RESEARCH REVIEW JOURNALS
Volume-04
Issue-04
April-2019

ISSN: 2455-3085 (Online)
RESEARCH REVIEW International Journal of Multidisciplinary
www.rrjournals.com[UGC Listed Journal]

An application of Multivariate Models on GSRTC Data

[1]Bhavika D. Shah and [2]Pravender

[1]Research Scholar, Department of Statistics, Gujarat University, Ahmedabad - 380009 (India)
[2]Research Guide, Department of Statistics, Gujarat University, Ahmedabad - 380009 (India)

ARTICLE DETAILS

Article History
Published Online: 15April2019

Keywords
Heteroskedasticity-Robust Standard Errors, Per-Unit Error Variances.

ABSTRACT

Till the time the study on Gujarat State Road Transport Corporation (GSRTC) has been studied for its economic evaluation, financial structures and managerial aspects. This research is attempting to conclude the results of GSRTC for predictive analysis. Thus, this research is developed with support of multivariate models on GSRTC data for financial year 2005 to 2016 for selected 12 parameters. This research is discussed with applications of Heteroskedasticity-Robust Standard Errors, Variant HC0, Heteroskedasticity-Robust Standard Errors, Variant HC1and Weights Based on Per-Unit Error Variances.

1. Introduction to Heteroskedasticity

The model study is applicable to test the explanatory variables of models have the same inherent variability. That is to say, some observation may have a larger or smaller variance than other. This describes the condition known as Heteroskedasticity. Just as in the simple linear regression model $e_i$have an average value of zero for each value of the independent variables and are uncorrelated with one another. The difference in the model is that the variance of $e_i$now depends on i,i.d. the observations to which it belongs. Indexing the variance with the i subscript is just a way of indicating that observations may have different amount of variability associated with them. The error assumptions can be summarized as e_i / x_{i2}, x_{i3}, …X_{ik}iid N (0, σ_{i2}).

The intercept and slope β_1, β_2, …$\beta_k$are consistently estimated by least squares even if the data are Heteroskedasticity. Unfortunately, the usual estimators of the least squares standard errors and test based on them are inconsistent and invalid. We apply several ways to detect Heteroskedasticity are considered, also statistically valid ways of estimating the parameters and listing hypothesis about the βs.

A simple model of GSRTC expenditure for 16depots of Gujarat State have been laying in a form of least square, as we know the general form of OLS is

$$Y_i = \beta_1 + \beta_2 X_i + \ldots + e_i,\quad i = 1, 2, \ldots N$$

Where Y_i is poverty head count ratio and X_i denotes the explanatory variables for cost Effective KM, No. of Passengers, Total EPKM, Total CPKM, Margin, Load Factor Percentage, Vehicle Utilized per day, Fleet Utilization, Crew Utilization, Diesel KMPL, Engine Oil KMPL, Break Down and Accidents.

When the errors of the model are heteroskedastic, then the least squares estimator of the coefficient is consistent, that means that the least squares point estimates of the intercept and slope are useful. However, when the errors are heteroskedastic the usual least squares standard errors are inconsistent and there for should not be used to form confidence intervals or to test hypothesis.

In laying out the standard regression model, we made the assumption of homoscedasticity of the regression error term: that its variance is assumed to be constant in the data conditional on the explanatory variables. The assumption of homoscedasticity fails when the variance changes in different segments of the study. In such cases, we say that the error process is Heteroskedastic. This does not affects the optimality of ordinary least squares for the computation of point estimates and the assumption of homoscedasticity did not underlay our derivation of the OLS formulas.

But if this assumption is not tenable, we may not be able to rely on the interval estimates of the parameters on their confidence intervals, and t – statistics derived from their estimated standard errors. If the error variance is not constant, then OLS estimators are no longer BLUE (Best Least Unbiased Estimator). The classical approach is to test for heteroskedasticity and if it is evident, we need to try to model it. Or have derived modified least squares estimators (known as weighted least squares) which will regain same of desirable properties enjoyed by OLS in a homoscedastic setting.

