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# Testing of Heteroscedastic Economic Model using Kernel Bootstrap Estimators: A Panel Data Perspective from Pakistan

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## Abstract

*This study focuses on testing of the heteroscedastic panel economic model through kernel bootstrap estimators developed by (Saeed and Aslam, 2016) for improved inferences. The heteroscedasticity consistent covariance matrix estimators have also been used for inference of the panel model. For the present article, the data from Pakistan Stock Exchange include micro and macroeconomic variables related to the stock prices of sugar and allied mills from 2010 to 2014.*

**Keywords:** Bootstrap; Heteroscedasticity; Heteroscedastic consistent covariance matrix estimator; Kernel estimator; Panel data.

## Introduction

Stock market plays a pivotal role in the economic growth of a country. For economic growth, the financial sector is stabilized by an efficient capital market. Micro and macroeconomic variables excessively influence the stock market. The change in these variables can significantly impact stock price return. According to the available information, stock prices regulate swiftly, reflect all evidence about the stocks. The expected future performance of corporate houses is revealed by stock prices (Çiftçi, 2014).

In the available literature (see (Mehar *et al.*, 2018), for example), it is observed that the study of impacts of micro and macroeconomic variables on the stock market is of a great importance for the researchers. Many factors are responsible for change in the stock indices. In the recent decades, researchers have applied numerous models in to determine the relationship between the stock prices and macro-economic variables.

Since the last decades, the panel data model (PDM) has become popular for the analysis of economic model due to its potential advantages over cross-sectional and time-series data. Two types of modelling approaches are used for PDM: the fixed effect model (FEM) approach and random effect model (REM) approach.

When analyzing a PDM, it is very common that a PDM is exposed of some group-wise heteroscedasticity. In such situation, the usual ordinary least squares (OLS) estimates may provide misleading inferences, depending upon severity of the heteroscedasticity. To improve the inference, there are many approaches available in the literature. (Saeed and Aslam, 2016) proposed few kernel bootstrap estimators (KBEs) in order to obtain adequate inference of the PDM with the issue of group-wise heteroscedasticity. The present article focuses on the estimation of PDM under FEM approach for the data, collected from Pakistan Stock Exchange (PSE), based on micro and macroeconomic variables. The detail

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about the data is available in a section ahead. (Shah and Khan, 2007, Mohsin and Rivers, 2010) also used similar PDM for their studies. However, these studied were not aimed for the inferential part of the analysis. Therefore, for testing and improvement in testing, KBEs (proposed by (Saeed and Aslam, 2016), were applied.

This article unfolds as follows: Review of literature is presented in Section II. The data and methodology used in the study are given in Section III. Section IV presents the results. Finally, Section V concludes the stated work.

## Review of literature

In the literature, the study of dynamic relationship of micro and macroeconomic variables with stock prices is of great importance for the researchers (see, for example, (Afzal and Hossain, 2011, Ali, 2011, Khan, 2014)). The study of such relationship is also significant for policy formulation and implications. Therefore, it is necessary to draw robust inference for the impact of micro and macro-economic variables on stock exchange indices.

Many researchers used different models to find out the relationship between stock market and macroeconomic variables. (Nazir *et al.*, 2010) found the determinants of stock-price volatility in Karachi stock exchange (KSE) and reported that dividend policy had a strong significant relationship with the stock-price volatility in the KSE. (Afzal and Hossain, 2011) studied relationship of the macroeconomic variables and Bangladesh stock prices and found that co-integration existed between stock prices with inflation rate and two money supply variables namely, M1 and M2.

It is observed, in the available literature, that the panel dataset is widely used for the study of economic problem due to its advantages over cross-sectional and times-series data. (Shah and Khan, 2007) studied the Pakistani panel data and considered the FEM. (Mohsin and Rivers, 2010) used the panel data of South Asian countries. (Ahmad *et al.*, 2012) considered the panel dataset and studied the determinants of profitability of Pakistani banks. They used the REM and found that cost-to-income ratio, ratio of share capital and loan loss reserves to gross loans ratio were statistically significant as independent variables. (Kilic, 2015) considered the PDM to study the effects of globalization on economic growth for developing countries. It was reported that levels of economic growth for the developing countries were positively affected by the economic and political globalization whereas social globalization negatively affected the economic growth. (Rehman and Ahmad, 2016), using the panel dataset, carried out a study to assess the impact of foreign capital inflows on economic growth for the developing countries. The objective of this study was to draw correct inference about the impact of micro and macro-economic variables on the stock prices.

