Trading Collar, Intraday Periodicity, and Stock Market Volatility

Satheesh V. Aradhyula
University of Arizona

A. Tolga Ergun
University of Arizona

May, 2002

Abstract:
Using 5 minute data, we examine market volatility in the Dow Jones Industrial Average in the presence of trading collars. We use a polynomial specification for capturing intraday seasonality. Results indicate that market volatility is 3.4 percent higher in declining markets when trading collars are in effect. Results also support a U-shaped intraday periodicity in volatility.

Key Words: Trading Collar, DJIA, GARCH, Volatility, Intraday, Seasonality

JEL Classification Codes: C22, G18

Paper accepted for presentation at the AAEA annual meetings, Long Beach, CA. July 2002.

Corresponding Author: Professor Satheesh Aradhyula, Economics Building # 23, PO Box 210023, University of Arizona, Tucson, AZ 85721-0023. USA. E-mail: satheesh@ag.arizona.edu. Phone: 520-621-6260. Fax: 520-621-6250.

Trading Collar, Intraday Periodicity, and Stock Market Volatility

In response to the stock market crash of 1987, the New York Stock Exchange (NYSE) established a set of regulations to contain excessive market volatility and to regain investor confidence. The most famous of these regulations are Rule 80A (trading collar), instituted on August 1, 1990 and Rule 80B (circuit breaker), instituted on October 19, 1988. The Rule 80A restricts index arbitrage form of program trading in component stocks of the S&P 500 stock price index.

When implemented originally in 1990, Rule 80A imposed restrictions on index arbitrage trading in component stocks of the S&P 500 index whenever the Dow Jones Industrial Average (DJIA) moved above or below the previous day's closing level by 50 points or more. Once imposed, these trading restrictions will be removed when the DJIA returns to within 25 points of previous day's closing level. In February 1999, percent based triggering levels (as opposed to absolute values of 50 and 25) were implemented. These triggering levels are adjusted quarterly and are announced by the NYSE at the beginning of each quarter. Table 1 lists historical collar levels that have been set by the NYSE.

Numerous researchers have studied the volatility of the stock markets and GARCH models have become ubiquitous for modeling market volatility. See Aydemir (1998) and Diebold and Lopez (1995) for recent surveys of volatility modeling in finance. A great majority of the GARCH models for market volatility have not taken the trading collars into modeling consideration. Forecasts from models that do not incorporate the institutional details might not be as accurate.

The presence of trading collars could conceivably alter volatility dynamics and volatility models should account for this. To successfully model trading collars and their effect on volatility one needs to use high frequency intraday data because trading collars are imposed during a trading session and typically do not last for long time periods. For example, one cannot discern the presence of trading collars from daily closing values of the DJIA. In this study, we estimate GARCH models that explicitly account for the NYSE's trading collar rules using high frequency data.

Financial markets exhibit strong periodic dependencies across the trading day – typically volatility is highest at the open and toward the close of the day – and failure to account for this may seriously distort the inferences made from the models (Bolleslev 2001). Two approaches have been used in the literature to capture intraday seasonal patterns in volatility in the context of ARCH models: use of dummy variables in the conditional variance equation (e.g., Baillie and Bollerslev 1990, and Ederington and Lee, 2001) and use of Flexible Fourier forms (e.g., Andersen and Bollerslev 1997, 1998 and Martens 2001).

In this paper, we use a polynomial function to capture systematic intraday periodicities in volatility and estimate the seasonal components simultaneously with the rest of the model. The polynomial functional form, like the Fourier form introduced by Andersen and Bollerslev (1997, 1998), can be viewed as a flexible form for approximating the true, unknown seasonal pattern. By increasing the number of polynomial terms, the function could be made arbitrary close to true seasonal component. Also, using simple parametric restrictions, the function could be made continuous and smooth as it cycles from one day to the next.

Andersen and Bollerslev (1997, 1998) and Martens (2001) estimate the seasonal component first and use the estimated seasonality to deseasonalize the returns data. Then, they fit ARCH models to the deseasonalized data. In this paper, we estimate the seasonal components and the ARCH parameters simultaneously. By estimating the seasonality (intraday effects) simultaneously with the GARCH parameters, this approach provides efficient estimates and avoids the short-falls of using estimated data (Pagan).

