

Direction of change at the Bucharest Stock Exchange

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The objective of our paper is to analyze the possibility to provide a forecast for the sign of the financial asset returns using the empirical prices of stocks listed at the Bucharest Stock Exchange. Previous research provided by Christoffersen and Di-ebold (2004) among others show that even if both the sign and the absolute value of returns are deterministic, their composure (the returns themselves) do not show autocorrelations. We focus on the deterministic nature of the signs by implementing a pure empirical analysis.

Key words: *financial asset returns, empirical analysis*

JEL classification code: F31, F37, G11, G12

Introduction and objective

Three characteristics of financial markets behavior feature prominently in the financial economics literature: 1) asset returns conditional mean independence; 2) sign dependence and 3) conditional variance dependence.

The first of these features, conditional mean independence, suggests that asset returns should not be easily forecasted with available information and forecasting techniques, and many empirical work found that data supports this theory (among these studies: Fama¹ (1970 and 1991).

¹ Fama, E, Efficient Capital Markets; A review of Theory and Empirical Work, Journal of Finance 25, 1970;

1991). On the other hand, Fama and French (1988², 1989³) or Campbell and Shiller⁴ (1988) found that weak conditional mean dependence may appear at long and time horizons, while showed that is possible for weak mean dependence to appear as well at short time horizon. Nonetheless, in spite of these latter findings, it is generally admitted that mean conditional independence is a good approximation of return behavior.

The second characteristic mentioned above, sign dependence is also supported by many empirical studies: Breen et al. (1989)⁵, Leitch and Tanner⁶ (1991), Wagner et al. (1992)⁷, Pesaran and Timmermann (1995)⁸, Kuan and Liu (1995)⁹, Larsen and Wozniak (1995)¹⁰, Womack (1996), Gencay (1998), Leung et al. (2000), Elliot and Ito (1999), White (2000),

Pesaran and Timmermann (2004)¹¹ or Cheung et al. (2005).

The third characteristic, volatility dependence, and hence volatility forecastability, is also strongly documented in financial literature. Volatility clustering has been successfully explained in studies employing ARCH

¹ Fama, E, Efficient Capital Markets II, *Journal of Finance* 46, 1991;

² Fama E, K French, Dividend yields and expected stock returns, *Journal of Financial Economics* 19, 1988;

³ Fama E, K French, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25, 1989;

⁴ Campbell J, R Shiller, Stock prices, earnings and expected dividends, *Journal of Finance*, 1991

⁵ Breen W, LR Glosten, R Jagannathan, Economic Significance of Predictable Variations in Stock Index Returns, *The Journal of Finance*, Vol. 44, 1989;

⁶ Gordon Leitch and J. Ernest Tanner, Economic forecast evaluation: Profit versus the conventional error measures, *American economic review* 81, 1991;

⁷ Wagner, Jerry, Steve Shellans, and Richard Paul, Market timing works where it matters most: in the real world, *Journal of Portfolio Management* 18, 1992;

⁸ Pesaran H, Allan Timmermann, Predictability of Stock Returns: Robustness and Economic Significance.. *The Journal of Finance*, Vol. 50, 1995;

⁹ Kuan C M, T Liu, Forecasting Exchange Rates Using Feedforward And Recurrent Neural Networks, *Journal of Applied Econometrics* 10, 1995;

¹⁰ Larsen, G.A., and G.D. Wozniak, Market timing can work in the real world, *Journal of Portfolio Management*, Spring, 74-81, 1995;

¹¹ Pesaran, M. Hashem, Timmermann, Allan, How costly is it to ignore breaks when forecasting the direction of a time series?, *International Journal of Forecasting* 20, 2004;

models. French, Schwert and Stambaugh (1987), Chou (1988), Akgiray (1989), Baillie and DeGennaro (1990), among others, have used GARCH models to characterize stock returns volatility on the US equity market. Jong, Kemna and Kloeg (1992) applied a similar methodology on the Dutch stock exchange, while Poon and Taylor investigated the UK stock market. All these authors documented the presence of ARCH effects on daily stock returns.

A study by Andersen, Bollerslev and Diebold from 2005 categorizes the various volatility concepts, measurement procedures, and modeling procedures in a unified continuous-time, frictionless and no-arbitrage framework. Andersen and Bollerslev (1998) show that volatility models produce strikingly accurate inter-daily forecasts for the volatility factor. The authors also present new methods for improved ex-post inter-daily volatility measurements based on high-frequency data.

