REU Project Summary

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Financial data typically show the spread and clustering of the volatility of the data. The ARCH (Engle, 1982) and GARCH (Bollerslev, 1986) were designed as a model by which to capture such features of volatility of data. More specifically, the time-series technique, GARCH allows for modeling the serial dependence of the volatility. Due to the conditional property of GARCH, the mechanism depends on the observations of the immediate past, thus including past variances into explanation of future variances. Hence, GARCH models rely on time–varying variance. The GARCH model also takes into account volatility clustering and tail behavior; important characteristics of financial time series. It provides an accurate assessment of variances and covariances through its ability to model time–varying conditional variances. Bollerslev (1986) developed GARCH based on Engle's original ARCH volatility modeling technique. Bollerslev (1986) designed GARCH using fewer parameters, which lessens computations and may provide a better fit for the data. When estimating a GARCH model, with normal errors, it becomes necessary to look at the amount of outliers as a means by which to determine which model gives a better fit. For further research, I want to perform likelihood ratio tests to detect outliers in GARCH models. If there are substantially more outliers than expected, it may become necessary to generate the outliers separately or to use dummy variables to remove them. Using the GARCH(1,1) there may be a new procedure for detecting outliers, and consequently removing them.

This semester I mainly focused on learning/improving my computer programming skills. I learned how to program using the statistical software, R. I created new programs which allowed me to generate the necessary GARCH processes. I used the asymmetric GARCH(1,1) model introduced by Glosten, Jagannathan and Runke (1993) defined as

$$y_k = \sigma_k \epsilon_k, \quad -\infty < k < \infty$$

and

$$\sigma_k^2 = \omega + \alpha_1 y_{k-1}^2 + \alpha_2 \max(0, -y_{k-1}) y_{k-1}^2 + \beta \sigma_{k-1}^2, \quad -\infty < k < \infty,$$

where $\boldsymbol{\theta} = (\omega, \alpha_1, \alpha_2, \beta)$ is the parameter of the process. It is assumed that the errors (innovations) $\epsilon_k, -\infty < k < \infty$ are independent identically distributed random variables. The observations (returns) are $y_k, -\infty < k < \infty$ and σ_k^2 denotes the (unobserved) volatility. The simulations allowed for more thorough research to supplement the more theoretical work that I worked on last semester. By generating at least 300 random variables during each process, I was able to plot a large sample size in order to best analyze the results. Furthermore, I looked at changes which occur using different values for the parameters. Additionally, I also tried changes such as generating 800 random variables, but only plotting the last 300. Subsequently, I designed programs where the plots consisted of random variables, without a constant value for the parameter. A sample of the results is attached. The first 150 observations are plotted with $\beta = 0.3$ while the next 150 use $\beta = 0.5$. For continued research, I want to experiment with programming in S plus, as well as C++.

References

T. Bollerslev (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, **31**:307–327.

R. F. Engle (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, **50**:987–1007.

L. Glosten, R. Jagannathan and D, Runke (1993). Relationship between expected value and the volatility of the nominal excess returns on stocks. *Journal of Finace*, **48**:1779–1801.