The said approach is sometimes problematic, since there are many plausible ways in which the error variance may differ in segments of the explanatory variables in our models. Fortunately, fairly recent developments in econometric theory have made it possible to avoid these quandaries. Method have been developed to adjust the estimated standard errors in an OLS context for Heteroskedasticity of unknown form to develop what are known as robust standard error. The OLS estimators can be written as:

$$bi = \beta + \frac{\sum(x_i - \overline{x}_i)ui}{\sum(xi - \overline{x})^2}$$

this gives rise to an estimated variance of the slope parameter:

$$var\,(bi) = \frac{\sum(xi - \overline{x})^2\,\sigma i^2}{(\sum(xi - \overline{x})^2)^2}$$

This expression reduces to the standard expression if $\sigma_i^2 = \sigma^2$for all observations

$$var\,(bi) = \frac{\sigma i^2}{\sum(xi - \overline{x}\,)^2}$$

But if$\sigma i2 \neq \sigma^2$this simplification cannot be performed on ----- (A)

Halbert white showed (Econometrica, 1980) that the unknown error variance of the i^{th} observation, σ^2can be consistently estimated by e_i^2 – that is, by the square of the OLS residual from the original equation. This enables us to compute robust variances of the parameters in the general case of k explanatory variables

$$var\ (bi) = \frac{\sum rij^2\ ei^2}{(\sum(xij - \overline{x})^2)^2}$$

Where, $e_i^2$is the square of the i^{th} OLS residual, and r_{ij} is the i^{th} residual from regressing variables j on all other explanatory variables. The square root of this quantity is the heteroskedasticity – robust standard error, or the "white standard error of the j^{th} estimated coefficient. It may be used to compute the heteroskedasticity – robust t –statistic, which then will be valid for tests of the coefficient even in the presence of heteroskedasticity of unknown form.

To assist with the notation involved in the construction of heteroskedasticity robust variance – covariance matrices (and subsequently the standard errors) we rewrite the white's (1980) initial proposal as:

$(X'X)^{-1}$. (X' D ΩX) $(X'X)^{-1}$ Where Ω = diag ($\hat{E}_1$, $\hat{E}_2$ …….. $\hat{E}_n$)

and D = I_n is the identity matrix. This setup is commonly known as HC_0 in the literature focusing on construction of heteroskedasticity robust standard error. A well-known shortcoming of this estimator is that it tends to be substantially biased in small samples when the data contain leverage points. (Chesher&Jewilt, 1987)

This bias works in the direction of being overly optimistic so that heteroskedasticity robust t – tests are oversized, or confidence intervals tend to be too large. The work of Mackinnon & White (1985) was the first to propose alternative constructions of heteroskedasticity robust standard error. Mackinnon & White noted that the HC_0 setup did not account for the well-known fact that Ω= diag ($\hat{E}_1$, $\hat{E}_2$ …….. $\hat{E}_n$) and suggested a degrees of freedom correction to remedy this.

1.1 APPLICATION RESULT & DISCUSSION ON GSRTC MODEL

1.1.1 THEORETICAL FRAME WORK The main objective of this study is to test the designed frame of factor analysis to test an application on GSRTC. The study is executed for selected sixteen depots of Gujarat Statefor financial year 2005 to 2016. The data are compiled in form of cross sectional time series – Panel structure. The defined parameters under construction of panel are defines as follows:

1.1.2 Effective KM

The total load carried by bus to provide services to the passengers is called effective kilometers.

6.1.2 No. of Passengers

Total number of passengers travelled during the year by taking services of GSRTC buses.

6.1.3 Total EPKM

Earning per Kilometer is the ratio between total revenue and effective kilometers.

6.1.4 Total CPKM

Cost per Kilometer is computed by taking ratio of total cost to effective kilometers.

6.1.5 Margin (Loss)

The margin is computed by subtracting the total cost from total earning. Positive margin values indicate the profit, while negative margin values indicate loss or deficit. Margin is calculated by following formula: Margin = Total Earnings – Total Cost

6.1.6 Load Factor Percentage

The load factor represent the percentage of seating capacity offered to seating capacity actually occupied.

6.1.7 Vehicle Utilized per day

Total running of vehicle travelled to complete shifts assigned to the crew.

6.1.8 Fleet Utilization

Fleet Utilization is a function, which allows GSRTC, to rely on transportation in business to remove or minimize the risks associated with vehicle investment, improving efficiency, productivity and reducing their overall transportation and staff costs, providing 100% compliance with government legislation.

6.1.9 Crew Utilization

Crew Utilization for GSRTC, otherwise known as crewing, are the services rendered highbred by GSRTC for operating the services.

