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MODELLING THE IMPACT OF OVERNIGHT SURPRISES ON INTRA-DAILY VOLATILITY

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Abstract

In this paper we evaluate the impact that stock returns recorded between market closing and opening the next business day have on intra-daily volatility. A simple test shows that the estimated volatility clustering of the intra-daily returns may be affected by a market opening surprise bias. An extension of the standard GARCH model is suggested here to include the effect of this surprise and is applied on a sample of largely traded US stocks. The performance of two specifications in which this effect is included is evaluated in an out-of-sample forecasting exercise relative to their standard counterparts.

Keywords: Volatility forecasting, univariate GARCH, market opening surprise bias.

*gallog@ds.unifi.it. Mailing Address: Dipartimento di Statistica "G.Parenti" – Università di Firenze – Viale G.B. Morgagni 59 - 50134 FIRENZE Italy. This paper originates from many conversations I have had with Barbara Pacini: some early thoughts took shape in Gallo and Pacini (1998). Participants in seminars at Texas A& M, UCSD, UC Berkeley and UC Riverside, in the EC^2 Conference Financial Econometrics in Madrid, and in the Conference *The Growth, Performance and Concentration of International Financial Markets* at the Monash European Studies Centre in Prato, but mostly an anonymous referee gave me useful insights in the matter. A special thanks goes to Marco J. Lombardi for skillful research assistance. Financial support from the Italian MURST and CNR is gratefully acknowledged.

I Introduction

The empirical study of asset price dynamics is often carried out on daily data and it is customary that returns are measured as the log-differences of the closing prices. Amihud and Mendelson (1987) [1] and Stoll and Whaley (1990) [11] offered a rationale for this practice, arguing that returns measured as open-to-open are affected by specific trading mechanisms at work when markets open, resulting in a number of unappealing statistical features in the corresponding time series. Some authors attribute to trading the feature of conveying a flow of information which is interrupted during closing times (Romer, 1993 [10], Dow and Gorton, 1993 [4],). Hence, opening prices are reckoned to be of interest, since they convey the impact of information accumulation during closing times. It is the claim of this paper that this information can be relevant when evaluating the intra-daily volatility, even without resorting to high frequency data. This is consistent with the findings in the literature that there is a higher *transitory* volatility at opening time and that this volatility declines during the day (e.g., Gerety and Mulherin, 1994 [8]). The results in this paper account for the transmission of the variability measured at the market opening to the volatility measured during that day.

Put differently, throughout this paper, we will consider (close-to-close) returns as the sum of (close-to-open) overnight returns and of (open-to-close) intra-daily returns, and examine the specific question as to whether the former can have a statistically significant impact on the volatility of the latter. The answer provided here is positive since the models suggested all point to the relevance of augmenting the information set to include market opening surprises.

This decomposition echoes the approach adopted by Lin *et al.* (1994) [9] who examine the effects on volatility of the interactions between stock indices from the Tokyo and New York stock exchanges. Such markets are never open at the same time, and therefore either market's intra-daily return can be seen as conveying relevant information for the other market when it opens. Yet, the present paper departs from that approach in various ways. On a substantive level, the present approach is of particular interest for assets traded in segmented markets, e.g., for individual stocks traded on a single specialized market for which there is no natural source of additional information coming from other markets. It is argued here that there is an asymmetry of behavior behind the realizations of the two components (one originating from the accumulation of news during times when exchanges are not possible, the other from active trading) which makes this analysis distinctive from the traditional analysis of returns in different markets. By the same token, therefore, the distinction between the meteor shower/heat waves nature of innovations across foreign exchange markets operating around the clock (Engle *et al.* 1990) [5] does not apply in this context, nor does the need for correcting the effects implied by simultaneous trading, as in Burns *et al.* (1998) [2].

We choose to address the characteristics of this interaction by first establishing some stylized facts on the two types of returns measured on a sample of 20 widely traded stocks (Section II); we then suggest a simple test in order to examine whether there is an *opening surprise bias*, i.e., whether the overnight innovation is potentially relevant in explaining the clustering in intra-daily conditional variance relative to the close-to-open return (Section III). In a univariate framework, a model for intra-daily conditional variance can be derived to account for the explanatory power of the opening innovation (Section IV). A forecasting comparison (Section V) shows that the extension has a better Mean Absolute Error than standard GARCH models although it is slightly outperformed in a Root Mean Squared Error sense. Concluding remarks follow.

II Opening and Closing Prices

Let us consider a single stock, and let us define daily returns as the difference between the logarithms of closing prices. Clark (1973) [3] considers the daily return on an asset at time t as the sum (arising from a random number of trades n_t) of independently and identically distributed price movements with mean 0 and variance σ^2. Accordingly, conditional on n_t, the variance of the daily returns is $n_t\sigma^2$. As noted by Gallo and Pacini (1998) [7], one should keep in mind that among these n_t trades, the first recorded price movement (occurring at market opening time) is bound to have different stochastic properties than the intra-day price movements. This different nature arises from the specific market microstructure and opening price formation process where, alongside the mechanisms adopted for market trading, the overnight accumulation of information plays a special role. Among the elements of this information flow, one can consider general stock exchange behavior around the world, macroeconomic or sector specific news released during market close and, of course, cross-listings of the same stock on other stock exchanges.

