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### Human Capital's importance in Initial Coin Offerings' (ICOs) success

José Campino  
*ISCTE-IUL*

Ana Brochado  
*ISCTE-IUL*

Álvaro Rosa  
*ISCTE-IUL*

#### Abstract

The Initial Coin Offerings (ICOs) are an emerging topic in the literature with several gaps still to fulfill. The ICOs have increased its importance not only due to the interest they have been raising but also due to the capital amounts involved in the projects, the innovative solutions they offer and the challenges they pose to regulators. There is some research on the ICOs' success factors but there is still no common measure of success as well as not many researches focused on the human capital importance for the projects success. In our research we will perform a literature review on the ICOs' topic and develop an econometric model with a database composed by 3158 profiles and 340 ICO projects in the banking/financial sector. We will be focusing on the human capital importance in these projects and propose three measures for project's success. With our research we intend to complement the literature on the ICOs projects and shed some light on the factors driving their success.

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**Contact:** José Campino - [jpmcampino@gmail.com](mailto:jpmcampino@gmail.com), Ana Brochado - [Ana.Brochado@iscte-iul.pt](mailto:Ana.Brochado@iscte-iul.pt), Álvaro Rosa - [alvaro.rosa@iscte-iul.pt](mailto:alvaro.rosa@iscte-iul.pt)

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## **1. Introduction**

The Initial Coin Offerings (ICOs) are an emerging topic in the literature but there is still a considerable literature gap due to their novelty. ICOs' main function is to fund innovative ventures which are based on a distributed ledger technology (DLT) such as blockchain. The funding is performed via the tokens selling by the cutting hedge technological ventures and the tokens purchase by worldwide investors (Chiu & Greene, 2019). Therefore, the investors are able to buy tokens directly from the new venture without the need to a third party involved. The tokens sold will be venture capital project's functional future units, in other words, they will have a utility function, right of ownership or royalties (Fisch, 2019). According to Howell, Niessner, & Yermack (2018) there are three main token categories: (i) currency token: used as a means of exchange and store such as a cryptocurrency; (ii) security token: used as a conventional security but recorded and exchanged on a blockchain. The underlying of this token type can range from corporate equity (typical share), to commodities, real estate or even currencies; (iii) utility token: is the most common token type and provides to the buyer consumptive rights to access a product or service. According to Kranz, Nagel, & Yoo, 2019 there is a fourth type of token, namely, the donation tokens which do not grant any rights to the investor and are used to raise money for entrepreneurial and idealistic projects. According to Brochado (2018) there are also hybrid tokens which combine more than one of the characteristics mentioned above and new token types should appear in the future (Fisch, 2019). All the characteristics and main information on the ICO should be described in the Whitepaper of the new venture which, although unregulated, tries to mimic a regulated prospectus (Chiu & Greene, 2019). According to Brochado (2018) we could define ICOs as an alternative investment form offering the possibility of direct financing from worldwide investors and which contributes to the democratization of entrepreneurship and access to capital markets. The ICOs are based on Blockchain's technology and offer the chance to invest in a project's initial phase through the acquisition of a token. It also allows tokens' transaction on secondary market which is essential to their success (Chen, 2018). This definition is in line with Fisch (2019) who also highlights the similar approaches of crowdfunding and ICOs although an innovative characteristic of the latter is the possibility of selling tokens in a secondary market not available in crowdfunding.

## **2. Literature review**

ICOs are frequently compared with other ways of financing young and risky ventures such as Initial Public Offerings (IPOs), Venture Capital (VC) and Crowdfunding. Nevertheless, ICOs are disruptive and although they share some of more traditional financing ways characteristics, they are very distinct from them (Biasi & Chakravorti, 2019). The main characteristics of ICOs are: less costly; lower investment thresholds; democratization of investments; blockchain based; no intermediaries involved (e.g. banks); low regulation; completely digital; existence of a secondary market (Brochado, 2018) and (OECD, 2019).

