Day-of-the-week in Returns and Conditional Volatility: A Fact or A Fiction? Evidence from Spot CAD/USD Foreign Exchange Rates

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Abstract

In this paper, we demonstrate that the day-of-the-week effect in logarithmic changes in spot CAD/USD foreign currency rates are not robust to a GARCH model with normal, student–*t*, GED or double exponential error distribution respectively. In addition, the degree of statistical significance varies inversely with the extent of leptokurtosis in the error distribution. Most strikingly, the day of the week effect in conditional variance disappears completely when we account for autocorrelation, heteroscedasticity and non-normality. We assert that earlier research in support of day of the week effect in returns and conditional variance may be the artifact of using inadequate methodology, ascribing attempts to give an economic explanation to an "effect" that may not exist.

JEL classification: G10, G12, C10, C22
Keywords: Day of the week effect; Volatility; GARCH, Error Distributional Assumptions.

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1. Introduction

There is overwhelming evidence of what has come to be known as day-of-the-week effect in stock market studies with numerous researchers endeavouring to proffer explanations of such behaviour based on economics and market microstructure arguments. Potential explanations include the release of adverse information over the weekend, thin trading, settlement procedures, specialists' strategies in response to informed traders, speculative short sales, bid-ask spread biases, measurement errors in stock prices, concentration of certain investment decisions at weekends, and dividend patterns.[1] However, none of the suggested explanations is able to consistently and fully explain the empirical results. One reason for this failure is likely due to the methodologies employed which fail to account for the stylized facts of financial time series (i.e. non-normality and volatility clustering) and as a result, researchers were induced into a process of finding cause(s) of an effect that may not exist. Indeed, these approaches suffer from several shortcomings. We have some limited evidence for making this assertion from stock market studies. For instance, Connolly (1989,1991) using more sophisticated procedure finds that the

[1] See, among others, Cross (1973), French (1980), Gibbons and Hess (1981), Lakonishok and Levi (1982), Theobald and Price (1984), Keim and Stambaugh (1984), Rogalski (1984), Jaffe and Westerfield (1985), Smirlock and Starks (1986), Penman (1987), Miller (1987), Baillie and DeGennaro (1989), Adamati and Pfleiderer (1989), Damodaran (1989), Porter (1990), Lakonishok and Maberly (1990), Yadav and Pope (1992), and Chang et al. (1993).

reported evidence of Monday effect is weak for the US stock market and show that once *t*-critical values are adjusted for sample size with a Bayesian approach, evidence of day of the week effects reported in earlier studies disappear. Chang et al. (1993) show that Connolly's observation holds not only for US stock market but for several other international markets as well. Peiró (1994) examines day-of-the-week effect in New York, Tokyo, London, Frankfurt, Paris and Madrid's stock markets to compare with existing literature which examines earlier periods, and finds quite different results from the patterns previously reported except for London stock market casting "doubt on the current validity of the seasonal pattern described in the existing literature which examines earlier periods". Aggrawal, Mehdian and Perry (2003) examine day-of-the-week effect in daily returns of six futures contracts, and find no consistent evidence of such regularities. A similar pattern of empirical findings exists for the foreign exchange markets.[2] Yamori and Kurihara (2004) examine the daily returns of twenty-nine foreign exchange rates, and report evidence of day-of-the-week effect in the 1980s for some currencies which disappears for almost all currencies in the 1990s. Evidence of day of week effects however, may be illusory if account is not made for the non-normality and volatility clustering observed for spot foreign exchange rate distributions (Hsieh, 1988).

Accordingly, the central objective of this paper is to examine potential day of the week effects in both the mean and the conditional variance for a large sample of CAD/USD daily rate of change. To account for autocorrelation, non-normality and volatility clustering in our sample, we use an AR(k)-GARCH(p,q) model under

[2] See for example, Goodhart and Giugale (1993), Bessembinder (1994), Breuer (1999), Bossaerts and Hillion (1991).

normal as well as three error distributions known to better represent financial time series: Student-*t*, generalized error distribution (GED) and double exponential. This allows us to test for robustness of day of the week effect to error distributional assumptions in both returns and conditional variance. Moreover, we explicitly test whether the GARCH error terms are independent and identically distributed (*i.i.d* hereafter) using the BDS test, a powerful test originally designed by Brock et al. (1996). This assumption is of great importance for an appropriate test for day-of the week effect that is, to our knowledge, ignored in published studies. Indeed, a rejection of *i.i.d* assumption indicates the existence of a hidden unexplained structure in the residual terms and if not accounted for, may spuriously increase the statistical significance of dummy variables 'days' leading an erroneous conclusion of evidence of a calendar anomaly. We add that testing for day of the week effect in conditional volatility is relatively novel to the literature on calendar anomalies. Moreover, to the best of our knowledge, none of empirical works examine the robustness of day-of the week effect to non-normal error distributional assumption. We believe that the previous empirical works are sensitive to the choice of the series distribution. Particularly, all the previous studies assume normal distribution. Given the stylized facts of financial time series, examining day of the week effect in mean or/and in variance based on normal distribution assumption is not appropriate.

Our findings show that evidence of day-of-the-week effect in returns is not robust to heteroscedasticity nor to our selected error distributional assumptions with weaker support under fat-tail distributions. However and most strikingly, day of the week effect in variance disappears completely when we deal with autocorrelation, heteroscedasticity and non-normality. These results are robust to outliers and trimming of 3 percent. We argue that earlier research in support of day of the week effect in returns and conditional variance may be the artefact of using inadequate methodology, ascribing attempts to give an economic explanation to an "effect" that may not exist.

The remainder of this paper is organized as follows. Section II presents a review of literature on day of the week effect. Section III describes our data and presents some initial tests for the day of the week effect in the mean and variance. Section IV considers a GARCH specification for normal, student-t, GED, and double exponential distributions and test for the day of the week effect only for the mean of the respective distribution. Section V presents the test for the day of the week effect in both the man and variance of the distribution. Section VI concludes the paper.

2. Literature review

The day-of-the-week effect on security returns and variances are well documented in the literature. The earliest evidence of mean return and variance being different across days of the week were reported by Fama (1965) and Cross (1973).[3] They find that both lowest mean return and highest variance occur on Monday offering a poor risk–returns relationship compared to those of the other days of the week. Since these influential papers, several empirical studies emerged supporting the day-of-the-week effect in stock returns (French (1980), Gibbons and Hess (1981), Keim and Stambaugh (1984), Lakonishok and Levi (1982), Rogalski (1984), Ho (1990), Berument and Kiymaz (2001) among others).

