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Johannes Klein
University of Muenster

Leonard Stuckenborg
University of Muenster

Jens Leker
University of Muenster

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Hot or not – Which features make FinTechs attractive for investors?

Johannes Klein
University of Muenster, Germany

Leonard Stuckenborg
University of Muenster, Germany

Jens Leker
University of Muenster, Germany

ABSTRACT

Attracting investors and generating funding is a key issue for all start-ups. The information asymmetries between investor and start-up need to be reduced. Despite the overwhelming literature on venture capital financing and different signals reflecting venture quality, pinpointing the signals which impact funding decisions remains an open issue. This study presents an empirical examination of the effectiveness of different signals to convince investors and generate funding. We examine the impact of signals concerning venture quality (classic ones such as human capital, intellectual capital and social alliance/network capital as well as the strategic orientation in terms of business model patterns. Based on a comprehensive sample of more than 101 German FinTechs, our study delivers empirical evidence that human capital as well as the strategic orientation positively impacts a FinTech's attractiveness. However, our chosen measures for intellectual capital and social network/alliance capital result in negative effects.

Keywords: Alliance capital, Intellectual capital, human capital, Strategic Orientation, FinTechs, Funding
JEL Codes: M13, G24, L26

I. Introduction

According to Burgmaier and Hüthig (2015), the FinTech market will undergo a major cleanup process, considering that a lot of start-ups offer the same services, and many will neither survive the necessary selection process nor reach a global presence. This assessment of the future development of the FinTech revolution in the financial market is accompanied by a problem that confronts different market players as well as other external stakeholders: How can successful FinTech start-ups be identified that will be able to establish a permanent position in the market and therefore, represent a suitable investment object? Investors in all markets seek for attractive investment opportunities,

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therefore we analyze the German FinTech market and the financing capacity of the different FinTechs.

The German market is of particular interest as Germany has one of the strongest financial industries in Europe after the UK. Furthermore, FinTech activity is increasing and there is an increasing number of start-ups, all of which are looking for investors sooner or later (Stuckenborg et al., 2017).

In the last years, there has been a steeply growing number of start-ups, which are trying to enter the market for financial services. These FinTech start-ups or just FinTechs (FinTech as a term consisting of "finance" and "technology") enter the market, confronting traditional players such as banks and insurance companies with innovative services (Dapp, 2014; Gulamhuseinwala et al. 2015). These young ventures focus on different areas of activity and try to fill different stages of the financial value chain (Stuckenborg et al., 2017). Comparing the FinTech development on an international level, it is noted that Great Britain (London in particular) is one of the biggest hot spots for these young firms. Nevertheless, when taking into account investment volumes, the FinTech development in Germany has also grown considerably in recent years (Ernst & Young, 2016).

This FinTech phenomenon is not only of high relevance for well-established companies in the financial sector, but also for external stakeholders such as investors or researchers – particularly evident in the increasing number of publications in this domain. Corresponding with the growing number of FinTechs, the share of companies that have given up their business activities increases equally. According to Song et al. (2008), within the area of technology start-ups, only 36% of these young companies still exist after four years from the date of company foundation. Due to the large number of newly founded start-ups and the increasing growth rates in the FinTech market, it is particularly relevant to identify those FinTechs that are successful and that will survive permanently in their respective markets. However, this prediction or separation of successful FinTechs is equally difficult for all external stakeholders. In order to separate and identify exactly the group of FinTechs with the prospect of promising success, it is necessary to identify certain characteristics or critical success factors which are likely to lead to a long-term market existence (see e.g. Nicoletti, 2017; Roure & Maidique, 1986).

In research, different methods are used to investigate signals or critical success factors. Besides qualitative research designs such (semi-structured) interviews (Roure & Maidique, 1986; Werth et al., 2019), there are randomized field experiments (Bernstein et al., 2017), or more quantitative designs that apply different econometric models such as different types of regression analyses (Ahlers et al., 2015; Baum & Silverman, 2004; Colombo & Grilli, 2010).

Several studies investigate the effect of financial sources on different success indicators for start-ups, including the survival rate (e.g. Cassar, 2004; Colombo & Grilli,

2010; Shane & Stuart, 2002). Drover et al. (2017) provide a literature review of entrepreneurial financing research and also give directions and recommendations for further research in this area. Åstebro and Bernhardt (2003), for instance, analyzed the effect of received bank loans on the survival prospects of start-ups and found a significant relationship. Therefore, it may be said that gaining capital in the early stages of start-up development is one of the most important aspects for young ventures. Generally, start-ups can rely on different financing sources including, for example, the initial capital provided by the founders themselves; financial resources of family and friends or outside capital (Au et al, 2016; Colombo & Grilli, 2010). Against the backdrop of limited resources of founders, start-ups frequently depend on external capital (Thornton-Trump & Fu, 2000). While large companies can rely on classical sources like bank loans, such types of financing are associated with high costs for nascent businesses due to their uncertain future prospects and high risk of failure (Gregory et al., 2005). Thus, one recurrent capital source in the start-up environment is private investment or venture capital. In previous research, studies have evaluated attributes of young firms which are more likely to be attractive for external investors. For instance, Islam et al. (2018) focus on government grants and their effect on further financing rounds.

We aim to analyze the financing capacity of FinTechs in Germany. Therefore, we see the quality of the venture as a key driver of the financing capacity. By analyzing the various signals of venture quality, we want to find out which factors and characteristics of a Fintech lead to its ability to attract investors and thus to acquire capital for further development. These signals may be evaluated in the context of signaling theory, which is often employed in entrepreneurship literature. Thereby, we rely on the human, social alliance/network, intellectual capital and the strategic orientation of start-ups and investigate different variables of these dimensions in accordance with their financing capacity. We contribute to existing research by transferring proven approaches to the German FinTech market and by also applying an empirical approach that complements current qualitative research. Furthermore, we introduce a new dimension of venture quality.

There appears to be a sizable lack of research focus that considers such a wide range of start-up characteristics and its association with the financing capacity. In order to close this gap in literature, the following research questions will be answered within the framework of our paper:

1. Which signals can be used to assess the quality of a FinTech with regards to the financing capacity, i.e. the funding success?

2. Which characteristics of FinTechs seem to be attractive from the view of external investors?

3. What is the impact of strategic decisions, such as chosen business models and areas of activity, on the financing capacity, i.e. funding success of FinTechs?

The remainder of the paper is structured as follows: In section two we outline the theoretical background regarding start-ups and present different signals of FinTechs. Section three presents the methodology of the data collection and the analysis carried out. Section four illustrates the findings and in section five we discuss the results of our research, explain its limitations and point out further research opportunities. The last section contains the final conclusion.

II. Theoretical Background and Hypothesis

A. Signaling Theory

Basically, investors must decide whether to invest in a FinTech or not. However, there exists an information asymmetry between both of them. As a rule, investors do not know all the details and find it difficult to assess the intentions of the FinTech and its management. On the one hand they do not know about some characteristics, such as exact details of the business idea, and on the other hand they cannot exactly assess the motivation and abilities of the founders, management and employees. In this respect, they must rely on the information they receive from the FinTech itself. The challenge for investors is therefore to evaluate both the quality and the prospects with the available information. Thus, investors are forced to make a decision with incomplete information and uncertainty (Baum & Wally, 2003; Eisenhardt, 1989). Ultimately the investment opportunity is a further example of the market for 'lemons' problem (Akerlof, 1970). One way to overcome or to reduce the information asymmetries are signals. However, effective signals need to fulfill the following criteria: they must be costly and observable (Spence, 1973, 1974). A signal serves as a proxy for a characteristic or an ability and must therefore have corresponding correlation with the characteristic or the ability.

