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Modelling the Daily Currency in Circulation in Turkey*

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Abstract

The main focus of this paper is to model the daily series of currency in circulation in Turkey. The currency in circulation is one of the most significant factors influencing the liquidity of the Turkish banking system. Therefore, the amount of currency in circulation has to be forecasted as accurately as possible. The currency in circulation displays an increasing long-term trend and strong seasonal factors which can be forecasted. This paper introduces the ARIMA-based approach to model seasonality in daily time series and evaluates the forecasting performance of the model. The results indicate that the forecasting performance of the model is better than the expert judgments both in the short-term and the long-term.

JEL Classification: C22, C53, E41, E47.
Keywords: Currency in circulation, Liquidity management, Time series models, Seasonality.

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* All the views expreased in this paper belong to the authors and do not represent those of the Central Bank of the Republic of Turkey, or its staff.

1. Introduction

The Central Bank of the Republic of Turkey (CBRT) is primarily committed to achieving and maintaining price stability. With this regard, CBRT directly determines and implements a collection of monetary policy instruments in order to influence interest rates and manage liquidity in the money markets. In other words, for a central bank to effectively steer interest rates it should manage the conditions that equilibrate demand and supply in the market for bank reserves. In this respect, liquidity management based on accurate liquidity forecasts has crucial role in controlling the short-term interest rates in line with the main goal of achieving price stability.

The main motive of this paper is to construct an econometric model to forecast daily currency in circulation (CiC). The daily liquidity forecast depends on the accuracy of its individual components. Since CiC is one of the most significant factors influencing the liquidity of the Turkish banking system, it is crucial for the CBRT to produce precise forecasts of CiC.

The paper is organized as follows. Section 2 describes the series of CiC in Turkey. The statistical properties of the series and some ratios are presented in this section. The ARIMA model is described in section 3. The forecasting performance of the model is discussed and the expert judgment approach is evaluated in this section. Section 4 presents some brief concluding remarks.

2. The Series of Currency in Circulation

The CiC is one of the major autonomous[1] liquidity factors in CBRT's balance sheet and it plays a major role in the context of CBRT's liquidity management, both in terms of absolute size and volatility. Therefore the volume of the series is an important factor in liquidity forecasting process. Since the volume of CiC is out of the control of the central bank, it cannot be determined exactly. Therefore, it is required to construct an econometric model in order to approximate the behaviour of the series as accurately as possible.

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[1] Liquidity factors affecting the supply of bank reserves, which are beyond the control of central bank or counterparties, are called autonomous.

For the purposes of this paper, CiC is defined as the volume of banknotes in circulation excluding the vault cash held by commercial banks.[2] The CiC includes all banknotes in domestic currency that the economic agents demand for a specific moment for transaction or as a store of value. When currency is returned to banks (the volume of CiC diminishes), it is considered to be a part of banks' reserve with the CBRT, thus liquidity of the banking sector increases. Similarly cash withdrawals from banks (the volume of CiC increases) leads to a decrease in the liquidity of the system.

As the series of CiC displays very significant seasonality; comprising daily, weekly, monthly, annual patterns and some calendar effects like public holidays, the modeling of daily series, which display seasonal patterns, is not simple. Table 1 presents basic statistics for the daily series.

Table 1
Descriptive Statistics of CiC in Turkey (million TL)

	2003	**2004**	**2005**	**2006**	**2007**	**2008**
Observation	250	252	254	248	255	251
Mean	9.361	13.108	16.812	22.021	24.474	29.270
Std. Dev.	1.179	1.056	1.986	1.576	2.102	2.395
Min.	7.297	10.426	13.242	18.871	20.971	25.559
Max.	13.067	16.107	22.098	27.221	32.043	38.391
Beginning	7.552	10.724	14.218	19.404	23.524	26.651
End	10.676	13.465	19.612	23.104	27.429	31.743

Source: CBRT.

There are several indicators for quantification of the relative importance of the CiC in every economy. The most important ones can be defined as i) the share of CiC in total assets of central bank balance sheet, and ii) the share of CiC in the nominal gross domestic product (Stavreski, 1998).

[2] The data used in this study is composed of "Currency issued" item in CBRT Analytical Balance Sheet, and can be accessed at http://evds.tcmb.gov.tr/yeni/cbt-uk.html.

Figure 1. CiC / CBRT Total Assets

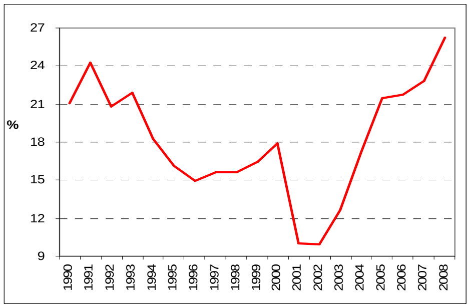
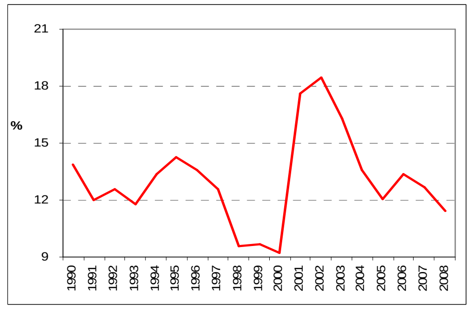


