# Volatility Clustering of Fine Wine Prices assuming Different Distributions

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## Abstract

*This study estimates fine wine market volatility using the generalized autoregressive conditional heteroscedastic (GARCH)and Exponential-GARCH (1, 1) models assuming three different residual distributions, and compare the results to identify a best fit model. This study examines volatility using the daily value of the Liv-ex Fine Wine 50 Index from February 26, 2010 through September 29, 2017. The results suggest that the EGARCH models assuming a student's t distribution or generalized error distribution are better models for the Liv-ex returns than the GARCH models. While the magnitude of the response to innovations may be equal for positive and negative innovations, the volatility associated with positive innovations is greater than negative innovations. Further the EGARCH model suggests the persistence of the volatility is 70 trading days.*

***Keywords:*** GARCH, volatility, fine wine

## 1. Introduction

Given the low interest rate environment following the financial crisis, investors have considered a wide range of investment vehicles to diversify portfolio risk and improve portfolio return. Less conventional investment assets that have gained the attention of investors are fine wines. Historically associated with the wealthy, and refined consumption, the opening of the London International Vintners Exchange (Liv-ex) in 1999 provided the transparency and liquidity needed to expand the investor base of fine wines. The Liv-ex is a global trading and settlement platform that tracks fine wine price developments and publishes several fine wine indices on a daily and monthly basis.

As with other investment instruments, understanding and measuring the volatility of fine wine prices is an important part of managing portfolio risk. Engle (1982)was the first to introduce the autoregressive conditional heteroscedastic (ARCH) model to measure market volatility. The ARCH model estimates the conditional variance of a time series as a simple quadratic function of its lagged values. By relating the current periods price change to past price changes, Engle produced a model that captured the intertemporal patterns found in financial asset returns. A limitation of the ARCH model was that volatility changes do not always occur at predictable time intervals but are stochastic for some markets. To address stochastic volatility changes, Bollerslev (1986) and Taylor (1986) introduced the generalized autoregressive conditional heteroscedastic (GARCH) model which extended the ARCH model by describing the conditional variance of a time series as a function of its own lagged values and the square of the lagged values of innovations and shocks. This allowed estimates to account for the presence of volatility clustering. An advantage of the GARCH model approach is that it typically reduces the number of required ARCH lags when predicting volatility. Later studies including Choudhry (1996) and Alexander and Lazar (2006) estimated price volatility and the persistence of shocks to volatility and found that low average returns induce more speculative activity and increase market volatility. Balaban, Bayar, Farr (2005), Alberg, Shalit, Yosef (2008),Clement and Samuel (2011), and Olbrys (2013) confirmed that stock market and exchange rates are no stationary return series with asymmetric residuals and persistent volatility that often require further GARCH extensions to avoid biased estimates.

This paper contributes to the literature by estimating the volatility in the fine wine market using GARCH (1, 1) and Exponential-GARCH (1, 1) models under three different residual distributions, Gaussian, student's t, and generalized error distribution (GED), and comparing the results to identify a best fit for the Liv-ex 50 fine wine index. This paper estimates the models using daily observations of the Live-ex Fine Wine 50 Index for the period February 26, 2010 through September 29, 2017. The remainder of the paper is organized as follows. Section 2 describes the methodology and data used in this paper. Section 3 describes the empirical results and Section 4 is the conclusion of the paper.

## 2. *Methodology and Data*

### 2.1 Specifications of GARCH Model Extensions

When modeling volatility using the GARCH approach, the first step is to specify the mean equation. Equation 1 is the basic GARCH model specification which assumes a constant only mean equation or zero autocorrelation.[1]The mean equations is:

(1) $r_t = \mu + \varepsilon_t$

where $r_t$ is the logarithm returns of Liv-Ex 50 Index series at time t, μ is the mean value of the returns, and $\varepsilon_t$ is the error term at time t.

The second step is to specify the variance equation to model the presence of volatility. Equation 2 is the general variance equation.