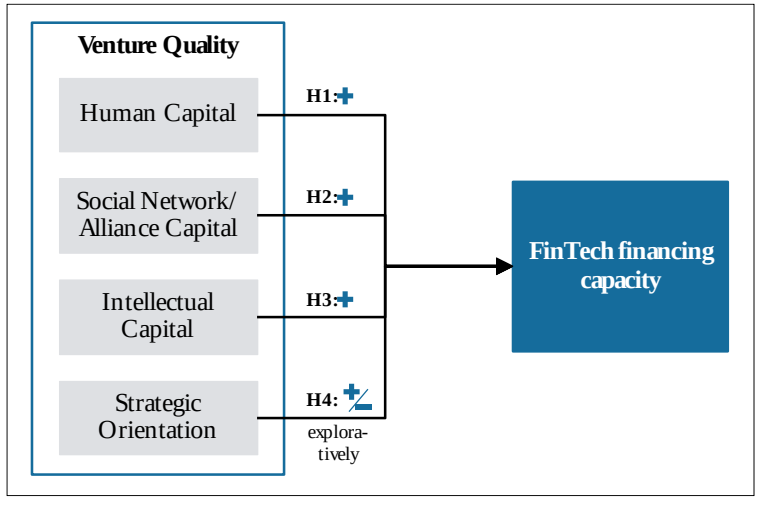
In the context of nascent businesses, signaling plays an important rule for all types of financing. Investors need to evaluate businesses in a very early stage that might only have ideas about what they want to implement. A business in this stage often only consists of a team and a business idea, sometimes with an already developed prototype. Financial data and key figures are often not available or have minor informative value. Large market studies or market assessments are also not available, meaning those investors, especially in early stages, need to rely on different signals as well as attributes of the FinTech that can help to evaluate a particular investment opportunity.

The topic of signals is largely elaborated in literature and many different signals have been analyzed regarding their effect on funding decisions (e.g. Ahlers et al., 2015; Backes-Gellner & Werner, 2007; Colombo et al., 2018; Hoenig & Henkel, 2015; Islam et al., 2018; Ko & McKelvie, 2018; Weiss, 1995). Connelly et al. (2011) provide a literature review on signaling theory.

B. Quality Signals for FinTechs

In order to analyze the attractiveness of German FinTechs we develop a model to show the relation between the dependent variable "financing capacity", which we use as an indicator of attractiveness, and the independent variables. We argue that basically the quality of the FinTech influences the ability to acquire funding from investors (see figure 1). We follow Baum and Silverman (2004) and Ahlers et al. (2015) who argue that venture quality can be signaled by human, social (alliance) and intellectual capital. In addition, we argue that the strategic orientation, i.e. the business model pattern, is also a quality signal, since it indicates how the FinTech aims to earn money.

Figure 1. Determinants of FinTechs' Financing Capacity.



1. Human Capital

Human capital is an important signal that can affect funding success. Numerous studies in academic literature analyzed the relationship and the impact on funding success. In the early stage of a company, the people and the team behind it are one of the most important aspects. This is claimed by business press (Byrne, 2000) and also analyzed by academic research. Recent studies evaluate the relationship between human

capital and the ability to generate funding or to acquire resources. Roure and Maidique (1986) show in their study the importance of the characteristics of the entrepreneurs and the founding team, especially previous experience in high growth ventures and also completeness of relevant functions in the team. Zacharakis and Meyer (2000) evaluate that skills and experience of the team are relevant selection criteria that are also frequently used by venture capitalists.

Recently, different studies haven proven a relationship between the success of the company and human capital (Ahlers et al., 2015; Almus & Nerlinger, 1999; Bates & Bradford, 1992; Baum & Silverman, 2004; Bernstein et al., 2017; Bollazzi et al., 2018; Colombo et al., 2004; Colombo & Grilli, 2010; Ismail & Medhat, 2019; Unger et al., 2011). Although, studies have indicated that human capital has an impact, they differ in terms of relative importance of human capital (Ahlers et al., 2015). For entrepreneurs it is of great importance to identify and also exploit new business opportunities (Shane & Venkataraman, 2000). Burton et al. (2002) show that previous employers of the founding team also impact the chance of receiving funds in early stages. These examples show that human capital can have different facets and elements.

Consequentially, the question arises on how human capital can be assessed by potential investors. Usually, venture capitalists perform a thorough due diligence, where they also evaluate the human capital. In face-to-face meetings they can get to know the founders and the management team. Whilst in research it is difficult to reflect personal impressions, there are characteristics that can serve as proxies for human capital.

Education, especially in terms of university degrees, is a good indicator for human capital (Backes-Gellner & Werner, 2007; Bollazzi et al., 2018; Hsu, 2007; Levie & Gimmon, 2008). University degrees also fulfil the signal criteria of Spence (1973), since they are costly and also measurable. Work experience also serves as a predictor of human capital and is an indicator for measuring the quality of applicants (Turban & Cable, 2003).

Hypothesis 1: FinTechs with more human capital (i.e. more work experience, higher education and more founders) are likely to have a larger financing capacity.

2. Intellectual Capital

Innovative ideas and innovations are important factors for companies in general (Baumol, 2002; Cefis & Marsili, 2005; Schumpeter, 2008) and also for FinTechs (Nicoletti, 2017) in particular and are therefore effective signals. With the help of good and new ideas, nascent firms are able to enter markets. Furthermore, in a valuation context, innovative firms often profit from an "innovation premium" (Cefis & Marsili, 2005, p. 1188). Recent studies have shown a positive relationship between the probability of survival and the number of patents and pending applications (Bollazzi et al., 2018; Rassenfosse & Fischer, 2016; Silverman & Baum, 2002). Patents also help to acquire capital from investors (Munari & Toschi, 2015). Patents help in providing information

about the maturity and the positioning of the firm (Cohen & Lemley, 2001) as well as serve as a protection of own ideas (Ahlers et al., 2015).

Next to patents, winning awards or being granted subsidies are also signals of the success of a firm. Usually, a prerequisite for winning an award or obtaining subsidies is a structured evaluation of the business idea and business plan. Often entrepreneurs need to apply for awards and subsidies and are at the same time in competition with others. Such signals are investigated, for instance, by Islam et al. (2018) who analyze the signaling effect of received governmental grants and find a positive relationship to the funding success. Thus, both patents and subsidies can serve as signals to indicate intellectual capital and are meeting the criteria of observable and costly as required for effective signals.

Hypothesis 2: FinTechs with more intellectual capital (i.e. obtained subsidies and granted patents) are likely to have a larger financing capacity.

3. Social Alliance/Network Capital

Start-ups face multiple opportunities and constraints in their first years. Alliances and personal networks provide the ability to manipulate those opportunities and constraints (Baum & Silverman, 2004). Alliances are also an important source to gain access to further resources (e.g. Baum & Silverman, 2004; Chung et al., 2000; Klus et al., 2019). Often these alternative channels can be used to gain insights on particular topics. There is vast literature regarding benefits and effects of alliances (e.g. Baum & Oliver, 1991; Chung et al., 2000; Dyer & Singh, 1998). According to Brüderl and Preisendörfer (1998) networks can facilitate access to suppliers, customers, financial resources, etc.

In the early stages of new ventures, venture capitalists play a pivotal role as they can offer coaching and consulting services as well as provide access to further resources. Besides professional investors, nowadays social networks also play a critical role. Social networking facilitates the exchange and knowledge sharing between and amongst founders whilst bringing entrepreneurs and potential customers together (Hsu, 2007; Nicoletti, 2017; Shane & Cable, 2002; Stuart & Sorenson, 2007). When entrepreneurs are able to effectively use their personal social networks, they are also able to improve their access to additional resources (Ferrary & Granovetter, 2009; Mollick, 2014).