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[3] The discovery of day of the week effect in stock returns goes back to Fields (1931).

This form of calendar anomaly is not limited to US equity markets but it is also reported for other developed as well as developing markets (Jaffe and Westerfield (1985), Kato and Schallheim (1985), Dubois (1986), Condoyanni et al. (1987), Solnik and Bouquet (1990), Barone (1990), Wong et al. (1992), Chang et al. (1993), Athanassakos and Robinson (1994), Doubois and Louvet (1996), Kiymaz and Berument (2003), among others). For instance, Cadsby (1989) and Steeley (2001) report evidence of day-of-the-week effect for Canada and UK stock markets respectively. Chen et al (2001) report evidence of day-of-the-week effect in China stock market. Ho and Cheung (1994) find that stock return variances of several Asia-Pacific markets are heterogeneous across day of the week with Monday having the highest volatility.

Others studies investigate day of the week effect in currency, future market, Treasury bill market and bond market (Cornell (1985), Dyl and Maberly (1986)). For example, Hsieh (1988) examines the statistical property of daily rates of change of five foreign currencies and find evidence of mean and variance being different across days of the week. Tang (1997) investigates the interaction between diversification and day-of-the-week effects on exchange risks in six foreign currencies. Corhay, Fatemi, and Rad (1995), Flannary and Protopapadakis (1988), Gay and Kim (1987), and Gesser and Poncet (1997) indicate that return distribution of futures and foreign exchange markets also varies by day of the week. Bessembinder (1994) motivates day-of-the-week effect in the foreign exchange market through inventory-carrying costs. He demonstrates that bid-ask spreads in the spot and forward market are higher on Fridays and prior to holidays. Glassman (1987) reports similar results while Breuer (1999) finds statistically insignificant evidence in favour of day-of-the-week effects in forward foreign exchange markets. Relatedly, Bossaerts and Hillion (1991) suggest a role for weekend effects since central banks are more likely to intervene over the weekend. Nippani and Pennathur (2004) find evidence of day-of-the-week effect in the daily rates of commercial paper.

On the others hand, several empirical studies show that financial time series have a fatter tails than the normal distribution and exhibit volatility clustering. For instance, Fama (1965), Simkowitz and Starks (1978), and Singleton and Wingender (1986) report departure from normality in stock returns. McFarland et al. (1982), Akgiray and Booth (1988), among others, find similar results in foreign exchange price changes. Bollerslev and Domowitz (1993), Takezawa (1995), Hsieh and Kleidon (1996), and Andersen and Bollerslev (1998) among others show that information clustering induces volatility clustering in the foreign exchange markets. Ignoring these stylized facts, virtually all previous studies use standard methods such as ANOVA or F and *t* tests to investigate day of the week effect which casts serious doubt on the reliability of their results and questions the existence of such effect given that one of the fundamental assumptions of such tests is the normality.[4] For example, paying no attention to the distributional properties of the sample used, empirical works such us of Santesmases (1986), Solnik and Bousquet (1990), Athanassakos and Robinson (1994) are limited to gauge means and variances for each trading day and use ANOVA analysis to test for equality of means or to estimate a random walk model including dummy variables for each day where their corresponding coefficients significance are assessed using F and *t* tests. Others, for instance, Abraham and Ikenberry (1994) and Peiro (1994) follow the same methodology but

[4] Note that the ANOVA requires data used to be (1) normal, (2) stationary and (3) independent.

use t-statistics and χ^2 calculated using heteroscedasticity-consistent standard errors, yet overlook the distributional properties of the time series used. To circumvent the problem with departure from normality some researchers use distribution-free approaches; for instance Board and Sutcliffe (1988) and Wong et al. (1992) use nonparametric tests while Wingender and Groff (1989) employ stochastic dominance analysis. Najad and Yung (1994), Berument and Kiymaz (2001), and Kiymaz and Berument (2003) investigate the statistical properties of returns series and then use a GARCH model assuming normal error distribution although reporting strong evidence of leptokurtosis.

3. Data and Some Preliminary Statistical Tests

The data consist of the daily closing spot exchange rate expressed as Canadian dollar per U.S. dollar from the Toronto Stock Exchange - Canadian Financial Markets Research Center (CFMRC) database. The data cover the period from January 03, 1975, through December 31, 2003, for a total of 7,306 observations. The daily rate of change is computed as the natural logarithmic first difference of the daily closing price of the CAD/USD exchange rate:

$$r_t = 100 \cdot \left(\ln S_t - \ln S_{t-1}\right)$$

where S_t denotes the daily CND/USD spot exchange rate for t = 0, 1, 2, 2…, 7306.

Table 1 provides some descriptive statistics of daily changes for each day of the week as well as for the entire period of study. The average daily changes are positive with a relatively high kurtosis indicating that the series is non-symmetric with higher peaks and fatter tails than the normal distribution. A closer look at each day statistics shows that all-days summary statistics are likely to be shaped by those of Monday. In comparison to the remaining weekday, Monday has the highest return, variance, kurtosis, skewness as well as range. The highest variance on Monday can be explained by larger volatility on the day following the exchange weekend (French and Roll (1986)).

The lowest return is observed on Thursday while the lowest variance is observed on Friday. It is noteworthy that Harvey and Huang (1991) argue that the most important of U.S. macroeconomic announcements usually are released between 8:30 and 9:30 A.M. EST on Fridays, which induce higher volatility. The result of Harvey and Huang are not necessarily conflicting with ours because these announcements are likely to affect mainly the volatility of opening price and since we are using closing price, the impact on volatility will lessen by the end of Friday's trading.

Figure I displays the autocorrelation function (ACF) up to lag 50. The horizontal dashed lines in ACF are the upper and lower 5% boundaries for rejecting the null hypothesis of zero autocorrelation. It is clear that the ACF decay fairly quickly; all the ACF are small and insignificant at 5% level, except for lag 16, 27 and 29. The likely non-normal feature of the daily distributions is further seen from *qq*-plot (not reported) where the series seems to have a fatter tail than the normal distribution. This is confirmed by a Jarque-Bera (*JB*) test statistic of 3786.77 and a kurtosis being significantly larger than 3 (see Table 1). We therefore reject the null hypothesis of the series being normally distributed. In short, the diagnostic tests strongly indicate that the series is autocorrelated and non-normal distributed.

We now employ some common tests to further validate the initial observations from the statistics in Table 1 and Figure I. Unlike previous empirical studies dealing with calendar anomalies, we first test for constancy of variance prior to comparing the mean across different days. This is because the choice of test of comparison of mean depends on whether the variance is homogenous across different days. If the variance is constant across the days we use a test such us of Bonferroni's test, otherwise we use a test that does not assume equal variances across different days, for instance Games & Howell's test.