## Data and methodology

### Fixed effect model

In the available literature, some traditional techniques like the OLS, within group (WG), and generalized least square (GLS) have been employed to analyze the impact of micro and macro-economic variables on the stock prices. Homoscedasticity is a usual assumption for application of the method of OLS, stating constancy of the variance of the error term. The OLS estimator (OLSE) remains no more a good choice if this assumption is not met. This is a mark of heteroscedasticity. In the presence of heteroscedasticity, the OLSE is not biased and inconsistent but does not remain efficient and it also leads to incorrect inference about the population parameter.

Following (Saeed and Aslam, 2016), consider the linear FEM,

$$y_{it} = x_{it}\beta + \mu_i + v_{it}, i = 1,2,\ldots,n; t = 1,2,\ldots,T, \tag{1}$$

where $\mu_i$ is the unit-specific heteroscedastic error term. Model (1) can be presented in the form of matrices, stacking the data over individual $i$ and time dimension $T$ can be shown as under:

$$y = \mu \otimes e_T + X\beta + v, \tag{2}$$

where $y = (y_1, \ldots, y_n)'$, $X = (X_1, \ldots, X_n)'$ and $v = (v_1, \ldots, v_n)'$. Here, $e_T$ is a $(T \times 1)$ vector of ones, the individual (unobserved) heterogeneity is captured by $\mu = (\mu_1, \ldots, \mu_n)'$ and $\otimes$ is the Kronecker product. Moreover, $y$ is an $nT \times 1$ response vector, $X$ is $nT \times q$ ($q < nT$) implicitly fixed regressors, $\beta$ is a $(q \times 1)$ vector of unknown parameters and $v$ is an $(nT \times 1)$ vector of error terms. For more details, see (Uchôa *et al.*, 2014). Additionally, we have some assumptions about the error term that $E(v_{it}) = 0$, $\mathrm{Var}(v_{it}) = \sigma_v^2$.

The estimation of the model, given in Eq. (2) can be obtained by using the WG estimator (WGE). It can be done by pre-multiplying Eq. (2) with the following matrix

$$M = I_{nT} - P,$$

where $P = Q(Q'Q)^{-1}Q$, $Q = I_n \otimes \bar{e}_T$ is an $(nT \times n)$ matrix of $n$ dummy variables associated with each of the cross-sectional unit, $I_{nT}$ and $I_n$ are the identity matrices of order $nT$ and $n$, respectively. $\bar{e}_T = T^{-1} \times e_T$ is a vector of one's index $T$ (for details; see (Greene, 2003)). Model (2) becomes

$$\tilde{y} = \tilde{X}\tilde{\beta} + \tilde{v}, \tag{3}$$

where $\tilde{X} = MX$, $\tilde{y} = My$ and $\tilde{v} = Mv$, the adequate estimator for Eq. (3) is the OLSE. The unbiased estimator of $\beta$ is

$$\hat{\tilde{\beta}} = \left(\tilde{X}'\tilde{X}\right)^{-1}\tilde{X}'\tilde{y}.$$

The variance of estimator is

$$\mathrm{Var}(\hat{\tilde{\beta}}) = \hat{\tilde{\sigma}}^2\left(\tilde{X}'\tilde{X}\right)^{-1}, \tag{4}$$

where $\hat{\tilde{\sigma}}^2 = \frac{\hat{\tilde{v}}'\hat{\tilde{v}}}{n(T-1)-tr(\tilde{H})}$, $\hat{\tilde{v}} = \tilde{y} - \tilde{X}\hat{\tilde{\beta}}$ and the hat matrix can be defined as $\tilde{H} = \tilde{X}\left(\tilde{X}'\tilde{X}\right)^{-1}\tilde{X}'$.

