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The survival of the German FinTech market: An accounting-based valuation

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ABSTRACT

The purpose of this paper is to examine the essential characteristics of the financial statements of FinTech start-ups and to investigate which figures of balance sheets are suitable indicators of failure for this still rising group of start-ups. We conduct a quantitative analysis of 595 annual reports of FinTech start-ups issued between 2007 and 2016. Our study reveals that the balance sheets have a high share of current assets and often show losses not covered by equity. Based on the financial variables, the period of three to five years after foundation could be identified as critical phase for the future survival of FinTech start-ups. Two years before failure significant changes in some balance sheet figures are recognizable. Using a logistic regression model, we identify accounting figures serving as indicators for the separation of the two groups, active and failed FinTech start-ups.

Keywords: FinTech, Accounting-based valuation, Business failure, Balance sheet analysis, Start-ups JEL Codes: C55, G21, G33, M13, M41

I. Introduction

FinTech is a young phenomenon, which can especially be observed since the financial crisis in 2007-2008. This FinTech development is mainly being led by start-ups, which are combining technological possibilities with the products and services of the financial industry (Arner, Barberis, & Buckey, 2017). But literature on this topic is rare due to the young age of FinTech development. Previous research contributions and studies show that the market for FinTech companies can be subdivided into different business areas, of which the area of payment is identified as the most prominent one. Other known areas include investment/asset management (e.g. Greenvesting Solutions), acting as an intermediary for insurance or other financial products like loans (e.g. smava),

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or data management (e.g. moneymeets) (Stuckenborg, Klein, & Leker, 2017; Winnefeld & Permantier, 2017). With the rising number of FinTech start-ups, traditional providers of the financial industry, such as banks and insurance companies, are increasingly being compelled to react to this recent development. In their early phase, FinTech start-ups were partly perceived as a threat or a temporary phenomenon by these traditional providers; however, the interaction between the new and established market participants has changed over time (Kiem, Potel, Trillmich, & Weir, 2016; Temelkov, 2018). The growing recognition of the FinTech area is evidenced by the rising number of mergers and acquisitions (M&A) in this sector by established companies of the financial industry. According to a study by the auditing company KPMG, the number of M&A deals in the FinTech domain grew from approximately 190 to 305 worldwide between 2012 and 2016 (KPMG, 2017). Furthermore, there is increasing willingness to cooperate between FinTech companies and traditional providers. More and more banks and insurance companies are cooperating with FinTechs or have founded so-called "labs" or "hubs" (Swisscom, 2017) to identify market or product solutions together with the start-ups and to facilitate mutual learning. According to a recent study, approximately 70% of the financial institutions in Germany are cooperating with FinTech start-ups (Kashyap, Shipman, Garfinkel, Davies, & Nicolacakis, 2017). Apart from the traditional providers of the financial industry, the FinTech sector is also highly interesting for investors. Both the amount of investment and the number of completed deals in the FinTech domain have risen. The investment volume in Germany has grown from 10 million Euro (number of deals: nine) in 2012 to 400 million Euro (number of deals: 57) in 2017 (Ernst and Young, 2017). In order to identify potential acquisition or investment objects among the large and steadily growing number of FinTech companies, external stakeholders rely on evaluation methods. Furthermore, FinTech start-ups have increasingly become in the focus of scientific studies evaluating the phenomenon of FinTech and its development. The number of scientific publications dealing with this topic has undergone a rise of around 3,100% in the last five years.¹ These previous research contributions mainly focus on the classification and definition of the market, on separating segments of the FinTech sector, on calculations of systematization criteria, and on regulatory issues (Brummer & Gorfine, 2014; Gulamhuseinwala, Bull, & Lewis, 2015; Zavolokina, Dolata, & Schwabe, 2016). For instance, Stuckenborg et al. (2017) divide the FinTech market into segments and evaluate the business model patterns and revenue models with which FinTechs enter the market.

¹ Based on Google Scholar (2018), a search engine for scientific documentation, the number of search results has increased from 138 in 2012 to 4,420 in 2017.

For all these identified stakeholder groups, one question is of high interest: How can FinTech start-ups with good market prospects be identified among the large number of new players in the financial sector and which of these have a higher probability of failure? To identify those FinTech start-ups that have the potential to establish themselves on the market, some suitable evaluation criteria are needed. Other studies, such as those investigating established companies, use annual accounts, which are available to third parties and which allow an assessment of the financial situation of the valuation object (Baetge, 1998, p. 9). In contrast to established firms, the financial data available for start-ups is limited due to their relatively young age and we could not identify any contribution which investigates annual accounts of FinTech start-ups. This non-availability does not merely result from the short period of market activity, but also due to limited disclosure obligations of small businesses. Depending on the accounting standard, there are certain legal relaxations regarding the publication obligations - for instance, according to the German Accounting Standards (hereinafter HGB), the disclosure of profit-and-loss statement is not needed for companies belonging to the size category of small enterprises in keeping with § 267 Para. 1-3 HGB². Most FinTech startups can be assigned to this category. Furthermore, start-ups are typically not-publicly traded companies; hence, there is no permanent indicator about the current market value of a company available (Maeschle, 2012). In contrast, large firms have to publish a lot of (financial) information, which can be used as a basis for valuation (Gregory, Rutherford, Oswald, & Gardiner, 2005).

Thus, on the one hand, limited financial data are available for the valuation of start-ups, while on the other hand, external stakeholders like investors need meaningful information to assess the future development of a start-up and to avoid losses, for instance through the insolvency of a supported company (Maeschle, 2012). The risk of total failure for investors is quite high, considering the failure rate of start-ups (D'Avino, Simone, Iannucci, & Schiraldi, 2015). With the rising number of FinTech start-ups in the market, the share of start-ups ceasing their business has increased as well. The probability of failure of start-ups in the first six years in Germany is about 45.5% across all industries (Diehm, 2014, p. 262). Also, several start-ups in the FinTech sector have given up their business activities, such as "Cashboard" and "Outbank" (Raeth, 2017; Wolff, 2017). This higher failure risk in the start-up environment can be ascribed to various factors. Due to the short history of start-ups and a heavily dynamic market environment, company structures have to be established. At the same time, strategic decisions have to be permanently revaluated in the first few years. Moreover, start-ups have restricted

² The size category of small enterprises is defined on the following criteria: balance sheet total per year ≤ 6 million Euro, revenues per year ≤ 12 million Euro and an average number of employees ≤ 50 .

resources in the beginning, which affects both staff and financial endowment. However, high investments are simultaneously needed to tap new market segments and build up the company. In consequence, high initial losses are recorded at the beginning, since the required investments are mostly not offset by high revenues (Diehm, 2014, pp. 21-25). Therefore, start-ups usually depend on external investors like banks and other investors (Thornton-Trump & Fu, 2000). But unlike in the case of large firms, lenders like commercial banks demand high costs of capital due to the uncertainty of the start-up's future prospects. Thus, start-ups are usually obliged to fall back on venture capitalists, own capital, or short-term debt (Berger & Udell, 1998; Gregory et al., 2005). There are also new forms of entrepreneurial finance available that could provide a solution to the financing problem, such as crowdfunding (Wright, Lumpkin, Zott, & Agarwal, 2016). Generally, the environment of start-ups, especially in the FinTech sector as a very young market segment, is characterized by high growth and strong dynamics (Dorfleitner, Hornuf, Schmitt, & Weber, 2017, p. 1). Against the backdrop of scant resource availability, high flexibility and a rapid growth rate are necessary in order to remain in the market (Diehm, 2014, pp. 21–25). Some start-ups cannot survive in such dynamic market conditions and are forced to give up their business. Such a negative development becomes apparent ahead of time (Duvivier, 2000). Corporate crises have several stages and are reflected in the key financial figures of the company. The investigation of balance sheets to examine the risk profile of a company is widely discussed in literature because this method lets external stakeholders gain a meaningful insight into the financial situation (Maeschle, 2012).

This risk of failure for FinTechs is addressed in this study by evaluating the balance sheet data of these young companies. Several empirical studies use balance sheet data to analyze the failure probability of firms. Such contributions often focus on large and established firms, for which a large amount of financial data are available.³ But the literature concerning the effects of balance sheet data on the survival prospects of start-ups is quite rare (D'Avino et al., 2015; Duvivier, 2000; Gaskill, van Auken, & Manning, 1993; Gregory et al., 2005; Huynh, Petrunia, & Voia, 2010; Marom & Lussier, 2014; Thornton-Trump & Fu, 2000). Considering the limitations of individual studies, it can be concluded that existing contributions consider only individual balance sheet items and no investigation of the complete annual accounts takes place (D'Avino et al., 2015; Duvivier, 2000; Gregory et al., 2005; Thornton-Trump & Fu, 2000). Furthermore, these studies concentrate on the different financing options of start-ups and try to evaluate the implications of different sources of funding on the survival prospects (Duvivier, 2000;

³ For an overview of studies regarding the prediction of failure probability, see Altman and Narayanan (1997), Altman and Saunders (1997), and Zavgren (1985).

Gregory et al., 2005). In addition, existing studies often focus on individual start-ups or only have a one-year review period. For instance, Huynh et al. (2010) investigate the effect of the initial financial conditions on the failure rate of start-ups and consider only the first year after founding. In their case study of an Italian start-up, D'Avino et al. (2015) use selected balance sheet items regarding only one business year. In contributions like Marom and Lussier (2014) as well as Gregory et al. (2005), the sample consists not only of start-ups, but medium-sized companies are also included in the analysis.