Figure 2. CiC / GDP



Source: CBRT

Because of the contraction of economic activity during the 1994 financial crisis the share of CiC in total assets of CBRT's balance sheet drops to 15% from 25% in early 1990s (Figure 1). Turkish economy experienced a recession in 2001 when the economic growth shrank by 6% in real terms and accordingly the share of CiC in total assets of CBRT's balance sheet drops to 10%. After the 2001 crisis, macro economic stability and market confidence was restored in the Turkish economy as a result of prudent monetary and fiscal policies along with widespread structural reforms. The share of CiC in total assets of CBRT's balance sheet reached up to 26% as a result of the increase in money demand and reverse dollarisation during this stable and high growth episode. The share of CiC in the nominal gross domestic product displays almost the mirror image of Figure 1 as the economic growth leads to a decline in the ratio during recessions.

The log of the series of CiC in Turkey is shown in Figure 3a. There is an increasing trend in the CiC between October 2003 and December 2008. This upward long-term trend can be attributed to factors like nominal economic growth, inflation and population growth. The weekly, monthly and annual seasonal patterns clearly appear in Figure 3b, 3c and 3d. The volume of CiC increases just before the weekend and decreases after the weekend. It also increases towards the midst of the month as a result of the payment of salaries. The volume of currency rises during summer holidays and towards the end of year and before the religious holidays especially like Feasts of Ramadan and Sacrifice.

Figure 3a. ln (CiC) - daily (2003–2008)

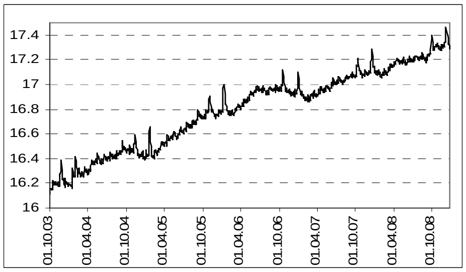


Figure 3b. ln (CiC) - daily (year 2008)

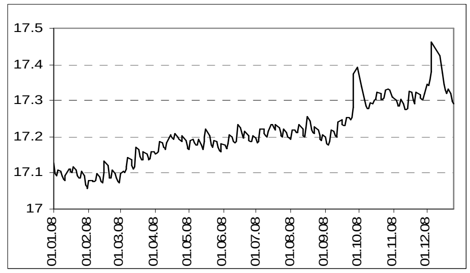
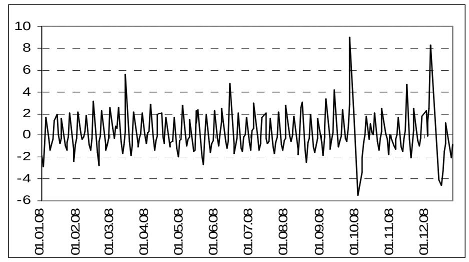


Figure 3c. ln (CiC) - daily (Aug. 2008)

Figure 3d. ln (CiC) - daily diff.(2008)



Source: CBRT.

3. Modelling the Currency in Circulation Using ARIMA

In the literature, CiC generally estimated by specifying a standard money demand equation based on the theory of transaction or portfolio demand for money. Such an equation could be estimated in isolation (Jadhav, 1994) or could be a part of a bigger macro economic model (Palanivel and Klein, 1999). Standard money demand equation includes income or its proxy, price level and the opportunity cost of holding cash as explanatory variables in these models (Baumol, 1952; Tobin, 1956; Friedman, 1956). The second approach in modelling the money demand is by using univariate time series model. Both of these approaches have been applied extensively for annual and quarterly series. Since univariate time series models could theoretically be applied to high frequency data, the main problem at high frequency is to specify calendar variation effects.

The most widely used econometric models in modelling the daily CiC are autoregressive integrated moving average (ARIMA, ARMAX, RegARIMA), structural time series (STS), ordinary least squares regression and error correction models with dummy variables. The ARIMA model presented in this paper is based on the methodology proposed by Box and Jenkins (1976). Box-Jenkins methodology can be applied not only to weekly stationary processes, but also to non-stationary processes that besides an ARMA process include various trends and seasonal and other deterministic and stochastic components. Bell and Hillmer (1983) suggest using the model stated below for series with calendar variations, which is a linear regression model with errors following an ARIMA process:

$$y_t = D_{t,i} + \eta_t$$

$$\eta_t = \frac{\theta(B)}{\phi(B)\delta(B)}\varepsilon_t \qquad \varepsilon_t \sim i.i.d(0,\sigma^2)$$

Here y_t is the daily CiC, $D_{t,i}$ is the linear regression part, B is the backshift operator and θ, ϕ, δ are polynomials in B. The polynomials θ and ϕ are moving-average and autoregressive operators, respectively. The polynomial δ is a difference operator that can also include a seasonal difference operator.

