of active managers as a proxy of divergent beliefs

regarding the stock market. Unlike the other differences in opinion proxies employed in the literature, the proxy employed in this study is available at high frequency, in this case weekly, and allows us to capture the dynamic relationship between differences in opinion and realized volatility of returns.

A novelty of this study is that we relate the proxy for divergent beliefs to realized volatility using a nonparametric causality-in-quantiles test developed by Jeong *et al.* (2012). This nonparametric approach not only guards against misspecification due to nonlinearity and regime changes, but also tests for causality over the entire conditional distribution of the dependent variable (i.e., realized volatility in our case). While the standard linear Granger causality test fails to detect any evidence for divergent beliefs causing return volatility, the quantile-based tests suggest that differences in opinion across active managers can predict realized volatility when the latter falls between the normal to moderately high phases, but not when volatility is below the median or exceptionally high.

The findings in general imply that the effect of divergent beliefs on subsequent returns is likely to be transmitted via the volatility channel which is consistent with the suggestion by Johnson (2004) that the effect of divergent beliefs on returns can be explained away by financial leverage. Furthermore, given the short-sale constraints that might prevent active managers from taking full advantage of negative information (e.g. Jiang and Sun, 2014), we argue that the effect of divergent beliefs on realized volatility is primarily driven by positive signals about stocks, either privately available to informed traders or as a result of superior skills that the manager has in interpreting those signals. Finally, the findings also reflect a possible herding effect among investors in that the causality between differences in opinion and return volatility breaks down at exceptionally high levels of volatility, during which investors would be more likely to follow each other's trades, thus driving the dispersion in equity market exposures lower.

Overall, the findings presented in this paper enhance our understanding of the channels through which divergent beliefs among active managers relate to financial returns and also highlight the importance of detecting and modeling nonlinearity when analyzing the information content of divergent beliefs across market participants.

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Table 1. Summary Statistics

Statistic	Variable	
	Realized Volatility (RV)	Dispersion in equity market exposure (DIB)
Mean	0.0008	52.3191
Median	0.0003	53.3450
Maximum	0.0228	89.9500
Minimum	0.0000	19.4200
Std. Dev.	0.0019	11.8887
Skewness	6.3147	-0.1207
Kurtosis	53.3851	2.7264
Jarque-Bera	59359.4800	2.9298
Probability	0.0000	0.2311

Note: Std. Dev. stands for standard deviation, while probability corresponds to the p-value for the Jarque-Bera test of normality.

Table 2. BDS Test Statistic

Model of Realized Volatility Equation	<i>m</i>				
	2	3	4	5	6
AR(2)	11.5248***	13.6661***	14.7291***	15.6664***	16.6257***
VAR(2)	11.3394***	13.4404***	14.6419***	15.6230***	16.6317***

Note: *m* stands for the number of (embedded) dimension which embed the time series into *m*-dimensional vectors, by taking each *m* successive points in the series. Values in the cells represent BDS $\hat{\alpha}$ -statistic; *** indicates rejection of the null of *i.i.d.* residuals at 1 percent level of significance.

