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FACTORS INFLUENCING US EQUITY-CROWDFUNDED COMPANIES' ABILITY TO SURVIVE AND ACQUIRE FOLLOW-UP FUNDING

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Factors influencing US equity-crowdfunded companies' ability to survive and acquire follow-up funding

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Abstract

The purpose of this paper is to determine the factors which influence equity-crowdfunded companies' likelihood of survival and obtaining additional funding after their first successful funding round. Cox proportional hazards model was used on a sample of 429 US equity-crowdfunded companies, based on data from a US equity-crowdfunding platform EquityNet for a period of minimum 3 years. The analysis reveals that the size of the funding goal, funding remaining at the end of the campaign, as well as the percentage of investor ownership have significant influence on equity-crowdfunded companies' probability of post-campaign survival. Moreover, the number of document requests during a campaign and the popularity of the campaign influence the companies' likelihood of having additional funding rounds. Two other determinants were associated with raising additional funding: the returns of SP500 index during the year in which a firm had its first funding round, and whether a firm operates in a manufacturing industry. Nevertheless, we find that Crunchbase rank – a variable calculated by Crunchbase startup-database – has no effect on companies' prospects for raising additional financing. We contribute to the existing literature by extending the research on equity-crowdfunded companies' campaign success and analyze the factors of the companies' post-campaign success for the first time in the US market.

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1. Introduction

The development of information and communication technology has had a positive influence on early-stage capital markets. The emergence of online crowdfunding platforms has made it easier than ever to match companies that need funding with people looking for investment opportunities. Such addition to the financing options available for start-up enterprises is especially important given the changes in early-phase funding landscape that resulted from the financial crisis (Wilson & Silva, 2013). Namely, traditional equity investors such as venture capitalists became more eager to finance later-phase start-ups, creating a gap among the financiers for start-up companies. At the same time, the early-stage segment of companies has inherent difficulties in attracting capital due to insufficient assets for loan collateral, information asymmetries, as well as a proper track record. Hence, the compound annual growth rate (CAGR) of total crowdfunding investment volume was around 76% during the time period of 2009-2013, signaling a significant rise in the popularity for this relatively new financing model (Wilson & Testoni, 2014). The authors add that geography-wise, the largest crowdfunding volumes can be attributed to North America (60%), followed by Europe (36%).

This research focuses mainly on equity-crowdfunding, which is one of the four types of crowdfunding. Equity-crowdfunding transaction values saw an approximately 50% cumulative annual growth rate (CAGR) between the years 2010 and 2012, but nevertheless constituted the smallest proportion of the general crowdfunding market (Wilson & Testoni, 2014). Despite the fact that the largest crowdfunding volumes can be attributed to North America, the abovementioned 50% CAGR can mainly be attributed to equity-crowdfunding platforms in Europe. This is mostly due to the legal barriers which hinder the development of equity-crowdfunding in the US, justifying why Europe is currently considered as the leading market for equity-crowdfunding.

Despite the rising popularity and importance of equity-crowdfunding, the research evidence is scant whether young firms funded by such novel financing model indeed manage to build enduring enterprises. For example, Vismara, Vanacker and Walthoff-Borm (2018) find that equity-crowdfunded companies have an 8.5 times higher failure rate compared to non-equity crowdfunded firms. Majority of the existing studies on equity-crowdfunding focus on the factors determining solely campaign success, that is, reaching the fundraising goal (e.g., Vismara, 2016; Piva & Rossi-Lamastra, 2018). It is thus the novelty of our paper to analyze the factors which lead to success in post-campaign performance of the funded companies. The few papers analyzing the post-campaign performance of funded companies, focus on European equity-crowdfunding platforms (Hornuf & Schmitt, 2017; Signori and Vismara, 2018). Given that the growth in equity-crowdfunding investment volumes has not been that significant in the US, the second contribution of our paper is to extend the analysis of post-campaign firm success for equity-crowdfunded companies in the US. Due to differences in legal environments, as well as equity-crowdfunding's smaller popularity as a financing form, the US market is still in an initial state compared to Europe (Wilson & Testoni, 2014). Considering the outlined novelties, we aim to answer the following research question:

RQ: Which factors influence the ability of equity-crowdfunded companies to survive and obtain follow-up funding after their first successful funding round?

2. *Literature review*

2.1. Crowdfunding

2.1.1 Crowdfunding definition and types

According to Poetz & Schreier (2012), crowdfunding has emerged from crowdsourcing, the latter referring to the action of financially supporting the launch of new business initiatives. Borello, Crescenzo & Pichler (2015) define crowdfunding as a setting in which numerous people contribute small quantities of funds to support projects and business plans through online platforms. Valanciene and Jegeleviciute (2013) determine three aspects which have to be present in the definition of crowdfunding: an entrepreneurial idea which needs funding, the existence of potential investors prepared to fund this idea, and the presence of an online platform for connecting the latter two. Furthermore, Wilson and Testoni (2014) reveal two underlying aspects of crowdfunding, both of which have emerged thanks to the development of the internet. Namely, due to reduced transaction costs, the internet allows to collect numerous small amounts from a large investor pool, which can total in a substantial sum of funds raised. Seconly, the internet eliminates the need for an active intermediary, as the investors and companies seeking funding are connected directly.

Kirby and Worner (2014) differentiate between community crowdfunding and crowdfunding which grants the investors a financial return. The former consists of donation-based and reward-based crowdfunding, whereas in equity-based and lending-based crowdfunding investors expect a monetary return. Wilson and Testoni (2014) specify that in donation-based crowdfunding, the funds are raised with either a philanthropic or supportive aim, so that in legal terms the transaction could be considered as a donation. In reward-based funding, however, an investor is granted a reward, such as a gift product or the first release of the product. Regarding the crowdfunding types providing financial return, lending-based crowdfunding (also *crowdlending*, or *p2p lending*) ascribes investors to receiving fixed periodic returns, as well as compensation for the principal amount invested. In equity-crowdfunding (also *crowdinvesting*), the returns take the form of equity-based revenue, which is further explained in a subsection dedicated to equity-crowdfunding.

2.1.2 Importance of crowdfunding

Borello, Crescenzo & Pichler (2015) claim that crowdfunding can significantly advance the financing process for SMEs and start-ups, as fund-seeking companies can approach a larger number of potential investors by reaching investors outside the country where the company is originated. Besides larger investor-reach, there are other rationales for enterprises to seek funding via crowdfunding, described as follows.

Mollick (2013) and Agrawal et al. (2014 & 2015) justify that crowdfunding improves efficiency in early-stage capital markets. While traditional equity investment channels such as angel investors make investment-decisions based on information circulating among investor networks, crowdfunding employs the intermediation of an online platform, providing faster and more accurate matches between investors and companies. Also, the employment of online data creates high potential for crowdfunding to take advantage from the development of big data, i.e. to employ the large and complex databases which can be created from the platforms' transaction data. Agrawal et al. (2015) explain that unlike business angels and venture capitalists, crowdfunding activity delivers information about the investors and companies that are involved in the transactions. Availability of such big data could enable platforms to develop methods for establishing even better investor-company matches in the future.

Moreover, Agrawal et al. (2014) and Hornuf and Schwienbacher (2014) claim that crowdfunding is a good opportunity for starting companies to promote themselves online during the first stages of development. Since crowdinvestors are likely to be the consumers of the product or service offered by the company seeking crowdfunding, the latter can use crowdinvesting platform as a channel for advertising, as well as gathering information about customers' demand and preferences. The possibility for companies to gain early insight into the attractiveness of their business idea can significantly lower the number of inefficient investments that would otherwise result from traditional equity investments into companies without the opportunity to interact with the market prior to launch.

2.2. Equity crowdfunding

2.2.1 Mechanics of equity-crowdfunding

In equity-crowdfunding, the fundraiser firm decides the amount of funds to be exchanged for a certain proportion of equity offered to the investors (Wilson & Testoni, 2014). Each investor then receives a pro-rata share of the firm's equity, respective to the funds contributed. For example, if a firm aims to raise €100,000 in exchange for 25% of equity, an investor contributing €1000 (which is 1% of the target amount), will receive 0.25% of the companies' total equity. From a legal perspective, equity-crowdfunding is the most complex form of crowdfunding, as the value of the equity purchased is merely an estimation. Further risks of crowdinvesting are described in a separate subsection.

It is common for equity-crowdfunding platforms to charge the companies raising funding a combination of fixed and percentage-based fee from the total investment amount. For example, a UK platform Crowdcube requires entrepreneurs to submit £1,750, as well as 5% from the amount raised in case of a successful campaign (Wilson & Testoni, 2014). The authors add that platforms such as Symbid and Seedrs charge also the investors with a percentage-based fee from the profit made by the crowdinvestor (2.5% and 7.5%, respectively).

2.2.2 Role of equity-crowdfunding in early-stage financing

According to Tomczak and Brem (2013), crowdfunding has become an alternative to the traditional early-stage funding channels such as venture capital and business angel financing. The main difference of equity-crowdfunding compared to these channels lies in the fact that the transactions are mediated via an online platform (Wilson & Testoni, 2014). There are, however, ambiguous findings on whether equity-crowdfunding as a new financing model supplements or substitutes these traditional financing channels. Studies by Hornuf and Schwienbacer (2014) and Borello, Crescenzo & Pichler (2015) conclude that equity-crowdfunding can serve both as a complement or a substitute to venture capitalists and business angels, mostly because the platforms differ in design and regulatory environment in which they operate. To understand how equity-crowdfunding differs from the traditional early-stage funding sources, it is important to look at factors such as investment size, incentives and riskiness, as well as investor characteristics – all of which are described as follows.

Wilson and Testoni (2014) state that one aspect in which crowdinvesting resembles angel investors is that financial return is not the major incentive for investing – similar to angel investors, crowdinvestors might make the contribution due to the business idea being in accordance with their emotional and social values or interests. Nevertheless, Kim and Moor (2017) find that social enterprises are more likely to achieve their target capital when financing via crowdinvesting – rather than by traditional investors -, which can suggest that non-financial values are more prevalent among equity-crowdfunding than business angel investors. Collins and Piearrakis (2012) add that the expectation for non-financial gains makes crowdinvestors more willing to face lower returns and hence invest into riskier initiatives.

Regarding industries and geographies, venture capitalists differ from equity-crowdinvestors mainly due to focusing on investment opportunities in technology, and therefore preferring companies which have a higher risk and return profile. Angel investors are more similar to crowdinvestors in that respect, as both groups of investors are ready to finance wider range of industries and locations, which venture capitalists often refrain from (OECD, 2011). Equity-crowdfunding can cover even broader investment segments than business angels, as crowdinvestors can have a diverse set of values and hence investment motives across various platforms. For instance, the campaigns on a UK platform Seedrs range from foods and drinks to real estate, arts and fashion (Seedrs, n.d.).

Geographically, equity-crowdfunding tends to reach the furthest compared to traditional early-stage financing channels - Agrawal et al. (2015) illustrate that the average distance between the crowdinvestors and the respective companies is around 4,800 kilometers, and only around 14% of the investors contribute to funding companies within the distance of 50 kilometers from them. This is supported by the findings of Borello, Crescenzo & Pichler (2015), who compare the cross-border activity of investors among equity- and lending-based crowdfunding platforms. The author finds that only investors in equity-crowdfunding gave their money to companies located outside the platforms' country of origin. Some authors argue, however, that such cross-border investments involve risks; this aspect is further discussed in a subsection about the risks of equity-crowdfunding.

Another feature in which equity-crowdfunding differs from venture capital and angel investors is that the companies are required to disclose their business strategy in public. Hemer (2011), Agrawal et al. (2014) and Hornuf & Schwienbacher (2014) have mentioned that such revelation of intellectual capital might lead to imitation of the product or service idea by other companies, and hence damaging the innovative companies who came up with the product or service in the first place. Hence, raising funds via crowdinvesting is more suitable for companies who are not outstandingly innovative, or who can protect their business idea other than merely keeping it confidential.

Besides comparing equity-crowdfunding to the traditional early-stage funding sources, there exist also different rationales between financing enterprises via crowdinvesting and other crowdfunding models. Belleflamme et al. (2014) conclude that young companies choose in favor of crowdinvesting rather than reward-based crowdfunding when the target investment amount is larger. Moreover, the authors note that crowdinvesting is preferred when the investment involves high information asymmetries, i.e. when the fund-seeking companies have more information about the product quality than the crowd. This is so, because in reward-based crowdfunding, specifically in case of product pre-ordering, the investors will also become the consumers of the product. When these investors cannot face sufficient information regarding product quality, they are less likely to fund the campaign. In equity-crowdfunding, however, the investor does not necessarily become the consumer of the product and is hence less sensitive to the information asymmetry. This is contradicting with Miglo & Miglo (2019), who find that such information asymmetries in online crowdfunding attract companies towards reward-based companies.

2.2.3 Risks in equity-crowdfunding

Whereas early-stage financing is already known to have high risk and return profile, certain characteristics of equity-crowdfunding can enhance this risk in investing to starting companies even further (Wilson & Testoni, 2014). For example, greater risk derives from the fact that compensation expected by the investors depends greatly on the fundraiser firm’s ability to create profits and increase the value of its equity. This is supported by Borello, Crescenzo & Pichler (2015), arguing that the risk posed by crowdinvesting is higher than for lending-based crowdfunding, as the former does not provide as great *investor protection mechanisms*. There are numerous other risk factors occurring in different stages of crowdinvesting, which are explained in the following paragraphs.

When selecting the projects to contribute to, investors in equity-crowdfunding platforms are less motivated to conduct a thorough due-diligence, since the financing amount by each investor is relatively small (Agrawal, Catalini & Goldfarb, 2014). This in turn may lead to lack of due diligence across the whole platform, as having small funds at stake makes it easy for crowdinvestors to *free-ride* on the efforts on the others. Such dependence of peer investors’ actions might also induce herding behavior (Agrawal, Catalini & Goldfarb, 2015), as well as unjustified optimism (Mollick, 2013). Also, collective lack of quality in assessing the value of the investment opportunities is increased by the fact that individual investors do not possess as sufficient *skills and knowledge* as professional investors about financial markets and investing into early-phase companies (Wilson & Testoni, 2014). However, the authors also emphasize that too intensive assessment by individual investors may increase the costs for the company to take all the suggestions made by the crowdinvestors into consideration, which is accentuated by the fact that fund-seeking companies do not possess control over the crowd who decide to become investors to the campaign.

Another shortcoming of equity-crowdfunding is that contracts between the investors and fundable companies are created by the platform (Hornuf & Schwienbacher, 2014). Traditional equity investors demand *customized contracts* that best align their interest (and the company offering equity). These contracts can include a range of covenants, such as anti-dilution arrangements and tag-along rights (i.e. the right of a minority shareholder to join a transaction when major shareholders decide to sell their shares), all of which protect the investors in allocating the rights for equity in profit-sharing. Standardization of the contracts by the platform, however, leaves the regular crowdinvestors without such protection.