The regression component is composed of dummy variables like day of week, day of month, religious and public holidays, month of year and interaction of these variables. The dummy variables in $D_{t,i}$ specify the seasonal effects of CiC. Apart from the seasonal effects, additional dummy variables are included for outliers and introduction of the New Turkish Lira (YTL).

Table 2
Seasonal Factors Included in the ARIMA Model

Trading day Effect	$\sum_{i=1}^{5} \alpha_i TD_{it}$	TD_{it}	$= \begin{cases} 1, \text{ If day i occurs at time t} \\ 0, \text{ otherwise} \end{cases}$
Intra-monthly Effect	$\sum_{i=1}^{31} \delta_i d_{it}$	d_{it}	$= \begin{cases} 1, \text{ If day of month i occurs at time t} \\ 0, \text{ otherwise} \end{cases}$
Monthly Effect	$\sum_{i=1}^{12} \pi_i M_{it}$	M_{it}	$= \begin{cases} 1, \text{ If month of year i occurs at time t} \\ 0, \text{ otherwise} \end{cases}$
Ramadan (Eid Al Fitr)	$(\beta_o + \beta_1 B + \beta_2 B^2 + ... + \beta_{10} B^{10}) B^{-5}$		
Feast of Sacrifice (Eid Al-Adha)	$(\beta_o + \beta_1 B + \beta_2 B^2 + ... + \beta_{11} B^{11}) B^{-6}$		
Day of month*Trading Day Interaction	$\sum_{i=1}^{5}\sum_{j=1}^{31} \lambda_{ij} TD_{it} d_{jt}$		
Public Holiday*Trading Day Interaction	$\sum_{i=1}^{5} \gamma_i TD_{it} PH_t$		
Outliers	$\sum_{i=1}^{4} \mu_i O_{it}$	O_{it}	$= \begin{cases} 1, \text{ If outlier i occurs at time t} \\ 0, \text{ otherwise} \end{cases}$
YTL	$r_i YTL_{it}$	YTL_{it}	$= \begin{cases} 1, \text{ If introduction of YTL i occurs at time t} \\ 0, \text{ otherwise} \end{cases}$

According to Bell and Hillmer (1983), it is crucial to construct the seasonal difference equation by analysing both the autocorrelation function (ACF) and function of partial autocorrelation function (PACF) in order to forecast the long-term trend in seasonal time series. Annual seasonal differencing is used extensively in the literature in modelling the daily CiC.

Franses (2004) states that by de-trending the long-term trend of time series and constructing constant deterministic seasonality models, one can account for the majority of trend-free variation in the data.

The time series of daily CiC includes only the trading days so the data on weekends and public holidays is the same as the previous trading day. Therefore, annual seasonal differencing is not an appropriate approach in this study because of high seasonality of the series in the short-term and the large number of missing values.

Although the robustness of the Augmented Dickey-Fuller (ADF) test is criticised in series with strong seasonality, the stationarity of log of daily series of CiC is tested by ADF test and the optimum lags are determined by Schwarz Information Criterion. According to ADF test results[3], CiC series become stationary by taking the first differences in this study.

Integration and moving average processes are determined by calculating the ACF and PACF.[4] Finally, deterministic variables composed of seasonal dummies and the ARIMA process variables are estimated simultaneously by Non-linear Least Squares. However, after the final estimation ARCH LM test results reveal autoregressive conditional heteroscedasticity problem.[5] In order to eliminate heteroscedasticity, GARCH process is included in the final model.

GARCH model is developed by Bollerslev (1986) and can be stated as follows:

$$y_t \sim N(x_t\beta, h_t)$$

$$h_t = h(e_{t-1}, e_{t-2}, \ldots\ldots e_{t-p}, \alpha), \quad h_t = \gamma_0 + \gamma_1 e^2_{t-1} + \gamma_2 h_{t-1} \qquad GARCH(1,1)$$

$$e_t = y_t - x_t\beta$$

[3] The results of ADF test are provided in Appendix 1.
[4] The figures related to autocorrelation function and residuals are provided in Appendix 2.
[5] The results of ARCH LM test are provided in Appendix 3.

In this study, both ARIMA and GARCH processes are estimated simultaneously for the first time in literature while modelling daily CiC. Deterministic variables, ARIMA and GARCH process variables are estimated simultaneously after the model specification by maximum likelihood-ARCH (Marquardt) procedure. By including GARCH (1,1) process in the final model, autoregressive conditional heteroscedasticity problem is eliminated. The lags of the AR and MA processes are chosen with respect to ACF and PACF. The 42nd lag for AR and 31st lag for MA, the seasonal ARMA coefficients are found statistically significant. The orders of integration, AR and MA processes are identified as below:

$$\delta(B) = (I - B) \quad \mathrm{I}(1)$$
$$\phi(B) = (I - B - B^{13} - B^{14} - B^{40})\,(I - B^{42})$$
$$\theta(B) = (I - B^{3} - B^{31})\,(I - B^{41})$$

The final ARIMA - GARCH(1,1) model is described by 79 parameters.[6] The specification of the model was finalised on the basis of significance of parameters and diagnostic tests on the structure of the residuals.[7] The tests reported are for skewness and kurtosis, for normality, the Ljung-Box statistic for serial correlation and BDS test[8] for independent and identical distribution.

