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HEALTHCARE SECTOR STARTUP VALUATION AND FUNDING: EXPLANATORY ANALYSIS OF FINANCIAL, HUMAN CAPITAL AND INTELLECTUAL PROPERTY DOMAINS

Master’s Thesis

Supervisor: Senior Research Fellow Oliver Lukason, PhD

Tartu 2020

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Abstract

The aim of the current study is to reveal whether total funding and estimated valuation of startup firms can be associated with financial, human capital, and intellectual property domain measures. 96 startup firms representing healthcare sector were selected for multiple linear regression analysis. Average employee cost and number of patents are associated with funding and valuation in a range of 50-60% of variance explained. Funding and valuation normalized to total assets are associated with profitability and leverage measures in a range of 15-25% of variance explained. Associations are stronger for more mature firms and firms with intellectual property portfolios.

Keywords: startup, funding, valuation, human capital, intellectual property

CERCS: S181, S190

1. Introduction

Rapid growth of technology leads to founding of numerous startup firms whose goal is to commercialize new inventions. Usually firm is considered to be a startup when it is managed by founders, it has not yet reached break-even, and they have fast growing business potential (Birley and Westhead 1994; Oe and Mitsuhashi 2013; Paternoster et al. 2014).

Startup firms require continuous funding for product development and market entry. Those funds usually are acquired from FFF (founders, family, friends), BA (business angels), VC (venture capital), crowdfunding or bank loans. Depending on a growth phase of startup, one of these financing instruments are used. However, in all these cases it is important to value the company prior any investment. Although there are several methods for startup valuation reviewed and analyzed in the literature (Aydın 2015; Damodaran 2009; Festel, Wuermseher, and Cattaneo 2013), none of them are perfect and in certain cases final decision drivers remain unclear. Therefore, *a posteriori* analysis to find what measures associate with startup firm value and funding is useful. This is important for both, entrepreneurs and funders. From entrepreneurs' perspective, knowing those key measures helps them to focus on those measures to improve their firm for higher valuation and better funding. From funders perspective, they need to foresee potential of future success and this can be based on present key measures.

Healthcare sector is highly regulated and thus market entry barrier is high in comparison with other sectors. Therefore, startup firms active in the healthcare sector require substantial funding. However, the sector has an annual growth rate of 8.9% according to a recent market analysis (Wood 2019) and with clear global needs it is attractive for investments. Considering previously mentioned aspects, funding decisions and valuations in this sector are more rational and less driven by emotions.

Objective of the study is to reveal whether total funding and estimated valuation of startup firms can be associated with financial, human capital, and intellectual property domain measures. Firms with known total funding and estimated valuations representing healthcare sector was selected. Further, information about their financial, human capital, and intellectual property domain measures were collected. Obtained data was analyzed with multivariate linear regression.

The results indicate that financial domain measures, specifically profitability measure NI/TA are associated with both ratios, funding and valuation to total assets. Likewise, human and intellectual property domain measures, specifically employee cost and number of patents are associated with both, funding and valuation. The associations between funding and valuation with given domains measures are similar in sign and magnitude.

This article is structured as follows: (i) Literature overview that provides main related findings from relevant literature, (ii) Methods and Data that introduce used methodology and data collection with variables calculated based on it, (iii) Results and Analysis that provides regression models with descriptions, (iv) Discussion that explains study findings and relates it with literature, and (v) Conclusion that summarizes the work.

2. Literature overview

Startup firms are oriented for rapid growth. They constantly need funds for their development activities. Despite that funding source can be different, firms need to be ongoingly valued.

The literature review focuses on the three domains provided in Figure 1 as most usually cited in the literature in conjunction with startup firm funding and valuation.

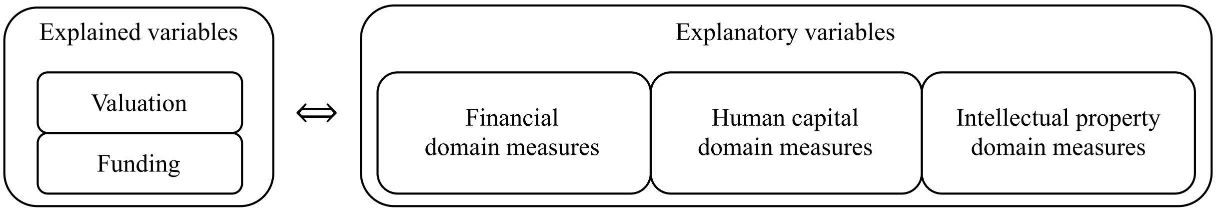

Figure 1. Associated variables and domains.

Internal finance is shown to be most prevalent among small firms in high-tech industries (Himmelberg and Petersen 1994). Startup firms can use credit lines (such as bank debt and term loans) to fund their development investments. Guney et al. study shows that there is a significant relationship between used credit lines and R&D investment and this effect is relatively stronger for small and younger firms (Guney, Karpuz, and Ozkan 2017). But importance of external finance such as private equity investments is growing over the years (Hirukawa and Ueda 2011; Ning, Wang, and Yu 2014). This growth is significantly higher in medical devices and biotechnology sectors (Greg Borenstein 2010). While startup firm funding sources can be different, mostly venture capital (VC) funding measures and drivers are analyzed in literature. Particularly, Marullo et al. modeled startup success with three domains (i) financial, (ii) human capital, and (iii) intellectual property measures (Marullo et al. 2018). The same domains are used in current study and are discussed below.