Andersen, Bollerslev, Diebold and Ebens (2000) employ high-frequency intraday data on individual stocks in the Dow Jones Industrial Average Index over a five-year period to characterize stock return volatility and correlation on NYSE. They find that the unconditional distributions of the variances and co variances for all thirty stocks are leptokurtic and highly skewed to the right, while the logarithmic standard deviations and correlations all appear approximately Gaussian.

Extensions of volatility dependence models include investigations of dependence in higher-ordered conditional moments (eg. skewness and kurtosis). Harvey and Siddique (1999)¹ present a way to jointly estimate time-varying conditional variance and skewness under a non-central t distribution for the error term in the mean equation. At the same time kurtosis is assumed to be non-varying. Their methodology is applied to several series of stock index returns, and it is found that autoregressive conditional skewness is significant and that the inclusion of skewness affects the persistence in variance.

¹ Harvey, C. R., Siddique A, Autoregressive conditional skewness, *Journal of Financial and Quantitative Analysis*, 34, 1999;

Jondeau and Rockinger (2000)¹ employ a conditional generalized Student's-t distribution to capture conditional skewness and kurtosis by imposing a time-varying structure for skewness and kurtosis, which control the probability mass in the assumed distribution.

However, these parameters do not follow a GARCH structure for either skewness or kurtosis.

Premaratne and Bera (2001)² suggested capturing asymmetry and excess kurtosis with the Pearson type IV distribution, which has three parameters that can be interpreted as volatility, skewness and kurtosis. This is an approximation to the non-central t distribution proposed by Pearson and Merrington³ (1958). However, these authors use time-varying conditional mean and variance, but maintain constant skewness and kurtosis over time.

Leon, Rubio and Serna (2005) propose a GARCH-type model allowing for time-varying volatility, skewness and kurtosis. Their model is further estimated assuming a Gram–Charlier (GC) series expansion of the normal density function for the error term, on daily returns of a variety of stock indices and exchange rates. The results indicate a significant presence of conditional skewness and kurtosis and, moreover, the specifications allowing for time-varying skewness and kurtosis outperform specifications with constant third and fourth moments.

Christoffersen and Diebold⁴ in their study from 2004 arrive at the following results: 1) volatility dependence produces sign dependence as long as expected returns are nonzero; 2) it is statistically possible to have sign and volatility dependence and at the same time mean inde-

¹ Jondeau, E, Rockinger, M., Conditional volatility, skewness and kurtosis: existence and persistence, Working paper, HEC School of Management, 2000;

² Premaratne, G. Bera, A. K., Modeling asymmetry and excess kurtosis in stock return data. Working paper, Department of Economics, University of Illinois, 2001;

³ Pearson, E. S., Merrington, M., An approximation to the distribution of non-central t, *Biometrika*, 45, 1958;

⁴ Christoffersen, P.F. and Diebold, F.X. (2004), "Financial Asset Returns, Direction-of-Change Forecasting, and Volatility Dynamics," *Management Science*, 52, 2006;

pendence; 3) sign dependence is highly nonlinear, which makes it improbable to be discovered via traditional linear tests; 4) it is more likely to discover sign dependence with intermediate frequency data (two or three months) than with very low or high frequencies (annual or daily); 5) the link between volatility forecastability and sign forecastability remains the same or is even improved in conditional non-Gaussian environments (such as time-varying conditional skewness and/or kurtosis).

In 2006, Christoffersen et al¹ extended the Christoffersen-Diebold (2004) direction-of-change forecasting framework to include the potentially important effects of higher-ordered conditional moments. They employed daily values for the period 1980:01 through 2004:06 of the MSCI index for Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Singapore, Sweden, Switzerland, UK, USA, as well as MSCI Europe, Far East, and World indexes and allowed for conditional mean and variance information and also for conditional skewness and kurtosis information, when forming direction-of-change forecasts.

In conclusion, existing empirical work in the financial literature suggests that there is a direct connection between asset return volatility dependence and asset return sign dependence. If this were true, this means that ultimately sign can be forecasted. Indeed, the volatility dependence in stock returns, corroborated with sign dependence, could produce direction-of-change forecasts.