The polynomial form advocated in this paper is parsimonious in parameters and is easy to estimate. For high frequency data, the dummy variable approach requires a lot of parameters to completely specify the intraday seasonality. For example, for the 5 minute interval data we use, it would take as many as 78 parameters using the dummy variables approach to capture the time of the day effects on conditional volatility. With a polynomial specification, a sufficiently flexible seasonal pattern can be estimated often times using just 4 or 5 parameters. This is the first study to examine the market volatility in the DJIA in the context of the trading collars while simultaneously accounting for intraday seasonality.

Data

To model market volatility and how it is affected by the presence of trading collar, one should use high frequency data for observing intraday fluctuations in returns that might trigger the collar. We use five-minute interval data for the DJIA. We obtained the data from the Tick Data Incorporated. The sample period is from February 16, 1999 to August 31, 2001, giving a total of 49,001 observations on returns. The sample period corresponds to the current regime of collar levels which are set based on a percent of the DJIA. Overnight returns are excluded so the sample contains exclusively 5 minute returns.

Three dummy variables, D^b, D^a, and D, have been created to represent the periods when the collar is in effect. Dummy variable D^b takes a value of one when the collar is in effect and if the collar has been triggered from below. Thus, D^b represents the periods when the Rule 80A is in effect due to decreases in the DJIA. Similarly, D^a takes a value of 1 whenever the collar is in effect due to increases in the DJIA. Finally, dummy variable D is created which takes the value of one whenever the collar is in effect and zero otherwise. Obviously, $D^a + D^b = D$.

The sample means for D^b, D^a, and D, respectively, are 0.0355, 0.0245 and 0.0600 indicating that the Rule 80A has been in effect for about 6.0% of sample observations. During the sample period, which is about two and years long, the collar was triggered a total of 99 times. Once triggered, the collar stayed on for about 30 observations on average. Given the 5 minutes data used in this study, this corresponds to about two hours and 30 minutes. Thus, the average length of trading collar is about two and half hours.

The sample mean and standard deviation for 5 minute returns for the DJIA are $8.540\text{x}10^{-6}$ and $1.182\text{x}10^{-5}$. Assuming returns are uncorrelated, the standard error for the mean equals $1.182 \times 10^{-5} / \sqrt{49{,}001} = 5.340\text{x}10^{-8}$ making the mean indistinguishable from zero at standard significance levels. The sample skewness and kurtosis are 0.0591 and 22.110 indicating that the distribution for returns have thick tails. A Jarque-Bera test static of 745,644.28 provides a strong evidence of departure from normality. To accommodate thick tails, we use a Student t distribution for modeling returns in our analysis.

The Model

We specify the following model for log-returns:

$$r_t = \mu + \varepsilon_t$$

$$\varepsilon_t \mid \psi_{t-1} \sim \phi(0, h_t, v)$$

where, $r_t = \ln(DJIA_t / DJIA_{t-1})$, ϕ is Student t distribution with $1/v$ degrees of freedom, zero mean and variance of h_t, and μ and v are parameters to be estimated. To capture volatility dynamics during the periods of trading collars, we estimate the following four specifications for the conditional variance:

Model A: $h_t = \left[\omega_t + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1}\right] \bullet (1+\gamma D_t)$

Model B: $h_t = \left[\omega_t + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1}\right] \bullet (1+\gamma^a D_t^a + \gamma^b D_t^b)$

Model C: $h_t = (1+\gamma_0 D_t)\omega_t + (1+\gamma_1 D_t)\alpha_1\varepsilon_{t-1}^2 + (1+\gamma_2 D_t)\beta_1 h_{t-1}$

Model D: $h_t = (1+\gamma_0^a D_t^a + \gamma_0^b D_t^b)\omega_t + (1+\gamma_1^a D_t^a + \gamma_1^b D_t^b)\alpha_1\varepsilon_{t-1}^2 + (1+\gamma_2^a D_t^a + \gamma_2^b D_t^b)\beta_1 h_{t-1}$