## THE HCCMEs

The covariance matrix of $\hat{\tilde{\beta}}$ can be defined as under:

$$\tilde{\varphi} = \left(\tilde{X}'\tilde{X}\right)^{-1}\tilde{X}'\tilde{\Omega}\tilde{X}\left(\tilde{X}'\tilde{X}\right)^{-1} = D\tilde{\Omega}D' \tag{5}$$

where $D = \left(\tilde{X}'\tilde{X}\right)^{-1}\tilde{X}$. Arellano (1987) improved the White estimator (1980) for the FEM which can be defined as

$$HC0 = \left(\tilde{X}'\tilde{X}\right)^{-1}\tilde{X}'\hat{\tilde{\Omega}}_0\tilde{X}\left(\tilde{X}'\tilde{X}\right)^{-1} = D\hat{\tilde{\Omega}}_0D' = \hat{\tilde{\varphi}}_0,$$

where $\hat{\tilde{\Omega}}_0 = diag\left\{\hat{\tilde{v}}_1^2, \hat{\tilde{v}}_2^2, \dots, \hat{\tilde{v}}_n^2\right\}$.

For the FEM, the HC3 can be found by replacement of $\ddot{\tilde{\Omega}}_0$ with following diagonal elements in Eq. (5):

$$\hat{\tilde{\Omega}}_3 = diag\left\{\frac{\hat{\tilde{v}}_1^2}{(1-\tilde{h}_1)^2}, \frac{\hat{\tilde{v}}_2^2}{(1-\tilde{h}_2)^2}, \dots, \frac{\hat{\tilde{v}}_n^2}{(1-\tilde{h}_n)^2}\right\},$$

where $\tilde{h}_i$ is the *i*th diagonal element of $\tilde{H}$.

Uchôa et al. (2014) used the HC4 for the FEM with high leverage points. For this estimator,

$$\hat{\tilde{\Omega}}_4 = diag\left\{\frac{\hat{\tilde{v}}_1^2}{(1-\tilde{h}_1)^{\pi_1}}, \frac{\hat{\tilde{v}}_2^2}{(1-\tilde{h}_2)^{\pi_2}}, \dots, \frac{\hat{\tilde{v}}_n^2}{(1-\tilde{h}_n)^{\pi_n}}\right\},$$

where $\pi_i = \min\left\{4, \frac{\tilde{h}_{i11}}{\tilde{h}_{i1}}\right\}, \dots, \min\left\{4, \frac{\tilde{h}_{inT}}{\tilde{h}_{nT}}\right\}$. Since $0 < \tilde{h}_i < 1$ and $\pi_i > 0$, therefore, $0 < \left(1 - \tilde{h}_i\right)^{\pi_i} < 1$.

(Saeed and Aslam, 2016) improved HC5, proposed by (Cribari-Neto *et al.*, 2007) for non-panel data, for the FEM. Its diagonal elements are

$$\hat{\tilde{\Omega}}_5 = diag\left\{\frac{\hat{\tilde{v}}_1^2}{(1-\tilde{h}_1)^{\delta_1}}, \frac{\hat{\tilde{v}}_2^2}{(1-\tilde{h}_2)^{\delta_2}}, \dots, \frac{\hat{\tilde{v}}_n^2}{(1-\tilde{h}_n)^{\delta_n}}\right\},$$

where

$$\delta_i = \min\left[\left(\left\{\frac{\tilde{h}_{i11}}{\tilde{h}_{i1}}\right\}, \dots, \left\{\frac{\tilde{h}_{inT}}{\tilde{h}_{nT}}\right\}\right), \max\left(\left\{4, \frac{c\tilde{h}_{max}}{\tilde{h}_{i1}}\{\}\left\{4, \frac{c\tilde{h}_{max}}{\tilde{h}_{nT}}\{\}\right\}\right\}\right), 0 < c < 1\right]$$

The condition implicates that $\delta_i$>0 and 0<$\tilde{h}_i$< 1, it leads that $0 < \left(1 - \tilde{h}_i\right)^{\delta_i} < 1$.

Thus, the general form of the HCCME is

$$HCr: \hat{\tilde{\varphi}}_r = D\ddot{\tilde{\Omega}}_r D,$$

where $r = 0,3,\dots,5$, $r$ = 0 indicates HC0, $r$ = 3 is for HC3 and so on.

