Finance Research Letters 74 (2025) 106735

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

# Predicting break-even in FinTech startups as a signal for success

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ARTICLE INFO

*Keywords:*
xAI
Growth
PSD2
PSD3
Machine learning
Start-ups

ABSTRACT

FinTech startups drive innovation and competition in the financial services industry. An early milestone for these startups is to achieve break-even, which sends out a positive signal to the market – and to potential partners and financial institutions – by demonstrating viability and lower perceived risks. Our analysis of proprietary survey data using logit and random forest, interpreted through SHAP values, indicates that external funding significantly decreases the likelihood of a startup reaching break-even. This negative impact can be traced to strategic misalignment with investor expectations, delays in the implementing of stringent financial management practices, and an emphatic focus on rapid growth.

## 1. Introduction

New technologies are transforming the financial services industry at its core (Gomber et al., 2018), with many innovations being introduced by FinTech startups. Subtly combining technology with finance (Collevecchio et al., 2024), FinTech startups operate in specific vertical sectors (Lee and Shin, 2018), applying new business models built around enhanced customer experience and integrated capabilities (Barroso and Laborda, 2022). The clout of FinTech startups has persuaded regulatory bodies to bring in their own innovations, for instance, in the form of sandboxes that facilitate market access (Allen, 2019) or broader regulatory initiatives (Chen et al., 2024).

More likely than not, startups will fail. Reports often mention the 90 % that collapse (Page and Holmstrom, 2023). Data furthermore reveal that a paltry 46 % of all new Europe-based ICT companies make it beyond five years (Eurostat, 2022). It follows that early indicators of a startup's break-even point and its potential for success can be invaluable to the various stakeholders. These indicators help venture capitalists and other investors recognize the most promising startups and add the potential “winners” to their portfolios. Financial institutions find these indicators equally valuable. Often fettered by legacy systems, financial institutions are increasingly partnering with FinTech startups to introduce innovative products, services, and technologies, moving beyond traditional make-or-buy decisions (Hornuf et al., 2021; Kueschnig and Schertler, 2024; Khan et al., 2024; Elliehausen and Hannon, 2024).

According to signalling theory (Spence, 1978), signals reduce information asymmetry (Ermilina et al., 2021; Krukowski et al., 2023) and recognizing these signals is critical in the tech-based new venture context, where uncertainty and rapid market changes are commonplace (Tumasjan et al., 2021). Break-even status signals potential for growth, indicating a stable foundation for scaling operations, an increasing market share, and profitability. Financially, it signals viability and lower risk, demonstrating the startup's ability to cover its costs and sustain its operations without additional capital. Breaking even reassures potential partners and stakeholders, strengthening the startup's market perception and reducing perceived risks, including reputational risk.

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https://doi.org/10.1016/j.frl.2024.106735
Received 19 June 2024; Received in revised form 30 December 2024; Accepted 31 December 2024
Available online 9 January 2025

While these considerations apply to startups in general, Werth et al. (2023) note that industry-specific research can identify successful traits unique to each context. Our paper covers FinTech startups, which differ from traditional and high-tech models for their unique blend of technology, entrepreneurship, and finance. Additionally, in the highly regulated financial sector, collaborations between financial incumbents and FinTech startups are decisive for the short- and medium-term success of both.

Given these dynamics, the research question of this study is as follows: "What key factors contribute to the break-even success of FinTech startups?" Unlike research into large, publicly traded companies with readily accessible financial data (Alarussi and Gao,

**Table 1**
Summary of articles identified through the Scopus research query. (Note: a further three articles were not included in this table because their full text was unavailable and, on reviewing their abstracts, they did not thoroughly address profitability in FinTech startups. One article was an erratum corrigendum.).

