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# A Simple Hypothesis Test for Heteroscedasticity

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**Abstract:** *The scope of this paper is the presentation of a simple hypothesis test that enables to discern heteroscedastic data from homoscedastic i.i.d. gaussian white noise. The main feature will be a test statistic that's easy applicable and serves well in committing such a test. The power of the statistic will be underlined by examples where it is applied to stock market data and time series from deterministic diffusion a chaotic time series process. It will turn out that in those cases the statistic rejects with a high degree of confidence the random walk hypothesis and is therefore highly reliable. Furthermore it will be discussed, that the test in most cases also may serve as a test for independence and heteroscedasticity in general. This will be exemplified by independent and equally distributed random numbers.*

## 1. Introduction

The history of this paper is basically, that it was originally part of [1] and was used to show that DAX and Model time series obey similar degrees of heteroscedasticity. However for the sake of economy it was left out of [1] since heteroscedasticity could also be easily demonstrated graphically. Nevertheless the used test procedure still has got a charm with respect to its simplicity and should therefore be presented in the following. It also contributes another measure in addition to the approaches shown in [2] and can be used complementary.

## 2. Heteroscedasticity

Heteroscedasticity is a common feature observed in certain time series e.g. financial time series like interest rates or stock returns. It happens to occur when a lot of large changes follow abruptly a series of moderate changes.

### Definition 4.2.1 (Heteroscedasticity)

Define the m-sample variance estimator at sample point k of a sample of N realizations of a variable  $x_1, x_2, \dots, x_N$  as:

$$\hat{\sigma}_{m,k}^2 = \frac{1}{m-1} \sum_{i=k}^{m+k} (x_i - \hat{\mu}_{m,k})^2$$

$$\text{where } \hat{\mu}_{m,k} = \frac{1}{m} \sum_{i=k}^{m+k} x_i$$

with  $1 < k < N$  and  $n+k < N \forall k$

is defined as the m-sample mean estimator at sample point k. And define the sample variance estimator by:

$$\hat{\sigma}_N^2 = \frac{1}{N-1} \sum_{i=1}^N (x_i - \hat{\mu}_N)^2$$

$$\text{where } \hat{\mu}_N = \frac{1}{N} \sum_{i=1}^N x_i$$

is defined as the sample mean estimator. In this context heteroscedasticity means that for N samples there exists significant many values k so that the m-sample estimators of non overlapping sample buckets differ significantly from the sample variance.

To have a clear discern between homoscedasticity and heteroscedasticity of course one needs a hypothesis test. By generating a test statistic, it can be defined what it means that there exist significantly many sample estimators that are distinct from the sample variance.

## 3. The Test Statistic

The hypothesis of heteroscedasticity will be tested against the Null Hypothesis of a homoscedastic Gaussian random process. To test for heteroscedasticity in time bucket  $\tau$  the following test statistic is suggested:

$$T(m, \alpha) = \frac{m \sum_{k=1}^{\text{int}(N/m)} I_{k,m}(\alpha)}{N}$$

Where  $I_k$  is an indicator function for the non overlapping buckets  $k = 1, 2, 3, \dots, N/m$  indicating:

$$I_{k,m}(\alpha) \left\{ \begin{array}{l} =1 \quad \text{if } \frac{\hat{\sigma}_{k,m}^2}{\hat{\sigma}_N^2} < \frac{1}{m-1} X_{\alpha/2}(m) \\ \text{or if } \frac{\hat{\sigma}_{k,m}^2}{\hat{\sigma}_N^2} > \frac{1}{m-1} X_{1-\alpha/2}(m) \\ =0 \quad \text{if } \frac{1}{m-1} X_{\alpha/2}(m) \\ < \frac{\hat{\sigma}_{k,m}^2}{\hat{\sigma}_N^2} < \frac{1}{m-1} X_{1-\alpha/2}(m) \end{array} \right.$$

Where  $X_\alpha(m)$  is the  $\alpha$ -Quantile of the  $\chi^2$  distribution with  $m$  degrees of freedom.