2.1. Domain of financial measures

Barth et al. analyzed market value correlation with equity book values as financial health (Barth, Beaver, and Landsman 1998). They found that investors emphasize the importance of equity book value or net income as financial health measure and account them in valuation with positive contribution. Relevance of financial versus non-financial measures in valuation of VC backed firms were analyzed in literature (Sievers, Mokwa, and Keienburg 2013). Their results show that financial information (revenues, sales, general & administrative expenses, research and development expenses, and cash) is as important as non-financial information (team composition, CEO education, team experience, reference customers, and number of patents), explaining individually about 50% of variation in valuation. Cash and general & administrative financial measures show the strongest association with valuation in their study models. However, they also show that in combination of financial and non-financial measures they reached 64% of explained variation in valuation.

Several approaches to measure firm's health in perspective to predict bankruptcy have been proposed and analyzed (Charitou, Neophytou, and Charalambous 2004; Pindado, Rodrigues, and Rodrigues 2017; Platt and Platt 2002; Pompe and Bilderbeek 2005). Those authors propose various financial ratios that are generalized into four groups according to Laitinen: (i) Profitability, (ii) Liquidity, (iii) Solidity, and (iv) Other factors (Laitinen 1992). The importance of these ratio domains is concluded in rather recent study where normalization to total assets (i.e. having total assets in the ratio denominator) has been applied, for example EBIT/TA, NI/TA, WC/TA, NFA/TA, RE/TA or S/TA (Lukason, Laitinen, and Suvas 2016, pp. 1972). Besides the latter, often is used normalization to Current Liabilities (CL) or Total Debt (TD).

Similarly, ratios to total assets are used in investment-cash flow sensitivities' modeling. The basis of their study was to substitute Tobin's Q with investment to total assets ratio and they show that cash flow, previous investments, and turnover are significantly positively associated with investment (D'Espallier, Vandemaele, and Peeters 2008). Therefore, the health of a particular firm among its financial measures is important for valuation and investment decision.

2.2. Domain of human capital measures

Human capital (HC) is important to most firms and it usually improves performance (Hitt 2001). Several components contribute to HC. For instance founder's and workers' education, age, experience, and skills are considered (Dimov 2017; Marullo et al. 2018; Rocha et al. 2019). Also, HC effect has been analyzed via labor (Lee 2019).

Baum et al. used time series regression techniques to analyze pre-IPO financing revenue, R&D spending, and number of R&D employees of startup firms with independent variables representing alliance capital, intellectual capital (IC), and HC domains. They found in contrary that VCs' funding decision is driven by their cognitive tendency to overemphasize HC in startup firm they invest (Baum and Silverman 2004). However, other authors have found that human and social capital are important for decision to fund (Bosma et al. 2004). Hormiga et al. showed that human capital is especially important for firms in their first stage of life (Hormiga, Batista-Canino, and Sánchez-Medina 2011). In addition to HC, another study found three important factors, (i) experience of prior funding, (ii) founders' ability to recruit executives, and (iii) founding teams with a doctoral degree to be important measures that increase the likelihood to be funded by VC (Hsu 2007). Relationship between HC, value creation, and employee reward have been analyzed in the literature (Massingham and Tam 2015). They found that employee capability has positive relationship with pay (wages, salary or compensation), hence employee cost. A recent study shows that the cost of the employees of the firm has significant positive association with its investment (Mulier, Schoors, and Merlevede 2016). Overall, all these works provide support that HC is one of the most important criteria for startup funding and valuation.

2.3. Domain of intellectual property measures

Recently, Comino et al. divided startup firm development and maturation into three stages: (i) investment stage, (ii) patenting stage, and (iii) payoff stage (Comino and Graziano 2015). Their basis to consider a firm as a true innovator is a number of patent applications. However, they assume that Patent and Trademark Office (PTO) is granting all applications otherwise the firm cannot be considered as a true innovator. Therefore, they also count PTO probability for investment decision in their analysis. The conclusion of their study is that patents play crucial information role between startups and external investors. Another study supports this by showing that startup firms with granted patents have raised higher amount of total investments than firms without patents (Mann and Sager 2007). The difference is significant for biotech firms, where the total investment median value for startups with patents is 32 million and without patents is 5 million. Therefore, an explanatory variable representing firm's patent portfolio as an intellectual property measure is important to consider in funding and valuation. However, they also noted that PTO have lowered their standard and thus number of granted "bad" patents is rising.