The ICO projects usually set boundaries for their financing, namely, a minimum amount of financing to be obtained in order to proceed with the project and a maximum amount of capital accepted once this is proved to positively influence tokens' valuation (Howell, Niessner, & Yermack, 2018). This is done by determining how many tokens are available for sale and their initial price. Therefore, the ICOs can have the following models: (i) not capped: where there are no limits for financing; (ii) soft-capped: where a minimum amount of financing is established in order to proceed with the project; (iii) hard-capped: maximum amount of financing accepted; (iv) combination of both soft- and hard-cap limits and hybrid methodologies such as accepting financing above the hard cap and setting several ceilings instead of only one (Kranz, Nagel, & Yoo, 2019).

In terms of determining the success of an ICO project the mostly commonly used measure is the amount raised (An, Duan, Hou, & Xu, 2019) and (Fisch, 2019). As most of the times the projects are capped, further strong measures of success should be the achievement of the minimum capital previously defined and, in positive cases, the percentage of the amount raised over it (Jong, Roosenboom, & Kolk, 2018).

## **2.1. Market Snapshot**

The first ICO was the MasterCoin in 2013 proposed by J.R. Willett and since then the ICO market has increased mainly due to its novelty and the hype caused by the valorization of cryptocurrencies, particularly Bitcoin, between the years of 2017-2018 (Masiak, Block, Masiak, Neuenkirch, & Pielen, 2018). Indeed, during the last 4 years the ones with the largest amount of funds raised are 2017 and 2018. The year of 2017 accounted 442 token sales concluded with USD 6.4 billion of funds raised and 2018 was even better for the ICO market with 1051 token sales concluded and with USD 21 billion of funds raised. However, with the depreciation of Bitcoin since the end-2018, the ICO market also refrained and 2019 registered much lower values compared with previous years, namely, 131 token sales concluded and USD 1.4 billion of funds raised (Coinschedule, 2020). The ICO's market represent significant amounts of investment despite the fact that in 2017 45% of them have failed (Risley et al. 2017, cited OECD 2019, p.49). Furthermore, prior to trading in 2018, 81% of the ICOs are considered as scams and only 8% move to trade from which only 3.8% are successful (Dowlat and Hodapp 2018, cited OECD 2019 p.35). The 3 ICOs which raised the largest amounts of funding represent USD 6.8 billion, namely, EOS (USD 4.1B), Telegram Open Network (USD 1.7B) and BITFINEX (USD 1B) (Coinschedule, 2020).

## **3. Methodology**

### **3.1. Database**

The data used in the research is secondary and collected from ICOBench a website which comprises a large database on ICOs (ICOBench, 2020). The information provided by the website is mostly related with the projects and concerns among other data: the project's year, amounts raised, type of cap, existence of pre-sales or bonus schemes. It also compiles information on the team, such as their composition and functions. The data was collected via a premium subscription which gave access to an API. As the main objective of the research is to study the ICO's teams, the complementary information was collected from the public LinkedIn profiles of the team members. This data treatment resulted in the collection of 556 ICO projects, on the banking/financial area, from which 216 were discarded due to lack on crucial information and leaving the database with 340 projects. The projects' teams were composed by 5025 profiles from which we were able to keep 3158 once 1867 were discarded due to lack of crucial information.

### **3.2. Model and Propositions**

The main objective of this research is to study the ICOs' teams and their impact on project's success. Therefore, we have collected 3 dependent variables, several independent variables related with the teams' characteristics and several control variables more focused on the projects' characteristics. We developed a univariate analysis and the purpose will be to develop an econometric model. The current research proposition is to understand the impact of the teams' characteristics on the projects' success.

## **4. Results**

In the current section we will present the database's descriptive statistics followed by the univariate analysis of the variables selected. Thus, we have selected as dependent variables: (i)



the regions represented in the database are the Middle East (38%), Africa (29%), South America (27%) and Central America (6%). The profiles are highly educated with 98% having a university degree. 52% of the profiles have a bachelor degree, 40% have a master degree and only 6% have a doctoral degree. In terms of professional experience, 56% of the profiles had a managerial experience, 21% had a technological experience, 9% had both and 14% had other or no experience at all. Below we present the summary statistics of the database variables