3.1. The Pattern of Currency in Circulation

The daily CiC data starts from 23 September, 2004 to 7 January, 2009 in this study. Various patterns of CiC series like trading day, intra-monthly and religious holiday effects are captured by using the ARIMA - GARCH(1,1) model. The trading day effect is one of the most significant seasonal effects of CiC. This effect indicates the presence of a very robust weekly seasonal cycle. The level of CiC declines on Mondays and the rate of decline increases on Tuesdays. The rate of decline in CiC starts to decrease on Wednesdays and this tendency strengthens further on Thursdays. The level of CiC almost does not change on Thursdays. Finally, the level of the series reaches its maximum on Fridays as the ATM network has to withstand all the shopping activity throughout the weekend. The cumulative change in the level of CiC is approximately equal to zero during a week. Cabrero et al. (2002) also find that the zero-sum effect of the trading day effect in Euro Zone is

[6] The model coefficient estimates are provided in Appendix 4.
[7] Diagnostic tests for the final specifications are reported in Appendix 5.
[8] Following Caporale et al. (2005), we examine the widely used Brock, Dechert, and Scheinkman (BDS) test when applied to the logarithm of the squared standardized residuals of the estimated model as a test for adequacy of this specification.

highly significant. According to the CiC series which excludes the effects of salary payments and religious holidays, the level of banknotes declines 0,7% on Mondays, 1,3% on Tuesdays, 0,4% on Wednesdays and then increases 0,1% on Thursdays and 2,1% on Fridays, on average (Figure 4a).

Intra-monthly patterns in the series of CiC are associated with the payment of salaries in the middle of the month and the increase towards the middle of the first week. The expected increase in the level of CiC on the first day of the month is observed towards the middle of the first week that indicates a lagged effect. The demand for cash is higher around the salary payment day (towards the middle of the month) and then decreases until salaries are paid again (Figure 4b). The effect of salary payment on CiC depends on the payment day in the week. Although some days of the month have no significant individual effect on cash demand, when salary payments coincide these days the effect on cash demand becomes significant. Thus, interaction dummies are included to capture these effects in this study.

There are two different categories of the public holiday effect in Turkey; one is the religious holidays when the level of CiC changes dramatically and the second one is the effect of fixed, national holidays. There are two religious holidays in Turkey (Feast of Ramadan and Feast of Sacrifice) celebrated every year and their starting date and duration varies year by year. There exist huge increases in domestic demand before these two holidays that lead to dramatic upsurge in cash demand. The main difference between these two holidays is that the effect of Feast of Sacrifice on cash demand is approximately two times greater than that of Feast of Ramadan. The effect of Feast of Ramadan on cash demand has t-6 and t+5 trading day lag where the Feast of Sacrifice has t-5 and t+5 trading day lag. In other words, the increase in the level of currency demand starts 6 (5) working days before the Feast of Ramadan (Feast of Sacrifice Holiday) and the cash demanded by households' returns to the banking system after the feast for 5 days (Figure 4c and 4d). According to the ARIMA - GARCH(1,1) model, other national holidays fixed to a particular date do not significantly increase the cash demand. However, if the national holiday is on a Monday or a Friday, the cash demand increases significantly.

Figure 4a. Trading Day Effect

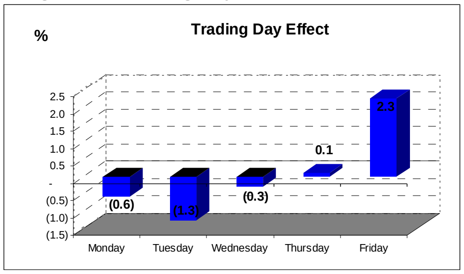


Figure 4b. Intra-monthly Effect

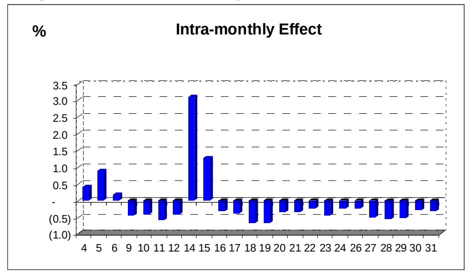


Figure 4c. Ramadan Effect

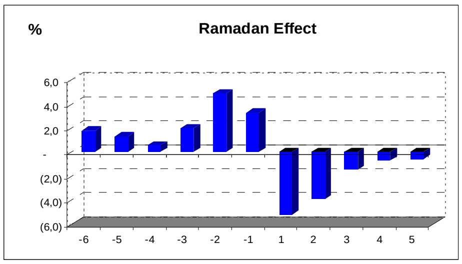
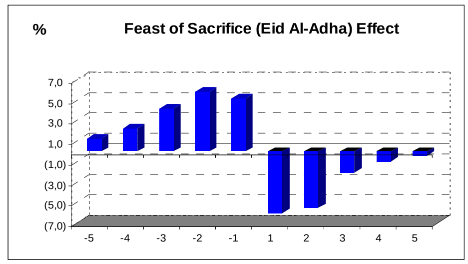


Figure 4d. Feast of Sacrifice Effect



3.2. ARIMA - GARCH (1,1) Model Forecast and Forecast Performance

The out-of-sample forecasts of the ARIMA-GARCH (1,1) model and the expert judgments are presented in Figure 5a and 5b. The expert judgments are composed of a set of rules used by liquidity forecast division at CBRT when predicting the daily CiC. Experts produce forecasts by taking into account the weekends, tourist seasons, religious holidays and salary payments which have significant effects on currency demanded.