Conti et al. found with their model that VCs value patents more than FFFs (founders, family, friends) and BAs (business angels) in startup firm financings (Conti, Thursby, and Rothaermel 2013). This also is supported by Nanda et al. findings that startup firms with bigger patent portfolio get higher valuation in comparison to those that have lower number of patents (Nanda and Rhodes-Kropf 2013). Also, they pinpointed that citations on firm's patents also increases the valuation. Another recent work analyzed values of patents and patent portfolios (Gambardella, Harhoff, and Verspagen 2017). They also considered inventors, their age, their educational degree (hence HC), work months invested for inventions, R&D expenditures, and others. Based on collected data of firms over various EU countries they derived decision making model. They conclude that bigger number of patents or portfolios lead to a higher firm value and any additional patent is not decreasing previous patent values. This all suggests that higher number of patent applications, granted patents, and portfolios in general are important measures for firm valuation and for any investment decision.

Greenberg analyzed 317 Israeli startup firms investments in 981 rounds where corresponding number of firms in life-science sector were 80 with 252 investment rounds (Greenberg 2013). In their study the patent applications and granted patents are analyzed separately, and their conclusion is that for valuations of early firms there is no significant difference whether patents are applications or granted. Their results also show that patents contribute 20% to valuation and patent value is 3.3 million USD in life-science sector.

Papageorgiadis et al. calculated over 1998–2011 time series an international patent systems' strengths based on three class components: (i) Property rights protection costs, (ii) Monitoring costs, and (iii) Servicing costs (Papageorgiadis, Cross, and Alexiou 2014). Their proposed International patent systems strength index scores showed highest value 9.5 for Denmark and Finland, where the lowest is 2.9 for Venezuela. Their scoring index can be useful for valuing patent portfolios in addition to number of patents.

In summary, given domain's measures in literature are associated with funding and valuation of firms. These discussed approaches and analyses are focused on different types of firms and with different objectives. To the knowledge of the author there is no such work that uses discussed domains measures in combination to explore associations with funding and valuation of early or startup firms.

3. Methods and data

Workflow of current study consists of several steps. The first step is data collection where data from different sources is combined. The next step is data modification and transformation where variables are calculated and winsorized when necessary. Further steps are multiple linear regression with variable selection and analysis of obtained multiple linear models. Final step is an interpretation of results. General workflow of this study is given in Figure 1 and described in detail below.

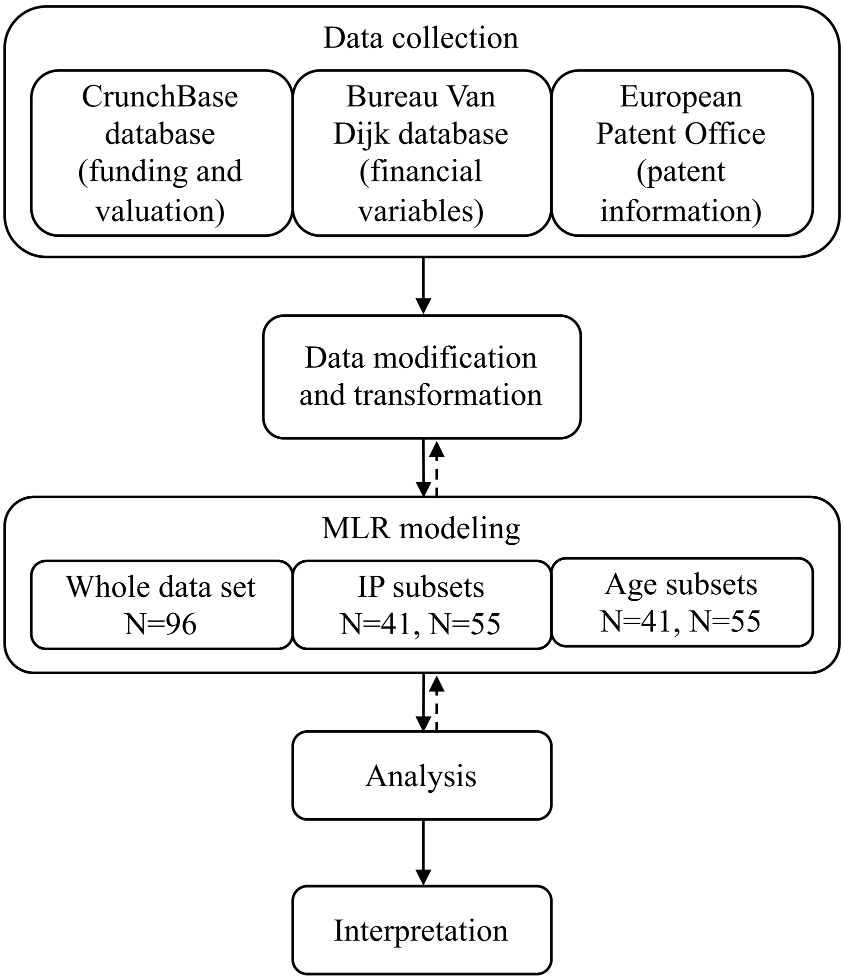

Figure 2. Study workflow.

