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LOGIT-MODEL FOR PREDICTING STARTUP'S VENTURE FUNDING

The paper is devoted to deepening the academic basics using forecasting modeling methods to determine the predictors of enterprises' success. A startup as a form of entrepreneurship is important today due to the ability to maintain the sustainability of the economic system through a flexible response to challenges. The startup's potential for receiving external, direct venture financing from other economic counterparties is important forits sustainable development and success. The empirical study puts forward two hypotheses. The first one is that successful startups have common features, which are the factors in obtaining venture financing, i.e. predictors of success. The second hypothesis is a continuation of the first one and requires testing the importance of information representation and clarity of future startup results among venture investors, in particular through the information available about the startup's activity over the Internet. The empirical study is based on data sets about startups in Ukraine over the last decade. The simulation is performed with logit models developed by the authors. The calculation allows us to confirm the identification of factors of direct influence on the startup's success according to the built models. The ability to obtain venture capital is one of the startup's characteristics. The logit model is used as the research tool to determine the relevant factors for defining the positive decision of venture investors to provide startup funding. Predictors of obtaining external funding are identified and considered as the prerequisites for the startup's success in general. According to the research results,the presence of previous investors, the startup's profit orientation, the startup's website, and availability of information about its activity in the social network are the important factors for receiving external financing by a startup. Thepaper argues that the startup's focus on the public good without profit orientation does not stimulate venture investors. Two periods of the startup founding are singled out among the influence signs in deciding whether a startup will receive external financing: before 2014 and after it. The recognizability of a startup became the determining factor for venture financing after 2014 due to the information provided through the Internet. Until 2014, the relationship with large corporations' clients had been the most important feature for a startup with external venture financing.

Keywords: venture financing, logit model, predictors, public goods, business management.

Жибер Т. В., Лігоненко Л. О., Піскунова О. В., Шрівастава П., Гузік Т. А. Логіт-модель для прогнозування венчурного фінансування стартапів

Стаття присвячена поглибленню академічного доробку у сфері використання методів прогностичного моделювання для визначення предикторів успіху підприємств. Розглянуто методичні аспекти побудови логістичної моделі, за допомогою якої можна спрогнозувати успіх молодих підприємств (стартапів) для швидкого зростання за допомогою зовнішнього венчурного фінансування від зацікавлених інвесторів. Охарактеризовані особливості попередньої підготовки інформаційної бази та інструментарії обґрунтування

параметрів моделі. Стартап як форма підприємництва важливий сьогодні завдяки спроможності зберігати стійкість економічної системи через гнучке реагування на виклики. Для сталого розвитку та успіху самого стартапу важлива його спроможність отримувати зовнішнє, безпосередньо венчурне фінансування від інших економічних контрагентів. Були висунуті дві гіпотези: перша полягає в тому, що успішні стартапи мають спільні ознаки, які є чинниками отримання венчурного фінансування – предикторами успіху. Друга гіпотеза є продовженням першої та вимагає перевірки важливості інформаційної представленості і зрозумілості майбутніх результатів стартапу серед венчурних інвесторів, зокрема через наявність інформації про стартапи в інтернет-мережах. Емпіричне дослідження побудоване на даних про стартапи України в останнє десятиріччя, виконана симуляція за допомогою розроблених авторами логіт-моделей. Розрахунок за моделями дозволив підтвердити виокремлення чинників безпосереднього впливу на отримання стартапом венчурного капіталу в ознаках, притаманних стартапам. Інструментом дослідження була логіт-модель, яка визначає релевантні фактори, що обумовлюють позитивне рішення венчурних інвесторів щодо надання фінансування. Виявлені предиктори отримання фінансування, які розглядаються як передумови успіху розвитку стартапу. Серед вагомих чинників для отримання стартапом зовнішнього фінансування за результатами дослідження виокремлені такі: наявність попередніх інвесторів, орієнтація стартапу на прибуток, наявність інтернет-сторінки та інформації про стартап у соціальних мережах. Визначено, що орієнтація стартапу на публічне благо не стимулює венчурних інвесторів. За результатами моделювання впливу чинників – ознак стартапу – на отримання ним зовнішнього фінансування виокремлено відмінності в періоди заснування стартапів до та після 2014 р. Після 2014 р. визначальним чинником для венчурного фінансування стартапу стала впізнаваність його засновників за інформацією в мережі «Інтернет», тоді як до 2014 р. для отримання зовнішнього венчурного фінансування засновниками стартапу найважливішою для цього його ознакою були зв'язки з клієнтами великих бізнес-корпорацій.