The out-of-sample forecasts are made one-step-ahead for 6 week forecast horizon starting from 8 January 2009. Forecasting performance is assessed on the basis of the mean absolute error, the root mean squared error, the mean absolute percentage error and Theil measure of inequality. All of these criteria are calculated both for ARIMA-GARCH(1,1) model forecasts and expert judgments by considering one-step-ahead forecasts for 6-week horizon and 5 day ahead, 10 day ahead, 20 day ahead and 30 day ahead recursive forecasts.[9] According to these four criteria, the ARIMA-GARCH (1,1) model displays a better forecasting performance than the expert judgments both over short-term and medium-term horizons.

[9] The results are provided in Appendix 6 and Appendix 7.

Figure 5a. ARIMA-GARCH (1,1) Model Forecasts

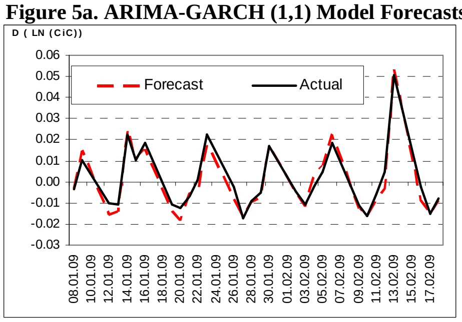
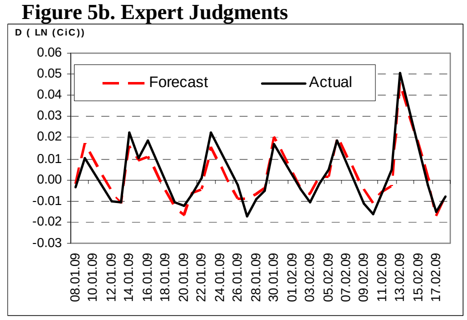


Figure 5b. Expert Judgments



4. Conclusion

The CBRT's objective of steering interest rates is achieved by managing the liquidity conditions that equilibrate supply and demand in the market for bank reserves. CBRT needs accurate forecast of certain autonomous factors like CiC in order to steer the interest rates efficiently.

The paper introduces the ARIMA-based approach for daily CiC forecasting and presents comparison of model forecasts with expert judgments. Results presented in this paper show that the ARIMA model could explain a large part of the variation in CiC. Although the model presented in this study outperforms the expert judgments both over the short and long-term horizon, the expert's viewpoint and judgments are crucial especially in capturing the exceptional effects on CiC.

The level of CiC is subject to various external fiscal shocks like agricultural payments, elections and irregular salary payments that the econometric models have difficulties in capturing the effects. These effects can be captured by expert knowledge, thus expert judgments play a prominent role during the times when these shocks observed.

In conclusion, CBRT's performance on forecasting daily CiC is enhanced by using the model presented in this paper. However, it should be noted that the model has to be continuously checked to improve the quality of the model forecast and adjusted whenever needed. In other words, with the CBRT's extensive use of the ARIMA model, expert judgments should remain as a supportive element in forecasting daily CiC.

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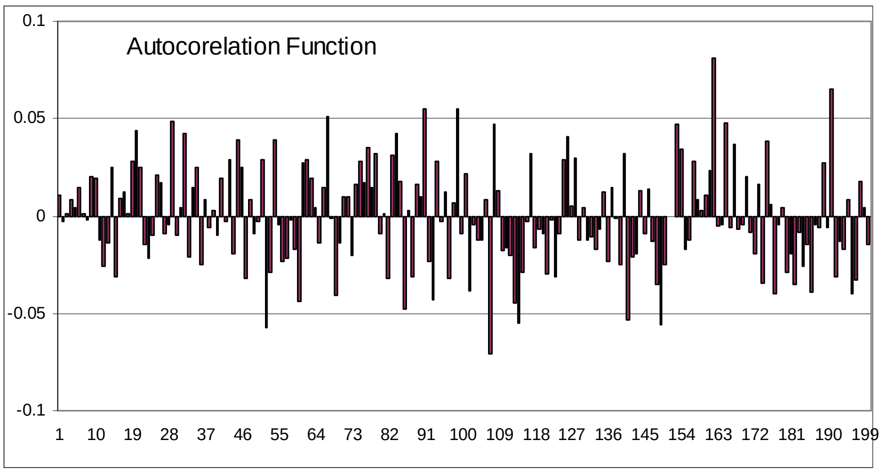
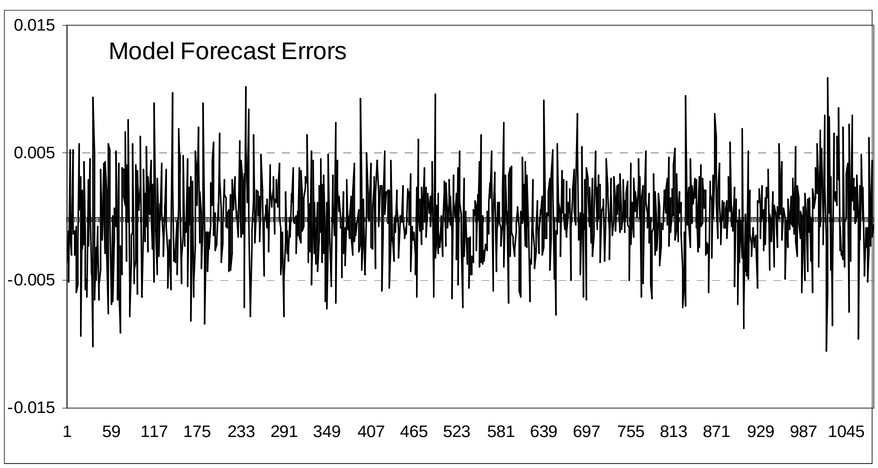
Appendix 1