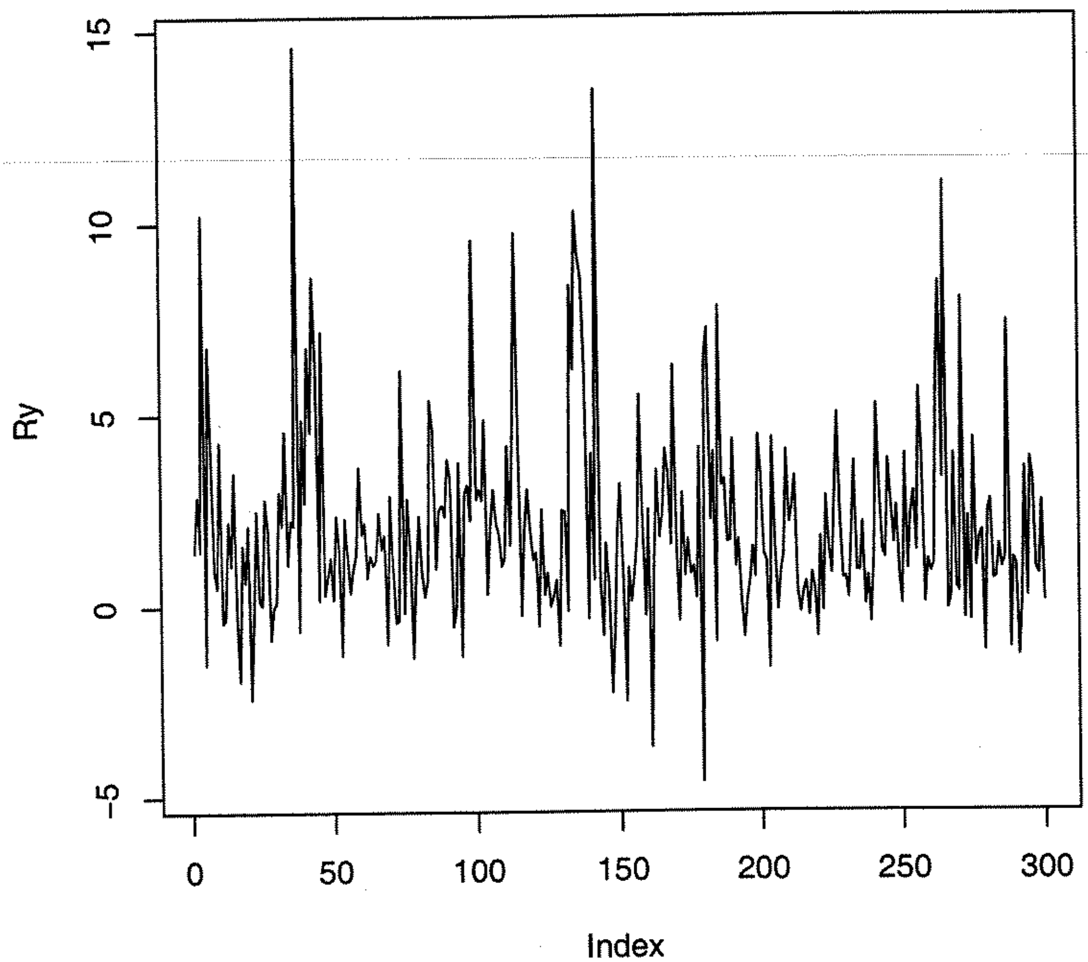

Figure 1

Graph of $y_k, 1 \leq k \leq 300$, when $\omega = 1, \alpha_1 = .2, \alpha_2 = .5, \beta = .3$