Equity-crowdfunding also limits crowdinvestors in *controlling the behavior* of the entrepreneurs in two ways. One commonly used mechanism of reducing investment risk by professional investors is the division of offered equity into performance-conditional tranches. Although early-stage investors use it to establish control over the funded companies' behavior, it is hard to reproduce in such mechanism crowdinvesting. (Hornuf & Schwienbacher, 2014). Secondly, Agrawal, Catalini & Goldfarb (2014) point out that investing via an online platform is a rather one-time interaction, lowering the motivation for the entrepreneurs to behave in the interest of crowdinvestors. This could be mitigated by platforms' attempt in monitoring the companies more thoroughly prior to opening a campaign, but such screening standards differ among platforms.

There are three other aspects which increase risk exposure for the regular investors. Firstly, the crowdinvestors may not be familiar with the concepts such as diversifying the investment portfolio, and are therefore likely to increase their risk exposure by allocating all of their funds to a single campaign. For example, according to the statistics of Seedrs plarform, 41 percent of crowdinvestors have invested their funds into a single campaign. (Seedrs, 2018) Secondly, Wilson and Testoni (2014) emphasize that it is important to educate crowdinvestors about the concept of long-term illiquidity, which is especially the case in equity-crowdfunding. Thirdly, the crowd might not be able to take part in the follow-on funding rounds, which may take place via channels other than equity-crowdfunding. As a result, the stock of the crowdinvestor can become diluted.

Another important risk factor of equity crowdfunding is the difficulties induced by dispersed ownership (Agrawal, Catalini & Goldfarb, 2014). The dispersion of equity into numerous small stakes may make it complicated for the company to exit or raise follow-up equity funding rounds, as professional investors to not promote such dispersion in the ownership of the funded company. The authors add, however, that several platforms have found a solution for such issue by structuring the equity offered. For example, AngelList assembles crowdinvestors into a single fund managed by a third party, so that only the latter is shown on a start-up's investor list instead of numerous individual investors. Another shortcoming posed by dispersed ownership is the various set of different values and visions each individual investor may have, which can result in harming the guidance offered by the crowdinvestors' community regarding the start-ups strategic decisions.

2.3. Determinants of firm success

2.3.1 Determinants of campaign success

Existing literature provides different definitions of equity-crowdfunding campaign success. Ahlers et al. (2015) and Vismara (2016) use the number of investors as a proxy for campaign success, whereas Ralcheva and Roosenboom (2016) define campaign success as the company's ability to fulfill the target funding goal, i.e. to reach as a minimum 100% of the target. The potential determinants of funding / campaign success can in general be divided into six groups – company and product characteristics, social capital, investor profile, financial performance and campaign characteristics – all of which are described in the following paragraphs.

One set of variables indicating equity-crowdfunding campaign success includes *company characteristics*, such as company age, location, industry, and *size*. Ralcheva and Roosenboom (2016), who analyze the regulated UK equity crowdfunding market, find that company age is negatively correlated with the likelihood of campaign success, the reasons of which could be that younger firms incorporate more risk and face greater information asymmetry problems. Hence it could be interpreted that younger firms are less likely to obtain funding, but the authors remind that equity crowdfunding is inherently made to address such younger, early-stage firms. Moreover, they conclude that companies who operate in large cities or in technology industry have a higher probability of receiving funding. Also, Nitani and Riding (2017) add that in order to reduce investment risk, equity-crowdfunding investors are more prone to invest in larger firms, provided that the latter have experienced and educated managements.

Regarding companies' *product characteristics*, Lukkarinen et al. (2016) investigate data from a leading equity-crowdfunding platform in Northern Europe and emphasize the importance of product 'understandability'. They find that the likelihood of success is higher for consumer-oriented rather than B2B products, as customers are more prone to invest into products they are familiar with. Ralcheva and Roosenboom (2016) find that companies who defend their intellectual property through trademarks, copyrights or patents, face greater likelihood of campaign success. However, this effect disappears after considering the effects of the awards a company has achieved, as well as how many strategic partnerships the company has established, meaning that the latter two factors have a greater importance than the existence of intellectual property in determining campaign success.

Another set of variables are related to the *human capital* of a company. Nitani and Riding (2017) conclude that investors are more prone to invest in companies with an experienced and educated managements who also retain a relatively big proportion of equity. Similarly, Piva and Rossi-Lamastra (2018) claim that entrepreneurs' business education and entrepreneurial experience indicate higher funding success. Ralcheva and Roosenboom (2016) find that having an advisory board increases success probability, further signaling that the quality of a company's management is an important indicator for it to successfully raise equity crowdfunding.

Further variables regarding *social capital* are suggested by Lukkarinen et al. (2016), who find that the ability to leverage social media networks has a positive effect on the likelihood of campaign success. This is supported by Nitani and Riding (2017), who claim that entrepreneurs' social network has such a strong effect that it weakens the significance of success variables such as firm size, expected sales growth and margin when added to the model. Social capital is also considered a good predictor of campaign success by Vismara (2016), who looked at companies from UK equity-crowdfunding platforms. The paper suggests that the extent of social connections enables investors to reduce the uncertainty and information asymmetry commonly attributed to starting companies, and gives further empirical evidence that these social connections promote pitch popularity and hence attract a larger investor base. Lastly, Ralcheva and Roosenboom (2016) add that companies which have formed strategic partnerships with more prominent partners benefit from 18% bigger probability of campaign success, and attract 30% more investors.

A group of factors indicating crowdinvesting campaign success are related to the *number and the profile of investors*. Ralcheva and Roosenboom (2016) state that backing by business angels or venture capitalists increases the campaign success probability by 18%, and leads to a 35% increase in the number of investors. Interestingly, they find that the strength of this 'certification effect' is stronger for younger companies, and it diminishes remarkably after certain time period. Moreover, Vismara (2018) studied the campaign dynamics in the

UK equity-crowdfunding market, and states that backing by investors with a public profile increase the attractiveness of a campaign among early investors. This indicates that early investors have the ability to influence later-stage investors, which in turn leads to greater likelihood of funding success. This is similar to the findings of Vulkan, Åstebro and Sierra (2016), who looked at a UK crowdinvesting platform and conclude that if a campaign were to succeed within a target time period, it needs to have a strong start in the funding round, i.e. a significant proportion of the target funds are obtained relatively soon after the launch of the campaign. Further complementing this idea, Lukkarinen et al. (2016) reveal that early funding from private networks has a positive effect on the number of investors, as well as on the total funding amount raised. A large amount of existing pledges to invest may indicate higher investment quality, and hence reduce the time and efforts of individual investors in conducting due diligence on the campaigns.

An important variable regarding company's campaign success is its *growth potential*. According to Nitani and Riding (2017), investors aim to maximize returns by funding companies that indicate better growth opportunities, i.e. mainly young companies that have higher expected profit margins, as well as sales forecasts. Ralcheva and Roosenboom (2016) argue that realizing the first sale has a positive effect on achieving the funding goal. The authors suggest that the emergence of the first sale refers to higher growth potential, which in turn attracts more retail type investors, as the latter seek for investments yielding quick and high returns. Contradictingly, Lukkarinen et al. (2016) conclude that sales growth forecast plays no role in determining the funding success.

Regarding other variables related to company's *financial or operating performance*, Angerer et al. (2017), who looked at German equity-crowdfunding platforms, claim that the attractiveness of the business model, sufficient preparation prior to starting the campaign, and company's operational activities (including advertising activities) have a positive effect on the start-ups' campaign success. This is again contradicted by Lukkarinen et al. (2016), who find that provision of financial data has a rather weak effect on the campaign success.

Several papers also reveal the effect of *campaign characteristics* on the probability of achieving funding. The most analyzed campaign characteristic in existing literature is the percentage of equity offered, or investor ownership. Vismara (2016) claims that larger stake of equity given out to investors decreases the probability that a campaign will be successful, possibly because when founders themselves keep a lower percentage of shares, it might refer to lower quality of the investment. Ahlers et al. (2015) agrees on this signaling function of equity retention, although Ralcheva and Roosenboom (2016) argue against. Namely, they find equity retention is an insignificant predictor of achieving funding target goal and propose that the quality signal of equity retention by founders is rather easily disregarded by investors, as they are seeking for more reliable ways of recognizing investment quality. They argue that the percentage of equity offered does not provide information about the absolute value the founders have been willing to invest into the company, reducing the information about the founders' credibility. The founders might have merely entered minimal amounts and hence equity retention does not solve the problem of information asymmetry.

Regarding other campaign characteristics, Lukkarinen et al. (2016) find correlation between the number of investors and the pre-selected crowdfunding campaign characteristics: larger minimum investment, as well as longer campaign duration are associated with smaller number of investors. Ralcheva and Roosenboom (2016) add that successful campaigns account for larger average investment amount per investor. When considering the absolute value of funding goal, however, the literature includes contrasting views. Lukkarinen et al. (2016) claim that funding goal is positively – but not strongly - associated with the number of investors, whereas Ralcheva and Roosenboom (2016) find no correlation between the funding goal and probability of the campaign success.

2.3.2 Determinants of post-campaign success

There is limited research on the post-campaign performance of equity-crowdfunded companies. The potential factors of post-campaign success covered by the existing literature can in general be divided into company, campaign and investor characteristics. The respective papers are reviewed briefly in this section.

One of the most similar analysis to our research is conducted by Hornuf and Schmitt (2017), who compare the probability of follow-up funding and firm-survival between startups from UK and Germany. They find that company age, the average age of the management, and the extent of overfunding during the equity-crowdfunding campaign have a negative effect on the companies' probability to obtain follow-up funding. Other company- and campaign-related variables such as the number of senior managers, registered trademarks, following successful equity-crowdfunding rounds, crowd exits, and the funding goal has a positive impact on the likelihood of obtaining post-campaign funding. As good predictors of firm survivorship, they consider following successful equity-crowdfunding rounds, crowd exits, and the number of venture capital investors.

A paper by Signori and Vismara (2018) analyze the factors influencing the post-campaign scenarios of 212 companies that were equity-crowdfunded via a British crowdinvesting platform Crowdcube. They conclude that greater ownership dispersion leads to smaller likelihood to issue further equity, which is in accordance with the analysis of Agrawal, Catalini and Goldfarb (2014) regarding risks in equity-crowdfunding, as described earlier. Moreover, Signori and Vismara (2018) find that companies who achieved campaign success faster are more prone to seek additional funding by starting follow-up financing rounds. Similar to the finding regarding ownership dispersion, the authors reveal that when an initial equity offering has attracted a large investor-base, the post-campaign scenario is less prone to face either a secondary equity offering or a merger & acquisition deal. Lastly, they claim that backing by venture capitalists and business angels is an important determinant in the post-campaign success of equity-crowdfunded companies, as there were no failures among the companies that were funded by certified investors in the initial campaign.

To sum up, there is sufficient rationale for analysing the post-campaign success of firms funded via equity-crowdfunding, especially given the risk of less (or lower quality) monitoring by the investor base. To analyse which factors influence the crowdfunded companies' post-campaign success, we collect information about several categories of variables outlined in the literature, such as company and campaign characteristics, as well as factors relating to companies' growth potential. The process of selecting and adjusting the variables is further explained under the Variables subsection. In Data section, we provide expectations regarding how each variable is likely to influence companies' ability to survive or raise follow-up funding. These hypotheses are summarized in Table 2.

3. Data and variables

3.1. Data

In order to obtain the necessary data, we used both databases of Crunchbase and EquityNet. Crunchbase is a web platform where investors can discover young companies, find information about those firms and connect with people behind them. For entrepreneurs, Crunchbase is a place where they can stay connected with potential investors and look for alternative partnerships. The platform allows market researchers identify upcoming trends and analyze market condition (Crunchbase Inc, 2019a). EquityNet, in turn, is one of the largest equity-crowdfunding platforms which operates worldwide. EquityNet connects privately-held businesses with retail investors, as well as with startup incubators, lenders and even government support entities. Before publishing a company's profile, EquityNet reviews it and performs its own analysis (Global Equity Fintech Inc, 2019). Also, EquityNet does not handle transactions, meaning that if investors want to invest in a company, they have to contact the company's management. Therefore, companies can decide from which investors they want to accept payments (Global Equity Fintech Inc, 2019). Communication between investors and companies happens privately, so it is not possible to check how many investors got rejected by companies. There is no specific information about the average campaign duration on EquityNet platform, but in general an equity-crowdfunding campaign lasts for approximately 2-3 months (Tarrida, n.d.), which is slightly longer than the 2-month period for reward-based crowdfunding platforms such as Kickstarter (Buck, 2012).

We started the data collection from Crunchbase and applied multiple inclusion criteria which will be discussed further. First, we selected companies which have headquarters in the United States of America, since we are interested in analyzing US companies. Second, we selected only those firms which were founded no later than 1st of January 2016, so there is at least a 3-year period from which to gather data. There is no information whether a campaign is finished or is ongoing, so we assume that all retrieved campaigns are finished, since campaigns usually do not last more than one year. Third, we filtered out non-profit companies, since those firms' goals and their investors' objectives are different from those of for-profit companies. Finally, we took only those companies whose first round was equity crowdfunding. If companies had funding other than equity crowdfunding in the first round, we excluded them from the list, since it would bias their performance.

As a result of the above listed filtering, we extracted 1,260 company names from Crunchbase. Next, we matched the names of the firms extracted from Crunchbase with the names of the companies in the EquityNet database, which resulted in a list of 429 companies. The reason why the initial list was reduced to one third is that only one third of the companies had their first funding round funded on EquityNet platform, while all other companies used alternative funding platforms. Also, might be the case that some companies are named differently on EquityNet platform and Crunchbase database.

3.2. Variables

3.2.1 Dependent Variables

The main goal of the paper is to determine factors influencing equity crowdfunded companies' survivability, as well as ability to obtain follow up funding. Therefore, we selected four dependent variables which represent these outcomes respectively. Two of the dependent variables are binary variables which are used in logit regressions. Another two variables measure time in months and are used in Cox proportional hazard model. The conducted analysis is described in more details in the methodology section of the paper. The variables are discussed further in this section. The data about the variables was retrieved on November 17th, 2019.

The first dependent variable measures if a company is still operating or not. This is a dummy variable which equals 1 if a company is dissolved, and 0 if a company still operates. This data was collected from Crunchbase, where it is stated if the company is closed or remains active.

The second dependent variable measures how long a company managed to stay alive after its first funding round. The variable is measured in months and is calculated as the time passed between the date when a company had its first funding round, and the date when a company was closed. If a company is still alive, the variable equals time between a company's first funding round and the day when the data was collected (November 17th, 2019). The observations in this case are right censored, meaning that it is unknown in which point of time a company will dissolve (Forthofer, Lee, & Hernandez, 2007). Further in the methodology section we will describe how we deal with the censoring in our analysis.