To test for homogeneity of variance we use Brown-Forsythe's test (Brown & Forsythe (1974)). We choose Brown-Forsythe's test because of its robustness to departure from the normality, an assumption that is strongly rejected in our data. There are numerous tests for equal variances, but as pointed out by Box (1953), many of which appear to be sensitive to departures from normality, such as Bartlett's test. Several tests have been proposed to deal with this problem. Conover al (1981) list and compare 60 methods for testing the homogeneity of variance assumption and shows that Brown & Forsythe's procedure outperforms all the procedures that are robust to normality. It is worth mentioning that to test for constancy of variance of S&P 500 across different days, Berument and Kiyamaz (2001) and Kiyamaz and Berument (2003) use Bartlett's test even though their summary results suggest rejection of the normality assumption.

Let R_{ij} be the i^{th} observation in the j^{th} group, let M_j be the sample median for the j^{th} group, and let

$$Z_{ij} = \left| R_{ij} - M_j \right| \tag{1}$$

The Brown-Forsythe test consists of simply performing an F test on the Z_{ij}'s. A significant F test indicates that the variances are not equal. Brown & Forsythe's statistic equals 3.59 with a p-value of 0.006 indicating rejection of the null hypothesis at 1% level that he variance are the same across different days of the week.

Based on the result from Brown-Forsythe test, we employ Games & Howell's test to compare the mean of each day to the remaining days. The results, reported in Table 2, reject the null hypothesis that the mean is constant over the week. Precisely, Monday mean change is significantly different from Tuesday and Thursday mean changes at the 5% and 1% level respectively.

To sum up, both the Brown & Forsythe and Games & Howell tests show a day of the week effect with the highest average return on Monday, lowest on Thursday, and a rejection of the constancy of volatility over the days of the week. There is a large body of empirical work that confirms heterogeneity of financial time series volatility, therefore this results is not new. However, testing for day of the week effect in volatility is relatively novel to the literature on calendar anomalies. Moreover, to the best of our knowledge, none of empirical works examine the robustness of day-of the week effect to non-normal error distributional assumption. We believe that the previous empirical works are sensitive to the choice of the series distribution. Particularly, all the previous studies assume normal distribution. Given the stylized fact of financial time series, examining day of the week effect in mean or/and in variance based on normal distribution assumption is not appropriate. In other words, considering a more suitable distribution, such as Student-t, may alter the results of previous papers.

- Table 1 about here -

-Table 2 about here-

- Figure I about here -

4. Testing for Day of the Week Effect in Mean under Different Error Distributional Regime

Although Tables 1 and 2 suggest the existence of day of the week in mean for CND/USD exchange rate, this result could be spurious because of the possibility of series being autocorrelated. The test for constancy of mean across time is best examined in a regression context. First, we follow the standard model used in previous studies and then we correct for non-normality and volatility clustering. This allows us to test the robustness of previous works and show their limitations.

Using the standard OLS methodology, we run a regression of the daily rates of change on a constant term and 5 dummy variables, one for each weekday. To deal with linear dependent, we include *k* lag values of the daily rates of change to the regression equation:[5]

$$r_t = \alpha + \beta_M D_{Mt} + \beta_T D_{Tt} + \beta_W D_{Wt} + \beta_H D_{Ht} + \sum_{i=1}^{K} r_{t-1} + \varepsilon_t \qquad (2)$$

where r_t is the daily rate of change at time *t*, α is a constant term, and $D_{Mt}, D_{Tt}, D_{Wt}, D_{Ht}$ are the dummy variables for Monday, Tuesday, Wednesday, Thursday respectively.

We exclude the dummy variable for Friday to circumvent the dummy variable trap. The choice of the lag length (*k*) is based on the lowest Akaike Information

[5] Hsieh (1991) shows that autocorrelation can be ruled out by prior fitting of an Akaike's Information Criterion (AIC)-minimizing autoregressive moving average (ARMA) model.

Criterion (AIC). To test for remaining non-captured linear dependencies, we employ Ljung-Box's test to the residuals from the above model. The variance is assumed to be homogenous over time and the error terms to be normally distributed. If the means are constant over time, then the coefficients for all dummy variables should be insignificantly different from zero. Tests of these hypotheses are the standard *t* and F statistics.[6] The OLS estimations are in the second column of Table 3. Consistent with the Games & Howell's test, the equality of means is rejected at 5 percent level in favour of the day of the week effect. In line with Table 1, Monday has the highest average rate of change and, although not significant, Thursday has the lowest. When compared to Friday's rate of change, Monday is 0.03 percent higher. As for Tuesday, Wednesday and Thursday there is no reliable evidence to suggest that their respective rate of changes are different from the one of Friday.

It is clear from the diagnostic statistics that the model described in Equation (2), with a lag length of 38, has successfully captured the linear dependence in the series; however, the assumptions of normality and homogeneity of variance across time are rejected by Jarque-Bera (JB) and Engle's (1982) Lagrange Multiplier (LM) test at 1 percent level. Furthermore, although the above model has captured the linear structure in the series, it may not have captured the nonlinear one which may affect the magnitude and statistical significance of the dummy variable coefficients resulting into spurious evidence of day of the week effect. To investigate the existence of nonlinear dependency we test whether the residuals in Equation (2) are *i.i.d.* To do so, we employ a powerful test originally proposed by Brock, Dechert and Scheinkman

[6] Needless to say, that the hypothesis testing using standard t and F test are meaningless given that the conventional assumptions about OLS error terms are violated.