Ключові слова: венчурне фінансування, логіт-модель, предиктори, публічне благо, управління бізнесом.

Problem statement. The entire history of civilizations' economic development may be described as the history of competitive struggle. Its severity has changed over time. These changes are related to the competition methods and organizing of entities. New methods of entities success activity have emerged alongside traditional competition methods. Creation and implementation of the innovations in response to the economic environment changing needs show the enterprises' ability for sustainable development [1].

The enterprise was and remains the base of the economy for all times; entrepreneurship is the driving force of creating an environment for change in order to adapt the economic activity to developing society needs [2]. In addition, new urgent innovations are needed to respond in a timely manner to current needs and challenges. [1]. The startup was recognized as the most dynamic activity among innovative economic activities, as a type of entrepreneurship in response to hither-unknown needs. Startups are able to find completely new niches for entrepreneurship for the economic traditions of a particular region [3]. They frequently grow up from the activities of universities, inventions of existing enterprise subdivisions, and freelancer's initiatives [4]. Startups can be a solution to problems that have accumulated during the application of previous management methods [4-5].

Startups are mostly formed spontaneously, so further deepening the basic academic knowledge for predicting their development is especially important. The development of startups in a market economy largely depends on the ability to attract funding [6], while the ways and proportions of this funding are diverse nowadays. In general, any method of obtaining financing can be divided into internal financing from the startup founder expense and external financing, which is separate from the change in the personal property status of the startup founders [7]. Venture financing is external in particular.

In order to investigate the controlling factors to predict the startup financing type, the data on startups activity in Ukraine have been applied. We offer a developed logit model with the identifying factors that will indicate successful attracting of external financing by the startups in the future. Publicity and clarity of informing other economic counterparties by the founders of a startup play a decisive role in its success – this assumption was placed among the factors of the model [8-9]. We consider the startup's success as its ability to sustainably exist and financially secure itself after gaining a space in the market [10]. We have come to the conclusion, based on the simulation results, that startups are more likely to receive financing from venture investors keeping in mind specific predictors regarding external market participation.

The article is organized as follows. The methods chosen to confirm the hypotheses, together with a review of supporting publications and data sources for the calculation are described in the first part of the article. The logit-model construction is described in the second section. The third part displays the model applications and main results of the study. The fourth section presents conclusions and prospects for further research.

The paper contributes to the academic literature on sustainable development of startups activity. The empirical examples of Ukraine were included in the research to identify and confirm the impact of external venture financing attraction factors within a developing economy.

Analysis of recent research. Logistic regression is one of the common methods of constructing a linear classifier, which allows estimating a posteriori probabilities of belonging to objects classes, as well as predicting the occurrence of a particular event. The dependent variable is binary (i.e. acquires one of two values). For example, the «zero» value means the event that did not occur, «one» means that the event occurred. That is, when applying logistic regression for linear classification, we will estimate the probability of a certain event occurrence depending on a certain list of predictors. The value of the dependent variable in the logistic model is always within 0 to 1, this eliminates the need for the researcher to apply an «artificial» restriction in the case of using a discriminant function. Predictive qualities in both discriminant and linear regression models are verified using a cross-validation procedure that means the

checking of the model results by substitutions with classifications data not used in modeling but known for the researcher [11-14]. There are numerous examples of successful applications of the logit models to solve economics problems in other researches, at a small sample in particular, with the use of various non-financial indicators as well [13].