Information about the dates of the first funding rounds (the dates when first rounds were announced, i.e. started) was retrieved from Crunchbase and was available for all companies in our list. The date of a company's closure was identified by collecting information from different sources. For some companies this information was clearly mentioned in their company profiles on Crunchbase. For 3 out of 46 closed companies Crunchbase provided exact closing dates, while for 11 firms the platform provided only a closing year. For other companies, the closing date was not available at the platform. To identify the date of company's closure more precisely, we searched information about those firms in alternative databases. Since we are examining US companies, and in the US every state has its own company register due to the differences in legal systems, we used multiple different databases. For example, we used business name search from Florida Department of State, Division of Corporations (State of Florida, Florida Department of State, 2020); or, a company search system provided by Oregon Secretary of State (2020); and other similar business search systems provided by the local government entities. In some company registers we managed to find exact dates when companies became dissolved or when their last financial statements were reported, which we assume to be a valid indicator of a company's closing date (n = 11). For other companies there were no publicly available information at all, or the information was provided only upon request and required additional payments.

Additionally, we searched the databases of Orbis or Thomson Reuters Datastream. However, since the companies were too young and/or small, and some of them were not properly registered, no information about the firms could be found on those data sources. Therefore, to identify approximate dates when the companies stopped their operations, we came up with alternative solutions. If the date of the company closure was unavailable in Crunchbase, in company registers, and in Orbis or Thomson Reuters, we took the date when the company was active in social medias for the last time. For example, the date when a company shared its last post on its Facebook or LinkedIn pages, or posted a tweet on Twitter. For some companies, links to their social media profiles were provided on the companies' Crunchbase or EquityNet pages. For others, we had to search manually in the internet by company names or names of the company's agents. With the abovementioned techniques, we managed to find precise closing date for 6 out of 46 dissolved companies in our sample. For the rest 15 companies with no closing date available we adopted the mean-substitution approach. Mean-substitution approach implies that missing values are substituted with the average value of the observed data for the variable, since the mean value is a reasonable estimation for the missing data points. This approach let us fully utilize the incomplete dataset (Kang, 2013).

The third dependent variable measures if a company raised additional funding after their first equity crowdfunding round. This is a dummy variable, which is 1 if a company had a follow-up funding, and 0 if it did not. This information was taken from Crunchbase website. In our case only 15 out of 429 companies had two or more funding rounds. Most popular types of additional funding rounds were venture capital (n = 5), seed rounds (n = 5), equity crowdfunding (n = 4). Also, some companies had Series A and series B funding rounds (n=3), as well as convertible notes (n=2), grants (n=1) and debt financing (n=1).

Finally, the fourth dependent variable measures how much time it took for a company to get additional funding after its first funding round. The time is measured in months, and the dates are also taken from Crunchbase. For companies which had only one additional funding, the variable equals time between a company's first funding round and the day when the data was collected. Again, the observations are right censored in this case, since it is unknown when the companies will have a second funding round (if at all). Exact dates of all funding rounds are available on Crunchbase.

3.2.2 Independent Variables

We use 34 explanatory variables to answer our research question. We divided the variables in the following categories: *company characteristics*, *campaign characteristics*, *growth potential*, *company riskiness*, *industry*, and *macroeconomic factors*. Some of the variables are taken from the companies' profiles on EquityNet, while others are retrieved from Crunchbase. These variables are described in this subsection. We also elaborate on our expectations about how particular variables affect a company's survivability and capability to obtain additional funding. The description of the variables and the expectations are summarized in Tables 1-2.

Table 1. Description of dependent variables: definition and data source

Dependent variables		
Variable	**Data description**	**Source**
Closed	Binary variable, equals 1 if a company is closed and 0 otherwise	Crunchbase
months_before_closed	Number of months for how long a company stayed alive. If a company is still alive, then this variable shows the number of months passed since the first funding round	Crunchbase, Company registries, others
had_additional_funding	Binary variable, equals 1 if a company had more than 1 funding rounds and 0 otherwise	Crunchbase
months_before_second_round	Number of months passed between the first and second funding rounds. If a company had only one funding round, then this variable shows the number of months passed since the first funding round	Crunchbase

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Table 2. Description of independent variables: definition, expectations and data source

Variable	Data description	Expected sign for survivability	Expected sign for additional funding	Source
Company characteristics				
ln_age	Natural logarithm of the age of a company (in months)	+	+	EquityNet
ln_employees	Natural logarithm of the number of a company's employees	+	+	EquityNet
response_rate	Response rate (in %)	+	+	EquityNet
cb_company_rank	Crunchbase company rank	-	-	Crunchbase
Campaign characteristics				
ln_premoney_val	Natural logarithm of a company's pre-money valuation	+	+	EquityNet
ln_funding_goal	Natural logarithm of a company's funding goal	+	+	EquityNet
funding_raised	Funding raised so far (in % of the funding goal)	+	+	EquityNet
funding_commitments	Funding commitments (in % of the funding goal)	+	+	EquityNet
funding_remaining	Funding remaining in % of the funding goal)	-	-	EquityNet
investor_ownership	Investor ownership (%)	+/-	+	EquityNet
doc_requests	Number of documents requests	+	+	EquityNet
popularity	Popularity value	+	+	EquityNet
Growth potential				
ln_revenue_0	Natural logarithm of a company's prior year revenues	+	+	EquityNet
ln_revenue_1	Natural logarithm of a company's current year revenues	+	+	EquityNet
ln_revenue_2	Natural logarithm of a company's next year revenues	+	+	EquityNet
revenue_growth_0	Revenue growth from prior year to current year	+	+	EquityNet
revenue_growth_1	Revenue growth from current year to next year	+	+	EquityNet
revenue0_rel_fun_goal	Prior year revenues (in % of the funding goal)	+/-	+/-	EquityNet
revenue1_rel_fgoal	Current year revenues (in % of the funding goal)	+/-	+/-	EquityNet
revenue2_rel_fgoal	Next year revenues (in % of the funding goal)	+/-	+/-	EquityNet
num_of_fun_rounds	Number of funding rounds	+	+	Crunchbase
benchmark_return	Benchmark return	+	+	EquityNet

Variable	Data description	Expected sign for survivability	Expected sign for additional funding	Source
Company riskiness				
business_risk	Business risk of a company	-	+/-	EquityNet
benchmark_risk	Benchmark risk of a company	-	+/-	EquityNet
Industry				
industry_d	Manufacturing industry	+/-	+/-	EquityNet, NAICS Association
industry_e	Transportation, communications, electric, gas and sanitary services	+/-	+/-	EquityNet, NAICS Association
industry_f	Wholesale trade	+/-	+/-	EquityNet, NAICS Association
industry_g	Retail trade	+/-	+/-	EquityNet, NAICS Association
industry_h	Finance, insurance, and real estate	+/-	+/-	EquityNet, NAICS Association
industry_i	Services	+/-	+/-	EquityNet, NAICS Association
Macroeconomic factors				
gdp_growth_0	GDP growth at year 0 (in %)	+	+	The World Bank Group
gdp_growth_1	GDP growth at year 1 (in %)	+	+	The World Bank Group
sp_growth_0	S&P500 return at year 0 (in %)	+	+	Macrotrends LLC
sp_growth_1	S&P500 return at year 1 (in %)	+	+	Macrotrends LLC

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The category of *company characteristics* includes four variables: natural logarithm of a company's age (*ln_age)*, natural logarithm of the number of employees within a company (*ln_employees)*, response rate (*response_rate)* and Crunchbase company rank (*cb_company_rank)*. Variable *ln_age* is a natural logarithm of a company's age, where age of a company is measured in months and is retrieved from EquityNet. We use natural logarithm for the age of a company instead of the absolute numbers, because the data is rather skewed and it fails the test for the normal distribution. The same logic applies to other variables described further for which we use logarithm value instead of absolute value. In their paper Hornuf and Schmitt (2017) argue that age of a company is a significant determinant of a company's ability to survive and obtain follow up funding. Even though the mentioned paper analyzes UK and German equity-crowdfunded companies, we assume this factor to be significant for US companies as well. Moreover, we expect the variable to positively affect both survivability of a company and its ability to obtain follow-up funding. Namely, older firms tend to accumulate more resources, connections and experience, which is beneficial for a company's survivability, and in turn makes older companies more attractive in investors' eyes. Also, there are more data available for older companies, so investors can perform more in-depth analysis and gain confidence prior to investing.

Variable *ln_employees* is calculated as a natural logarithm of the number of employees in a company. This factor appeared to be an important determinant for success in equity-crowdfunding campaigns, as revealed in an analysis by Nitani and Riding (2017). Also, Brüderl, Preisendörfer and Ziegler (1992) discovered that start-ups with higher number of employees have higher survivability rate. Data about the variable was obtained from a company's profile on EquityNet. We expect companies with more employees to have greater prospects for survival and additional funding than smaller companies, since large number of employees signals that a company has enough resources to maintain the employee-base, as well as to run numerous operations – another sign of a healthy business.

Variable *response_rate*, in turn, considers the different documents investors can request from the companies on EquityNet platform. The variable measures the percentage of documents provided from total number of document requests. The documents can include business plans, details of a campaign, financial statements and other related information. The company, in turn, is eligible to decide to which investors they are willing to provide those documents. The variable is expressed in percentage, ranging from 0 to 100. For example, if a company responds to investors in 6% of all cases, then the value of the variable equals 6. We applied the same approach for all variables being expressed as fractions (see Table 2) which allows us a more straightforward interpretation of the results from the Cox model. Even though the variable has never been examined in the literature before, we assume it to be significant, as companies that are more active in communication with investors are likely to perform better and manage to attract more funding. Therefore, we suppose that companies with higher response rate are more successful in obtaining follow-up funding. We also assume that higher response rate leads to higher survivability chances, because ability to attract investors during a company's very first funding rounds can "make or break" the business, since investors play an important role in young companies' development (CFI Education Inc., 2020).

Finally, we obtained Crunchbase rank as another independent variable, for which we collected information from Crunchbase platform. Even though this variable has not been covered by previous literature, we investigate its influence on survivability likelihood. Variable *cb_company_rank* denotes Crunchbase company rank, which is calculated by the platform's algorithm. The algorithm considers a company's popularity, number of news and articles (media coverage) associated with a firm, the number of followers, as well as community engagement and other factors. The variable is an integer number, where smaller number refers to greater popularity of a company (Crunchbase Inc, 2019b). We assume this variable to be an important factor, since companies which are more engaged with the community and are better covered by the media are typically more successful (Signori and Vismara, 2018). By this reason we expect the variable to have a negative sign for both the companies' survivability, as well as the ability to raise additional capital (lower rank number denoting higher popularity).

The category of *campaign characteristics* includes variables such as a natural logarithm of a company's pre-money valuation (*ln_premoney_val)*, natural logarithm of a company's initial funding goal (*ln_funding_goal)*, funding raised (*funding_raised)*, funding commitments (*funding_commitments)*, funding remaining *(funding_remaining)*, investor ownership within a company (*investor_ownership)*, number of document requests (*doc_requests)* and a company's popularity index (*popularity)*. Variable *ln_premoney_val* stands for the natural logarithm of pre-money valuation. Pre-money valuation measures price per which a company is offered to investors and is measured in US dollars. Again, we are taking natural logarithm of the variable instead of the absolute values, because the data is rather skewed and fails the normality test. We expect that this variable will positively affect a company's survivability and ability to gain additional funding due to economies of scale and greater brand recognition (BBC, 2020). Also, we believe that high price of a firm signals that a company is well established and is more stable in its operations which makes a company less prone to dissolve.

Variable *ln_funding_goal*, denotes natural logarithm of a company's funding goal. Funding goal represents how much money a company is willing to raise (in US dollars) with its equity crowdfunding campaign. While some investors prefer to invest in larger projects, some other investors may be more interested in smaller projects. Therefore, the net effect of the variable on a company's ability to obtain follow up funding seems ambiguous for us. At time, we assume that more expensive projects receive more attention from business partners and clients, as well as allow economies of scales to take place. All of this is favorable for a company's survivability. On top of that, Farinha and Santos (2006) discover that start-ups with more tangible assets have higher chances to survive in the long run. Therefore, we assume that *ln_funding_goal* variable has a positive effect on a company's ability to survive.

Funding_raised variable represents amount of money a company managed to attract from investors in a particular campaign. The variable is measured as a percentage of a company's funding goal. We expect this variable to have a positive impact on a company's capability to survive and to obtain additional funding. Firstly, we assume that the amount of funds raised plays a crucial role for young companies, because start-ups usually do not have large retained earnings or other reserves, and without such initial investment majority of the early-phase firms will not manage to launch the business. Secondly, funding_raised variable acts as a signal of the crowds' perception about the future prospects of a company, thus how eager crowdinvestors are to invest in the firm. It is worth to mention that on average *funding_raised* equals 23% which implies that majority of the companies do not manage to attract enough funds in their first funding round (Appendix B). *Funding_commitments*, in turn, represents the amount of money investors promised to invest in a particular company, but which had not been transferred yet. This variable also is measured as a percentage of total funding goal. By the same reasons described above, we expect this factor to have a positive influence on a company's survivability and probability to obtain follow up funding.

F*unding_remaining* variable equals funding goal minus sum of funding raised so far and funding commitments. Since we assume that all of the campaigns are finished, the variable shows how much funds a company did not manage to attract (relative to the initial funding goal). This variable is expressed as percentage of funding goal as well. Since we measure all three aforementioned variables as a percentage of a funding goal, the relationship shown in Eq.1 holds:

$$1 - funding\_remaining = funding\_raised + funding\_commitments \quad (Eq.1)$$

The difference between *funding_remaining* and *funding_commitment* variables is that *funding_comitments* represent amount of funds which were promised to be transferred (and most likely will be), while *funding_remaining* is amount of money which a company did not manage to obtain in their first funding round. As this variable can be derived from the previously mentioned factors, the conclusion can be made that this variable is likely to have a negative effect on a company's survivability and additional funding. It is reasonable to assume that the larger the funding remaining for a firm, the larger is probability that a company will dissolve and will not gain any additional funding.

Investor_ownership variable represents the fraction of a company's equity which is offered to investors, measured in per cents of total equity. We assume this variable to be relevant, since companies with large investor ownership tend to be monitored and controlled more, which lead to better firm performance. At the same time, companies with too small management ownership tend to perform worse, since top managers are less motivated than if they would have a larger stake in a company. Therefore, the net effect of the factor on a firm's survivability is ambiguous, even though Vismara (2016) states that higher percentage of equity offered within a funding campaign decreases probability of a campaign success. At time, we expect the variable to have a positive impact on a company's ability to obtain follow-up funding, since in our view investors prefer larger stakes in companies, because it gives them more voting rights and more overall control over a company. Again, values of the variables *funding_raised*, *funding_commitments*, *funding_remaining* and *investor_ownership* represent respective percentage points.

As it was mentioned above, investors on EquityNet platform have a right to request particular documents from a company. Therefore, variable *doc_requests* measures how many documents have been requested from a company (in absolute numbers). Large number of documents requested indicates that investors' have high interest in a company, which increases the company's chances to obtain funding. Consequently, higher chances to receive investments results in higher probability to launch the business properly, because more resources will be available, and this is especially important for companies in their very first funding rounds, which we examine. Therefore, we expect this factor to have a positive influence on both the company's survivability and ability to attract additional funding. Finally, variable *popularity* is generated by EquityNet platform's algorithm. It determines popularity of a campaign within a platform based on multiple different factors, such as how often a campaign is visited by investor or how often investors contact the management of a company. As it was discussed before, we believe that popularity and media attention is important for companies in their very first funding rounds, which is why we forecast this variable to have a positive impact on a company's capability to survive and obtain additional funding.