| Authors | Year | Title | Journal | Research questions / Objectives | Country / Region | Methodology | Additional details |
|---|---|---|---|---|---|---|---|
| Staykova & Damsgaard | 2018 | Dual-track's strategy for incumbent's transformation: the case of Danske Bank adopting a platform business model | Digitalization Cases. Management for Professionals. Springer | Investigation into how an incumbent financial institution can successfully develop and manage a digital payment platform, and protect itself from disruption | Denmark | Qualitative case study | The study focuses on the launch and expansion of Danske Bank's MobilePay platform, using first-hand observations, semi-structured interviews, and archival documents |
| Schwienbacher | 2019 | Equity crowdfunding: anything to celebrate? | Venture Capital | Review of the development, successes, and challenges of equity crowdfunding over the past 10 years, covering its impact on entrepreneurial finance and platform profitability | Europe | Review and analysis of empirical research | N.A. |
| Carbó-Valverde, et al. | 2022 | Entrepreneurial, institutional, and financial strategies for FinTech profitability | Financial Innovation | Examination of the main managerial, institutional, and financial drivers of FinTech profitability, and the time it takes for these firms to break even | Spain | Empirical analysis, panel data, and survival analysis | The study uses data covering 2005 to 2017 from 170 FinTech startups operating in Spain |
| Prieger | 2023 | Local banking markets and barriers to entrepreneurship in minority and other areas | Journal of Economics and Business | Investigation into the impact of local banking markets and broadband availability on entrepreneurship | United States of America | Empirical study, Poisson regression analysis | The study uses county-level data from the USA covering 2009 to 2017, focusing on establishment births in minority and non-minority areas |
| Thelisson | 2024 | Alliance or joint venture? Decisions on autonomy versus dependence | Journal of Business Strategy | Exploration of decisions about whether to set up a strategic alliance or a joint venture, focusing on autonomy versus dependence in business collaborations | France | Qualitative case study | In-depth interviews with CEOs, analysis of a French startup and its alliance with a Dutch group |
| Iman | 2024 | Idiosyncrasies, isomorphic pressures and decoupling in technology platform business | Journal of Science and Technology Policy Management | Investigation into how FinTech firms in Indonesia respond to competitive pressures and technological changes through isomorphism and decoupling mechanisms to balance distinctiveness and profitability | Indonesia | Qualitative case study | Focus group discussions and interviews with 8 FinTech startups, 5 banks, Bank Indonesia, and the Ministry of Communication and Information Technology (Kominfo) |
| Hudz et al. | 2024 | The role of financial technologies in the development of new financial instruments and markets | Economic Affairs | Outline of the impact and significance of financial technologies in shaping new financial instruments and markets | Europe | Qualitative case study | Description of the new financial instruments introduced by digital banks, with a focus on Atom Bank, N26, and Revolut |

2023; Aydoğmuş et al., 2022; Chen et al., 2018; Goddard et al., 2005; Lee, 2009), studies on the break-even point and profitability of startups (Kang, 2020) are scarce, particularly within the FinTech sector. A Scopus search in July 2024 using the keywords "FinTech" *and* ("startup" *or* "start-up") *and* ("breakeven" *or* "break-even" *or* "profitability") yields a grand total of 11 results (see Table 1). Only Carbó-Valverde et al. (2022) investigate the features of profitable FinTech startups.

To get around the problem of accessing private and confidential break-even data, in 2023, we conduct a survey on Italian FinTech startups and analyse the ensuing data through a logistic regression model and a random forest machine learning model. Our findings indicate that funded startups are less likely to be profitable, with funding from external sources emerging as the most significant predictor. Among several factors that come into play are prioritizing growth over immediate financial stability – a common practice in earlier funding rounds – and getting sidetracked during negotiations. The results are financially relevant for investors, financial institutions, policymakers, and other FinTech stakeholders. By identifying the key determinants of break-even success, this research provides actionable insights to guide investment decisions and strategic partnerships, promoting financial sustainability in a sector of rapid growth and high failure rates. Our study also contributes to the existing literature by applying signalling theory more widely within the FinTech context, showing that funding from external sources, often seen as a catalyst for growth, may paradoxically curb profitability. While challenging traditional views on startup financing, we offer new perspectives on how funding structures influence financial independence. Additionally, advanced machine learning techniques can help explain complex models (Klein and Walther, 2024), and our use of SHAP (SHapley Additive exPlanations) sets a methodological precedent for future research on startup performance.

