“Size of issue leader as determinant of debt offerings yields”

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Size of issue leader as determinant of debt offerings yields

Abstract

This papers focuses on analysis of impact of size of leading underwriter and bookrunners on primary bond yields using ordinary and generalized least squares. The results indicate that yields spreads increase with the size of the leader and bookrunners. It suggests that cooperation with global leaders increases the yields of offering. However, it might also indicate, that issuers with worse credit rating and credit quality intentionally select larger issue leaders in order to cover the intended volume of issue. Based on obtained results it might be concluded that generalized least squares performed better than OLS primarily due to the increase of determination coefficients and decline of information criteria.

Keywords: corporate bond offering, generalized least squares, ordinary least squares, underwriting.
JEL Classification: C22, C24, G12.

Introduction

Regarding underwriter selection, several studies showed advantages of hiring a high reputation issue leader (Carter and Manaster, 1990; Wang and Yung, 2011) with strong connection to institutional investors (Chen and Wilhelm, 2008; Neupane and Thapa, 2013). Underwriter reputation had been also examined by Beckman et al. (2001), Hajduova (2014), Roten and Mullineaux (2002), Loureiro (2010), Andres et al. (2014), and Chua (2014) stating that the selection of top-tier underwriters had significant impact on security valuation and long-term performance. McKenzie and Takaoka (2008) explored the role of the leading underwriter's reputation in defining the probability of switching of underwriters between the particular issues. They argued that the probability of a switch significantly increased if the rating of the leading underwriter of the initial issue declined. There was also an evidence that leaders who raised the degree of overpricing of the initial issue were more likely to be selected to act as the leading underwriter of the consequent offering. Krigman et al. (2001) stated that offerings of switching companies had been significantly less underpriced than those of non-switching companies and firms usually switched leaders mostly to graduate to higher reputation underwriter.

1. Methodology

1.1. Ordinary least squares. In a multiple linear regression we focus on estimation of linear relationship between dependent (endogenous, explained, controlled, regressands) variable Y_i and independent (exogenous, explanatory, control, regressors) variables:

$$X_{ki} = Y_i = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + ... + \beta_K X_{Ki} + u_i,$$

where i = 1, 2,…,n denotes the number of observation, k = 1, 2,…,K represents the k-th independent variable, α is the intercept, $\beta_1,\ldots, \beta_K$ define the slopes of linear relationships between Y_i and X_{ki} and u_i represents the random error (disturbance). u_i might be for instance a result of wrong specification of the linear relationship (when in fact is nonlinear), omission of crucial factors that might influence the relationship, or measurement error. α and $\beta_1,\ldots, \beta_K$ are not known and have to be properly estimated (hat symbol denotes estimates):

$$\hat{Y}_i = \hat{\alpha} + \hat{\beta}_1 X_{1i} + \hat{\beta}_2 X_{2i} + ... + \hat{\beta}_K X_{Kii}.$$

Every observation i has a corresponding error attached which is defined as $e_i = Y_i - \hat{Y}_i$ (Tkáč, 2001). The difference between the disturbance u_i and residual e_i is in fact that while e_i is directly observable, u_i is unknown. The idea behind ordinary least squares method is in the minimization of the residual sum of squares given as:

$$RRS = \sum_{i=1}^{n} e_i^{\,2} =$$

$$= \sum_{i=1}^{n} \left(Y_i - \hat{\alpha} - \hat{\beta}_1 X_{1i} -_2 \hat{\beta} X_{2i} - ... - \hat{\beta}_K X_{Ki} \right)^2$$

by minimizing first-order conditions:

$$\frac{\partial RSS}{\partial \alpha} = -2\sum_{i=1}^{n} e_i = 0 \text{ and}$$

$$\frac{\partial RSS}{\partial \beta} = -2\sum_{i=1}^{n} e_i X_{ki} = 0.$$

for $k = 1,\ 2,...,K$.

