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IPO Underpricing in the Russian Stock Market

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Abstract

This paper investigates stock underpricing in the Russian capital market during initial public offerings in the present-day situation. The econometric study of initial public offerings in the Russian market for 2006–2024 shows that such factors as dividend policy, technological profile of the company, and the difference between the actual and expected offering price increase IPO underpricing. Additionally a positive correlation between the capital raised by the company and the reduction of the underpricing IPO effect is revealed: large companies have more stable financial indicators, which brings their valuation closer to the real value in the market.

Keywords: IPO underpricing, stock underpricing, initial public offerings, IPO, Russian capital markets, technological companies, capital raised, expected IPO price

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Introduction

In today's world, companies seeking to expand their business attract additional financing in several main ways, including bank lending, venture capital funding, bond issue, and public stock offering. Another method of raising additional capital is for a private company to go public. Initial public offerings (IPO) provide unparalleled advantages such as reducing the debt burden, increasing share liquidity, and attracting market attention to the company.

However, IPOs also have some disadvantages, including considerable expenditures of time and money before the offering, the possibility of an unsuccessful offering, etc. Nevertheless, the demand for public offerings remains. According to ExpertRA [1], there is a currently a renaissance in the IPO market in Russia as the country is adapting to foreign sanctions. At year-end 2023, the funds raised from IPOs exceeded RUB 40 billion in seven transactions. This amount is lower than the market peak result achieved in 2021 when approximately RUB 300 billion were raised. At the same time, according to the forecasts of Aigenis Investment Company [2], the funds raised from IPOs will double in 2024, amounting to RUB 83 billion.

In this research, we focus on IPO underpricing. IPO underpricing is a phenomenon when company stock prices in an initial public offering (IPO) are below their real value, which often leads to a significant price escalation on the first trading day. As a result, the company and its investors may lose a significant part of their potential capital or, on the contrary, investors may derive greater revenue. Thus, the purpose of the present paper is to identify the main factors that influence the underpricing of corporate stocks during initial public offerings in the Russian market. To this end, we use statistical analysis with multiple OLS regressions.

Theoretical aspects of the IPO underpricing phenomenon

Scholars have taken great interest in the IPO underpricing phenomenon, studying the factors that influence the extent of company underpricing during an IPO. F. Reilly and K. Hatfield (1969) [3], D. Logue (1973) [4], R. Ibbotson (1975) [5] and others were among the first fundamental studies to analyse the underpricing of companies holding IPOs in the USA in 1960–1969. Subsequently, studies conducted in the 1980s and 1990s proposed four basic groups of theories about the factors that influence the extent of IPO underpricing. Behavioural theory posits that IPOs are accompanied by situations in which investors or issuers are driven by behavioural factors to manipulate stock prices without consideration for their actual value [6–8]. Institutional theory, in turn, analyses the influence of legal proceedings, the activity of banks aimed at price stabilization after the start of trading, and taxes on the market [6; 9]. According to control theory, a reduction in stock prices contributes to the creation of a shareholder structure which limits the influence of external investors when a company issues an IPO [10–13]. However, the most popular approach is information asymmetry theory, which is used in the present paper to formulate the research hypotheses.

Information asymmetry theory presupposes that one of the IPO participants, whether an underwriting bank, issuer or investor, is more informed than the other participants. This leads to an uncertainty in the market and a benefit/loss for one of the three parties as a result of IPO underpricing. Information asymmetry may be inherent in any of the three parties. Therefore, such models as the winner's curse [14], information revelation [15; 16], principal agent [6; 17] and the signalling model [6] are widespread. Papers studying the information asymmetry problem on the part of investors have made the following key conclusions:

1) The higher the uncertainty about the company, the greater the extent of IPO underpricing [18; 19].
2) The extent of IPO underpricing may be reduced by a decrease in information asymmetry between informed and uninformed participants [6].

Authors mostly make use of company characteristics, characteristics of the offer made when holding the IPO, and information about the secondary market as uncertainty factors [6]. For example, J. Ritter (1984) [18] and W. Megginson and K. Wiess (1991) came to the conclusion that, as a company grows more mature, the amount of information about it in the market increases, and thus the extent of uncertainty and IPO underpricing lessens [20]. Empirical studies confirm the negative dependence of the company age on the extent of IPO underpricing [21].

Various authors also studied industry affiliation. The problem of IPO underpricing was particularly acute for the technology industry when the dot-com bubble emerged in the US market. Such authors as A. Ljungvist and W. Wilhelm (2003) explained this distinctive feature by the hypothesis that technology companies tend to be young, rapidly growing firms whose age and business activities give reasons for greater uncertainty and information asymmetry in the market [22]. This conclusion has also been confirmed by more recent studies [23; 24].

The amount of capital raised by an IPO is often taken as a characteristic feature of the offering itself. As studies show, the larger the capital, the more advantageous it is for underwriting banks to sell it due to commission payments and the lower the issue's underpricing. According to D. Logue (1973), this is due to a greater competition among underwriting banks, which provides the issuer with greater bargaining power in relation to the offering price [4]. Another prevalent theory is that larger capital raised in an IPO is indicative of lower uncertainty concerning the issue and a lower extent of underpricing [19]. A recent study by N. Watanabel et al. (2022) for the Japanese market for 2009–2016 shows a negative dependence between the offering amount and the underpricing extent [25]. This relationship is confirmed by a large-scale study by L. He et al. (2022) on a sample of 20 countries in 2005–2016 [26].

The partial adjustment phenomenon models proposed by L. Benveniste and P. Spindt (1989) [15] and K. Hanley

(1993) [16] are among the most popular information disclosure models. The conclusions made in these papers boil down to the idea that the more positive information investors provide about a company, the higher the final offering price as compared to the average price. Ultimately this results in greater IPO underpricing. These conclusions are confirmed by I. Ivashkovskaya and L. Kharlamov (2007), who use data from the Russian market for 1996–2007 [27]. However, a more recent study of the Russian market by V. Nazarova and D. Anisina (2021) for 1996–2021 points to the insignificance of this factor for underpricing [28].

According to the signalling model that implies information asymmetry on the part of the issuer, the reputation of the organizing bank at the time of an IPO [29], the venture capital [20] and the composition of directors [30] are some of the available factors that can act as signals to the market during the IPO. For example, J. Wang et al. (2023) examined the factor of dividend payments by the company in the year preceding the IPO for a sample of Chinese companies from 2006 to 2019 to confirm the hypothesis that companies use dividend payments in the year preceding the IPO as a positive signal to attract investors yet afterwards often decrease the extent of stock underpricing in the IPO to cover the dividend expenses. This is confirmed by a negative relationship between dividend payments in the year preceding the IPO and the extent of company underpricing [31].