## 2. Materials and method

### 2.1. The sample

We examine Italian FinTech startups founded since 2015, similarly to the single-country analyses conducted by Barz et al. (2023) and Carbó-Valverde et al. (2022). In 2023, we gather our data through a survey among FinTech startups, as most determinants (e.g. funding, partners) are not publicly available. Following Gazel & Schwienbacher (2021), we create a database of startups by sifting through Pitchbook, Crunchbase, and LinkedIn. We begin by screening all the results generated from FinTech keywords (e.g. digital payments, InsurTech). Each entry is reviewed and confirmed or not, checking its business description (Collevecchio et al., 2024) to distinguish between FinTech and non-FinTech entities. Of the 512 startups contacted, 251 respond, a 49 % response rate significantly higher than in similar surveys (Pielsticker and Hiebl, 2020). However, 66 startups decline to share their profitability information, giving a final sample of 185.

### 2.2. Methodology

Profitability, our dependent variable, is measured dichotomously to indicate whether a startup has reached break-even (Neville and Lucey, 2022). We start with logistic regression given that it is a binary technique, and also use a random forest model to capture potential mixed effects and non-linear interactions (Berger, 2023; Liao et al., 2019). We choose random forest for its versatility and ability to handle classification problems while mitigating overfitting (Presciuttini et al., 2024). The model is trained on 80 % of the data, with 20 % being used for validation. In order to address the problem of interpreting the random forest "black box" model (Zhou et al., 2023), we use SHAP, which breaks down the output (i.e. the prediction) to explain the impact of each input feature (Li and Wu, 2024).

Our study examines several factors that influence a FinTech startup's profitability, in first place the business itself and its regulatory requirements. Many entrepreneurial ideas in the financial sector are regulated (*Reg_activity*). Compliance with these regulations impacts on business opportunities and the timeline, thus affecting profitability. FinTech startups must obtain a licence or a charter (*Licence*), which entails significant time and investment. Whatever method chosen – owning a charter, leveraging on Banking-as-a-Service (BaaS) or on embedded finance models, or operating without a licence – affects operational flexibility and market engagement (Grassi, 2023), ultimately impacting on when the startup breaks even.

In the FinTech sector, the differences between B2B startups (*B2B_model)* and B2C startups (*B2C_model)* go deeper than their strategies for customer acquisition, revenue generation, and scalability. Distinguishing between the two also means understanding their role within the financial ecosystem. Startups serving financial intermediaries can tap into a broader customer base (Hornuf et al., 2021) and scale productively, their solutions adding value to the ecosystem. We also measure platformization (*Platform*), a trend whereby startups could place growth above profitability (Hasselwander, 2024).

Second, financial and industrial support (*Funding*) is crucial for startup success (Barz et al., 2023), driving growth and innovation. However, funding from venture capitalists (VCs), banks, government, and other external sources can be a challenge. Kang (2020) suggests that greater VC investment could hinder profitability. Unlike traditional VC investors whose interest is primarily financial, industrial players seeking to integrate the startup's products or services into their own offer (Lee and Shin, 2018) can boost the startup's growth prospects, enable closer strategic alignment and provide access to resources. These players may take equity stakes in the startup (*Partner_equityinv*). If a startup has industrial partners (*Partnership*), and the more of them it has (*#Partners*), the greater its market reach, operational capacities, and overall resource base (Ruhland and Wiese, 2023). The startup teams' experience can also influence profitability, with greater expertise leading to more efficient financial navigation (*Avg_age*). Co-founding teams (*Multiple_founders*) can draw on several perspectives, although single founders often reach profitability earlier (Carbó-Valverde et al., 2022). Older startups (*Founding_year*) are more likely to reach break-even, reflecting their resilience over time.