We will then consider the decomposition of the daily returns by adding and subtracting the log of opening prices. We will depart from standard practice by referring to the closing price at time t as C_t (instead of P_t), and to the opening price as O_t leaving lower case letters to denote (natural) logarithms of the corresponding quantities. Thus, the daily returns are seen as

$$\begin{aligned} r_t &= \log(C_t) - \log(C_{t-1}) \\ &= c_t - o_t + o_t - c_{t-1} \\ &= r_{i,t} + r_{o,t}, \end{aligned} \tag{1}$$

where $r_{i,t}$ denotes the intra-daily return and $r_{o,t}$ is the overnight return. By so doing we design a suitable framework to investigate whether the latter has an impact on the former's conditional mean and variance[1]. Thus, given the assumptions on conditional moments

$$r_{i,t}|I_{t-1} \sim (\mu_t^{r_i}, h_t^{r_i}) \tag{2}$$

what will follow will focus on whether enlarging the information set I_{t-1} to include $r_{i,t}$ is relevant for the conditional variance $h_{t-1}^{r_i}$[2].

Let us start by considering 20 large caps stocks (the complete list of tickers and explanations is in Table I) traded on the New York Stock Exchange (NYSE): many of these stocks are included in the sample examined by various authors (Amihud and Mendelson, 1987, among others) and therefore can be deemed representative of other actively traded stocks. The chosen sample period is from Jan. 4, 1994 to Oct. 1, 1998 (a total of 1235 days). We will work on the residuals of the least squares regressions

$$\begin{aligned} r_{i,t} &= a + br_{o,t} + \zeta_t \\ r_{o,t} &= c + dr_{i,t-1} + \eta_t, \end{aligned}$$

that is:

$$\begin{aligned} \zeta_t &= r_{i,t} - \hat{r}_{i,t} \\ &= r_{i,t} - (a + br_{o,t}) \\ \eta_t &= r_{o,t} - \hat{r}_{o,t} \\ &= r_{o,t} - (c + dr_{i,t-1}). \end{aligned}$$

Extracting the residual from the mean equation does not affect the estimation of conditional variance (Engle and Ng (1993) [6]), and thus allows us to concentrate just on the volatility modelling.

Table I about here

For the purposes of this paper, it suffices to report just a few stylized facts about some relevant characteristics of the η_t's and the ζ_t's:

1. Figure 1 presents the time series profile of the three series ($r_{o,t}$, $r_{i,t}$ and their sum r_t) for a few of the stocks under scrutiny here, from which we can see that, by and large, the familiar pattern of volatility clustering is replicated in the two component series, justifying the claim that *the series of overnight innovations has some distinctive features* which make the first trade of the day qualitatively different from each successive single trade during the day.

   Figure 1 about here

2. Table II shows the results of the ARCH LM test performed on both η_t and ζ_t (p-values are reported for each stock in the second row). This table shows that *conditional volatility clustering in overnight innovations is present in many stocks but it is not a widespread distinctive feature* of the series, while the presence of ARCH effects is detected in all the stocks for the intra-daily innovations.

   Table II about here

III The Opening Surprise Bias Test

Having established that ARCH effects are present in the ζ_t's, while they may or may not be present in the η_t's, the relevance of the latter in a model for the former can be seen, more formally, in terms of a set of estimation residuals standardized by the conditional standard deviation using information on ζ alone. In particular, one would not be able to find any significant parameter from regressing the squared standardized residuals of ζ_t on a constant, η_t and η_t^2. The test can be seen as a specification for the conditional variance model and can be called an *opening surprise bias* test in a spirit analogous to the negative size bias test suggested by Engle and Ng (1993). In Table III, we report the results for the t-statistics on single coefficients, and the joint

F-test (with p-values in the second row) for the regression

$$\frac{\zeta_t^2}{h_t^\zeta} = \phi_0 + \phi_1 \eta_t + \phi_2 \eta_t \mathbb{I}_{\eta_t<0} + \phi_3 \eta_t^2 + u_t \tag{3}$$

where h_t^ζ is estimated by a standard GARCH(1,1) and a term for possible asymmetric effects in the opening surprise was inserted.

Table III around here

Having both the value of η_t and its square in the auxiliary regression ensures that possible asymmetries of effects are captured (a point to which we will return later). It is clear that, at least judging from the p-value of the joint F-test, the informational value of the overnight news is quite relevant, since for only four out of the twenty stocks does the test accept the null hypothesis of zero effects (Bethlehem Steel, Eastman Kodak, Goodyear and Exxon). The issue of the sign of the impact does not seem as important as its presence, since most $\hat{\phi}_1$'s are not significant.

we have thus established the potential for investigating the consequences for intra-daily volatility (evaluated as of the opening time in t), deriving from the insertion of η_t in the information set and its role in the presence of asymmetric ("leverage") effects. Moving now to its full measurement we will adopt the framework of a simple, univariate Threshold GARCH(1,1) specification, applied on the original process ζ_t with η_t^2 included as a predetermined variable.

The appealing feature of this specification is that it can be used both in an *ex ante* framework, when η_t is observed, but also, as of $t-1$, on the basis of scenarios about what the overnight surprise could be.

IV OPENING NEWS IN THE CONDITIONAL VARIANCE

The model begins with the consideration that the realization of η_t is observed at the opening of the markets and hence can be used to form a modified prediction of the intra-daily volatility[3].