The test is motivated by the fact that one can show under the assumption of a homoscedastic random process that:

$$\frac{\hat{\sigma}_{k,m}^2}{\hat{\sigma}_N^2} \cong \frac{1}{1-m} \chi^2(m)$$

where  $\cong$  means is distributed as. I.e. under the assumption of a homoscedasticity gaussian random process the ratio of the sample variance and a  $m$ -sample variance should behave like a  $\chi^2$  distributed random variable with  $m$  degrees of freedom multiplied by  $1/(m-1)$ .

Thus the Indicator function always indicates on the test level  $\alpha$  if the  $m$ -sample variance differs significantly from its expected value at either the upside or the downside that should be measured best by the sample variance. Finally we conclude that:

$$T \cong \frac{1}{n} B(n, p) : n = \text{int}(N/m), p = \alpha$$

I.e.  $T$  follows a binominal distribution multiplied by  $1/n$  with parameters  $n=\text{int}(N/m)$ , which is the number of time buckets yielded by the choice of time bucket length  $m$ , and  $\alpha$  is the chosen test level. To commit a statistical test regarding  $T$ , one has to check whether the observed quantity of as significant indicated variance changes exceeds a certain  $1-\beta$ -quantile of the binominal distribution multiplied by  $1/N$  or not:

$$T > \frac{1}{n} B_{\beta-1}(\text{int}(N/m), \alpha) \text{ reject null}$$

$$T < \frac{1}{n} B_{\beta-1}(\text{int}(N/m), \alpha) \text{ not reject null}$$

The value  $\beta$  will then be the level of confidence of the test.

## 4. Examples

Table 1 and 2 show the results of the test statistic  $T$  for the DAX and Model time series of [1]. Test parameters chosen where  $\alpha=\beta=0.01$ . The null hypothesis of a homoscedastic i.i.d Gaussian random process is rejected for every time bucket significantly at a confidence level of one percent.

TimeBuckets	Lower-T	Upper-T	Sum-T	P-Value	Reject
50	10,00%	75,00%	85,00%	2,50%	TRUE
60	15,15%	75,76%	90,91%	3,03%	TRUE
70	14,29%	82,14%	96,43%	3,57%	TRUE
80	12,00%	72,00%	84,00%	4,00%	TRUE
90	18,18%	72,73%	90,91%	4,55%	TRUE
100	15,00%	80,00%	95,00%	5,00%	TRUE
110	16,67%	77,78%	94,44%	5,56%	TRUE
120	25,00%	75,00%	100,00%	6,25%	TRUE
130	20,00%	73,33%	93,33%	6,67%	TRUE
140	21,43%	78,57%	100,00%	7,14%	TRUE
150	23,08%	69,23%	92,31%	7,69%	TRUE
160	16,67%	66,67%	83,33%	8,33%	TRUE
170	18,18%	63,64%	81,82%	9,09%	TRUE
180	27,27%	63,64%	90,91%	9,09%	TRUE
190	20,00%	70,00%	90,00%	10,00%	TRUE
200	20,00%	70,00%	90,00%	10,00%	TRUE
220	22,22%	66,67%	88,89%	11,11%	TRUE
250	25,00%	62,50%	87,50%	12,50%	TRUE

Table 1

TimeBuckets	Lower-T	Upper-T	Sum-T	P-Value	Reject
50	17,31%	48,08%	65,38%	1,92%	TRUE
60	16,28%	44,19%	60,47%	2,33%	TRUE
70	18,92%	45,95%	64,86%	2,70%	TRUE
80	18,75%	50,00%	68,75%	3,13%	TRUE
90	21,43%	46,43%	67,86%	3,57%	TRUE
100	23,08%	50,00%	73,08%	3,85%	TRUE
110	17,39%	47,83%	65,22%	4,35%	TRUE
120	23,81%	47,62%	71,43%	4,76%	TRUE
130	25,00%	55,00%	80,00%	5,00%	TRUE
140	22,22%	50,00%	72,22%	5,56%	TRUE
150	23,53%	47,06%	70,59%	5,88%	TRUE
160	25,00%	50,00%	75,00%	6,25%	TRUE
170	26,67%	53,33%	80,00%	6,67%	TRUE
180	28,57%	50,00%	78,57%	7,14%	TRUE
190	15,38%	38,46%	53,85%	7,69%	TRUE
200	30,77%	46,15%	76,92%	7,69%	TRUE
220	27,27%	45,45%	72,73%	9,09%	TRUE
250	30,00%	50,00%	80,00%	10,00%	TRUE