Based on the limitations of these existing contributions, there is a research gap to investigate which accounting differences exist between active and failed start-ups regarding the complete balance sheet data of a sample of start-ups over an extended period of years. In addition, we could not identify any contribution which investigates special characteristics of start-up balance sheets over time. To address this research gap, the purpose of this paper is to examine the essential features of start-up balance sheets regarding the exemplary group of FinTech start-ups using 595 balance sheets over a period of 10 years (2007–2016). Moreover, we aim to evaluate those balance sheet items which are suitable indicators of failure and allow conclusions on the failure probability of start-ups. Overall, we address the following research questions: What are the main characteristics of the balance sheets of FinTech start-ups and can any patterns be identified? Which accounting indicators of balance sheets can be used for predicting the probability of failure?

Our paper contributes to the existing literature by providing one of the first empirical investigations of balance sheets of FinTech start-ups and possible failure indicators based on financial data. Our analyses reveal that the balance sheets of FinTech start-ups are often marked by a high share of current assets, debt intensity, and frequent losses not covered by equity, especially in the initial years. The period of three to five years after foundation is identified as critical regarding the future survival prospects of FinTech companies. Differences between the groups of active and failed FinTechs are mainly observed in the balance sheet items of fixed assets, equity, cash, and debt capital. Furthermore, the results of the logistic regression show that the probability of failure decreases with a higher share of seven balance sheet items.

To address these research questions, the rest of this paper is organized as follows: First, we outline the legal framework regarding the annual reports of FinTech companies. Next, we illustrate the methodological approach as well as the process of data collection and adjustments. Afterward, the results of the empirical analysis are presented. In the concluding section, limitations to be considered in the interpretation of the results are shown along with implications for practice and theory. Finally, the results are summarized and discussed.

II. Legal framework

Since the FinTech development is a relatively young phenomenon and most FinTech start-ups were founded only recently, the availability of annual financial data is related to restrictions. Concurrently, there are certain legal conditions that have a strong influence on the availability of annual financial data, in particular due to the company size of start-ups. For this reason, the relevant legal aspects with regard to start-ups are briefly explained in this section. In accordance with § 267 HGB, corporations are to be assigned to different size categories, which form the basis for the definition of rights and obligations concerning the extent and type of the company's reporting as well as the audit and disclosure of the annual accounts. In § 267 Para. 1-3 HGB, three size categories are defined - small, medium, and large. Of these, small companies include a subset micro-enterprises (§ 267a HGB). The classification criteria for the individual categories are total assets, revenues, and the number of employees (Table 1), of which at least two parameters have to fall below or exceed the criterion threshold on two consecutive reporting dates in order to be assigned to another size category (§§ 267, 267a HGB). In case of newly founded companies, the assignment is done on the basis of the first reporting date (§ 267 Para. 4 HGB). FinTech start-ups are mostly classified as microenterprises or small companies and thus have certain relaxations in terms of financial reporting.

	Micro- enterprises	Small enterprises	Medium enterprises
Balance sheet total	≤ 350,000 Euro	≤ 6,000,000 Euro	≤ 20,000,000 Euro
Revenues	≤ 700,000 Euro	≤ 12,000,000 Euro	≤ 40,000,000 Euro
Average number of employees in a year	≤ 10 Employees	≤ 50 Employees	≤ 250 Employees

Table 1: Criteria of the size categories

Source: § 267 Para. 1 and § 267a Para. 1 HGB

In general, every company is obligated to prepare its balance sheet and profitand-loss accounts at the end of each year, according to § 242 Para. 1-2 HGB. Moreover, in accordance with § 264 HGB, there is an obligation to complement the annual account with an appendix and to prepare a situation report. However, there are certain relaxations of these regulations depending on the respective size category. In the following section, the disclosure obligations for micro- and small companies in particular are briefly discussed. Extent of the reporting. Regarding the extent of the financial data to be disclosed, micro-companies have the option to limit their balance sheet by only considering the first structure level, in accordance with § 266 Para. 1 Sent. 1 HGB. Small companies, however, have to consider the second structure level as well. Both micro- and small companies are exempt from the obligations to disclose deferred taxes (§ 274a HGB) and to prepare a situation report in accordance with § 264 Para. 1 Sent. 4 HGB. Moreover, profit-and-loss accounts need not be published (§ 326 Para. 1 HGB). Micro-companies have no obligation to complement the annual account with an appendix, according to § 264 Para. 1 Sent. 5 HGB, provided certain information is included in the balance sheet. In terms of the balance sheet, there are no relaxations for medium and large companies. Only certain information in the appendix may be omitted. While investigating the annual accounts of FinTechs, it should be noted that the relevant balance sheets contain data up to only the second level of detail.

Place and period of disclosure. While the annual account generally has to be published in the Federal Gazette, there is a separate regulation for micro-companies. For companies belonging to this size category, it is sufficient to submit the balance sheet to the Federal Gazette for permanent deposit, according to § 326 Para. 2 HGB. Third parties can access these financial statements subject to a charge. In accordance with § 325 Para. 1a HGB, the annual account has to be submitted within one year of the reporting date of the corresponding business year.

Auditing duty. In accordance with § 316 Para. 1 Sent. 1 HGB, micro- and small companies are exempt from annual auditing duty. Apart from these obligations concerning the publication of the annual report, there is another special characteristic, as coded in § 264 Para. 3-4 and § 264b HGB, which has to be considered while gathering the annual accounts of FinTech start-ups. According to this regulation, subsidiaries included in a consolidated financial statement need not publish their individual financial statement. For example, the FinTech start-up "mr. Commerce GmbH," being a subsidiary of the "net group Beteiligungen GmbH & Co. KG," does not publish any individual financial statement because it is included in the consolidated financial statement of the concern.⁴

From these legal frameworks, the following implications arise for the examination carried out in this study. The annual accounts of FinTech start-ups, particularly of micro- and small companies, are not necessarily publicly accessible in the Federal Gazette. In the case of micro-companies, the annual accounts are deposited with the official Business Register. Furthermore, in most cases, the annual accounts do not

⁴ According to the announcement of "mr. Commerce GmbH" on January 2, 2017 in Federal Gazette (2017).

include profit-and-loss accounts or an appendix. Another restriction is the extent of the balance sheet, which needs to be up to the second structure level only.

III. Methodological framework and data sample

A. Methodology

1.

Balance sheet analysis

For the investigations in this study, a balance sheet analysis of FinTech start-ups is conducted. Basically, a balance sheet analysis involves the preparation (compression) and evaluation of insight-targeted business information using key figures, systems of figures, and other methods (Kueting & Weber, 2015, p. 1). The objective of a balance sheet analysis is to assess the economic situation of companies on the basis of annual accounts (Barth, Barth, Nassadil, & Werner, 2014, p. 17). Balance sheet analyses are of two types – qualitative and quantitative. In quantitative balance sheet analyses, the focus is on the figures of the annual accounts, which, for instance, are condensed by creating accounting indicators, so that the financial situation of the company can be more accurately assessed. Qualitative balance sheet analyses evaluate verbal reports like the appendix, management report, etc. Here, the focus can be, for example, semantical analyses or modifications in exercising of accounting options (Kueting & Weber, 2015, pp. 14, 414). Since no knowledge about qualitative aspects, such as the quality of the management or the employees, is available in the case of FinTech start-ups, these aspects are not considered. Therefore, a quantitative balance sheet analysis is selected in this study as the analytical framework. Another differentiation lies in the perspective of the balance analyses - internal or external. Since the investigations reported in this study are based on publicly available information, an external balance sheet analysis is applied. In the context of the external balance sheet analyses, individual analyses, time-based comparisons, and intercompany comparisons are possible (Krueger, 2014, pp. 8–9; Nicolini, 2008, p. 75).

There are some restrictions related to the analysis of the annual financial data to be considered while evaluating and interpreting the results. Thus, it is a consideration of the past in a double sense – on the one hand, annual accounts refer to a previous business year and on the other hand, the financial statements are published after a certain period from the end of the business year in accordance with the legal publication obligations specified in the HGB. Furthermore, in annual accounts, accounting policies in relation to the exercise of certain accounting options can be used by the accounting company to influence the business figures (Krueger, 2014, pp. 4–5). Another restriction in the external balance sheet analysis is the incompleteness of the data, as only the publicly available information can be used for the investigation (Graefer & Schneider, 2010, p. 10).

2. Multivariate analysis

To evaluate the probability of failure, different methods can be employed in general. In recent years, insolvency research has primarily applied discriminant analyses, artificial neural networks, and logistic regressions. In the last decade, logistic regression analysis has prevailed (Fischer, 2012, p. 93)⁵; it is a suitable method for answering dichotomous questions such as those in our study (Ge & Whitmore, 2010). To address the second research question by identifying accounting variables having a statistically significant impact on the failure probability, we use a binary logistic regression model with the specification reported in Figure 1.

Figure 1. Model specification



For this purpose, the dependent variable in our model represents the status whether a FinTech failed or is still active. As independent variables, the shares of each accounting item of the balance sheet scaled by the balance sheet total are included in our regression model. To consider further effects that may have an impact on the firm failure, we control for the activity period by measuring how many years the FinTech has operated in the market. Generally, there are different methods to process a logistic regression. In our investigation, we conduct a stepwise backward logistic regression to identify the most suitable model.