Determinants of IPO Underpricing and hypothesis

The systematization of previous academic papers and available relevant information led us to advance five main hypotheses for the Russian IPO market.

1) The first hypothesis states that, the greater the raised capital, the lower the IPO underpricing. Apart from the reduction in underpricing detected when comparing mean values and weighted average values in the previous section, this assumption aligns with the literature: underwriters may perceive a large amount of capital raised in an IPO as a more gainful transaction, leading to quasi-competition among investment bankers, so a company interested in an IPO at a higher price has a wider choice of partners and a greater relative strength in negotiations [4; 25; 26]. For these reasons, we expect a negative relationship between the raised capital and IPO underpricing.
2) The second hypothesis asserts that, the larger the dividends distributed during the preceding period, the lower the expected IPO underpricing. According to recent studies [31], such dividends are a signal of the quality of companies and their willingness to make payments from revenue as an investor attraction strategy. Later on, they may well raise the IPO price threshold to cover the expenses for previous and future dividend payments. As a result, investors will estimate stocks higher, leading to lower underpricing.
3) The third hypothesis posits that technology companies are more often underpriced in IPOs than companies from other industries. This observation has already been noted in the previous section when comparing IPO underpricing. For the most part, technology companies are young, rapidly growing firms, whose age and business activities, which many investors do not understand, lead to greater uncertainty and information asymmetry in the market [22]. Furthermore, due to the higher possible volatility of tech company shares in general, underwriters are unwilling to establish stock prices which the market is ready to pay, because they anticipate a drop in quotations shortly after the listing. This also explains their involvement in reputational and legal suits [32].
4) The fourth hypothesis is related to the partial adjustment theory advanced in IPO underpricing studies [16; 27; 28]: the wider the spread between the actual and expected offering price, the greater the IPO underpricing. This is effect is due to the fact that preliminary information that potentially increases the stock price strengthens investors' willingness to participate in the issue. It is impossible to transfer completely the effect produced by such information into stock price growth due to the risks of losing the planned shareholding structure, because such news attracts new investors.
5) The fifth hypothesis states that the more mature the company, the smaller the IPO underpricing. In the case of companies with a short history, uninformed investors face uncertainty (adverse selection problem [18]) as well as a serious asymmetry of information about the company. This eventually leads issuers to reduce the offering price for external investors [20]. Nevertheless, several papers dedicated to related topics present statistical evidence for the insignificance of the age parameter [26].

Empirical research

Data and Descriptive Statistics

The present paper presents the results of an empirical study of the Russian IPO market for 2006–2024 (until April 2024). The sample consists of companies whose business (or its main part) was located in Russia at the time of the IPO. The data used in the research was collected by the authors manually from publicly available Internet sources: the Moscow Exchange [33], official websites of companies and their consolidated IFRS statements, online versions of popular Russian newspapers [34–41], and open databases of issues [42–48].

The sample for the aforementioned time interval comprises 80 observations related to separate public offerings of non-financial organizations. Financial organizations such as banks, funds, insurance enterprises and other companies rendering financial services were removed from the sample.

Industries and Raised Capital

The 80 observations represent 9 non-financial industries (Figure 1). Companies were assigned to a single industry on the basis of their principal source of revenue.

The following industries are present in the sample:

- Mining – extraction of natural resources except for oil and gas;
- Technology – development of technological products, in particular software, or delivery of technological services;
- Retail – sales of consumer goods and services;
- Real estate – construction and renovation of immovable property;
- Food – food production and sales;
- Health – healthcare, pharmaceuticals, manufacturing and development of medication and medical technologies;
- Oil – extraction or sales of liquid hydrocarbons and/or natural gas;
- Transport – transportation services and logistics;
- Power – generation of electricity.

A dummy variable is introduced for each industry, taking the value "1" if a company is affiliated to the industry and "0" otherwise.

Figure 2 presents the size of IPO offerings (IPO volumes) in Russia. The raised capital was calculated as the product of the stock offer price (in roubles) and the number of issued stocks (*cap*).

We may compare leaps in amounts of raised funds to economic phenomena in modern Russia such as the significant market activity in 2006 and 2007 caused by the oil price surge and economic ramp-up, or the minimal IPO volumes in 2009, 2014 and 2022 as a result of economic and foreign-policy crises. These indicators are contained in the *cap* variable, which reflects the IPO volume and gives an indirect estimate of the company size.