ADF Test Results	Level ln(CiC)	First Difference Dln(CiC)
ADF test stat.	-2,45	-19,41***

ADF test values are compared with critical values tabulated by Mackinnon (1996).

Appendix 2
Autocorrelation Function and Residual Correlogram





Appendix 3

F-stat.	2.48	**Prob.** 0.03
Obs. R-squared	12.32	**Prob.** 0.03

Dependent Variable: STD_RESID^2

Variable	Coefficient	t-stat.
C	0.00	10.68***
STD_RESID^2(-1)	0.07	2.21**
STD_RESID^2(-2)	0.06	1.94*
STD_RESID^2(-3)	0.03	0.98
STD_RESID^2(-4)	0.03	0.97
STD_RESID^2(-5)	-0.01	-0.17

One, two and three asteriks denote significance at the 10, 5 and 1 percent levels respectively.

F-stat.	0.77	**Prob.** 0.57
Obs. R-squared	3.88	**Prob.** 0.57

Dependent Variable: STD_RESID^2

Variable	Coefficient	t-stat.
C	1.06	12.96***
STD_RESID^2(-1)	0.02	0.66
STD_RESID^2(-2)	0.00	0.04
STD_RESID^2(-3)	-0.01	-0.31
STD_RESID^2(-4)	-0.02	-0.63
STD_RESID^2(-5)	-0.05	-1.68*

Appendix 4
Model Coefficient Estimates

Dependent Variable: D(Ln(CiC))
Method: ML - ARCH(Marquardt)
Sample: 23/09/2004 : 07/01/2009
Included Observations: 1081

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Trading Day (TD)				
Monday	-0,0058	0,0004	-16,6185	0,0000
Tuesday	-0,0127	0,0004	-35,2398	0,0000
Wednesday	-0,0027	0,0004	-7,1862	0,0000
Thursday	0,0010	0,0004	2,8200	0,0048
Friday	0,0225	0,0004	62,4751	0,0000
Intra-monthly Effect (d)				
4	0,0043	0,0005	8,6533	0,0000
5	0,0090	0,0006	15,5429	0,0000
6	0,0019	0,0006	3,0862	0,0000
9	-0,0044	0,0007	-6,3424	0,0000
10	-0,0042	0,0008	-5,5480	0,0000
11	-0,0058	0,0006	-8,9748	0,0000
12	-0,0047	0,0007	-6,7237	0,0000
14	0,0313	0,0004	71,2694	0,0000
15	0,0129	0,0008	15,5922	0,0000
16	-0,0032	0,0007	-4,8639	0,0000
17	-0,0038	0,0007	-5,7301	0,0000
18	-0,0068	0,0008	-9,0486	0,0000
19	-0,0067	0,0006	-11,7180	0,0000
20	-0,0034	0,0007	-4,6327	0,0000
21	-0,0033	0,0008	-3,9630	0,0001
22	-0,0025	0,0007	-3,3327	0,0009
23	-0,0048	0,0008	-6,2809	0,0000
24	-0,0025	0,0007	-3,8114	0,0001
26	-0,0027	0,0006	-4,2550	0,0000
27	-0,0051	0,0007	-7,0971	0,0000
28	-0,0055	0,0006	-9,0214	0,0000
29	-0,0049	0,0006	-8,0718	0,0000
30	-0,0030	0,0006	-4,7096	0,0000
31	-0,0033	0,0005	-6,2794	0,0000
d*TD				
7*Friday	-0,0044	0,0017	-2,6553	0,0079
8*Friday	-0,0053	0,0015	-3,5262	0,0004
12*Friday	0,0193	0,0016	11,9433	0,0000
13*Friday	0,0270	0,0013	20,7816	0,0000
14*Wednesday	-0,0030	0,0012	-2,4049	0,0162
27*Monday	0,0025	0,0012	2,1096	0,0349
Monthly Effect (M)				
January	-0,0030	0,0006	-5,0640	0,0000
March	0,0018	0,0006	2,9941	0,0028
April	0,0029	0,0005	6,2843	0,0000
June	0,0017	0,0006	2,7579	0,0058