## 4.2. Correspondence analysis

Table 2 - Correspondence analysis

		Soft cap achieved				Log of capital raised/softCap				Log of capital raised			
		No	%	Yes	%	Below median	%	Equal/Above median	%	Below median	%	Equal/Above median	%
Person Location	North America	283	9%	265	8%	262	8%	286	9%	295	9%	253	8%
	Europe	747	24%	809	26%	702	22%	854	27%	754	24%	802	25%
	Asia	359	11%	420	13%	328	10%	451	14%	352	11%	427	14%
	Africa	44	1%	33	1%	43	1%	34	1%	50	2%	27	1%
	Central America	14	0%	4	0%	13	0%	5	0%	13	0%	5	0%
	South America	52	2%	22	1%	52	2%	22	1%	51	2%	23	1%
	Middle East	56	2%	50	2%	53	2%	53	2%	56	2%	50	2%
Number of projects per person	1 to 3	1509	48%	1564	50%	1408	45%	1665	53%	1520	48%	1553	49%
	4 to 6	19	1%	25	1%	18	1%	26	1%	22	1%	22	1%
	9 to 12	27	1%	14	0%	27	1%	14	0%	29	1%	12	0%
LinkedIn Connections	0 to 100	149	5%	97	3%	137	4%	109	3%	154	5%	92	3%
	101 to 200	115	4%	74	2%	109	3%	80	3%	111	4%	78	2%
	201 to 300	95	3%	90	3%	92	3%	93	3%	101	3%	84	3%
	301 to 400	69	2%	58	2%	62	2%	65	2%	64	2%	63	2%
	401 to 500+	1127	36%	1284	41%	1053	33%	1358	43%	1141	36%	1270	40%
Managerial Experience	No	506	16%	479	15%	469	15%	516	16%	511	16%	474	15%
	Yes	1049	33%	1124	36%	984	31%	1189	38%	1060	34%	1113	35%
Technology Experience	No	1143	36%	1212	38%	1062	34%	1293	41%	1147	36%	1208	38%
	Yes	412	13%	391	12%	391	12%	412	13%	424	13%	379	12%
Education	<Bachelor	22	1%	39	1%	22	1%	39	1%	25	1%	36	1%
	Bachelor	851	27%	811	26%	794	25%	868	27%	863	27%	799	25%
	Master	590	19%	660	21%	555	18%	695	22%	593	19%	657	21%
	PhD	92	3%	93	3%	82	3%	103	3%	90	3%	95	3%
Business Degree	No	902	29%	870	28%	834	26%	938	30%	904	29%	868	27%
	Yes	653	21%	733	23%	619	20%	767	24%	667	21%	719	23%
Technology degree	No	981	31%	1062	34%	916	29%	1127	36%	990	31%	1053	33%
	Yes	574	18%	541	17%	537	17%	578	18%	581	18%	534	17%
Team Rating	0 to 2,9	672	21%	392	12%	654	21%	410	13%	657	21%	407	13%
	3 to 3,9	262	8%	286	9%	203	6%	345	11%	243	8%	305	10%
	4 to 5	621	20%	925	29%	596	19%	950	30%	671	21%	875	28%
Vision Rating	0 to 2,9	592	19%	387	12%	574	18%	405	13%	577	18%	402	13%
	3 to 3,9	400	13%	538	17%	335	11%	603	19%	419	13%	519	16%
	4 to 5	563	18%	678	21%	544	17%	697	22%	575	18%	666	21%
Number of team elements	0 to 10	363	11%	193	6%	342	11%	214	7%	347	11%	209	7%
	11 to 20	750	24%	670	21%	683	22%	737	23%	779	25%	641	20%
	21 to 30	281	9%	454	14%	244	8%	491	16%	295	9%	440	14%
	31 to 40	161	5%	219	7%	184	6%	196	6%	150	5%	230	7%
	41 to 50	0	0%	67	2%	0	0%	67	2%	0	0%	67	2%
Soft Cap Limit	No	416	13%	456	14%	416	13%	456	14%	462	15%	410	13%
	Yes	1139	36%	1147	36%	1037	33%	1249	40%	1109	35%	1177	37%
Hard Cap Limit	No	189	6%	77	2%	187	6%	79	3%	188	6%	78	2%
	Yes	1366	43%	1526	48%	1266	40%	1626	51%	1383	44%	1509	48%
Token Price	< Median	910	29%	973	31%	803	25%	1080	34%	945	30%	938	30%
	>= Median	645	20%	630	20%	650	21%	625	20%	626	20%	649	21%
Currencies Accepted	1	661	21%	751	24%	641	20%	771	24%	724	23%	688	22%
	2	203	6%	252	8%	171	5%	284	9%	194	6%	261	8%
	3	269	9%	238	8%	245	8%	262	8%	262	8%	245	8%
	4	229	7%	184	6%	231	7%	182	6%	228	7%	185	6%
	5	87	3%	62	2%	87	3%	62	2%	99	3%	50	2%
	6	44	1%	73	2%	27	1%	90	3%	15	0%	102	3%
	7	20	1%	24	1%	9	0%	35	1%	20	1%	24	1%
	8+	42	1%	19	1%	42	1%	19	1%	29	1%	32	1%
Ethereum Platform	No	286	9%	128	4%	255	8%	159	5%	255	8%	159	5%
	Yes	1269	40%	1475	47%	1198	38%	1546	49%	1316	42%	1428	45%
Bonus Scheme	No	774	25%	683	22%	727	23%	730	23%	794	25%	663	21%
	Yes	781	25%	920	29%	726	23%	975	31%	777	25%	924	29%
ICO Rating	0 to 2,9	453	14%	230	7%	439	14%	244	8%	450	14%	233	7%
	3 to 3,9	706	22%	852	27%	647	20%	911	29%	730	23%	828	26%
	4 to 5	396	13%	521	16%	367	12%	550	17%	391	12%	526	17%
ICO Year	2017	105	3%	311	10%	110	3%	306	10%	136	4%	280	9%
	2018	1001	32%	1137	36%	912	29%	1226	39%	1004	32%	1134	36%
	2019	442	14%	155	5%	424	13%	173	5%	424	13%	173	5%
	2020	7	0%	0	0%	7	0%	0	0%	7	0%	0	0%
	Total	1555	49%	1603	51%	1453	46%	1705	54%	1571	50%	1587	50%