6.1.10 Diesel KMPL

It shows usage of diesel in kilometer per liter during a year.

6.1.11 Engine Oil KMPL

It shows the usage of engine oil top up in kilometer per liter during a year.

6.1.12 Break Down

It shows until how many times a failure of the engine or other working parts of a vehicle or machine during a year.

6.1.13 Accidents

Disaster type term used to describe technological transport accidents involving mechanized modes of transport.

Table 1.1 shows the 12 variables are explanatory variables, thus 12operational factors have been selected for Heteroskedasticity – robust standard errors variant HC0.

TABLE: 1.1 DEPENDENT VARIABLE–MARGIN (LOSS)
HETEROSKEDASTICITY-ROBUST STANDARD ERRORS, VARIANT HC0

Variable	*Coff.*	*SE*	*t-ratio*	*p-value*	
Const	80.3	1.88	42.65	<0.00001	***
Effective KM	2.41	0.00	8329.9	0.5134	
No. of Passengers	23.5	0.05	495.34	0.00072	***
Total EPKM	-2.04	0.04	-50.57	<0.00001	***
Total CPKM	-35.32	0.03	-1180	<0.00001	***
Load Factor Percentage	-3.29	0.09	-38.11	0.00001	***
Vehicle Utilized per day	0.34	0.00	2282.5	<0.00001	***
Fleet Utilization	0.27	0.03	8.3351	0.00002	***
Crew Utilization	6.94	0.04	187.07	<0.00001	***

Diesel KMPL	-61.5	0.87	-70.94	0.00067	***
Engine Oil KMPL	-41.2	0.05	-773	0.00021	***
Breakdowns	-8.27	0.89	-9.34	0.0001	***
Accidents	-15.19	0.49	-31.21	0.00014	***

TABLE 1.2 STATISTICS BASED ON THE WEIGHTED DATA

Sum squared resid	54121514	S.E. of regression	384.6
R-squared	0.84	Adj. R-squared	0.83
F(9, 326)	91.2	P-value(F)	3.71E-21
Log-likelihood	-2316.41	Akaike criterion	2341.5
Schwarz criterion	4721.2	Hannan-Quinn	2246.2
Mean dept. var	54.3	S.D.	14.28
Sum squared resid	26532.8	S.E. of regression	7.124

The multiple regression have applied on the margins for selected 16GSRTC depots, as dependent variable and rest 12 variables are the explanatory variables. After applying the Heteroskedasticity-robust standard errors, variant HC0 it is observed from the table 1.2 that Total EPKM, Total CPKM, Load Factor Percentage, Diesel KMPL, Breakdowns and Accidentsare the variables which affect margins of GSRTC negatively and seems to be main causes in reduction of income of the depots. Also it is noticed that Effective KM, Vehicle Utilized per day, Fleet Utilization have a minor positive effect on model. The effective kilometers is not significant at 5% level of significance as well the weighted data base shows that the sum squared residuals are very high – compare to the original data, also the Standard Error of regression is very high for weighted data than original data sets. The adjusted R^2 is 0.83 and all the model testing measures have highest values. The p – value for F statistic is very least but rest of the measures can not satisfy the criteria. It indicates that the variance between the observations is very high and they highly correlated with independent variable. The high variability between the observations cannot justify the model may it have proper understanding but it is required to test the variability with estimated error variance.

TABLE 1.3: DEPENDENT VARIABLE: MARGIN (LOSS)
HETEROSKEDASTICITY-ROBUST STANDARD ERRORS, VARIANT HC1

Variables	*Coefficient*	*SE*	*t-ratio*	*p-value*	
Const	79.2	1.91376	41.384	<0.00001	***
Effective KM	1.34	0.00029	4620.7	0.31219	
No. of Passengers	22.8	0.0482	473.03	0.00084	***
Total EPKM	-1.98	0.04098	-48.32	<0.00001	***
Total CPKM	-32.45	0.03042	-1067	<0.00001	***
Load Factor Percentage	-3.41	0.08776	-38.86	0.00002	***
Vehicle Utilized per day	0.31	0.00015	2066.7	<0.00001	***
Fleet Utilization	0.21	0.03289	6.3849	0.00003	***
Crew Utilization	6.24	0.0377	165.52	<0.00001	***
Diesel KMPL	-64.3	0.8804	-73.03	0.00077	***
Engine Oil KMPL	-45.8	0.05	-954.2	<0.00001	***
Breakdowns	-0.78	0.84	-0.929	<0.00001	***
Accidents	-21.4	0.32	-66.88	<0.00001	***