Solving these equations we get the ordinary least squares estimators. This can be more easily done in matrix form. If we consider the regression $y = X\beta + u$, where:

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$$y = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix}, \quad X = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1k} \\ X_{21} & X_{22} & \cdots & X_{2k} \\ \vdots & \vdots & \vdots & \vdots \\ X_{n1} & X_{n2} & \cdots & X_{nk} \end{bmatrix}, \quad \beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_k \end{bmatrix}, \quad u = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{bmatrix}.$$

n defines the number of observation samples and k is the number of independent variables with $n > k$. If we denote the vector of residuals as $e = y - X\hat{\beta}$, the residual sum of squares might be introduced as:

$$RSS = \sum_{i=1}^{n} e_i^2 = e^T e = \left(y - X\beta\right)^T \left(y - X\beta\right) =$$

$$= y^T y - y^T X\beta - \beta^T X^T y + \beta^T X^T X\beta.$$

By differentiating the residual sum of squares with respect to β we obtain $\frac{\partial RSS}{\partial \beta} = -2X^T y + 2XX^T \beta$, which should be equal to zero. The solution to this equation results into ordinary least squares estimates of regression coefficients:

$$\hat{\beta}_{OLS} = \left(X^T X\right)^{-1} X^T y.$$

Although the ordinary least squares is presumably the most popular method for estimating parameters in linear regression, their correct application requires several assumptions:

- disturbances u_i have zero mean, *i.e.* $E(u_i) = 0$;
- disturbances u_i have constant variance, *i.e.* $\mathrm{var}(u_i) = \sigma_i^2$;
- disturbances u_i are not correlated, *i.e.* $E(u_i u_j) = 0$ for $i \neq j,\ i, j = 1,2,\ldots,n$;
- independent variables are nonstochastic;
- linear specification is correct.

Given above mentioned assumptions, $\hat{\beta}_{OLS}$ is the best linear unbiased estimate (BLUE) of β. In addition to above mentioned assumptions it holds that:

- If u_i are independent and identically distributed $N\left(0,\sigma^2\right)$, OLS is also maximum likelihood estimator and it can be showed that it is minimum variance unbiased estimator.
- If explanatory variables are not perfectly correlated (no perfect multicollinearity), there exists unique solution to normal equations.

The crucial efficiency assumptions of ordinary least squares regarding disturbances may therefore be summarized into variance-covariance matrix, i.e. $u \sim \left(0,\sigma^2 I_n\right)$.

1.2. Generalized least squares. Violations of first group of above mentioned assumptions means that $\hat{\beta}_{OLS}$ is no longer the best linear unbiased estimate (BLUE) of β. If disturbances do not have constant variance (heteroskedasticity) or are correlated, ordinary least square might be misleading and inefficient. Generalized least squares method relaxes the assumptions that $u \sim \left(0,\sigma^2 I_n\right)$ so that $u \sim u \sim \left(0,\sigma^2 \Omega\right)$ where Ω is positive definite matrix of dimension ($n \times n$), i.e. the variance-covariance matrix of residuals has changed. This model applies the fact that for every positive definite matrix Ω there exists a nonsingular matrix Γ such that $\Gamma\Gamma^T = \Omega$. Therefore we can transform the original model $y = X\beta + u$ by premultiplying it by Γ^{-1}: $\Gamma^{-1}y = \Gamma^{-1}X\beta + \Gamma^{-1}u$ i.e. $\tilde{y} = \tilde{X}\beta + \tilde{u}$, where $\tilde{y} = \Gamma^{-1}y$, $\tilde{X} = \Gamma^{-1}\beta$ and $\tilde{u} = \Gamma^{-1}u$ with $\tilde{u}$ having zero mean and $var(\tilde{u}) = \sigma^2 I_n$. Consequently, the ordinary least squares applied on transformed model is the best linear unbiased estimate of β:

$$\hat{\beta}_{GLS} = \left(\tilde{X}^T \tilde{X}\right)^{-1} \tilde{X}^T \tilde{y} =$$

$$= \left(X^T \Gamma^{-1T} \Gamma^{-1} X\right)^{-1} X^T \Gamma^{-1T} \Gamma^{-1} y = .$$

$$= \left(X^T \Omega^{-1} X\right)^{-1} X^T \Omega^{-1} y^{-1}.$$

2. Data

We focused on 23 844 EUR and USD denominated straight bond offerings with fixed coupon issued between January 2003 and April 2015 from the BondRadar information service. Regarding analyzed sample, we examined following independent variables:

- prestige of issue leader (in total size of led issues);
- prestige of bookrunner 1 to 4 (in total size of led issues).

Independent variable was the spread over middle value of interest rate swaps (in case of EUR issues) or over US Treasury yields (in case of USD issues) with corresponding maturity in basis points. Yields of US Treasuries are approximately equal to USD interest rate swaps.

3. Results

Ordinary least squares are the most popular econometric method and under several assumptions they might be the best linear unbiased estimator. They are simple, easy to solve and available in almost every statistical and econometrical software.