We have tried four specifications for h_t^ζ, namely,

$$\begin{aligned} h_t^\zeta &= \omega + \alpha_1 \zeta_{t-1}^2 + \beta_1 h_{t-1}^\zeta; & (4)\\ &= \omega + \alpha_1 \zeta_{t-1}^2 + \beta_1 h_{t-1}^\zeta + \phi \eta_t^2; & (5)\\ &= \omega + \alpha_1 \zeta_{t-1}^2 + \gamma_1 \zeta_{t-1}^2 \mathbb{I}_{\zeta_{t-1}<0} + \beta_1 h_{t-1}^\zeta; & (6)\\ &= \omega + \alpha_1 \zeta_{t-1}^2 + \gamma_1 \zeta_{t-1}^2 \mathbb{I}_{\zeta_{t-1}<0} + \beta_1 h_{t-1}^\zeta + \phi \eta_t^2. & (7) \end{aligned}$$

The first model is the standard GARCH(1,1) already commented on earlier (labeled **G**), followed by a GARCH(1,1) with predetermined variables (GARCH-X) with η_t^2 as the predetermined variable (labeled **GX**); the third and the fourth models, in parallel with the first two, are Threshold GARCH(1,1) models where a term is inserted accounting for the possibility that negative past innovations in ζ can increase its volatility (labelled, respectively, **TG** and **TGX**). Table IV summarizes all estimation results (parameter values with associated t-values), as well as some diagnostics on the estimation results (value of the Schwarz Information Criterion and of an ARCH LM test statistic for 4 lags and its associated p-values).

Table IV around here

The results warrant the following comments:

- The absence of an opening surprise bias would be confirmed, based on the lack of significance of the estimated coefficients $\hat{\phi}$ in models (**GX**) and (**TGX**) for the stocks which had not signaled such a bias in the test before. However, judging from the outcome of a likelihood ratio test (the critical values for a significance of 5% are 3.84 for one degree of freedom and 5.99 for two), the pair-wise comparison between the nested models shows a significant difference when η_t^2 is inserted in the specification;

- The consideration of the Threshold GARCH models aims at assessing whether the opening surprise bias could be due to the neglected asymmetric effects, but this occurs only once (for the Disney stock for which the leverage effect is significant). One way of looking at the interaction between the two effects is to arrange the instances in a 2×2 table in which either rejection is or is not accounted for in the model (**TGX**).

	$\phi = 0$	$\phi \neq 0$
$\gamma_1 = 0$	5	5
$\gamma_1 \neq 0$	1	9

Note that in this context the occurrence of opening surprise biases is more frequent than the presence of asymmetric effects. As a matter of fact, less qualitatively, likelihood ratio test statistics can be computed for the zero restrictions imposed on Model (**TGX**) which result, respectively, in a. Model (**G**) (Augmented T-GARCH versus GARCH -

two restrictions corresponding to opening surprise and leverage effect), b. Model (**GX**) (one restriction - leverage effect) and c. Model (**TG**) (one restriction - opening surprise). This is done in Table V, where for each stock, the first row reports the value of the test statistic relative to Model (**TGX**), and the second row reports the corresponding p-value associated with the null of the validity of the zero restrictions.

Table V around here

The results are overwhelmingly in favor of the opening surprise effect, in that only in the case of Exxon is the restriction $\phi = 0$ accepted while in all other cases it is rejected. The pure leverage effect is less supported by the data, with the restriction being accepted for Chevron, Procter & Gamble, Texaco and Exxon. Finally, the absence of joint effects is always rejected (with the exception, again, of Exxon).

- There are three instances in which the insertion of a leverage effect gives a negative estimated value for α_1. This, in principle, may create problems with the non-negativity requirement for the estimated variance, although this was not the case for the series at hand;

- Finally, the results on asymmetric effects from η_t itself (not reported here) do not signal any significant impact of negative values of η_t on the conditional variance.

V A Forecasting Comparison

A full comparison among the four models can be performed in an out-of-sample forecasting context as well, over the period Oct. 2, 1998 to Jan. 7, 1999, which immediately follows the estimation period and includes 195 observations. The forecasting strategy is one step ahead, by computing the values of ζ's and η's on the basis of the coefficients estimated over the sample Jan. 7, 1994 to Oct. 2, 1998. The forecast errors are computed as the difference between the squared realized ζ's and the variance forecasts according to each model. As synthetic indicators, we use the out-of-sample Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE) as shown in Table VI. This complements the analysis presented in Section IV regarding the evaluation of estimated models. We report, therefore, the simple GARCH (**G**), the GARCH with η_t^2 (**GX**), the Threshold GARCH (**TG**), and the Threshold GARCH with η_t^2 (**TGX**). Note that we have reported in boldface character the lowest value of each indicator among the four models, and that, for ease of reference, we have added an asterisk next to the ticker when the joint opening surprise bias test above turned out to be significant (cf. Table III).

Table VI around here

The results point out at least two interesting features:

1. if the criterion used is the mean of forecast errors in absolute value, the performance of the models where the η's are included is outstanding, dominating the more standard models in all cases (14 best performances for the GARCH-X and 6 for the TGARCH-X).

2. When the other indicator is used, though, this predominance disappears mainly in favor of the standard GARCH models (13 for the GARCH and 4 for the TGARCH).

An explanation for these features might be that the extended models perform less satisfactorily than their standard counterparts *when extreme episodes of volatility are involved*: in such instances, in fact, one can expect larger forecast errors which, when weighed more heavily as squares, reveal a poorer performance in the augmented models. The issue of deciding which kind of metric translates best into a suitable evaluation criterion still stands and will not be pursued here (Gallo and Pacini, 1998, [7] adopt an asymmetric criterion for negative and positive forecast errors). However, limiting ourselves to the comparison between the absolute and the quadratic criteria presented here, we can draw some suggestions as to the behavior of the models by looking at the scatterplots of the forecasts obtained using the best performing model according to the MAE (which as we said include the opening surprise effect) and the ones obtained using the best performing model according to the RMSE (when this is a standard model). We have selected twelve cases (neglecting those where the difference was not informative), showing different situations and a common feature: standard GARCH– or TGARCH–based forecasts, reported on the x-axis are sistematically higher than their GARCH-X or TGARCH-X counterparts. This may explain the fact that, when episodes of higher volatility are involved, traditional GARCH models seem to react more than their augmented counterparts, avoiding those large errors associated with such extreme phenomena. On the other hand, augmented models fit better the actual volatility, so when extreme values are not squared (i.e. when MAE is used instead than RMSE) they perform better.