Where ω_t is intraday seasonality term, D, D^a, and D^b are dummy variables defined earlier, and $\alpha_1, \beta_1, \gamma, \gamma^a, \gamma^b, \gamma_0, \gamma_1, \gamma_2, \gamma_0^a, \gamma_0^b, \gamma_1^a, \gamma_1^b, \gamma_2^a$, and γ_2^b are parameters to be estimated. The intraday seasonality component is defined as:

$$\omega_t = \exp\left(a_0 + a_1 S_t + a_2 S_t^2 + a_3 S_t^3 + \ldots + a_k S_t^k\right)$$

where, S_t is a seasonality time index variable that takes values between 0 and 1 and $a_0, a_1, \ldots, a_k$ are parameters to be estimated. Data on S are obtained as follows. Let n represent the number of periods in a day (which is the length of the seasonality cycle). Then, for given trading day with n five minute returns, the ith observation of variable S for that day is given by i/n. The seasonality term can be made continuous by restricting $\omega_t\big|_{S_t=0} = \omega_t\big|_{S_t=1}$, i.e., $\sum_{i=1}^{k} a_i = 0$. Similarly, the seasonality term can be made smooth as it cycles from one day to the next by imposing $\left.\frac{d\omega_t}{dS_t}\right|_{S_t=0} = \left.\frac{d\omega_t}{dS_t}\right|_{S_t=1}$, i.e., $\sum_{i=2}^{k} i \bullet a_i = 0$. All four models reduce to conventional GARCH models with no seasonality when the parameters a_1, a_2, …, a_k are restricted to zero.

Given a previous day's closing value for the DJIA (which is will be in the conditioning information set), the models can endogenously determine whether a collar would be in effect for the next period. Thus, conditional volatility forecasts from these models appropriately account for the presence of collars, if any.

Models A and B allow the conditional variance dynamics to be different during the trading collar periods without allowing the GARCH parameters to be different when the trading collar is in effect. Models C and D allow conditional variance dynamics to be different during the trading collars by allowing the GARCH parameters to vary when the trading collar is in effect. Models A and C treat up and down markets the same while models B and D allow the volatility dynamics to behave differently during up and down markets. Model D is the most general model and nests the other three models in it while model A is the most restrictive and nests in the other three models.

Results

Maximum likelihood estimates of the parameters for the four models are given in table 2. One over the degrees of freedom parameter (1/*v*) is significantly different from zero for all four models supporting the choice of t distribution over the normal. Estimated degrees of freedom for all four models is remarkably close at 7.2.

Estimated GARCH coefficients, α_1 and β_1, are highly significant in all four models. Estimated magnitudes of the coefficients are similar across the four models. In all models, β_1 coefficient is estimated to be much higher than α_1 and the sum of estimated GARCH coefficients is close to 1 indicating persistence of memory. This is expected in high frequency data.

In model A, γ is positive and significant. An estimated value of 0.02 indicates that market volatility is 2.0% higher during the periods of trading collar. However, model A does not distinguish rising and declining markets. To distinguish the effects of trading collar in rising and declining markets, we look at results from model B. The γ^a coefficient is insignificant indicating that in rising markets, the presence of collar has no bearing on market volatility. In contrast, γ^b is significant indicating that market volatility is appreciably higher in declining markets. A value of 0.034 indicates that market volatility is 3.4% higher when the collar is in effect in declining markets. All three trading collar coefficients ($\gamma_0, \gamma_1, \gamma_2$) are significant in Model C implying that volatility dynamics are different during trading collar regimes. However, results from Model D indicate that volatility dynamics are not affected by the presence of trading collar during rising markets. However, volatility dynamics are significantly affected by the presence of trading collar in declining markets.

In the estimation, a third order polynomial was found to adequately model the intraday seasonal patterns. Results in table 2 indicate that the estimated seasonality parameters, a_0, a_1, and a_2, are highly significant for all four models. These seasonality parameters are markedly similar for all the four models indicating that the estimated intraday seasonality polynomial is robust across the four model specifications. The null hypothesis on no intraday seasonality ($a_1 = a_2 = 0$) is soundly rejected for all four models. Empirical results indicate the presence of significant intraday seasonal patterns in the DJIA.

Figure 1 is a graphical depiction of the estimated intraday seasonal pattern in volatility for model D. Seasonal patterns for other three models are similar. Figure 1 indicates that the

DJIA is about three times more volatile at the open and the end of the day than at midday. Estimated seasonality polynomial supports a U shaped volatility pattern reported by earlier studies for other equity markets (e.g., Andersen and Bollerslev, 1997).

Likelihood ratio tests favor Model D over the other three models. Testing one at a time, the null hypothesis of restrictive model (A,B, and C) is rejected in favor of model D at standard levels of significance. Akaike Information Criteria given in table 2 also indicate that Model D is the preferred model. Thus, empirical results suggest that volatility dynamics are significantly different when trading collar is imposed and that these dynamics are not identical during up and down markets.