The correspondence analysis done through a cross-table allows the understanding of the behavior of the independent variables in relation to the dependent variable. In this case, we can understand the distribution of the profiles within the independent variables when exposed to the binary version of the dependent variable. We have selected three dependent variables: (i) soft-cap limit achieved; (ii) the log of the percentage of capital obtained above the soft-cap; (iii) the log of the total capital raised. The percentage of profiles linked to successful projects is similar across the three models proposed with a higher tendency for successful projects. The distribution of profiles within the independent variables is similar across models which leads us to similar conclusions regardless of the dependent variable.

We have also created a chi-square table in order to attest the statistical significance of each independent variable having in mind the dependent variables selected. The significance levels adopted below are the following: 0,001 (\*\*\*), 0,01 (\*\*), 0,05 (\*).

Most of the significant variables are consistent across models, in other words, the models seem to provide similar results again. The most significant variables accepted at 0,001 significance level are the person's location, number of LinkedIn connections, team rating, vision rating and number of team elements. These variables are accepted regardless of the dependent variable selected. The variable number of projects per person is also significant at 0,05 level for the dependent variables related with soft-cap achievement and the percentage achieved above that threshold. The variables related with technological profiles (i.e. technology experience and technology degree) are only relevant with 0,05 significance level for the dependent variables related with total capital achieved. The variables education and business degree are only relevant for the dependent variable related with soft-cap achievement at 0,05% significance level. Therefore, we conclude that the first variables are the strongest to build a model with the current data.