## KERNEL BOOTSTRAP ESTIMATORS

(Mujaddad and Ahmad, 2016) used the data development analysis double bootstrap technique to measure the efficiency of manufacturing industries in Pakistan. (Saeed and Aslam, 2016) developed the kernel bootstrap estimators for the PDM. They have improved the residual bootstrap kernel (RBK) and wild bootstrap kernel (WBK) estimators and showed that the kernel bootstrap estimators performed well in the presence of unknown heteroscedasticity.

## THE RB ESTIMATOR (RBE)

The scheme for bootstrap of the residual resampling is as follows:

1. Create a pseudo-sample of residuals$v$ by resampling of the residuals $\hat{\tilde{v}}$.
2. Construct a bootstrap sample ($y_{RB}$,$\tilde{X}$), as$y_{RB} = \tilde{X}\hat{\tilde{\beta}} + v$,
   where $\hat{\tilde{\beta}}$ and $v$ are the WG coefficients and residuals, respectively.
3. Estimate$\hat{\beta}_{RB} = (X'MX)^{-1}X'My_{RB}$.
4. Compute$\hat{\tau}_{RB} = \frac{(\hat{\beta}_{RB} - \hat{\tilde{\beta}})}{\sqrt{\mathrm{Var}(\hat{\beta}_{RB})}}$.
5. Repeat Steps 1 to 4 for large number of (say, $B$) times.

## THE WB ESTIMATOR (WBE)

It has been proposed by (Liu, 1988), following the work of (Wu, 1986) and (Beran, 1987). Its scheme is as under:

1. For each $f, f = 1,2, \ldots, n$,draw a random number$R_f$ from a population that has zero mean and unit variance.
2. Construct a bootstrap sample ( $y_{WB}, \tilde{X}$ ), as

$$y_{WB} = \tilde{X}\hat{\hat{\beta}} + \frac{\hat{\hat{v}}}{1-\tilde{h}_i} R_f, \tag{7}$$

where $\tilde{h}_i$ is the $i$th diagonal element of hat matrix, $\hat{\hat{\beta}}$ and $\hat{\hat{v}}$are the WG coefficient and residuals, respectively.

Steps 3 to 5 are similar to the scheme of RB ($t$). The weight in Eq. (7) is based on the HC3.

## THE RBK ESTIMATOR (RBKE)

The RBKE can be defined as

$$\hat{P}_{RBK} = 1 - \hat{F}_d(\hat{\tau}) = 1 - \frac{1}{B}\sum_{j=1}^{B} K\left(\hat{\tau}_{j(RB)}, \hat{\hat{t}}, d\right),$$

where $\hat{F}_d(\hat{\tau}) = \frac{1}{B}\sum_{j=1}^{B} K\left(\hat{\tau}_{j(RB)}, \hat{\hat{t}}, d\right), j = 1, \ldots, B$, $\hat{F}_d(\hat{\tau})$ is the cumulative distribution function (CDF), $d$ is the bandwidth, $\hat{\hat{t}}$ is the $t$ test statistic for the WGE and$\hat{\tau}_{RB}$ is the quasi-$t$ test statistic acquired from the RBE.

## THE WBK ESTIMATOR (WBKE)

The WBKE can be defined as

$$\hat{P}_{WBK} = 1 - \hat{F}_w(\hat{\tau}) = 1 - \frac{1}{B}\sum_{j=1}^{B} K\left(\hat{\tau}_{j(WB)}, \hat{\hat{t}}, w\right),$$

where $\hat{F}_w(\hat{\tau}) = \frac{1}{B}\sum_{j=1}^{B} K\left(\hat{\tau}_{j(WB)}, \hat{\hat{t}}, w\right)$,$\hat{F}_w(\hat{\tau})$ is the CDF, $w$ is the bandwidth and $\hat{\tau}_{WB}$ is the quasi-$t$ test statistic obtained from the WBE. Our interest is to test the heteroscedastic micro and macroeconomic model of Pakistan using the kernel bootstrap estimators. Gretl 1.9.91 is used for the analysis.