3.1. Data collection

In November 2017 total funding and estimated valuation values of 463 European startup companies that are active in the healthcare sector were collected. Total funding accounts all known investments and awarded grants. Estimated valuation is calculated by the data platform based on known information. The data source was startup global funding & trading platform FunderBeam that refers CrunchBase which is known social media platform for startups. Although Crunchbase data is self-reported and not always claimed to be fully accurate, it has previously been used in research (Ter Wal et al. 2016). The data is covering total funding for the past 10 years. Estimated valuations span from 65 thousand euros to 723 million euros and total funding from 9 thousand to 537 million euros. Original values in dollars were transformed into euros based on UN Operational Rates of Exchange on the 1st of November 2017.

Financial data of selected startup firms was extracted in October 2019 from Amadeus, Bureau Van Dijk database. Supposedly by that time all annual reports of 2016 are submitted in national authorities and are accessible in Amadeus. All the collected financial data represents the year 2016 statements (or year before for growth measures) that in turn reflects a year before reported total funding and valuation. Corresponding derived variables are given in Table 1.

Table 1. Financial variables used in this study

Abb.	Amadeus name
TA	Total assets th EUR 2016
TA-1	Total assets th EUR 2015
NI	P/L for period [= Net Income] th EUR 2016
OR	Operating revenue (Turnover) th EUR 2016
OR-1	Operating revenue (Turnover) th EUR 2015
SF	Shareholders' funds th EUR 2016
IA	Intangible fixed assets th EUR 2016
IA-1	Intangible fixed assets th EUR 2015
NE	Number of employees 2016
EBIT	Operating P/L [=EBIT] th EUR 2016
EBIT-1	Operating P/L [=EBIT] th EUR 2015
CE	Costs of employees th EUR 2016

Table combined by Author.

Human capital data is based on annual report figures from Amadeus and are calculated as an average employee_cost, i.e. total cost of employees is divided by number of employees.

Intellectual property data such as number of patents and patent kind list was extracted from European Patent Office Espacenet database using tailored php script via Open Patent Services (OPS) API. Number of granted patents was derived from patent kind list where kind code B represents granted patent. Although kind code meaning may vary between different countries, in the USA and Europe code A and B means patent application and granted patent, respectively. These are also regions where mostly IP protection is used in the field of healthcare.

In summary, after collecting data that excludes firms with missing values (incomplete financial statements), the database contains 96 startup firms for further analysis.

3.2. Data modification and transformation

Explained variables, total funding (Fund) and estimated valuation (Val) were logarithmically transformed as it is commonly used in literature (Greenberg 2013). In order to analyze associations with finance ratios, a modification was derived to reflect dependence to size. For that Fund and Val were divided with total assets. This approach is commonly used in financial health analyses (Charitou et al. 2004; Lukason et al. 2016).

Further, explanatory variables were derived as they are used in literature. Particularly financial measures dependence to total assets or operating revenue reflecting profitability or leverage measures. Certain growth measures reflecting a difference between current and previous year are also applied. In addition, EBIT and OR measures were binarized to proxy the presence of (negative) cash flows. IP measures were logarithmically transformed. All derived variables of this study are given in Table 2. There are 4 explained (dependent) and 14 explanatory (independent) variables, where the latter cover three groups: (i) financial, (ii) human capital (HC), and (iii) intellectual property (IP).

Table 2. Variables used in the study.

Domain		Name	Formula	Description
Explained		log(Fund)	$\log(Funding)$	Logarithm of funding
		log(Val)	$\log(Valuation)$	Logarithm of valuation
		Fund/TA	$Funding/TA$	Size dependent funding ratio
		Val/TA	$Valuation/TA$	Size dependent valuation ratio
Explanatory	Financial	EBIT/TA	$EBIT/TA$	Profitability measure, ROA
		NI/TA	NI/TA	Profitability measure
		E/TA	E/TA	Leverage measure
		OR/TA	OR/TA	Efficiency measure, asset turnover
		EBIT/OR	$EBIT/OR$	Profitability measure, profit margin
		OR_growth	$(OR_{2016} - OR_{2015})/OR_{2015}$	Growth measure
		TA_growth	$(TA_{2016} - TA_{2015})/TA_{2015}$	Growth measure
		IA_growth	$(IA_{2016} - IA_{2015})/IA_{2015}$	Growth measure
		EBIT_growth	$(EBIT_{2016} - EBIT_{2015})/EBIT_{2015}$	Growth measure
		b(EBIT)	$\begin{Bmatrix} 0\ if\ EBIT < 0 \\ 1\ if\ EBIT\ \geq 0 \end{Bmatrix}$	Binary indicator variable, 0 if negative, 1 if positive
		b(EBIT_growth)*	$\begin{Bmatrix} 0\ if\ EBIT\_growth < 0 \\ 1\ if\ EBIT\_growth\ \geq 0 \end{Bmatrix}$	
		b(OR)	$\begin{Bmatrix} 0\ if\ OR = 0 \\ 1\ if\ OR > 0 \end{Bmatrix}$	Binary indicator variable, 0 if no revenue, 1 if positive
	HC**	employee_cost	$CE/n_{employee}$	Average cost of one employee
	IP***	log(patent)	$\log(1 + n_{patent})$	Log of unique patent documents, IP measure
		log(Gpatent)	$\log(1 + n_{granted\ patent})$	Log of granted patents, IP measure

Notes. * b(EBIT_growth) is indicating whether EBIT change between 2015 and 2016 is positive or negative, ** HC is an abbreviation of human capital, *** IP is an abbreviation of intellectual property. Table combined by Author.

