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CAN WE PREDICT HIGH GROWTH FIRMS WITH FINANCIAL RATIOS?

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Abstract

This study attempts to predict high growth firm (HGF) status with financial ratios. Measures related to the firm's effectiveness in using assets to generate profits, EBITDA margin, debt ratio, equity-to-debt ratio and return on assets are associated with HGF status. While the financial ratios improve HGF prediction, prediction remains modest (AUC = 0.627). This study suggests it is difficult to assume a very good HGF forecast from only financial ratios; therefore, the recommendation for researchers and policymakers building models for predicting HGFs is to incorporate non-financial ratio variables, like the intangible innovation and team-related variables. Finally, study suggests a standardized reporting of prediction performance metrics in the out-of-sample and out-of-time simulation for HGF prediction studies.

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Introduction

A small 3-6% of the total number of firms, so-called high growth firms (HGFs) have been found to create 30-50% of all new jobs in the economy[2]. Improvement in prediction of HGFs could assist in better allocation of funds by banks and investors to firms, but also better targeting of growth and innovation policies towards firms with potential. For example, public grants are found to cause additional growth in sales and employment (reviewed in Dvouletý et. al., 2021), while export boosting policies were found to cause the introduction of new exported products, and access to new export markets (reviewed in Srhoj et. al., 2020). Can these policies be better tailored to focus on firms with growth potential? A natural first step in answering this question is asking whether it is possible to predict HGFs? Studying prediction of HGFs has been the objective of many academic researchers (Coad et. al., 2014) and international organizations like the World Bank and the European Commission (i.e. Flachenecker et. al., 2020; Goswami et. al., 2019).

However, the attempts to predict HGFs have been rather challenging. Coad and Srhoj (2020; Table 1) review previous attempts to predict HGFs and suggest attempts have been rather unsatisfactory. The same authors use census dataset with hundreds of variables and machine learning techniques to predict HGFs, however, this yielded sensitivity y score of just 56% and Pseudo R2 of about 10%. Weinblat (2018) use random forest on the sample of seven European countries to predict HGFs with accuracy ranging from 73-90%, at the expense of precision metric as low as 11%. Daunfeldt and Halvarsson (2014) termed HGFs as "one-hit-wonders", and Coad et al. (2013) have suggested firm growth can be best modelled as a random walk.

If one stacks all the firm growth rates in a distribution, the right side of the distribution (i.e. the right tail) are the HGFs (or high growth episodes), while the left side of the distribution are the fast-declining firms from which some end-up in bankruptcy. The finance literature (Altman, 1968; Crosato, Domenech, & Liberati, 2021) has found that financial ratios do exceptionally well in predicting firm bankruptcy. Strangely, there are very few attempts to investigate the importance of financial ratios for prediction of HGFs, although practitioners at a daily level (i.e. banks, investors) use financial ratios. This study investigates 16 financial ratios and their capability to predict HGF status. In other words, the aim of this study is to test financial ratios[3] power in predicting HGFs.

Materials and methods

Dataset for the analysis stems from the Financial Agency (FINA) in the Republic of Croatia. FINA dataset provides a universe of all firms in the economy with as many as 300 balance sheet and profit and loss statement variables for each firm-year over a period of 2010 -2019. In the period 2010-2019 there are 101–137 thousand firms. To define HGF indicator I apply a standard Eurostat-OECD definition (Eurostat-OECD, 2007), with a modification of threshold at 5 employees (OECD 2013, p. 49). An HGF indicator is a dummy of 1 for firms with 5 or more employees (E) in the initial period (t = 0), and a geometric average of at least 20% growth per year over 3 years, thus 72.8% over 3 years (in turnover, or employment). In other words, HGFt = 1 if the following conditions are satisfied:

$$\left(\frac{E_{t+3}}{E_t}\right)^{\frac{1}{3}} - 1 \geq 20\%$$

With a restriction on initial size:

