Assignment 3

Advanced Econometrics

2022

Econometrics and Operations Research

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Question 1

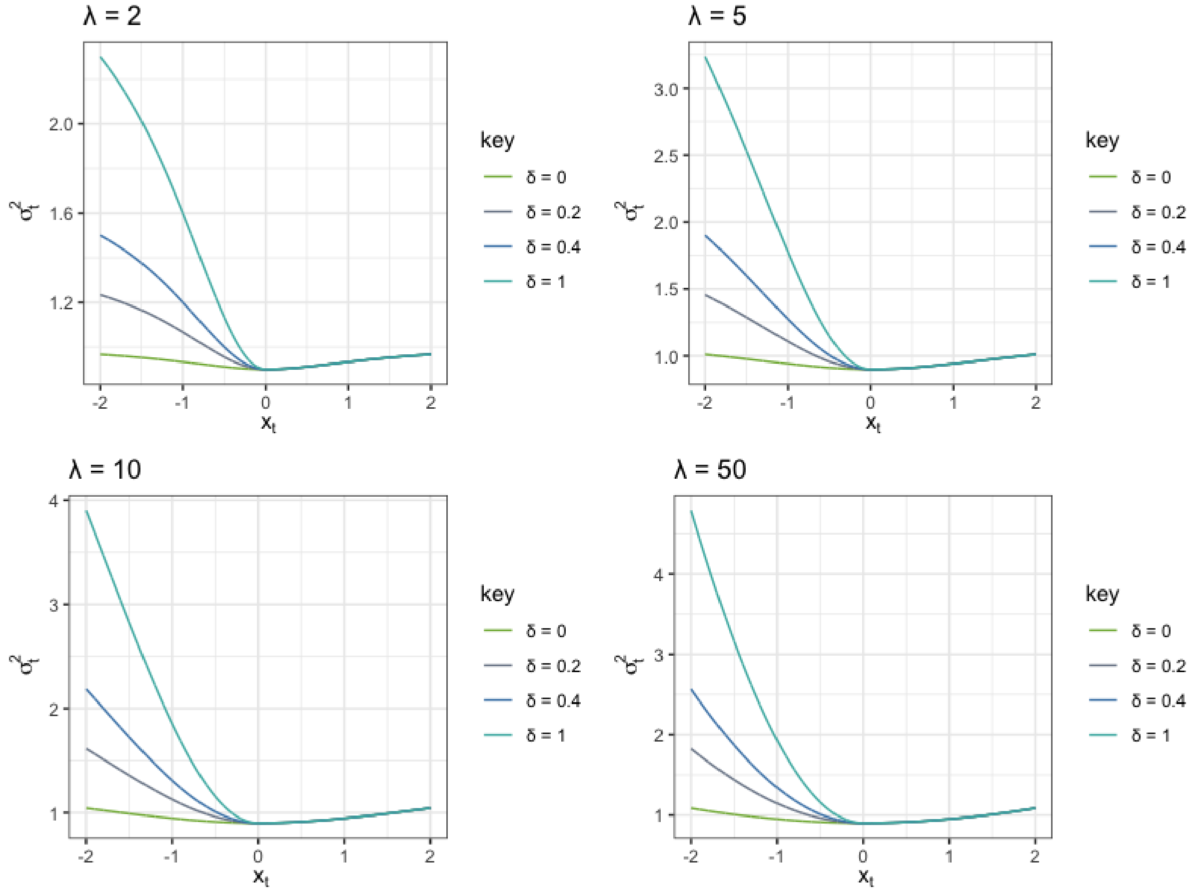

Figure 1: Plots of the News-Impact-Curves for different values of λ and δ

The Figure 1 evaluates new impact curves for different values of lambda and delta. As we can see, as the value of lambda increases, our impact curve takes a more concave shape for negative values in x. Let us analyze how the following scenarios affect our filter function:

1. $\lambda \to \infty$: $x_t - 1^2$ loses weight in the denominator, and in consequence, it becomes very close to 1. Therefore, this new model is similar to the QGARCH Model, where δ picks up the leverage effect for negative values of x.

2. $\lambda \to \infty$ and $\delta \to 0$: we have the same model as in scenario 1, but our δ converges to 0. This causes the elimination of the leverage effect. Therefore, we end up with a GARCH Model.