The forecast model of the small manufacturing firms' attitude to export was proposed in [15] based on a small sample of small producers-exporters and non-exporters. The model predictors were the following: the level of small enterprises technologies, their ability to innovate, and their ability to develop inter-organization relations or partnerships. Lee T.-R et al. (2014) presented the possibility of building a binary logistic model (BLM) of testing results to determine target-oriented customers who are interested in certain types of marketing activities. These activities were identified to form standards for the model of sales monitoring (SOM) [16]. The questionnaire of the research contained indicators of demographic variables of lifestyle and a list of used marketing tools, forming basic information for the model. Skrzypek K. et al. (2017) developed the binary logistic model of industrial enterprises innovativeness estimation to create a synthetic integral indicator for considering various signs and characteristics of the enterprise [17]. Thus, there is a variety of experience in the econometric models constructed to predict the occurrence of certain events. The construction of models is based on the use of different economic indicators, social indicators, or evaluation characteristics as predictors.

The paper purpose is to identify the factors of influence (predictors of impact), which impact the external (venture) financing of startups in the market through the design of a particular logit model and its application with the public data.

Major research findings. Considering publicity and clarity of information about the startups, we put forward two hypotheses in the research:

1. There are certain factors of influence (predictors of impact) to obtain external (venture) financing for a startup in the market. According to the factors list, the startup must meet certain criteria and demonstrate specific characteristics.

2. The ability to formulate and show significant performance potential to market participants is the lead criteria for obtaining funding by a startup, among the other criteria.

We exploited the logistic regression to apply first hypothesis testing through the modelling. The Startup ranking service data [18] gathers information about the startups in Ukraine. This information was used to model the venture funding and measure predictors. The main purpose of the Startup ranking service is to track startups' growth placed on it. A description is provided for each startup registered on the site. The information is based on the country in which the startup is founded, its specific region (city), and the year of establishment. It provides information about the startup's activity directions, its products, spheres, key clients, the rank of novelty, patent

availability, investors, sums, dates of funding, competitors, team members, etc. In addition, the Startup ranking service calculates the SR Score, which shows each startup's representation in the Internet and its social impact. Several characteristics for the startup enterprise were included in the modelling. They were described in the next part of this article together with data on startups in Ukraine. Within our investigation, the software package StatSoftStatistica v. 8.0 was applied to construct the model.

The research covers 167 Ukrainian startups. 29 of them received external venture funding in 2010-2020. The predictors of impact on Ukrainian startups' venture funding have been suggested. In the previous research [19], the structure of Ukrainian startups' interrelations was examined based on the log-linear analysis. In order to deepen the previous analysis, the relationships between one dependent variable (response or the result of funding in particular) and other variables (independent variables or the predictors of funding) are investigated with the econometric modeling method, namely the logistic regression model.

The binary variable Y was considered to be an indicator in econometric models. The following factors were calculated to predict the availability of getting external funding for a startup enterprise: $Y = 1$ if external funding was received, $Y = 0$ – if otherwise. Taking into account the presented in [11] logline analysis results, the following variables were selected as the predictors:

X_1 is a source of funding. $X_1 = 1$ means the presence of previous investors. Previous investing of a startup indirectly indicates its experience in attracting external funding and ability to interact with investors. $X_1 = 0$ means self-financing (using only own sources of funds);

X_2 is a startup orientation. $X_2 = 1$ means startup orientation for profit (business orientation), $X_2 = 0$ – orientation for other goals of the startup (orientation only on the public good in particular);

X_3 is online presence and social impact. $X_3 = 1$ means availability of the startup's site and its presence in social networks, $X_3 = 0$ means otherwise;

X_4 is key customers. $X_4 = 1$ means B2B-orientation on business customers, $X_4 = 0$ is B2C – focus on individual customers as clients;

X_5 is the duration of the startup. $X_5 = 1$ means the startup was founded before 2014, $X_5 = 0$ means the startup was founded after 2014;

X_6 is the intellectual property rights. $X_6 = 1$ means the availability of a patent, $X_6 = 0$ means forbidding of a patent.