## The data

The sugar industry in Pakistan is considered to be the second largest agro-based industry in Pakistan (Raheman *et al.*, 2009). The data set, collected from Pakistan Stock Exchange (PSE), is based on micro and macroeconomic variables. It includes 35 sugar and allied mills, observed from 2010 to 2014. Microeconomic variables include leverage, firm size, earning per share (EPS) as explanatory variables while macroeconomic variables are inflation, gross domestic product (GDP) and oil prices. The stock prices are used as dependent variable.

Let the model of interest is

$$y_{it} = \beta_0 + \beta_1 x_{1it} + \beta_2 x_{2it} + \beta_3 x_{3it} + \beta_4 x_{4it} + \beta_5 x_{5it} + \beta_6 x_{6it} + u_{it}, \tag{8}$$

where$i = 1,2, \ldots, 35; t = 1,2, \ldots, 5$,$y_{it}$ denotes stock prices, $x_{1it}$ is leverage,$x_{2it}$ is firm size, $x_{3it}$ is EPS, $x_{4it}$ is the inflation, $x_{5it}$ is the GDP, $x_{6it}$are the oil prices and $u_{it}$ is the random error term.

## Results

The OLS was applied to the stated data in order to carry out the Wald test to detect group-wise heteroscedasticity (for details, see (Greene, 2003). The group-wise heteroscedasticity was observed (with Wald statistic=70724.6, *p*-

value<0.01). Then the Hausman test (for details: see (Greene, 2003) was applied. The Hausman test (with Hausman statistic = 15.53, *p*-value<0.01) suggested to use the FEM for the given dataset.

Following estimators are used

a. The WGE
b. The HCCMEs
c. The Bootstrap estimators (RB, WB)
d. The Kernel estimators (RBK, WBK)

Table 1 shows comparative statistics for all the estimators mentioned above. The estimates, standard error (s.e), *t*-statistic and *p*-values for the given estimators are reported here.

It should be noted that all the estimators other than the WG, do not deal with estimation but improve testing only, therefore, no coefficient estimates have been given for them. The HCCMEs provide adequate standard errors, the RB and WB improve t-statistics and the RBK and WBK improves p-values only.

The WG estimation shows that firm size affects negatively, and the oil prices affect positively the stock prices. However, all the remaining variables do not play any significant role in the prediction of the stock prices. The WGE produces larger standard errors than the HCCMEs do except for the estimated coefficient of firm size. All the HCCMEs yield non-significant *p*-values for all the stated regressors except for the oil prices at 5% nominal LOS.

The RBE shows that all the stated explanatory variables contribute significantly except the leverage to predict the stock prices. The leverage and inflation do not play a significant role to predict stock price if the WBE is used. The use of WBKE considers all the regressors to be statistically significant except EPS. There is only one estimator, RBKE that provide statistically significant contribution for all the stated regressors to predict the stock price. Since (Saeed and Aslam, 2016) have already provided the adequacy of the WBKE, thus, these results are acceptable. Finally, the estimated Model (8) can be given as follows:

$$\hat{y}_{it} = 6.599 - 0.069x_{1it} - 0.137x_{2it} + 0.139x_{3it} + 0.319x_{4it} - 0.103x_{5it} + 0.540x_{6it}.$$

Or

$$(\widehat{Stock\ Prices})_{it} = 6.599 - 0.069(Leverage)_{it} - 0.137(Firm\ Size)_{it} + 0.139(EPS)_{it} + 0.319(Inflation)_{it} - 103(GDP)_{it} + 0.540(Oil\ Prices)_{it}.$$

## Conclusion

This study has focused on testing of the heteroscedastic economic model of Pakistan. A panel data-set has been obtained from the Pakistan Stock Exchange. It includes 35 sugar and allied mills, studied from 2010 to 2014. The kernel bootstrap technique, proposed by (Saeed and Aslam, 2016), has been used. The Wald test shows that PDM is exposed by group-wise heteroscedasticity. The Hausman test indicates that the FEM is a suitable model for the given data-set.

Following (Saeed and Aslam, 2016), when the PDM coefficients are tested, it is concluded that the leverage, firm size, EPS, inflation, GDP and oil prices play statistically significant role to predict stock prices of the sugar and allied mills, registered with the Stock Exchange of Pakistan.