Figure 1. Number of IPOs by industry in 2006–2024

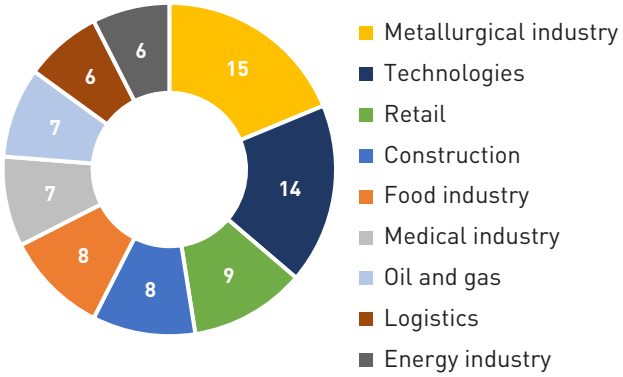


Figure 2. Funds raised through IPOs by industry, RUB mln

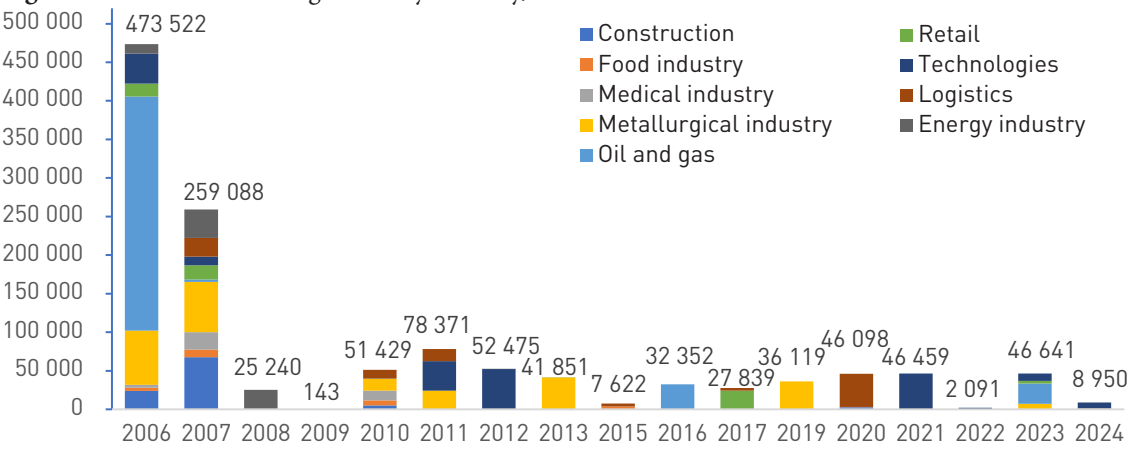
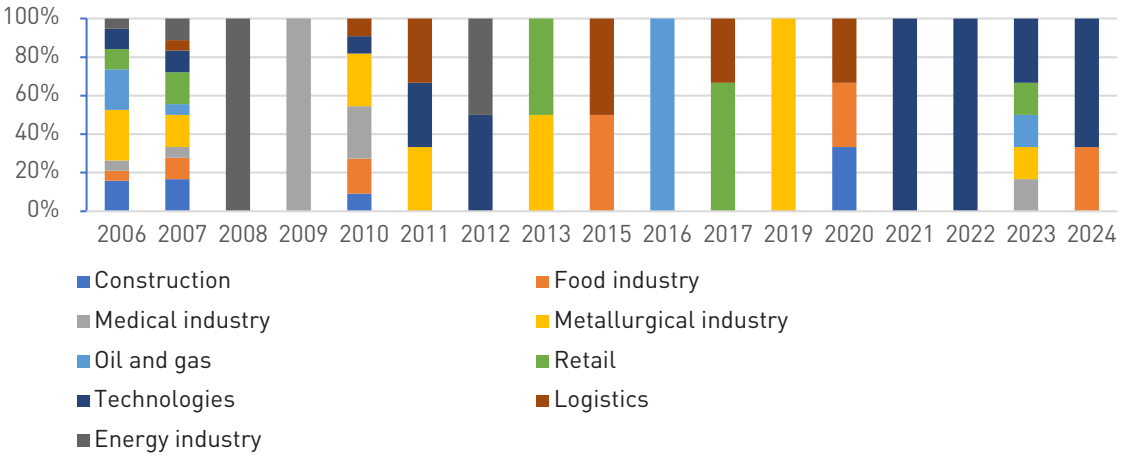


Figure 3. IPOs by industry, normalized by the number of IPOs



The dependence between the amount of raised funds and industries within the considered time interval (Figure 2) is ambiguous: when an industry shows peak IPO volumes in a certain year, further fund raising in subsequent years may differ, which is indicative of the absence of an obvious relationship between the IPO volume in a given year and the IPO volume in the subsequent year.

Figure 3 shows a normalized diagram indicating the percentage of IPOs by industry. It is remarkable that there is no single industry that has the same share of IPOs consistently from year to year: there is always an interval of 1–3 years. It is also notable that IPOs of technology companies predominate for several years in a row (2010–2013 and 2021–2024), which is related to the surge of investor interest in technology solutions, including domestic ones.

IPO underpricing

To study IPO underpricing, we collected the stock quotations of companies whose IPOs were included in the sample. To calculate the IPO underpricing variable, we used the initial public offering price and further stock quotations at the closing of the exchange:

$$l\_und\_id\ (underpricing\ on\ nth\text{-}day) = \ln \frac{P_n}{P_0}, \quad (1)$$

where P_n – closing price on trading day n;

P_o – initial public offering price.

For further research it is important to obtain a statistical confirmation that underpricing is statistically significant. According to the t-test presented in Table 1 for the hypothesis which states that this variable is insignificant, underpricing turned out to be significant for the intervals of 1 day, 7 days and 30 days at the 5% significance level.

Table 1. Significance of IPO Underpricing

und_1d	und_7d	und_30d	und_180d
	t-stat		
2.999	2.784	2.186	0.383
	5%-conf. Level		
	1I: und < 0	H1: und ≠ 0	H1: und > 0
und_1d	0.998	0.004	0.002
und_7d	0.997	0.007	0.003
und_30d	0.984	0.032	0.016
und_180d	0.649	0.703	0.351

Generally speaking, IPO underpricing refers to the prices on the *days immediately following* the offering. A measurement of the extent of underpricing on later dates may involve more "noise" which impairs the effectiveness of the estimation. In this research, we use the most popular time intervals: the 1st trading day, the 7th trading day, and the 30th trading day. The 180th day was included as a comparison with the primary underpricing detected at shorter, less "noisy" and statistically more significant intervals.

As long as the amount of company listing in our sample ranges from RUB 143 million to RUB 281 billion, it makes sense to calculate the IPO underpricing using the amount of raised funds. In Table 2 we recalculated the IPO underpricing values for several time intervals according to the amount of the funds raised by a company in a particular year: the IPO underpricing values within the interval were multiplied by the weights which were obtained as the ratio of the volume of a particular IPO to the total amount of funds raised in that year.

Table 2. Weighted average values of IPO underpricing (%)

	1 day	7 days	30 days	180 days
2006	1.6	2.9	1.5	18.0
2007	5.4	5.9	5.6	25.6
2008	-11.0	-10.6	-15.2	-84.7
2009	30.5	110.5	88.4	16.8
2010	-1.8	-2.5	-2.1	-8.0
2011	18.1	13.7	4.3	-15.6
2012	-0.7	11.1	18.4	71.5
2013	-0.6	2.4	-0.2	1.7

	1 day	7 days	30 days	180 days
2015	-2.5	-2.1	-14.0	-18.1
2016	1.5	1.7	1.7	6.7
2017	0.3	-0.7	-1.1	2.6
2019	3.5	4.0	7.8	17.0
2020	-3.7	-3.8	-6.7	-9.4
2021	42.2	25.4	15.2	37.3
2022	0.2	-13.8	-12.5	15.6
2023	-0.6	8.0	5.2	9.8
2024	16.8	12.2	15.9	–
Weighted average values, total	4.2	4.8	3.2	14.4

We see that weighted average values indicate the underpricing of stocks across the whole sample at the 3–4% level. This may be indicative of the impact of IPO volume on a decrease in IPO underpricing [4; 25; 26]. The diminishing correlation of the weighted average underpricing in Table 3 gives additional relevance to calculations.

Table 3. Correlation of weighted average values of IPO underpricing

	1–7 days	1–30 days	1–180 days
Correlation	0.6884	0.6557	0.3839

Technology companies

Another factor which may impact the extent of underpricing is the industry where the company operates – for example, a technology firm providing technological solutions, products or services to the market. Table 4 presents the results of weighted average values of IPO underpricing for technology companies calculated as the product of underpricing and the share of the funds raised by the technology company in the total amount of the funds raised by the companies of this industry in a given year.