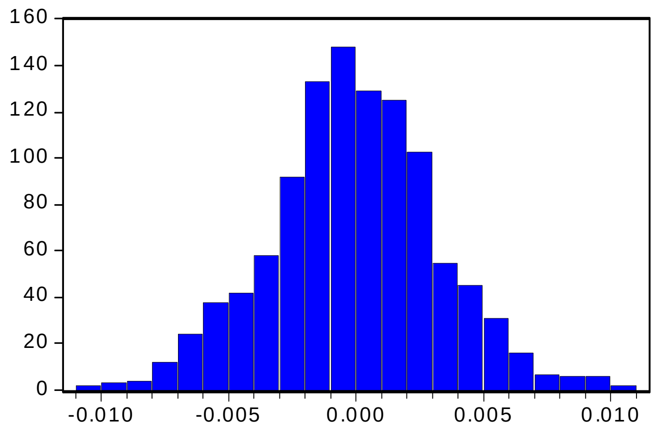
Religious Holidays				
Ram(-5)	-0,0059	0,0018	-3,1860	0,0014
Ram(-4)	-0,0072	0,0029	-2,4491	0,0143
Ram(-3)	-0,0152	0,0012	-12,1795	0,0000
Ram(-2)	-0,0393	0,0015	-26,2462	0,0000
Ram(-1)	-0,0522	0,0016	-33,2191	0,0000
Ram	0,0327	0,0017	19,6912	0,0000
Ram(1)	0,0492	0,0014	34,3122	0,0000
Ram(2)	0,0198	0,0013	14,7429	0,0000
Ram(3)	0,0056	0,0011	5,0657	0,0000
Ram(4)	0,0131	0,0019	6,8889	0,0000
Ram(5)	0,0177	0,0024	7,3005	0,0000
Sac(-5)	-0,0045	0,0016	-2,8467	0,0044
Sac(-4)	-0,0095	0,0031	-3,0693	0,0021
Sac(-3)	-0,0206	0,0018	-11,1924	0,0000
Sac(-2)	-0,0549	0,0019	-28,9197	0,0000
Sac(-1)	-0,0600	0,0018	-33,8957	0,0000
Sac	0,0518	0,0020	25,8787	0,0000
Sac(1)	0,0585	0,0015	39,6445	0,0000
Sac(2)	0,0414	0,0021	19,7588	0,0000
Sac(3)	0,0230	0,0015	15,6751	0,0000
Sac(4)	0,0122	0,0021	5,9502	0,0000
Public Holiday (PH) * (TD)				
PH*Thursday	0,0311	0,0020	15,8310	0,0000
PH*Friday	0,0065	0,0012	5,4176	0,0000
PH*Wednesday	0,0107	0,0052	2,0794	0,0376
YTL	0,0298	0,0030	10,0580	0,0000
Outliers (O)				
O(1)	-0,0142	0,0006	-23,1843	0,0000
O(2)	0,0143	0,0007	21,4185	0,0000
O(3)	-0,0144	0,0018	-8,1954	0,0000
O(4)	0,0193	0,0016	12,2731	0,0000
ARMA Terms				
AR(1)	0,4055	0,0325	12,4755	0,0000
AR(13)	-0,1080	0,0264	-4,0894	0,0000
AR(14)	0,0569	0,0274	2,0805	0,0375
AR(40)	0,0825	0,0277	2,9769	0,0029
SAR(42)	0,0682	0,0254	2,6888	0,0072
MA(3)	-0,0733	0,0361	-2,0318	0,0422
MA(31)	-0,0938	0,0308	-3,0467	0,0023
SMA(41)	-0,0729	0,0360	-2,0238	0,0430
Variance Equation GARCH (1,1)				
γ_0	0,0000	0,0000	2,1809	0,0292
γ_1	0,0845	0,0266	3,1805	0,0015
γ_2	0,8357	0,0556	15,0301	0,0000

R-squared	0,970871	**Mean Dep. Var.**	0,000735
Adjusted R-squared	0,968604	**S.D. Dep. Var.**	0,019254
S.E. of Regression	0,003412	**Akaike Inf. Cri.**	-8,497046
Sum Squared Resid	0,011663	**Schwarz Cri.**	-8,132693
Log Likelihood	4671,654	**Durbin-Watson Stat.**	1,970987

Appendix 5
Specification Tests on Residuals

	t- Statistics	p-Value
Skewness	0.033	0.084
Kurtosis	3.368	0.137
Normality	6.288	0.0431
Ljung-Box on Residuals		
Q(5)	0.2233	0.153
Q(10)	1.3366	0.513
Q(20)	7.4658	0.825