Access to valuable resources is also facilitated by the location of the start-up. Start-ups residing in "FinTech-Hot-spots" might be able to build up a network or an alliance with other founders and supporters more easily. Therefore, the location serves as a signal for the social alliance/network capital.

Hypothesis 3: FinTechs with more social alliance/network capital (i.e. Facebook likes, twitter followers, located in hot spots and cooperating with a partner) are likely to have a larger financing capacity.

4. Strategic Orientation

Before setting up a business, the founders need to make strategic decisions to implement their ideas. One very important landmark criterion is the business model. Start-ups need to make clear how they want to set-up their business and want to earn money, thus the underlying decision inevitably impacts the prospects of start-ups and is the *strategic orientation* of a FinTech. Many studies have focused on the effect of the strategic positioning on funding (Lieberman & Montgomery, 1988; Rassenfosse & Fischer, 2016; Shepherd, 1999). In such studies, different elements regarding the strategic position, including the business model have been investigated.

"A business model articulates the logic and provides data and other evidence that demonstrates how a business creates and delivers value to customers" (Teece, 2010, p. 173). The configuration of the business model is one of the most important steps in setting up a business (Nicoletti, 2017; Trimi & Berbegal-Mirabent, 2012). It is a crucial aspect regarding the further prospects of a company and is related with its performance. This is also exemplified by Zott and Amit (2007) who found a positive relationship between novelty-centered business models and the performance of start-ups. According to Johnson et al. (2008), a business model consists of the following four elements: the *customer value proposition*, *profit formula*, *key resources* and *key processes*.

We extend current literature and evaluate how the strategic orientation in terms of the business model pattern of a FinTech influences its funding success. Therefore, we employ an explorative study for the business model patterns. We argue that some of these business model patterns are more attractive for external investors than others. For example, directly earning money with a pay-per-use model might be more attractive than a freemium model, which requires users to develop from the free version to the paid version.

Hypothesis 4: The strategic orientation of a FinTech (i.e. the choice of business model pattern) affects the funding capacity.

C. Acquisition of External Funding for FinTechs

The acquisition of financial resources is very important for start-ups. Especially in the initial phase, young firms are facing different challenges due to their maturity level. The first source of financing is usually self-funding through either the founders and the team themselves, relatives (families and friends) or (professional) angel investors (Rassenfosse & Fischer, 2016). According to Berger and Udell (1995), these sources of insider financing are essential in the first stages since information asymmetries are at a maximum. Insider financing is also often a necessary condition to generate further funding as it reduces the problems of adverse selection and moral hazard (Berger &

Udell, 1995). When generating further funding, founders can rely on both debt and equity. In both cases, the investors must be convinced of the positive prospects of the business as well as its ability to repay or generate an adequate return. For entrepreneurial science it is important to analyze what makes investors invest money in a start-up and what are their decision-making criteria. The decision process and the criteria of venture capitalists has been widely studied in literature. Venture capitalists use different criteria that also depend on the maturity level and the evaluation stage[1] of a start-up (Fried & Hisrich, 1994; Hall & Hofer, 1993; Rassenfosse & Fischer, 2016). Individual and venture capitalists' specific criteria include, for instance, accordance to investment guidelines as well as personal fit (Hisrich & Jankowicz, 1990). Rassenfosse and Fischer (2016) propose and determine three parent decision criteria: strategic positioning, quality of the team and probability of success. Strategic positioning includes different factors such as market, competition, capital intensity of the business model and timing (Lieberman & Montgomery, 1988; Rassenfosse & Fischer, 2016; Shepherd, 1999). Those factors impact the probability of survival and are also critical in the decision-making process. In the following, we translate strategic positioning into business model pattern and area of activity. Furthermore, the quality of the team is another critical evaluation criteria that has been widely studied in literature (e.g. Colombo et al., 2004; Macmillan et al., 1985; Silverman & Baum, 2002; Tyebjee & Bruno, 1984). The probability of success also appears as a key factor in the evaluation process, and investors usually spend a lot of time trying to determine this probability (Rassenfosse & Fischer, 2016). However, since nascent businesses are highly opaque, investors often rely on different signals. Those signals need to be observable but are costly to acquire (Spence, 1973) and also correlated with the probability of success. The signals studied to date include the quality of the team, the intellectual capital or the social alliance capital (e.g. Ahlers et al., 2015; Baum & Silverman, 2004; Hoenig & Henkel, 2015; Hsu, 2007).

III. Data and Method

A. Data Set Construction and Sample

To evaluate different signals of a FinTech that have a positive or negative impact on the financing capacity of FinTechs, we use a quantitative-empirical approach. This method, based on a large dataset, allows us to verify various characteristics of these companies according to their suitability as efficient signals.

We generated our own database of FinTechs by using a wide range of data sources. To begin with, we provided a detailed definition of a FinTech by focusing on

[1] Fried and Hisrich (1994) propose a six-stage decision making process.

three key characteristics: business segment, founding year and location. Start-ups that offer services in the financial industry by using new technologies were considered. Furthermore, the considered start-ups needed to be founded after January 1st, 2007 and operate in Germany.[2] The German market is very dynamic and marked by a very attractive environment for start-ups. Data collection was finished in October 2017.

To identify FinTechs complying with our above-mentioned restrictions, we used three different data sources: crunchbase, Gruenderszene as well as "Payment and banking" to obtain a sample of the German market.[3] Using these different data sources, we have created a list of FinTechs that comply with the definition stated above. A database was then set up which was used to collect all relevant and required information. The built-up database contains relevant general information about all the FinTechs (e.g. location, founding year, founders and number of employees), information about the funding (e.g. funding volume per funding round, date of the funding round) as well as information on the business model pattern and the area of activity. From the above-mentioned sources as well as the webpages of the FinTechs, we derived the individual characteristics and business model patterns per FinTech. Since the mapping of the business model pattern is essential as one part of the analysis of the financing capacity, all FinTech companies were analyzed by two persons independently. Both coders have deep knowledge of the FinTech market as well as comprehensive knowledge on business models and areas of activity.[4] In order to validate and measure the quality of the mapping, the inter-coder reliability was calculated. Hayes and Krippendorff (2007) describe and analyze different measures of the inter-coder reliability. One measure to describe the agreement between two coders for nominal data is the percentage agreement (Hayes & Krippendorff, 2007). A level of agreement of over 90% is generally accepted by researchers (Neuendorf, 2002). We achieved an inter-coder reliability of 94.6% for business model patterns and 97.8% for the areas of activity. Thus, the required level was exceeded. In order to achieve a final mapping, we performed a joint verification to discuss and correct mistakes and different perceptions. The data acquisition was finalized at the end of March 2018 which resulted in the database including 101 FinTechs with funding information.

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[2] One can state that the FinTech hype started to emerge around 2007.

[3] See www.crunchbase.com, www.gruenderszene.de and www.paymentandbanking.com.

[4] Coding was done by the authors of this paper who have both scientific and practical experience in the Financial Services industry as well as experience in the field of business models and areas of activities.

B. Measures

1. Dependent Variable

We operationalized the financing capacity of a FinTech, our dependent variable, as the generated total funding volume (i.e. the financing capacity). The funding volume reflects how much money a company can attract from investors. As a rule, high investment volumes are a sign of investors' confidence in start-up performance and prospect. Nevertheless, a high funding amount does not necessarily imply business success, but from the point of view of the investors the business concept seems to be a promising approach.

2. Independent Variables

We also need to operationalize the independent variables, i.e. the signals that are supposed to have an impact on the financing capacity of the FinTechs.