Data of all variables in this category was collected from EquityNet platform. We did not find any prior analysis of these variable in existing literature. However, as argued beforehand we assume the variables to be significant determinants of companies' survivability and ability to obtain follow up funding.

Growth potential category includes variables which indicate a company's capabilities to develop and expand further. The category contains 10 variables (see Table 2). The first eight variables in this category are derived from three variables from a company's profile on EquityNet. Those are *prior year revenue*, *current year revenue* and *next year revenue* (for all three variables, the reference year is the year the campaign was launched). These variables are expressed in absolute numbers in US dollars. It is expected that some of the variables formed may have a high correlation, which will be tested further in the paper.

Variables *revenue_growth_0* and *revenue_growth_1* represent revenue growth from prior year to current year, and from current year to the next year, respectively. Both variables represent growth in per cents. We forecast both factors to have a positive impact on a company's survivability and ability to receive additional funds, because growth of revenues is likely to indicate a company's good performance in the future. Values of both variables represent respective percentage points.

Variables *ln_revenue_0*, *ln_revenue_1* and *ln_revenue_*2, in turn, denote natural logarithm of prior year revenue, current year revenue and next year revenue respectively. We expect all three variables to have a positive effect on a company's ability to survive and to obtain follow up funding, since companies with larger revenues not only have more resources to sustain and develop a company's operations, but also indicates that a company has potential to grow. On top of that, Farinha and Santos (2006) have found that companies with larger revenues tend to survive more often.

Next, variables *revenue0_rel_f_goal*, *revenue1_rel_fgoal* and *revenue2_rel_fgoal* are calculated as a company's prior year revenue, current year revenue and next year revenue relative to the company's funding goal respectively. The effect of all three factors on a company's survivability and ability to gain follow up funding is rather ambiguous. On the one hand, a company with high revenue relative to the funding goal is less dependent on that funding, since it will manage to generate cash in relatively short period. However, on the other hand, profit margins may differ significantly across different companies, and profit is more important factor than revenue for a company's survivability and ability to obtain additional funds.

Variable *num_of_fun_rounds* stands for the number of funding rounds a company had. The variable, in turn, is retrieved from Crunchbase and is measured in absolute values. We assume this variable to be a significant factor in post-campaign success, since firms with more funding rounds tend to survive with a higher probability and be acquired more often, because large number of funding rounds signals that a company is performing well and investors trust it. At the same time the more funding rounds a company has had, the smaller is the probability that the company will continue raising additional funds, as it has already achieved its optimal funding level. (Rowley, 2017)

Finally, *benchmark_return* variable is a value calculated by EquityNet platform, which represents a firm's return relative to its peers. Unfortunately, EquityNet platform does not disclose how exactly returns are calculated. Therefore, from the name of the variable, we assume that the variable is calculated as a ratio between a company and its peer's returns on investment. However, variable *benchmark_return* is rather subjective, because it is estimated by EquityNet platform. We assume that firms which perform better than their peers tend to survive and receive follow up funding more often. In this case values of the variables serve as absolute numbers of percentage points.

Company riskiness category includes two variables which determine how risky a particular firm is. The variables are *business_risk* and *benchmark_risk*, and are calculated by EquityNet, since the platform not only provides investors with opportunities to invest in particular companies, but also performs analysis of those firms before publishing their profiles. *Business_risk* variable is measured in per cents and represents the total risk of a firm, while *benchmark_risk* measures a firm's riskiness relative to its peers. B*enchmark_risk* is calculated as a company's total risk divided by risk of its peers. The platform does not disclose how precisely total risk is calculated; we assume that EquityNet analysts have a specific model for this purpose which is adjusted for young crowdfunded companies. We did not find coverage of these variables in prior literature as well. However, we assume these factors to be significant in a company's ability to survive, since less risky companies tend to survive more often than risky ones. However, we assume that the effect of the variables is ambiguous on a company's ability to obtain additional funding, since investors have different risk preferences. Again, values of both variables stand for percentage points.

Industries category includes six binary variables which represent sectors in which the companies are operating. The variables are *industry_d*, *industry_e*, *industry_f*, *industry_g*, *industry_h* and *industry_f*, where each letter denote a specific industry (see Table 2). For example, variable *industry_d* indicates that a company operates in manufacturing sector, while variable *industry_h* represents finance, insurance and real estate businesses.

EquityNet platform provides information about the sectors in which the companies are operating. Since the sectors provided by EquityNet are too detailed, we have rather used the grouping of the Standard Industry Classification (SIC) system (NAICS Association, 2018). Even though the system has ten main industry categories, we have used only six of them, because none of the sample companies operate in the mining, agriculture, constructions or public administration sectors. All industry variables are binary variables; so, value of a binary variable equals 1 if a company is operating within a specific industry, and 0 otherwise. Each company is assigned only to single industry; therefore, only one out of the six industry variables will equal 1, while the remaining variables will be 0.

Even though we assume that a company's ability to survive or to obtain additional funding is highly influenced by the industry the company is operating in, its effect is still ambiguous due to multiple reasons. Firstly, in a few cases it was unclear to which industry a company should be allocated, since some of the companies fits multiple sectors. For instance, a company which is producing and selling goods fits both manufacturing and retail industries. When we faced such ambiguity, we did additional research on those companies in order to decide which sector the company fits better. Secondly, young companies pivot a lot and change their plans and industries rather frequently in their early stages. Continuous tests and changes in the business model are absolutely necessary for a startup's survivability and success (Ries, 2011). Lastly, industry effect is very different in different times. For example, television used to be rather successful 10-30 years ago; however, now the traditional television is out-dated due to its digital rivals like Netflix and Hulu.

Finally, the category of *macroeconomic factors* includes the following four independent variables: US GDP growth the same year a company has its first funding round; GDP growth the next year after the first funding; S&P500 index returns the year a company has its first funding round; and S&P500 returns one year after the first funding. We assume that state of the economy and economic cycle are important factors of a company's survivability and ability to raise additional funds. It is expected that a company is more likely to survive when the economy is in its growth phase, rather when the economy is in recession, because there are more resources in circulation and people's and companies' purchasing power is larger. The same applies for a company's ability to raise additional funding – there are more funds available when the economy is in the growth stage, making it more likely that investors contribute to the funding of early-phase companies. We have chosen GDP growth and yearly S&P 500 index returns as a proxy for the state of the economy of the United States. GDP growth represents the overall growth of the US economy, while S&P500 index returns describes the performance of the US's 500 main companies in leading industries. In our view, the state of the economy is important not only in the year in which the company had its first funding round, but also the next year. Thus, we expect that all four variables have a positive impact on a company's ability to survive and obtain additional funding. Each variable in this category is expressed in percentages, ranging from 0 to 100.

3.3. Missing values and outliers

In our dataset 17 out of 23 independent variables have missing values, while 15 out of 23 determinants contain outliers. We use the mean imputation method as a technique for filling missing values. This implies that we calculated mean value for each variable and substituted missing values accordingly. The outliers were not considered in the mean value calculations. As a result of the mean imputation method, average values of the variables remained the same. See Appendix A for detailed data about outliers and missing values.

For outlier detection, we used the box plot method. At first, 1st and 3rd quartiles (Q1 and Q3) were calculated for each variable. Then, the interquartile range (IQR) is calculated, which is the difference between the first quartile and the third quartile. Finally, an outlier is a data point which is below Q1 – k * IQR or above Q3 + k * IQR (Tukey, 1977; McGill, Tukey, and Larson, 1978). Traditionally, coefficient k equals 1.5 or 3. Thus, values outside Q1 – 1.5 * IQR and Q3 + 1.5 * IQR borders are considered as "mild" outliers, while values outside Q1 – 3 * IQR and Q3 + 3 * IQR boundaries are extreme outliers (Dawson, 2011). In our case the data is rather disperse;the companies operate in different industries, as well as they differ in size, age and other factors quite a bit. Therefore, we consider only extreme outliers as outliers, the values of which are below Q1 – 3 * IQR or above Q3 + 3 * IQR.

Once outliers were detected, they have been excluded from the data. Excluded outliers were substituted with winsorization technique. According to the technique, outliers are substituted with the maximum or minimum threshold values, depending whether the outliers are extremely small or extremely large. If an outlier is higher than the upper limit, it is replaced by the value of Q3 + k * IQR. If an outlier is lower than the lower threshold, than it is substituted with the value of Q1 – k * IQR.

Summary statistics of the raw data is presented in Appendix B, while summary statistics of the processed data (when outliers are substituted with winsorization technique) is provided in Appendix C.

4. Methodology

4.1. Survivorship model

The main objectives of this paper are to identify which factors influence a company's survivability after a company's first funding round, as well as its ability to raise additional capital in further rounds. We therefore analyze effects of explanatory variables on four independent variables that were described in the Data section. We employ a Cox proportional hazard model as our main model. Also, we use logit model for the robustness check.

Cox proportional hazard model is one of the most widely used techniques for survivability analysis. The model is used not only in medicine, but also in various other industries for different purposes (Bujang et al., 2016; Ishak et al., 2013; Wakounig, Heinze & Schemper, 2015). Unlike the logit or probit models, the Cox proportional hazard model considers the time when a specific event occurred. In our analysis, the two respective events are the closure of the company after its first funding round, as well as receiving additional funding.

The survival function $\lambda(t, x)$ can be approximated and derived from the baseline hazard function $\lambda_0(t)$. In the baseline hazard function all the variables within an observation are 0. Therefore, the hazard is as follows:

$$\lambda(t, x) = \lambda_0(t)e^{x\beta} \qquad \text{(Eq. 2)}$$

In Eq. 2 beta denotes a p x 1 vector of parameters (where p is number of parameters); x is a vector of covariates and t is time (Cox, 1972).

Cox proportional hazard model has several main assumptions. Firstly, the model assumes that the effect of the independent variables (also called covariates) should increase or decrease the hazard proportionally over time (Rodriguez, 2001; Cox, 1972). This assumption can be tested with Schoenfeld residuals test (UCLA, 2017), which is performed latter in the paper. However, if the proportionality test fails, time varying covariates may be included in the regression. Another solution is to perform stratification (UCLA, 2017). Secondly, the model assumes that covariates have a linear relationship with a hazard's natural logarithm (Waldron, 2014; LaMorte, 2016), which also can be checked with Schoenfeld residuals test (UCLA, 2017). The third assumption is that every observation is independent and does not affect other observations (Waldron, 2014; LaMorte, 2016). In our case it means that the failure of one company does not affect the survivability of another company. Or, if one company received additional funding, this event does not impact other companies' chances of receiving additional funding.

As it was mentioned before, variables like *months_before_closed* and *months_before_second_round* in our dataset are right-censored. That implies that for some companies the exact closing date or the date of the second round are not known, since closing or second funding round has not happened yet, but may happen in the future. Also, in our dataset some variables are highly correlated. Therefore, to test all regressors and avoid multicollinearity, we run multiple regressions with different combinations of independent variables. The goal is to avoid regressions which includes variables with a correlation coefficient 0.7 or higher (or -0,7 and lower). We have one pair of highly correlated independent variables, *funding_raised* and *funding_remaining*, which is 0.86. High correlation between those two variables was expected, since equation 1 (Eq. 1) holds and *funding_commitment* for the most companies is either not available or very small. Variables from the category of growth potential, in turn, appeared to have relatively low correlation, which allows us to use them in the same regression.

Also, for Cox and logit regressions on a company's ability to have a follow up funding, variable *num_of_fun_rounds*, which is number of funding rounds, is perfectly correlated with our dependent binary variable *had_additional_funding*. This happens because if variable *num_of_fun_rounds* equals 2 or more for a company, then variable *had_additional_funding* is automatically 1. By this obvious reason variable *num_of_fun_rounds* is excluded from both Cox and logit regressions on a company's ability to have a follow up funding. See summary correlation table in Appendix D.

4.2. Robustness of results

We use logit regression model to examine robustness of results obtained from the Cox model. The logit model (Stock and Watson, 2003) is defined as shown in Eq. 3:

$$\Pr(Y_i = 1 | X_i = 1) = \phi(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_k X_k), \qquad \text{(Eq. 3)}$$

where Y is a dependent variable and X_1, X_2, … , X_i are independent determinants which were described in the Data section. We run two types of regressions. At first, we test which independent factors influence a company's probability to survive after its first funding round. In that case, the dependent variable is the binary variable *closed*, which equals 1 if a company is dissolved and 0 if a company still operates. Then we analyze how independent variables impact a company's chances to obtain additional funding. Here, the dependent variable is a binary variable *had_additional_funding* which equals 1 if a company had two or more funding rounds and 0 if it had only a single round. Again, we run multiple regressions with different combinations of independent variables in order to avoid multicollinearity.

Additionally, as a robustness check, we perform numerous other specifications for the Cox regressions. In our dataset we have ten independent variables with more than 50% of missing values. Since the majority of the missing values were substituted with the mean substitution approach, they may bias the results. In order to test how those variables impact the results, we run additional Cox regressions where those variables were excluded (regressions 9 and 10 on survivability, and regressions 15 and 16 on a company's ability to obtain additional funding). Again, in robustness check regressions we also use multiple regressions to avoid multicollinearity. Next, as we have already mentioned in the Data section, we do not consider industry variables to be very precise. Therefore, we perform Cox regressions with excluded industry variables (additionally to the excluded variables with more than 50% of missing values) to check how they alter the results (regressions 11-12 for survivability, and 17-18 for additional funding).

Next, as we already mentioned in the Data section, for 15 out of 46 companies closing dates were not available, so we use mean-substitute approach for *months_before_closed* variable (for closed companies), which represents the number of months between a company's first funding round and the date when the company is dissolved. To test whether the mean substitute approach for the dependent variables alter the results, we run the same regressions as regressions 1 and 2 (Cox regressions with all independent variables on a company's survivability), but only on those companies where the closing dates were available (n = 31) (regressions 13 and 14). In those two regressions we excluded the number of funding rounds variable (*num_of_fun_rounds*), since all companies for which closing dates were available had only one funding round, and the same value for all observations would cause multicollinearity.

Finally, we use Akaike's Information Criteria (AIC) and Bayesian Information Criteria (BIC) to evaluate variable fit within Cox and logit models. AIC and BIC are calculated in the following way:

$$\text{AIC} = -2 \times \ln(\text{likelihood}) + 2 \times \text{k} \qquad \text{(Eq. 4)}$$

$$\text{BIC} = -2 \times \ln(\text{likelihood}) + \ln(\text{N}) \times \text{k} \qquad \text{(Eq. 5)}$$

where k is the number of parameters estimated and N is number of observations.