(1987) (henceforth BDS) and designed by Brock *et al.* (1996). The BDS test is a non-parametric test with the null hypothesis that the series in question are *i.i.d* against an unspecified alternative. The test is based on the concept of correlation integral, a measure of spatial correlation in *n*-dimensional space originally developed by Grassberger and Procacccia (1983). To be more specific, consider a vector of *m* histories of the CAD/USD rate of change,

$$r_t^m = (r_t, r_{t+1}, \ldots, r_{t+m-1}) \tag{3}$$

the correlation integral measures the number of *m* vectors within a distance of ε of one another. The correlation integral is defined as

$$C_m(\varepsilon, T) = \frac{2}{T_m(T_m - 1)} \sum_{t<s} I_\varepsilon(r_t^m, r_s^m) \tag{4}$$

where the parameter m is the embedding dimension, T is the sample size, $T_m =$ $T - m + 1$ is the maximum number of overlapping vectors that we can form with a sample of size *T*, I_ε is an indicator function that is equal to one if $\left\| r_t^m - r_s^m \right\| < \varepsilon$ and equal to zero otherwise. A pair of vectors r_t^m and r_s^m is said to be ε apart, if the maximum-norm $\| \, . \, \|$ is greater or equal to ε. Under the null hypothesis of independently and identically distributed random variables, $C_m(\varepsilon) = C_1(\varepsilon)^m$. Using this relation the BDS test statistic is defined as,

$$BDS(m, \varepsilon) = \frac{C_m(\varepsilon, T) - [C_1(\varepsilon)]^m}{\sigma_m(\varepsilon, T) / \sqrt{T}} \tag{5}$$

where $\sigma_m(\varepsilon, T)/\sqrt{T}$ is the standard deviation of the difference between the two correlation measures $C_m(\varepsilon, T)$ and $[C_1(\varepsilon)]^m$. For large samples, the BDS statistic has a standard normal limiting distribution under the null of *i.i.d*. If asset price changes are not identically and independent random variables, then $C_m(\varepsilon) > C_1(\varepsilon)^m$. It is important to note that the BDS test statistic is sensitive to the choice of the embedding dimension *m* and the bound ε. As mentioned by Scheinkman and LeBaron, (1989) if we attribute a value that is too small for ε, the null hypothesis of a random *i.i.d* process will be accepted too often irrespective of it being true or false. As well, it is not safe to choose too large a value for ε. To deal with this problem Brock et al. (1991) suggest that, for a large sample size (T > 500), ε should equal 0.5, 1.0, 1.5 and 2 times standard deviations of the data. As for the choice of the relevant embedding dimension *m*, Hsieh (1989) suggests consideration of a broad range of values from 2 to 10 for this parameter. Following recent studies of Barnett et al. (1995), we implement the BDS test for the range of *m*-values from 2 to an upper bond of 8. In general, a rejection of the null hypothesis is consistent with some type of dependence in the returns that could result from a linear stochastic process, non-stationarity, a non-linear stochastic process, or a non-linear deterministic system.[7] Results for BDS test (not reported here but available from the author upon request) for embedding dimension 2 to 8 and for epsilon values starting from 0.5 to 2 times the standard deviation of the rate of change series strongly reject the *i.i.d* assumption at 5% and 1% significance level. Since the BDS test has a good power against linear as well as non-linear system, and given that we have already remove the serial dependence in the series, evidence of nonlinear structure could be due to volatility clustering as suggested by *LM* test.

[7] The Simulation studies of Brock, Hsieh and LeBaron (1991) show that the BDS test has power against a variety of linear and non-linear processes, including for example GARCH and EGARCH processes.

Although some previous work on calendar anomalies has considered volatility clustering in financial time series, the strong departure from normality was uncared for. In the present paper we examine whether evidence of day of the week effect are robust to modeling of volatility clustering as well as to the choice of alternative distributions to the normal that better portray financial series. A variety of volatility models have been proposed in the literature. A particular class of models that demonstrate great flexibility in capturing multiplicative dependence in a series called ARCH type models, originally introduced by Engle (1982). For instance, the generalized ARCH (GARCH) models, designed by Bollerslev (1986), are widely used in financial time series modeling.[8] Assuming that the rate of changes expressed in Equation (2), conditional on information set up to time t-1, ε_t is an *i.i.d* random variable with mean 0 and variance σ_t^2, a GARCH (p,q) model is expressed as follows:

$$\sigma_t^2 = \eta + \lambda(L)\omega_t^2 + \theta(L)\sigma_t^2 \tag{6}$$

where L is the lag operator, $\lambda(L) = \sum_{i=1}^{p} \lambda_i L^i$ and $\theta(L) = \sum_{i=1}^{q} \theta_i L^i$.

with constraints:

$$\begin{aligned}
&\sum_{i=1}^{p} \lambda_i + \sum_{i=1}^{q} \theta_i < 1 \\
&\eta > 0 \\
&\lambda_i \geq 0 \qquad i = 1,2,\ldots,p \\
&\theta_j \geq 0 \qquad j = 1,2,\ldots,q
\end{aligned}$$

Based on Log-likelihood, BIC and AIC criteria, GARCH (1,1) outperforms all the attempts (not reported) to model the data series with other ARCH type models such as PGARCH, GARCH-*M* and FIEGARCH. The third column in Table 3

[8] For a more detailed discussion on estimating the GARCH models, see Engle (1982), Bollerslev (1986), and Bollerslev et al. (1994).

contains the results of GARCH (1,1) specification. What is striking is that the rate of change on Monday is no longer significant, as under the OLS regression, and instead Tuesday's, Thursday and the constant term are, at 5 and 1 percent level respectively. This implies that day of the week effect is sensitive to assumption on volatility status. Notably Monday and Thursday rate of changes are still respectively the highest and the lowest among the weekday changes.

In addition, ARCH (λ) and GARCH (θ) coefficients are significant at 1 percent level, with a sum (0.0946 + 0.9016) close to unity indicating that shocks to the conditional variance are persistent over future horizons. The sum of λ_1 and θ_1 is also an estimation of the rate at which the response function decays on daily basis. Since the rates are quite high, the response functions to shocks are likely to die slowly. Moreover, although GARCH (1,1) captures all the volatility clustering (*LM* statistic of 15.76), *JB* test suggests that the normality assumption is rejected at 1 percent level. The *qq*-plot illustrated in Figure II corroborates the results from *JB* test; the tails of the residuals of GARCH model are indeed fatter than the normal distribution. This suggests the use of a distribution with a fatter tail to fit our data. In order to examine whether the day of the week effect is sensitive to the error distributional assumption and to capture the fat tail in our series, we allow for three types of error distribution known to better represent financial time series: Student-*t*, the generalized error distribution (GED) proposed by Nelson (1991), and double exponential.[9] The results are reported in Table 3. Some interesting observations emerge.

First, the results from GARCH models are quite different from those of standard OLS estimation. Monday's coefficient is no longer significant and instead Thursday's and the constant term's are, except for GARCH normal where Tuesday's coefficient is significant as well. These findings show that evidence of day-of-the-week effect in returns varies depending on the assumption made on variance which cast serious double on the seasonal pattern described in the existing literature.