(2) $\varepsilon_t = \sigma_t v_t$ , $v_t \sim$ iid(0,1)

where $\sigma_t$ is a time dependent standard deviation, and $v_t$ is a time dependent stochastic part of the error term at time t. The GARCH and Exponential-GARCH modelsare usedto estimate the time dependent standard deviation in this paper. Equation 2a is the GARCH (1,1) specification which assumes that the error variance follows an autoregressive moving average model. Equation 2b is the Exponential-GARCH (1,1) or the E-GARCH (1,1)specification which relaxes the nonnegative constraints on the paraments allowing for asymmetric function of the lagged disturbances.The extension specifications are:

(2a) GARCH (1,1): $\sigma_t = \eta + \alpha\varepsilon_{t-1}^2 + \beta\ln(\sigma^2{}_{t-1})$

(2b) EGARCH (1,1): $\ln\sigma_t = \eta + \alpha\left(\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}}\right) + \Upsilon\left(\left|\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}}\right| - \sqrt{2/\pi}\right) + \beta\ln(\sigma^2{}_{t-1})$

where $\eta > 0$, $\alpha \geq 0$, and $\beta \geq 0$. The parameter α measures the asymmetric effectsor captures the possibility that positive and negative innovations may impact the market by different magnitudes. The parameter β is the influence of past conditional volatility on the current conditional volatility or reveals the persistency of volatility associated with innovations. The persistence of volatility may also be quantified by calculating the time-period required for innovation impacts to be reduced to one-half the original size. The half-life calculation is

$$\text{Half-life} = \frac{\ln(0.5)}{\ln|\beta|}$$

The sum of the asymmetric effect and persistence should be less than unity ($\alpha + \beta < 1$) to ensure that $\varepsilon_t$ is stationary and the variance is positive. ϒ is the parameter that captures the symmetry effects. Each equation was estimated assuming different distributions – normal (Gaussian) distribution, student's t distribution (t-distribution), and the generalized error distribution (GED). The t-distribution and the GED adjust for a fat-tail, which are often found in financial market data. This suggests that extreme values are more likely than with a normal distribution.

### 2.2 Data

The data used in this paper is the daily value of the Liv-ex Fine Wine 50 Index from February 26, 2010 through September 29, 2017. The Liv-ex Fine Wine 50 Index includes the ten most recent vintages of the Bordeaux First-Growths. It also represents the most heavily traded fine wines on the exchange. Since the index is nonstationary, the logarithm differenced was generated and then the continuously compounded rate of return is calculated. The formula is

[1] Mean equations using a one autoregressive variable, AR(1), and two autoregressive variables, AR(2), were also estimated. The AR(1) and AR(2) variables were insignificant so the results are not included in this paper.

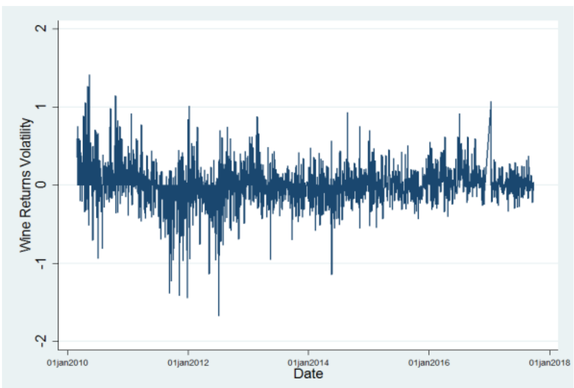
$$r_t = \ln(W_t) - \ln(W_{t-1})$$

where W is the Liv-ex Fine Wine 50 Index value at time t or t-1.