Figure 1a. Realized Volatility of S&P500

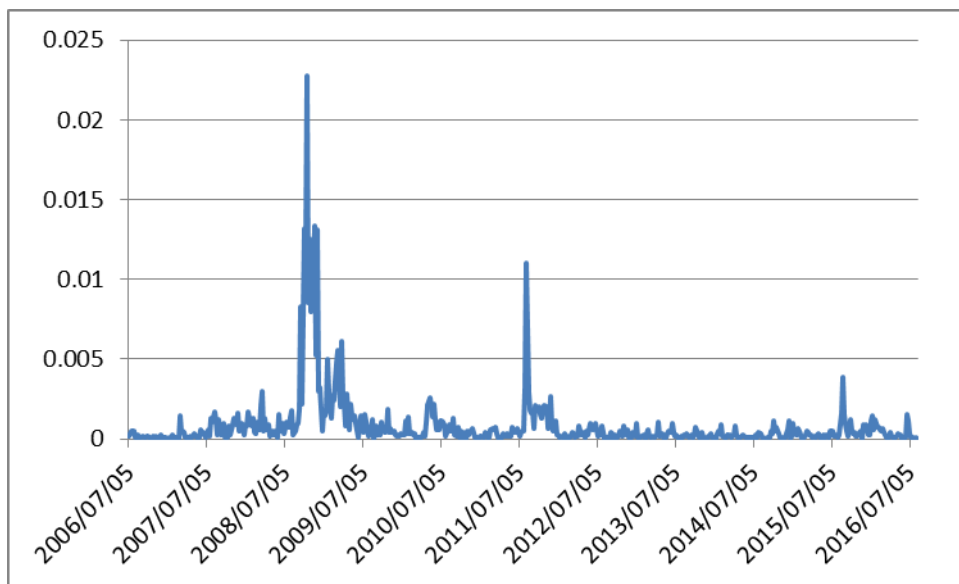


Figure 1b. Dispersion in equity market exposures

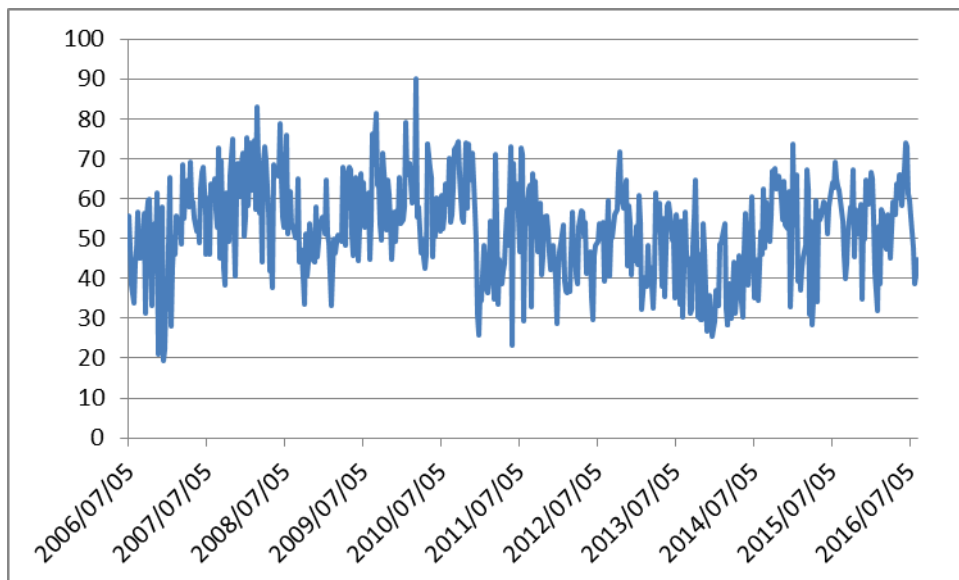
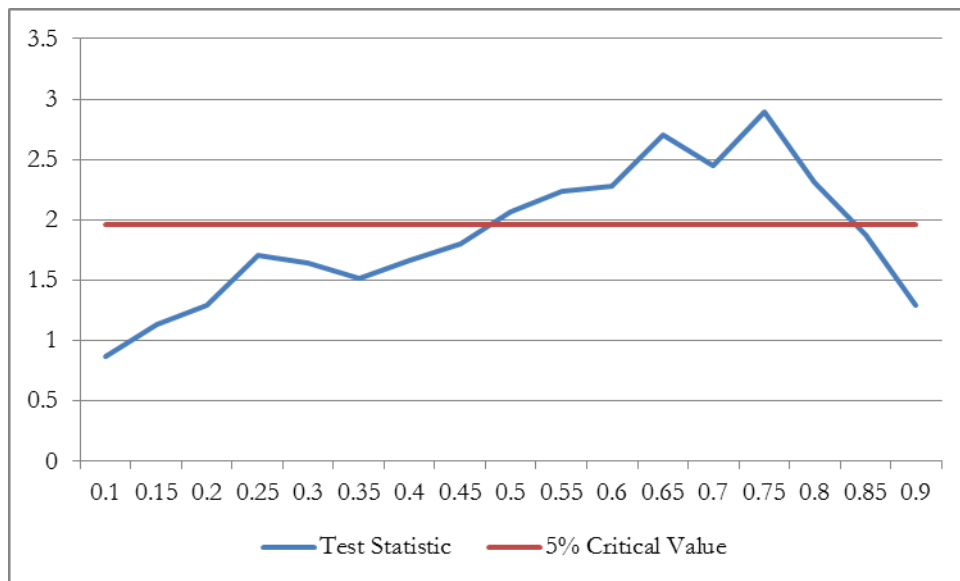


Figure 2. Causality-in-Quantiles Tests.



Note: The vertical axis presents the test statistics corresponding to the null hypothesis that the proxy for differences in opinion (DIB) does not Granger cause S&P500 Realized Volatility (RV). Horizontal axis measures the quantiles; 5 percent critical value is 1.96.