Second, while under normal distribution, OLS and GARCH estimations show that Monday has the highest rate of change and Thursday has the lowest, under fatter tails distributions the results tend to change. With Student-*t* and GED, Friday seems to have the highest rate of change and Thursday the lowest, while under double exponential error distribution the highest rate of change occurs on Wednesday and the lowest on Thursday. Remarkably, the instability of the results seems to be limited to

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[9] If a random variable X_t has a *GED* with mean zero and unit variance, the probability density function of X_t is given by:

$$f(X_t) = \frac{\upsilon^{-(1/2)|X_t/\lambda|^{\upsilon}}}{\lambda \cdot 2^{(\upsilon+1)/\upsilon}\Gamma(1/\upsilon)}$$

where $\Gamma(\ )$ is the gamma function, υ is a positive parameter governing the thickness of the tails of the distribution λ is a constant given by

$$\lambda = \left[\frac{2^{-2\ /\upsilon}\Gamma(1/\upsilon)}{\Gamma(3/\upsilon)}\right]^{1/2}$$

Note that for υ=2 and constant λ=1, the GED is the standard normal distribution. For more details about the generalized error distribution, see Hamilton (1994).

the day in which the highest rate of change occurs. Further, the statistical significance of the constant term is lower when fatter tail distributions are considered. Under the normal distribution the constant term is significant at 1 percent level, but it is such at 5 percent level under student-*t* and GED distribution and insignificant under double exponential distribution.

Third, to examine whether each GARCH model has succeeded in capturing all the nonlinear structure in the data, we employ the BDS test to their standardized residuals. A rejection of the *i.i.d* hypothesis will imply that the conditional heteroscedasticity is not responsible for all the nonlinearity in series, and there is some other hidden structure in the data. The BDS statistics (not reported) fails to reject the null hypothesis that the standardized residuals are *i.i.d* random variables at 5 percent and 1 percent degree of significance. Thus each model captures all the non-linearity in the data used, and that the conditional heteroscedasticity is the cause of the non-linearity structure. This shows that the nonlinear dependence caused by volatility clustering is the reason of the difference in the results of standard tests and standard OLS and those of GARCH models. Hence failure to model volatility clustering, to consider fat tail distribution and to test for *i.i.d* assumption may cause spurious results or evidence of day-of-the-week effect.

In summary, regardless of the error distributional assumption, the lowest rate of change occurs on Thursday; however the highest rate seems to occur on different days depending on the error distributional assumption. When assuming constancy of variance, only Monday's dummy variable is significant. However, when we drop the homogeneity of variance assumption and model volatility clustering accordingly our results show that day of the week effect in mean changes. Furthermore, the results change depending on the error distributional assumption. Under normal distribution, dummy variable for Monday, Wednesday and Friday are significant, but under fatter tail distributions (.i.e. student-*t,* GED and Double exponential) only Friday's dummy variable is significant.

The results of the diagnostic tests show that all the GARCH models are correctly specified. The *LB* statistics up to lag 100 could not reject the null hypothesis of no autocorrelation. *LM* tests are also significant, indicating that three GARCH processes are successful at modeling the conditional volatility. *JB* test for normality rejects the null hypothesis that the standardized residuals are normally distributed. This result confirms the one from the *qq*-lot shown in Figure II. Note, however, that for all the three models the sum of the parameters estimated by the variance equation is close to one. A sum of λ_1 and θ_1 near one is an indication of a covariance stationary model with a high degree of persistence; and long memory in the conditional variance. Finally, it is worthwhile to note that all the three model-selection criteria favour GARCH with Student-*t* error distribution.

5. Testing for Day of the Week Effect in Variance under Different Error Distributional Regime

Recall that Brown-Forsythe's test rejects the assumption of homogeneity of variance, a result that is corroborated by LM test, accordingly we have modeled volatility clustering using GRACH (1,1) model under different error distributional assumptions. To exam whether volatility change across day of the week, we introduce the week-day dummies into the mean and conditional variance equation of the GARCH (1,1) model. To circumvent the dummy-variable trap Berument and Kiyamaz (2001) exclude the intercept of a GARCH(1,1) model. This approach is not appropriate because it may not be possible to specify a conditional variance without an intercept. In fact, a positive intercept is necessary for a sound GARCH model. In the present paper, we exclude the dummy variable for Friday:

$$\sigma_t^2 = \eta + \lambda(L)\omega_t^2 + \theta(L)\sigma_t^2 + B_M D_{Mt} + B_T D_{Tt} + B_W D_{Wt} + B_H D_{Ht} \tag{7}$$

where σ_t^2 is the conditionally variance, η is a constant term, and $D_{Mt}, D_{Tt}, D_{Wt}, D_{Ht}$ are the dummy variables for Monday, Tuesday, Wednesday, Thursday respectively.

Equation 2 and 7 are estimated jointly. If all the coefficients for dummy variables in Equation 7 are insignificantly different from zero, then we reject the day of the week effect assumption in volatility. Again, we consider the normal distribution as well as the student-*t*, GED and double exponential to capture fat tails observed earlier in the data and examine whether day of the week effect in conditional volatility, if any, is sensitive to the particular specification of the underlying distribution. Table 4 displays the results of introducing dummy variables into the mean and conditional variance equations under normal, Student-*t*, GED and double exponential distributions. The results for mean equation are similar to those of Section IV.[10] We therefore focus on the variance equation where several interesting observations emerge.

[10] Except that when we introduce the dummy variables into the conditional variance equation the intercept in GARCH normal is significant only at 5 percent level and in GARCH double exponential the highest rate of change occurs on Monday instead of Wednesday.

First, while GARCH (1,1) normal model suggests the existence of day of the week effect in conditional variance, GARCH (1,1) student-*t*, GARCH (1,1) GED and GARCH (1,1) double exponential show that variance does not change across days. Assuming normal distribution, Monday and Thursday dummy variables are significant at 5 percent level. However, all dummy variables in conditional variance equation of the three alternative distributions, known to cope with fat tails, are insignificantly different from zero. In other words, when we consider error distribution that better fit fat tails displayed by the data used, indications of day of the week in variance disappear. Thus, evidence of day effect in variance is spurious and it is due to fat tails in the data. Since financial time series are known to exhibit fat tails, our results cast serious doubt on the results of Hsieh (1988), Berument and Kiymaz (2001), and Kiymaz and Berument (2003). It is important to note that our results for GARCH normal are similar to those of Hsieh (1988) where he finds that for CND/USD daily rate of change series, starting from January 1974 to December 1983, in a AR (16)-GARCH (1,1) normal model's mean equation the Tuesday and Thursday dummy variables are significant, while in the conditional variance equation only Monday and Thursday dummy variables are significant.