$$E_{t=0} \geq 5$$

There are three three-year periods (2010-2013, 2013-2016, and 2016-2019). Study undertakes the 'real -time HGF prediction simulation' by training the model on the first two, and testing on the last period. In the train sample there are 2012 employment, and 4966 turnover HGFs. In the test sample there are 1575 employment, and 3175 turnover HGFs[4]. To obtain balanced data, study randomly selects the same per-year number of non-HGFs in train and test samples. For the potential independent variables, study includes a list of 16 financial ratios, Altman Z' and Z'' score (Altman, Iwanicz-Drozdowska, Laitinen, & Suvas, 2017; Weinblat, 2018), as well as Z' categories (Table 1). The independent variables are measured in time period t, while the dependent variable is based on the information in t + 3,

[2] For multiple countries: Goswami, Medvedev and Olafsen (2019), in United Kingdom (Du & Temouri, 2015), in Slovenia (Srhoj et. al., 2018), or in Peru (Coad & Scott, 2018).

[3] One of the rare studies is Weinblat (2018) who uses seven financial ratios and random forest algorithm.

[4] Majority of firms are below 5 employees, which is why a large share of firms cannot be HGFs in period t by definition, for example. if a firm has 3 employees in 2010 it cannot be HGF for the period 2010-2013. For details on why size restrictions are implemented in the HGF, authors can consult: Eurostat-OECD (2007).

Table 1: Financial ratios

Variable	Definition
X1	Working capital / total assets
X2	Retained earnings / total assets
X3	EBIT / total assets
X4	Book value of equity / total liabilities
X5	Sales / total assets
X6	Current ratio = current assets (non-financial)/ current liabilities (non-financial)
X7	Quick ratio = cash / current liabilities (non-financial)
X8	EBITDA / turnover
X9	Cost of goods sold / turnover
X10	Value added / fixed assets
X11	EBIT / total investments
X12	Debt ratio = total debt / total assets
X13	Return on assets = (net profits + interests on borrowed capital) / total assets
X14	Return on sales = (net profits / sales)
X15	Fixed assets / total assets
X16	Book value of equity / fixed assets
Altman Z' Score	0.717*X1 + 0.847*X2 + 3.107*X3 + 0.420* X4+ 0.998*X5
Altman Z'' Score	3.25 + 6.56*X1 + 3.26*X2 + 6.72* X3 + 1.05*X4
Altman Safe Zone	Altman Z' score > 2.99
Altman Grey Zone	1.81 < Altman Z' score < 2.99
Altman Distress Zone	Altman Z' score < 1.81

Source: Own elaboration.

Least absolute shortage and shrinkage operator (LASSO) algorithm is applied for variable selection (details in: Belloni, Chernozhukov & Wei, 2016; Tibshirani, 2011) in the train samples. To do so, I follow steps on applying LASSO with firm-level data (as in: Coad & Srhoj, 2020). I then conduct a logit model with selected variables on the train sample. Based on the predictions in the train sample, I predict HGF status on the out-of-sample and out-of-time test sample.

Results

The logit model

For selecting financial ratios from Table 1 I apply LASSO algorithm (Coad & Srhoj, 2020). Four financial ratios are selected per HGF indicator (see Table 2). These financial ratios are checked with respect to their correlation, and additionally, multicollinarity is inspected with variance inflation factors (VIFs). Correlations and VIFs do not pose a problem in the analysis. Logit models are run with these financial ratios and include several standard controls: industry NACE 1-digit dummy. Results shown in Table 2 indicate 1% increase in the firm's effectiveness in using assets to generate profits (EBIT / Total assets) in period t is associated with 3% increase in the probability of being HGF employment status. Interestingly, an increase in debt ratio of 1% in period t is positively associated with 0.6% higher probability of being HGF turnover status. This indicates HGFs use financial leverage already in period t to preparing for the turnover growth episode. Increase in gross profit margin (Cost of goods sold / turnover) is negatively associated with the probability of HGF employment or sales status. A 1% increase in gross profit margin is associated with a decreased probability of becoming HGF employment (-0.3%) and HGF turnover (-0.7%) status. An increase in ROA is associated with 0.5% lower probability of HGF employment status, but there is no relationship for the HGF turnover indicator. EBITDA margin (EBITDA / turnover) is negatively associated with the HGF turnover status. An 1% increase in EBITDA margin is associated with 0.5% decrease in the probability of being HGF turnover status.