⁵Nowadays, logistic regression, which has some advantages over other methods like discriminant analysis, is used for the practical forecasting of insolvencies. Logistic regression is based on fewer assumptions and is more robust against outliers than discriminant analysis (Hair, Black, Babin, Anderson, & Tatham, 2006, p. 368; Backhaus, Erichson, Plinke, & Weiber, 2016, p. 287).

To interpret the results of the logistic regression in a suitable way, the independent variables should not be highly correlated with one another to avoid multicollinearity (Tabachnick & Fidell, 2007, p. 443). For assessing the degree of multicollinearity, the variance inflation factor (VIF) is a suitable indicator (Lim, Ding, & Charoenwong, 2013). If the value of the VIF is clearly below ten for all variables, the requirement of absence of multicollinearity is fulfilled (Hair et al., 2006, p. 230).

To assess the results of the logistic regression in terms of classification of the performance and separability of the two groups, the receiver operation characteristic (ROC) curve is a suitable valuation method, which is often used in ratings (Thomas, 2009, p. 115). By presenting the sensitivity (assignment rate "negative control") and specificity (assignment rate "false positive") of the regression model, the classification performance can be displayed (Pospeschill, 2010, p. 195). For perfect separation, the ROC curve would consist of two straight lines (points 0;0 to 0;1 and 0;1 to 1;1); for an ineffective model, however, the ROC curve would form a 45° diagonal (Kuhn & Johnson, 2013, p. 264). As a quantitative measure, the area under the curve (AUC) can be determined, which serves as the value of separability of the model. The higher the deviation to 0.5 (no separability), the better the separability and classification performance of the model (Backhaus et al., 2016, p. 301).

B. Sample selection

In order to address the research questions, an extensive database has been prepared with annual financial statements of FinTech start-ups. The database has been generated with the following restrictions: First, only FinTech start-ups with headquarters in Germany are considered. This geographical restriction was implemented due to two reasons: First, Germany is one of the fastest growing markets in the FinTech sector, as mentioned in former sections, and second, by considering only German FinTechs, differences in annual financial data due to country-specific accounting standards can be excluded (Anandarajan, Francis, Hasan, & John, 2011). In addition, only FinTech companies that have provided their annual account in accordance with the HGB have been included in order to avoid distortions in comparisons through accounting differences (Krueger, 2014, p. 4). Another restriction exists in the underlying definition of FinTech start-ups used in this study, especially regarding the field of activity. For instance, broker portals for real estate, like the start-up "Maklaro," which are subsumed under the term FinTech by certain platforms, are excluded from our investigation. Moreover, multiple platforms list product offerings under the term FinTech start-up, which, however, are only one of several products of a corporation and not an independent company. Not only are these not a FinTech start-up according to our definition, the influence of such single products on the annual accounts cannot be determined.

For building a database with the explained restrictions, all German companies listed under the term FinTech by various sources were collected initially. These sources are Crunchbase (2017), PaymentandBanking (2017), and ZEB (2017) which are freely accessible on the internet. In this initial step, 396 FinTech start-ups could be gathered for our database. This number of FinTech start-ups also corresponds to the results of other studies about the German FinTech market (Dorfleitner et al., 2017, pp. 11–13). From this list, 146 start-ups were eliminated by applying the set restrictions. Among the 146 eliminated from the database of 396 start-ups, 123 FinTech companies were excluded from the investigation because of non-conformity with the underlying definition of FinTech, while the remaining 23 were excluded because of the used accounting standard. After restriction-based elimination, a total of 250 FinTech start-ups remained on the list. Subsequently, general information, such as the date of foundation or the company name (full legal name) as listed in the Commercial Register, was collected for this sample of FinTech start-ups.⁶ In order to capture the balance sheets of all companies in a structured and similar form, a data acquisition scheme was set up following § 266 HGB; it contains the first, second, and third structure levels. For all FinTech start-ups included in the database, we examined whether the annual accounts are available by using both the Federal Gazette (2017) and the official Business Register (2017)⁷. While 595 annual accounts of 131 FinTech start-ups could be collected in total, the annual accounts of the remaining companies were not available or were incomplete. This can be attributed to several causes. First, many FinTechs are subsidiaries and hence mostly do not publish an individual financial statement but are included in the consolidated financial statement, as already pointed out. Second, the non-availability can be attributed to the disclosure deadlines. For example, annual accounts for start-ups founded in 2016/2017 could not be obtained at the date of investigation.

The resulting sample of start-ups was finally checked to see, whether they are still actively represented in the market or have already given up their business activity. If a start-up has already been liquidated or declared insolvent through an official announcement, the status "failed" was assigned and the official failure date was recorded.⁸ In total, the dataset for our investigation comprises 595 annual accounts of 131 FinTech start-ups in Germany. Of these, 22 start-ups have already failed, which implies a failure rate of 17%. The level of detail of the publications, especially concerning

⁶ The founding information was approved on Commercial Register (2017).

⁷ The business register was used for deposited annual accounts in the case of micro-entities as illustrated in the previous section. While the Federal Gazette and the Commercial register are freely accessible by third parties, the access to the business register for deposited annual accounts is fee-based per session.

⁸ In addition, Insolvency Announcements (2017) was checked for official announcements.

the extent of the balance sheet, is different for the 595 collected annual accounts. While some start-ups only fulfil the minimal requirements and publish the first structure level for all or certain years, other FinTech companies publish the second and, in part, the third structure level as well. Of the 595 gathered balance sheets, 469 include, apart from the first, also data of the second structure level, but usually only in a fragmented manner. Before the data were prepared for the balance sheet analysis, a plausibility check of the collected data was conducted to ensure that no transmission errors or inconsistent balance sheets would distort the results of the investigation. For this plausibility check, individual sums were formed and cross-checked for every individual balance sheet and its intermediate positions.

C. Data adjustments

In order to properly conduct an intercompany comparison, the collected data have to be standardized and made comparable. If accounting options are exercised differently in the annual accounts, for instance, this can lead to distortions and limitations in terms of comparability. For this reason, the data must be transferred to standardized balance sheets (Nicolini, 2008, p. 76). Such a standardized balance sheet is intended to contribute to an improvement of the comparability of annual accounts through the neutralization of the accounting policy measures applied (Kueting & Weber, 2015, p. 83). When preparing a standardized balance sheet, individual items of the original annual account are netted (for example, offset with other fields), revaluated, or reclassified. After this, the individual balance sheet items of the asset side are summarized under fixed and current assets, while the items of the equity and liability side are summarized under equity and debt capital (Kueting & Weber, 2015, p. 81). Finally, all balance sheet items are assigned to two upper fields on each balance sheet side, thus providing the basis for further analyses and enabling a suitable intercompany comparison. In the following section, the modifications of the individual items of the annual accounts of the FinTech start-ups that are netted and reclassified within this preparation process are presented in brief.

Outstanding deposits on subscribed capital. If the subscribed capital has not been fully paid up yet, the remaining amount must be declared in the balance sheet. In accordance with § 272 Para. 1 HGB, there is a right to choose between the net and gross method for the statement of outstanding, unclaimed deposits. In the net method, the outstanding deposits are shown as a special item above the assets on the asset side. In the gross method, however, these deposits are deducted from the subscribed capital (Baetge, 1998, p. 91). If the gross method is used, the subscribed capital has to be reduced by this amount (Lachnit & Mueller, 2017, p. 21). Since such a deduction from the subscribed capital is already carried out in the net method, no change in the standardized balance

sheet is required. This field is relatively common in the considered balance sheets, since the objects of investigation in this study are relatively young companies.

Prepaid expenses/Deferred income. Since there are only two upper fields on each side of the standardized balance sheet, the prepaid expenses field has to be reclassified. In general, prepaid expenses are recognized in order to achieve a period-appropriate distribution of assets (Nicolini, 2008, p. 86). However, even in accordance with the HGB, this field does not represent an asset itself and from a business point of view, its characteristics are similar to that of receivables (Broesel, 2017, p. 186). Thus, for the purpose of a balance sheet analysis, prepaid expenses have to be reclassified as current assets. Similarly, the deferred income has to be reclassified as debt capital (Rheinboldt, 1998, p. 119).

Deferred tax assets and liabilities. Under § 274 HGB, there is an option granted for the valuation of the deferred tax assets in the balance sheet, while the deferred tax liabilities have to be valued. Different approaches are presented in the literature regarding the handling of deferred taxes while preparing a standardized balance sheet. While Lachnit and Mueller (2017, p. 22) suggest that deferred tax assets should be reclassified as current assets and deferred tax liabilities as debt capital, there is another approach that involves netting out the two fields. If an asset surplus arises, this should be offset against equity, while a surplus of liabilities should be reclassified as debt capital (Kueting & Weber, 2015, 92). In this study, we select the approach of netting out because this method is widespread and well-accepted in literature; moreover, better comparability is ensured because of the elimination of optional capitalization influences (Broesel, 2017, p. 129).

Losses not covered by equity. Another field that is particularly common in the area of start-ups is "losses not covered by equity." If companies cannot show shareholders' equity in their balance sheet, an appropriate field on the asset side has to be disclosed, in accordance with § 268 Para. 3 HGB. This is neither an asset nor an accounting convenience; rather, it is a correction value to avoid the disclosure of negative equity (Kueting & Weber, 2015, pp. 142–143; Theile, 2017, p. 71). While preparing a standardized balance sheet, such a field is handled as follows: Since it would lead to distortions on the asset side and this field implies negative shareholders' equity (Broesel, 2017, p. 124; Lachnit & Mueller, 2017, p. 22). In consequence, the shareholders' equity could be negative in the considered standardized balance sheets.