Accordingly, we focus on the analysis of the direction of change forecastability at the Bucharest Stock Exchange, taking into account eight stocks that are part of the BET index and have enough history to allow for empirical study. We conjectured that for differences between the mean and the median there is higher probability for the change to have one sign than the other, assuming that the means and the medians are

¹ Christoffersen, Peter F., Francis X. Diebold, Roberto S. Mariano, Anthony S. Tay, Yiu Kuen Tse, Direction-of-Change Forecasts Based on Conditional Variance, Skewness and Kurtosis Dynamics: International Evidence, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=908317;

deterministic too. For instance, if we can predict the next difference between the mean and the median, then we could say that, if the mean is higher (smaller) than the median there is a higher probability for the sign to be positive (negative) with the amount of the probability of the return to be between the mean and the median.

This kind of analysis will provide information of the probabilities of the signs only in the case of skewed distributions (negative or positive skewness), which means that we will allow for dynamic skewness of our conditional distribution of returns. We also expect to find no significant differences between the mean and the median due to volatilities of the returns and, as a consequence, of the means and medians themselves. However, we aim at testing the predicting power of the differences, by checking for out-of-sample performance.

Data and methodology

We included in our analysis the following securities: Antibiotice Iași (ATB), BRD Societe Generale (BRD), SSIF Broker Cluj (BRK), Impact Developer & Contractor SA (IMP), Rompetrol Rafinare Constanța (RRC), Petrom (SNP) and Banca Transilvania (TLV). The companies were chosen so that they have enough liquidity (they are part of the BET index presently) and they have enough history to allow for an empirical analysis. In order to take into account all the splits and consolidations we computed the logarithmic returns as changes in the market capitalizations of the respective companies for the whole sample. The returns were then used to compute two series of statistics as results of moving windows of 100 observations each. The two series are composed of moving averages and moving medians.

The next step consists in finding the differences between the means and the medians for each of the stocks in our analysis and then computing their innovations (first difference of the time series). For this last series an ARMA analysis will be implemented in order to check for its inner deterministic performance. As we saw in previous research, the

volatilities are expected to provide important information about the direction of change so, we will try to forecast the signs of the returns by using both the differences between the means and the medians and the conditional volatilities of the returns. These conditional volatilities will be estimated using the GARCH methodology. The final result of the analysis will consist in the estimation of the coefficients of a logit regression which will provide information about the sign of the returns as a function of the estimated conditional volatility and the estimated conditional difference between the mean and the median. As such, we can say that we are going to investigate the forecastability of the sign for returns on the respective assets as a function of the second and the third moments of the conditional distribution of returns.

The statistical properties of the differences between the means and the medians as well as those for the shocks (innovations or first difference in this time series) are shown in the appendix for all the returns computed for all the stocks in our analysis. According to the Jarque-Bera test all the shocks look normally distributed while many of the differences seem to have a non-normal distribution. This situation might be due to the fact that the differences contain high autocorrelations as the means and the medians are computed as moving averages for samples of 100 observations, which means that each statistic contains 99 observations that are used for the computation of the previous statistic of the same type. The same conclusion can be obtained by looking at the Quantile-Quantile graphs in the appendix, computed with respect to the normal distribution.

With this data we built possible explanatory variables for the prediction of the sign of the returns in next period. Previous research showed that there is a relation between the sign dynamics and the second, third and fourth moments of the distribution of the returns. We built forecasts for the variances of returns using the EGARCH model and we used the innovations in the differences between the means and the medians or simply these differences as a non-standardized way of measuring the asymmetry of the distribution. In this manner we try to find the relation

of the sign forecasting possibility as a linear function of the second moment (represented by the forecasted variances according to EGARCH) and of the third moment (represented by the last realization of the series of the differences between the means and the medians and their innovations or shocks, computed as the first difference of the series of differences).