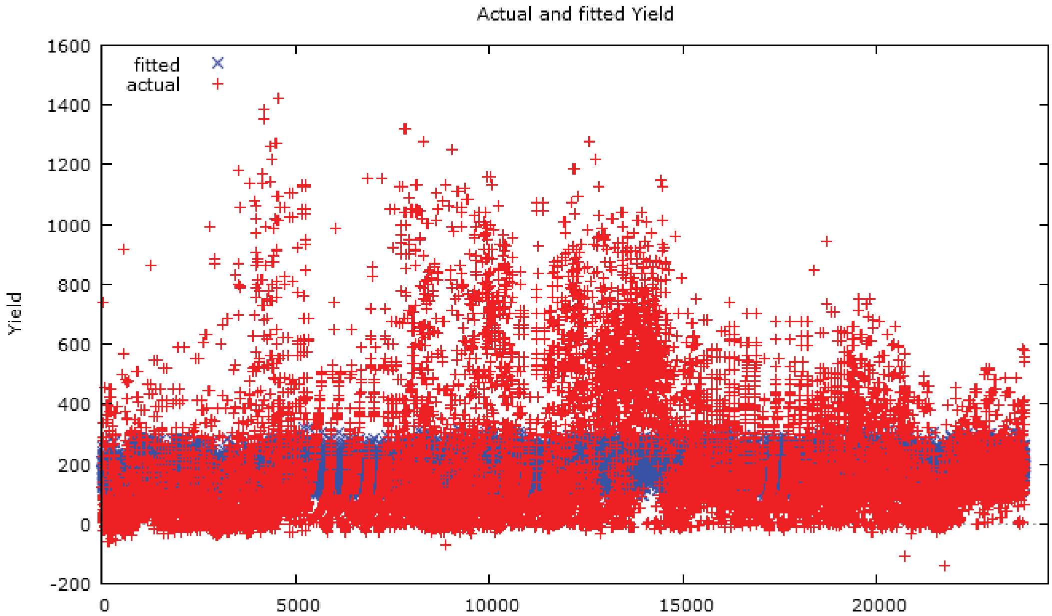
Table 1 presents the results of ordinary least squares regression coefficient estimation on our sample of 23 844 initial bond offerings.

Table 1. Estimation results of ordinary least squares

Variable	Coefficient	Std. error	t-ratio	*p*-value
const	111.464	3.7538	29.69	2.70E-190***
LEADER	5.71E-05	2.64E-06	21.61	1.31E-102***
BOOK1	8.38E-06	2.16E-06	3.884	0.0001***
BOOK2	-1.81E-05	2.18E-06	-8.316	9.57E-17***
BOOK3	1.15E-05	2.60E-06	4.443	8.91E-06***
BOOK4	4.98E-05	3.41E-06	14.62	3.47E-48***

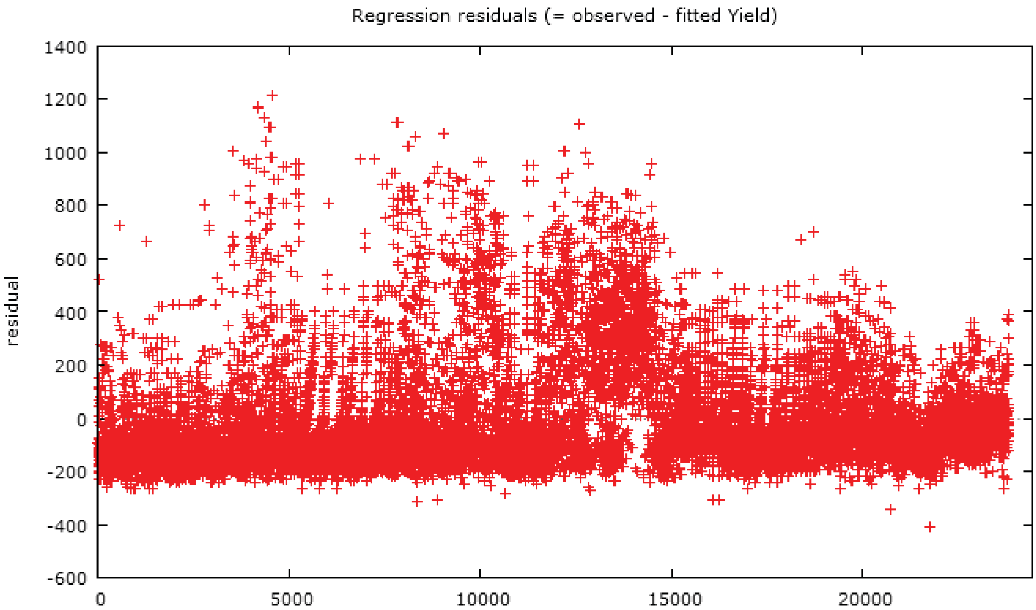
Source: Processed by authors.