Table 3 - Chi-square table

		Soft cap achieved	Log of capital raised/softCap	Log of capital raised			Soft cap achieved	Log of capital raised/softCap	Log of capital raised
Person Location	Chi-square	26,744	32,186	33,2	Number of team elements	Chi-square	647,849	766,152	640,861
	df	6	6	6		df	40	40	40
	Sig.	,000***	,000***	,000***		Sig.	,000***	,000***	,000***
Number of projects per person	Chi-square	15,939	18,424	12,412	Soft Cap Limit	Chi-square	1,134	1,395	5,043
	df	8	8	8		df	1	1	1
	Sig.	,043*	,018*	,134		Sig.	,287	,238	,025*
LinkedIn Connections	Chi-square	45,958	38,104	43,675	Hard Cap Limit	Chi-square	55,293	68,993	50,899
	df	19	19	19		df	1	1	1
	Sig.	,001***	,006**	,001***		Sig.	,000***	,000***	,000***
Managerial Experience	Chi-square	2,6	1,483	2,602	Token Price	Chi-square	1945,01	1987,91	2010,225
	df	1	1	1		df	202	202	202
	Sig.	0,107	0,223	,107		Sig.	,000***	,000***	,000***
Technology Experience	Chi-square	1,842	3,119	4,021	Currencies Accepted	Chi-square	89,85	141,691	157,924
	df	1	1	1		df	9	9	9
	Sig.	,175	,077	,045*		Sig.	,000***	,000***	,000***
Education	Chi-square	8,898	6,026	7,779	Ethereum Platform	Chi-square	75,052	46,583	26,752
	df	3	3	3		df	1	1	1
	Sig.	,031*	,11	,051		Sig.	,000***	,000***	,000***
Business Degree	Chi-square	4,467	1,81	2,601	Bonus Scheme	Chi-square	16,316	16,452	24,402
	df	1	1	1		df	1	1	1
	Sig.	,035*	,178	,107		Sig.	,000***	,000***	,000***
Technology degree	Chi-square	3,459	3,211	3,843	ICO Rating	Chi-square	102,825	117,568	94,905
	df	1	1	1		df	2	2	2
	Sig.	0,063	,073	,050*		Sig.	,000***	,000***	,000***
Team Rating	Chi-square	133,814	154,685	92,595	ICO Year	Chi-square	254,962	232,362	170,203
	df	2	2	2		df	3	3	3
	Sig.	,000***	,000***	,000***		Sig.	,000***	,000***	,000***
Vision Rating	Chi-square	73,173	105,169	48,536					
	df	2	2	2					
	Sig.	,000***	,000***	,000***					

## **5. Discussion**

From the descriptive statistics performed on the data collected we conclude that most of the projects' promoters on the banking/financial sector are currently located in Europe and that social networks are important in order to keep contacts. Most of the people prefer the professional network LinkedIn in order to feed their network which tends to be large due to the number of connections each profile has. The project's promoters tend to be very educated people with university degree, most of them at bachelor's level. The majority of the profiles had a managerial experience and about 21% of them had a technological experience. Looking at the correspondence analysis, we conclude that these projects do not have a high degree of success measured by our dependent variables. The independent variables which can be considered significant are the profile location, once we confirmed that the most successful projects are promoted by people located in Europe, Asia-Pacific and the United States. The remaining regions are less significant in the sample and are related with less successful outcomes. The number of projects per person can also be considered significant for two of the three dependent variables and is related with the experience of each profile. While most of the profiles had participated only in one project, we see that if the promoter has participated in one up to six projects, they tend to be more successful. For higher projects participation (i.e. more than 6) the results are negative. The variables measuring the professional experience of the profiles as well as the ones measuring the education turned out to be not much significant. The variable measuring the level of education (i.e. ranging from less than bachelor up to PhD) is only significant for the dependent variable related with soft-cap achievement. This conclusion is indeed expected once the great majority of the profiles have higher education making them less distinct in this factor. The variables related with the ratings attributed by experts revealed to be significant regardless of the dependent variable. The ratings are one of the most visible and impactful factors when an investor decides to engage with a project once they are presumed to reflect the expert's opinion on the project as well as the rating automatically attributed by an algorithm. The teams' size revealed also significant regardless of the dependent variable and we conclude that smaller teams tend to have worst results.

## **6. Conclusion**

We have engaged in exploring the new concept of ICO and particularly the composition of the projects' teams and their impact on the success of a project. Therefore, we have helped filling a literature gap on this subject by proposing three different measures of success and several measures for team's characteristics. We have concluded that several of the variables we propose tend to be significant, having in mind our dependent variables, and we were also able to describe a large set of profiles who are promoters of ICO projects. The avenues to complement these preliminary results are to enlarge the literature review and develop an econometric model based on our conclusions until now. Despite the contributions made the main limitations foreseen in the current research is the predominance of European projects/profiles in the database as well as limited variables for profiles which could in the future be complemented with new variables (e.g. data on profile's socioeconomic details). A larger database could also be tested including other type of projects beyond the banking/financial sector.

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