Figure 2 about here

VI Conclusions

In this paper we have examined the question of whether the information contained in the overnight returns (measured as open–to–previous close) can be useful in explaining the volatility of the intra–daily returns (measured as close–to–open differences). The results obtained provide a positive answer in that a test suggested here reveals a so–called *opening surprise bias.* As such, the overnight return has an explanatory power for the squared residuals of the intra–daily returns when they are standardized with a univariate estimate of the conditional variance. An extension of the univariate GARCH model to include the squares of overnight returns in the specification shows that the information set thus enlarged is helpful and often provides a better fit for the conditional variance estimates. The approach followed consists of inserting the squared overnight innovation directly into the intra-daily variance equation and has the advantage of being general and simple to compute. The new suggestion is evaluated in a forecasting framework where one-step ahead and out-of-sample forecasts are computed with each model. The extended models outperform the simple GARCH or threshold GARCH as far as mean absolute error is concerned, while a more mixed result holds for the RMSE, favoring the standard model.

[1]Notice that this decomposition has the interesting aspect of allowing a decomposition of daily variance into the sum of conditional variances of the components and twice the conditional covariance. We examine the issue of comparing these estimates of the conditional variance of r_t to those obtained by using the time series on r_t alone in a separate note.

[2]We also found that there is a mild effect on the conditional mean μ^{r_i}, but in general this result is consistent with market efficiency.

[3]For example, Gallo and Pacini (1998) [7] show that the insertion of the overnight innovation in a GARCH or EGARCH specification has the effect of significantly changing the profile in the news impact curve (Engle and Ng, 1993, [6]).

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Tables and Figures

Table I: List of tickers and companies

TICKER	Company
BA	Boeing
BS	Bethlehem Steel
CHV	Chevron
DD	Dupont
DIS	Disney
EK	Eastman Kodak
GM	General Motors
GT	Goodyear Tires Co.
HWP	Hewlett Packard
IBM	IBM Co.
JNJ	Johnson & Johnson
JPM	J.P. Morgan
MCD	McDonald's
MMM	Minnesota Mng & Mfg
MO	Phillip Morris
MRK	Merck
PG	Procter & Gamble
TX	Texaco
WMT	Walmart
XON	Exxon

Table II: ARCH(2) LM Test

TICKER	η_t	ζ_t	TICKER	η_t	ζ_t
BA	**7.6892**	**154.23**	JNJ	5.5504	**50.944**
	0.0214	0.0000		0.0623	0.0000
BS	2.0688	**12.477**	JPM	**44.226**	**221.82**
	0.3554	0.0020		0.0000	0.0000
CHV	2.7124	**33.741**	MCD	**23.220**	**77.014**
	0.2576	0.0000		0.0000	0.0000
DD	0.0283	**85.019**	MMM	0.2296	**21.554**
	0.9860	0.0000		0.8915	0.0000
DIS	**9.9599**	**73.003**	MO	3.9628	**6.5071**
	0.0069	0.0000		0.1379	0.0386
EK	0.1052	**26.451**	MRK	3.1517	**38.161**
	0.9488	0.0000		0.2068	0.0000
GM	1.7647	**14.155**	PG	**37.823**	**58.136**
	0.4138	0.0008		0.0000	0.0000
GT	**29.330**	**46.501**	TX	2.2271	**103.90**
	0.0000	0.0000		0.3284	0.0000
HWP	0.1237	**25.327**	WMT	1.0620	**47.088**
	0.9400	0.0000		0.5880	0.0000
IBM	1.2814	**37.408**	XON	4.1017	**127.38**
	0.5269	0.0000		0.1286	0.0000

Table III: Opening Surprise Bias Test

TICKER	η_t	$\eta_t \mathbb{1}_{\eta_t<0}$	η_t^2	**Joint**	TICKER	η_t	$\eta_t \mathbb{1}_{\eta_t<0}$	η_t^2	**Joint**
BA	-1.166	0.065	3.751	16.35	JNJ	1.492	-1.329	0.745	7.512
	0.244	0.948	0.000	0.000		0.136	0.184	0.457	0.000
BS	2.266	-1.964	-0.921	2.392	JPM	1.434	-2.849	0.023	11.07
	0.024	0.050	0.357	0.067		0.152	0.004	0.982	0.000
CHV	2.154	-2.125	0.930	13.80	MCD	0.484	-0.564	1.094	3.483
	0.031	0.034	0.353	0.000		0.629	0.572	0.274	0.015
DD	1.190	-2.165	0.813	8.406	MMM	2.472	-1.461	0.890	5.720
	0.234	0.031	0.416	0.000		0.014	0.144	0.373	0.001
DIS	-0.423	0.244	1.767	3.965	MO	1.484	-2.216	-0.610	5.354
	0.672	0.807	0.077	0.008		0.138	0.027	0.542	0.001
EK	1.308	-1.563	-0.618	1.261	MRK	1.230	-0.794	1.088	4.615
	0.191	0.118	0.537	0.286		0.219	0.427	0.277	0.003
GM	1.575	-1.968	-0.109	6.471	PG	0.949	-2.079	0.375	9.373
	0.116	0.049	0.913	0.000		0.343	0.038	0.707	0.000
GT	1.840	-1.933	-1.028	2.205	TX	1.381	-0.633	0.263	2.901
	0.066	0.053	0.304	0.086		0.168	0.527	0.792	0.034
HWP	6.863	-5.798	-2.179	18.28	WMT	-0.886	0.228	2.292	7.015
	0.000	0.000	0.029	0.000		0.376	0.819	0.022	0.000
IBM	2.875	-1.776	1.572	17.05	XON	0.790	-0.646	-0.333	0.301
	0.004	0.076	0.116	0.000		0.430	0.518	0.739	0.825