Second, the results of GARCH with fat tail distributions are not consistent with those of Brown-Forsythe test which reject the homoskedasticiy of volatility across days of the week. This demonstrates the unsuitability to employ such test on financial time series since it does not consider the nature of the distribution of such data. This may be explained by Brown-Forsythe test confusing facts of volatility clustering as evidence of variance being significantly different across days of the week.[11] Our results cost doubt on studies using such procedure. For instance, Harvey and Huang (1991) use Brown-Forsthe-modified Levene test to reject the homogeneity of variance of price changes for future of major currencies across days of the week. They attribute this "day of the week effect" to a concentration of announcement of macroeconomic indicators on Thursday and Friday.

Third, groping mean and conditional variance equation parameters in Table 4, it is evident that the nature of relationship between returns and volatility depends on error distributional assumption. In the GARCH normal model, the mean equation estimation shows that the highest change take place on Monday while the tiniest on Thursday, whereas the conditional variance equation demonstrates that the volatility peak is reached on Thursday and all-week low volatility occurs on Tuesday. This suggests a negative relationship between returns and volatility in the series.[12] The same pattern is observed in the GARCH double exponential model. Now if we consider GARCH student-*t* model, the maximum change occurs on Friday and minimum on Thursday, while the highest conditional variance occurs on Monday and lowest conditional variance on Tuesday. We notice the same pattern in the GARCH GED model.[13] Thus, there is no evidence of relationship between returns and conditional volatility. This implies that studies investigating the relationship between

[11] Variance may change across weeks or months but not across days.

[12] Nelson (1991) and Glosten, Jagannathan, and Runkle (1993) state that unanticipated stock market returns are negatively related to unanticipated movement in conditional volatility.

[13] Baillie and DeGennaro (1990) find no relationship between mean returns on portfolio of stocks and their corresponding variance. Chan, Karoli and Stulz (1992) show that the conditional expected excess return on S&P500 is not related to its conditional volatility.

asset price and conditional volatility should take into account the error distributional assumption.

Table 4 presents some diagnostics tests to check how well the models fit the data. Same as in Table 3, evidence of non-normality is confirmed by the *JB* test at 1 percent level for all the GARCH models. *LB* and *LM* test statistics show that the AR(k)-GARCH models are successful in capturing the linear dependencies and volatility clustering in data. The sum of the variance parameters for each model, $\lambda + \theta$, is close to one, suggesting a very high magnitude of persistence and implying that the conditional variance is nearly integrated. The three model selection criteria, Log Likelihood, AIC and BIC rank GARCH student-*t* as the best model to fit the series, followed by GARCH GED, then GARCH double exponential and at last GARCH normal. This shows the superiority of models dealing with fat tails in financial time series over those assuming normality of error terms. The BDS statistics (not reported) on the standardized residuals from each GARCH process fails to reject the null hypothesis that the standardized residuals are *i.i.d* random variables at 5 percent and 1 percent degree of significance. Thus all forms of dependency in the series are captured and the dummy variable coefficients are not contaminated by any hidden structure.

Finally, to see if the conclusions were due to a few anomalous in our data, the analysis has been repeated excluding the returns with higher absolute values, cutting down the sample by 3 percent and to further reduce potential outlier problems, we exclude 10 daily observations from the sample before and after the October 19, 1987 and October 27, 1997 stock market crashes as well as the September 11, 2001 event.. Again, the results obtained are very similar to those obtained with the full sample.

Consequently, we may conclude that the results stated above are not influenced by outliers.

6. Summary and Conclusions

This paper provides a comprehensive analysis of the day of the week in returns and volatility using a large sample of CND/USD rate of changes starting on January 03, 1975, ending on December 31, 2003. The purpose of this paper is to scrutinize the overwhelming support for what is now considered a calendar anomaly since the earlier studies stand on assumptions which are strongly rejected in financial time series. Our analysis first provides an assessment based on a standard method used in earlier studies which assumes both homoskedasticiy and normality although the diagnostic tests affirm the opposite. Consistent with the Games & Howell's test, the standard OLS estimations reject the equality of means at 5 percent level in favour of the day of the week effect in returns, with Monday having the highest average rate of change and, although not statistically significant, Thursday has the lowest.

However, after modeling volatility clustering with a GARCH (1,1) model allowing for normal as well as three types of error distribution known to better portray financial time series (Student-*t*, GED, and double exponential) the above results change dramatically. First, Monday's coefficient is no longer significant and instead Thursday's and the constant term's are, except for GARCH normal where Tuesday's coefficient is significant as well. Second, quite the opposite to OLS and GARCH estimations, under normal distribution, GARCH Student-*t* and GARCH GED suggest that Friday has the highest rate of change, while under double exponential error distribution the highest rate of change occurs on Wednesday and the lowest on Thursday. These results show that evidence of day-of-the-week effect is not robust to a GARCH model with normal, student–*t*, GED or double exponential error distribution respectively

Unlike seasonal patterns of daily returns, seasonality of daily volatility has received little attention in the finance and econometrics literature, particularly in foreign exchange rate, even within the broadly used GARCH framework. Moreover, the few studies that investigate day-of-the-week effect in volatility assume normal error distribution whereas this assumption is strongly rejected. To fill this gap in literature, we introduce the week-day dummies into the conditional variance equation of the GARCH model and again consider the normal distribution as well as the student-*t*, GED and double exponential to check whether earlier reported evidence for day of the week effect in conditional volatility is sensitive to the particular specification of the underlying error distribution. The results are even more spectacular than those of the daily returns. While under GARCH normal, Monday and Thursday dummy variables are significant at 5 percent level, all dummy variables in conditional variance equation of the three alternative distributions are insignificantly different from zero. In other words, evidence of day-of-the-week effect disappears completely when a fat tail distribution is considered. To check whether our results are influenced by outliers, we repeat the analysis with a 3 percent trimming and elimination of 10 daily observations before and after the October 19, 1987 and October 27, 1997 stock market crashes as well as the September 11, 2001 event. The conclusions remain the same as those obtained with the full sample.

In the light of these results, and given that financial time series are known to have fatter tail than normal distribution and exhibit volatility clustering, we argue that the seasonal pattern in daily returns and daily volatility described in the existing literature may be spurious and are the artefact of using inadequate methodology. Our findings ascribe the numerous attempts to give an economic explanation to an "effect" that may not exist.