3.3. Multiple linear regression

This study relies on the assumption that startup funding and valuation are associated in a linear manner with measures representing (i) financial, (ii) human capital, and (iii) intellectual property domains. For finding the associations among given variables multiple linear regression (MLR) was used, given in general form by Equation 1.

$$y = f(x_1, x_2, \dots, x_K) + \varepsilon \qquad \text{Equation 1.}$$

Where y is the explained variable, $x_1,\ldots,x_K$ are the explanatory variables and ε denotes unexplained variance.

For MLR modeling SAS® University Edition software package was used. For variable selection a stepwise selection method with Schwarz Bayesian information criterion was used. It adjusts average check loss with degrees of freedom (taking into consideration number of observations and number of parameters including the intercept). This procedure is eliminating insignificant variables and avoids overfitting of models. Also highly intercorrelated variables were avoided in models.

In some cases, when modeling reveals that variables need to be further transformed (for example, when creating a subset), it is necessary to go back to the data modification and transformation stage, as shown in the dashed line in Figure 2.

Further, in analysis of MLR models regression coefficients (b) and its signs show magnitude and direction of corresponding variable association to explained variable. Percentages that are described by explanatory variable unique contribution into explained variable are described by squared semi-partial correlation coefficients (sr^2).

4. Results and Analysis

In this study four explained variables are used that can be divided into two groups. First, logarithmically transformed total funding log(Fund) and estimated valuation log(Val) of startup firms. They represent a magnitude of investments and business potential. Second, the same total funding and valuation normalized to total assets, Fund/TA and Val/TA, respectively. They consider size dependency via normalization and represent efficiency of business potential.

Association of financial, human capital, and intellectual property measures with funding and valuation are analyzed over the whole sample set that is representing a startup firms from healthcare sector. In addition, the association of the same variables among subsets where (i) the whole set is divided by the presence of intellectual property (patents) and (ii) divided into two groups by the age of firms were analyzed.

4.1. Analysis of the whole data set

Four linear models were derived on the whole data set (Table 3). Particularly, log(Fund) and log(Val) models are describing 40% of their variance (Model 1 and Model 2). Relevant variables in those models are employee_cost and log(patent) representing human capital and intellectual property, associating uniquely 16% and 13% to log(Fund) variance, and correspondingly 18% and 11% to log(Val), and roughly 10% is shared contribution for both. Shared contribution is what remains after subtracting unique contributions from the total variance described. Intercept and regression coefficients for both variables are positive. Thus, higher worth of team and bigger IP portfolio contribute to higher valuation end eventually to bigger funding. Regression coefficients of these explanatory variables are in the same range for both log(Fund) and log(Val) meaning that their association is similar. But the intercept for log(Val) is bigger than the intercept for log(Fund) meaning that valuations are about five times bigger than funding. For comparison, the median value of valuation is about four times bigger than median value of funding in the sample set.

However, in both models about 60% of variance remains unexplained. This includes error as well as other parameters, such as social capital, market potential, and reputation as they are described in the literature (Banerji and Reimer 2019; Hsu 2004; Petty and Gruber 2011; Yang and Berger 2017) but not used in current study.

Among Fund/TA and Val/TA datasets were spotted 7 serious outliers that were removed from further analysis resulting with 89 cases for modeling. Again, similar two parameter models were derived for funding and valuation with EBIT/TA and E/TA as explanatory variables. Regression coefficients of them are both negative meaning that high profitability and leverage measures probably reduce a need for funding. Particularly, with positive efficiency (EBIT/TA) the investment into firm is less significant in terms of assets, or even firm can use its own profit for growth and do not need external funding. This makes an investment expensive for investor and thus less attractive. Thus, in contrary, negative efficiency shows better funding potential and market potential, and eventually strong business plan. Negative leverage measure E/TA shows accumulated loss.

Table 3. log(Fund) and log(Val) models over the entire sample set.

		*b**	*p***	*sr*^{2}***	*b*	*p*	*sr*^{2}
Whole set		*Model 1, log(Fund)*			*Model 2, log(Val)*		
	Intercept	5.76	<.0001		6.47	<.0001	
	employee_cost	$9.29 \bullet 10^{-06}$	<.0001	0.16	$9.27 \bullet 10^{-06}$	<.0001	0.18
	log(patent)	0.411	<.0001	0.13	0.360	<.0001	0.11
	n	96			96		
	R^2	0.40			0.40		
	F value	31			31		
		Model 3, Fund/TA			*Model 4, Val/TA*		
	Intercept	1.83	<.0001		9.13	<.0001	
	EBIT/TA	-1.82	0.0006	0.10	-9.21	0.001	0.093
	E/TA	-0.643	0.026	0.042	-3.74	0.014	0.051
	n	89			89		
	R^2	0.31			0.31		
	F value	19			20		

Notes. * b is a regression coefficient, ** p is a p-value, *** sr^2 is a squared semi-partial correlation. Table combined by Author.