Obtained results indicate that all independent variables have significant impact on offering yields. If we look at the sign of the coefficient estimate (except second bookrunner in order), the larger the leading institution, the larger yield spreads. This outcome is remarkable since it suggests that cooperation with global leaders increases the yields of offering. However, it might also indicate, that issuers with worse credit rating (credit quality) select larger leaders in order to cover the intended volume of issue. Figure 1 introduces the plot of actual and fitted values by observations, while Figure 2 shows the residuals by observations.



Source: Processed by authors.

Fig. 1. Actual vs. OLS fitted values by observation



Source: Processed by authors.

Fig. 2. OLS residuals by observation

Table 2 presents the performance measures of ordinary least squares. The determination (R-squared) and adjusted determination coefficient are around 23.4% which is low value for financial data. Adjusted determination coefficient is always lower or equal to standard determination coefficient, since it penalizes the model for quantity of parameters. Akaike (Akaike, 1974), Hannan-Quinn (Hannan and Quinn, 1979) and Schwarz (Schwarz, 1978) are criteria for the model selection. The goal is to find the model with the lowest information criterion.

Table 2. Performance of ordinary least squares

Mean dependent variable	183.7421	S.D. dependent var	204.1883
Sum squared residuals	9.60E+08	S.E. of regression	200.6518
R-squared	0.234542	Adjusted R-square	0.23434
F (5,23838)	170.5757	P-valued (F)	6.80E-179
Log-likelihood	-160240.8	Akaike criterion	320493.7
Schwarz criterion	320542.1	Hannan-Quinn	320509.4

Source: Processed by authors.

Constant variance of residuals was tested by Breusch-Pagan test (Breusch and Pagan, 1979). Test statistic of 595.372 and zero p-value rejected the null hypothesis of homoskedasticity, i.e. ordinary least squares estimates of regression coefficient are significant, but possibly inefficient. Generalized least squares may therefore constitute better linear alternative. In order to check the correct specification of linear model we performed RESET test (Ramsey, 1969) with linear specification as null hypothesis. RESET test rejected the null hypothesis with F-statistic of 6.546 and p-value of 0.00144. Thus as we assumed, a nonlinear choice might be more suitable.

Table 3 introduces the results of coefficients estimation produced by generalized least squares. Comparing to OLS, coefficient estimates have little changed, however, all of them are significant.

Table 3. Estimation results of generalized least squares

Variable	Coefficient	Std. error	t-ratio	p-value
const	109.046	3.36066	32.45	4.78E-226***
LEADER	5.54E-05	2.44E-06	22.71	5.17E-113***
BOOK1	1.15E-05	2.07E-06	5.556	2.79E-08***
BOOK2	-1.55E-05	2.03E-06	-7.606	2.94E-14***
BOOK3	1.09E-05	2.53E-06	4.319	1.58E-05***
BOOK4	4.85E-05	3.77E-06	12.84	1.24E-37***

Source: Processed by authors.

Figures 3 and 4 show the actual and fitted values produced by generalized least squares as well as GLS residuals by observations.