**Table 1:** Comparative Statistic

| | WG | HC0 | HC3 | HC4 | HC5 | RB | RBK | WB | WBK |
|---|---|---|---|---|---|---|---|---|---|
| $\hat{\beta}_0$ | 6.599 | - | - | - | - | - | - | - | - |
| $\hat{\beta}_1$ | -0.069 | - | - | - | - | - | - | - | - |
| $\hat{\beta}_2$ | -0.137 | - | - | - | - | - | - | - | - |
| $\hat{\beta}_3$ | 0.139 | - | - | - | - | - | - | - | - |
| $\hat{\beta}_4$ | 0.319 | - | - | - | - | - | - | - | - |
| $\hat{\beta}_5$ | -0.103 | - | - | - | - | - | - | - | - |
| $\hat{\beta}_6$ | 0.540 | - | - | - | - | - | - | - | - |
| $se(\hat{\beta}_0)$ | 17.465 | 0.874 | 0.940 | 0.958 | 0.958 | - | - | - | - |
| $se(\hat{\beta}_1)$ | 0.154 | 0.075 | 0.084 | 0.088 | 0.088 | - | - | - | - |
| $se(\hat{\beta}_2)$ | 0.069 | 0.164 | 0.185 | 0.195 | 0.195 | - | - | - | - |
| $se(\hat{\beta}_3)$ | 0.141 | 0.095 | 0.103 | 0.105 | 0.105 | - | - | - | - |
| $se(\hat{\beta}_4)$ | 0.756 | 0.522 | 0.547 | 0.546 | 0.546 | - | - | - | - |
| $se(\hat{\beta}_5)$ | 0.147 | 0.094 | 0.098 | 0.097 | 0.097 | - | - | - | - |
| $se(\hat{\beta}_6)$ | 0.308 | 0.232 | 0.250 | 0.254 | 0.254 | - | - | - | - |
| $t(\hat{\beta}_0)$ | 0.378 | 7.555 | 7.019 | 6.888 | 6.888 | 3.732 | - | 0.796 | - |
| $t(\hat{\beta}_1)$ | -0.454 | -0.931 | -0.834 | -0.793 | -0.793 | -1.131 | - | -1.515 | - |
| $t(\hat{\beta}_2)$ | -1.957 | -0.832 | -0.738 | -0.699 | -0.699 | -6.651 | - | -3.136 | - |
| $t(\hat{\beta}_3)$ | 0.985 | 1.467 | 1.351 | 1.325 | 1.325 | 2.534 | - | 1.466 | - |
| $t(\hat{\beta}_4)$ | 0.421 | 0.609 | 0.582 | 0.584 | 0.584 | 2.170 | - | 1.473 | - |
| $t(\hat{\beta}_5)$ | -0.699 | -1.098 | -1.048 | -1.054 | -1.054 | -5.469 | - | -1.023 | - |
| $t(\hat{\beta}_6)$ | 1.756 | 2.325 | 2.159 | 2.121 | 2.121 | 8.615 | - | 2.931 | - |
| $p(\hat{\beta}_0)$ | 0.706 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.426 | 0.025 |
| $p(\hat{\beta}_1)$ | 0.649 | 0.352 | 0.404 | 0.428 | 0.428 | 0.258 | 0.003 | 0.129 | 0.000 |
| $p(\hat{\beta}_2)$ | 0.050 | 0.405 | 0.461 | 0.484 | 0.484 | 0.000 | 0.000 | 0.000 | 0.000 |
| $p(\hat{\beta}_3)$ | 0.325 | 0.142 | 0.177 | 0.185 | 0.185 | 0.011 | 0.003 | 0.144 | 0.252 |
| $p(\hat{\beta}_4)$ | 0.673 | 0.542 | 0.560 | 0.559 | 0.559 | 0.030 | 0.001 | 0.142 | 0.044 |
| $p(\hat{\beta}_5)$ | 0.484 | 0.272 | 0.295 | 0.291 | 0.291 | 0.000 | 0.000 | 0.306 | 0.001 |
| $p(\hat{\beta}_6)$ | 0.079 | 0.020 | 0.031 | 0.034 | 0.033 | 0.000 | 0.000 | 0.003 | 0.025 |

Source: Author's calculations

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