The model that we used for the estimation of the new variances was the general EGARCH(P,Q) model:

$$\log(\sigma_t^2) = k + \sum_{i=1}^p G_i \log(\sigma_{t-i}^2) + \sum_{j=1}^q A_j \left[\frac{|\varepsilon_{t-j}|}{\sigma_{t-j}} - E \left\{ \frac{|\varepsilon_{t-j}|}{\sigma_{t-j}} \right\} \right] + \sum_{j=1}^q L_j \left(\frac{\varepsilon_{t-j}}{\sigma_{t-j}} \right)$$

EGARCH(P,Q) models are treated as ARMA(P,Q) models for $\log(\sigma_t^2)$ and they are fundamentally different from the classical GARCH model in that the standardized innovation, z_t , serves as the forcing variable for both the conditional variance and the error. On the other hand the GARCH model allows for volatility clustering (i.e., persistence) by a combination of the G_i and A_j terms, whereas persistence in EGARCH models is entirely captured by the G_i terms. Previous research done by Lupu et. al. (2007) showed that the EGARCH(1,1) model is suitable for the Romanian capital market and as a result, we decided to use it here for variance forecasting for each moving window of 100 observations. In order to develop this kind of analysis, we used the E-views program that allowed us to re-estimate the coefficients of the model for the moving sample. As a result we had to calibrate 8271 models for all the 7 series of variables in our analysis.

The next step in our analysis consisted in the estimation of the power of variances of returns and the differences in the means and medians to forecast the sign of the next return. The skewness, proxied by the difference between the mean and the median, intuitively provides the information about which sign has a higher probability. According to this reasoning, we will test the power of sign prediction of these two central moments of the distribution by running a regression of the sign of re-

turns at day $t+1$ on the variance provided by the EGARCH moment for moment $t+1$ and the lags of the series of skewness proxies. As such, significance of some of the coefficients of this regression will show that, on average, the sign depends on these two moments. The regression was done in two ways – first we built the dependent variable as a dummy variable which takes the value of 1 if the return is positive and 0 otherwise. Another analysis was done by using the probit model as built in the E-views program, in which the dependent variable was again the dummy with 0 or 1 and the independent variables were the first three lags of the differences between the means and the medians. The explanatory variable that proxies the skewness was used to be the innovations (shocks) in the differences between the means and the medians in order to avoid problems that could be created by correlated errors – each difference between the mean and the median contains 99 observations that were previously used to compute the previous mean and median.

Results

The first estimation procedure that we developed dealt with the computation of the predicted variances for each day of the sample. The calibration of the EGARCH model was redone for each series of stock returns according to the number of observations available. Some information about the estimated variances is presented in Table 1. As these variables will be used in regressions we analyzed the unit root of each of the series of variances and we found stationarity for all of them.

Table 1 – Descriptive statistics for the forecasted variances using the EGARCH model

	ATB	BRD	BRK	IMP	RRC	SNP	TLV
Mean	12440634	5.63E+50	49178.62	886.7930	0.000665	0.000412	0.000648
Median	0.000261	0.000396	0.000564	0.000531	0.000620	0.000388	0.000241
Maximum	7.91E+09	3.59E+53	28124190	564886.7	0.001966	0.001438	0.154651
Minimum	3.97E-07	1.17E-05	2.21E-05	7.48E-06	8.37E-05	0.000178	2.04E-05
Std. Dev.	3.14E+08	1.42E+52	1121324.	22381.63	0.000244	0.000125	0.006148
Skewness	25.17936	25.17939	24.73226	25.17939	1.447656	1.801015	24.74434
Kurtosis	635.0006	635.0016	618.9411	635.0016	7.221504	14.33114	619.9755

The results of our study are presented in the following table. We have bolded all the coefficients that were significant in our regression analyses. We can see that there are 5 stocks with coefficients for which the p-values are not very large (less than 15%) for the model 1 (regression of the signs dummy variable on the forecasted variances and the shocks in differences) and one case of significance for the second model (the probit model).

Table 2 – Coefficients results for regressions of the signs of returns with respect to forecasted variances and shocks in the mean-median differences

Indicators	ATB		BRD		BRK		IMP	
	coefficients	p-values	coefficients	p-values	coefficients	p-values	coefficients	p-values
Model 1								
Constant	0.393598	0.0000	0.450650	0.0000	0.455894	0.0000	0.429113	0.0000
Coefficients variances	5.56E-16	0.2125	-1.6E-114	0.3719	1.69E-08	0.3380	-1.06E-26	0.3978
Coefficients shocks in differences lag 1	0.247429	0.1262	0.016475	0.9241	0.486732	0.0474	0.189035	0.2441
Coeffi-	0.094476	0.5957	-	0.285	0.2277	0.3569	0.24139	0.1324