Special reserves with an equity portion. Special reserves with an equity portion, arising as a result of special depreciations, for instance, are a kind of mixed field containing a tax component that is uncertain in terms of the amount (character of a provision) (Nicolini, 2008, p. 89). For a standardized balance sheet, this "special reserves" field shall be divided into the equity and the debt capital. A 50% apportionment of the two components is recommended (Baetge, 1998, p. 148).

Assets	Equity and liabilities
Fixed assets	Equity
Intangible assets Tangible assets Financial assets Current assets Inventories Accounts receivable Securities Cash + Prepaid expenses + Other assets	Subscribed capital Capital reserves Retained earnings Net income/(loss) carry forward (c.f.) Net income/(loss) - Outstanding deposits on subscribed capital - If applicable, overhang of deferred tax assets - Losses not covered by equity + 50% of the special reserve items Debt Capital Provisions Liabilities Thereof: Current Liabilities + Deferred income + If applicable, overhang of deferred tax liabilities + 50% of the special reserve items
Total assets	Total equity and liabilities

Table 2: Standardized balance sheet: Results of the data adjustments

Notes: Corrections resulting from the processing measures are highlighted in grey. Additionally, the signs (+) and (-) indicate whether the concerned balance sheet items are to be added or deducted.

Further adjustments and processing measures have to be carried out, especially if comparability is to be maintained between annual accounts that are prepared according to different accounting standards, such as the HGB and the International Financial Reporting Standards (IFRS). Thus, for instance, self-created intangible assets (with capitalization prohibition according to the HGB and capitalization obligation according to the IFRS) have to be unified in the standardized balance sheet (Nicolini, 2008, p. 91). Since the balance sheets in our database are all prepared according to the HGB, such pruning measures can be omitted. Table 2 shows the final standardized balance sheet format, including the pruning measures conducted.

IV. Empirical results

A. Summary statistics

On the whole, our sample comprises 595 annual accounts of 131 FinTech startups. All annual accounts contain the first level of balance sheet fields, while the second level is partially available for 469 financial statements.⁹ Most of the gathered annual accounts (61%) pertain to the first three years after foundation (Table 3). With increasing business years, the number of available balance sheets declines. Thus, the period from the sixth year is reflected by around 14% of the annual accounts. There are only two annual accounts in the database for the year ten after foundation; thus, these years are excluded from further consideration due to the small number of observations.

Table 3: Number of balance sheets in the sample (by years after foundation)

	Years after foundation									
	t1	t ₂	t3	t4	t5	t ₆	t7	t ₈	t9	t ₁₀
No. of balance sheets in the sample	131	123	110	90	57	37	23	12	10	2

Regarding the different legal forms contained in our sample (Table 4), the form of the limited liability corporation (GmbH), at 86%, is the predominant and most frequently used one. The German "Unternehmergesellschaft (UG),"¹⁰ an entrepreneurial company as a precursor of the limited liability corporation, is represented in our database by two FinTech start-ups. Especially in the area of start-ups, the launch of the business is often related with a so-called UG due to the low level of required initial share capital. However, this is converted into a limited liability corporation relatively quickly. The shares of limited liability partnerships (GmbH & Co. KG), at 3%, and of stock corporations (AG), at 9%, are relatively small, so these legal forms are rather rare in the area of start-ups. FinTech start-ups with the legal form of stock corporations are, for example, the "Exporo AG," "Vaamo Finanz AG," and the "Vexcash AG." Classification into size categories following the presented legal terms concerning the publication obligations can only be carried out on the basis of the criterion of the balance sheet total,

⁹ The second structure level of the fields liabilities and provisions is generally not available.

¹⁰ The initial share capital which has to be deposited in the founding process of an UG is a minimum of one Euro. In the following business years, a share of the generated revenues has to be deposited in the share capital up to an amount of 25,000 Euro (the minimum share capital of a limited liability corporation). On reaching this amount, the UG is converted into a limited liability corporation.

since data on revenues or employees per fiscal year are not available. Of the annual accounts, 95% belong to the category of micro- or small companies. This results in the aforementioned restrictions in relation to the published data, which can be used for the investigation.

		Size categories according to the balance sheet total							
Legal Form	Number of FinTechs	Micro- enterprises	Small enterprises	Medium enterprises	Large enterprises				
GmbH	113	336	156	19	5				
GmbH & Co. KG	4	12	10	0	0				
UG	2	5	0	0	0				
AG	12	13	34	3	0				
Σ	131	366	200	22	5				

Table 4: Distribution of legal forms and size categories

To evaluate the values of the balance sheet items of FinTech start-ups, Table 5 shows the descriptive statistics of our sample, containing 25 variables. Basically, the financial statements of FinTech start-ups are characterized by a high intensity of *current assets* as well as *debt capital*. On the asset side, *financial assets* and *inventories* are not issued by the majority of FinTech start-ups. Since FinTech companies are mainly service-intensive companies, this is comprehensible with regard to the *inventories* field. *Financial assets* play a subordinate role in the first few years. The high intensity of *current assets* can mainly be traced to a high share of *accounts receivable* and *cash*.

On the equity and liability side, a high level of *debt capital* intensity is generally observed, which is attributable to a high proportion of *liabilities*, of which a large proportion is short-term in nature. This finding corresponds with other studies, according to which start-ups are often obliged to borrow in the short term, because long-term debts are usually not granted due to the uncertainty of their future prospects (Gregory et al., 2005). While the median of the *capital reserves* and the *subscribed capital* is relatively strong, high losses in the fields of *net income/ (loss)* and *net income/ (loss) c.f.* can be noted. This point also corresponds with findings from other studies and is typical for the first years of start-ups. Frequently, the balance sheets show *losses not covered by equity*, whereby over-indebtedness is reflected. This field is examined in the following section.

	Obs.	Mean	Median	Std. dev.	Min.	Max.
Year after foundation	593	3 24	3	1 97	1	9
Fixed assets	593	365 608	27 754	2 283 710	0	45 462 809
Intangihle assets	435	131 253	9 581	333 884	Ő	2 938 378
Tanoihle assets	435	31 255	4 884	79 443	0	755 504
Financial assets	435	300,938	0	2 558 490	Ő	44 850 000
Current assets	593	993 648	108 767	4 031 479	22	76,130,460
Inventories	435	48,529	0	297.001	0	4,579,745
Accounts receivable	435	707.042	42.066	2.615.547	0	27.651.807
Securities	435	2,080	0	20,201	0	231,163
Cash	435	521,695	69,272	2,508,287	0	48,192,352
Prepaid expenses	593	18,446	375	155,924	0	2,851,870
Other assets	593	714	0	7,614	0	120,788
Equity	593	373,056	20,240	3,685,825	-20,393,735	63,491,239
Subscribed capital	469	117,409	31,250	414,822	100	3,051,000
Capital reserves	447	2,280,818	93,735	7,252,670	0	114,516,992
Retained earnings	443	376	0	3,796	0	55,500
Net income/ (loss) c.f.	448	-1,111,147	-54,779	2,943,788	-23,509,506	3,418,863
Net income/ (loss)	443	-797,492	-85,842	2,193,754	-27,665,337	3,518,880
Losses not covered by equity	593	229,898	0	1,251,951	0	20,393,735
Debt capital	593	986,200	132,984	3,133,335	39	32,508,584
Provisions	593	115,011	6,350	437,597	0	6,297,005
Liabilities	593	842,865	102,861	2,881,341	0	31,276,275
thereof: Current liabilities	464	638,083	61,916	2,417,257	0	31,276,275
Deferred income	593	20,444	0	195,046	0	4,201,019
Balance sheet total	593	1,359,256	184,079	5,328,634	105	92,770,629

Table 5: Descriptive statistics

Notes: Absolute values based on full dataset. All data in Euro.

Based on this overview across all years, Figure 2 shows the medians¹¹ for each year after foundation for the main fields of the balance sheets. Whereas the intensity of *current assets* becomes apparent from the first year, the proportion of *debt capital* increases significantly over time. Particularly in the first years of a start-up, which are characterized by high growth, there is often a high degree of dependence on external investors. From the fourth year, the share of equity also increases significantly. One reason could be that the capital increases, for example through the admission of new shareholders.

¹¹ As measure of central tendency, the median is mainly used in this study, since it is much more robust against outliers compared to the arithmetic mean (Homburg, Klarmann, & Krohmer, 2009, p. 218). Thus, the median is a suitable measure for our examination of differently growing start-ups and consideration of different business years.



Figure 2: Development of selected balance sheet items over time [absolute values]

Even if the absolute value of *fixed assets* rises over time, the relative share of 15-20% remains relatively small. The growth of FinTech companies is reflected by the balance of total assets. Its median increases in the period of consideration from 50,000 to 600,000 Euro. This corresponds to an average annual growth rate per year (CAGR) of 36%.