The smaller the value of AIC or BIC, the better the fit of a model. It is worth mentioning that the same dataset should be used in order to perform an unbiased comparison between the models. The results from AIC and BIC for all regressions are provided at the bottom of the tables in Appendices E, F, G and H. Even though we calculated both AIC and BIC, it is worth noting that AIC is proved to suit better for survival analysis, since the technique's evaluation depends on the number of parameters to be estimated instead if the number of observations (Liang & Zou, 2008; Stata, 2017). Therefore, we perceive the results form AIC to be more reliable and discuss them further in the paper.

5. Results

To determine the factors of equity-crowdfunded companies' likelihood of survival and obtaining follow-up financing, we conduct four Cox hazards' regressions on two dependent variables. The sample consists of 429 companies with an average age of 6.8 years and 32 of the companies closed their operations during the 3-year period after the first funding round. More detailed descriptive statistics are provided in Appendices B and C. Regressions 1 and 2 show the determinants of companies' survivability, whereas regressions 3 and 4 analyze the factors influencing companies' ability to obtain additional funding. The results are summarized in Appendix E, and are supplemented with robustness check (logit regressions), which are summarized in Appendix F. As an additional robustness check, we conducted six Cox regressions on the likelihood of survivability in which we excluded variables with more than 50% of missing values, companies without available closing dates, and industry variables. Also, due to multicollinearity, we used two sets of regressions to test the effect of *funding_remaining* and *funding_raised* separately. The results are summarized in Appendix G (regressions 9-14). Similar alterations are made to the likelihood of obtaining additional funding (Appendix H, regressions 15-18). The reason for excluding industry variables in regressions 11, 12, 17 and 18 is that we perceive that the SIC industry categorization is not entirely applicable to startups and might not thus lead to the most precise results.

To determine the regression models with best fit, we considered the AIC value (in the bottom of the tables in Appendices E, F, G and H) for reasons mentioned in the Methodology section. As lower AIC refers to better fit of the model, we concluded that regressions 13 and 14 provide superior robustness check of Cox hazards model for survivability analysis (compared to regressions 9 – 12). Regarding the results of the main model (Appendix E), logit regressions (Appendix F), and the additional Cox hazards models for additional funding (Appendix H), the differences across AIC values are negligibly small and thus we make inferences based on all the regressions equally. For numerical interpretations in the main model, we nevertheless select regressions with the lowest AIC figure (regressions 1 and 3).

5.1. Determinants of survivability

A determinant with a strong effect on the companies' survival probability is the proportion of *investor ownership* - with a 1 percentage point increase in equity stake shared out to investors, the likelihood of default of an equity-crowdfunded company increases by 3.1%. This result is significant at a 5% confidence level. Furthermore, we found three variables that increase the likelihood of survival. If the *funding goal* or *current year revenue* increase by 10%, the likelihoods of survival increase by 82% and 89%, at confidence levels of 1% and 5%, respectively. (We adjusted these hazard ratios (HR) in Appendix E to a scale corresponding to a 10% increase in the independent variable as follows: adj.HR = ln(1.1)*e*prev.HR, where adj.HR is the HR hazard ratio with respect to the 10% increase in funding goal and current year revenue, e is the mathematical constant, and prev.HR is the original hazard ratio, which shows a change in survival likelihood with respect to a 2.7 times increase in the independent variable). It can therefore be concluded that higher funding target set in the campaign, as well as the higher estimated revenue for the year in which the campaign was launched both signal company's stronger performance in the post-campaign period. The results regarding the third variable, *funding remaining* reveal that when the value of funding remaining at the end of the campaign increases by 1 percentage point, the probability of survival increases by 1.3%. This finding, however, is only significant at a 10% confidence level, and enables to conclude that the variable has only a minor impact on companies' survivability.

5.2. Determinants of additional funding

Regarding factors influencing additional funding, we found five significant determinants. Number of *document requests* and *popularity* are two campaign characteristics that are both significant at a 10% confidence level. A one unit increase in the amount of *document requests* decreases the probability of obtaining follow-up funding by 35%. Since the average number of document requests per campaign is 2.17, then it is understandable why an additional document request can have such an impact. Moreover, when the *popularity* value of a campaign increases by one unit, the probability of obtaining follow-up funding decreases by 66%. Here again, the average popularity value for the campaigns is 2.86 (on a scale of 5), justifying the influence on the independent variable. Nevertheless, the negative effect of *doc_requests* and *popularity* variables is counter-intuitive and will be further elaborated in Discussion.

Two other significant variables come apparent under the macroeconomic and industry categories. When the *returns of SP500 index* are higher by one percentage point in the year the company closed its first successful funding round, the company faces 11% higher probability of raising an additional funding round. The finding is significant only at a 10% confidence level, but aligns with our expectations by indicating that better economic conditions at the time of a company's first funding round have a positive effect on investors' decisions to invest more into the equity-crowdfunded company in the near future. Regarding the industry variables, we reveal that compared to operating in the *services industry*, a company in the *manufacturing industry* has 83 times higher probability of raising additional funding. The figure is rather extreme, which may be due to the small sample of companies that had an additional funding round. Lastly, we find that that although the *Crunchbase ranking* is significant at 1% confidence level, it has no effect on the probability of obtaining additional funding as the hazard ratio is 1.

Prior to moving to a more thorough analysis of the significant variables in the Discussion section, it is important to mention once again that the findings regarding additional funding can be biased due to the relatively small sample size of equity-crowdfunded companies that raised funding in more than one round – only 15 out of 429 examined companies had additional funding rounds. This aspect is further addressed under the Limitations and future research section.

6. Discussion

6.1. Determinants of survivability

6.1.1. Campaign characteristics

A highly significant variable among campaign characteristic is *investor ownership*, referring to the fact that the higher is the proportion of equity offered to crowdinvestors, the lower the probability of companies' survival. Although this variable has not been covered in research on post-campaign success, Vismara (2016) revealed that higher proportion of equity offered to crowdinvestors decreases the probability of campaign success (as it refers to lower investment quality), which is also supported by Ahlers et al. (2015). This argument is, however, against Ralcheva and Roosenboom (2016), who emphasize the insignificance of investor ownership as a signaling variable when assessing crowdfunding campaigns, and that investors look for more promising factors that might refer to the quality of the investment. We find that the negative effect of investor ownership to campaign success as suggested by Vismara (2016) and Ahlers et al. (2015) can be extended to the companies' post-campaign success, as it comes apparent that crowdfunding companies who have granted crowdinvestors a greater stake of their company, do face greater risk in maintaining the business operations.

Regarding other variables among campaign characteristics, the results show that *funding goal* has a significant positive effect on the equity-crowdfunded companies' likelihood of survival at a 1% confidence level, which is accordance with our set hypothesis. The closest prior literature suggests that the importance of the size of funding goal is rather weak regarding campaign success – Lukkarinen et al. (2016) report a weak link between a campaign's funding goal and the number of investors, whereas Ralcheva and Roosenboom (2016) find no correlation between funding goal and campaign success at all. Our findings would thus add to the literature that although the size of the funding goal does not influence campaign success, companies with larger target funding amount tend to have greater prospects for survival. One possible reasoning could be that larger funding goal reflects larger project size, which may benefit from economies of scale and hence aid the firm in maintaining its operations for longer.

In contrast with our hypothesis, we find that *funding remaining* has a positive – albeit rather weak - effect on the companies' probability of survival, which would mean that the more funds are missing from the target funding goal, the greater the prospect of company's future performance. The variable has not been covered in existing literature, but one possible explanation for this counterintuitive finding could be the link with funding goal, which had a strong positive effect on the companies' survivability. Namely, it can be assumed that when a funding goal has been set too high, it is more likely that at the end of the campaign such high goal is not reached, resulting in a higher value for the *funding remaining* variable. However, this is contradicting with the correlation coefficient between funding goal and funding remaining (-0.03). An alternative speculation could be that larger amount of funding remaining at the end of the campaign sets pressure on the management to work harder, which consequently leads to company's higher likelihood of survival.

6.1.2. Company characteristics

In terms of company characteristics, we find one variable which is linked to higher probability of the companies' post-campaign survival - *current year revenue*. Literature on how revenue impacts the companies' performance is limited to papers that look into campaign success. Ralcheva and Roosenboom (2016) find that when a company has realized its first sale by the time of the campaign start, the firm is more likely to reach the funding goal. This is so, as the completion of the first successful sales refers to the firm's higher growth opportunities in the future. Our paper contributes to the literature by adding that the positive effect of the companies' revenue at the year when campaign was launched also indicates stronger performance in the post-campaign period as well. Since the companies in our sample use equity-crowdfunding as their first attempt to raise funding, it is likely that their first sales are captured by the *current year revenue* variable. A contradicting claim - again regarding campaign-success – is made by Lukkarinen et al. (2016), who find that sales growth forecast has no effect on the companies' campaign success. It motivates us to think critically regarding our finding of the positive effect of *current year revenue* on the companies' post-campaign survivability, especially given that the variable *prior year revenue* yields insignificant results, and the correlation coefficient between the variables is rather high - 0.61. Also, *current year revenue* comprises partly of realized revenue, but is partly a mere estimation of the most likely revenues the fund-seeking company will face throughout the year in which the campaign was started. This could reflect that the management is optimistic and has a good understanding of the company, but nevertheless a more thorough analysis ought to be conducted which separates these effects (of revenue growth estimates and of revenues that are realized) on companies' probability of survival.

6.2. Determinants of additional funding

6.2.1. Campaign characteristics

The two campaign-related variables that influence equity-crowdfunded companies' probability of raising additional funding are the number of *document requests* and *popularity*. However, as the effect of these variables on additional funding is negative, the results are contradicting with our hypotheses. With an additional document request by the crowdinvestors, the respective company is 35% less likely to raise a follow-round. We expected this variable to have a positive effect, as a larger number of document requests by the crowdinvestors likely indicates an active communication between the founders and investors, and thus higher chances of investors to contribute even more funds to the company. A possible interpretation of why *doc_requests* has a negative effect instead, could be that investors are more skeptical about the companies' operations and require more quantitative information for performing a thorough due diligence before investing into an equity-crowdfunding campaign. There could be a reason behind such investors' skepticism – the company might indeed intend to hide facts that refer to poorer performance in the future, and such poorer performance attracts less investors to invest into the firm's later financing rounds. Similarly, we expected the *popularity* variable to have a positive effect on the likelihood of obtaining follow-up funding, since the *popularity* measure considers how often the campaign is investigated by the visitors, as well as media coverage. Here, an alternative interpretation could be that problematic companies attract more visitor flow, as well as media coverage, which would also explain why these companies are less likely to attract financing for future rounds. However, both of the variables discussed are significant at only 10% confidence level. As a result, it is important to conduct future research with a larger sample size of companies with several funding rounds, as well as separate the effects of media coverage and other components under the *popularity* measure.

6.2.2. Macroeconomic and industry variables

Furthermore, we find that when the *returns of S&P500 index* are higher in the year a company accomplished its first successful funding round, the company is more likely to obtain follow-up funding. This is in accordance with our expectations, and can be explained by the fact that an early-stage company can benefit from the general good economic conditions, which would promote the growth of this equity-crowdfunded company. Companies with higher growth rate are, in turn, more likely to raise next funding rounds. Another finding regarding the macroeconomic and industry variables, is that equity-crowdfunded companies operating in *manufacturing industry* are 83 times more likely to raise additional financing when compared to *service industry's* companies. Due to the vague nature and poor applicability of the industry categories to start-ups, we did not expect these variables to have a significant effect. Nevertheless, a potential interpretation for the latter finding could be that manufacturing enterprises have a higher proportion of tangible assets and investors perceive these companies to have a higher recovery rate – and thus lower investment risk - in the case of possible default. Companies operating in services industry, however, could have difficulties in selling their intellectual property or know-how, which could be a reason behind why these companies attract relatively less additional financing.

Lastly, we find significant results regarding the *Crunchbase rank* variable. Our hypothesis suggested that a better rank would indicate greater likelihood of raising additional funding, but a hazard ratio of 1 indicates that *cb_company_rank* has no influence on the additional funding prospects at all. However, as mentioned before, the variable might be biased due to the relatively small size of the sample. Existing literature includes several findings that would lead to the assumption that a better *Crunchbase rank* would increase the companies' prospects in raising additional funding. Namely, one of the factors which the algorithms behind Crunchbase considers is the extent of the companies' social networks, and Lukkarinen et al. (2016) find that companies that are able to leverage their social networks are more likely to succeed with their campaign. Similar argument is made by Vismara (2016) and Nitani & Riding (2017), who reveal that companies' social connections indicate greater campaign success, possibly due to reduction in information asymmetry that might arise from lack of awareness among the crowd regarding the company's activities. However, the *Crunchbase rank* variable does consist of several factors, which is why further investigation needs to be conducted to determine the significance of the social connections' effect alone on companies' campaign and post-campaign success.

6.3. Robustness check

We have validated our results with a logit regression model (Appendix F), as well as several additional Cox proportional hazards model specifications. These specifications represent various combinations of certain variables; several variables were excluded as described in section Robustness of results (Appendices G & H). The results of Schoenfeld residuals test are described in next section - Limitations and future research.

6.3.1. Logit model

The results of the Cox proportional hazards model regarding the likelihood of firms' survival (regressions 5-6) are strongly in accordance with the logit model. The variables of *funding goal*, *funding remaining*, and *current year revenue* indicate a higher likelihood of survivability, and the coefficients are negative and significant in the logit model. Similarly, the hazard ratio showing an increased risk of default with an increase in investor ownership is reflected by a positive coefficient in the logit regression. One differences between the Cox hazards and logit regressions, however, comes apparent for the *revenue1_rel_fgoal*, where the logit model indicates that the ratio of current year revenue to funding goal should have a positive effect on the companies' survival probability. The coefficient is yet only significant at 10% confidence level.

Regarding the likelihood of additional funding (regressions 7 – 8), the results are robust for the effect of Crunchbase rank variable – both the Cox hazards and logit model indicate at 1% confidence level that the variable has no influence on the likelihood of obtaining additional funding after the first successful funding round. Moreover, the logit regressions confirm that the *number of document requests* has a negative effect, while the *manufacturing industry* and *S&P500 index returns* on the first funding year have a positive effect on the likelihood of raising follow-on rounds. Here, one discrepancy between the Cox regressions and the logit model is that the logit model also assigns a positive effect to the industry of transportation, communications, electric, gas and sanitary services, meaning that companies in this industry are more likely to attract additional financing compared to firms in services industry. A second contradiction is that the logit model indicates a negative effect of GDP growth rate in the following year after the first successful funding round. This would mean that if the economic conditions improve in the year after the equity-crowdfunded companies' first successful funding round, the company is less likely to have an additional funding round. This finding would, however, be in contrast with the fact that *S&P500 index returns* during the year in which an equity-crowdfunding succeeded have a positive effect on the company's prospects in raising follow-on funding. To investigate this relationship in more depth, a larger sample size of companies with several funding rounds is needed.