coefficients shocks in differences lag 2			0.1878 52	1	87		0	
Coefficients shocks in differences lag 3	0.072651	0.6532	- 0.3334 35	0.054 1	- 0.0461 49	0.8507	0.24417 9	0.1324
Model 2								
Constant	-0.295098	0.0000	- 0.1421 33	0.000 0	- 0.1113 08	0.0262	- 0.20316 4	0.0000
Coefficients variances	9.79E-13	0.9953	- 6.21E- 89	0.854 4	6.35E- 08	0.4426	-1.97E- 25	1.0000
Coefficients shocks in differences lag 1	-0.692990	0.1056	0.0453 26	0.917 6	1.2454 71	0.0485	0.54264 3	0.1873
Coefficients shocks in differences lag 2	0.258261	0.5786	- 0.5419 14	0.226 9	0.5931 37	0.3508	0.68816 9	0.1083
Coefficients shocks in differences lag 3	0.206636	0.6220	- 0.9695 60	0.028 6	- 0.1218 85	0.8437	0.71038 1	0.0857

Indicators	RRC		SNP		TLV	
	coefficients	p-values	coefficients	p-values	coefficients	p-values
Model 1						
Constant	0.450479	0.0000	0.429215	0.0000	0.415347	0.0000
Coefficients variances	2.430259	0.1301	-1.70E-08	0.3608	3.63E-28	0.2361
Coefficients shocks in differences lag 1	0.180148	0.4449	-0.162466	0.5743	-0.014548	0.9394
Coefficients shocks in differences lag 2	-0.271164	0.2505	-0.008557	0.9762	-0.033735	0.8621

Coefficients shocks in differences lag 3	-0.166809	0.4793	-0.129001	0.6601	-0.164905	0.3888
Model 2						
Constant	-0.130313	0.0055	-0.177613	0.0000	-0.211588	0.0000
Coefficients variances	13.88074	0.5843	-2.00E-05	0.7622	6.92E-24	1.0000
Coefficients shocks in differences lag 1	0.456858	0.4430	-0.407874	0.5789	-0.041948	0.9315
Coefficients shocks in differences lag 2	-0.692785	0.2511	-0.008643	0.9905	-0.094302	0.8479
Coefficients shocks in differences lag 3	-0.426337	0.4795	-0.343539	0.6445	-0.471059	0.3380

Model 1 is a simple regression model in which the dependent variable is a dummy of signs (0 for negative or 0 and 1 for positive returns) and the independent variables are the forecasted variances and each of the first three lags of shocks in the differences between the mean and the median of the stock returns.

These results provide some information about the power of the second and the third moments of the distribution of returns to forecast the sign of the future returns. As far as the shocks in the differences between the means and the medians are concerned, we can also notice that, even if we had found a significant distance between the two statistics, this difference might not determine the next sign but probabilistically. In other words, the significance of the distance might be accomplished but its size is so low that it might only communicate that the probability of a positive sign is only a bit higher than the probability of a negative sign (slightly higher than 50%). The small number of signifi-

cant coefficients might be just the result of using samples with only small distances (that are not even statistically significantly different from 0).

Conclusions and further possible developments

This paper is based on previous research concerning the possibility to forecast the direction of change of future returns (their sign) using information about the second and the third moments of the distribution of these returns. We based our analysis on the empirical finding that stock returns for the Romanian capital market companies seem to be well fitted by the EGARCH model (Lupu et. al. 2007) and the empirical and theoretical findings on different markets concerning the possibility to forecast the sign and the size of returns, even if their composure (the actual returns) seems not to be correlated linearly.

The EGARCH model was used to provide forecasts for the next variances of the returns in the next moment (next day) and we computed the differences between the means and the medians of moving window returns in order to build a proxy for the movement of skewness in the conditional distribution of returns. These two factors were used in regressions in which the dependent variable was a dummy variable with the sign of the returns. The proxy for the asymmetry of the distribution was computed as innovations in the differences of the means and medians (the first difference of the series of these differences) in order to avoid regression problems related to the correlation of the residuals. The results showed that some of the coefficients were significant, meaning that the research could be continued to look for further evidence on the other stocks in the market.

We appreciate that the reduced number of significant coefficients is also due to the fact that usually the size of the distance between the means and the medians is small and almost all the time not significantly different from zero, which means that the probability of the next sign is usually not very much higher than 50%.