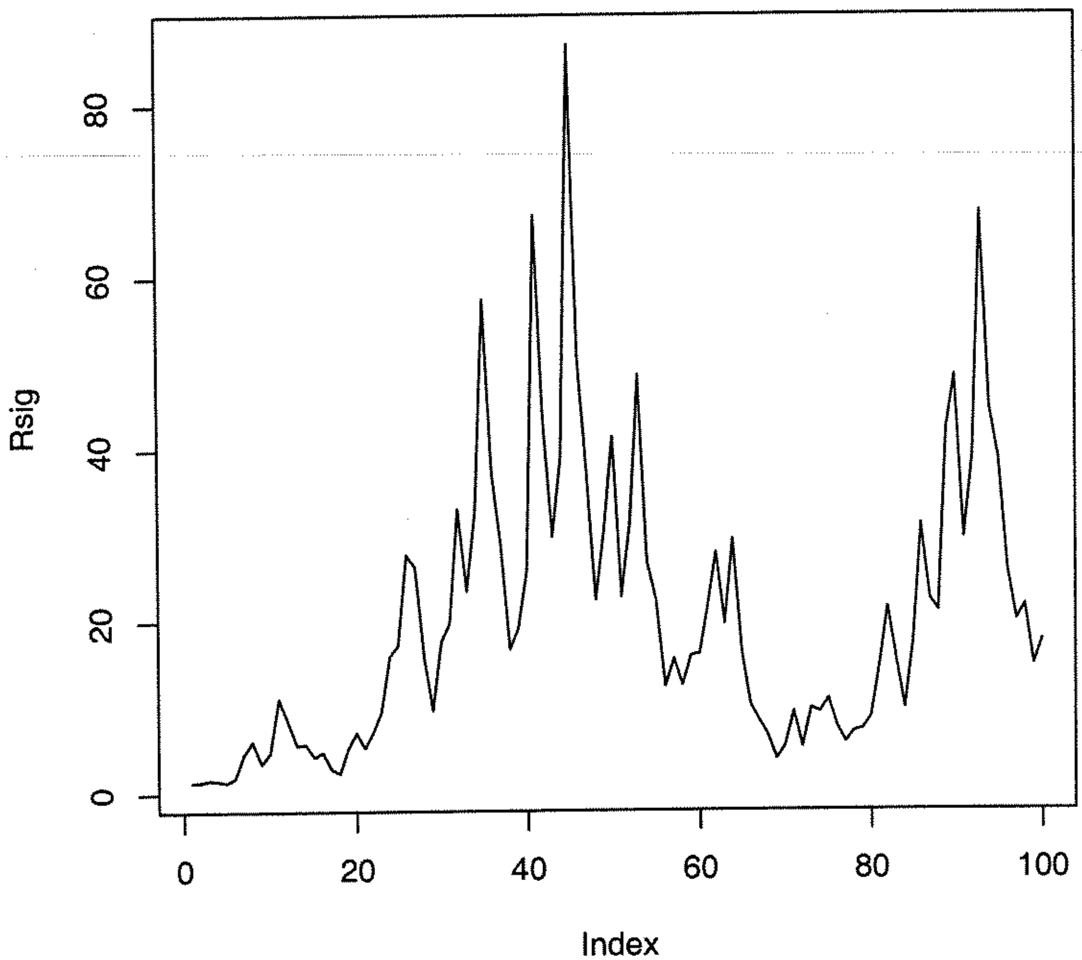

Figure 2

Graph of $\sigma_k^2, 1 \leq k \leq 300$, when $\omega = 1, \alpha_1 = .2, \alpha_2 = .5, \beta = .3$