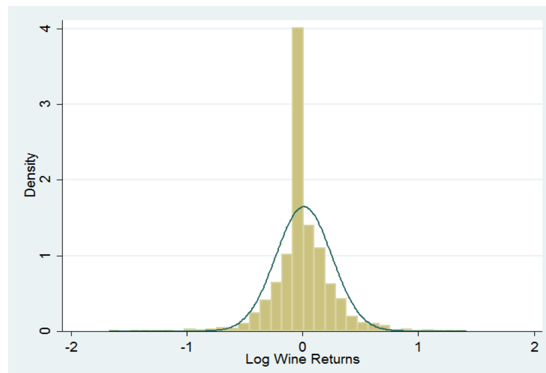
## *3. Empirical Results*

### 3.1 Normal distribution

Two preconditions necessary before using the GARCH modelsare to show that the data are heteroscedastic, where the data tend to experience periods of low volatility and periods of high volatility, or cluster volatility, and the data have an ARCH effect, where the squared residuals exhibit autocorrelation. While studies have shown financial markets exhibit these conditions, it is not obvious that the less conventional Liv-ex 50market meets these conditions since buyers may purchase fine wines for consumption or as investment instruments. A visual examination of the data reveals that data likely meet the two preconditions. The logarithmof Liv-exreturns in Graph 1 reveals clustering volatility, periods of high volatility and periods of low volatility. The logarithmof Liv-ex returns histogram in Graph 2 shows a high peak and fat tails suggesting that the data are not normally distributed.




Graph 1: Logarithm Wine Returns Volatility




Graph2: Logarithm Wine Returns histogram

Table 1 reports the summary statistics and autoregressive conditional heteroscedastic test results. To formally test the two preconditions, Equation 1 is estimated using OLS and the Engle's Lagrange multiplier test for autoregressive conditional heteroscedasticity (ArchLM) is estimated. The ArchLM test for AR(1) has a p-value of .0005 rejecting the null hypothesis of no ARCH(1) effect. A mean of .0001338 and Kurtosis greater than 3supports that the data are heavy-tailed relative to a normal distribution. The negative skewness indicates that the left tail, negative wine returns, is longer which suggests relatively more extreme losses. All tests support a heavy tailed or non-normal distribution. Although the ArchLM, kurtosis, and skewness results reveal that the residual distribution is not a normal distribution, the GARCH and EGARCH models were estimated assuming a Gaussian or normal distribution and reported in Table 2. A comparison of the Log-Likelihood suggests the student's t-distribution and generalized error distribution fit the data better than the Gaussian distribution. Assuming the Gaussian or normal distribution does not capture all elements of the Liv-ex market volatility regardless is the model is GARCH or EGARCH.

**Table 1: Descriptive Statistics for the logarithm wine returns daily**

| Mean | Minimum | Maximum | Std Dev | Kurtosis | Skewness | ArchLM |
|---|---|---|---|---|---|---|
| .0001338 | -.016736 | .017043 | .0027925 | 7.435722 | -.0593486 | 12.290* (.0005) |

Note: * denotes significance at 1 percent level. The test statistic for skewness and excess kurtosis is the conventional t-statistic. The ArchLM test is the $\chi^2$ for the autoregressive conditional heteroscedasticity test with the probability value in parenthesis.

### 3.2 Student's t-distribution and Generalized error distribution

The GARCH and EGARCH models were estimated accounting for the heavy-tailed conditional distributions of the error term $\varepsilon_t$by assuming a t-distribution and a GED.The GARCH model assumes that only the magnitude of unanticipated excess returns determines volatility.

EGARCH model assumes the magnitude and direction of the unanticipated excess returns determine volatility - negative (positive) innovations tend to impact volatility more than positive (negative) innovations. The model results for the two distributions are reported in Table 2and reveal several interesting observations and conclusions.

**Table 2: GARCH (1,1) and EGARCH model results for the logarithm wine returns assuming the Gaussian distribution, student's t distribution, and generalized error distribution (GED)**