Table 4. Weighted average values of IPO underpricing for technology companies (%)

	1 day	7 days	30 days	180 days
2006	0.61	-0.14	0.40	1.92
2007	-4.51	-7.08	-10.65	-40.46
2010	3.19	1.84	-1.44	-8.54
2011	37.80	34.08	26.20	-9.65
2012	-0.75	11.17	18.40	71.56
2021	42.16	25.40	15.25	37.27
2022	0.22	-13.84	-12.45	15.63
2023	23.60	41.13	36.85	38.44
2024	22.10	15.90	19.94	–
Weighted average values, total	18.1	16.8	14.8	24.7

Values for technology companies are indicative of much higher initial underpricing than across the sample as a whole: on the first day – 18.1% versus 4.2%, in 7 days – 16.8% versus 4.8%, in 30 days – 14.8% versus 3.2%. This confirms the assumption that technology companies experience greater asymmetry in the offering price of the company [24].

Financial indicators

In our research we used the financial indicators of a company which describe various aspects of financial standing, including total assets and revenue (TA, rev) [18], profitability (EBITDA margin, ROA) [28], debt burden (TD/E) [24], and dividend policy (div, div_ni_return) [31].

It is impossible to use such financial indicators for financial organizations such as banks, funds, and insurance enterprises, because their financial structure is different. Although financial organizations have a relatively high share of capitalization, they are far less represented in the IPO market, so modernizing the existing indicators would be unreasonable for our purposes and is left for future study by the authors.

Offering and shareholding indicators

To give a complete picture of company listings on the stock exchange, non-financial indicators were added to the database. In particular, we took the number of shares in the offering (*shares_n*), the amount of funds raised at IPO (*l_cap*) and free float shares (*ff_share*) [23] which are related to liquidity and may potentially influence the share price. We also used the company age at the time of IPO (*age*), the government's share in the company before the IPO (*gov_share*) [49] and a dummy variable related to listing on the Russian stock exchange (*rus_floor*). Additionally, we took the variable which presents the declared range of the IPO price – the width of the price range (*WRP*), calculated as follows [16; 27; 28]:

$$WRP\ (width\ of\ price\ range) = \frac{(Ph - Pl)}{Pe}, \quad (2)$$

where WRP – width of price range;

P_h – upper limit of price range;

P_l – lower limit of price range;

P_e – middle of price range.

We also calculated the change of the actual closing price in comparison to the expected offering price (*l_PRI*) as follows [16; 27]:

$$l\_PRI\ (price\ revision\ index) = \ln\frac{P_0}{Pe}, \quad (3)$$

where PRI – price revision index;

$P_e = \frac{(Ph + Pl)}{2}$ – expected offering price;

P_o – initial public offering price.

The list of variables with their descriptions and abbreviations is given in Appendix 1. In Table 5, we present the descriptive statistics of the aforementioned explanatory variables.

Table 5. Descriptive statistics of variables

Variables[1]		N	Mean	St. deviation	Min.	Max.
Categorial	food	80	0.100	0.302	0	1
	tech	80	0.163	0.371	0	1
	mining	80	0.163	0.371	0	1
	oil	80	0.113	0.318	0	1
	retail	80	0.113	0.318	0	1
	health	80	0.088	0.284	0	1
	estate	80	0.100	0.302	0	1
	transport	80	0.088	0.284	0	1
	utilities	80	0.075	0.265	0	1
	rus_floor	80	0.762	0.428	0	1
Organizational	gov_share	80	8.7%	20.8%	0.0%	100%
	age	80	12	7.382	0	33
Offering	ff_share	80	0.212	0.110	5.0%	51.0%
	shares_n	80	15,215	92,186	0.110	603,925
	WRP	80	0.180	0.110	0,0001	0.500
	PRI	80	0.974	0.080	0,697	1.191
	cap	80	15,454	32,713	7	280,899

[1] See the detailed description of variable values in Appendix 1.

Variables		N	Mean	St. deviation	Min.	Max.
Financial	rev	80	42,970	112,590	0.01	915,960
	EBITDA_margin	80	16.8%	50.9%	-131%	67.0%
	ta	80	82,561	205,002	6.97	1,282,702
	TD/E	80	1.674	2.348	0	8.375
	ROA	80	7.8%	19.0%	-27.6%	62.2%
	div	80	1,973	10,101	0	88,200
	div_ni_return	80	13.1%	22.5%	-9.35%	86.3%

The range of financial variable values reveals private data on particularly prominent offerings. For example, Norilsk Nickel attains its maximum value in assets and paid dividends, while Rosneft is the leader in terms of capitalization (281 billion roubles) and has the largest offering in Russia. Due to the limited number of observations, we expanded the sample with newly formed companies which did not derive steady revenues at the time of the IPO.

Research Methodology

To verify the hypotheses, we used a series of multiple OLS regressions with IPO underpricing as the dependent variable for several time intervals to test significance of the target exogenous variables. As the sample consists of various companies over different years, we applied logarithmic equations to stabilize estimates. We also used robust standard errors to minimize statistical outliers.

The regression models have the following form[2]:

$$ln\ (Underpricing\ on\ nth\ day)_j =$$
$$= cons + \sum Categorial\ parameter_j +$$
$$+ \sum Organizational\ parameterj +$$
$$+ \sum Offering\ parameter_j +$$
$$+ \sum Financial\ parameter\ p_j, \quad (4)$$

where n – number of days since the start of the IPO;

j – company from the sample.

After evaluating the OLS regressions, we performed tests and corrections for heteroscedasticity, multicollinearity and endogeneity by building an additional model using the two-stage least squares method (2SLS) with instrumental variables.

For building the regression models and conducting additional tests, we used the statistical package Stata 12.0 (http://www.stata.com).

The collected data allowed us to describe each observation with 24 parameters. The rational algorithm of enumeration was applied to make sets of regressors:

1) Amount of capital raised at the IPO and tech industry. These variables are used in most papers (A. Ljungvist and W. Wilhelm (2003); L. He et al. (2022); V. Nazarova and D. Anisina (2021) [22; 26; 28]), especially when a relationship with underpricing is suspected in the sample. This makes them the key parameters of the regression.
2) Other industries and time (categorial) variables. We focused our approach by taking the possible significance of industries and time into consideration.
3) Financial parameters. We added financial parameters to take the probable correlation into account.
4) Organizational and offering parameters. We studied the influence of the parameters of issue, age, and shareholding to get the final regression.
5) Additional verification. We added categorial variables to verify the significance and stability of estimates.

Selection of Parameters for the Empirical Model

Tables 6–10 in Appendix 2 show the results of the selection of regressors for evaluating the influence on the dependent variable of IPO underpricing on the 1st day.