Table 2: Logit: predicting HGFs

	Dependent variable:			
	HGF employment		HGF sales	
	Train sample	Full sample	Train sample	Full sample
	(1)	(2)	(3)	(4)
EBIT / total assets	3.510***	2.961***		
	(0.155)	(0.119)		
Book value of equity /total liabilities	0.900***	0.894***	0.976**	0.956***
	(0.016)	(0.011)	(0.010)	(0.008)
EBITDA / turnover			0.507***	0.542***
			(0.074)	(0.060)
Cost of goods sold /turnover	0.690**	0.741***	0.284***	0.343***
	(0.148)	(0.114)	(0.102)	(0.082)
Return on assets	0.535***	0.625***		
	(0.117)	(0.082)		
Debt ratio			1.563***	1.544***
			(0.067)	(0.053)
Constant	2.561***	1.745***	1.743***	1.470***
	(0.254)	(0.185)	(0.161)	(0.128)
Observations	4,024	7,174	9,932	16,282
Log Likelihood	-2,640.867	-4,736.964	-6,546.471	-10,751.010
Akaike Inf. Crit.	5,369.733	9,561.929	13,180.940	21,590.020

Note: Coefficients in the table represent the relative risk ratios, calculated as the exponentiated value of the logit coefficients. Logit regressions include NACE 1-digit industry dummies, county dummies and firm size dummies. *p**p***p < 0.01.

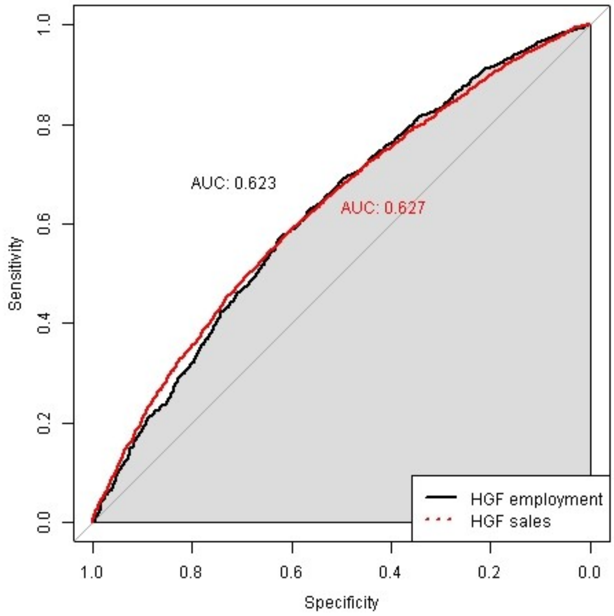
Source: FINA based on author calculations.

Out-of-sample and out-of-time prediction

After running the logit models (Table 2) on the training data, models are tested on the test sample. Figure 1 shows the ROC curve and the AUC.

Some studies report AUC or Pseudo R2, others accuracy, precision, sensitivity or specificity. This study reports multiple prediction metrics (Table 3), compares them to two related studies (Coad & Srhoj, 2020; Weinblat, 2018) and suggest this reporting for the forthcoming studies. Overall, the AUC, accuracy sensitivity and specificity show modest performance (compared to Coad & Srhoj, 2020; Weinblat, 2018), however, precision outperforms Weinblat (2018).

Figure 1: Receiver operating characteristic curve



Source: Own elaboration.