Table IV: GARCH Estimation

TICKER	Model	ω	α_1	γ_1	β_1	ϕ_1	SIC	LM(4)
BA	G	0.6030	0.2238		0.5028		3.5237	2.58
		3.7775	2.9385		4.5476			0.63
	GX	0.8431	0.2453		0.2939	0.1588	3.5059	3.89
		5.0533	2.9715		2.7231	2.3754		0.42
	TG	0.6859	0.0937	0.2177	0.4754		3.5190	1.96
		3.8951	2.3277	1.9353	4.1950			0.74
	TGX	0.8466	0.1150	0.2072	0.3166	0.1391	3.5047	4.33
		4.4914	2.3213	1.6932	2.6013	2.2165		0.36
BS	G	0.0294	0.0214		0.9738		4.4664	6.88
		0.7713	2.2165		67.087			0.14
	GX	0.0959	0.0179		0.9474	0.0526	4.4647	5.12
		1.2742	1.6678		30.813	1.4302		0.28
	TG	0.0444	0.0152	0.0213	0.9673		4.4688	6.41
		0.9705	1.5537	1.6904	59.343			0.17
	TGX	0.1122	0.0068	0.0277	0.9422	0.0527	4.4660	5.18
		1.2165	0.6071	1.5523	26.932	1.3823		0.27
CHV	G	0.0270	0.0449		0.9411		3.3334	8.60
		1.8835	3.8961		62.495			0.07
	GX	0.7505	0.1406		0.2989	0.5463	3.3395	2.85
		5.6055	4.0517		3.1495	4.3474		0.58
	TG	0.03174	0.0352	0.0265	0.9350		3.3376	7.60
		2.0128	2.0960	1.0088	55.226			0.11
	TGX	0.0442	0.0280	0.0379	0.9073	0.0905	3.3379	5.73
		2.1383	1.6708	1.3089	39.569	2.3766		0.22
DD	G	0.0270	0.0545		0.9359		3.5634	15.13
		1.4373	3.0183		42.811			0.00
	GX	0.0484	0.0385		0.9163	0.0724	3.5564	15.61
		1.8059	2.6229		31.448	2.4469		0.00
	TG	0.3888	0.0962	0.2280	0.6339		3.5664	3.79
		3.3892	2.2187	3.0413	7.6998			0.44
	TGX	0.3553	0.0691	0.2062	0.6212	0.1866	3.5560	3.32
		3.5256	1.7342	2.8786	8.0468	3.3184		0.51
DIS	G	0.0780	0.0567		0.9062		3.5080	10.26
		0.9410	2.0210		13.980			0.04
	GX	0.2262	0.03971		0.7804	0.1881	3.4787	7.36
		2.3521	1.7839		9.5623	1.5880		0.12
	TG	0.1281	-0.002 2	0.1007	0.8891		3.4944	4.21
		1.2205	-0.1938	2.0828	11.771			0.38
	TGX	0.2964	-0.019	0.1149	0.7500	0.1717	3.4750	2.04
		2.8579	-0.9775	2.3391	9.5893	1.6030		0.73
EK	G	0.7651	0.0798		0.5628		3.5984	0.89
		2.0198	2.2269		2.8615			0.93
	GX	0.8978	0.0687		0.4598	0.1511	3.5915	0.79
		2.9846	1.8186		2.8877	2.1698		0.94
	TG	0.3598	0.0187	0.1070	0.7660		3.5965	0.87
		2.4369	0.7159	1.9879	9.8236			0.93
	TGX	0.6408	0.0128	0.1292	0.5908	0.1102	3.5696	0.29
		3.9592	0.2756	1.8506	6.4810	2.0030		0.99