Due to the high correlation of the parameters with each other, estimates for 1, 7 and 30 days will demonstrate similar results. Moreover, information about the issue, namely the full list of considered variables from Table 5, remains unchanged after 7, 30, and 180 days. Thus, the effects detected within the one-day interval will not strengthen in 7 or 30 days, nor will any new significant effects emerge. Intuitively this thesis is confirmed by the fact that investors and traders will not bide their time to implement a strategy if they receive no new information concerning the variables (from Table 5) when this period is over. Nevertheless, it is expedient to analyse longer time intervals for (1) testing the adequacy of the collected data and (2) verifying the durability of the effect.

It is useless to study the parameters which influence IPO underpricing beyond the horizon of 180 days due to "noise" and the limited publication of financial data in the course of a year. Nevertheless, using the dummy variable in the OLS regression, one should test the influence of these parameters on the years with the highest number of IPOs,

[2] The parameters mentioned in this equation are divided into subgroups in Table 5.

that is 2006 and 2007. The results show that their effect is insignificant (Table 7, Appendix 2). Although the sample is asymmetric from year to year, the inclusion of years with significant fluctuations in underpricing (2008, 2009, and 2013) is of no statistical significance, because these years have only 1 or 2 observations each.

The tech dummy variable demonstrated high significance in all versions (Tables 6–8, Appendix 2). The coefficients of other industries showed much weaker results.

The obtained estimates show that the variables of revenue (*l_rev*), total assets (*l_ta*) and capitalization (*l_cap*) give similar results (Tables 6–8, Appendix 2). *l_cap* was chosen as the final version of the company size variable, because this variable has a slightly higher R^2 and a better confirmed statistical significance in the literature than *l_rev* or *l_assets*. When the dividend variable (*l_div*) is added, the significance of *l_cap* grows.

After adding the variable *pri,* which shows the change in the actual offering price in comparison to the expected offering price, the significance of both the model and the individual regressors, including the constant, increase (Table 9, Appendix 2), which has not been observed up to now.

The reverification of earlier versions of the models with the addition of the variable *PRI* (Table 10, Appendix 2) showed that neither *age* nor *gov_share* are significant in different combinations with *PRI*. The dummy variables of 2006 and 2007 with a positive coefficient remain insignificant as before. As the capitalization of the IPO market for the sample was at the maximum point during these years, the addition of these variables draws off part of the effect from the capitalization variable (*cap*), which has been and remains significant. Similarly, while the industry variables could drive the estimates of other regressors up or down, they did not impact their own significance or that of others. After the addition of other dummy variables, the previously insignificant constant did not change its positive sign or lose its statistical significance, which confirms the consistent underpricing in the Russian IPO market.

Research Results

The final regression for IPO underpricing for 1 day, 7 days and 30 days (Model 2, same as Model 1.16 from Appendix 2) is presented in Table 11.

Table 11. Regression

Variable	Model 2		
	1 day	7 days	30 days
l_div	0.00297**	0.00193	0.00279
	(0.00132)	(0.00198)	(0.00243)
l_cap	-0.0223**	-0.0281	-0.0296
	(0.00959)	(0.0170)	(0.0183)
tech	0.134***	0.141***	0.151***
	(0.0373)	(0.0490)	(0.0522)
l_PRI	0.644***	0.868***	0.870***
	(0.199)	(0.243)	(0.327)
constant	0.205**	0.279*	0.266
	(0.0893)	(0.156)	(0.166)
Observations	80	80	80
R-squared	0.339	0.268	0.206
R-adjusted	0.304	0.229	0.162

*** p < 0.01, ** p < 0.05, * p < 0.1.

As we can see, the significance of these variables and the regression as a whole (R^2) decreases as the time interval of underpricing increases. Generally speaking, this is not surprising, because the same explanatory data are used for different dependent variables which come under the influence of the new parameters over time.

All variables turned out to be significant at the 5% level and within the one-day interval. However, the significance of *l_div*, *l_cap* and the constant decreased as the time lag grew. The coefficient of the dividend payment variable (*l_div*) was estimated as 0.2–0.3%, which means that, when dividend payments grow by 1% in the year preceding the IPO, the initial underpricing increases by 0.2–0.3%. An inverse dependence was detected for the raised capital variable in the IPO period (*l_cap*), which is related to the company size. So, when the raised capital grows by 1%, the extent of underpricing decreases by 2.2%. Another variable – the deviation of the actual offering price from the expected one (*l_PRI*) – showed high significance for the estimate and the effect on underpricing. When the prices deviate by 1%, underpricing can grow from 0.64 to 0.87% within a month. A company from the technology sector statistically influences the basic level of IPO underpricing, increasing it by 14–16%. Also, the initial level of underpricing[3] of any Russian company is 23% on the first trading day and can rise as high as 32% subsequently, confirming the significant positive constant. This result aligns with all previous studies on the existence of IPO underpricing in the capital market as well as being additionally confirmed in our study by the t-test for significance (Table 1) and our data sample (Table 2), which shows IPO underpricing.

The evaluation results confirm the first hypothesis about a negative relationship between company size and IPO underpricing, the third hypothesis about the higher underpricing of technology companies, and the fourth hypothesis about a positive relationship between underpric-

[3] Disregarding the effects of other parameters – in particular, the diminishing effect of the amount of raised funds on underpricing (l_cap).

ing and the deviation of the actual offering price from the expected one. The second hypothesis about an inverse relationship between paid dividends and underpricing is rejected by our results, which show a positive influence of dividends on underpricing in the Russian market. The fifth hypothesis, which already showed statistical insignificance in some studies [25; 26], is also rejected, because the company age variable at the time of IPO (*age*) turned out to be insignificant.

The fact that we obtained similar results in three different time intervals is indicative of the reliability of the empirical study (robustness check).

Model Testing

To verify that the results of OLS regression are correct from the econometric point of view, we performed a series of classical tests for detecting errors in the evaluation of parameters. Table 12 presents the results.

Table 12. Testing the regression

F-test for the general significance of the regression			
F-stat (4, 75)	7.60	8.60	5.61
Prob > F	0.000	0.000	0.001
Ramsey Reset test for the correctness of the functional form			
F-stat (3, 72)	1.18	0.09	0.16
Prob > F	0.325	0.964	0.921
Breusch-Pagan test for heteroscedasticity			
Chi-squared (1)	0.18	9.29	1.34
Prob > Chi-squared	0.668	0.002	0.248
VIF-test for multicollinearity			
VIF	1 day	7 days	30 days
l_cap	1.12	1.12	1.12
l_div	1.11	1.11	1.11
l_PRI	1.08	1.08	1.08
tech	1.08	1.08	1.08
Average	1.08	1.08	1.08

First, F-tests for the significance of the regression showed that the regression as a whole is significant. Furthermore, the chosen logarithmic type of model suited the research, which is confirmed by the Ramsey test. The estimates were not exaggerated by a multicollinearity effect, as shown by the calculated Variance Inflation Factor (VIF) and the absence of highly correlated regressors in the same equation (Table 3). As the sample is heterogeneous and the evaluated residuals may have different dispersions, we applied robust standard errors of the regressors characterized by robustness to outliers. According to the Breusch-Pagan test for heteroscedasticity with non-robust estimates, this precaution was necessary, as significant heteroscedasticity was indeed detected in the model for underpricing for 7 days.