Human Capital. We obtained comprehensive data about the founders of each FinTech in order to reflect and estimate human capital. We collected information on the number of founders, the individual work experience of the founders, and the education.

The *number of founders* was split in three categories: one founder, two or three founders and more than 4 founders (each measured by a binary 0/1 variable). The size of the team has two different effects. On the one hand, in larger teams, tasks can be shared, and knowledge and capabilities can be complemented. On the other hand, larger teams complicate decision processes and require more internal coordination.

Work experience is the second indicator for human capital and was measured via the pure work experience in years (1-2 years, 2-5 years and more than 5 years) as well as the work experience with start-ups (all reflected by a binary 0/1 variable).

Furthermore, another important signal is the *education* (Backes-Gellner & Werner, 2007; Levie & Gimmon, 2008). Therefore, we evaluated how many team members have a university degree (Bachelor, Master, and Diploma), an advanced university degree (Dr., Ph.D.) or an MBA.

Intellectual capital. For estimating the effect of intellectual capital, we used two different binary variables (1 = yes, 0 = no) including granted awards/subsidies and applications for/or granted patents. We follow recent research from Islam et al. (2014) and Islam et al. (2018) and use granted awards, e.g. EXIST-Gruenderstipendium, as an indicator of intellectual capital. In order to win an award, start-ups usually must apply in advance and meet various requirements. The application is usually checked by experts. Accordingly, a start-up is subjected to a kind of quality test. The use of patents as an indicator of intellectual capital is common across literature (Ahlers et al., 2015; Baum & Silverman, 2004; Conti et al., 2013a; Conti et al. 2013b; Häussler et al., 2009; Silverman & Baum, 2002). On the one hand, patents reflect innovation through the development

of new technologies and on the other hand serve as a protection of ideas. We follow those previous analyses and, in detail, use a binary 0/1 variable to assess whether a FinTech either possesses or applied for a patent.

Social alliance/network capital. Network capital and human capital are often related and are mutually dependent. We measure the social alliance/network capital in two segments: (1) professional alliances and (2) social networks. At first, we assess whether a FinTech is cooperating with a partner. A partner can have a twofold effect in that it can help FinTechs to get access to further resources, but may also be an obstacle for investors since, depending on the partnership, they must also deal with the partner. Furthermore, we also take the location of the FinTech as another indicator, since hot spots are cities that offer good conditions and a fertile environment for start-ups. We define the cities Berlin, Frankfurt and Munich as hot spots. The city or region can serve as an accelerator. In general, cities or regions offer different framework conditions that can have a positive or negative impact on the development of the start-ups. Hot spots are characterized by many FinTechs, an attractiveness for young talents, established networks, favorable business space, proximity to investors or partners, etc. In our research we use a dummy variable if a FinTech is placed in a hot spot (1) or not (0).

Presence in social media as well as feedback from the users, e.g. through a "like" function nowadays is a standard and gives access to many customers (Bi et al., 2017; Jiménez & Mendoza, 2013). For our analysis, we operationalize the social network effect by the variables "Twitter followers" and "Facebook likes". Users of social networks that "like" or "follow" a firm, receive all updates from them and can also react and give feedback, ask questions or share requests, e.g. job advertisements. Thus, FinTechs can draw attention to marketing campaigns or can acquire resources with the help of the crowd.

Strategic orientation. To capture the firm's strategic orientation, we use the business model patterns of each FinTech. Such patterns are based on similarities between the single elements of a business model. While Osterwalder and Pigneur (2010) develop a scheme of five different patterns, Gassmann et al. (2013) provide an extensive overview of 55 different business model patterns, which cover a wide range of different industries. In our study, we use the patterns of Gassmann et al. (2013)[5] and assign each FinTech to these various categories. In this way, we can consider the strategic decision of the business model and its signaling value in our analysis of the financing capacity. The

[5] For an overview of the various business model patterns and its definitions, see Gassmann et al. (2013), p. 94ff.

business model pattern is coded for all FinTechs, whereby each pattern is defined as a dummy variable (0 = no, 1 = yes).

3. Control Variables

In order to consider further effects that may have an impact on the funding process, we use five different control variables. First, we control for the size of the FinTech by the number of its employees. The size of a company reflects the maturity of a company and is a measure for already required funding. A small number of employees is often related to a very young company that is currently being in its set up phase. The number of employees is classified into 5 different clusters: 1 to 10, 11 to 50, 51 to 100, 101 to 250, >250. Secondly, we control for the activity period, i.e. how many years the FinTech has been operating in the market, to account for possible unobserved heterogeneity between the different FinTechs. Thirdly, we also control for the industry (area of activity), since different segments of the financial services industry require different amounts of funding. Establishing a completely new bank or insurance company requires much more capital than setting up a crowdfunding platform or a comparison portal. For the area of activity, we use the typology of Stuckenborg et al. (2017) in our study and differentiate between 13 categories.

Fourthly, we also consider the share of female founders since studies have shown that female founders have an impact on the funding (e.g. Marom et al., 2014). Finally, we control for the number of funding rounds that were necessary to generate the funding.

IV. Results

In order to investigate the signals of venture quality in accordance with the financing capacity, we apply a two-step approach. We start with a descriptive data analysis to provide an overview of our database and the characteristics of the German FinTech market. Thus, we set the theoretical backdrop to determine the right variables for the regression (Stock & Watson, 2012). A regression analysis is then applied to further identify and quantify the correlations between the variables and the funding success. The individual factors can be assessed using a regression analysis (it should be noted, though, that the individual variables have different scale levels). We will test the specified model on heteroscedasticity and multicollinearity and, if necessary, a robust regression will be used (Greene, 2012).

A. Descriptive Statistics

The descriptive statistics of the variables are provided in table 1. The mean (median) total funding of the sample FinTechs was EUR 16 m (2.5 m).

As expected, when analyzing FinTechs, the firm size measured by the number of employees is relatively small in our sample. The largest part of the included start-ups shows an employee range of up to 50. The activity period of the FinTechs is at least two years, since it often takes some time to generate financing capacity and go for the first funding. As shown in the previous sections, start-ups rely on capital provided by relatives (or the founders themselves) in the early-stages.

Table 1. Descriptive statistics.