Intercept and regression coefficients are bigger for Val/TA model in absolute values. However, unique contribution by squared semi-partial correlation are similar for both models, about 10% and 5% for EBIT/TA and E/TA, respectively. This shows that association and contribution of these explanatory variables into Fund/TA and Val/TA are similar, but the magnitude is about 5 times different.

4.2. Analysis of subsets separated by presence of patent

Some business models do not foresee patenting of inventions. They may rely on public domain inventions, licensed inventions or keeping inventions as a trade secret. Therefore, for further analysis two subsets for separate modeling were generated – one without and one with startup firms who have patents.

Among firms without patents only employee_cost is associated with log(Fund) and log(Val) (*Model 5* and *Model 6* in Table 4). Association for log(Val) is stronger, covering 32% of variance while coverage for log(Fun) is 26%. The same explanatory variables as for the whole set (employee_cost and log(patent)) are associated with log(Fund) and log(Val), and additional binary variable bEBIT_growth for log(Fund) model (*Model 9* and *Model 10*). Total variance described by these models are 62% and 51% for log(Fund) and log(Val), respectively. In this subset log(patent) plays an important role contributing uniquely 30% of variance while the others, employee_cost and bEBIT_growth contribute uniquely 10% or less. Regression coefficients of log(patent) and employee_cost are positive and follow the same logic as described above. But bEBIT_growth regression coefficient is negative, and this can be explained by increase in startup firm burn rate which reflects its capability to be fast in product development. This also may mean that a startup firm has been successful to attract funding and is in growth phase.

Table 4. Models of with/without patent divided subsets.

		b	***p***	***sr²***	***b***	***p***	***sr²***
Without patent		*Model 5, log(Fund)*			*Model 6, log(Val)*		
	Intercept	5.78	<.0001		6.46	<.0001	
	employee_cost	$1.10 \cdot 10^{-05}$	0.0006	0.26	$1.15 \cdot 10^{-05}$	0.0001	0.32
	n	41			41		
	R^2	0.26			0.32		
	F value	14			18		
		Model 7, Fund/TA			*Model 8, Val/TA*		
	Intercept	0.439	0.51		11.8	0.0003	
	NI/TA	-3.27	0.0015	0.27	-9.26	0.011	0.14
	bEBIT	1.68	0.059	0.086			
	E/TA				-9.11	0.030	0.10
	n	35			35		
	R^2	0.28			0.37		
	F value	6.2			9.5		
With patent		*Model 9, log(Fund)*			*Model 10, log(Val)*		
	Intercept	5.31	<.0001		5.9	<.0001	
	bEBIT_growth	-0.323	0.027	0.039			
	employee_cost	$6.27 \cdot 10^{-06}$	0.0029	0.073	$6.88 \cdot 10^{-06}$	0.0016	0.10
	log_patent_	0.902	<.0001	0.34	0.82	<.0001	0.32
	n	55			55		
	R^2	0.62			0.51		
	F value	27.4			27.4		
		Model 11, Fund/TA			*Model 12, Val/TA*		
	Intercept	1.49	<.0001		7.08	0.0003	
	EBIT/TA	-1.96	<.0001	0.29	-10.58	<.0001	0.27
	n	54			54		
	R^2	0.29			0.27		
	F value	21			19		

Notes. Table combined by Author.

Models in regard to funding and valuation ratios show slightly better results in terms of variance explained among without patent subset. Similarly, profitability and leverage measures are important. However, instead of EBIT/TA, NI/TA comes up to me more relevant. And in the case of Fund/TA (*Model 7*) E/TA is substituted with binary bEBIT categorizing firms into two classes, with negative and positive EBIT. Regression coefficient sign is positive meaning that positive EBIT is generally favored. However, unique contribution of bEBIT is less than 10% and statistical significance is slightly over 0.05, thus this association should be treated with caution. In a case of subset with patent only profitability ratio EBIT/TA is relevant covering about 30% of the variance in both cases, for Fund/TA and Val/TA (*Model 11* and *Model 12*).

4.3. Analysis of subsets separated by firm age

Young startup firms are usually at a very early stage in their development. They usually are in (pre)seed investment phase where investment decisions are emotional, especially in a case of FFF (founders, family, friends). Therefore, the whole data set under current study were divided into two subsets where the first accounts startup firms up to five years old and the second accounts 6-10 years old ones.

Among models based on younger firms (1-5 years old) subset employee_cost is associated with log(Fund) and log(Val) (*Model 13* and *Model 14* in Table 5). Results are very similar to models of without patent subset. Employee_cost association to log(Fund) and log(Val) covers 24% and 28% of variance, respectively.