Conclusions

In this paper, we estimate volatility models for the DJIA that account for the presence of trading collars that have been instituted by the NYSE. Using a polynomial specification, we simultaneously estimate intraday seasonality in volatility. Results support a U-shaped intraday periodicity in market volatility. We estimate that market volatility is 2% higher when trading collars are in effect and 3.4% higher when trading collars are in effect in declining markets.

References:

Andersen, T. G., and T. Bollerslev, 1997, Intraday periodicity and volatility persistence in financial markets, Journal of empirical finance, 4, 115-158.

Andersen, T. G., and T. Bollerslev, 1998, Deutsche Mark-Dollar volatility: Intraday activity patterns, macroeconomic announcements, and longer run dependencies, Journal of finance, 53, 219-65.

Aydemir, A. B., 1998, Volatility modeling in finance in: J. Knight and S. Satchell, eds., Forecasting volatility in the financial markets (Butterworth Heinemann) 1-46.

Bollerslev, T., 2001, Financial econometrics: Past developments and future challenges, Journal of Econometrics 100, 41-51.

Baillie, R. T., and Bollerslev, T., 1990, Intra day and inter market volatility in foreign exchange rates, Review of Economic Studies 58, 565-585.

Diebold F. and J.A. Lopez, 1995, Modeling volatility dynamics in: K. Hoover ed., Macroeconometrics: Developments, tensions and prospects(Kluwer Academic), 427-466.

Ederington, L., and J. H. Lee, 2001, Intraday volatility in interest-rate and foreign-exchange markets: ARCH, announcement, and seasonality effects, Journal of futures markets, 21, 517-552.

Martens, M., 2001, Forecasting daily exchange rate volatility using intraday returns, Journal of International Money and Finance 20, 1-23.

Table 1. New York Stock Exchange's Historical Trading Collar Levels

Period			Collar Level
August 1, 1990	-	February 15, 1999	50-25
February 16, 1999	-	March 31, 1999	180-90
April 1, 1999	-	June 30, 1999	190-90
July 1, 1999	-	December 31, 1999	210-100
January 3, 2000	-	March 31, 2000	220-110
April 3, 2000	-	June 30, 2000	200-100
July 3, 2000	-	March 30, 2001	210-100
April 2, 2001	-	June 29, 2001	200-100
July 2, 2001	-	September 28, 2001	210-100

Table 2. Maximum likelihood estimates of market volatility models for the DJIA.

Parameter	Model A	Model B	Model C	Model D
μ	0.00066 (1.71)	0.00065 (1.67)	0.00064 (1.65)	0.00062 (1.60)
a_0	-6.75 (-78.65)	-6.74 (-92.61)	-6.82 (-81.23)	-6.74 (-99.75)
a_1	-18.26 (-13.49)	-18.11 (-19.57)	-18.35 (-13.43)	-18.02 (-22.05)
a_2	38.52 (10.94)	38.12 (15.87)	38.97 (11.00)	37.62 (17.99)
α_1	0.0740 (23.05)	0.0732 (24.98)	0.0701 (22.03)	0.0709 (24.93)
β_1	0.888 (187.94)	0.888 (232.74)	0.893 (199.93)	0.891 (252.98)
γ	0.020 (5.24)			
γ^a		-0.0016 (-0.27)		
γ^b		0.034 (7.63)		
γ_0			1.228 (2.76)	
γ_1			0.843 (3.16)	
γ_2			-0.060 (-3.14)	
γ_0^a				0.752 (3.02)
γ_0^b				1.156 (2.46)
γ_1^a				-0.013 (-0.06)
γ_1^b				0.807 (2.94)
γ_2^a				-0.026 (-1.35)
γ_2^b				-0.037 (-2.16)
$1/\upsilon$	0.1395 (34.21)	0.1395 (34.26)	0.1393 (34.21)	0.1393 (34.26)
Log-likelihood	71169.33	71182.55	71192.63	71205.94
Akaike Information Criterion	142322.66	142347.10	142365.26	142385.88

Note: Numbers in parentheses are *t*-ratios. Estimation period is 2/16/1999 – 8/31/2001 with a sample size of 49,001.

Figure 1. Estimated intraday seasonal patterns in volatility of the Dow Jones Industrial Average