A next possible investigation will deal with finding a relationship between the distances computed in this paper and the values of the skewness in order to build a model that allows for sign forecasting. The use of wavelets decomposition as well as reference to standardized technical analysis indicators will be taken into account. The use of such a model is obvious, especially for risk management and investment planning but also for the development of better fitted event-study analyses.

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Appendix

Descriptive statistics of moving averages

	ATB	BRD	BRK	IMP	RRC	SNP	TLV
Mean	0.032834	0.041550	0.294834	0.061937	-0.032351	-0.056747	0.068020
Median	0.023721	0.102656	0.342910	0.177985	0.020211	-0.064302	0.104826
Maximum	0.373756	0.399409	1.075396	0.803063	0.338131	0.302542	0.337418
Minimum	-0.367901	-0.460217	-0.708394	-1.133153	-0.593724	-0.343518	-0.268865
Std. Dev.	0.157141	0.191084	0.439851	0.454922	0.240353	0.131337	0.153592
Skewness	0.213860	-0.694727	-0.226103	-0.956465	-0.700543	0.187493	-0.417283
Kurtosis	2.803564	2.552541	2.082481	2.973355	2.422921	2.707055	2.078398
Jarque-Bera	4.282942	41.19555	20.22908	70.76016	44.39049	4.377682	29.88642
Probability	0.117482	0.000000	0.000040	0.000000	0.000000	0.112047	0.000000

Descriptive statistics of moving medians

	ATB	BRD	BRK	IMP	RRC	SNP	TLV
Mean	-0.007524	0.015991	0.089042	-0.113213	-0.147344	-0.000866	0.047146
Median	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	0.000000	0.479617	0.788440	0.569802	0.573067	0.000000	0.569802
Minimum	-0.498754	-0.566574	-0.481929	-1.069529	-0.843887	-0.201005	0.000000
Std. Dev.	0.060862	0.245354	0.217041	0.316193	0.424890	0.013182	0.155824
Skewness	-7.956195	0.141102	1.275626	-1.292315	-0.435648	-15.13289	2.999564
Kurtosis	64.30103	3.153875	4.678129	4.761350	1.942746	230.0043	10.00061
Jarque-Bera	77546.40	1.997450	180.2833	189.1315	36.28759	1013975.	1643.296
Probability	0.000000	0.368349	0.000000	0.000000	0.000000	0.000000	0.000000

Descriptive statistics of differences from means to medians

	ATB	BRD	BRK	IMP	RRC	SNP	TLV
Mean	0.040359	0.025559	0.205792	0.175150	0.114994	-0.055881	0.020874
Median	0.028042	0.087890	0.235535	0.162398	0.030203	-0.063817	0.028061
Maximum	0.373756	0.441571	1.075396	0.764084	0.906921	0.302542	0.319802
Minimum	-0.354947	-0.548094	-0.558162	-0.455951	-0.398606	-0.343518	-0.347049
Std. Dev.	0.152696	0.211535	0.351349	0.238980	0.286617	0.130648	0.169369
Skewness	0.283911	-0.567291	0.103275	-0.183813	0.922931	0.187037	-0.430269
Kurtosis	2.693503	2.523802	2.831850	2.664133	3.638242	2.733583	2.036684
Jarque-Bera	8.049685	29.27149	1.371459	4.793794	73.74817	4.077578	32.25772
Probability	0.017866	0.000000	0.503723	0.091000	0.000000	0.130186	0.000000

Descriptive statistics of shocks in differences

	ATB	BRD	BRK	IMP	RRC	SNP	TLV
Mean	0.000587	0.001102	0.001016	0.000968	0.000588	-0.000419	0.000583
Median	0.000000	-0.001063	0.001107	0.000000	0.001279	0.000000	0.000000
Maximum	0.493424	0.532427	0.757133	0.518481	0.315859	0.176861	0.560851
Minimum	-0.485968	-0.485581	-0.770809	-0.512499	-0.392971	-0.145077	-0.535564
Std. Dev.	0.067470	0.090642	0.077378	0.082884	0.062890	0.031014	0.069039

Skewness	0.316738	0.407319	-0.062929	-0.520482	-1.201328	0.258940	-0.061876
Kurtosis	41.71622	16.85549	46.85661	23.10774	16.27483	6.801370	47.54467
Jarque-Bera	28924.91	3716.313	37105.94	7820.933	3510.964	283.9467	38279.36
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

The quantile-quantile plots with respect to the normal distribution for all the innovations in the differences between the means and the medians