Distributions of Residuals - Histogram



BDS Test for Natural Logarithm of the Squared Standardized Residuals

Epsilon = 0.5
Dimension = 10
Sample: 1 1081
Included observations: 1081

Dimension	BDS Statistic	Std. Error	Z-Statistic	Prob.
2	-0.000838	0.002012	-0.416610	0.6770
3	-0.001264	0.002287	-0.552799	0.5804
4	-0.000676	0.001950	-0.346746	0.7288
5	-0.001022	0.001455	-0.702237	0.4825
6	-0.000850	0.001005	-0.845538	0.3978
7	-0.000647	0.000660	-0.980068	0.3271
8	-0.000371	0.000418	-0.887592	0.3748
9	-0.000260	0.000258	-1.010525	0.3122
10	-0.000180	0.000156	-1.157841	0.2469

Appendix 6
Forecasting Performance (One Step Ahead)

	Mean Absolute Error		Root Mean Squared Error		Mean Absolute Percentage Error		Theil Inequality	
	Model	**Expert**	**Model**	**Expert**	**Model**	**Expert**	**Model**	**Expert**
08.01.2009	0,0007	0,0019	0,0007	0,0019	0,21	0,55	0,12	0,38
09.01.2009	0,0025	0,0043	0,0031	0,0049	0,31	0,59	0,17	0,24
12.01.2009	0,0036	0,0042	0,0041	0,0046	0,39	0,52	0,19	0,24
13.01.2009	0,0036	0,0033	0,0040	0,0040	0,38	0,41	0,18	0,20
14.01.2009	0,0033	0,0040	0,0037	0,0047	0,32	0,38	0,13	0,19
15.01.2009	0,0029	0,0035	0,0034	0,0043	0,28	0,34	0,12	0,18
16.01.2009	0,0030	0,0041	0,0034	0,0049	0,27	0,35	0,12	0,20
19.01.2009	0,0030	0,0040	0,0034	0,0047	0,27	0,34	0,12	0,19
20.01.2009	0,0033	0,0040	0,0037	0,0047	0,29	0,34	0,13	0,18
21.01.2009	0,0031	0,0037	0,0036	0,0045	0,28	0,32	0,13	0,18
22.01.2009	0,0033	0,0039	0,0037	0,0046	0,88	1,00	0,14	0,19
23.01.2009	0,0034	0,0041	0,0038	0,0049	0,83	0,94	0,14	0,19
26.01.2009	0,0036	0,0044	0,0040	0,0051	0,97	1,12	0,15	0,21
27.01.2009	0,0034	0,0046	0,0039	0,0053	0,90	1,07	0,14	0,22
28.01.2009	0,0031	0,0045	0,0037	0,0052	0,84	1,02	0,14	0,21
29.01.2009	0,0031	0,0043	0,0037	0,0050	0,82	0,97	0,14	0,21
30.01.2009	0,0029	0,0042	0,0035	0,0049	0,77	0,92	0,13	0,20
02.02.2009	0,0028	0,0040	0,0035	0,0048	0,74	0,88	0,13	0,20
03.02.2009	0,0027	0,0040	0,0034	0,0047	0,71	0,85	0,13	0,20
04.02.2009	0,0028	0,0039	0,0035	0,0046	0,80	0,88	0,14	0,20
05.02.2009	0,0028	0,0038	0,0034	0,0046	0,79	0,87	0,14	0,20
06.02.2009	0,0029	0,0037	0,0035	0,0045	0,77	0,83	0,13	0,19
09.02.2009	0,0028	0,0039	0,0034	0,0046	0,74	0,82	0,13	0,20
10.02.2009	0,0027	0,0039	0,0033	0,0046	0,71	0,80	0,13	0,20
11.02.2009	0,0027	0,0038	0,0033	0,0045	0,70	0,77	0,13	0,20
12.02.2009	0,0030	0,0039	0,0037	0,0047	0,74	0,80	0,14	0,21
13.02.2009	0,0030	0,0040	0,0036	0,0047	0,72	0,78	0,11	0,16
16.02.2009	0,0031	0,0039	0,0038	0,0047	0,78	0,79	0,12	0,16
17.02.2009	0,0030	0,0039	0,0037	0,0046	0,75	0,77	0,12	0,16
18.02.2009	0,0029	0,0038	0,0036	0,0045	0,73	0,75	0,12	0,16

Appendix 7
Forecasting Performance (Recursive)

	Mean Absolute Error		Root Mean Squared Error		Mean Absolute Percentage Error		Theil Inequality	
	Model	**Expert**	**Model**	**Expert**	**Model**	**Expert**	**Model**	**Expert**
1 Day Ahead	0,0007	0,0019	0,0007	0,0019	0,21	0,55	0,12	0,38
5 Day Ahead	0,0028	0,0044	0,0035	0,0052	0,30	0,43	0,12	0,21
10 Day Ahead	0,0032	0,0036	0,0039	0,0048	0,30	0,31	0,14	0,20
20 Day Ahead	0,0033	0,0042	0,0041	0,0051	0,92	0,93	0,16	0,23
30 Day Ahead	0,0034	0,0040	0,0043	0,0049	0,84	0,79	0,14	0,18