| | GARCH (1,1) | | | EGARCH (1,1) | | |
|---|---|---|---|---|---|---|
| | Gaussian | Student's t | GED | Gaussian | Student's t | GED |
| *Conditional mean equation* | | | | | | |
| μ | .0001516* | .0001049** | .000108** | .0001432** | .0001111** | .000111** |
| | (.0000591) | (.000506) | (.0000486) | (.0000638) | (.0000501) | .0000482) |
| *Conditional variance equation* | | | | | | |
| η | 7.70e-08* | 8.23e-08** | 7.92e-08** | -22.67732* | -.1101392* | .1126664*** |
| | (1.83e-08) | (3.44e-08) | (3.25e-08) | (.1176152) | (.0579123) | (.0578585) |
| α | .0518966* | .0535207* | .0514574* | -.071162* | -.0067381 | -.0073259 |
| | (.0062674) | (.0112017) | (.0106036) | (.0059083) | (.0066234) | (.00619) |
| β | .9375229* | .9370205 | .9370914* | .9273185* | .9901715* | .990146* |
| | (.0074338) | (.0123483) | (.0125246) | (.009357) | (.0048952) | (.0048716) |
| ϒ | - | - | - | .0831465* | .1268475* | .1219954* |
| | | | | (.0084608) | (.0229116) | (.0227572) |
| Asymmetry effect | | | | | | |
| Unit test ($\chi^2$) | 11.37* | 2.38 | 4.21** | 13637.63* | 1471.79* | 1514.55* |
| | (.0007) | (0.1226) | (.0403) | (.0000) | (.0000) | (.0000) |
| Half-life | 10.74 | 10.66 | 10.67 | 9.19 | 70.12 | 69.99 |
| Log-Likelihood | 8386.861 | 8467.768 | 8456.639 | 8241.546 | 8467.686 | 8457.11 |
| Shape | - | - | 1.255282 | - | - | 1.259183 |

Note: The asymmetry effect unit test null hypothesis is α + β = 1. The half-life is the time it takes for an innovation to reduce its impact by one-half. A shape value less than 2 indicates that the distribution of the errors has tails that are fatter than they would be when normally distributed. Shape is only reported when assuming GED.

For the GARCH model results, the α coefficient represents the magnitude of asymmetric effects. A positive α coefficient implies that positive innovations are more destabilizing than negative innovations, which in the financial literature is called the leverage effect. With positive and significant α coefficients, the GARCH model results support a leverage effect for Liv-ex returns.The β coefficient reveals that long-term volatility persistence is significant and has a half-life of just under eleven trading days when assuming the GED but insignificant when assuming the t-distribution. The t-distribution results are unexpected and are not supported by the results reported previously. The GED shape value of 1.255282 confirms a heavy tailed distribution.

For the EGARCH model results, once the variance assumption allows for heavy tails, t-distribution or GED, the α coefficient is negative but not significantly different from zero. This implies a negative innovation has a greater impact on volatility than a positive innovation of the same magnitude, although the response is not signification different from zero. The ϒ coefficients indicate that the market responds with much more volatility to unexpected positive return (good news or innovation) than it does to decreases in returns (bad news or innovations). The asymmetric effect unit tests confirm these results. When comparing the relative scales and significance, the asymmetric effect ϒ dominates the leverage effect or magnitude of the innovation. An innovation, positive or negative, leads to the same magnitude effect but positive innovation lead to greater volatility. The β coefficient reveals that long-term volatility persistence is significant and has a half-life of just of approximately 70 trading days, seven times higher than estimated using the GARCH models. Only when assuming a normal distribution does the EGARCH model underestimate the persistence of innovations on Liv-ex returns. Since shape value is less than 2, the distribution of the errors has tails that are fatter than they would be if the errors were normally distributed suggesting the Gaussian distribution not the best assumption.

## 4. Conclusion

This paper examined Liv-ex wine returns from February 26, 2010 through September 30, 2017 using the GARCH and EGARCH models assuming different residual distributions – Gaussian distribution, student’s t-distribution, and generalized error distribution. A comparison of the Log-Likelihood along with other test results concludes the t-distribution and GED fit the data better than the Gaussian distribution for both the GARCH and EGARCH models. A comparison of the results identifies the EGARCH models assuming a student’s t distribution or generalized error distribution are better models for the Liv-ex returns than the GARCH models. While the magnitude of the response to innovations may be equal for positive and negative innovations, the volatility associated with positive innovations is greater than negative innovations. Further the EGARCH model suggests the persistence of the volatility is 70 trading days so including the asymmetric effects is important for evaluating investment returns. Examining the conflicting GARCH and EGARCH leverage effect results offer opportunities for further research.

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