Table IV: GARCH Estimation - Cont.'d

TICKER	Model	ω	α_1	γ_1	β_1	ϕ_1	SIC	LM(4)
GM	G	1.2382	0.0981		0.3718		3.6896	1.32
		2.3686	2.4659		1.5924			0.86
	GX	1.3180	0.0664		0.2641	0.3447	3.6806	2.17
		3.8664	1.9022		1.7102	3.3308		0.71
	TG	0.7773	0.0043	0.1365	0.5982		3.6872	1.61
		2.4128	0.1594	2.2685	3.7868			0.81
	TGX	1.2418	0.0090	0.1191	0.3151	0.2765	3.6823	1.44
		3.9644	0.2979	1.8834	2.1851	3.1137		0.84
GT	G	1.2088	0.1627		0.2244		3.4986	0.16
		3.6987	2.9577		1.2398			0.99
	GX	1.0004	0.1442		0.2750	0.2843	3.4942	0.28
		3.5881	2.6407		1.7225	2.8330		0.99
	TG	0.8289	0.0720	0.1701	0.4303		3.4978	1.36
		3.3066	1.6171	1.9137	2.9122			0.85
	TGX	0.8047	0.0627	0.1640	0.3861	0.2576	3.4932	1.02
		3.3102	1.2174	1.8081	2.6521	2.8519		0.91
HWP	G	0.0108	0.0170		0.9811		4.0898	21.80
		1.2416	2.6945		132.70			0.00
	GX	1.2562	0.1406		0.3900	0.3984	4.0870	0.48
		5.7456	4.0332		4.7879	3.2403		0.98
	TG	1.4392	0.0732	0.2179	0.4320		4.1062	0.74
		4.1229	2.1283	2.6840	3.7006			0.95
	TGX	1.3820	0.0279	0.2239	0.3525	0.4068	4.0823	1.25
		6.0823	0.9188	3.2955	4.0651	3.1325		0.87
IBM	G	0.6858	0.1646		0.6099		3.8773	1.25
		2.8905	3.5224		5.4828			0.87
	GX	0.8449	0.1250		0.4896	0.3635	3.8481	1.12
		4.2655	3.0308		5.2791	3.6037		0.89
	TG	0.7102	0.0518	0.3121	0.5718		3.8581	1.70
		3.5927	1.5570	3.9475	6.2590			0.79
	TGX	0.8049	0.0350	0.2528	0.4856	0.3220	3.8359	1.93
		4.1231	0.8634	3.2681	5.0017	3.4453		0.75
JNJ	G	0.1263	0.0694		0.8637		3.4438	5.66
		1.8769	2.8948		16.164			0.23
	GX	0.2332	0.0653		0.7370	0.2545	3.4234	2.70
		2.6430	2.6382		10.176	3.1387		0.61
	TG	0.1326	0.0290	0.0799	0.8606		3.4418	5.13
		2.2168	1.2858	2.2140	17.792			0.19
	TGX	0.3570	0.0261	0.1277	0.6334	0.3043	3.4230	3.00
		3.3873	0.9799	2.5107	7.6089	3.0700		0.56
JPM	G	0.0168	0.0529		0.9413		3.3986	28.90
		1.2260	3.8145		54.134			0.00
	GX	0.1861	0.1072		0.7160	0.3139	3.3765	4.76
		3.2326	3.5440		11.862	3.0697		0.31
	TG	0.0201	0.0311	0.0406	0.9416		3.3992	24.77
		1.4367	2.2438	1.8487	55.303			0.00
	TGX	0.1956	0.0551	0.1108	0.7133	0.2958	3.3757	4.35
		3.3503	1.8221	2.1064	11.796	2.9169		0.36

Table IV: GARCH Estimation - Cont.'d

TICKER	Model	ω	α_1	γ_1	β_1	ϕ_1	SIC	LM(4)
MCD	G	0.5368	0.0888		0.6125		3.4174	3.92
		1.3451	1.6298		2.3892			0.42
	GX	0.8084	0.0410		0.3907	0.3164	3.3973	7.86
		1.8081	0.9104		1.1672	2.2634		0.10
	TG	0.4155	0.0091	0.1176	0.6992		3.4155	3.32
		1.8331	0.3199	1.6218	4.6754			0.51
	TGX	0.6632	-0.0395	0.1070	0.5089	0.2780	3.3977	7.83
		1.7973	-1.3586	2.3031	1.8795	2.6013		0.10
MMM	G	0.6563	0.1829		0.3896		3.2268	1.69
		3.4350	3.3522		2.5769			0.79
	GX	0.6619	0.1594		0.3460	0.1878	3.2234	1.28
		3.7739	3.3406		2.4352	2.3928		0.86
	TG	0.6909	0.1036	0.1702	0.3630		3.2277	2.65
		4.3537	2.4713	1.7425	2.9505			0.62
	TGX	0.7109	0.0785	0.1927	0.3030	0.1884	3.2234	3.14
		4.7700	1.9761	2.0312	2.5631	2.4028		0.53
MO	G	0.2699	0.0895		0.8067		3.7017	0.15
		1.5922	2.7333		9.7707			0.99
	GX	1.0818	0.0621		0.2163	0.9899	3.6412	0.51
		2.6893	1.2664		1.7263	3.3740		0.97
	TG	0.2950	0.0755	0.0300	0.7957		3.7070	0.16
		1.5761	2.3297	0.6756	8.7783			0.99
	TGX	1.1009	0.0138	0.1045	0.2128	0.9579	3.6434	0.34
		2.8002	0.3551	1.6350	1.7272	3.3320		0.99
MRK	G	1.1981	0.1878		0.2398		3.5475	1.20
		4.3852	3.2139		1.6323			0.88
	GX	0.1627	0.0392		0.8291	0.1870	3.5289	6.94
		3.0685	2.3936		20.962	3.1600		0.14
	TG	1.0226	0.0588	0.2619	0.3271		3.5395	1.71
		5.1929	1.4452	2.1616	2.9594			0.79
	TGX	0.3781	0.0004	0.1418	0.6780	0.2447	3.5260	3.17
		4.2345	0.0196	2.0307	10.752	3.3725		0.53
PG	G	0.0128	0.0360		0.9587		3.4456	19.18
		1.1402	2.4693		62.736			0.00
	GX	0.0214	0.0326		0.9344	0.0889	3.4415	18.28
		1.3503	2.2857		39.701	1.6870		0.00
	TG	0.02096	0.0224	0.0308	0.9525		3.4491	17.14
		1.3273	1.9815	1.1400	50.229			0.00
	TGX	0.0259	0.0239	0.0188	0.9321	0.0857	3.4467	16.35
		1.4459	1.8102	0.8075	38.077	1.6681		0.00
TX[4]	G	0.0005	-0.0020		1.0031		3.0819	43.54
		1.1078	-0.7635		430.29			0.00
	GX	0.0149	0.0377		0.9352	0.0875	3.0932	11.50
		1.9086	3.1655		51.734	1.4204		0.02
	TG	0.0005	0.0008	-0.0037	1.0020		3.0870	44.29
		1.0773	0.1025	-0.4146	257.05			0.00
	TGX	0.0116	0.0379	-0.0117	0.9448	0.0767	3.0986	16.63
		1.7477	2.8290	-0.3689	57.094	1.3950		0.00

[4]Note that the estimation of Models (4) and (6) for this stock yields not acceptable results.