During the econometric model construction, various assumptions are possible regarding the dependence of Y_i ($i = \overline{1,n}$, n - the number of observations) on X_{ji} ($i = \overline{1,n}, j = \overline{1,m}$, m - the number of predictors in the model). We used the usual linear regression model $Y_i = b_0 + b_1 X_{1i} + ... + b_m X_{mi} + \varepsilon_i$ and obtained the linear probability model line:

$$E(Y_i) = 1 \cdot P(Y_i = 1) + 0 \cdot P(Y_i = 0) = P(Y_i = 1) = b_0 + b_1 X_{1i} + ... + b_m X_{mi} + \varepsilon_i.$$

where $E(Y_i)$ - mathematical expectation Y_i .

Previous model construction has a number of disadvantages. The most significant disadvantage is that

predicted by such a model values of the indicator Y_i may gobeyond the segment [0; 1] and may not be reasonably interpreted. To overcome this shortcoming in probability

modeling, the $P(Y_i=1)$ function was selected to unobservable (latent) variable $Z_i = b_0 + b_1 X_{1i} + ... + b_m X_{mi} + \varepsilon_i$, which values range is in the segment [0; 1]:

$$P(Y = 1) = F(Z_i).$$

Z_i can be interpreted as some unobservable (latent) variable, which determines the case of receiving the startup funding: if the Z_i value exceeds zero ($Z_i > 0$), then the case occurs and $Y_i = 1$. Otherwise, if $Z_i < 0$, then the case does not occur and $Y_i = 0$ [20].

The function selection $F(\bullet)$ determines the type of the binary model. This function $F(\bullet)$ can be as the standard normal distribution function (then we will have a probit-model) or the logistic distribution function (in this case we will create a logit-model). For samples with a small scatter of the explanatory variable's values, as in our case, obtaining the qualitative conclusions by using probit-models and logit-models has no difference.

Next, we will construct the model of logistic regression as follows:

$$p_i = P(Y = 1) = \frac{1}{1 + e^{-Z_i}} = \frac{e^{Z_i}}{1 + e^{Z_i}}. \tag{1}$$

Because p_i is the probability of receiving funding for the startup i, then $1 - p_i$ means the probability for the startup i not to obtain venture external funding. Then the ratio between chances of getting and not getting the funding will be equal to $\frac{p_i}{1-p_i}$. For the logit-model, the natural logarithm of the odds ratio depends linearly on the model's factors as follows:

$$\ln\left(\frac{p_i}{1 - p_i}\right) = b_0 + b_1 X_{1i} + b_2 X_{2i} + ... + b_m X_{mi} + \varepsilon_i \tag{2}$$

or

$$\frac{p_i}{1 - p_i} = e^{b_0 + b_1 X_{1i} + b_2 X_{2i} + ... + b_m X_{mi} + \varepsilon_i}. \tag{3}$$

The formula 2 will help us with the meaningful interpretation of the logit-model parameters: for the j-th binary independent variable, the regression coefficient in exponential form e^{bj} shows how much the odds ratio will change if the value of the variable is equal to 1.

The Stata application package was used for further calculations. The logit-model evaluation results contain estimates of the parameters obtained by the method of maximum plausibility b_j, corresponding p-values of Wald's statistics (p-level), and the value of the exponent e^{bj} parameters as shown in Table 1. The table also contains the final statistics: the value of logarithmic likelihood function Log likelihood; the value of likelihood ratio LR, the values of Hosmer-Lemeshaw statistics, and their corresponding p-values.