Similarly to models based on with patent subset, for older firms (6-10 years old) subset log(patent) variable is additionally associated with both explained variables. However, EBIT/OR becomes also significant for log(Val) (*Model 18*). The sign of regression coefficient of given profit margin measure is negative, and this can be explained similarly to *Model 9*, i.e. it can be related firm’s burn rate. Association strength is here bigger, in total 45% and 56% of explained variance for log(Fund) and log(Val), respectively. The best explanatory variable is log(patent) showing slightly more than 20% of unique contribution.

Table 5. Models of subsets divided by firm age.

		b	*p*	*sr²*	*b*	*p*	*sr²*
1-5 years old		*Model 13, log(Fund)*			*Model 14, log(Val)*		
	Intercept	5.78	<.0001		6.48	<.0001	
	employee_cost	$1.26 \cdot 10^{-05}$	0.001	0.240	$1.28 \cdot 10^{-05}$	0.0004	0.2814
	n	41			41		
	R^2	0.24			0.28		
	F value	12.5			15.3		
		Model 15, Fund/TA			*Model 16, Val/TA*		
	Intercept	1.60	<.0001		8.05	0.0006	
	NI/TA	-1.31	0.04	0.11	-9.86	0.02	0.15
	n	36			36		
	R^2	0.11			0.15		
	F value	4			6.04		
6-10 years old		*Model 17, log(Fund)*			*Model 18, log(Val)*		
	Intercept	5.80	<.0001		6.45	<.0001	
	employee_cost	$8.59 \cdot 10^{-06}$	0.0002	0.18	$6.55 \cdot 10^{-06}$	0.0014	0.10
	log(patent)	0.438	<.0001	0.22	0.440	<.0001	0.24
	EBIT/OR				-0.0255	0.0105	0.061
	n	55			55		
	R^2	0.45			0.56		
	F value	21			21		
		Model 19, Fund/TA			*Model 20, Val/TA*		
	Intercept	1.27	0.002		2.80	0.1772	
	bEBIT_growth				5.73	0.0276	0.060
	NI/TA	-3.01	<.0001	0.33	-15.81	<.0001	0.39
	n	53			53		
	R^2	0.33			0.42		
	F value	25.6			18.1		

Notes. Table combined by Author.

In respect to ratios reflecting financial domain NI/TA is significant for both subsets, younger and older firms. For younger firms it is associated with 11% and 15% of Fund/TA and Val/TA variation, respectively (*Model 15* and *Model 16* in Table 5). In turn, for Val/TA model binary bEBIT_growth becomes additionally relevant for older, 6-10 years old firms (*Model 20*). Regression coefficient sign of bEBIT_growth is positive, reflecting that profitability growth is favorable for valuation. However, covering just 6% of unique contribution, but in overall increasing roughly 10% of explained variance in comparison to Fund/TA. Here again, older firms are better explained in terms of explained variance due to more stable business model.

In overall, explanatory variables included in the study and in the models supplemented with their direction are given in Table 6. In the table association with explained variables are given in separate columns, one for whole set and four for subset models. Particularly 0 denotes no association, – and + denotes negative or positive association, respectively. For log(Fund) and log(Val) variables log(patent), employee_cost are important with positive association and binary b(EBIT_growth) with negative association. As expected, for Fund/TA and Val/TA are important other ratios, EBIT/TA, NI/TA, E/TA with negative association and b(EBIT) with positive association. Other used explanatory variables OR/TA, NI/TA, E/TA, OR_growth, TA_growth, IA_growth, b(OR), and log(Gpatent) have no significant association in the compiled models. In the whole data set there are only 11 startup firms that have granted patents and thus log(Gpatent) is not significant as it is often described in literature (Festel et al. 2013; Mann and Sager 2007; Marullo et al. 2018).

Table 6. Association of explanatory variables.

	log(Fund)		log(Val)		Fund/TA		Val/TA	
	whole*	subsets**	whole	subsets	whole	subsets	whole	subsets
EBIT/TA	0	0000	0	0000	–	0–00	–	0–00
NI/TA	0	0000	0	0000	0	–0—	0	–0—
E/TA	0	0000	0	0000	–	0000	–	–000
OR/TA	0	0000	0	0000	0	0000	0	0000
EBIT/OR	0	0000	0	000–	0	0000	0	0000
OR_growth	0	0000	0	0000	0	0000	0	0000
TA_growth	0	0000	0	0000	0	0000	0	0000
IA_growth	0	0000	0	0000	0	0000	0	0000
b(EBIT)	0	0000	0	0000	0	+000	0	0000
b(OR)	0	0000	0	0000	0	0000	0	0000
b(EBIT_growth)	0	0–00	0	0000	0	0000	0	000+
employee_cost	+	++++	+	++++	0	0000	0	0000
log(patent)	+	0+0+	+	0+0+	0	0000	0	0000
log(Gpatent)	0	0000	0	0000	0	0000	0	0000

Notes. * the whole data set (96 firms), ** subsets in following order: without patent subset (41 firms), with patent subset (55 firms), 1-5 years old firms subset (41 firms), 6-10 years old firms subset (55 firms), and where 0 is no association, – is negative association, + is positive association. Table combined by Author.