TABLE 1.4 STATISTICS BASED ON THE WEIGHTED DATA

Sum squared resid	51234716	S.E. of regression	241.14
R-squared	0.832	Adj. R-squared	0.83
F(9, 326)	89.4	P-value(F)	2.54E-27
Log-likelihood	-2145.2	Akaike criterion	1234.1
Schwarz criterion	2741.2	Hannan-Quinn	1341.2

Mean dept. var	50.1	S.D.	16.41
Sum squared resid	23144.2	S.E. of regression	6.32

In case of HC0 the standard errors of original data are very high, which violated the Heteroskedasticity so it is requires testing HC1. The said model gives comparative statements as follows:

TABLE: 1.5 COMPARATIVE VALUES OF HC0 AND HC1

Particulars	HC0		HC1	
	SE	t- ratio	SE	t- ratio
Effective KM	0.00028932	8329.87695	0.0003	4620.69
No. of Passengers	0.0474421	495.340636	0.0482	473.029
Total EPKM	0.0403413	-50.568524	0.041	-48.3163
Total CPKM	0.0299444	-1179.5194	0.0304	-1066.73
Load Factor Percentage	0.0863332	-38.108167	0.0878	-38.856
Vehicle Utilized per day	0.00014896	2282.49194	0.0002	2066.67
Fleet Utilization	0.032393	8.33513413	0.0329	6.38492
Crew Utilization	0.0370994	187.06502	0.0377	165.517
Diesel KMPL	0.8669	-70.942439	0.8804	-73.035
Engine Oil KMPL	0.0532959	-773.04258	0.048	-954.167
Breakdowns	0.8854497	-9.3398868	0.84	-0.92857
Accidents	0.4867459	-31.207248	0.32	-66.875
R^2	0.83		0.832	
Adj. R^2	0.84		0.83	
AIC	2341.5		**1234.1**	
Hannan-Quinn	2246.2		**1341.2**	
Schwarz Criterion	4721.2		**2741.2**	
S.E. of Regression	7.124		**6.32**	

After changing the degree of freedom for HC0 the HC1 model indicated the standard error of regression is 6.32 as well the p – value of F is even less than HC0. We notice gigantic changes with sum squared residuals as it also reduced the standard error of each parameter which may be best fit of p – value, for effective kilometers we have negligible value which may not affect the variability of model other results of model also proved that the HC1 gives best fit to model.

1.2 METHODS FOR IMPROVED PARAMETER

There are two basic approaches to obtaining improved parameter estimators for data in which the standard deviation of error is not constant across all combinations of predictor variables values. This paper coves a discussion of Weighted Least Square Method.

1.2.1 WEIGHTED LEAST SQUARE METHOD

The discussed model HC0 and HC1 produced high variance of observations Heteroskedasticity models, where observations that are observed with high variance do not contain as much information about the location of the regression line as those observations having low variance.

The basic idea to get more precise estimates using generalization of least squares in this context is to reweigh the data so that all the observations contain the same level of information about the location of the regression line, so observations that contain more single a high weight. Reweighting the data in this way is known as weighted least squares.

Now letting Y represent the margins of GSRTC and X_i is given the details of explanatory variables. we run the following regression model to test WLS:

$$\frac{Y_i}{\sigma_i} = \hat{\beta}1\left({}^{1}/_{\sigma_i}\right) + \hat{\beta}2\left({}^{1}/_{\sigma_i}\right) + \dots\dots + {}^{e_i}/_{\sigma_i}$$

Where, $\sigma_i$are the standard deviation of Margin (Loss).

One of the critical assumptions of OLS regression is homoscedasticity: that the variance of residual error should be constant for all values of the independents. If the independents have different error variance at different ranges of their values, then the estimates of the regression coefficients will have unduly large standard errors for some ranges of the dependent and too small for other ranges. The power of significance tests will be reduced, which is to say regression estimates will be inefficient. Weighted least squares (WLS) regression compensates for violation of the homoscedasticity assumption by weighting cases differentially: cases whose value on the dependent variable corresponds to large variances on the independent variables countless and those with small variances count more in estimating the regression coefficients. That is, cases with greater weights contribute more to the fit of the regression line. The result is that the estimated coefficients are usually very close to what they would be in OLS regression, but under WLS regression their standard errors are smaller. Apart from its main function in correcting for heteroskedasticity, WLS regression is sometimes also used to adjust fit to give less weight to distant points and outliers, or to give less weight to observations thought to be less reliable.