6.3.2. Additional Cox proportional hazards models

The regressions 9 – 14 (additional Cox regressions on survivability) are consistent with the findings from the main Cox hazards model – *ln_funding_goal, investor ownership* and *funding_remaining* are significant predictors of companies' survivability. However, when companies without available closing dates are excluded (regressions 13 - 14), two other variables become significant (at 10% confidence level) – the ratios of *current year revenue* and *next year revenue to the funding goal*. The interpretation of these variables is similar to the explanations under the logit model in the previous section.

Cox hazard model regressions 15 – 18 (additional Cox regressions on the likelihood of additional funding) are, in general, in accordance with the results from the main Cox regressions. The effects of *doc_requests* and *sp_growth_0* become stronger, and an additional variable becomes significant - *ln_age*. Namely, when a company is 2.7 years older, the likelihood of obtaining additional funding decreases by 90%, possibly because older companies are more likely to be able to fund their future growth from internal funds. This is in accordance with Hornuf and Schmitt (2017), who reveal that company's age is negatively correlated with the likelihood of obtaining additional funding.

6.4. Limitations and future research

There are several limitations linked to the methodology and data chosen for our research. The first and most prominent means of improving the validity of our findings would be to have a larger sample size. Gathering a sufficient number of companies that raised follow-up rounds (instead of current 15) would allow to perform a better analysis on the determinants of equity-crowdfunded companies' likelihood of obtaining additional funding. Increasing the total size of the sample would also help in reducing the number of missing values – a concern that is currently problematic for variables under the *growth potential* category (see Appendix A). It is important to note, that the sample size can only be increased by time – as of now, we gathered the maximum possible sample.

Secondly, the research could be further developed if it included more specific variables regarding the companies' financials – data which, at the time of the research was not possible to obtain, as the empirical data regarding equity-crowdfunded companies is yet in early stages. For example, with more specific financials we could address the concern raised in the discussion regarding differentiating between the effects of revenue growth estimates and realized revenues on the likelihood of survival and acquiring follow-up funding. Therefore, we consider the inclusion of more specific financial variables as an important aspect in future research.

The third limitation regarding our sample data is the reliance of data about companies from only one country – the US, which is again due to the absence of data from other countries that would cover long enough time period. Future research could most likely include data from Scandinavian countries, as equity-crowdfunding has seen great growth in this region, and the high disclosure standards of these countries would most likely enable to get better access to companies' financials.

The fourth limitation consists in the fact that although we used SIC industry codes, the classification into industry groups from *a-i* was done by us and may thus be biased and subjective.

Fifth, two of the analyzed variables would provide more accurate results if they were separated into multiple elements. As mentioned in the Discussion section, it might provide additional insights if the impact of media coverage could be separated from other components included in the *popularity* measure. Similarly, the *current year revenue* variable consists of a realized revenue, as well as revenue forecast until the end of the respective year; separating these two effects could provide a better understanding of the underlying mechanisms.

Regarding the data chosen for our research, the results of the Schoenfeld residuals test show that the independent variables in our research are not proportional for *industry e, benchmark risk, current year revenue, number of document requests, Crunchbase rank* and *number of employees* in regressions 1 – 2 (survivability analysis). None but *current year revenue* are significant determinants for likelihood of survivability, and hence do not influence the validity of our findings. For *current year revenue*, however, the results are robust in the logit regressions (Appendix F), which allows us to consider it as a valid determinant for survivability. Several of the above mentioned variables also fail the proportionality test in regressions 10, 13, 14 and 15, but as none of these variables have any significance in the main regressions (1 – 2), it does not affect the quality of our findings. For regressions on companies' ability to obtain additional funding, the proportionality holds for all variables in the Cox regressions, except for the variable *Crunchbase rank*. As the logit regressions confirm the significance of *crunchbase_rank*, here again we continue to consider the variable as significant.

One additional direction for future research is to include not only more financial variables, but also variables that capture the social and human capital of the equity-crowdfunded companies. For example, more data is needed to investigate the individual effects of variables that are included in the calculation of *Crunchbase rank* variable. As noted in the discussion, one reason to do so is to determine the effect of social connections (a component of *Crunchbase rank* variable) alone on companies' campaign and post-campaign success. Other variables that capture the companies' human and social capital and that are well covered in existing literature on campaign success include information such as firms' media coverage (number of articles), number and background of the management, participation of professional investors (VCs and BAs), as well as companies' engagement with the community. It is likely that with the development of equity-crowdfunding platforms, as well as databases that aggregate data about start-ups (e.g. Crunchbase) will make it possible to gather such data in the future.

7. Conclusion

The aim of the paper was to determine factors which influence equity-crowdfunded firms to survive or raise follow-up funding after their first funding round. This forms the basis of our research question, which is answered as follows:

Regarding variables determining companies' probability of survival, we find that the higher the *investor ownership*, the less likely is the company to survive, which is in accordance with Vismara (2016). Another significant campaign characteristic was *funding goal;* we contribute to the prior literature by proving that larger funding goal does not only lead to higher campaign success, but also to equity-crowdfunded companies' post-campaign success. A slightly contradicting finding is the positive effect of *funding remaining* at the end of the campaign on the likelihood of survivability. We assume that this effect might be due to the pressure set on the managers at the end of an under-funded campaign, which then leads to a superior post-campaign performance. Moreover, we find that the higher the companies' revenue in the year of their first successful funding round, the higher are their chances of survival. A probable explanation is that higher revenue signals a "running" successful business – without traction, the product or service cannot succeed. However, one has to be careful with interpreting this variable, as it consists of two components - realized revenue and revenue forecast. As mentioned earlier, the analysis might yield more accurate results when the effects of the latter two variables on survivability are determined separately.

From the regressions on companies' likelihood of obtaining follow-up funding, we find that higher *returns for S&P500* in the year of the first funding round are linked to higher likelihood of additional financing, which can be explained via benefits an early-stage company can obtain due to the general good economic conditions that promote the start-up's growth opportunities. Moreover, we find that companies within *manufacturing industry* are more likely to run an additional funding round compared to firms in service industry – possibly because an early-phase manufacturing firm have a higher recovery value in case of default compared to a service start-up with more intangible assets. For campaign characteristics, we find that *Crunchbase rank* – a variable calculated by the platform – has no effect on the companies' likelihood of obtaining follow-up financing. This latter finding signals that there is no correlation between better funding prospects and the social capital characteristics a company has – the rank provides no useful hints regarding which companies are more successful in future financing rounds. For other campaign characteristic variables, we find somewhat contradicting results. The higher the *number of document requests* during the campaign, as well as the higher the campaign's *popularity*, the less likely will the equity-crowdfunded company raise further financing. Possible explanations for these rather counterintuitive findings are that higher number of document requests reflects higher investor skepticism, and that problematic companies might have larger media coverage than a typical company– both factors affect negatively the prospects for raising new rounds in the future.

Our findings contribute to existing literature by several means. Majority of the research on equity-crowdfunding focuses on the determinants of campaign success – we have extended the analysis for post-campaign success. Moreover, the findings are based on a sample of US companies – region with the biggest worldwide crowdfunding volumes, but a proportionately low empirical data regarding equity-crowdfunding. This research is the first one for the US in the field of equity-crowdfunded companies' post-campaign performance. Another value from our research derives from including numerous variables in the model that have not been covered in previous literature on equity-crowdfunding such as industry variables, *campaign popularity*, and *number of document requests*.

As equity-crowdfunding is a rather novel means of alternative funding, the empirical data is scant, and poses several limitations to our paper. Most importantly, the validity of our findings could be improved by gathering information about more equity-crowdfunded companies which raised more than one funding round. This criterion can only be filled with time – as of now, we collected information about the highest number of companies possible. Another limitation which is due to the lack of empirical data is the inclusion of financial variables. We assume that the first region to provide such data for future research consists of Scandinavian countries due to their better disclosure standards. Including companies from Scandinavia or other regions would also increase the validity of the research due to a larger geographical scope. For future research, we would also suggest including variables regarding companies' social capital – e.g. media coverage (number of articles, background of the management, participation of professional BA and VC investors, and companies' engagement with the crowdinvestors' community). With the growth of equity-crowdfunding as an alternative funding source, we expect the databases which aggregate data about start-ups (e.g. Crunchbase) to provide such data in the future.

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Appendix A. Summary on outliers and missing values (n=429, n/2 = 214)

Variable	Missing values	Outliers	Q1	Q3	IQR
Company characteristics					
ln_age	17	3	4.04	4.60	0.55
ln_employees	36	3	0.69	1.61	0.92
response_rate	0	27	2.00	6.00	4.00
cb_company_rank	0	0	150,598	542,279	391,681
Campaign characteristics					
ln_premoney_val	162	5	13.10	15.42	2.33
ln_funding_goal	15	0	11.51	14.22	2.71
funding_raised	81	12	0	17.50	17.50
funding_commitments	336	9	0	8.33	8.33
funding_remaining	15	18	84.25	100.00	15.75
investor_ownership	172	0	13.34	42.86	29.52
doc_requests	0	28	0	2.00	2.00
popularity	0	12	2.60	3.10	0.50
Growth potential					
ln_revenue_0	286	0	10.75	13.69	2.94
ln_revenue_1	239	0	10.89	13.82	2.92
ln_revenue_2	313	0	13.74	15.70	1.96
revenue_growth_0	286	14	-34.52	81.38	115.91
revenue_growth_1	239	17	-100.00	199.27	299.27
revenue0_rel_fun_goal	289	12	0.10	1.51	1.41
revenue1_rel_fgoal	244	16	0.13	1.54	1.41
revenue2_rel_fgoal	315	7	1.00	6.17	5.17
num_of_fun_rounds	0	0	1.00	1.00	0
benchmark_return	182	9	-7.00	42.00	49.00
Company riskiness					
benchmark_risk	0	0	-20.00	8.00	28.00
business_risk	253	0	22.00	44.25	22.25
Industry					
industry_d	0	0	-	-	-
industry_e	0	0	-	-	-
industry_f	0	0	-	-	-
industry_g	0	0	-	-	-
industry_h	0	0	-	-	-
industry_i	0	0	-	-	-
Macroeconomic factors					
gdp_growth_0	1	2	2.45	2.88	0.43
gdp_growth_1	1	2	1.57	2.88	1.31
sp_growth_0	1	2	-0.73	11.39	12.12
sp_growth_1	1	1	-0.73	9.54	10.27

Note. Created by the authors

Appendix B. Summary statistics of the initial (raw, unprocessed) data

Variable	Mean	Min	Max	St. dev.
Dependent variables				
closed	0.11	0	1	0.31
months_before_closed	58.53	1	149	16.02
had_additional_funding	0.03	0	1	0.18
months_before_second_round	56.51	1	137	16.9
Independent variables				
Company characteristics				
ln_age	4.40	3.04	6.89	0.52
ln_employees	1.26	0	10.6	1.14
response_rate (%)	6.08	0	100	9.13
cb_company_rank	351,440.56	17,763	729,888	209,974.8
Campaign characteristics				
ln_premoney_val	13.93	0	19.81	2.6
ln_funding_goal	12.97	9.21	17.8	1.82
funding_raised (%)	22.59	0	1714.29	129.43
funding_commitments (%)	9.13	0	100.0	20.3
funding_remaining (%)	87.36	0	100	22.03
investor_ownership (%)	31.30	0	100	25.10
doc_requests	2.17	0	51	4.92
popularity	2.86	0.2	5	0.75
Growth potential				
ln_revenue_0	12.19	4.5	17.66	2.35
ln_revenue_1	12.28	5.3	17.69	2.27
ln_revenue_2	14.64	10.82	18.83	1.61
revenue_growth_0 (%)	465.31	-100	39900	3452.92
revenue_growth_1 (%)	1358.32	-100	112980.0	9533.65
revenue0_rel_fun_goal	2.71	0	70.7	9.22
revenue1_rel_fgoal	3.12	0	169.9	13.59
revenue2_rel_fgoal	16.33	0.02	994.10	94.23
num_of_fun_rounds	1.06	1	6	0.39
benchmark_return (%)	29.68	-99.00	388.00	63.56
Company riskiness				
benchmark_risk (%)	-5.27	-43.00	41.00	18.40
business_risk (%)	36.09	5.00	83.00	17.86
Industry				
industry_d	0.09	0	1	0.29
industry_e	0.09	0	1	0.28
industry_f	0.01	0	1	0.12
industry_g	0.19	0	1	0.39
industry_h	0.09	0	1	0.28
industry_i	0.53	0	1	0.50

Variable	Mean	Min	Max	St. dev.
Macroeconomic factors				
gdp_growth_0 (%)	2.48	-0.14	2.88	0.39
gdp_growth_1 (%)	2.36	-2.54	2.88	0.69
sp_growth_0 (%)	9.07	-38.49	29.60	9.15
sp_growth_1 (%)	4.92	-38.49	29.60	7.44

Note. Created by the authors

Appendix C. Summary statistics of the processed data (outliers are substituted with winsorization technique)

Variable	Mean	Min	Max	St. dev.
Dependent variables				
closed	0.11	0	1	0.31
months_before_closed	58.53	1	149	16.02
had_additional_funding	0.03	0	1	0.18
months_before_second_round	56.51	1	137	16.9
Independent variables				
Company characteristics				
ln_age	4.4	3.04	6.26	0.5
ln_employees	1.22	0	4.36	0.9
response_rate (%)	5.11	0	18.00	4.81
cb_company_rank	351,440.56	17,763	729,888	209,974.8
Campaign characteristics				
ln_premoney_val	14.05	6.11	19.81	1.81
ln_funding_goal	12.97	9.21	17.8	1.79
funding_raised (%)	11.38	0	70.0	15.98
funding_commitments (%)	3.87	0	33.33	5.17
funding_remaining (%)	88.66	37.00	100	17.59
investor_ownership (%)	31.30	0	100	19.41
doc_requests	1.54	0	8	2.4
popularity	2.87	1.1	4.6	0.72
Growth potential				
ln_revenue_0	12.19	4.5	17.66	1.35
ln_revenue_1	12.28	5.3	17.69	1.51
ln_revenue_2	14.64	10.82	18.83	0.83
revenue_growth_0 (%)	31.05	-100	429.11	89.33
revenue_growth_1 (%)	93.62	-100	1097.09	260.54
revenue0_rel_fun_goal	1.04	0	5.74	1.02
revenue1_rel_fgoal	1.12	0	5.76	1.18
revenue2_rel_fgoal	4.14	0.02	21.68	3.09
num_of_fun_rounds	1.06	1	6	0.39
benchmark_return (%)	23.93	-99.00	189.00	38.25

Variable	Mean	Min	Max	St. dev.
Company riskiness				
benchmark_risk (%)	-5.27	-43.00	41.00	18.40
business_risk (%)	36.09	5.00	83.00	11.42
Industry				
industry_d	0.09	0	1	0.29
industry_e	0.09	0	1	0.28
industry_f	0.01	0	1	0.12
industry_g	0.19	0	1	0.39
industry_h	0.09	0	1	0.28
industry_i	0.53	0	1	0.50
Macroeconomic factors				
gdp_growth_0 (%)	1.87	1.17	2.88	0.71
gdp_growth_1 (%)	0.16	-2.37	2.88	2.38
sp_growth_0 (%)	-12.02	-37.09	29.60	24.09
sp_growth_1 (%)	-2.30	-31.54	29.60	15.85