Table 3: Standardized prediction performance metrics reporting

Metric	This study		Other HGF studies		
			Coad and Srhoj (2020)		Weinblat (2018)
	HGF empl.	HGF sales	HGF empl.	HGF sales	HGF Birch-Schreyer definition
AUC	0.623	0.627	-	-	0.577 – 0.701
Pseudo R^2	0.053	0.049	0.096 – 0.130	0.133 – 0.155	-
Accuracy	0.595	0.594	0.765 – 0.948	0.724 – 0.888	0.630 – 0.902
Sensitivity	0.601	0.591	0.248 – 0.569	0.381 – 0.578	0.158 – 0.653
Specificity	0.590	0.598	0.773 – 0.958	0.739 – 0.911	0.655 - 0.962
Precision	0.566	0.612	-	-	0.109 – 0.299
Kappa	0.190	0.189	-	-	-
Accuracy Lower	0.578	0.582	-	-	-
Accuracy Upper	0.612	0.606	-	-	-
Accuracy Null	0.530	0.518	-	-	-
Accuracy P Value	0.000	0.000	-	-	-
Mcnemar P Value	0.010	0.029	-	-	-
Pos Pred Value	0.566	0.612	-	-	-
Neg Pred Value	0.625	0.577	-	-	-
Recall	0.601	0.591	-	-	-
F1	0.583	0.601	-	-	-
Prevalence	0.470	0.518	-	-	-
Detection Rate	0.283	0.306	-	-	-
Detection Prevalence	0.500	0.500	-	-	-
Balanced Accuracy	0.596	0.594	-	-	-

Note: The majority of are calculated by R's function confusionMatrix from the caret package based on test sample. The cut-off is set to the value of detection prevalence (0.5).

Source: FINA based on author calculations.

Conclusions

Can we predict high growth firms with financial ratios? This study tries to answer this question by making an attempt to predict HGFs with financial ratios. LASSO algorithm selected financial ratios on the training sample and confirmed them in the out-of-time test sample. Positive associations include firm's effectiveness in using assets to generate profits, and debt ratio, while negative associations include equity-to-debt ratio, EBITDA margin and ROA. Even though financial ratios do improve prediction, the overall prediction performance is below the acceptable level (AUC = 0.627). It is difficult to assume high growth can be predicted from financial ratios. Future studies could non-financial ratio variables, like intangible innovation and team related variables in the prediction of the HGFs. For example, Megaravalli and Sampagnaro (2019) obtain an AUC of 0.7, but in addition to financial variables also use non-financial ratio variables like firm age which is found to be important for HGFs (Coad & Karlsson, 2022). Future research should examine other non-financial ratio variables that can improve prediction performance for HGF status, conduct sector-specific analyses and separate analyses for main firm characteristics, like acceptance of new technology, new product introductions, export status, firm size, age, etc. Finally, to assist in comparison of any forthcoming studies on predicting HGFs, a standardized reporting of prediction metrics is suggested.

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Appendix

Table A1: Correlation in the sample for HGF employment indicator

	EBIT / Total assets	Book value of equity / Total liabilities	Cost of goods sold / Turnover	Return on assets
EBIT / Total assets	1.00	0.20	-0.08	0.20
Book value of equity/ Total liabilities	0.20	1.00	-0.10	0.31
Cost of goods sold / Turnover	-0.08	-0.10	1.00	0.10
Return on assets	0.20	0.31	0.10	1.00

Source: Own elaboration.

Table A2: Correlation in the sample for HGF turnover indicator

	Book value of equity / Total liabilities	EBITDA / Turnover	Cost of goods sold / Turnover	Debt ratio
Book value of equity / Total liabilities	1.00	0.06	-0.08	-0.60
EBITDA / Turnover	0.06	1.00	-0.31	-0.24
Cost of goods sold / Turnover	-0.08	-0.31	1.00	0.00
Debt ratio	-0.60	-0.24	0.00	1.00

Source: Own elaboration.

Table A3: Variance inflation factor: HGF employment and turnover status

	HGF employment	HGF turnover
EBIT/ Total assets	1.109	
Book value of equity / Total liabilities	1.165	1.642
EBITDA / Turnover		1.211
Cost of goods sold / Turnover	1.037	1.165
Debt ratio		1.691
Return on assets	1.170	

Source: Own elaboration.