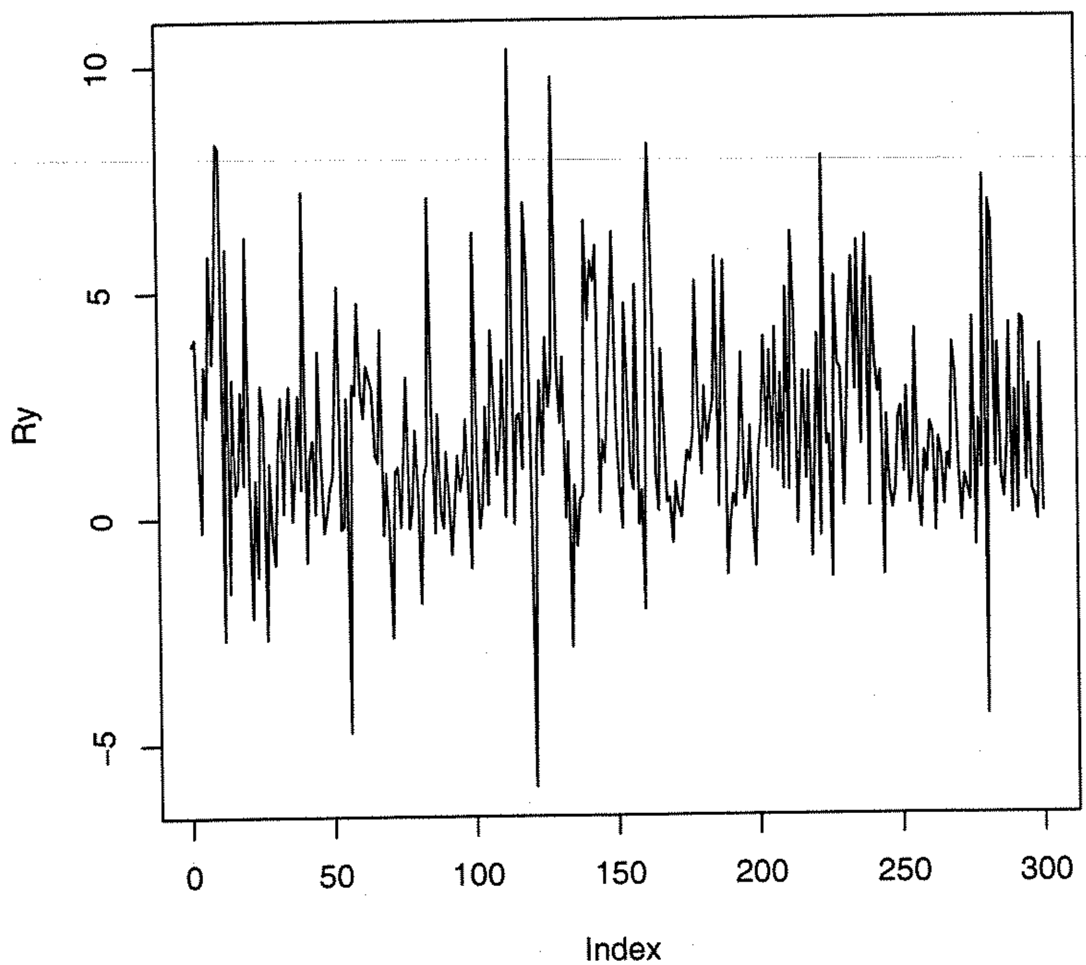

Figure 3

Graph of $y_k, 1 \leq k \leq 300$, when $\omega = 1, \alpha_1 = .5, \alpha_2 = .2, \beta = .3$

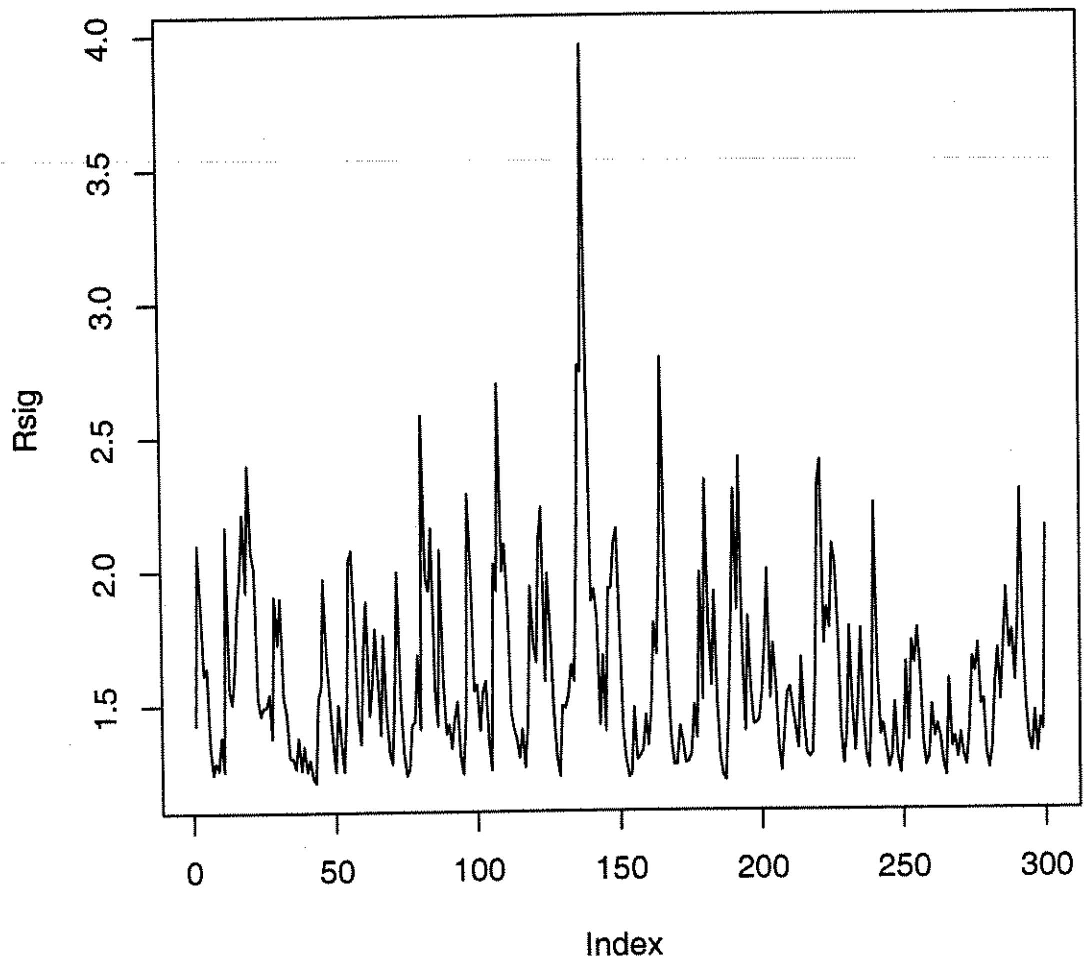

Figure 4

Graph of $\sigma_k^2, 1 \leq k \leq 300$, when $\omega = 1, \alpha_1 = .5, \alpha_2 = .2, \beta = .3$