B. Patterns in FinTech's balance sheets

As shown in the previous section, the balance sheets of FinTech start-ups are usually characterized by a very low equity ratio and high losses, especially in the initial periods. If the equity is completely used up by losses, the field *losses not covered by equity* has to be disclosed in the balance sheet in accordance with § 268 Para. 3 HGB. This field signals over-indebtedness of the company, which, however, does not necessarily entail an insolvency declaration. If a company has no balance sheet equity, certain conditions must be met in accordance with the insolvency law (§ 19 InsO, German Insolvency Act) for averting an insolvency declaration. In this section, the balance sheets of FinTech start-ups are differentiated according to whether such a field is listed or not (Table 6). Of the 593 recorded balance sheets, around one-third (206) show an uncovered deficit. While the median of the *fixed assets* does not differ between the two groups in terms of amount, the balance sheets that disclose a deficit show a low intensity of *current assets*. This is due to a lower amount of *accounts receivable*, but above all due to lower *cash* equivalents. The balance sheets without uncovered deficit show a three-times higher median in the variable *cash*. This higher liquidity is accompanied by a fast adaptability, which makes it possible to react more flexibly to employment fluctuations, for instance.

Assets			Equity and liabilities				
	Losses not covered by equity			Losses not covered by equity			
	Yes	No		Yes	No		
Fixed Assets	28,673	26,975	Equity	-99,915	87,914		
Intangible Assets	8,542	9,734	Subscribed capital	25,000	33,929		
Tangible Assets	3,648	5,530	Capital reserves	0	199,853		
Financial Assets	0	0	Retained earnings	0	0		
			Net income/ (loss) c.f.	-129,770	-16,434		
			Net income/ (loss)	-134,089	-41,853		
Current Assets	69,391	150,559	Debt capital	257,822	86,836		
Inventories	0	0	Provisions	6,325	6,400		
Accounts receivable	38,539	43,676	Liabilities	248,224	55,286		
Securities	0	0	Thereof: Current Liabilities	85,387	55,052		
Cash	29,970	106,786	Deferred income	0	0		
Prepaid expenses	671	230					
Balance sheet total	130,526	261,417	Balance sheet total	130,526	261,417		

Table 6: Classification according to the disclosure of uncovered losses

Notes: All data are medians of the absolute values in Euro.

On the equity and liability side, it becomes clear how the available equity is used up. For one thing, FinTech companies with a deficit in most cases have no *capital reserves*, which can be generated through the entry of investors, for example. Furthermore, high losses are registered, which are not covered by enough capital, resulting in overindebtedness. In case of FinTech companies without deficit, the losses are significantly lower and can be offset by the existing *capital reserves*. The fields of the *liabilities* in the balance sheets of the two groups also differ significantly. Thus, the median of the balance sheets with deficit is about four times as high.

If these two identified balance sheet patterns are considered over time (Table 7), it is noticeable that the proportional distribution does not change significantly. For example, the share of balance sheets with deficit varies around 30% per year. However, it is not always the same companies that report such a deficit over time. Rather, there is often an exchange between these two balance sheet patterns, especially within the first few years. For example, around a quarter of the companies (23.66%) that have not reported a deficit in the first year disclose such a shortfall in the second year after

foundation. In contrast, one-third (34.21%) of FinTech companies that have reported a deficit in the first year could avoid the disclosure of over-indebtedness in the second year.

	Losses not by equity	covered		Change of this balance sheet pattern			
	Yes)	No → Y	Yes	Yes → No	
Years after foundation	ears after Share in % undation (number of firms)		re in % nber of firms)	Share in (number	% of firms)	Share in % (number of firms)	
t ₁	29.01% (3	58) 70.9	9% (93)	-	-	-	-
t_2	34.15% (4	(2) 65.8	5% (81)	23.66%	(22)	34.21%	(13)
t3	39.09% (4	(3) 60.9	1% (67)	19.75%	(16)	19.05%	(8)
t4	43.33% (3	59) 56.6	7% (51)	17.91%	(12)	18.60%	(8)
t5	35.09% (2	20) 64.9	1% (37)	3.92%	(2)	7.69%	(3)
t ₆	21.62% (8	3) 78.3	8% (29)	2.70%	(1)	5.00%	(1)
t ₇	34.78% (8	3) 65.2	2% (15)	13.79%	(4)	12.50%	(1)
t_8	33.33% (4	66.6	7% (8)	6.67%	(1)	25.00%	(2)
t9	40.00% (4	60.0	0% (6)	25.00%	(2)	25.00%	(1)

Table 7: Distribution of uncovered losses and switching rates

Over the course of time, a frequent exchange between the two balance sheet patterns can be determined in the first four years. From the fifth year, the exchange rates are usually in the single-digit percentage range. This analysis reveals that many FinTech companies report over-indebtedness in individual periods in the first years, which are characterized by high initial losses. From the fifth year, the financial situation consolidates, for example through increase in revenues or the entry of investors. If startups continue to report over-indebtedness, their insolvency and failure are likely. Such failed start-ups and their characteristics are examined in comparison with still active companies in the following sections.

C. Empirical comparison of active and failed FinTech start-ups

1. Classification of FinTech start-ups according to their activity status

The purpose of further analysis is to examine how far balance sheet items of active FinTech start-ups differ in comparison to those FinTech companies that have already given up their business. The failed FinTech companies include those that have either filed for insolvency or whose liquidation has been registered in the Commercial Register (2017). This definition of a failure is in accordance with other studies, in which both insolvency declaration and liquidation define a failure (Maeschle, 2012). For recording the time of failure, the date of the insolvency declaration or the liquidation announcement in the Commercial Register was used.

Our database includes a total of 109 active and 22 failed FinTech companies, which corresponds to a failure rate of 16.8%. This section examines whether certain balance sheet items of these two groups differ (significantly) from one another. Otherwise, it is shown which fields are already developing negatively before the complete failure compared to the industry average. In this way, fields can be identified on which special focus should be placed in the evaluation of FinTech start-ups with regard to their future prospects. Of the 22 considered FinTech start-ups that have already given up their business, the majority (87%) failed within three to six years after their foundation (Figure 3). It is also striking that in the first two years after foundation, no failure is observed. After the peak in the fourth year, the failure rate decreases over time. Thus, the start-ups that could pass a certain stage seem to have a higher probability of continuation.



Figure 3: Distribution of failed FinTechs over time

2. Median comparison

Since the majority of FinTech start-ups fail within the first six years of their foundation, the focus of this section is on this period, which seems to be critical for the continuation of a FinTech company. A median comparison of the individual balance sheet items identifies those fields that show clear differences between the groups of active and failed start-ups. In order to evaluate statistically significant differences in the distribution between two independent samples and to examine individual fields of the balance sheet with regard to their univariate separability, the Mann-Whitney U-Test can be used. This test verifies that the two groups differ significantly in their distribution (Anderson, 2010, p. 740). The significant balance sheet items are labelled accordingly in Table 8 and 9. The medians of each balance sheet item are shown for the absolute values and for the respective relative shares of the balance sheet total, both over the entire period of observation as well as for each year after foundation separately.

Variable	C			Yea	rs after foundat	ion		
variable	Group	t ₁ - t ₆	t ₁	t ₂	t ₃	t ₄	t ₅	t ₆
Fixed	Active	27,311** 11.09%	3,707 6.32%	18,405 8.89%	36,438 12.45%	38,899 11.09%	52,304 16.71%	65,187 23.56%
assets	Failed	18,577** 17.37%	1,673 7.42%	33,463 23.79%	18,893 26.80%	25,245 17.42%	41,411 1.51%	122,537 41.27%
Intangible assets	Active	8,222 2.58%	0 0.00%	6,690 3.90%	12,297 3.23%	15,212 2.60%	35,819 3.70%	36,529 4.44%
	Failed	21,883 12.24%	0 0.00%	20,750 13.03%	73,515 20.98%	119,032 21.22%	82,114 39.76%	232,450 78.01%
Tanoihle	Active	4,904** 1.29%	655 0.55%	3,648 1.27%	8,490 1.88%	11,716 1.65%	18,655 1.54%	28,204 1.36%
assets	Failed	1,166** 0.78%	0 0.00%	1,846 3.41%	3,779 1.05%	4,126 1.95%	1,774 0.37%	12,596 4.23%
Financial	Active	0** 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%
assets	Failed	0** 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%
Current assets	Active	125,252** 88.91%	38,845 93.68%	116,137** 91.11%	150,953** 87.55%	295,462** 88.91%	332,502 83.29%	524,980 76.44%
	Failed	25,468** 82.63%	25,677 92.58%	28,962** 76.21%	26,004** 73.20%	13,982** 82.58%	42,292 98.49%	30,788 58.73%

Table 8: Median comparison for variables of the asset side

Variable	Group			Year	s after found	ation		
Vallable	Gloup	t ₁ - t ₆	t ₁	t ₂	t ₃	t ₄	t ₅	t ₆
Activ Inventories Faile	Active	0** 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%
	Failed	0** 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%
Accounts receivable Failed	Active	42,300** 18.38%	7,725 11.83%	23,727 17.83%	81,027 29.98%	96,052 29.81%	121,562 15.29%	130,954 13.57%
	Failed	9,085** 10.00%	8,349 11.31%	3,644 8.89%	48,041 11.88%	8,723 3.01%	42,621 50.74%	24,487 8.22%
Carl	Active	78,841** 42.69%	25,045 52.47%	71,131 43.28%	89,437** 35.05%	144,076** 41.36%	182,738** 45.07%	324,905 29.07%
Cash	Failed	10,220** 22.01%	11,843 41.98%	11,533 55.37%	10 , 288** 10.42%	255** 0.13%	3,185** 4.32%	25,421 8.53%
Prepaid expenses	Active	418** 0.16%	0 0.00%	391 0.22%	701 0.20%	1,013** 0.18%	3,259 0.41%	2,250 0.22%
	Failed	0** 0.00%	0 0.00%	198 0.22%	0 0.00%	0** 0.00%	0 0.00%	1,250 0.42%

Table 8: Median comparison for variables of the asset side (continued)

Notes: Absolute values in Euro. The medians per balance sheet item are shown for the absolute values and for the respective relative shares scaled by the balance sheet total. For examining the significance for the univariate separability in absolute values, the Mann-Whitney U-Test was conducted at a significance level of 5%. The variable *securities* was eliminated because no significant disparity was detected, and all values were zero. Significant disparities of the two groups at a significance level of 5% are marked with **.