	Obs.	Mean	Median	Std. dev.	Min.	Max.
			Control Variables			
Total funding	101	16,031,386.0754	2,500,000.0000	49,043,484.0407	2,500.0000	432,109,188.0000
No. Funding rounds	101	2.6634	2.0000	1.8181	1.0000	13.0000
Activity period	101	5.0000	4.0000	2.1541	2.0000	11.0000
Share of female founders	101	0.0314	0.0000	0.1540	0.0000	1.0000
Emp. Range 1-10	101	0.2475	0.0000	0.4337	0.0000	1.0000
Emp. Range 11-50	101	0.4554	0.0000	0.5005	0.0000	1.0000
Emp. Range 51-100	101	0.1881	0.0000	0.3928	0.0000	1.0000
Emp. Range 101-250	101	0.0495	0.0000	0.2180	0.0000	1.0000
Emp. Range >250	101	0.0594	0.0000	0.2376	0.0000	1.0000
AA - Asset/Investment Mgmt.	101	0.2178	0.0000	0.4148	0.0000	1.0000
AA - Banking Services	101	0.1782	0.0000	0.3846	0.0000	1.0000
AA - Blockchain	101	0.0396	0.0000	0.1960	0.0000	1.0000
AA - Comparison Portals	101	0.1089	0.0000	0.3131	0.0000	1.0000
AA - Crowdfinancing	101	0.1089	0.0000	0.3131	0.0000	1.0000
AA - Data Management	101	0.1386	0.0000	0.3473	0.0000	1.0000
AA - Insurance	101	0.0297	0.0000	0.1706	0.0000	1.0000
AA - Intermediaries	101	0.2574	0.0000	0.4394	0.0000	1.0000
AA - Payment	101	0.2970	0.0000	0.4592	0.0000	1.0000
			Venture Quality - Human Capital			
No. Founder 1	101	0.1881	0.0000	0.3928	0.0000	1.0000
No. Founders 2-3	101	0.6535	1.0000	0.4782	0.0000	1.0000
No. Founders 4-5	101	0.1584	0.0000	0.3670	0.0000	1.0000
Work experience >2y	101	0.9802	1.0000	0.1400	0.0000	1.0000
Work experience >5y	101	0.8317	1.0000	0.3760	0.0000	1.0000
Work experience start-up	101	0.4752	0.0000	0.5019	0.0000	1.0000
Edu share 1 (Univ. Degree)	101	0.8528	1.0000	0.2631	0.0000	1.0000
Edu share 2 (PhD, MBA)	101	0.2398	0.0000	0.3447	0.0000	1.0000
			Venture Quality - Social Alliance/Network Capital			
Twitter followers	101	1,374.9208	553.0000	3,286.9823	0.0000	25,900.0000
Facebook Likes	101	12,683.8614	1,247.0000	62,121.9366	0.0000	537,579.0000
Hot spot	101	0.6931	1.0000	0.4635	0.0000	1.0000
Partners	101	0.5149	1.0000	0.5023	0.0000	1.0000
			Venture Quality - Intellectual Capital			
Patents	101	0.0693	0.0000	0.2552	0.0000	1.0000
Awards/Subsidies	101	0.0990	0.0000	0.3002	0.0000	1.0000
			Venture Quality - Strategic Orientation			
BM - Add on	101	0.1089	0.0000	0.3131	0.0000	1.0000
BM - Digitalization	101	0.1782	0.0000	0.3846	0.0000	1.0000
BM - Flatrate	101	0.1188	0.0000	0.3252	0.0000	1.0000
BM - Freemium	101	0.1485	0.0000	0.3574	0.0000	1.0000

BM - Layer Player	101	0.3564	0.0000	0.4813	0.0000	1.0000
BM - Pay per Use	101	0.3366	0.0000	0.4749	0.0000	1.0000
BM - Peer to peer	101	0.2475	0.0000	0.4337	0.0000	1.0000
BM - Performance-based Contracting	101	0.0990	0.0000	0.3002	0.0000	1.0000
BM - 2-sided market	101	0.1881	0.0000	0.3928	0.0000	1.0000
BM - White Label	101	0.1089	0.0000	0.3131	0.0000	1.0000

AA = Area of activity; BM = Business model pattern

Table 2. Correlation matrix (Pearson).