1.2.1.1 ASSUMPTIONS OF WLS METHOD

- **PROPER SPECIFICATION.** As pointed out by Downs &Rocke (1979), heteroskedasticity can indicate model misspecification. Simply adjusting for it through WLS rather than re-specifying the model may lead the researcher into serious errors in drawing causal inferences.
- **DATA LEVEL**. The dependent and the weight variable (the independent variable which is the source of heteroskedasticity) must be interval. The other independents must be interval, dichotomous, or dummy variables coded from categorical variables.
- **MULTIVARIATE NORMALITY**. The dependent variable is assumed to be normally distributed for each independent variable in one-IV models or for each combination of values of the independent variables in multi-IV models.
- **LINEARITY**. The dependent is assumed to be linearly related to each independent.
- **INDEPENDENCE**. All observations are assumed to be independent of one another.
- **PREDICTABLE VARIANCE**. While homoscedasticity is not assumed, the manner in which the variance of the dependent variable changes with increases in magnitude of the independent(s) must be predictable (and reflected in the weight variable).

1.2.1.2 RESULT AND DISCUSSION

The Margin (Loss) is considering as dependent variable and all nine variables as used earlier as a explanatory variables for the construction of model of WLS is taken the per unit error variances as a weight for each parameter can give the regression model as follow:

TABLE 1.6: WLS, DEPENDENT VARIABLE: MARGIN (LOSS)
WEIGHTS BASED ON PER-UNIT ERROR VARIANCES

Variables	*Coefficient*	*SE*	*t-ratio*	*p-value*	
Const	74.13	1.45748	50.862	<0.00001	***
Effective KM	1.29	0.00025	5160	0.00646	***
No. of Passengers	19.54	0.0358	545.81	0.00637	***
Total EPKM	-1.32	0.02981	-44.28	<0.00001	***
Total CPKM	-12.8	0.02047	-625.3	<0.00001	***
Load Factor Percentage	-2.17	0.06508	-33.34	<0.00001	***
Vehicle Utilized per day	0.314	0.0001	3140	<0.00001	***
Fleet Utilization	0.195	0.0238	8.1933	<0.00001	***
Crew Utilization	5.89	0.0261	225.67	<0.00001	***
Diesel KMPL	-59.3	0.58702	-101	0.00014	***
Engine Oil KMPL	-41.24	0.04	-981.9	<0.00001	***
Breakdowns	-0.69	0.82	-0.84	<0.00001	***
Accidents	-19.21	0.31	-62.57	<0.00001	***

TABLE 1.7 STATISTICS BASED ON THE WEIGHTED DATA

Sum Sqrd.Resid.	321.45	S.E. of regression	0.8421
R-squared	0.84	Adj. R-squared	0.84
F(9, 326)	314.12	P-value(F)	7.90E-01
Log-likelihood	-354.3	Akaike criterion	818.3
Schwarz criterion	895.2	Hannan-Quinn	917.23

1.3 CONCLUSION:

With comparison of HC0 and HC1 the WLS model precise well outputs as shown in model. It can be seen that the impact of irrigation, electricity, literacy, productivity growth and wages are negative and are cause for poverty reduction as well with compare to HC0 and HC1 this model produce the effect of development expenditure negative which can be one more effective parameter on poverty model to make it in reduction direction, also with compare to the above models all the values of model are fitted significant. The standard error of regression in similar to HC1 and this model have the less values of AIC, Hannan – Quinn and Schwarz Criterion it indicates the improvement in model. The standard error of original statistics is counted high than the weighted data as 0.84 is shows the best fit of model. The values of R^2 and adjusted R^2 are found progressive. It is also notice the values of standard error and t – ratio for each parameter is enhanced step – wise. We can easily conclude that comparatively WLS model has best fit than HC0 and HC1.