Regarding the asset side, many significant differences are found for the entire period of observation, while for the separate years after foundation the picture is more fragmented (Table 8). Across all years, there are significant disparities regarding *fixed* and *current assets*. While failed FinTechs show a slightly higher intensity of *fixed assets*, they exhibit significantly lower values in terms of absolute values in comparison to active FinTechs. Concerning the *current assets*, the medians of active FinTech companies, with 125,252 Euro, are five times higher. This can be attributed to higher *accounts receivable* ratio and a significantly higher proportion of *cash* in case of active start-ups. The higher intensity of *fixed assets*, coupled with a relatively small amount of *cash* equivalents of failed FinTech companies, expresses high values of fixed cost and long-term capital commitment. If, for example, sales fluctuations or other unforeseen events occur, this leads to a lower cost flexibility as well as adaptability than in the case of active FinTech companies. By regarding the individual years after foundation, it becomes clear that there are significant differences between failed and active FinTech companies, especially in the third to fifth year after foundation, although the two groups do not differ significantly

in the year of their foundation. Significant disparities become particularly apparent in the fields of *current assets* and *cash*. Here, both groups differ significantly in the second to fifth year, in which active FinTechs show higher amounts - both relative as well absolute.

Variable	Crown			Yee	ars after found	ation		
	Gloup	t ₁ - t ₆	t ₁	t ₂	t ₃	t ₄	t5	t ₆
Eit.	Active	23,877** 30.36%	14,035 46.59%	18,314 23.53%	24,348 14.45%	25,000** 21.87%	85,949 32.52%	168,823 56.73%
<i></i>	Failed	7,751** 34.75%	16,628 74.66%	13,584 34.41%	4,356 31.29%	-7,521** -40.02%	-214,669 -125.49%	-208,800 -58.45%
Subscribed	Active	31,250 15.70%	25,000 50.44%	30,000 13.20%	36,000 13.33%	40,048 11.23%	44,772 9.03%	50,000 6.38%
capital	Failed	25,200 36.33%	25,000 97.37%	27,500 47.71%	28,408 26.30%	26,704 11.54%	26,704 14.24%	45,556 15.29%
Capital reserves	Active	81,471 36.44%	0 0.00%	35,889 27.77%	200,000 105.00%	229,707 111.45%	403,614 166.39%	2,055,184 249.85%
	Failed	22,000 27.92%	0 0.00%	110,544 81.87%	110,544 106.04%	11,000 13.83%	140,883 18.51%	1,832,392 614.94%
Net income/	Active	-41,719 -15.18%	0 0.00%	-22,215 -12.04%	-139,513 -49.62%	-221,974 -116.31%	-354,412 -95.38%	-1,234,028 -153.84%
(loss) c.f.	Failed	-23,754 -16.80%	0 0.00%	-23,425 -28.50%	-197,298 -249.84%	-306,338 -155.86%	-319,504 -176.67%	-381,957 -128.18%
Net income/	Active	-94,222 -46.26%	-20,936 -37.73%	-100,198 -76.99%	-152,152 -53.96%	-243,094 -39.68%	-138,594 -37.20%	-455,273 -36.28%
(loss)	Failed	-61,295 -54.81%	-19,899 -32.10%	-102,790 -112.66%	-74,866 -59.31%	-99,729 -53.14%	-43,518 -26.49%	-1,915,667 -642.88%
Losses not	Active	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%
covered by equity	Failed	0 0.00%	0 0.00%	0 0.00%	0 0.00%	7,521 64.93%	214,669 130.69%	209,838 70.42%
Deht capital	Active	134,049** 69.64%	26,946 53.41%	109 , 359 76.47%	208,212** 85.55%	299,808 78.13%	334,242 67.48%	345,989 43.27%
· · · · I · · · ·	Failed	47,830** 65.25%	11,645 25.34%	55,133 65.59%	65,986** 68.71%	69,689 140.02%	504,182 225.49%	362,124 158.45%

Table 9: Median comparison for variables of the equity and liability side

Variable	Casura			Year	s after found	lation		
vanable	Group	t ₁ - t ₆	t ₁	t ₂	t ₃	t ₄	t5	t ₆
Provisions	Active	6,746** 5.05%	2,100 3.99%	5,458 6.37%	8,011** 5.33%	14,807** 5.21%	19,640 5.24%	55,929 4.87%
	Failed	2,500** 5.87%	1,089 3.81%	2,575 4.82%	3,325** 5.71%	3,500** 9.60%	8,094 11.69%	19,005 18.70%
Ac <i>Liabilities</i> Fa	Active	109,202** 54.32%	21,560 30.76%	83,004 65.05%	135,390** 59.12%	196,293 67.22%	227,880 46.93%	273,560 34.23%
	Failed	43,010** 50.67%	10,738 21.55%	45,101 51.69%	61,027** 47.38%	56,934 133.72%	477,535 213.58%	343,119 139.75%
Current	Active	71,101** 27.82%	13,567 23.73%	39,697 26.70%	87,690** 33.85%	125,710 27.78%	196,419 30.84%	163,125 25.98%
<i>Liabilities</i> Fa	Failed	22,235** 27.15%	10,000 11.50%	22,235 23.36%	36,441** 34.20%	25,093 93.28%	722,519 38.68%	559,190 187.66%
Balance sheet	Active	197 , 210** 100.00%	52,327 100.00%	180,544 100.00%	281,747** 100.00%	475,609** 100.00%	525,428 100.00%	723,979 100.00%
total	Failed	59,808** 100.00%	42,090 100.00%	68,820 100.00%	64,981** 100.00%	44,374** 100.00%	164 , 253 100.00%	153,324 100.00%

Table 9: Median comparison for variables of the equity and liability side (continued)

Notes: Absolute values in Euro. The medians per balance sheet item are shown for the absolute values and for the respective relative shares scaled by the balance sheet total. For examining the significance for the univariate separability in absolute values, the Mann-Whitney U-Test was conducted at a significance level of 5%. The variables *retained earnings* and *deferred income* were eliminated because no significant disparity was detected, and all values were zero. Significant disparities of the two groups at a significance level of 5% are marked with **.

Looking at the equity and liability side of the balance sheet (Table 9), the picture is similar to the asset side, with significant differences in the whole period as well as in the third to fourth year after foundation. Thus, the group of active FinTech companies show significantly higher amounts for *equity* as well as *debt capital* for both individual years and the entire period. The *equity* of failed FinTechs decreases significantly over the individual years. This development also becomes apparent regarding the variable of *losses not covered by equity*, which occurs since the fourth year in case of failed companies. There are also significant differences by *provisions* and *liabilities*, which are explicitly higher for active FinTech companies. Looking at the *balance sheet total*, active FinTech companies show higher values. The absolute difference between them and the failed FinTech companies increases each year, which can be used as an indicator of significantly higher companies is 55%, which is more than twice as high as for failed FinTechs (25%). Overall, it can be concluded from the median comparison that the groups of failed and active FinTech companies differ significantly in individual items of the balance sheet. Differences are particularly observable in the third to fifth year after foundation, which could be identified as the critical period for continuation.

3. Analysis of the failure date

This section focusses on the development of individual balance sheet items in the period prior to the failure of a FinTech company. It is evaluated how long before the failure changes in selected balance sheet items become visible. For this purpose, the course of individual balance sheet figures of failed companies for a period of three years prior to the failure t₀ is shown. As a comparison group, the medians of the corresponding figures of the active FinTechs in the first six years are presented. In the previous section, significant differences in *debt capital* between the two groups become apparent. While three years before failure (Figure 4), the failed FinTech companies still have a significantly lower debt ratio than the active FinTech companies, the ratio of *debt capital* and *liabilities* exceeds the values of the comparison group one to two years before failure. These values continue to increase up to the failure date. This development is mainly attributable to the increase in the uncovered deficit, which also rises significantly two years before the failure.



Figure 4: Development of selected items of the equity and liability side in the period before failure t₀

Regarding the asset side (Figure 5), differences become visible especially in the development of the share of *fixed* and *intangible assets*. On average, the median of the fixed asset shares for the group of active FinTech start-ups is around 11%, while it is twice as high for failed FinTech companies three years before the failure date, at around 21%. Only one year before failure, the share of *fixed assets* falls below the level of 11%. The proportion of *intangible assets*, which is still relatively strong three years before failure, behaves similarly. It declines significantly from this date. Thus, on the asset side, the one or two years before failure can be identified as the years in which remarkable changes in balance sheet items of failed FinTech companies are observable.