Note. Created by the authors

Appendix D. Correlation coefficients between determinants

	ln_age	ln_employees	response_rate	cb_company_rank	ln_premoney_val	ln_funding_goal	funding_raised_so_far	funding_commitments	funding_remaining	investor_ownership
ln_age	1									
ln_employees	0.31	1								
response_rate	0.21	0.35	1							
cb_company_rank	-0.01	-0.14	-0.17	1						
ln_premoney_val	0.06	0.22	0.21	-0.08	1					
ln_funding_goal	0.07	0.29	0.33	-0.17	0.47	1				
funding_raised_so_far	0.10	0.08	0.08	-0.30	-0.02	-0.02	1			
funding_commitments	0.08	0.12	0.10	-0.04	0.08	0.06	0.02	1		
funding_remaining	-0.10	-0.12	-0.14	0.34	-0.02	-0.03	-0.87	-0.45	1	
investor_ownership	-0.01	-0.08	-0.05	0.01	-0.62	0.09	-0.11	-0.07	0.11	1
doc_requests	0.12	0.28	0.54	-0.16	0.27	0.31	0.12	0.09	-0.17	-0.12
popularity	0.05	0.21	0.50	-0.09	0.10	0.19	0.03	0.09	-0.10	-0.01
ln_revenue_0	0.21	0.41	0.28	0.02	0.24	0.29	-0.04	0.13	-0.01	-0.07
ln_revenue_1	0.21	0.39	0.30	-0.01	0.29	0.33	-0.05	0.10	0.02	-0.11
ln_revenue_2	0.08	0.21	0.23	-0.08	0.17	0.22	0.02	0.03	0.00	-0.05
revenue_growth_0	0.05	0.08	0.04	-0.04	0.06	0.03	0.02	0.08	-0.04	-0.02
revenue_growth_1	-0.03	0.10	0.17	0.01	0.14	0.15	0.03	-0.06	-0.04	-0.05
revenue0_rel_fgoal	0.22	0.28	0.09	0.08	-0.01	-0.15	0.02	0.04	-0.01	-0.11
revenue1_rel_fgoal	0.21	0.19	0.15	0.08	-0.03	-0.18	0.03	0.04	0.00	-0.18
revenue2_rel_fgoal	0.17	0.12	0.18	-0.01	0.04	-0.16	0.03	-0.04	0.02	-0.21
num_of_fun_rounds	0.04	0.00	0.01	-0.21	-0.05	-0.02	0.10	-0.01	-0.09	0.01
benchmark_return	-0.04	-0.06	0.00	0.01	-0.17	-0.06	-0.01	-0.05	0.03	0.13
benchmark_risk	-0.09	-0.12	-0.14	0.01	-0.11	-0.13	-0.02	-0.03	0.03	0.03
business_risk	-0.16	-0.12	-0.14	0.03	-0.12	-0.13	-0.04	-0.07	0.07	0.03
industry_d	0.08	0.05	0.23	-0.06	0.10	0.09	-0.02	0.00	0.00	-0.04
industry_e	-0.03	0.12	0.11	0.02	0.04	0.04	-0.06	0.02	0.02	-0.03
industry_f	0.20	0.13	0.02	-0.01	0.14	0.10	-0.02	-0.03	0.01	-0.06
industry_g	0.01	-0.14	-0.03	0.05	-0.09	-0.17	0.06	0.04	-0.06	-0.07
industry_h	0.02	0.01	-0.02	-0.03	-0.01	0.16	0.01	0.06	-0.04	0.13
industry_i	-0.09	-0.02	-0.16	0.00	-0.03	-0.06	0.00	-0.07	0.06	0.04
gdp_growth_0	-0.16	-0.10	-0.12	0.07	0.01	0.03	-0.11	0.04	0.03	-0.01
gdp_growth_1	-0.02	-0.06	-0.11	0.01	-0.12	-0.08	0.07	-0.05	-0.02	0.03
sp_growth_0	0.10	0.06	0.07	0.00	-0.08	0.01	0.12	-0.07	-0.04	0.07
sp_growth_1	0.07	0.11	0.25	0.00	0.19	0.16	-0.05	0.05	0.02	-0.07

	doc_requests	popularity	ln_revenue_0	ln_revenue_1	ln_revenue_2	revenue_growth_0	revenue_growth_1	revenue0_rel_fgoal	revenue1_rel_fgoal	revenue2_rel_fgoal
doc_requests	1									
popularity	0.22	1								
ln_revenue_0	0.19	0.15	1							
ln_revenue_1	0.26	0.20	0.61	1						
ln_revenue_2	0.15	0.14	0.24	0.33	1					
revenue_growth_0	0.07	0.10	-0.28	0.11	0.07	1				
revenue_growth_1	0.09	0.13	-0.06	-0.03	0.05	0.10	1			
revenue0_rel_fgoal	0.07	0.05	0.48	0.30	0.09	-0.08	-0.07	1		
revenue1_rel_fgoal	0.08	0.11	0.26	0.49	0.15	0.23	-0.16	0.68	1	
revenue2_rel_fgoal	0.11	0.08	0.12	0.18	0.42	0.13	0.16	0.42	0.49	1
num_of_fun_rounds	-0.04	-0.01	-0.03	0.01	0.02	-0.04	0.00	0.00	-0.01	0.00
benchmark_return	-0.02	0.05	-0.01	0.02	0.02	-0.06	-0.08	-0.01	0.01	0.08
benchmark_risk	-0.13	-0.17	-0.07	-0.12	-0.12	-0.05	-0.15	-0.02	-0.05	-0.10
business_risk	-0.12	-0.20	-0.07	-0.12	-0.16	-0.05	-0.05	-0.03	-0.06	-0.09
industry_d	0.17	0.18	0.02	0.06	0.02	0.02	-0.03	-0.04	-0.02	-0.01
industry_e	0.09	0.09	0.09	0.14	0.13	0.06	-0.05	0.11	0.12	0.07
industry_f	-0.02	-0.02	-0.03	0.04	0.13	0.14	0.19	0.06	0.02	0.11
industry_g	0.01	-0.03	-0.04	-0.13	-0.06	-0.09	0.02	0.06	0.03	0.07
industry_h	0.10	-0.03	0.10	0.11	0.04	0.01	-0.06	-0.04	-0.03	-0.02
industry_i	-0.21	-0.11	-0.08	-0.08	-0.10	-0.01	0.02	-0.08	-0.07	-0.10
gdp_growth_0	-0.08	0.00	-0.06	-0.05	-0.18	-0.01	0.08	-0.11	-0.09	-0.16
gdp_growth_1	-0.11	-0.14	0.01	-0.09	0.02	-0.09	-0.29	-0.08	-0.05	-0.15
sp_growth_0	-0.02	-0.01	0.02	-0.07	0.08	-0.07	-0.16	-0.07	-0.08	-0.08
sp_growth_1	0.20	0.20	0.05	0.10	0.06	0.14	0.25	0.04	0.02	0.13

	num_of_fun_rounds	benchmark_return	benchmark_risk	business_risk	industry_d	industry_e	industry_f	industry_g	industry_h	industry_i
num_of_fun_rounds	1									
benchmark_return	-0.01	1								
benchmark_risk	0.14	-0.16	1							
business_risk	0.02	-0.08	0.60	1						
industry_d	0.16	-0.02	-0.02	-0.02	1					
industry_e	0.08	0.01	-0.02	-0.05	-0.10	1				
industry_f	-0.02	-0.08	0.02	-0.03	-0.04	-0.04	1			
industry_g	-0.06	-0.04	-0.02	0.01	-0.15	-0.15	-0.06	1		
industry_h	-0.05	0.02	-0.05	-0.05	-0.10	-0.10	-0.04	-0.15	1	
industry_i	-0.06	0.04	0.06	0.07	-0.34	-0.33	-0.13	-0.51	-0.33	1
gdp_growth_0	-0.30	-0.02	-0.01	0.01	0.02	0.02	0.01	0.09	0.05	-0.12
gdp_growth_1	-0.26	0.05	0.07	0.00	0.01	-0.06	-0.04	-0.05	0.04	0.05
sp_growth_0	-0.09	0.05	-0.07	-0.05	0.04	-0.04	-0.07	-0.03	-0.02	0.06
sp_growth_1	0.02	-0.03	-0.14	-0.03	0.03	0.00	0.03	0.05	-0.04	-0.04

	gdp_growth_0	gdp_growth_1	sp_growth_0	sp_growth_1
gdp_growth_0	1			
gdp_growth_1	-0.13	1		
sp_growth_0	-0.49	0.66	1	
sp_growth_1	-0.12	-0.54	-0.13	1
sp_growth_1	-0.12	-0.54	-0.13	1

Note. Created by the authors

Appendix E. Results of Cox proportional hazards model on the companies' survivability (regressions 1-2) and ability to obtain additional funding (regressions 3-4)

Cox proportional hazards model Survivability				
	Survivability		Additional funding	
Variable	(1) Haz. Ratio (p -value)	(2) Haz. Ratio (p -value)	(3) Haz. Ratio (p -value)	(4) Haz. Ratio (p -value)
Company characteristics				
ln_age	1.083 (0.82)	1.094 (0.8)	0.171 (0.145)	0.167 (0.138)
ln_employees	1.077 (0.73)	1.066 (0.766)	1.834 (0.302)	1.825 (0.299)
response_rate	1.033 (0.487)	1.031 (0.507)	0.966 (0.73)	0.958 (0.681)
cb_company_rank	1 (0.974)	1 (0.837)	1*** (0.002)	1*** (0.002)
Campaign characteristics				
ln_premoney_val	1.213 (0.177)	1.209 (0.183)	0.601 (0.219)	0.614 (0.236)
ln_funding_goal	0.712*** (0.008)	0.716*** (0.009)	1.257 (0.568)	1.238 (0.593)
funding_raised	-	1.011 (0.199)	-	1.003 (0.877)
funding_commitments	-	1.046 (0.101)	-	1.023 (0.789)
funding_remaining	0.987* (0.094)	-	1 (0.983)	-
investor_ownership	1.031** (0.012)	1.031** (0.012)	0.951 (0.181)	0.952 (0.194)
doc_requests	1.027 (0.76)	1.029 (0.746)	0.647* (0.075)	0.646* (0.076)
popularity	1.044 (0.881)	1.038 (0.898)	0.346* (0.081)	0.354* (0.088)

	Survivability		Additional funding	
Variable	(1) Haz. Ratio (p -value)	(2) Haz. Ratio (p -value)	(3) Haz. Ratio (p -value)	(4) Haz. Ratio (p -value)
Growth potential				
ln_revenue_0	1.315 (0.128)	1.286 (0.165)	1.536 (0.4)	1.506 (0.422)
ln_revenue_1	0.74** (0.024)	0.748** (0.03)	0.736 (0.471)	0.751 (0.504)
ln_revenue_2	1.213 (0.458)	1.209 (0.464)	1.443 (0.64)	1.386 (0.685)
revenue_growth_0	0.997 (0.347)	0.997 (0.286)	1.002 (0.645)	1.002 (0.657)
revenue_growth_1	1 (0.39)	1 (0.344)	1.002 (0.271)	1.002 (0.261)
revenue0_rel_fun_goal	0.689 (0.15)	0.69 (0.147)	0.68 (0.515)	0.684 (0.528)
revenue1_rel_fgoal	1.444 (0.127)	1.454 (0.114)	2.106 (0.21)	2.026 (0.254)
revenue2_rel_fgoal	0.991 (0.887)	0.989 (0.859)	0.942 (0.733)	0.954 (0.798)
num_of_fun_rounds	0.918 (0.87)	0.933 (0.894)	-	-
benchmark_return	0.998 (0.635)	0.998 (0.667)	1.004 (0.593)	1.004 (0.618)
Company riskiness				
benchmark_risk	0.994 (0.562)	0.993 (0.51)	1.013 (0.583)	1.014 (0.563)
business_risk	0.998 (0.916)	0.999 (0.948)	1.007 (0.857)	1.008 (0.842)
Industry				
industry_d	-	-	82.791*** (0.000)	82.513*** (0.000)
industry_e	0.91 (0.905)	1.026 (0.975)	5.249 (0.127)	5.234 (0.129)
industry_f	-	-	-	-
industry_g	0.788 (0.722)	0.899 (0.878)	1.39 (0.801)	1.296 (0.844)
industry_h	0.887 (0.883)	0.98 (0.981)	-	-
industry_i	1.407 (0.546)	1.588 (0.434)	-	-

	Survivability		Additional funding	
Variable	(1) Haz. Ratio (p -value)	(2) Haz. Ratio (p -value)	(3) Haz. Ratio (p -value)	(4) Haz. Ratio (p -value)
Macroeconomic factors				
gdp_growth_0	0.583 (0.398)	0.54 (0.339)	0.664 (0.777)	0.594 (0.722)
gdp_growth_1	1.076 (0.867)	1.099 (0.83)	0.402 (0.287)	0.418 (0.301)
sp_growth_0	0.999 (0.969)	0.998 (0.959)	1.114* (0.063)	1.113* (0.062)
sp_growth_1	0.995 (0.662)	0.996 (0.753)	1.012 (0.62)	1.013 (0.601)
No. of Obs.	429	429	429	429
AIC	577.11	578.14	164.49	166.41
BIC	698.95	704.05	278.22	284.2

Note. Created by the authors. Significance indicated as: *p < .1 **p < .05 ***p < .01

Regression (1) – Cox model on the companies' survivability; with funding_remaining variable

Regression (2) – Cox model on the companies' survivability; with funding_raised and funding_commitments variables

Regression (3) – Cox model on the companies' ability to obtain additional funding; with funding_remaining variable

Regression (4) – Cox model on the companies' ability to obtain additional funding; with funding_raised and funding_commitments variables

Appendix F. Results of the robustness check (logit regressions) on the companies' ability to survive (regressions 5 - 6) and to obtain additional funding (regressions 7 - 8)

Logit regressions				
Dependent variable (Y)	**Closed**		**Had additional funding**	
Variable	(5) Haz. Ratio (p -value)	(6) Haz. Ratio (p -value)	(7) Haz. Ratio (p -value)	(8) Haz. Ratio (p -value)
Company characteristics				
ln_age	0.12 (0.747)	0.123 (0.743)	-1.203 (0.394)	-1.306 (0.367)
ln_employees	0.065 (0.782)	0.062 (0.792)	0.657 (0.358)	0.685 (0.341)
response_rate	0.0275 (0.585)	0.025 (0.62)	-0.009 (0.949)	-0.008 (0.953)
cb_company_rank	0 (0.907)	0 (0.771)	0*** (0.002)	0*** (0.002)
Campaign characteristics				
ln_premoney_val	0.212 (0.185)	0.214 (0.183)	-0.709 (0.143)	-0.686 (0.152)
ln_funding_goal	-0.383*** (0.006)	-0.382*** (0.007)	0.268 (0.530)	0.267 (0.535)
funding_raised	-	0.012 (0.208)	-	0.007 (0.753)
funding_commitments	-	0.057* (0.072)	-	-0.008 (0.945)
funding_remaining	-0.0162* (0.082)	-	-0.003 (0.901)	-
investor_ownership	0.035*** (0.01)	0.035*** (0.009)	-0.067 (0.144)	-0.065 (0.152)
doc_requests	0.046 (0.623)	0.048 (0.613)	-0.553* (0.071)	-0.551* (0.071)
popularity	-0.018 (0.954)	-0.025 (0.935)	-1.138 (0.128)	-1.16 (0.128)