Question 2

Table 1: Descriptive statistics for Johnson Johnson, Merck, Plizer and Coca Cola

	JNJ	KO	MRK	PFE
Number of observations	5284	5284	5284	5284
Mean	8.656e-18	8.262e-18	2.263e-17	2.563e-18
Standard deviation	1.169	1.225	1.651	1.528
Median	-0.009	0.013	-0.002	-0.031
Minimum	-15.885	-10.092	-26.807	-11.177
Maximum	12.190	13.848	13.007	10.824
Skewness	-0.256	-0.071	-0.916	-0.015
Kurtosis	14.875	10.684	21.084	6.060

Table 1 shows the relevant descriptive statistics for all stocks. The mean for all stocks are really close to zero implying that the returns of the stocks are almost zero on average. The values for the median for each stock support this conclusion as these are also close to zero. The magnitude of the minimum returns are substantially higher than the magnitude of the maximum return for each stock. The skewness for all stocks are close to zero implying a more or less symmetrical distribution. The kurtosis does seem high, which means that there are some outliers or the distribution has heavy tails.

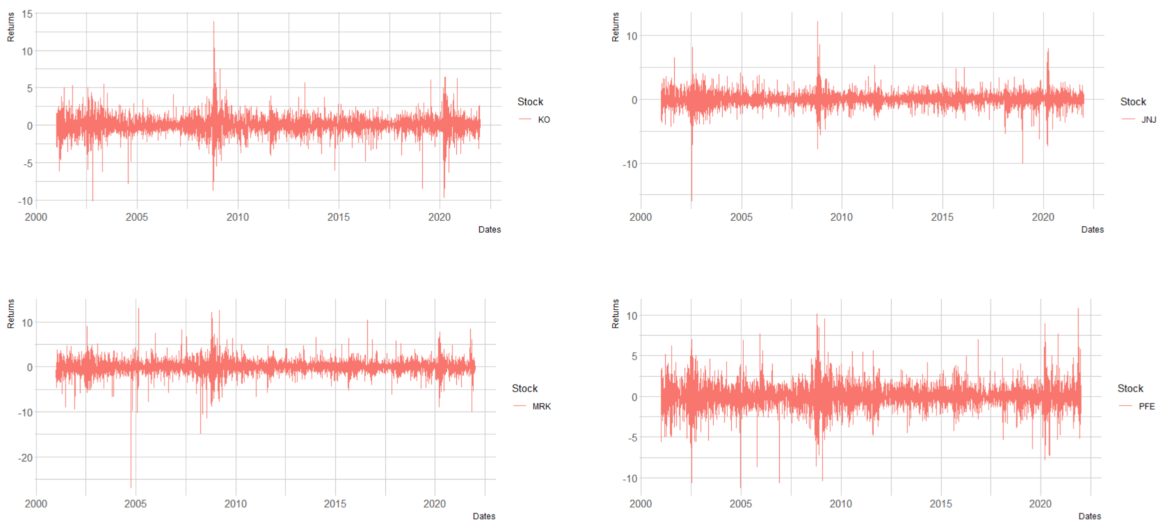

Figure 2: Returns for Johnson Johnson, Merck, Plizer and Coca Cola

Notes: Returns for Johnson Johnson, Merck, Plizer and Coca Cola stock market returns. The plots show the daily stock market returns for Coca Cola (top left panel), Johnson Johnson (top right panel), Merck (bottom left panel) and Plizer (bottom right panel). The x-axis shows the returns (once subtracted the mean) of the stocks whereas the y-axis for the four panels is a daily time-axis from Monday 2 January 2001 to Friday 30 December 2021 symbolizing day 1 and day 5281, respectively.

Figure 2 displays the returns among the four different stocks. For all of them, the data is distributed around 0. That can be easily explained due to the mean being subtracted from those returns. We can see extreme values such as the minimum and maximum of the returns, as well as the distribution of this data. For instance, Merck shows the lowest value whereas the maximum can be found on Coca Cola's plot.

Question 3

Table 2: Results of Log Likelihood estimation for Robust GARCH-with-Leverage-Effect

	JNJ		MRK		PFE	
	No Lev.	Lev.	No Lev.	Lev.	No Lev.	Lev.
ω	0,013	0,013	0,049	0,041	0,028	0,013
	(0,004)	(0,003)	(0,019)	(0,017)	(0,011)	(0,006)
α	0,154	0,041	0.162	0,425	0,118	0,028
	(0,021)	(0,019)	(0,030)	(0,025)	(0,021)	(0,018)
β	0,853	0,877	0,839	0,874	0,881	0,919
	(0,019)	(0,017)	(0,032)	(0,031)	(0,021)	(0,016)
δ		0,167		0,165		0,111
		(0,028)		(0,034)		(0,022)
λ	6,011	6,388	4,384	4,424	6,173	6,006
	(0,664)	(0,734)	(0,350)	(0,351)	(0,662)	(0,623)
Log-Lik	-3567,363	-3549,143	-4685,030	-4671,066	-4542,309	-4531,755
AIC	7142,727	7108,287	9378,061	9352,132	9092,618	9073,509
BIC	7166,023	7137,407	9401,357	9381,252	9115,915	9102,629

Notes:Parameters and measures obtained for each stock for the two estimated models: with leverage ($\delta = 0$), and without leverage ($\delta \neq 0$).