Table 1

The results of logit models evaluation based on the information about startups

Model factors X_j	Model 1			Model 2			Model 3		
	b_j	p-level	b^{bj}	b_j	p-level	b^{bj}	b_j	p-level	b^{bj}
const	-5.52	0.000	0.004	-5.06	0.000	0.01	-6.22	0.000	0.00
X_1	2.89	0.000	18.0	3.00	0.000	20.1	3.14	0.000	23.0
X_2	1.40	0.055	4.06	1.37	0.056	3.95			
X_3	1.08	0.076	2.96	1.10	0.059	3.01	3.24	0.009	25.4
X_4	0.60	0.360	1.83				0.74	0.281	2.10
X_5	0.82	0.156	2.28						
$X_2 \cdot X_5$							3.26	0.003	26.0
$X_3 \cdot X_5$							-2.75	0.029	0.06
$X_4 \cdot X_5$				1.20	0.099	3.33			
Log likelihood	-48.7			-48.7			-44.4		
LR-statistics	56.8			56.8			65.3		
p-values for LR - statistics	0.000			0.000			0.000		
Hosmer-Lemeshaw statistics	2.52			3.61			3.26		
p-values for Hosmer-Lemeshaw statistics	0.9607			0.6073			0.8601		

Source: developed by the authors.

The variables included in the models were analyzed for multicollinearity in terms of tolerance $1 - R_j^2$, where R_j^2 is the square of the multiple correlation coefficient of j-th independent variable with all other predictors. The indicator VIF is called the coefficient or the factor of «removal» of the variance. It is calculated as $VIF = \frac{1}{1-R_j^2}$ and put inverse to this value. The tolerance of the variable approaches 0 and the value of the indicator VIF will grow

rapidly in the presence of multicollinearity. It is believed that the value of this indicator exceeding 5 indicates the presence of multicollinearity. In all cases considered in our research evaluation values VIF did not exceed 2.5.

Table 1 content shows that values of LR-statistics exceed the critical values and the corresponding p-values are less than 0.001 for all three models. The ratio of the maximum value of plausibility function for regression without constraints to the maximum value of the plausibility function for regression with constraints is much greater than 1, displayed by modelling. That is, the null hypothesis of the simultaneous equality to zero for all coefficients of the model should be rejected with the less than 1% probability error for all three models. Thus, the observed data can be considered adequate. Note that the statistics LR has a distribution χ^2 and it is an analogue to F- statistics in linear regression models.

Hosmer-Lemeshow's criterion χ^2 is an additional test to verify the observation data adequacy of the constructed model. This criterion of agreement serves to assess models fitting to the quality standard. The Hosmer-Lemeshow test compares the observed and expected frequencies of cases, when $y_i = 1$ in cases of obtaining external funding. The p-value for Hosmer-Lemeshow statistics in each considered model is greater than critical as you can see from Table 1, which does not allow toreject the null hypothesis when observed and expected frequencies of obtaining funding are different. That is, the evaluation results of built models can be considered adequate, as presented in Table 1.

Let us move on to obtained results interpretation. Initially, the logistic regression model (model 1) was constructed including factors $X_1,...,X_5$ described above. Positive estimates of the model parameters were obtained for all included in the model factors, as shown in Table 1. Evaluation analysis of the model 1 results shows that the factor X_1 is the greatest influencer on obtaining the funding–the presence of previous investors: this factor is significant at less than 0.001 significance level. Factors X_2, X_3 – orientation of the startup to make a profit and its presence on the Internet (presence of the site and presence in social networks) – also have a significant positive impact. At the same time, parameters for variables X_4, X_5 were positive but insignificant, so we can consider the impact of these factors on the explored indicator as accidental.

The value of the exponent e^{bj} shows how the ratio of the chance for getting external funding to the chance of not getting external funding will change if the factor X_j is equal to 1. As you can see in Table 1, with the presence of previous investors and other things being equal, the odds increase 18 times, while with the business orientation of the startup – up to 4 times. The fact that a startup provides proper Internet activity means site promotion and a large number of subscribers in social networks, the odds increase almost 3 times.