5. Discussion

Results of the study show that log(Fund) and log(Val) are associated with employee_cost and log(patent) among selected variables (Table 6). Employee_cost can be related to firm's average team value accounting for both, development and management teams. The use of employee cost in such context is rather new to the author's knowledge. It reflects human capital domain that is found to be important in previous studies as well (Baum and Silverman 2004; Bosma et al. 2004; Hsu 2007). Log(patent) on another hand is describing a strength of firm's technology and reflects intellectual property domain. An importance of patents, especially granted patents, is also reported in literature by other authors (Marullo et al. 2018).

When considering models compiled for log(Fund) and log(Val) in subsets, additionally EBIT related variables are significant with negative association for log(Val). This can be explained by higher burn rate which is due to intense product or service development and refers to significant prior funding based on good business plan and market potential.

Looking at startup firms by age and patents, it can be concluded that the age of a startup firm does not indicate the stage of its development. Particularly, in the current data set there are 18 firms that have patents but they are 5 or less years old, and at the same time there are 18 firms that do not have patents but are 6 to 10 years old. Nonetheless, models for age and patent subsets show similar associations, although the quality of the models is lower for younger and without patent firms, covering roughly 25-30% of variance for both, log(Fund) and log(Val). The lack to describe younger and early stage firms is a clear limitation of this study. For better results, variables that are describing entrepreneurial capability, social capital, market potential, and reputation could be added as it is described in the literature and are considered important especially on early stage funding decisions made by FFFs (founders, family, friends) and BAs (business angels) (Banerji and Reimer 2019; Hsu 2004; Petty and Gruber 2011; Yang and Berger 2017).

However, models on firms that are older or with more developed technology (patent exists) are showing moderately better associations, covering roughly 50-60% of variance for both, log(Fund) and log(Val). The most important variable in those models is log(patent) contributing uniquely 20-30%. This increased strength of associations can be explained by the fact that older and technology-rich firms have significantly higher valuations (and correspondingly funding) and are made by VCs. This is supported also by literature where is concluded, that VCs value patents more than FFFs and BAs (Conti et al. 2013).

Funding and valuation ratio to total assets models mostly show association with profitability measure, either EBIT/TA or NI/A supplemented few times by binary bEBIT or binary bEBIT_growth with slight contribution. Despite lower quality of models in terms of variance explained, certain explanations can be given. Particularly, profitability measure's regression coefficient has a negative sign in all these models, meaning that generally profitability is not preferred. This is in accordance with general rule of venture capitalists who are seeking an investment opportunity into high growth potential business plans and with a clear focus on product development. They consider other sales as distraction. On the other hand, if a startup firm already generates sales, they may not need any more substantial investment and can bootstrap their growth.

6. Conclusion

This study focused on explaining total funding and estimated valuation of healthcare sector startup firms through financial, human capital, and intellectual property domain measures. For explained variables logarithmical transformation and normalization to total assets was used. All together there are four explained and fourteen explanatory variables among 96 startup firms.

Multiple linear regression analysis revealed that human capital and intellectual property measures are positively associated with funding and valuation covering 40-50% of total variance. For more mature firms, additionally EBIT related financial measures are negatively associated with funding and valuation. However, the association of EBIT related financial measures are weaker than others, adding less than 10% to explained variance.

On the other hand, if total funding and estimated valuation is normalized to total assets then only financial measures can be associated. Particularly, profitability measures are negatively associated covering roughly 10-25% of variance explained. Additionally, leverage measures are also negatively associated covering approximately 5% of variance explained for both explained ratio variables, normalized finding and valuation. The negative association is explained by general rule of venture capitalists who are seeking an investment opportunity into high growth potential business plans and with a clear focus on product development. There is also a positive association of binary EBIT and binary EBIT growth measures covering approximately 5% of variance explained. These explanatory variables are fitting those startup firms in the sample set that are bootstrapping their growth.

Startup firms that are older and have patent portfolio show better association with financial, human capital, and intellectual property domain measures in terms of explained variance. This is related to more stable stage of firms and tendency to attract venture capital investments where the decision to invest is more rational than in case of founder-family-friends and business angel investments.

Overall, the main finding of this study is that using logarithmically transformed funding and valuation values show clear association with human capital and intellectual property domain measures. Association with financial domain measures is rather weak. On another hand, funding and valuation to total assets ratios are more associated with financial domain measures and not with human capital and intellectual property measures. However, the association is generally weaker with ratio type explained variables than with logarithmically transformed variables. The association between funding and valuation with financial, human capital, and intellectual property domain measures is very similar in both cases.

Limitations of the current study are that the sample set used is rather small because of absent data, particularly incomplete financial statements. Also, the sample set consists of startup firms in different growth phases. This gives a bigger effect on an individual value and may skew regressions. In addition, the study does not account social capital domain measures that are often reported in literature to be significant and well human capital domain could be elaborated more widely. The latter aspects should be considered for future work.

Acknowledgement

The author is grateful to Janek Hiis who helped him in writing the script for EPO database API.

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