Table 2 summarizes the parameters, the standard errors, total log likelihood, AIC and BIC obtained from the log likelihood estimation for each stock and model. The models do not report significant difference in AIC and BIC between the stocks, since it is less than 1%. Therefore both have a similar fit. However, the Leverage Model reports lower values for the standard errors and slightly lower values for the total log likelihood in all the stocks, which implies that there is some evidence that a model with leverage better fits the data better than the model without leverage.

Question 4

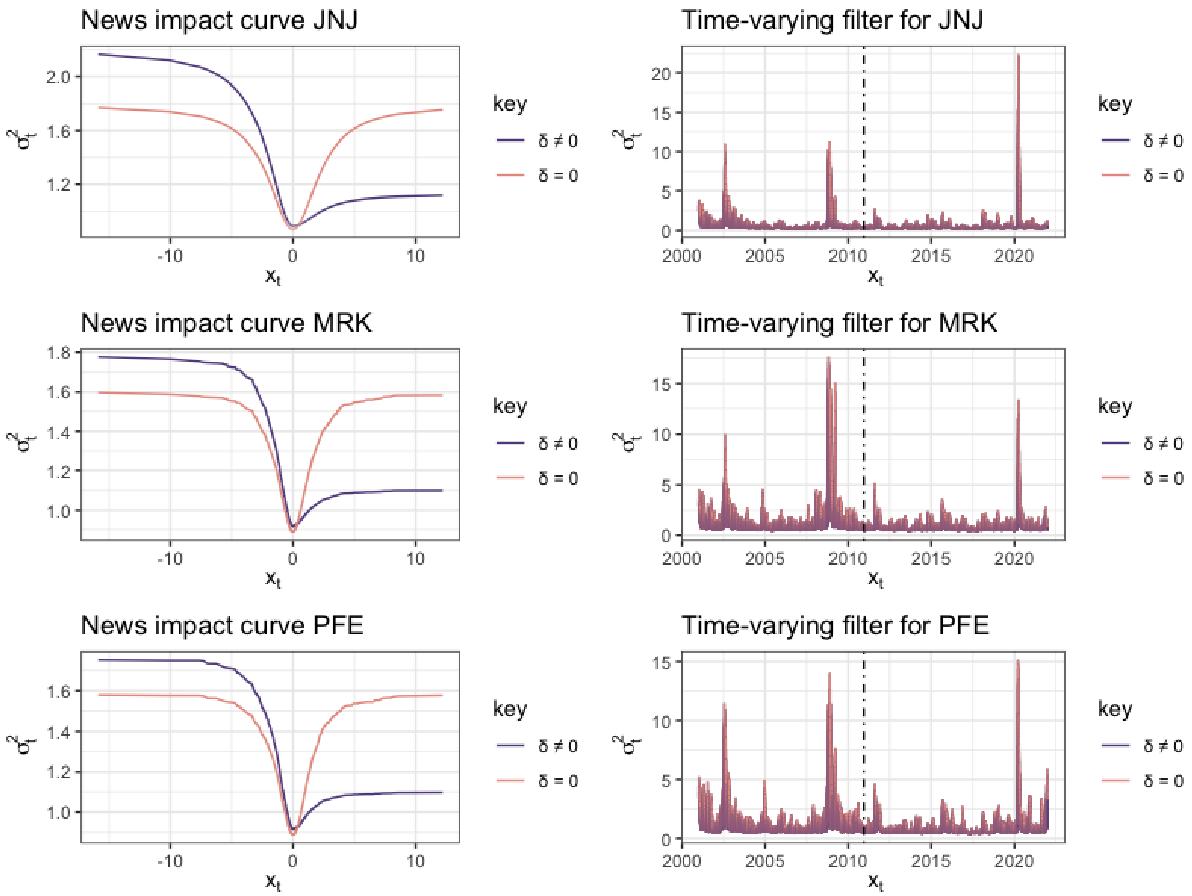

Figure 3: Estimated News Impact curves (left) and estimated filter $\hat{\sigma}_t^2$ (right) for the three stocks

Figure 3 shows plots for the estimated News Impact curves (NIC) on the left side, and the estimated time-varying filter on the right side, for both models with and without leverage effect.

On the left we see that the NIC are symmetric for the model without leverage effect and non-symmetric for the model with leverage effect, as expected. The NIC curves seem to be relatively similar for the three companies. The effect of large negative shocks has a bigger effect on volatility for Jhonson and Jhonson compared to the other companies.