References:

1. Aiken, L. S., & West, S. G. (1991). Multiple regressions: Testing and interpreting interactions. Newbury Park, CA: Sage.
2. Bakker, A. B., Demerouti, E., De Boer, E., &Schaufeli, W. B. (2003). Job demands and job resources as predictors of absence duration and frequency. Journal of VacationalBehavior,62 (2), 341–356. doi: 10.1016/S0001-8791(02)00030-1
3. Cook, R. D., & Weisberg, S. (1982). Residuals and influence in regression. New York: Chapman and Hall.
4. Cortina, J. M. (1993). Interaction, nonlinearity and multicollinearity: Implications formultiple regression. Journal of Management,19(4), 915 – 922.
5. Davidson, R., & MacKinnon, J. G. (1993). Estimation and inference in econometrics. New York: Oxford University Press.
6. deJonge, J., &Schaufeli, W. B. (1998). Job characteristics and employee well-being:A test of Warr's vitamin model in health care workers using structural equationmodelling. Journal of Organizational Behavior,19(4), 387–407.
7. Demerouti, E., Bakker, A. B., Nachreiner, F., &Schaufeli, W. B. (2001). The jobdemands-resources model of burnout. Journal of Applied Psychology,86(3), 499–512.
8. Diestel, S., & Schmidt, K.-H. (2009). Mediator and moderator effects of demands onself-control in the relationship between work load and indicators of job strain. Work& Stress,23(1), 60–79. doi: 10.1080/02678370902846686
9. Dijkstra, T. K., &Schermelleh-Engel, K. (2014). Consistent partial least squaresfor nonlinear structural equation models. Psychometrika,79(4), 585–604. doi:10.1007/s11336-013-9370-0
10. Engle, R. F. (1984). Wald, likelihood ratio and Lagrange multiplier tests in econometrics.In Z. Griliches& M. D. Intriligator (Eds.), Handbook of Econometrics (Vol. 2, pp.775–826). Amsterdam: Elsevier.
11. Gray-Stanley, J. A., &Muramatsu, N. (2011). Work stress, burnout, and social andpersonal resources among direct care workers. Research in Developmental Disabilities,32(3), 1065–1074. doi: 10.1016/j.ridd.2011.01.025
12. Greene, W. H. (2003). Econometric Analysis (5th ed.). Upper Saddle River, NJ: PrenticeHall.
13. Test for heteroscedasticity in regression models 591
14. Häusser, J. A., Mojzisch, A., Niesel, M., & Schulz-Hardt, S. (2010). Ten years on: A re-view of recent research on the job demand-control (-support) model and psychologicalwell-being. Work & Stress,24(1), 1–35. doi: 10.1080/02678371003683747
15. Jackson, P. R., Wall, T. D., Martin, R., &Davids, K. (1993). New measures ofjob control, cognitive demand, and production responsibility. Journal of AppliedPsychology,78(5), 753–762. doi: 10.1037/0021-9010.78.5.753
16. Jamal, M. (2008). Burnout among employees of a multinational corporation in Malaysiaand Pakistan: An empirical examination. International Management Review,4(1),60–71.
17. Karasek, R. A. (1979). Job demands, job decision latitude, and mental strain: Impli-cations for job redesign. Administrative Science Quarterly,24(2), 285–308. doi:10.2307/2392498
18. Klein, A. G., &Moosbrugger, H. (2000). Maximum likelihood estimation of latent interaction effects with the LMS method. Psychometrika,65(4), 457–474. doi:10.1007/BF02296338
19. MacKinnon, J. G., & White, H. (1985). Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties. Journal of Econometrics,29(3), 305-325. doi: 10.1016/0304-4076(85)90158-7
20. Maslach, C., & Jackson, S. E. (1981). The measurement of experienced burnout. Journalof Occupational Behaviour,2(2), 99-113. doi: 10.1002/job.4030020205
21. Prumper, J., Hartmannsgruber, K., &Frese, M. (1995). KFZA. Kurz-FragebogenzurArbeitsanalyse [Short-Questionnaire for Job Analysis]. ZeitschriftfürArbeits- und Organization spsychologie,39(3), 125-132.
22. R Core Team. (2015). R: A language and environment for statistical computing (Version3.2.2.) [Computer software manual]. Vienna, Austria: R Foundation for Statistical Computing.
23. Schmidt, K.-H., &Neubach, B. (2009). Self-control demands as a specific source of stress at work. Zeitschriftfür Personal psychology,8(4), 169-179. doi: 10.1026/1617-6391.8.4.169