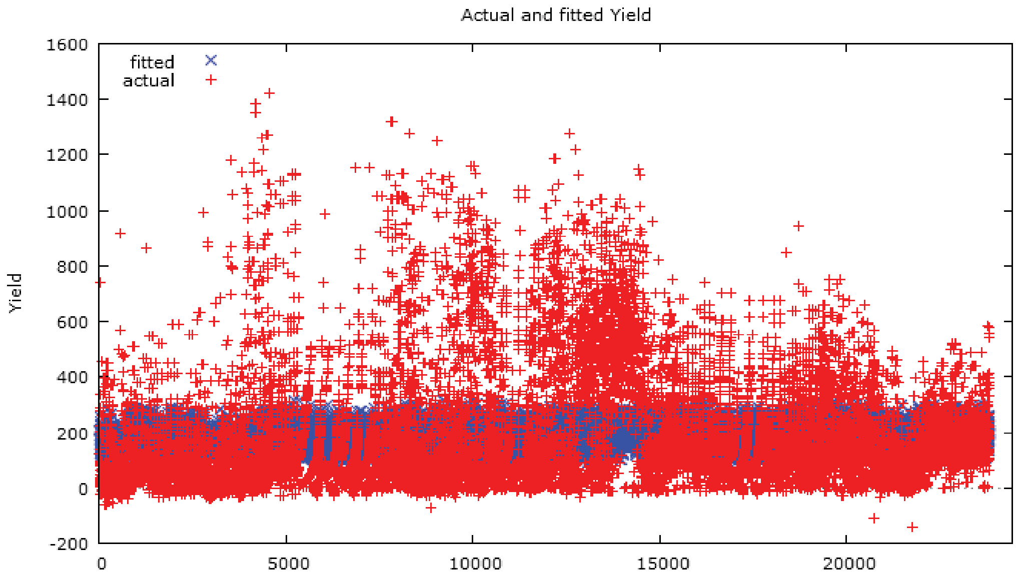
If we look on the performance of generalized least squares estimates (Table 4), we might argue that in comparison with OLS they had slightly higher determination coefficient (26.46% vs. 23.45%), which in simplicity means that they better fitted the data. All three information criteria were more than three time lower as well.

Table 4. Performance of generalized least squares

Sum squared residuals	96878	S.E. of regression	2.01594
R-squared	0.2646	Adjusted R-square	0.264398
F (5.23838)	170.8712	P-valued (F)	3.40E-179
Log-likelihood	-50546.86	Akaike criterion	101105.7
Schwarz criterion	101154.2	Hannan-Quinn	101121.4

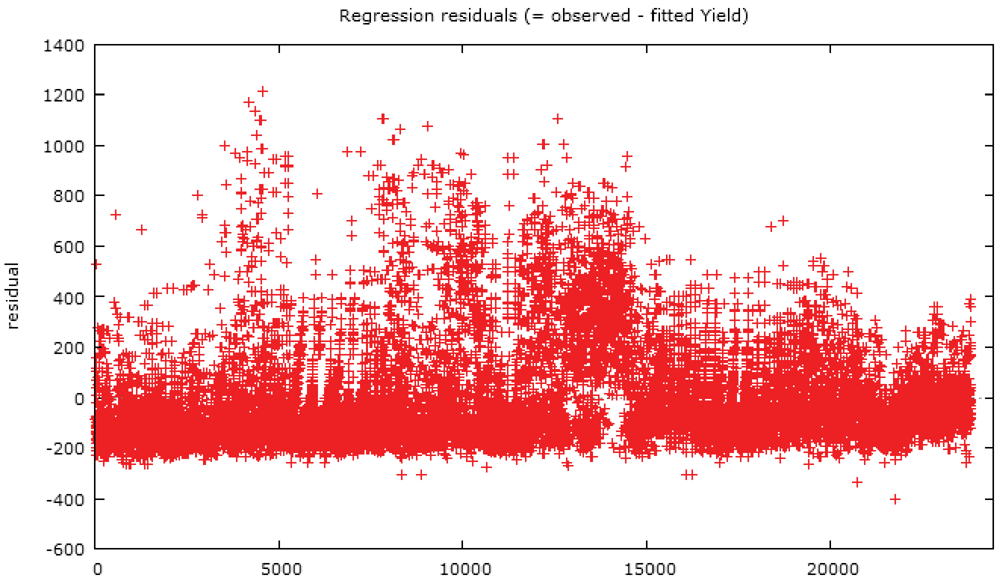
Source: Processed by author.

It might be concluded that generalized least squares performed better than OLS primarily due to the increase of determination coefficients and decline of information criteria.



Source: Processed by authors.

Fig. 3. Actual vs. GLS fitted values by observation



Source: Processed by authors.

Fig. 4. GLS residuals by observation

Conclusion

Despite the ongoing uncertainty, corporations continue to massively offer their debt (Koblen, Szabo & Krnáčová, 2013). In this work we aimed at analysis of impact of leading underwriter and bookrunners on primary bond yields using ordinary and generalized least squares. Obtained outcomes suggest that yield spreads are growing with size if the leader and bookrunners. This fact might indicate, that issuers with worse credit rating and credit quality intentionally select larger issue leaders in order to cover the intended volume of issue. Based on obtained results it might be concluded that generalized least squares performed better than OLS primarily due to the increase of determination coefficients and decline of information criteria.

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