Volatility seems to be similar across the three companies, suggesting that large spikes are due to unstable market conditions rather than asset-specific volatility. The is no discernible significant difference in the filter for both types of models.

Question 5

Table 3: VaR estimates for the compound returns on April 1, 2020

		1%			5%			10%		
Stock	Leverage	h = 1	h = 5	h = 20	h = 1	h = 5	h = 20	h = 1	h = 5	h = 20
JNJ	$\delta = 0$	-12,659	-24,319	-42,387	-7,899	-17,347	-31,614	-5,781	-13,595	-25,893
	$\delta \neq 0$	-11.295	-22,987	-38,773	-7,214	-15,787	-28,985	-5,393	-12,436	-23,544
MRK	$\delta = 0$	-12.267	-23,591	-37,446	-7,152	-15,685	-27,626	-5,191	-12,121	-22,281
	$\delta \neq 0$	-11,690	-21,922	-37,074	-6,658	-14,938	-26,655	-4,909	-11,533	-21,163
PFE	$\delta = 0$	-10,568	-21,448	-36,074	-6,760	-14,814	-26,955	-4,999	-11,538	-22,014
	$\delta \neq 0$	-10,689	-20,347	-34,512	-6,404	-14,044	-25,667	-4,791	-10,954	-20,883

Notes: VaR estimates rows are displayed in three blocks, one for each stock, of two lines. Each block's first line is for the model without leverage ($\delta = 0$) and the second line for the model with leverage ($\delta \neq 0$). Each of the column holds, first, for each significance level, and second, at this horizon for how many days-ahead was computed the VaR compound returns.

Question 6

In order to calculate the estimated out-of-sample hit rate, a backtesting procedure is applied. The sample is divided into two sub-samples: The estimation window, which starts at $t = 1$ and ends at $t = 2500$, and a testing window, which starts at $t = 2501$ until the end of the sample.

The estimation window is used to fit both robust GARCH models with and without leverage effect. The parameter estimates are used to construct the time-varying filter $\hat{\sigma}_t^2(\hat{\theta}, \hat{\sigma}_1^2)$, which is used to calculate the time-varying filter during the testing window. The parametric VaR forecast is calculated as $\hat{\sigma}_t^2 * T^{-1}(\gamma, \hat{\lambda})$, where T^{-1} is the inverse of the cumulative distribution function of the T-distribution, at point γ with $\hat{\lambda}$ degrees of freedom. The γ corresponds to the VaR levels 1%, 5%, or 10%, and $\hat{\lambda}$ is estimated from the robust GARCH models.

A VaR violation occurs whenever the VaR forecast at time t $\hat{\sigma}_t^2 * T^{-1}(\gamma, \hat{\lambda})$ is larger than the actual return at time t. For a a VaR 5% for instance, we expect this to happen only five percent of the times. We construct a vector of length equal to the testing

Table 4: Backtesting results for VaR forecasting: The first number in each cell corresponds to the estimated out-of-sample hit rate. The second number corresponds to the standard error, and the third is the mis-specification robust (Newey-West) standard error.

	Model	VaR 1%	VaR 5%	VaR 10%
JNJ	$\delta \neq 0$	0.0143	0.0506	0.0948
		(0.0022)	(0.0041)	(0.0055)
		(0.0024)	(0.0048)	(0.0070)
	$\delta = 0$	0.0154	0.0492	0.0919
		(0.0023)	(0.0041)	(0.0054)
		(0.0025)	(0.0048)	(0.0069)
MRK	$\delta \neq 0$	0.0057	0.0330	0.0779
		(0.0014)	(0.0033)	(0.0050)
		(0.0015)	(0.0038)	(0.0061)
	$\delta = 0$	0.0064	0.0330	0.0754
		(0.0015)	(0.0033)	(0.0050)
		(0.0016)	(0.0038)	(0.0061)
PFE	$\delta \neq 0$	0.0053	0.0380	0.0797
		(0.0013)	(0.0036)	(0.0051)
		(0.0014)	(0.0043)	(0.0064)
	$\delta = 0$	0.0064	0.0348	0.0743
		(0.0015)	(0.0034)	(0.0049)
		(0.0016)	(0.0041)	(0.0062)

window, that contains 1's whenever a VaR violation has occurred and 0's otherwise. The sum of the elements of this vector divided by the length of the vector, which results in the estimated hit rate.

The standard errors are calculated as the standard deviation of the 0-1 vector, divided by the square root of the number of observations. This is the definition of the standard error. Since VaR violations tend to be autocorrelated, we also report robust Newey-West standard errors, which are calculated according to the original paper published in Econometrica. For more information you can also consult the Wikipedia page