Dependent variable (Y)	Closed		Had additional funding	
Variable	(5) Haz. Ratio (p -value)	(6) Haz. Ratio (p -value)	(7) Haz. Ratio (p -value)	(8) Haz. Ratio (p -value)
Growth potential				
ln_revenue_0	0.337 (0.11)	0.317 (0.136)	-0.354 (0.477)	-0.352 (0.483)
ln_revenue_1	-0.362** (0.027)	-0.364** (0.026)	0.089 (0.873)	0.072 (0.899)
ln_revenue_2	0.237 (0.37)	0.24 (0.369)	0.258 (0.773)	0.294 (0.751)
revenue_growth_0	-0.003 (0.311)	-0.004 (0.232)	-0.003 (0.632)	-0.003 (0.621)
revenue_growth_1	0.001 (0.418)	0.001 (0.343)	0.002 (0.234)	0.002 (0.265)
revenue0_rel_fun_goal	-0.447 (0.115)	-0.455 (0.105)	0.09 (0.901)	0.076 (0.917)
revenue1_rel_fgoal	0.424 (0.105)	0.445* (0.086)	0.487 (0.56)	0.532 (0.535)
revenue2_rel_fgoal	0 (0.998)	-0.002 (0.975)	-0.077 (0.707)	-0.082 (0.697)
num_of_fun_rounds	-0.096 (0.862)	-0.081 (0.883)	-	-
benchmark_return	-0.002 (0.594)	-0.002 (0.633)	0.005 (0.575)	0.006 (0.559)
Company riskiness				
benchmark_risk	-0.007 (0.551)	-0.008 (0.519)	0.039 (0.207)	0.039 (0.201)
business_risk	-0.004 (0.84)	-0.003 (0.863)	0.015 (0.730)	0.013 (0.763)
Industry				
industry_d	-	-	4.951*** (0.003)	4.943*** (0.003)
industry_e	-0.1 (0.907)	-0.053 (0.951)	2.943** (0.023)	2.932** (0.023)
industry_f	-	-	-	-
industry_g	-0.339 (0.646)	-0.291 (0.7)	-0.291 (0.850)	-0.239 (0.883)
industry_h	-0.23 (0.794)	-0.212 (0.814)	-	-
industry_i	0.295 (0.64)	0.35 (0.59)	-	-

Dependent variable (Y)	Closed		Had additional funding	
Variable	(5) Haz. Ratio (p -value)	(6) Haz. Ratio (p -value)	(7) Haz. Ratio (p -value)	(8) Haz. Ratio (p -value)
Macroeconomic factors				
gdp_growth_0	-0.669 (0.311)	-0.779 (0.247)	1.626 (0.381)	1.734 (0.398)
gdp_growth_1	0.178 (0.708)	0.208 (0.662)	-2.728** (0.033)	-2.777** (0.038)
sp_growth_0	-0.009 (0.802)	-0.010 (0.792)	0.249*** (0.006)	0.252*** (0.006)
sp_growth_1	-0.008 (0.522)	-0.007 (0.575)	-0.004 (0.892)	-0.003 (0.915)
Constant	-2.631 (0.569)	-4.103 (0.376)	14.036 (0.364)	13.308 (0.392)
No. of Obs.	429	429	429	429
Log-pseudolikelihood	-129.18	-128.53	-28.06	-28.01
Pseudo R2	0.1161	0.1206	0.5686	0.5693
AIC	320.36	321.05	114.12	116.02
BIC	446.26	451.02	231.9	237.87

Note. Created by the authors. Significance indicated as: *p < .1 **p < .05 ***p < .01

Regression (5) – Logit regression on the companies' survivability; with funding_remaining variable

Regression (6) – Logit regression on the companies' survivability; with funding_raised and funding_commitments variables

Regression (7) – Logit regression on the companies' ability to obtain additional funding; with funding_remaining variable

Regression (8) – Logit regression on the companies' ability to obtain additional funding; with funding_raised and funding_commitments variables

Appendix G. Results from the Cox proportional hazard models for robustness check on the companies' survivability

Additional Cox models as a robustness check on a company's Survivability						
Variable	(9) Haz. Ratio (p -value)	(10) Haz. Ratio (p -value)	(11) Haz. Ratio (p -value)	(12) Haz. Ratio (p -value)	(13) Haz. Ratio (p -value)	(14) Haz. Ratio (p -value)
Company characteristics						
ln_age	0.98 (0.952)	0.974 (0.935)	0.944 (0.859)	0.938 (0.842)	0.9 (0.815)	0.885 (0.787)
ln_employees	1.107 (0.598)	1.109 (0.59)	1.129 (0.522)	1.128 (0.524)	1.06 (0.821)	1.045 (0.866)
response_rate	1.056 (0.213)	1.056 (0.212)	1.057 (0.186)	1.057 (0.187)	0.996 (0.94)	0.997 (0.958)
cb_company_rank	1 (0.898)	1 (0.977)	1 (0.96)	1 (0.926)	1 (0.626)	1 (0.623)
Campaign characteristics						
ln_premoney_val	1.193 (0.195)	1.183 (0.216)	1.212 (0.148)	1.204 (0.162)	1.299 (0.181)	1.303 (0.178)
ln_funding_goal	0.72*** (0.004)	0.724*** (0.004)	0.711*** (0.002)	0.714*** (0.003)	0.726* (0.057)	0.727* (0.058)
funding_raised	-	1.011 (0.186)	-	1.012 (0.161)	-	1.012 (0.237)
funding_commitments	-	-	-	-	-	1.012 (0.774)
funding_remaining	0.986* (0.06)	-	0.986* (0.062)	-	0.989 (0.303)	-
investor_ownership	1.031*** (0.008)	1.03*** (0.01)	1.032*** (0.005)	1.031*** (0.006)	1.034** (0.029)	1.035** (0.027)
doc_requests	1.006 (0.949)	1.01 (0.911)	0.986 (0.858)	0.992 (0.924)	0.995 (0.967)	0.995 (0.967)
popularity	1.008 (0.978)	1.021 (0.941)	0.968 (0.905)	0.979 (0.938)	1.084 (0.825)	1.07 (0.853)

Variable	(9) Haz. Ratio (p -value)	(10) Haz. Ratio (p -value)	(11) Haz. Ratio (p -value)	(12) Haz. Ratio (p -value)	(13) Haz. Ratio (p -value)	(14) Haz. Ratio (p -value)
Growth potential						
ln_revenue_0	-	-	-	-	1.585* (0.072)	1.598* (0.077)
ln_revenue_1	-	-	-	-	0.737 (0.111)	0.734 (0.113)
ln_revenue_2	-	-	-	-	0.926 (0.806)	0.926 (0.809)
revenue_growth_0	-	-	-	-	1 (0.882)	1 (0.888)
revenue_growth_1	-	-	-	-	1 (0.127)	1.001 (0.133)
revenue0_rel_fun_goal	-	-	-	-	0.541* (0.07)	0.541* (0.071)
revenue1_rel_fgoal	-	-	-	-	1.649* (0.069)	1.65* (0.07)
revenue2_rel_fgoal	-	-	-	-	1.043 (0.579)	1.042 (0.589)
num_of_fun_rounds	0.869 (0.793)	0.878 (0.806)	0.787 (0.667)	0.799 (0.683)	-	-
benchmark_return	0.997 (0.553)	0.998 (0.54)	0.998 (0.586)	0.998 (0.575)	0.988 (0.13)	0.988 (0.133)
Company riskiness						
benchmark_risk	0.993 (0.427)	0.993 (0.407)	0.993 (0.397)	0.992 (0.392)	1.006 (0.657)	1.001 (0.654)
business_risk	-	-	-	-	0.977 (0.323)	0.976 (0.31)
Industry						
industry_d	-	-	-	-	-	-
industry_e	0.9 (0.892)	0.91 (0.903)	-	-	1.295 (0.761)	1.29 (0.768)
industry_f	-	-	-	-	-	-
industry_g	1.029 (0.965)	1.006 (0.993)	-	-	0.472 (0.381)	0.451 (0.366)
industry_h	0.875 (0.868)	0.884 (0.878)	-	-	0.793 (0.811)	0.763 (0.783)
industry_i	1.502 (0.471)	1.462 (0.504)	-	-	1.047 (0.945)	1.009 (0.989)

Variable	(9) Haz. Ratio (p -value)	(10) Haz. Ratio (p -value)	(11) Haz. Ratio (p -value)	(12) Haz. Ratio (p -value)	(13) Haz. Ratio (p -value)	(14) Haz. Ratio (p -value)
Macroeconomic factors						
gdp_growth_0	0.562 (0.342)	0.580 (0.373)	0.547 (0.325)	0.568 (0.362)	0.549 (0.463)	0.575 (0.504)
gdp_growth_1	1.112 (0.802)	1.120 (0.788)	1.109 (0.809)	1.112 (0.804)	0.833 (0.739)	0.825 (0.727)
sp_growth_0	0.996 (0.907)	0.995 (0.877)	0.998 (0.949)	0.997 (0.928)	1.027 (0.497)	1.027 (0.496)
sp_growth_1	0.996 (0.724)	0.996 (0.73)	0.995 (0.627)	0.995 (0.62)	1 (0.934)	1.002 (0.919)
No. of Obs.	429	429	429	429	412	412
AIC	566.98	568.55	560.96	562.32	374.8	376.45
BIC	652.27	653.84	630	631.36	491.4	497.08

Note. Created by the authors. Significance indicated as: *p < .1 **p < .05 ***p < .01

Regression (9) – Cox model on the companies' survivability, with funding_remaining variable; variables with more than 50% of missing values are excluded

Regression (10) – Cox model on the companies' survivability, with funding_raised and funding_commitments variables; variables with more than 50% of missing values are excluded

Regression (11) – Cox model on the companies' survivability, with funding_remaining variable; industry variables and variables with more than 50% of missing values are excluded

Regression (12) – Cox model on the companies' survivability, with funding_raised and funding_commitments variables; industry variables and variables with more than 50% of missing values are excluded

Regression (13) – Cox model on the companies' survivability, with funding_remaining variable. Companies without available closing dates are excluded

Regression (14) – Cox model on the companies' survivability, with funding_raised and funding_commitments variables. Companies without available closing dates are excluded

Appendix H. Results from the Cox proportional hazard models for robustness check on the companies' ability to obtain additional funding

Robustness check on additional funding. Cox models				
Variable	(15) Haz. Ratio (p -value)	(16) Haz. Ratio (p -value)	(17) Haz. Ratio (p -value)	(18) Haz. Ratio (p -value)
Company characteristics				
ln_age	0.097* (0.063)	0.095* (0.064)	0.459 (0.386)	0.441 (0.363)
ln_employees	2.333 (0.101)	2.338 (0.101)	1.384 (0.4)	1.391 (0.394)
response_rate	1.025 (0.773)	1.024 (0.777)	1.092 (0.27)	1.092 (0.27)
cb_company_rank	1*** (0.001)	1*** (0.001)	1*** (0.002)	1*** (0.003)
Campaign characteristics				
ln_premoney_val	0.644 (0.249)	0.645 (0.249)	0.916 (0.783)	0.93 (0.816)
ln_funding_goal	1.345 (0.441)	1.344 (0.439)	0.986 (0.96)	0.978 (0.937)
funding_raised	-	1.001 (0.945)	-	1.001 (0.934)
funding_commitments	-	-	-	-
funding_remaining	1 (0.986)	-	1.002 (0.899)	-
investor_ownership	0.947 (0.136)	0.948 (0.136)	0.985 (0.585)	0.987 (0.619)
doc_requests	0.545** (0.015)	0.545** (0.015)	0.762 (0.121)	0.764 (0.123)
popularity	0.383* (0.099)	0.384* (0.1)	0.654 (0.394)	0.651 (0.388)

Variable	(15) Haz. Ratio (p -value)	(16) Haz. Ratio (p -value)	(17) Haz. Ratio (p -value)	(18) Haz. Ratio (p -value)
Growth potential				
ln_revenue_0	-	-	-	-
ln_revenue_1	-	-	-	-
ln_revenue_2	-	-	-	-
revenue_growth_0	-	-	-	-
revenue_growth_1	-	-	-	-
revenue0_rel_fun_goal	-	-	-	-
revenue1_rel_fgoal	-	-	-	-
revenue2_rel_fgoal	-	-	-	-
num_of_fun_rounds	-	-	-	-
benchmark_return	1.006 (0.421)	1.006 (0.423)	1.001 (0.898)	1.001 (0.88)
Company riskiness				
benchmark_risk	1.011 (0.557)	1.011 (0.556)	1.016 (0.375)	1.016 (0.372)
business_risk	-	-	-	-
Industry				
industry_d	72.22*** (0.000)	72.453*** (0.000)	-	-
industry_e	4.089 (0.174)	4.073 (0.175)	-	-
industry_f	-	-	-	-
industry_g	1.563 (0.705)	1.555 (0.706)	-	-
industry_h	-	-	-	-
industry_i	-	-	-	-

Variable	(15) Haz. Ratio (p -value)	(16) Haz. Ratio (p -value)	(17) Haz. Ratio (p -value)	(18) Haz. Ratio (p -value)
Macroeconomic factors				
gdp_growth_0	1.632 (0.664)	1.643 (0.655)	1.1096 (0.922)	1.086 (0.928)
gdp_growth_1	0.328 (0.117)	0.328 (0.112)	0.44 (0.156)	0.44 (0.156)
sp_growth_0	1.115** (0.036)	1.115** (0.035)	1.089** (0.034)	1.09** (0.033)
sp_growth_1	1.017 (0.456)	1.017 (0.455)	1.004 (0.828)	1.005 (0.788)
No. of Obs.	429	429	429	429
AIC	150.83	150.82	161.3	161.31
BIC	228	227.99	226.29	226.3

Note. Created by the authors. Significance indicated as: *p < .1 **p < .05 ***p < .01

Regression (15) – Cox model on the companies' ability to obtain additional funding; with funding_remaining variable; variables with more than 50% of missing values are excluded

Regression (16) – Cox model on the companies' ability to obtain additional funding; with funding_raised and funding_commitments variables; variables with more than 50% of missing values are excluded

Regression (17) – Cox model on the companies' ability to obtain additional funding; with funding_remaining variable; industry variables and variables with more than 50% of missing values are excluded

Regression (18) – Cox model on the companies' ability to obtain additional funding; with funding_raised and funding_commitments variables; industry variables and variables with more than 50% of missing values are excluded