Endogeneity

Estimates may be distorted by omitted variables, although the F-tests confirmed the significance of the regression: in other words, the endogeneity of regressors is possible. In more formal terms, omitted variables cause a correlation between the regressor and an error, making the estimate exaggerated and inconsistent. One of the most common solutions is the use of instrumental variables (IV) in the two-stage least squares model (2SLS).

Instrumental variables should have the two following characteristics: no correlation with errors in the basic model and a correlation with the target regressor.

Although almost all the variables in this study may be suspected of endogeneity, we focused on paid dividends (*l_div*) and capital (*l_cap*). It is extremely difficult to run an endogeneity test on the variable of deviation from the expected price (*l_PRI*), as it relates to investors' expectations. There is no standard list of factors which influence investors' expectations, and any hypothetical list would most likely be different for each case. From the mathematical point of view, the deviation is calculated as the average of the upper and lower limits of the range, yet in the case of investors' expectations these limits have no clear or readily available formula, and this issue is furthermore not raised in the reviewed literature [16; 27; 28]. As for technology companies, the dummy variable format is often applied in studies [22; 32], yet the present study additionally verified the effects of other industries and years, which turned out to be insignificant. Therefore, there are reasons to believe that use of the *tech* dummy variable is quite exogenous enough.

To select relevant instrumental variables, we calculated separately the residuals of Model 2 for the 1, 7 and 30 days (*res1, res7, res30*) and verified the absence of a correlation between the residuals and the errors and the presence of a correlation with *l_div* and *l_cap* (see Appendix 3).Table 13 presents the results of the 2SLS model with robust errors.

Table 13. 2SLS Regression

	2SLS c IV (*l_div*)			2SLS c IV (*l_cap*)		
Variable	1st day Model 2	7 days Model 2	30 days Model 2	1st day Model 2	7 days Model 2	30 days Model 2
l_div	0.00377**	0.00325	0.00175	0.00307**	0.00179	0.00265
	(0.00190)	(0.00306)	(0.00398)	(0.00133)	(0.00216)	(0.00260)
Tech	0.134***	0.141***	0.151***	0.134***	0.141***	0.151***
	(0.0354)	(0.0470)	(0.0511)	(0.0360)	(0.0477)	(0.0507)
l_PRI	0.629***	0.842***	0.890***	0.652***	0.857***	0.859***
	(0.191)	(0.235)	(0.308)	(0.191)	(0.226)	(0.310)
L_cap	-0.0234**	-0.0299*	-0.0281	-0.0245**	-0.0249	-0.0263
	(0.00940)	(0.0173)	(0.0190)	(0.0104)	(0.0210)	(0.0225)
Constant	0.207**	0.283*	0.263	0.224**	0.253	0.239
	(0.0858)	(0.152)	(0.164)	(0.0940)	(0.183)	(0.193)
Observations	80	80	80	80	80	80
R-squared	0.336	0.264	0.204	0.338	0.267	0.205
R-adjusted	0.301	0.224	0.161	0.303	0.228	0.163
Endogeneity tests						
Chi-squared (1)	0.415	0.649	0.186	0.164	0.113	0.075
Prob > Chi-squared	0.520	0.421	0.666	0.685	0.737	0.785
F-stat (1,74)	0.367	0.588	0.176	0.155	0.102	0.067
Prob > F	0.546	0.446	0.676	0.700	0.750	0.796
J-test for endogeneity IV / overidentifying restrictions						
Chi-squared (6)	2.042	2.649	2.574	0.638	0.671	1.198
Prob > Chi-squared	0.916	0.851	0.860	0.888	0.880	0.754

*** p < 0.01, ** p < 0.05, * p < 0.1.

Note that the coefficients of all variables and R^2 remained the same as in the standard OLS regression (Table 13). The tests show that the assumptions of the significance of endogeneity of *l_div* and *l_cap* are erroneous (the zero hypothesis about exogeneity is not rejected) and that the selected set of instrumental variables is also exogenous (J-test).

The results of all the aforementioned tests allow us to assert that Model 2 shows the estimated results for our data sample correctly.

In view of the endogeneity problem, we should pay attention to the significant positive constant, which was formed after identifying the price deviation variable *l_PRI* and which may provide indirect evidence of factors increasing IPO underpricing that were not taken into account in the model. Most likely, many parameters which influence underpricing are not represented in the model due to the limited information at our disposal, which is a problem for all econometric studies. Nevertheless, the significant constant is balanced by another significant but negative variable – raised capital (*l_cap*) – which mitigates the effect of inserting an average raised capital of 15.5 billion into the sample.

Conclusion

The Russian IPO market is relatively young, having emerged at the end of 1996 when the first Russian company OJSC VimpelCom was listed on the New York Stock Exchange. Nevertheless, the phenomenon of IPO underpricing during foreign offerings is also characteristic of the Russian market.

We reviewed the main theories which explain this phenomenon, including behavioural theory, institutional theory, control theory and information asymmetry theory, taking the latter as the basis for our research hypotheses. We used these theories to select the individual parameters that influence underpricing during an initial public offering. Running multiple OLS regressions on data from Russian companies relating to both IPO characteristics and company indicators, we obtained a statistical estimate of the impact of different company parameters.

First, we confirmed statistically the fact of stock underpricing in an average IPO. Second, testing the advanced hypotheses, we confirmed the positive effect of capital raised by a company on the decrease of company underpricing in a public offering, which was also noted in earlier papers (D. Logue,1973; N. Watanabel et al., 2022; L. He et al., 2022) [4; 25; 26]. We also revealed that previously paid dividends, company affiliation to the technology industry (A. Ljungqvist and W. Wilhelm, 2003; T. Loughran and J. Ritter, 2004; J. Kim et al., 2008) [22; 24; 32] and a positive deviation of the actual offering price from the expected offering price (partial adjustment phenomenon) increase IPO underpricing (K. Hanley, 1993; I. Ivashkovskaya and K. Kharlamov, 2007; V. Nazarova and D. Anisina, 2021) [16; 27; 28].

For the qualitative improvement of the estimates, one can increase the number of explanatory variables related to market expectations – for example, by introducing a variable describing the news coverage of the IPO or conducting in-depth studies of individual cases accompanied by an analysis of the opinions of investment banks along with an analysis of multipliers. Be that as it may, the obtained results will be useful as indicative values to determine underpricing at initial public offerings of shares – for example, to external investors for adjusting potential revenues and to issuers for regulating underpricing when taking decisions on launching an IPO.