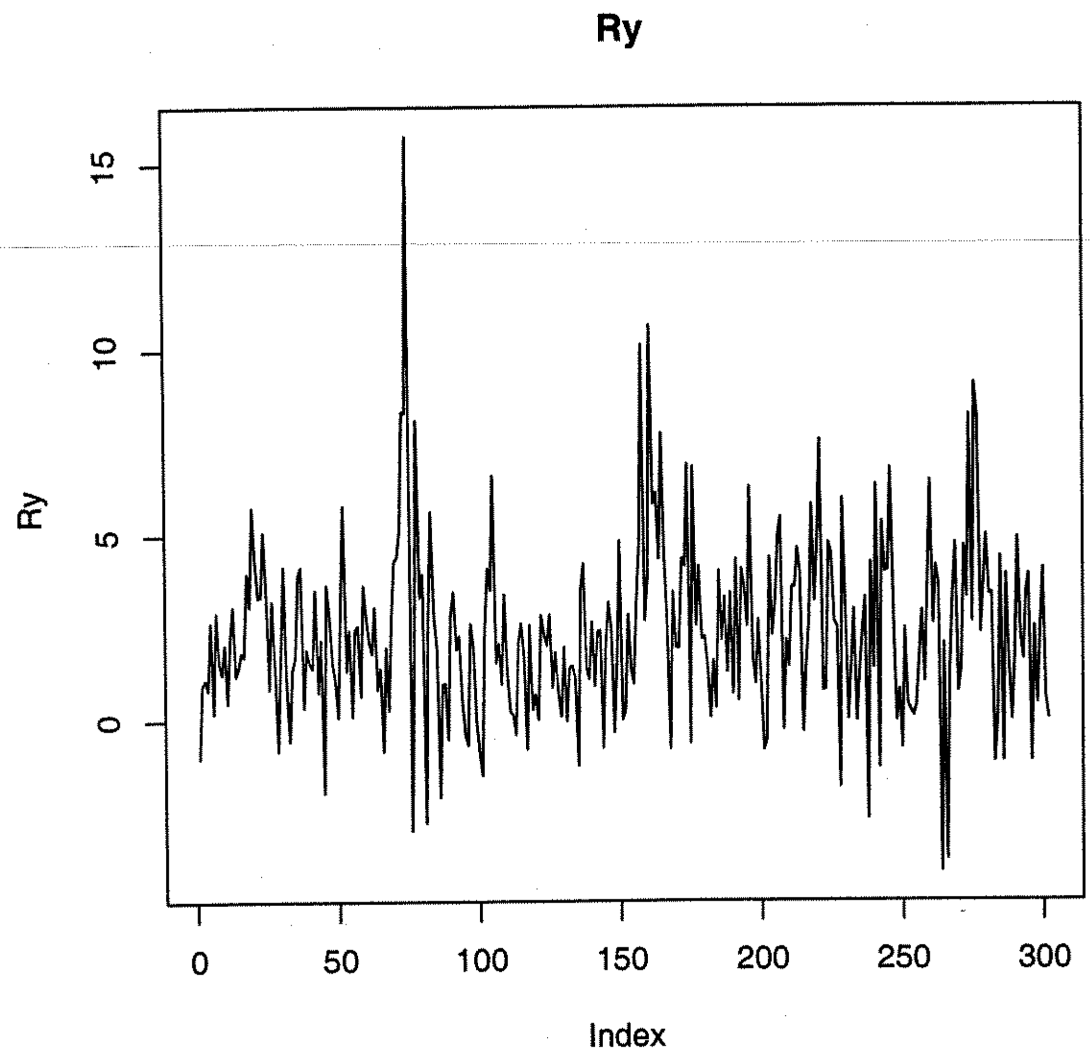

Figure 5

Graph of $y_k, 1 \leq k \leq 300$, when $\omega = 1, \alpha_1 = .5, \alpha_2 = .2, \beta = .3$ in the first 150 observations and $\beta = .5$ in the last 150 observations