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41
1	Total funding	1																																									
2	No. Founder 1	-0.098	1																																								
3	No. Founders 2-3	0.100	-,661**	1																																							
4	No. Founders 4-5	-0.026	-,209*	-,596**	1																																						
5	Work exp. >5y	-0.138	-0.190	0.173	-0.022	1																																				
6	Work exp. start-up	0.132	-,204*	0.068	0.130	,269**	1																																				
7	Edu share 1	0.043	0.077	-0.036	-0.036	-0.051	0.103	1																																			
8	Edu share 2	-0.013	0.107	-0.101	0.017	0.064	0.075	,299**	1																																			
9	Twitter followers	0.113	-0.134	0.112	-0.002	0.045	0.019	0.087	0.052	1																																		
10	FB Likes	0.122	-0.080	-0.062	0.167	0.069	0.136	0.015	0.096	0.148	1																																	
11	Awards/Subsidies	-0.063	0.010	0.032	-0.053	-0.117	-0.183	0.123	-0.055	,204*	0.009	1																																
12	Patent	,283**	-0.131	0.117	-0.012	-0.086	,209*	-0.132	-0.087	-0.071	-0.036	-0.090	1																															
13	Hot spot	-0.143	-0.064	0.012	0.054	0.045	0.031	0.063	-0.015	0.031	0.106	-,211*	0.013	1																														
14	Partners	-0.070	-0.090	0.042	0.041	0.146	0.130	0.024	0.136	-0.016	-0.052	-0.010	-0.047	0.127	1																													
15	BM – Add on	-0.098	0.157	-0.079	-0.065	-0.013	0.113	0.075	-0.037	0.071	-0.054	0.097	0.030	-0.043	0.021	1																												
16	BM - Digitalization	0.066	0.107	-0.041	-0.060	0.002	0.023	0.023	0.152	,244*	-0.031	-0.068	-0.025	0.029	-0.066	0.086	1																											
17	BM - Flatrate	-0.043	-0.020	0.010	0.008	0.002	-0.043	-0.183	-0.019	0.121	-0.058	-0.019	0.020	-0.154	0.050	-0.030	0.069	1																										
18	BM - Freemium	-0.079	-0.059	0.187	-0.181	-0.035	-0.007	0.058	-,211*	0.147	-0.022	0.141	0.105	-0.145	-0.152	,301**	-0.122	-0.067	1																									
19	BM - Layer Player	-0.082	0.065	-,197*	0.187	-0.052	0.078	0.001	,227*	-0.085	0.145	0.099	-0.122	-0.087	-0.022	-0.061	-0.076	-,209*	-0.136	1																								
20	BM - Pay per Use	0.074	-0.021	-0.098	0.150	0.040	-0.049	-0.129	-0.062	-0.089	0.179	0.044	0.053	0.156	-0.021	0.020	-0.167	0.062	-0.180	-0.005	1																					
21	BM - Peer to peer	0.004	-0.041	0.032	0.002	-0.049	-0.040	-0.050	-0.100	-0.084	-0.066	0.040	0.024	-0.016	0.190	0.020	-0.147	-0.069	0.019	-,283**	-0.117	1																				
22	BM - Perf.-ba. Contr.	-0.070	-0.160	-0.107	,310**	-0.028	-0.116	-0.088	-0.121	0.038	-0.038	0.112	-0.090	0.149	0.189	-0.009	-0.154	-0.019	-0.138	-0.039	-0.096	-0.037	1																			
23	BM - 2-sided market	-0.047	-0.167	0.084	0.069	-0.054	0.049	-0.125	-0.023	-0.028	-0.067	-0.160	-0.032	-0.009	-0.040	-0.168	0.107	-0.020	-0.130	0.065	-0.021	0.135	0.010	1																		
24	BM - White Label	-0.042	-0.168	0.188	-0.065	0.072	0.049	-0.026	-0.013	-0.071	-0.061	-0.116	0.030	-0.043	-0.042	-0.122	-0.080	-0.128	-0.057	0.005	-,249*	0.020	0.097	-0.006	1																	
25	AA - Asset/Inv. Mgmt.	0.030	0.114	-0.120	0.034	0.173	-0.118	0.037	0.166	-0.079	-0.071	0.066	-0.144	-0.013	0.176	0.124	-0.058	0.029	0.049	-,242*	0.081	0.031	0.146	-0.070	-0.107	1																
26	AA - Banking Services	,272**	-0.092	0.122	-0.060	0.140	0.075	0.171	-0.143	0.134	-0.030	-0.068	0.077	0.029	-0.066	0.003	0.189	0.069	0.169	-,293**	0.106	-0.027	-0.154	-0.092	-0.080	-0.183	1															
27	AA - Blockchain	-0.057	0.032	-0.065	0.051	-0.180	0.010	0.066	-0.043	0.004	-0.036	-0.067	-0.055	0.025	-,209*	-0.071	0.171	-0.075	-0.085	-0.151	-0.037	0.119	-0.067	-0.098	0.092	-0.107	0.038	1														
28	AA – Comp. Portals	0.044	-0.087	0.188	-0.152	-0.013	-0.014	-0.026	0.080	-0.066	-0.064	-0.116	-0.095	-,250*	0.149	-0.122	0.169	0.068	-0.057	0.072	-,249*	0.094	-0.116	,238*	-0.020	-0.030	-0.080	-0.071	1													
29	AA - Crowdfinancing	0.114	-0.087	0.054	0.022	-0.013	-0.078	-0.006	-0.121	-0.008	-0.016	0.097	-0.095	0.026	0.085	-0.122	-0.080	-0.128	-0.146	-,260**	0.087	,462**	0.097	,238*	0.082	0.047	0.003	0.092	-0.020	1												
30	AA - Data Mgmt.	-0.075	0.027	-0.069	0.061	0.027	0.020	0.007	0.019	0.166	-0.062	-0.133	-0.109	-0.044	-0.127	0.136	0.038	0.030	0.074	0.120	-0.164	-0.164	-0.037	0.100	-0.048	-,212*	-0.037	-0.081	-0.048	-0.140	1											
31	AA - Insurance	-0.020	,214*	-0.118	-0.076	-,233*	-0.050	0.024	0.104	-0.071	-0.026	-0.058	0.182	-0.010	0.053	-0.061	,223*	-0.064	-0.073	-0.008	-0.125	-0.100	-0.058	0.065	0.126	-0.092	-0.081	-0.036	-0.061	-0.061	-0.070	1										
32	AA - Intermediaries	-0.059	0.006	0.048	-0.069	-0.159	-0.062	0.050	0.183	-0.127	-0.102	-0.195	0.107	-0.001	0.118	-,206*	0.081	-0.006	-0.182	0.129	-0.132	0.030	-0.044	,238*	0.012	-0.091	-0.156	-0.003	,376**	-0.060	0.091	0.164	1								
33	AA - Payment	-0.124	-0.036	-0.028	0.074	0.003	0.119	-,237*	-0.045	-0.076	0.182	0.147	-0.007	0.010	0.111	0.051	-0.189	0.029	0.094	,331**	,225*	-0.072	-0.070	-,257**	0.051	-,291**	-0.076	-0.021	-,227*	-0.158	-0.135	-0.114	-,333**	1							
34	Emp. Range 1-10	-0.183	0.135	-0.016	-0.123	-0.171	-0.178	-0.160	-0.128	-0.168	-0.109	0.040	,205*	-,215*	-0.132	0.094	0.033	0.073	0.148	-0.092	-0.020	-0.010	-0.037	0.076	0.094	-0.025	-0.027	0.119	0.020	-0.127	-,230*	0.170	-0.023	0.079	1						
35	Emp. Range 11-50	-,201*	0.119	-0.002	-0.125	0.093	0.125	0.160	0.026	-0.132	-0.143	-0.037	-0.171	0.178	0.013	0.063	-0.062	-0.090	0.009	-0.016	0.022	0.028	0.030	-0.084	-0.128	0.047	0.042	0.018	-0.128	0.063	,208*	-0.160	0.053	-0.072	-,525**	1					
36	Emp. Range 51-100	0.015	-,232*	-0.022	,277**	0.081	-0.103	-0.004	0.051	0.139	-0.069	0.010	-0.131	0.046	0.062	-0.087	-0.026	0.136	-,201*	0.065	0.032	0.017	0.010	0.092	-0.006	-0.009	-0.092	-0.098	-0.006	-0.006	0.100	-0.084	-0.052	0.020	-,276**	-,440**	1				
37	Emp. Range 101-250	,257**	-0.110	0.166	-0.099	-0.019	0.148	-0.104	0.040	-0.033	,229*	-0.076	0.117	-0.046	0.130	-0.080	0.013	-0.084	0.033	0.021	-0.066	-0.025	-0.076	-0.110	,213*	-0.010	-0.106	-0.046	0.067	0.067	-0.092	,229*	0.074	0.051	-0.131	-,209*	-0.110	1			
38	Emp. Range >250	,497**	-0.014	-0.081	0.120	0.001	0.096	0.056	0.056	,384**	,403**	0.057	0.096	-0.014	-0.007	-0.088	0.102	-0.092	0.013	0.075	-0.002	-0.047	0.057	-0.014	-0.088	-0.031	,211*	-0.051	0.181	0.047	-0.101	-0.044	-0.052	-0.072	-0.144	-,230*	-0.121	-0.057	1	*		
39	No. Funding rounds	,665**	-0.106	0.049	0.051	0.004	0.122	0.001	-0.052	0.171	,270**	-0.067	0.180	0.090	0.104	-0.058	0.001	-0.016	-0.061	-0.079	0.040	-0.058	0.098	-0.050	-0.005	-0.048	,230*	-0.103	0.047	-0.058	0.106	0.000	-0.053	0.001	-,350**	-0.192	,216*	,219*	,487**	1		
40	Activity period	,238*	0.012	0.010	-0.025	-0.049	-0.139	-,266**	-0.177	0.036	0.097	0.186	0.000	-0.110	0.074	-0.044	-0.133	0.043	0.091	0.096	-0.137	0.021	0.186	-0.142	0.074	0.078	-0.048	-0.095	0.015	0.104	0.027	-0.109	-0.116	0.131	-0.161	-0.148	0.106	,213*	,235*	,281**	1	
41	Share fem. founders	-0.059	,232*	-0.123	-0.089	-0.167	-0.152	0.053	0.134	-0.058	-0.041	-0.068	-0.056	-0.074	-,211*	-0.072	-0.095	0.025	-0.085	0.118	0.059	-0.067	-0.068	0.067	-0.002	-0.108	-0.095	0.069	-0.072	-0.072	-0.020	,345**	-0.120	-0.062	0.107	-0.014	-0.043	-0.047	-0.051	-0.152	-0.116	1

Notes: * Correlation is significant at the 0.05 level (2-tailed) / ** Correlation is significant at the 0.01 level (2-tailed)

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Most FinTechs (65.5%) have been founded by 2 or 3 people, which indicates that most founders prefer this team size as it seems to be a good tradeoff between diversification and coordination efforts. In most of the founding teams (83.2%), at least one founder has work experience of more than five years. Thus, founders often generate some working experience before establishing a new business. This might also be helpful in terms of capital, since after some years in a job, people often have some financial resources that help initiate a new business. Regarding the education, it should be noted that about 85% of the founders have an academic degree (Bachelor, Master or Diploma), while almost 24% even have a PhD or an MBA. In terms of network activity, the FinTechs are more prominent on Facebook pages (measured in terms of likes) than on Twitter. Most FinTechs are located in Hot spots and more than 50% have a partner with whom they are cooperating.

Most FinTechs operate with the business model pattern layer player (35.6%) and pay per use (33.7%). Of particular interest are business model patterns that already give a hint on the way FinTechs are earning money. Patterns such as flat rate (11.9%) generate constant revenue streams (depending on the number of users), whereas pay per use indicates a direct relationship between performance and profit. However, with freemium, users must be first convinced to switch from services free of charge to paid services.

The correlation matrix (table 2) show several significances and thus, we employ multivariate analyses to validate our hypotheses.

B. Multivariate analysis

For investigating the effect of venture quality on the financing capacity, we provide several regression models. To capture the financing capacity, we use the dependent variable of total funding. We conduct three regression models to investigate the individual effects of (1) human, social network/alliance and intellectual capital as classical signals of venture quality, (2) strategic orientation as new signal and (3) an all-in model (full model).

Table 3 provides the results of the OLS regression with robust standard errors between the dependent variable total funding and the independent as well as the control variables. Both the models for the individual effects and the model containing all variables show several significant coefficients providing empirical evidence for the different signals analyzed.