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Table 1: Summary Statistics of log CND/USD daily price changes:

Weekday	N	Mean	Median	Std. Error of Mean	Std. Deviation	Kurtosis	Std. Error of Kurtosis	Skewness	Std. Error of Skewness	Min	Max
Monday	1360	0.02873	0.00841	0.00000	0.31031	4.14487	0.13260	0.42644	0.06635	-1.92906	1.88167
Tuesday	1493	-0.00616	0.00758	0.00000	0.29301	3.19402	0.12658	-0.02014	0.06333	-1.42087	1.65960
Wednesday	1496	0.00440	0.00770	0.00000	0.29776	3.76284	0.12645	-0.33857	0.06327	-1.68987	1.53849
Thursday	1495	-0.00980	0.00763	-0.00624	0.29520	3.55922	0.12649	0.31165	0.06329	-1.41281	1.81176
Friday	1462	0.00340	0.00762	0.00000	0.29121	2.80603	0.12791	-0.07441	0.06400	-1.37632	1.40518
All Days	7306	0.00367	0.00348	0.00000	0.29758	3.52741	0.05730	0.07009	0.02865	-1.92906	1.88167

The Daily return is computed as the natural logarithmic first difference of the daily closing price of CND/USD exchange rate: $r_t = 100 \cdot \ln(S_t / S_{t-1})$, where S_t and S_{t-1} are exchange rate at date t and t-1 respectively. Sample period: 03 January 1975 to December 2003. Jarque-Bera test statistic is 3786.77 which rejects the null hypothesis of the series being normally distributed

Table 2: Testing for Day of the Week Effect in the Mean of CND/USD daily price changes: Games & Howell's Test

(I) Weekday	(J) Weekday	Mean Difference (I-J)	Std. Error	P-value	95% Confidence Interval	
					Lower Bound	*Upper Bound*
Monday	Tuesday	0.0349 *	0.0113	0.0178	0.0040	0.0658
	Wednesday	0.0243	0.0114	0.2061	-0.0068	0.0555
	Thursday	0.0385 **	0.0114	0.0063	0.0075	0.0695
	Friday	0.0253	0.0113	0.1682	-0.0056	0.0563
Tuesday	Monday	-0.0349 *	0.0113	0.0178	-0.0658	-0.0040
	Wednesday	-0.0106	0.0108	0.8656	-0.0401	0.0189
	Thursday	0.0036	0.0108	0.9972	-0.0257	0.0330
	Friday	-0.0096	0.0107	0.9008	-0.0389	0.0198
Wednesday	Monday	-0.0243	0.0114	0.2061	-0.0555	0.0068
	Tuesday	0.0106	0.0108	0.8656	-0.0189	0.0401
	Thursday	0.0142	0.0108	0.6853	-0.0154	0.0438
	Friday	0.0010	0.0108	1.0000	-0.0286	0.0306
Thursday	Monday	-0.0385 **	0.0114	0.0063	-0.0695	-0.0075
	Tuesday	-0.0036	0.0108	0.9972	-0.0330	0.0257
	Wednesday	-0.0142	0.0108	0.6853	-0.0438	0.0154
	Friday	-0.0132	0.0108	0.7373	-0.0426	0.0162
Friday	Monday	-0.0253	0.0113	0.1682	-0.0563	0.0056
	Tuesday	0.0096	0.0107	0.9008	-0.0198	0.0389
	Wednesday	-0.0010	0.0108	1.0000	-0.0306	0.0286
	Thursday	0.0132	0.0108	0.7373	-0.0162	0.0426

** The mean difference is significant at the 1% level. The Daily return is computed as the natural logarithmic first difference of the daily closing price of CND/USD exchange rate: $r_t = 100 \cdot \ln(S_t / S_{t-1})$, where S_t and S_{t-1} are exchange rate at date t and t-1 respectively. Sample period: 03 January 1975 to December 2003.

Table 3: Introducing Dummy Variables into the Mean Equation only

	OLS			Garch (1,1) with Normal Error Distribution			Garch (1,1) with *Student-t* Error Distribution			Garch (1,1) with *GED* Error Distribution			Garch (1,1) with Double Exp. Error Distribution		
Coefficients	Value	Std.Error	P-value	Value	Std.Error	P-value	Value	Std.Error	P-value	Value	Std.Error	P-value	Value	Std.Error	P-value
α	0.0000	0.0001	0.7782	0.0141	0.0059	0.0089**	0.0112	0.0055	0.0211*	0.0104	0.0053	0.0242*	0.0072	0.0045	0.0529
Monday	0.0003	0.0001	0.0164*	0.0011	0.0082	0.4484	-0.0037	0.0077	0.3172	-0.0018	0.0075	0.4053	0.0004	0.0064	0.4731
Tuesday	-0.0001	0.0001	0.4961	-0.0187	0.0084	0.0127*	-0.0125	0.0078	0.0547	-0.0108	0.0075	0.0743	-0.0056	0.0063	0.1865
Wednesday	0.0000	0.0001	0.8594	-0.0053	0.0081	0.2567	-0.0048	0.0077	0.2671	-0.0031	0.0073	0.3353	0.0006	0.0063	0.4626
Thursday	-0.0001	0.0001	0.2617	-0.0320	0.0082	0.0000**	-0.0285	0.0077	0.0001**	-0.0266	0.0074	0.0002**	-0.0219	0.0063	0.0002**
η				0.0009	0.0001	0.0000**	0.0006	0.0001	0.0000**	0.0007	0.0001	0.0000**	0.0008	0.0002	0.0000**
λ				0.0946	0.0043	0.0000**	0.0927	0.0072	0.0000**	0.0890	0.0069	0.0000**	0.0994	0.0096	0.0000**
θ				0.9016	0.0037	0.0000**	0.9088	0.0062	0.0000**	0.9082	0.0062	0.0000**	0.9078	0.0079	0.0000**
Jarque-Bera	3491		0.0000**	2051		0.0000**	2392		0.0000**	2288		0.0000**	2339		0.0000**
Ljung-Box (20)	0.03		1.0000	9.86		0.9706	19.30		0.5025	24.30		0.2295	31.62		0.0475
Ljung-Box (30)	0.10		1.0000	12.83		0.9974	20.96		0.8892	27.48		0.5980	37.06		0.1753
Ljung-Box (40)	1.49		1.0000	19.86		0.9968	27.58		0.9318	34.48		0.7165	45.49		0.2541
Ljung-Box (50)	8.24		1.0000	24.12		0.9993	31.78		0.9792	38.54		0.8809	49.52		0.4926
Ljung-Box (100)	61.65		0.9991	75.29		0.9691	82.21		0.9021	88.82		0.7807	100.45		0.4685
LM Test	694.10		0.0000**	15.76		0.2026	16.38		0.1744	16.43		0.1725	16.46		0.1712
F-stat	1.63		0.0065**	1.44		0.2569	1.493		0.2317	1.50		0.2300	1.50		0.2288
Log Likelihood				-647			-412			-417			-463		
AIC				1386			918			928			1019		
BIC				1703			1242			1252			1336		

AR(38)- GARCH (1,1): $R_t = \alpha + B_M D_{Mt} + B_T D_{Tt} + B_W D_{Wt} + B_H D_{Ht} + + \sum_{i=1}^{21} \mathrm{Re}\,turn_{t-1} + \varepsilon_t$, Where Rt is the daily return at time t, α is a constant term, $D_{Mt}, D_{Ft}, D_{Wt}, D_{Ht}$ are the dummy variables for Monday, Tuesday Wednesday, and Thursday respectively. λ, θ, are the ARCH and GARCH parameters respectively. * Statistically significant at the 5% level. ** Statistically significant at the 1% level..