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Appendix 1. Description of variables

Designation of the variable in the model	Variable	Variable description
l_und_1d l_und_7d l_und_30d l_und_180d	IPO underpricing for 1, 7, 30, 180 days	Logarithm of the dependent variable that indicates the difference between the price over a time period and the offering price $l\_und\_id\ (\text{underpricing on ith day}) = \ln \frac{P_i}{P_0}$, where P_i – closing price on trading day i; P_o – initial offering price
tech	Technology company	Dummy variables which identify company affiliation to some industry
food	Food company	
mining	Mining company	
oil	Oil and/or gas extraction company	
retail	Retail company	
health	Medical or pharmaceutical company	
estate	Real estate developer	
transport	Transport and/or logistics company	
utilities	Power company	
rus_floor	Listing in Russia	Issue's affiliation with MICEX and/or RTS, among others
year_ipo	IPO year	Year when the company held the IPO, during the period 2006–2024
l_shares_n	Number of shares	Logarithm of the number of shares issued for the IPO
l_rev	Revenue	Logarithm of revenue during the last full year preceding the IPO
EBITDA_margin	EBITDA margin	EBITDA margin during the last full year preceding the IPO

l_ta	Total assets (company size)	Logarithm of all assets during the last full year preceding the IPO
age	Company age	Company age in years at the time of the IPO
TD/E	Debt burden	Total debt to capital during the last full year preceding the IPO
l_cap	Capitalization/company size	Logarithm of the product of the offering price and the number of shares
ROA	Return on assets	Return on assets during the last full year preceding the IPO
div_l	Paid dividends	Logarithm of all the paid dividends during the last full year preceding the IPO
div_ni_return	Return on dividends	Ratio of paid dividends to capital during the last full year preceding the IPO
ff_share	Free-float	Free float shares immediately after the IPO in % of all company shares
gov_share	Government share	Government share in company capital before the IPO
l_WRP	Width of price range	$WRP\ (\text{width of price range}) = \frac{(Ph - Pl)}{Pe}$, where WRP – width of price range; P_h – upper limit of price range; P_l – lower limit of price range; P_e – middle of price range.
l_PRI	Deviation of the offering price from the expected one	$l\_PRI\ (\text{price revision index}) = \frac{\ln P_0}{Pe}$, where PRI – price revision index; $P_e = \frac{(Ph + Pl)}{2}$ – expected offering price; P_o – initial offering price. P_h – upper limit of price range; P_l – lower limit of price range
2006_y	IPO of 2006	Dummy variable indicating that the IPO was held in 2006
2007_y	IPO of 2007	Dummy variable indicating that the IPO was held in 2007

Appendix 2

Table 6. Regression. Selection of Parameters (1/5)4

Variables	(1) Model 1.1	(2) Model 1.2.	(3) Model 1.3.	(4) Model 1.4.	(5) Model 1.5.	(6) Model 1.6
Tech	0.148***	0.144***	0.145***	0.144***	0.143***	0.139***
	(0.0480)	(0.0474)	(0.0484)	(0.0481)	(0.0418)	(0.0415)
l_rev	-0.00446					
	(0.00331)					
l_ta		-0.00772		-0.00368		
		(0.00623)		(0.00594)		
l_cap			-0.0110	-0.00786	-0.0171*	-0.0122
			(0.00969)	(0.0108)	(0.00968)	(0.00915)
l_div					0.00386**	
					(0.00147)	
div_ni_return						0.147**
						(0.0683)
Constant	0.0550	0.0904	0.112	0.120	0.132	0.104
	(0.0344)	(0.0679)	(0.0912)	(0.0930)	(0.0876)	(0.0864)
Observations	80	80	80	80	80	80
R-squared	0.145	0.148	0.151	0.153	0.216	0.201
R-adj	0.123	0.130	0.130	0.121	0.185	0.170

*** p < 0.01, ** p < 0.05, * p < 0.1.

Table 7. Regression. Selection of Parameters (2/5)

Variables	(1) Model 1.5.	(2) Model 1.7.	(3) Model 1.8.	(4) Model 1.9.	(5) Model 1.10.	(6) Model 1.11.
l_div	0.00386**	0.00399***	0.00412***	0.00422**	0.00455**	0.00466**
	(0.00147)	(0.00150)	(0.00151)	(0.00181)	(0.00175)	(0.00176)
l_cap	-0.0171*	-0.0178*	-0.0187*	-0.0148	-0.0149	-0.0152
	(0.00968)	(0.00989)	(0.00956)	(0.00934)	(0.00916)	(0.00937)
food				-0.115	-0.00263	-0.00103
				(0.0958)	(0.102)	(0.102)

[4] Colouring is used in the regression models to single out logical subgroups.

Variables	(1) Model 1.5.	(2) Model 1.7.	(3) Model 1.8.	(4) Model 1.9.	(5) Model 1.10.	(6) Model 1.11.
mining				-0.119***	-0.00862	-0.0120
				(0.0436)	(0.0529)	(0.0535)
Oil				-0.103**	0.00873	-0.000479
				(0.0477)	(0.0572)	(0.0603)
retail				-0.105**	0.00820	0.00749
				(0.0499)	(0.0608)	(0.0613)
health				-0.0111	0.102	0.103
				(0.0678)	(0.0776)	(0.0792)
estate				-0.0403	0.0733	0.0691
				(0.0492)	(0.0611)	(0.0598)
transport				-0.107**	0.00210	0.00590
				(0.0499)	(0.0567)	(0.0582)
tech	0.143***	0.145***	0.146***		0.162**	0.163**
	(0.0418)	(0.0432)	(0.0441)		(0.0626)	(0.0641)
y_2006		0.0219				0.0250
		(0.0305)				(0.0320)
y_2007			0.0410			
			(0.0303)			
Constant	0.132	0.131	0.134	0.201**	0.0876	0.0841
	(0.0876)	(0.0905)	(0.0872)	(0.0768)	(0.0862)	(0.0903)
Observations	80	80	80	80	80	80
R-squared	0.216	0.220	0.227	0.202	0.265	0.270
R-adj	0.185	0.178	0.175	0.100	0.159	0.152

*** p < 0.01, ** p < 0.05, * p < 0.1.

Table 8. Regression. Selection of Parameters (3/5)