For model 1, the following linear function Z_j is obtained:

$$\hat{Z}_i = -5{,}52 + 3{,}00 \cdot X_{1i} + 1{,}40 \cdot X_{2i} + 1{,}08 \cdot X_{3i} + \cdot 0{,}60 \cdot X_{4i} + 0{,}82 \cdot X_{5i}. \tag{4}$$

As mentioned above, we can consider the magnitude Z_j as some latent variable that determines the fact (case) of receiving external funding. A startup is expected to receive external funding if the value of this function exceeds 0. Formula 3 displays that the following conditions are met for expected venture financing for the startups founded after 2014 ($X_{4i} = 0$): the presence of previous investors, B2B startup orientation, availability of its site and presence in social networks, business orientation of the startup (for profit). Venture financing expectations for startups founded before 2014 ($X_{4i} = 1$) were affected by the previous investors and a division of the existing business. And at least two of the following conditions were to be met: the startup profit orientation as well as the availability of its site and presence in social networks. Therefore, our second hypothesis statement, that is, the growth of the ability to show a startup performance and information about it on the Internet, started gaining importance. Thus, it has been partly confirmed. Consequently, if several market venture investors approved performance information of the startup, it was the best predictor to obtain more venture capital in 2010-2013.

To deepen the research, the interaction of the factors was analyzed. The factors X_1, X_2, X_3 were included in model 2 and $X_4 \cdot X_5$ factors were added, reflecting the interaction of the factors X_4 and X_5. All coefficients in the model are positive and significant. As in model 1, the indicator is significantly influenced by such factors as the presence of previous investors, the startup orientation to make a profit and the availability of the startup's site, and

the information about its performance in the social networks. The positive coefficient of factors $X_4 \cdot X_5$ means that the focus of the startup's activities on business clients had a positive impact on obtaining the external funding for the startups established before 2014.

Model 3 takes into account the interaction of factors X_2 and X_5, as well as the interaction of the factors X_3 and X_5. According to the evaluation results presented in Table 1, the factors X_2 i X_3 impact the indicator Y in different ways depending on when the startup was founded. Thus, the profit orientation of the startup has a significant positive impact on the indicator Y for the startups founded before 2014. The availability of a website and a startup's presence in social networks significantly increase the likelihood of receiving external funding, but for startups founded before 2014, this impact was much lower than for startups founded in 2014 or later.

It should be noted that only 17% of the total number of startups considered among our sample of data on 167 startups in Ukraine received external venture financing. This distribution of the dependent variable can lead to distortion of the simulation results. It is possible to change the distribution by using the method of thinning or the method of weighing the sample.

We composed data to obtain a sparse sample with 100% of startups that received funding and randomly selected 58% of startups that did not receive funding. The transformation led to the reduction of the data sample to 109 startups. The second sampling strategy for the modelling, i.e. statistical weighing, is better in our case because of a relatively small sample size. The results of

logit-regression models constructed for sparse and weighted samples are given in Table 2.

The results obtained for the original sample, as well as for the adjusted samples, do not differ significantly as the comparative analysis of Table 1 and Table 2 shows.

To examine the factor X_6 (protection of intellectual property rights) influence on obtaining the external funding, Model 4 was built with included factors X_2, X_3, X_6 and the interaction of factors X_4 and X_5. After the parameter estimation by the method of maximum likelihood, the next model is obtained:

$$\ln\left(\frac{p_i}{1-p_i}\right) = -2{,}84 \quad +1{,}22 \cdot X_{2i} \quad +1{,}47 \cdot X_{3i} \quad -1{,}04 \cdot X_{6i} \quad +1{,}38 \cdot X_{4i} \cdot X_{5i}.$$

$$(0{,}064) \qquad (0{,}004) \qquad (0{,}050) \qquad (0{,}020)$$

(5)