Table 3. OLS-Regression with robust standard errors for total funding.

	Dependent variable:		
	Total Funding (EUR m)		
	Classic Signals (1)	Strat Orientation (2)	Full Model (3)

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Constant	69.04* (41.01)	1.78 (29.09)	41.81 (35.23)
	Venture Quality – Human Capital		
No. Founders 2-3	8.87 (6.97)		20.87*** (7.06)
No. Founders 4-5	-2.68 (9.72)		7.27 (9.25)
Work Experience >5y	-27.75** (11.61)		-30.34*** (11.25)
Work Experience Start-up	7.56 (5.43)		8.80* (5.24)
Edu share 1 (Univ. degree)	5.17 (11.12)		13.80 (9.06)
Edu share 2 (PhD, MBA)	8.97 (7.02)		-0.76 (7.19)
	Venture Quality – Social Alliance/Network Capital		
Twitter followers (in thousand)	-0.84 (0.85)		-0.20 (0.80)
FB Likes (in thousand)	-0.11* (0.07)		-0.14** (0.06)
Hot spot	-21.39** (9.41)		-23.35*** (8.57)
Partners	-11.97** (5.47)		-13.39*** (4.81)
	Venture Quality – Intellectual Capital		
Awards/Subsidies	-18.23** (8.50)		-24.14*** (8.97)
Patent	20.15 (16.64)		18.42 (14.85)
	Venture Quality – Strategic Orientation		
BM - Add on		-4.45 (7.28)	-9.22 (7.59)
BM - Digitalization		6.42 (7.62)	14.35** (6.76)
BM - Flatrate		0.45 (8.85)	-4.93 (7.67)
BM - Freemium		-11.05 (8.34)	-22.69*** (8.55)
BM - Layer Player		8.60 (6.82)	10.16 (6.29)
BM - Pay per Use		-0.67 (6.96)	5.09 (6.50)
BM - Peer to peer		0.42 (5.92)	6.78 (6.14)
BM - Perform.-based Contract.		-27.52* (14.45)	-14.51 (10.43)
BM - 2-sided market		-6.67 (6.93)	-13.13* (7.08)
BM - White Label		-6.32 (9.51)	-13.50 (9.53)
	Controls		
AA - Asset/Investment Mgmt.	11.11 (9.24)	4.23 (8.74)	17.52* (9.36)
AA - Banking Services	13.16 (9.25)	10.85 (9.12)	9.93 (9.27)
AA - Blockchain	-16.34 (11.95)	-12.98 (13.78)	-29.88* (15.30)
AA - Comparison Portals	-19.60 (13.47)	-15.12 (9.42)	-23.32* (12.56)
AA - Crowdfinancing	19.79** (9.95)	21.89* (12.01)	21.18** (10.08)
AA - Data Management	-12.27 (9.44)	-12.75 (10.65)	-7.86 (7.90)
AA - Insurance	-35.05 (22.60)	-36.04** (15.84)	-35.48* (18.19)
AA - Intermediaries	-3.02 (6.02)	-1.86 (6.18)	-5.73 (6.45)
AA - Payment	-6.40 (7.71)	-19.22* (11.57)	-8.16 (8.93)
Emp. Range 1-10	-64.06** (31.32)	-19.49 (23.57)	-46.21 (28.85)
Emp. Range 11-50	-63.03** (31.42)	-33.86 (22.58)	-53.63* (29.16)
Emp. Range 51-100	-60.26* (32.83)	-41.41 (25.46)	-58.38* (30.06)
Emp. Range 101-250	-21.45 (35.37)	1.36 (34.69)	-15.56 (29.81)
Activity period	-0.06 (1.70)	1.18 (1.48)	1.10 (1.42)
Share of female founders	8.22 (17.29)	20.79 (13.89)	9.75 (17.32)
No. Funding rounds	13.81*** (4.72)	16.62** (7.93)	14.85*** (4.29)
Observations	101	101	101
R^2	0.70	0.61	0.76
Adjusted R^2	0.58	0.47	0.61
Residual Std. Error	33.33 (df = 72)	35.69 (df = 74)	30.80 (df = 62)
F Statistic	5.05*** (df = 28; 72)	3.09*** (df = 26; 74)	6.26*** (df = 38; 62)
VIF	3.34	2.55	4.09
Durbin Watson Test	2.31	1.80	2.29
Breusch-Pagan Test	74.36***	56.78***	74.65***

Notes: *p<0.1; **p<0.05; ***p<0.01. A Durbin-Watson test for autocorrelation and a Breusch-Pagan Test for heteroskedasticity were performed for each model. Due to heteroskedasticity in all models, following (White, 1980), we used robust standard errors for each regression. (Robust standard errors in parenthesis.) Furthermore, we calculated for each regression analysis the variance inflation factor (VIF) to ensure that our results are not influenced by multicollinearity. The results show a VIF of 4.09 for the full model and 3.34 and 2.55 for the classic and strategic model respectively; a VIF up to 10 is generally said acceptable (Jacob Cohen, 2010). In order to test the linear specification of the full model, we applied the RESET test (Ramsey, 1969), which confirmed our model specification (F=1.27, df1 = 38, df2 = 24, p-value = 0.27).

Corresponding with other studies, we hypothesized a positive relation between the human capital and the funding success. Regarding the number of founders, the full model indicates a positive and significant relationship with the total funding for a team size of 2-3 founders, which seems to be optimal from the point of view of investors. We argue that this number is a consequence of the tradeoff between a higher degree of coordination in large teams and the presence of synergies from different competencies. Another important component of the human capital is the founders' experience. For this aspect, our results show a varied response. While general work experience larger than five years results in a negative relation, the variable for experience in the start-up environment reveals a positive association with the financing capacity (in the full model). According to these results, work experience greater than five years appears to be unattractive for investors. As a possible explanation, we propose that the ways of thinking and working are already settled with the founders and they may be less susceptible for suggestions and guidelines made by external investors. It may also be deduced that founders with an established and proven work experience are less dependent on external capital, since they are in a better position to provide their own financial resources for the early years which also enables them to keep a greater share of their business. In contrast, investors appreciate experience made in a start-up environment, indicated by the positive relationship of the variable "start-up experience". Such founders know the peculiarities of the business in young ventures and seem to generate more trust by investors. Overall, the experience of founders has an influence on the funding success. However, it must be stated in a more differentiated way. Further to this, the impact of the educational background of the founders was analyzed. While the respective coefficients show no significant relationship to the funding success, the signs are positive for university degrees and negative for MBA or PhD degrees. Despite their insignificance, we presume that higher university degrees are not attractive for investors. In summation, our hypothesis concerning human capital can be confirmed. Human capital serves as signal of venture quality measured via the funding success. But in contrast to other studies, the impact of working experience is not necessarily positive by investigating the generated funding volume.

The variables for the social alliance/network capital, Partner, hot spot and number of FB likes, show negative and significant coefficients, indicating a negative association between the funding success and the social alliance/network capital. Our

results are in contrast to the results of other studies (e.g. Baum & Silverman, 2004) which leads us to reject our hypothesis of a positive relationship. Although at first glance the results are astonishing, we can conclude that partners have, from the viewpoint of an investor, not a positive impact, since investors dread the conflict with other stakeholders of the FinTech. This might be of relevance if the partners hold shares. It is also suggested that start-ups having a large network of partners, do not rely on external capital, since they are supported by their partners.