Variables	(1) Model 1.5	(2) Model 1.12	(3) Model 1.13	(4) Model 1.14	(5) Model 1.15
tech	0.143***	0.140***	0.139***	0.139***	0.131***
	(0.0418)	(0.0425)	(0.0422)	(0.0438)	(0.0449)
l_div	0.00386**	0.00362**	0.00370**	0.00364**	0.00322**
	(0.00147)	(0.00153)	(0.00143)	(0.00158)	(0.00156)
l_cap	-0.0171*	-0.0173*	-0.0155	-0.0172*	-0.0157
	(0.00968)	(0.00975)	(0.00977)	(0.00973)	(0.00988)
ROA				0.0340	0.0358
				(0.0606)	(0.0593)

Variables	(1) Model 1.5	(2) Model 1.12	(3) Model 1.13	(4) Model 1.14	(5) Model 1.15
TD/E			-0.00639		-0.00682
			(0.00676)		(0.00688)
EBITDA_margin		0.0163*			0.0167*
		(0.00947)			(0.00897)
Constant	0.132	0.133	0.131	0.133	0.133
	(0.0876)	(0.0883)	(0.0880)	(0.0880)	(0.0892)
Observations	80	80	80	80	80
R-squared	0.216	0.219	0.226	0.217	0.231
R-adjusted	0.185	0.177	0.184	0.176	0.168

*** p < 0.01, ** p < 0.05, * p < 0.1.

Table 9. Regression. Selection of Parameters (4/5)

Variables	(1) Model 1.16	(2) Model 1.17	(3) Model 1.18	(4) Model 1.19	(5) Model 1.20	(6) Model 1.21
l_div	0.00297**	0.00378**	0.00389**	0.00385**	0.00367**	0.00428***
	(0.00132)	(0.00151)	(0.00149)	(0.00147)	(0.00153)	(0.00156)
l_cap	-0.0223**	-0.0168*	-0.0162*	-0.0175*	-0.0165*	-0.0162
	(0.00959)	(0.00961)	(0.00952)	(0.00976)	(0.00959)	(0.00980)
tech	0.134***	0.139***	0.141***	0.144***	0.138***	0.139***
	(0.0373)	(0.0427)	(0.0426)	(0.0421)	(0.0446)	(0.0409)
l_PRI	0.644***					
	(0.199)					
l_wrp		0.00465				
		(0.00792)				
age			0.000611			
			(0.00200)			
shares_n				0.001		
				(0.006)		
ff_share					-0.0663	
					(0.113)	
gov_share						-0.0614
						(0.0497)
Constant	0.205**	0.142	-1.097	0.134	0.144	0.126
	(0.0893)	(0.0883)	(4.016)	(0.0881)	(0.0948)	(0.0883)
Observations	80	80	80	80	80	80
R-squared	0.339	0.220	0.217	0.216	0.218	0.222
R-adjusted	0.304	0.179	0.175	0.174	0.176	0.181

*** p < 0.01, ** p < 0.05, * p < 0.1.

Table 10. Regression. Selection of Parameters (5/5)

Variables	(1) Model 1.16	(2) Model 1.23	(3) Model 1.24	(4) Model 1.25	(5) Model 1.26	(6) Model 1.27
l_div	0.00297**	0.00298**	0.00326**	0.00326**	0.00326**	0.00363**
	(0.00132)	(0.00132)	(0.00138)	(0.00139)	(0.00144)	(0.00160)
l_cap	-0.0223**	-0.0220**	-0.0216**	-0.0215**	-0.0239**	-0.0219**
	(0.00959)	(0.00928)	(0.00975)	(0.00943)	(0.00959)	(0.00968)
tech	0.134***	0.134***	0.131***	0.131***	0.138***	0.162***
	(0.0373)	(0.0382)	(0.0367)	(0.0376)	(0.0420)	(0.0609)
l_PRI	0.644***	0.643***	0.637***	0.637***	0.644***	0.664***
	(0.199)	(0.197)	(0.202)	(0.200)	(0.212)	(0.245)
food						-0.0133
						(0.107)
mining						0.00764
						(0.0547)
oil						0.00824
						(0.0556)
retail						0.0496
						(0.0616)
health						0.0711
						(0.0729)
estate						0.0909
						(0.0572)
transport						0.0219
						(0.0550)
age		0.000178		0.0003		
		(0.00194)		(0.00200)		
gov_share			-0.0398	-0.0396		
			(0.0502)	(0.0525)		
y_2006					0.00157	
					(0.0359)	
y_2007					0.0425	
					(0.0333)	
Constant	0.205**	-0.154	0.200**	0.150	0.206**	0.169*
	(0.0893)	(3.884)	(0.0904)	(3.990)	(0.0921)	(0.0947)
Observations	80	80	80	80	80	80
R-squared	0.339	0.339	0.342	0.342	0.353	0.381
R-adjusted	0.304	0.295	0.297	0.288	0.300	0.281

*** p < 0.01, ** p < 0.05, * p < 0.1.

Appendix 3. Correlation matrices with residuals of Model 2

Variables	res1	res7	res30	l_cap	l_div	l_ta	EBITDA_ margin	TD/E	div_ni_ return	ROA
res1	1.00									
res7	0.80***	1.00								
res30	0.80***	0.87***	1.00							
l_cap	0.00	0.00	0.00	1.00						
l_div	0.00	0.00	0.00	0.28**	1.00					
l_ta	-0.01	-0.01	0.01	0.66***	0.29***	1.00				
EBITDA_ Margin	0.06	0.03	0.02	0.11	0.30***	0.11	1.000			
TD/E	-0.06	-0.05	-0.13	0.16	-0.05	0.28**	0.032	1.00		
div_ni_return	0.06	0.05	-0.06	0.07	0.70***	0.03	0.232**	-0.01	1.00	
ROA	0.02	0.02	-0.01	0.12	0.35***	0.31***	0.241**	0.03	0.31***	1.00

Variables	res1	res7	res30	l_cap	l_div	rus_floor	l_shares_n	age	gov_share	ff_share	l_WRP
res1	1.00										
res7	0.78***	1.00									
res30	0.80***	0.87***	1.00								
l_cap	0.00	0.00	0.00	1.00							
l_div	0.00	0.00	0.00	0.28**	1.00						
rus_floor	-0.08	0.05	0.02	0.04	0.12	1.00					
l_shares_n	-0.03	0.07	0.07	0.47***	0.18*	-0.09	1.00				
age	0.01	-0.04	0.05	-0.34***	-0.15	-0.06	-0.22**	1.00			
gov_share	-0.06	0.06	0.05	0.23**	0.38***	0.20*	0.29***	-0.25**	1.00		
ff_share	-0.05	-0.10	-0.08	0.07	-0.22*	-0.19*	-0.11	-0.03	-0.12	1.00	
l_WRP	0.08	0.11	0.11	-0.03	0.07	0.03	-0.20*	-0.01	0.04	-0.21*	1.00

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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