Table 2

Estimates of model parameters obtained from different sampling strategies

Model factors	Weighed data			Thinning data		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
const	-4.752 (0.000)	-4.146 (0.000)	-5.487 (0.000)	-4.673 (0.000)	-4.319 (0.000)	-5.572 (0.000)
X_1	2.775 (0.000)	2.919 (0.000)	3.097 (0.000)	2.584 (0.000)	2.753 (0.000)	2.890 (0.000)
X_2	1.285 (0.028)	1.298 (0.025)		1.168 (0.130)	1.219 (0.104)	
X_3	1.242 (0.014)	1.167 (0.018)	3.255 (0.001)	0.929 (0.145)	0.961 (0.116)	3.111 (0.015)
X_4	1.156 (0.047)		1.238 (0.041)	0.618 (0.370)		0.859 (0.246)
X_5	0.990 (0.041)			0.865 (0.150)		
$X_2 \cdot X_5$			3.427 (0.000)			3.250 (0.005)
$X_3 \cdot X_5$			-2.721 (0.006)			-2.825 (0.032)
$X_4 \cdot X_5$		2.026 (0.006)			1.309 (0.094)	
Log likelihood	-64.50	-64.07	-57.67	-42.29	-42.27	-38.05
LR- statistics	86.68	87.55	100.34	41.71	41.74	50.18
p-values for LR-statistics	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hosmer-Lemeshaw's statistics	5.52	6.89	6.08	2.69	3.88	2.87
p-values for Hosmer-Lemeshaw's statistics	0.7009	0.2288	0.5303	0.9523	0.5665	0.8969

Source: developed by the authors.

Formula 4 implies the negative effect of a patent presence on the probability to receive external startup funding: the negative and significant coefficient of the model for the factor X_6 is the protection of intellectual property rights. This may indicate that with fixed values of other factors – the startup orientation, Internet presence and its social impact, key customers, and startup activity duration – investors will prefer innovative startups whose products and ideas are not protected by intellectual property rights yet.

Conclusions. The results of the analysis show the possibility of forecasting the successful obtaining of venture financing by enterprises (for example, startups) through the use of logistic regression methods. While researching, it was possible to develop models with acceptable statistical characteristics and good predictive properties. The built models show consistent results, so the first stated hypothesis about the common influencing factors as the signs of positive decision about startup venture financing was confirmed. The presence of previous investors, the startup's focus on profit, the existence of the startup's Internet page, and the

information about the startup in the social networks are the main and important impact factors on the startup's external funding. All these mean the expanding of the second hypothesis.

The startup's focus on business customers had a significant positive impact. Its influence depended on the startup establishment year. Summing up, the ability to perform for investors, startup focus on profit, and its Internet presence are the key factors for obtaining external funding by a startup. The impact of website availability and information about activities on the Internet has increased significantly since 2014. The X_4 predictor that means «key customers of the startup are representatives of business structures» had had the main influence on the external funding by 2014.

Despite the positive research result in general, a clear and critical limitation of further attempts in building economic and mathematical models should be emphasized. The following sufficient data is lacking for forecasting various manifestations of the enterprise success: obtaining financing, conducting an IPO, selling a startup to a strategic investor, etc. However, with quality data, the models may comply with the requirements of

logistical analysis and increase the number of freedom degrees. Logistic regression is more suitable for classification models in general because it determines the critical level of probability beyond which a successful event can be predicted. Despite the advantages of logistic regression, the discriminant model for additional comparison of results can be used. The similarity of the results may indicate the correctness of classification, while the discrepancy is a reason for more in-depth analysis.

The process of improving the prediction of Ukrainian enterprises success on the example of startups can be divided into two interrelated components: the first one, the quality and availability of the information about various aspects of changes of the startup activities will increase the sample, the other one, more advanced methods, including simulation and neural networks, can be effective on small sample sizes.

The results of this study are expected to become a solid background to continue the scientific debate on whether innovative startups that are really useful with public goods to society but whose unprofitability cannot attract economic agents will not be able to obtain venture financing from the market. For example, part of society rejects the idea of global climate change. Is it obvious that in order to solve such common problems in society as energy security or cybersecurity, the state should support activities of innovative startups with public funds [10] still unknown to society or controversial in terms of profitability to find the latest effective market solution?

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