Table IV: GARCH Estimation - Cont.'d

TICKER	Model	ω	α_1	γ_1	β_1	ϕ_1	SIC	LM(4)
WMT	G	2.0394	0.2380		0.0338		3.8253	8.83
		7.6848	3.3416		0.4379			0.07
	GX	1.6181	0.1450		0.1808	0.2747	3.8213	10.89
		4.6951	2.7701		1.3131	2.2290		0.03
	TG	1.4790	0.0566	0.2668	0.2781		3.8200	6.94
		4.8927	1.5196	2.5672	2.2713			0.14
	TGX	1.0961	-0.0051	0.2344	0.4275	0.1946	3.8139	13.00
		3.8973	-0.23802	2.8575	3.2682	2.2898		0.01
XON	G	0.1171	0.1748		0.7539		3.1165	1.68
		3.4271	4.4815		17.302			0.79
	GX	0.0967	0.1477		0.7713	0.1036	3.1204	2.07
		3.1249	4.9609		17.622	1.3821		0.72
	TG	0.1219	0.1296	0.0860	0.7522		3.1193	1.21
		3.3764	4.1895	1.2180	16.705			0.88
	TGX	0.1081	0.1168	0.0743	0.7622	0.0794	3.1239	1.36
		3.1915	3.7072	1.1425	16.600	1.2202		0.85

Table V: Likelihood Ratio Tests on Model Restrictions

TICKER	$\gamma_1 = \phi = 0$	$\gamma_1 = 0$	$\phi = 0$	TICKER	$\gamma_1 = \phi = 0$	$\gamma_1 = 0$	$\phi = 0$
BA	37.75	8.648	24.84	JNJ	39.95	7.558	30.28
	0.000	0.003	0.000		0.000	0.006	0.000
BS	14.04	4.822	9.860	JPM	42.47	8.072	36.10
	0.001	0.028	0.002		0.000	0.004	0.000
CHV	8.666	9.150	6.698	MCD	38.59	6.641	29.17
	0.013	0.002	0.010		0.000	0.010	0.000
DD	23.46	7.612	20.07	MMM	18.42	7.061	12.47
	0.000	0.006	0.000		0.000	0.008	0.000
DIS	55.03	11.76	31.11	MO	86.27	4.417	85.64
	0.000	0.001	0.000		0.000	0.036	0.000
EK	24.25	8.580	14.82	MRK	40.73	10.67	23.77
	0.000	0.003	0.000		0.000	0.001	0.000
GM	23.21	4.989	13.19	PG	12.94	0.721	10.20
	0.000	0.026	0.000		0.002	0.396	0.001
GT	20.85	8.330	12.71	TX[5]	1.978	0.136	1.946
	0.000	0.004	0.000		0.372	0.712	0.163
HWP	23.54	12.96	36.63	WMT	28.36	16.25	14.64
	0.000	0.000	0.000		0.000	0.000	0.000
IBM	65.41	22.23	34.52	XON	5.172	2.801	1.490
	0.000	0.000	0.000		0.075	0.094	0.222

[5]Because of the inconsistency of the Model (**G**) and (**TG**) estimates, the Wald test was used instead for this stock.

Table VI: Intra-daily Conditional Variance

Out-of-sample MAE and RMSE Comparisons

	BA*		BS		CHV*		DD*	
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
G	4.422	**9.466**	10.91	**16.02**	2.793	**4.449**	4.454	**6.409**
GX	4.296	9.467	**9.584**	16.67	**2.541**	4.657	**3.949**	6.604
TG	4.329	9.483	10.96	16.06	2.803	4.475	4.214	6.581
TGX	**4.238**	9.491	9.673	16.64	2.595	4.548	4.016	6.641
	DIS*		EK		GM*		GT	
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
G	4.840	**8.145**	2.460	**5.207**	3.558	**6.250**	3.238	**5.332**
GX	**4.315**	8.520	**2.374**	5.221	**3.474**	6.353	**3.196**	5.379
TG	4.660	8.263	2.592	5.316	3.641	6.336	3.353	5.386
TGX	4.420	8.606	2.456	5.317	3.527	6.408	3.291	5.436
	HWP*		IBM*		JNJ*		JPM*	
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
G	6.071	**9.499**	3.453	**5.283**	2.465	4.340	4.786	7.027
GX	**5.424**	9.681	**3.192**	5.296	2.290	4.442	4.273	7.474
TG	5.679	9.599	3.394	5.296	2.396	**4.314**	4.748	**6.903**
TGX	5.425	9.723	3.196	5.296	**2.260**	4.400	**4.259**	7.345
	MCD*		MMM*		MO		MRK*	
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
G	2.696	**4.415**	3.074	**4.557**	3.885	**8.391**	2.787	5.369
GX	**2.666**	4.569	**3.036**	4.624	**3.641**	8.710	**2.580**	5.370
TG	2.685	4.444	3.062	4.561	3.898	8.398	2.888	5.461
TGX	2.700	4.638	3.036	4.624	3.688	8.708	2.674	**5.322**
	PG*		TX*		WMT*		XON	
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
G	3.270	4.834	3.714	7.770	4.047	6.978	2.373	3.592
GX	2.838	4.946	3.619	7.889	3.822	6.927	**2.293**	**3.590**
TG	3.151	**4.785**	3.724	**7.767**	3.944	6.899	2.390	3.643
TGX	**2.829**	4.932	**3.618**	7.891	**3.794**	**6.845**	2.333	3.635