Regarding the third dimension of venture quality, the intellectual capital, measured by subsidy and patent, our results suggest a negative association for subsidy and awards in contrast to our stated hypothesis. This variable shows negative and statistically significant coefficients in both the full model and the model measuring the individual effects. We can explain these findings by the fact, that founders who go through such an application process might not focus on the main business of their start-up and spend much time in gaining such a subsidy. On the other hand, FinTechs supported by any kind of subsidy need a lower level of external capital in comparison to other start-ups.

The variable for the intellectual capital (patent) shows a positive but insignificant coefficient. Similar findings have been provided by Ahlers et al. (2015). Such patents are a unique feature of a start-up and make it more likely to survive the selection process in the FinTech area, as shown in other studies (e.g. Baum & Silverman, 2004; Munari & Toschi, 2015; Rassenfosse & Fischer, 2016). Overall, our third hypothesis of a positive relationship between the funding success and the intellectual capital cannot be confirmed with our data.

Next, we focus on the strategic orientation, where we include 10 business model patterns in our investigation. The regression results show statistically significant coefficients for four (model 2: 1, model 3: 3) of these strategic elements.

The results suggest that business models in which generating a high number of users is relevant, are less attractive for investors, indicated by a negative sign of the respective coefficients. Such strategic elements are e.g. Freemium that focuses on free offerings of basic services or products and comparison portals. However, the business model digitalization, which aims at digitizing physical products and processes positively affects the financing capacity. The empirical results provide evidence and also support previous research (e.g. Shepherd, 1999) that strategic decisions have an impact on the generated funding and therefore, can serve as effective signals of the funding success.

V. Discussion and Contributions

A. Theoretical Contributions

Our research contributes to the growing literature on entrepreneurial funding and financing of FinTechs in particular. Recent literature focusses on different elements of funding of nascent businesses. The making of investment decisions by venture capitalists is of great interest in research (e.g. Fried & Hisrich, 1994; Hall & Hofer, 1993; Hisrich & Jankowicz, 1990; Rassenfosse & Fischer, 2016). Moreover, further research streams focus on signals in venture financing (Baum & Silverman, 2004; Hoenig & Henkel, 2015; Silverman & Baum, 2002).

Research on signals in funding decisions is emerging, particularly notable is research on signals such as human capital (Colombo & Grilli, 2010; Ko & McKelvie, 2018; Unger et al., 2011; Zarutskie, 2010) or intellectual capital, often reflected by patents (Conti at al., 2013a; Häussler et al., 2009), or network capital (Brüderl & Preisendörfer, 1998; Shane & Cable, 2002; Stuart & Sorenson, 2007). Many previous studies have only focused on single signals. For studies that have defined venture quality through more than one signal, the main three signals considered are human, intellectual and social alliance capital (Ahlers et al., 2015; Baum & Silverman, 2004). Thus, research evaluating simultaneous effects of different signals is still emerging. This research contributes to signaling theory and to entrepreneurial research through analyzing different signals of venture quality concurrently instead of focusing only on the effects of single signals. We present evidence of the importance of human capital for the ability to generate funding for FinTechs. Our results regarding intellectual capital as well as social network/alliance capital may be contrary to other studies, however, we develop and explore valid explanations for the direction of the effects. For instance, "partners" as indicator for network capital, might have a negative impact on the funding volume as they can be an obstacle for further external investors due to their strong connection with the FinTech.

The analysis of strategic elements and their impact on funding decisions or the attractiveness of start-ups is very popular in research (Lieberman & Montgomery, 1988; Rassenfosse & Fischer, 2016; Shepherd, 1999). Previous studies have often applied exploratory research and performed interviews to evaluate decision criteria (Shepherd, 1999). We contribute by delivering empirical evidence from the FinTech market in Germany regarding the impact of strategic decisions. In order to reflect strategic orientation, we apply new measures by operationalizing business model patterns. These patterns are widely accepted in research as strategic elements. We have proven the impact and importance of strategic decisions on the financing capacity.

As stated above, different signals have been analyzed independently from each other, but all have been proven to have an impact on the funding. In this sense, we pioneer in combining and applying the "classical" as well as "strategic" signals on the German FinTech market. Moreover, we also contribute to an emerging research stream

that focusses on the evaluation of FinTech markets and we do so by delivering particular insights on the German FinTech market. This research is the first to develop and analyze a comprehensive sample of start-ups in the German financial sector.

B. Practical Implications

Our study is of particular relevance in practice. The results are important for all market participants, entrepreneurs as well as investors.

Founders can draw valuable insights about which characteristics made FinTechs successfully raise funding in the past. The study provides evidence that human capital as well as the strategic orientation of a FinTech serve as a signal of venture quality and increase the chance of generating funding. Of notable worth are the number of funders, i.e. the key composition of the founding team as well as previous experience with start-ups which increase the generated funding of FinTechs. Furthermore, specific business model patterns have a positive or a negative impact on the funding success which is valuable information for founders to consider. Founders are able to use the results to derive an assessment of the current market and competitive situation. In using this research, entrepreneurs obtain the advantage to choose the right framework conditions based on our results for their start-up business to increase their chance of funding success.

The results of this research are also of interest to other players in the financial industry. This is due to the fact that the research offers the opportunity to identify potential cooperation partners for new business ideas with a promising future. One is also able to measure the maturity of a FinTech by considering the indicator of already generated funding, for security of investment.

C. Limitations and Avenues for Future Research

Despite its merits, our analysis leaves us with some open questions. First, the start-up and the FinTech market is a rapidly changing market and is currently very popular among venture capital investors. However, these investors often reject applications for funding and thus only "successful" projects can be analyzed here. Thus, research should be extended on the selection process itself.

Second, our dataset only reflects FinTechs in the German market and in a certain time frame. It may be the case that other markets or industries and timeframes may function in a different way. In addition, some of our generated data is very crude, and could be collected in more detail, e.g. we do not measure the quality of subsidies or awards and we also do not assess the quality of work experience and education. Thus,

the methodology and the research approach would benefit from the need to be extended on other industries and countries.

From a practical point of view our research suggests which signals might have a positive effect on funding. However, we focus on an ex post view, where we postulate a relationship between the FinTech characteristic and the generated funding. In our research design we primarily employ variables whose validity has already been empirically confirmed in other studies. In addition, there are other factors that may have an influence, and which have already been identified in exploratory studies. Examples in the FinTech area are regulatory knowledge or technological advantages (Werth et al., 2019). The validity of these signals should be checked in future by further empirical studies. In addition, we only analyze signals and are understating the quality of applications for funding. Application documents that are given to potential investors contain a plethora of information. The personal contact to investors is also critical. However, such information is scarcely available. Therefore, we recommend that further studies include the application documents and also focus on the original selection process when analyzing the attractiveness of FinTechs.

Finally, we cover the strategic orientation through business model patterns, which in reality form an interaction with the market environment. With the use of the funding data, we implicitly obtain information about competition and capital requirements in the market and attempt to explain their impact as stated above. However, further studies are needed to further incorporate the market and competitive environment whilst evaluating the implications.

VI. Conclusion

With consideration of the available literature, this paper is probably the first to conduct an empirical analysis of different signals, i.e. venture quality and strategic orientation, on the financing capacity (in terms of generated funding) of German FinTechs. Building on earlier entrepreneurial research, our study advances the understanding of the effectiveness of signals and suggests that different FinTechs can signal their attractiveness and their financing capacity via different means. We have exploited a large data set of German FinTechs and their generated funding to expand on previous research on the funding of start-ups. We evaluated which signals impact the generated funding. The findings indicated that human capital positively impacts the funding and that there are some business model patterns that impact the generated funding. An important finding is that the choice of the business model pattern can have a positive or negative impact. Accordingly, certain business models and areas of activity can support and reduce the generated funding. Our results emphasize the importance for start-ups to select and exude the right signals in order to generate funding for the growth of their business.

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