Table 4: Introducing Dummy Variables into the Mean Equation as well as Conditional Variance Equation

	Garch (1,1) with Normal Error Distribution			Garch (1,1) with *Student-t* Error Distribution			Garch (1,1) with *GED* Error Distribution			Garch (1,1) with Double Exp. Error Distribution		
Coefficients	Value	Std.Error	P-value	Value	Std.Error	P-value	Value	Std.Error	P-value	Value	Std.Error	P-value
α	0.0122	0.0060	0.0209*	0.0108	0.0055	0.0242*	0.0098	0.0052	0.0308*	0.0071	0.0045	0.0550
Monday	0.0030	0.0086	0.3644	-0.0024	0.0080	0.3794	-0.0013	0.0076	0.4349	0.0005	0.0066	0.4712
Tuesday	-0.0169	0.0083	0.0209*	-0.0114	0.0077	0.0680	-0.0094	0.0072	0.0976	-0.0059	0.0062	0.1712
Wednesday	-0.0036	0.0081	0.3280	-0.0042	0.0076	0.2908	-0.0024	0.0072	0.3687	0.0003	0.0062	0.4782
Thursday	-0.0303	0.0084	0.0001**	-0.0279	0.0077	0.0001**	-0.0260	0.0073	0.0002**	-0.0217	0.0063	0.0003**
η	-0.0001	0.0013	0.4799	0.0001	0.0021	0.4880	0.0000	0.0021	0.4954	0.0001	0.0030	0.4820
λ	0.0887	0.0041	0.0000**	0.0910	0.0072	0.0000**	0.0899	0.0068	0.0000**	0.0985	0.0096	0.0000**
θ	0.9076	0.0036	0.0000**	0.9101	0.0062	0.0000**	0.9080	0.0061	0.0000**	0.9084	0.0079	0.0000**
Monday	0.0034	0.0020	0.0466*	0.0041	0.0032	0.0993	0.0042	0.0032	0.0929	0.0046	0.0046	0.1585
Tuesday	-0.0029	0.0020	0.0754	-0.0039	0.0033	0.1229	-0.0043	0.0033	0.0922	-0.0047	0.0047	0.1599
Wednesday	0.0000	0.0020	0.4985	0.0011	0.0031	0.3569	0.0008	0.0030	0.3969	0.0007	0.0044	0.4362
Thursday	0.0041	0.0022	0.0302*	0.0016	0.0039	0.3388	0.0031	0.0036	0.1987	0.0030	0.0054	0.2876
Jarque-Bera	2055		0.0000**	2442		0.0000**	2392		0.0000**	2405		0.0000**
Ljung-Box (20)	9.34		0.9786	18.93		0.5263	24.26		0.2311	31.62		0.0876
Ljung-Box (30)	12.14		0.9984	20.53		0.9022	27.62		0.5908	36.94		0.1790
Ljung-Box (40)	18.84		0.9982	27.32		0.9366	35.15		0.6880	45.41		0.2569
Ljung-Box (50)	23.04		0.9996	31.43		0.9815	39.14		0.8662	49.32		0.5005
Ljung-Box (100)	74.38		0.9742	81.93		0.9059	90.38		0.7440	100.58		0.4648
LM Test	16.68		0.1619	16.38		0.1743	16.66		0.1627	16.63		0.1641
F-stat	1.52		0.2204	1.49		0.2316	1.52		0.2211	1.52		0.2224
Log Likelihood	-642			-409			-414			-461		
AIC	1385			920			930			1021		
BIC	1729			1272			1281			1366		

AR(38)- GARCH (1,1): $R_t = \alpha + B_M D_{Mt} + B_T D_{Tt} + B_W D_{Wt} + B_H D_{Ht} + \sum_{i=1}^{38} \mathrm{Re}\,turn_{t-1} + \varepsilon_t$, $\sigma_t^2 = \eta + \lambda\,\omega_t^2 + \theta\,\sigma_t^2 + B_M D_{Mt} + B_T D_{Tt} + B_W D_{Wt} + B_H D_{Ht}$, where Rt is the daily return at time t, α is a constant term, $D_{Mt}, D_{Ft}, D_{Wt}, D_{Ht}$ are the dummy variables for Monday, Tuesday Wednesday, and Thursday respectively. λ, θ, are the ARCH and GARCH parameters respectively.

* Statistically significant at the 5% level. ** Statistically significant at the 1% level.

Figure I: ACF of log CND/USD daily price changes

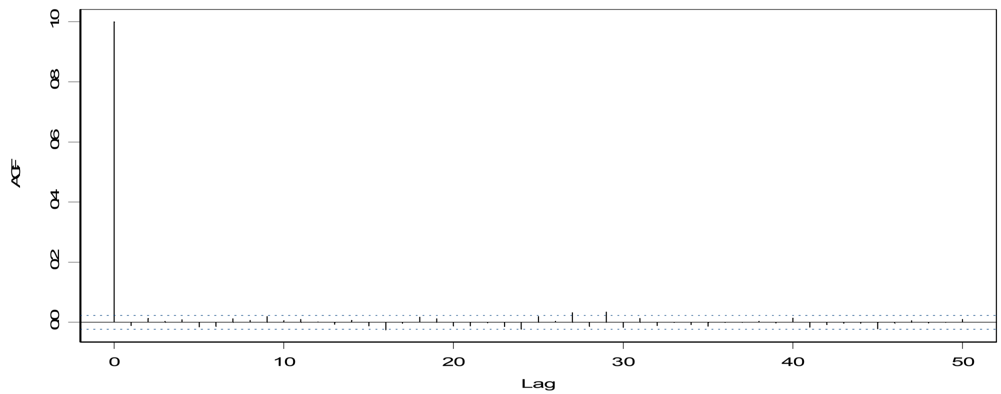

Figure II: Quantile of Comparison: Normal vs. Student error distribution