Figure 5: Development of selected items of the asset side in the period before failure t₀

Results of the logistic regression

In the next step, combinations of accounting indicators which separate the two groups optimally shall be identified. By developing a logistic regression model, those balance sheet figures will be revealed that have a statistically significant impact on the probability of failure. Our resulting model (Table 10) consists of six independent variables, whereby the *year after foundation* serves as control variable. Our analysis reveals that all independent variables captured in our model have a statistically significant impact on the failure probability. The sign of the regression coefficients shows the direction of the relationship with respect to the probability of failure. The first variable *year after foundation* shows a high statistically significant impact and a negative coefficient, indicating that with an increasing market affiliation, the probability of failure declines. This finding could be expected, and it corresponds with our previous findings that from the fourth year of market activity, the risk of failing decreases. The variable *tangible assets* also shows a negative coefficient and a statistically significant relation. Thus, when a FinTech has accumulated a higher level of these *fixed assets*, the probability of being assigned to the group of failed companies decreases. Depending on the area of activity of the FinTech, high initial investments are necessary for *fixed assets*, but if this phase can be overcome successfully, the probability of failure declines. The next two variables *accounts receivable* and *cash*, as positions of the *current assets*, show the same type of relationship, which also corresponds with our previous results, wherein the values of active start-ups were strongly pronounced in these fields. The higher is the ratio of these balance sheet items, the lower is the probability of failure.

Dependent variable: Firm Failure with $y=0$ (active) and $y=1$ (failed)										
Independent variables	Coeff.	p-value		Robust Std. error	VIF					
INTERCEPT	0.579	0.231		0.483	_					
TANGIBLE ASSETS	-7.250**	0.026		3.249	1.391					
ACCOUNTS REVEIVABLE	-1.779**	0.024		0.789	1.544					
CASH	-2.205***	0.000		0.594	1.613					
NET INCOME/(LOSS) C.F.	-0.175***	0.001		0.053	1.487					
NET INCOME / (LOSS)	-0.318***	0.006		0.117	1.732					
PROVISIONS	-5.165***	0.002		1.704	1.423					
YEAR AFTER FOUNDATION	-0.424***	0.000		0.114	1.113					
n Wald X ²			417 33 4							
Prob. $> X^2$			0.0000							
Nagelkerke R²			0.234							

Table 10: Results of the logistic regression

Notes: 417 of the 593 observations in our sample were used to estimate the model. The not considered cases were not included due to missing data for at least one of the variables. The whole model shows a Nagelkerke Pseudo R² of over 0.2, which is regarded as acceptable. Before we performed the logistic regression, our sample was checked for outliers. No observations were detected that deviate more than three standard deviations from the mean. The last column displays the VIF of the respective predictors for addressing the condition of no multicollinearity. Since the value of the VIF is clearly below ten for all variables, the requirement of absence of multicollinearity is fulfilled. Coefficients that are significant at the 5%/1% level are labeled with **/***.

Another statistically significant impact with negative coefficients is revealed by our model in the items *net income/(loss)* and *net income/(loss) c.f.*. If a FinTech has already made profits, this has a positive impact on its survival prospects. The *provisions* ratio is also highly significant. As already mentioned, the field of the *provisions* is very low, especially in the initial years. As the proportion of *provisions* increases, our model assumes that the failure probability of a FinTech decreases. This finding corresponds with our expectations, since companies that are on the brink of insolvency pay less attention to accumulating high reserves in their balance sheet.

We were able to identify the balance sheet ratios that significantly influence the probability of failure and therefore are of high interest to the valuation of FinTech companies by means of this regression model. It is also clear that fields such as *losses not covered by equity* do not make significant statements about the continuation of a FinTech company. Generated losses can be compensated by receiving capital from outside creditors, for instance, so that the declaration of uncovered losses can be omitted. Rather, it is important to observe the annual net income, which reflects the development of actually sold products or services and the performance in the fiscal year.

For assessing the results of the logistic regression in terms of classification of performance and separability of the two groups, the resulting ROC curve for our determined regression model is shown in Figure 6. Our model has an AUC value of 78.74%, which is considered to be very good in literature; thus, our model reveals a suitable separation between the groups of active and failed FinTech companies.



Figure 6: ROC curve based on the probabilities resulting from the conducted logistic regression

V. Conclusion

In this paper, an analysis of annual accounts of FinTech start-ups is carried out in order to present specific features of balance sheets of FinTech companies and identify balance sheet ratios that influence the probability of failure. First of all, the legal implications that have to be taken into account in the balance sheet analysis of FinTech companies as well as start-ups in general and their impact on the available data are highlighted. We subsequently show that balance sheets of FinTech companies are fundamentally characterized by the high intensity of *current assets* as well as *debt capital* and an uncovered deficit is often disclosed, especially in the initial business years. Such overindebtedness is often attributable to high losses and lack of *capital reserves*, for instance through investors. We also show that the balance sheets of failed and active FinTech companies differ significantly in terms of some balance sheet fields. We could identify the third to fifth year after foundation as the critical period for the future survival prospects of FinTechs, which is revealed by both the median comparison and the consideration of failure rates over time. Furthermore, active FinTech companies generally have higher *equity*, higher *current assets*, and higher liquidity, which leads to higher responsiveness to employment fluctuations, for example. Finally, we evaluate those balance sheet ratios that have a significant impact on the probability of failure and have a good ability to separate the groups of active and failed FinTech companies. This includes the intensity of tangible assets, accounts receivable, and cash on the asset side and the net income/ (loss), net income/ (loss) c.f., and provisions on the equity and liability side. The more these fields are pronounced in the balance sheets, the lower is the probability of failure. Thus, FinTechs that have overcome the initial phase by building *fixed assets* and high liquidity, making profits, and building up *provisions* can be assigned a higher probability of survival according to our logistic regression model.

The research conducted, and the results presented in this paper are relevant both theoretically and practically. The illustrated proportions of balance sheet items and the particularities of FinTech companies have initially created a better understanding and transparency, which can be used for both sides in the further analyses and evaluation of FinTech start-ups. In addition, the balance sheet ratios were identified through median comparison and regression analysis, which act as a significant indicator of the failure probability of FinTech start-ups. For example, investors searching for investment decisions or companies assessing acquisition objects can focus more on these key figures. The results are also of interest for the regulatory authorities who observe the FinTech development and have to manage the tradeoff between the ongoing technological change and the associated risks. Countries like Germany have to search for new regulatory approaches to control the risk associated with the FinTech business and to ensure financial stability. Likewise, the results are also important for the theory. Thus, the insights generated in this article can be used to compare start-ups from other industries with the FinTech segment, for example. Furthermore, the structure and special

characteristics of FinTechs' balance sheets are shown, so that further research works can use our findings as a basis.

When considering the examinations and results presented in this article, some limitations must be considered. On the one hand, the examined FinTech companies are only a sample. As shown, some start-ups could not be considered due to unpublished data. Likewise, there is no guarantee that all FinTech start-ups that were active in Germany at the time of the investigation have been taken into account. One possible reason is, for instance, such FinTech companies that are still in the so-called "stealthmode" and not vet active or visible in the market. On the other hand, there are limitations due to the availability of data, as explained in previous sections in detail. Only certain financial measures could be included in the investigation due to the legal relaxations regarding the disclosure obligations and the extent of disclosures. In light of the missing profit-and-loss statements that are not accessible to third parties, no detailed conclusions can be drawn e.g. about sales indicators. Finally, the past-orientation of the annual financial data is a limitation, since ultimately only data up to 2016 could be taken into account. Overall, the research carried out in this paper provides impulses for further research efforts. Here, for instance, it would be suitable to repeat the analysis if other failed FinTech companies can be included and if more annual financial data are available. Also, a comparison with other start-up segments or even established firms could be a research motivation. Similarly, a comparison with conventional indicator catalogues from other rating models could be appropriate to assess which specific features play a role in the evaluation of FinTech start-ups in particular. Furthermore, it could be of great interest to further investigate the failed FinTech start-ups with respect to the specific business field of the FinTech segment (e.g. payment), the applied business models, and the product solutions. In this way, regulatory authorities, for instance, can gain an overview of the sub-segments of the FinTech area with a higher risk of failure.

REFERENCES

- Altman, E. I., & Narayanan, P. (1997). An international survey of business failure classification models. Financial Markets, Institutions and Instruments, 6(2), 1– 57. https://doi.org/10.1111/1468-0416.00010
- Altman, E. I., & Saunders, A. (1997). Credit risk measurement: Developments over the last 20 years. Journal of Banking & Finance, 21(11-12), 1721–1742. https://doi.org/10.1016/S0378-4266(97)00036-8

- Anandarajan, A., Francis, B., Hasan, I., & John, K. (2011). Value relevance of banks: Global evidence. Review of Quantitative Finance and Accounting, 36(1), 33–55. https://doi.org/10.1007/s11156-010-0170-7
- Anderson, D. R. (2010). Statistics for business and economics (2nd ed.). Andover: South-Western Cengage Learning.
- Arner, D. W., Barberis, J. N., & Buckey, R. P. (2017). FinTech, RegTech, and the reconceptualization of financial regulation. Northwestern Journal of International Law Business, 37(3), 371–414.
- Backhaus, K., Erichson, B., Plinke, W., & Weiber, R. (2016). Multivariate Analysemethoden (14th ed.). Berlin, Heidelberg: Springer Gabler.
- Baetge, J. (1998). Bilanzanalyse. Duesseldorf: IDW.
- Barth, T., Barth, D., Nassadil, J., & Werner, F. (2014). Jahresabschlussanalyse mit Bilanzkennzahlen. Konstanz: UVK.
- Berger, A. N., & Udell, G. F. (1998). The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle. Journal of Banking & Finance, 22(6-8), 613–673. https://doi.org/10.1016/S0378-4266(98)00038-7
- Broesel, G. (2017). Bilanzanalyse (16th ed.). Berlin: Erich Schmidt.
- Brummer, C., & Gorfine, D. (2014). FinTech: Building a 21st century regulator's toolkit. Santa Monica: Milken Institute.
- Business Register. (2017). The central platform for the storage of company data. Retrieved from http://www.unternehmensregister.de [Aug 31, 2017].
- Commercial Register. (2017). Common register portal of the German federal states. Retrieved from http://www.handelsregister.de [Aug 31, 2017].
- Crunchbase. (2017). Crunchbase data exports. Retrieved from http://www.crunchbase.com [Aug 31, 2017].
- D'Avino, M., Simone, V. de, Iannucci, M., & Schiraldi, M. M. (2015). Guidelines for estartup promotion strategy. Journal of Technology Management & Innovation, 10(1), 1–16. https://doi.org/10.4067/S0718-27242015000100001

Diehm, J. (2014). Controlling in Start-up-Unternehmen. Wiesbaden: Springer.