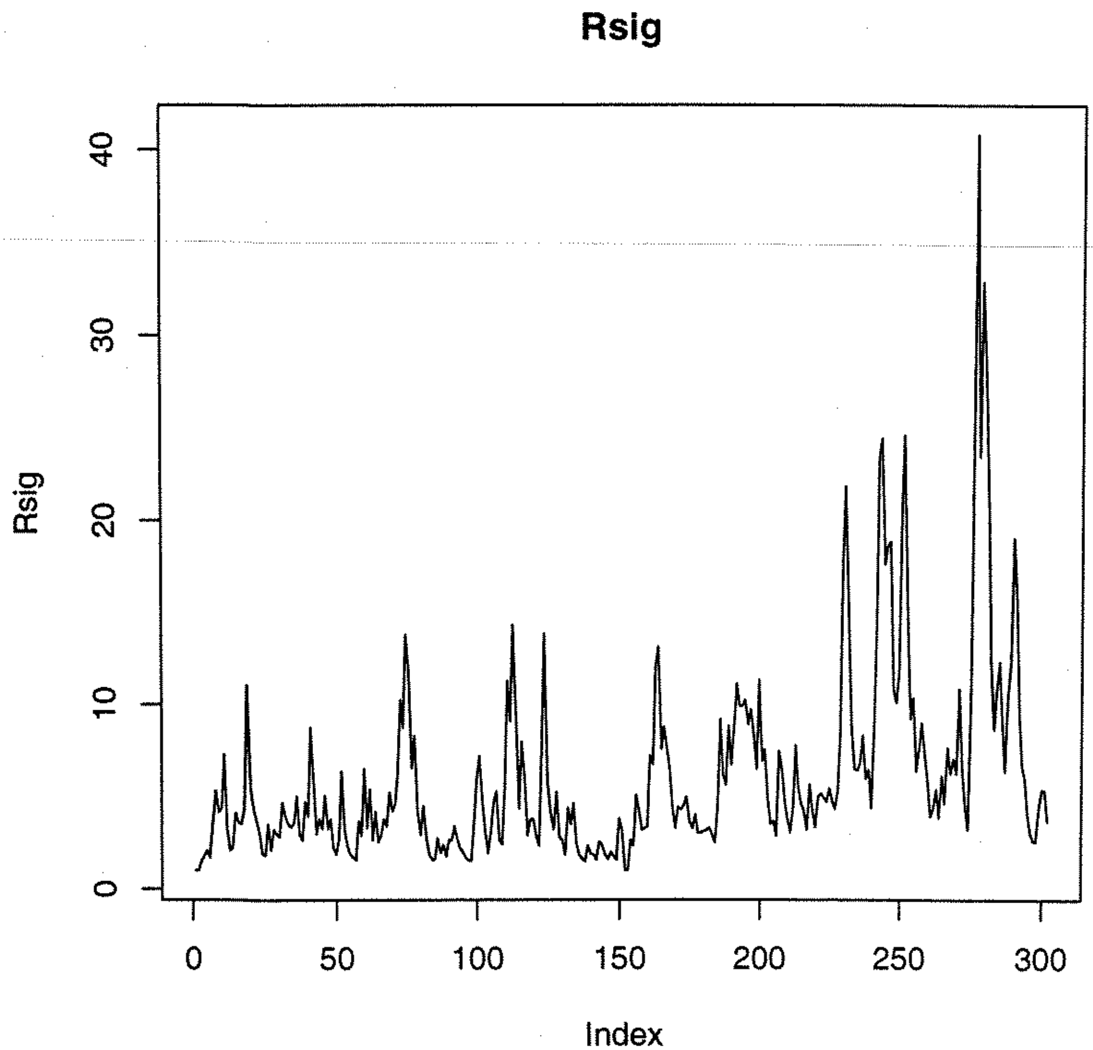

Figure 6

Graph of $\sigma_k^2, 1 \leq k \leq 300$, when $\omega = 1, \alpha_1 = .5, \alpha_2 = .2, \beta = .3$ in the first 150 observations and $\beta = .5$ in the last 150 observations