Table 2

**Table 1, 2 Results for model time series of the test statistic  $T$  for various time buckets by observing  $N=2000$  sample date points for the model time series and DAX time series respectively. Upper-T, Lower-T percentage of samples for which the  $m$ -sample bucket variance differs significantly from its expected value indicated by  $I$  at either the upside or the downside respectively. Sum-T total percentage of  $m$ -sample bucket variance being significantly different from its expected value. P-Value is the  $1-\beta$  Quantil of the Binomial Distribution  $B(n,p)$  Multiplied by  $1/N$  with  $\beta = 0,01$**

From the proof of general limit theorem in [3], one could conjecture, that the intermediate distribution of squares of i.i.d. random variables is a  $\chi^2$  distributed random variable until also these sums of i.i.d. random variables converge to a normal distribution.

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[3] Heinz Bauer: Wahrscheinlichkeitstheorie und Grundzüge der Maßtheorie. 4. Auflage. DeGruyter, Berlin 1991

Therefore the test should also serve as a test for independence and a homoscedasticity in general. Finally table 3 shows the test results independent and equally on the interval [0,1] distributed random numbers. Please note that the test statistic only rejects the homoscedasticity and independence hypothesis for the smallest time bucket.

TimeBuckets	UpperP	LowerP	LowerP+UpperP	P-Value	Reject
20	0,00%	4,00%	4,00%	1,00%	TRUE
30	0,00%	0,00%	0,00%	1,52%	FALSE
40	0,00%	0,00%	0,00%	2,00%	FALSE
50	0,00%	0,00%	0,00%	2,50%	FALSE
60	0,00%	0,00%	0,00%	3,03%	FALSE
70	0,00%	0,00%	0,00%	3,57%	FALSE
80	0,00%	0,00%	0,00%	4,00%	FALSE
90	0,00%	0,00%	0,00%	4,55%	FALSE
100	0,00%	0,00%	0,00%	5,00%	FALSE
110	0,00%	0,00%	0,00%	5,56%	FALSE
120	0,00%	0,00%	0,00%	6,25%	FALSE
130	0,00%	0,00%	0,00%	6,67%	FALSE
140	0,00%	0,00%	0,00%	7,14%	FALSE
150	0,00%	0,00%	0,00%	7,69%	FALSE
160	0,00%	0,00%	0,00%	8,33%	FALSE
170	0,00%	0,00%	0,00%	9,09%	FALSE
180	0,00%	0,00%	0,00%	9,09%	FALSE
190	0,00%	0,00%	0,00%	10,00%	FALSE
200	0,00%	0,00%	0,00%	10,00%	FALSE
210	0,00%	0,00%	0,00%	11,11%	FALSE
220	0,00%	0,00%	0,00%	11,11%	FALSE
230	0,00%	0,00%	0,00%	12,50%	FALSE
240	0,00%	0,00%	0,00%	12,50%	FALSE
250	0,00%	0,00%	0,00%	12,50%	FALSE

**Table 1, 2 Results for model time series of the test statistic T for various time buckets by observing N=2000 sample date points of an i.i.d random variable equally distributed on the interval [0,1].**

## 5. Summary and Conclusions

The presented method is straight forward and shows, when applied, significant results indicating its power. It can be used in addition to the methods of [2] but should also work stand alone. Furthermore the test seems to have power in general to verify homoscedasticity and independence at the same time.

## 6 References

[1] Guido Venier “A New Model for Stock Price Movements” JAES “Journal of Applied Economic Sciences” <http://www.jaes.uv.ro>. Volume III Issue2(4) Fall2008

[2] Andrew W. Lo & A. Craig MacKinlay (1987) “Stock Market Prices do not follow Random Walks: evidence from a simple specification Test” Department of Finance,