- Dorfleitner, G., Hornuf, L., Schmitt, M., & Weber, M. (2017). FinTech in Germany. Cham: Springer International Publishing.
- Duvivier, A. (2000). Financing and risks of internet start-ups: A preliminary assessment. Banque de France paper.
- Ernst and Young. (2017). Germany FinTech landscape. Retrieved from http://www.ey.com/Publication/vwLUAssets/ey-germany-fin-tech-landscape-2017/\$FILE/ey-germany-fin-tech-landscape.pdf [Jan 07, 2018].
- Federal Gazette. (2017). Publication Platform. Retrieved from http://www.bundesanzeiger.de [Aug 31, 2017].
- Fischer, A. (2012). Entwicklung eines länderübergreifenden Bilanzratingmodells. Lohmar: Eul.
- Gaskill, L. R., van Auken, H. E., & Manning, R. A. (1993). A factor analytic study of the perceived causes of small business failure. Journal of Small Business Management, 31(4), 18–31.
- Ge, W., & Whitmore, G. A. (2010). Binary response and logistic regression in recent accounting research publications: A methodological note. Review of Quantitative Finance and Accounting, 34(1), 81–93. https://doi.org/10.1007/s11156-009-0123-1
- Google Scholar. (2018). About Google Scholar. Retrieved from https://scholar.google.com/intl/de/scholar/about.html [Aug 31, 2018].
- Graefer, H., & Schneider, G. (2010). Bilanzanalyse: Traditionelle Kennzahlenanalyse des Einzeljahresabschlusses (11th ed.). NWB-Studium. Herne: nwb.
- Gregory, B. T., Rutherford, M. W., Oswald, S., & Gardiner, L. (2005). An empirical investigation of the growth cycle theory of small firm financing. Journal of Small Business Management, 43(4), 382–392. https://doi.org/10.1111/j.1540-627X.2005.00143.x
- Gulamhuseinwala, I., Bull, T., & Lewis, S. (2015). FinTech is gaining traction and young, high-income users are the early adopters. Journal of Financial Perspectives, 3(3), 16–23.

- Hair, J. F., Black, B., Babin, B., Anderson, R. E., & Tatham, R. L. (2006). Multivariate data analysis (6th ed.). Upper Saddle River: Pearson/Prentice Hall.
- Homburg, C., Klarmann, M., & Krohmer, H. (2009). Statistische Grundlagen der Datenanalyse. In A. Herrmann, C. Homburg, & M. Klarmann (Eds.), Handbuch Marktforschung (3rd ed., pp. 213–240). Wiesbaden: Springer Gabler.
- Huynh, K. P., Petrunia, R. J., & Voia, M. C. (2010). The impact of initial financial state on firm duration across entry cohorts. The Journal of Industrial Economics, 58(3), 661–689. https://doi.org/10.1111/j.1467-6451.2010.00429.x
- Insolvency Announcements. (2017). Publication platform of the Federal Ministry for Justice of North Rhine Westphalia, Germany. Retrieved from https://www.insolvenzbekanntmachungen.de/ [Aug 31, 2017].
- Kashyap, M., Shipman, J., Garfinkel, H., Davies, S., & Nicolacakis, D. (2017). Global FinTech report 2017. Retrieved from https://www.pwc.com/jg/en/ publications/pwc-global-fintech-report-17.3.17-final.pdf [Jan 07, 2018].
- Kiem, R., Potel, G., Trillmich, P., & Weir, G. (2016). FinTech M&A: From threat to opportunity. Retrieved from https://www.whitecase.com/sites/whitecase/ files/files/download/publications/fintech-mergers-acquisitions-from-threat-toopportunity.pdf [Jan 07, 2018].
- KPMG. (2017). The pulse of FinTech Q3 2017. Retrieved from https://assets.kpmg.com/content/dam/kpmg/xx/pdf/2017/11/pulse-offintech-q3-17.pdf [Jan 07, 2018].
- Krueger, G. H. (2014). Jahresabschlussanalyse in KMU. Herne: nwb.
- Kueting, P., & Weber, C.-P. (2015). Die Bilanzanalyse: Beurteilung von Abschlüssen nach HGB und IFRS (11th ed.): Schaeffer-Poeschel.
- Kuhn, M., & Johnson, K. (2013). Applied predictive modeling. New York: Springer.
- Lachnit, L., & Mueller, S. (2017). Bilanzanalyse (2nd ed.). Wiesbaden: Springer.
- Lim, C. Y., Ding, D. K., & Charoenwong, C. (2013). Non-audit fees, institutional monitoring, and audit quality. Review of Quantitative Finance and Accounting, 41(2), 343–384. https://doi.org/10.1007/s11156-012-0312-1

- Maeschle, O. (2012). Which information should entrepreneurs on German crowdinvesting-platforms disclose? Thünen-Series of Applied Economic Theory, Working Paper No. 127.
- Marom, S., & Lussier, R. N. (2014). A business success versus failure prediction model for small businesses in Israel. Business and Economic Research, 4(2), 63–81. https://doi.org/10.5296/ber.v4i2.5997
- Nicolini, H. J. (2008). Jahresabschlussanalyse (3rd ed.). Muenchen: Beck.
- PaymentandBanking. (2017). Data exports. Retrieved from http://www.paymentandbanking.com [Aug 31, 2017].
- Pospeschill, M. (2010). Testtheorie, Testkonstruktion, Testevaluation. Muenchen, Basel: Ernst Reinhardt.
- Raeth, G. (2017). Insolvency announcement of Cashboard. Retrieved from https://www.gruenderszene.de/allgemein/cashboard-meldet-insolvenz-an-wir-sind-auf-den-letzten-metern-gescheitert [Jan 07, 2018].
- Rheinboldt, R. (1998). Analyse von Konzernabschlüssen mit Hilfe von Kennzahlen. Lohmar: Eul.
- Stuckenborg, L., Klein, J., & Leker, J. (2017). FinTech start-ups: How do business model, area of activity and revenue model relate? A study of the German market. Corporate Finance. (09-10), 257–268.
- Swisscom. (2017). Swisscom launches Open Banking Hub. Retrieved from https://www.swisscom.ch/content/dam/swisscom/en/about/media/factcheck/documents/2017/20171106-fc-swisscom-launches-open-banking-huben.pdf.res/20171106-fc-swisscom-launches-open-banking-hub-en.pdf [Jan 07, 2018].
- Tabachnick, B. G., & Fidell, L. S. (2007). Using multivariate statistics (5th ed.). Boston: Pearson/Allyn and Bacon.
- Temelkov, Z. (2018). Fintech firms opportunity or threat for banks? International Journal of Information, Business and Management, 10(1), 138–144.
- Theile, C. (2017). Jahresabschluss der Klein- und Kleinstkapitalgesellschaften (2nd ed.). Herne: nwb.

Thomas, L. C. (2009). Consumer credit models: Oxford University Press.

- Thornton-Trump, A. B., & Fu, W. (2000). Small business modeling within the financial accounting conceptual framework. Data Mining 2, 35–43.
- Winnefeld, C. H., & Permantier, A. (2017). FinTech The digital (r)evolution in the German banking sector? Business and Management Research, 6(3), 65–84. https://doi.org/10.5430/bmr.v6n3p65
- Wolff, J. (2017). Insolvency announcement of Outbank. Retrieved from https://www.gruenderszene.de/allgemein/banking-startup-outbankinsolvenzantrag [Jan 07, 2018].
- Wright, M., Lumpkin, T., Zott, C., & Agarwal, R. (2016). The evolving entrepreneurial finance landscape. Strategic Entrepreneurship Journal, 10(3), 229–234. https://doi.org/10.1002/sej.1232
- Zavgren, C. V. (1985). Assessing the vulnerability to failure of American industrial firms: A logistic analysis. Journal of Business Finance & Accounting, 12(1), 19–45. https://doi.org/10.1111/j.1468-5957.1985.tb00077.x
- Zavolokina, L., Dolata, M., & Schwabe, G. (2016). FinTech What's in a name: A logistic analysis. Thirty Seventh International Conference on Information Systems Dublin 2016.
- ZEB. (2017). FinTech Profiles. Retrieved from https://www.fintechhub.eu/searchprofiles [Aug 31, 2017].