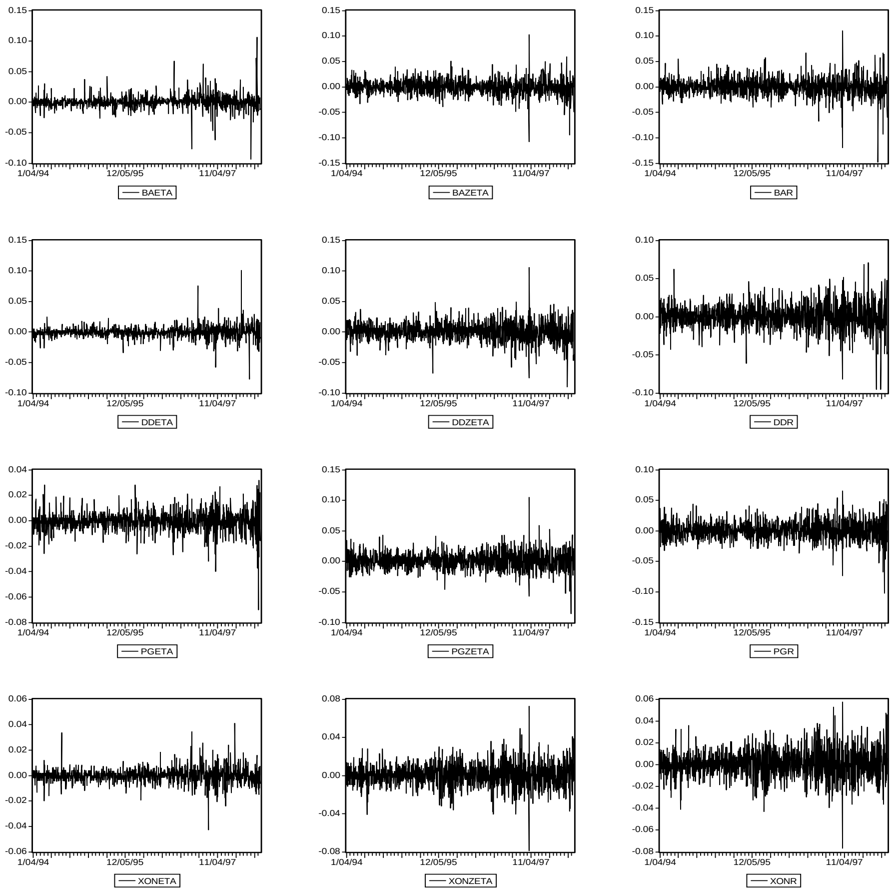

Figure 1: Time Series Profile of $r_{o,t}$, $r_{i,t}$ and their sum r_t for four selected stocks.

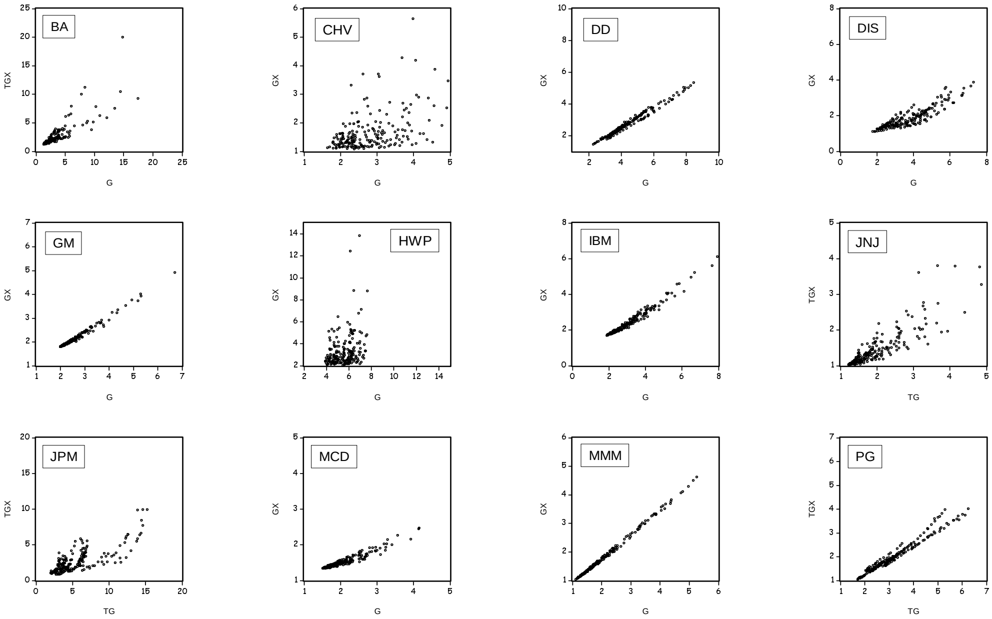

Figure 2: Variance Forecast Comparison: Best RMSE model versus best MAE model.