**Table 2**
Descriptive statistics of the sample (N = 185 FinTech startups). Source: survey data.

| Variable | Type | Category | Occ. | Freq. | Description |
|---|---|---|---|---|---|
| *Break-even* | Binary | Yes | 77 | 42 % | The startup is profitable |
| | | No | 108 | 58 % | |
| *Reg_activity* | Binary | Yes | 89 | 48 % | The startup offers a service that requires authorization |
| | | No | 96 | 52 % | |
| *Licence* | Categorical | No | 107 | 58 % | Indicates whether the startup already has a charter, is in the process of obtaining it, or relies on a third-party licence |
| | | Working on it | 9 | 5 % | |
| | | Own charter | 48 | 26 % | |
| | | Third party charter | 21 | 11 % | |
| *B2B_model* | Binary | Yes | 120 | 65 % | The startup targets financial intermediaries in its offer |
| | | No | 65 | 35 % | |
| *B2C_model* | Binary | Yes | 162 | 88 % | The startup sells directly to consumers or SMEs |
| | | No | 23 | 12 % | |
| *Platform* | Binary | Yes | 138 | 75 % | The startup considers itself a platform |
| | | No | 47 | 25 % | |
| *Funding* | Binary | Yes | 124 | 67 % | The startup has received funding from external investors (i.e. not from the founding team) in any form (e.g. equity, debt, convertibles) since its foundation |
| | | No | 61 | 33 % | |
| *Partner_equityinv* | Binary | Yes | 55 | 29 % | The startup has received equity investment from industrial partner(s) |
| | | No | 130 | 71 % | |
| *Partnership* | Binary | Yes | 150 | 81 % | The startup has at least one strategic partner |
| | | No | 35 | 19 % | |
| *#Partners* | Binary | Yes | 70 | 38 % | The startup has more than the median number of strategic partners |
| | | No | 115 | 62 % | |
| *Multiple_founders* | Binary | Yes | 140 | 76 % | The startup has multiple co-founders |
| | | No | 45 | 24 % | |
| *Avg_age* | Categorical | 25–30 | 55 | 29 % | Average age range of the startup's team members |
| | | 30–40 | 101 | 55 % | |
| | | 40–50 | 27 | 15 % | |
| | | 50+ | 2 | 1 % | |
| *Founding_year* | Categorical | 2015 | 15 | 9 % | The year the startup was founded |
| | | 2016 | 12 | 6 % | |
| | | 2017 | 22 | 12 % | |
| | | 2018 | 29 | 16 % | |
| | | 2019 | 32 | 17 % | |
| | | 2020 | 21 | 11 % | |
| | | 2021 | 28 | 15 % | |
| | | 2022 | 18 | 10 % | |
| | | 2023 | 8 | 4 % | |
| *Internationalization* | Binary | Yes | 74 | 40 % | The startup also has customers abroad |
| | | No | 111 | 60 % | |
| *Main_HQ_location* | Categorical | Abroad | 14 | 8 % | The geographical location of the startup's headquarters |
| | | Northern Italy | 133 | 72 % | |
| | | Central Italy | 25 | 13 % | |
| | | Southern Italy and Islands | 12 | 6 % | |
| | | Fully online | 1 | 1 % | |

Third, our study explores the role of *Internationalization*. Expanding into international markets can speed up profitability by diversifying revenue streams and broadening customer bases; it may also mean prioritizing growth over short-term profitability. The location of a startup's headquarters (*Main_HQ_location*) affects its financial viability, as vibrant ecosystems and networks giving access to resources and partners (Cojoianu et al., 2021; Gazel and Schwienbacher, 2021; Haddad and Hornuf, 2022) ease the path to profitability. It is worth noting that, while measures such as the foreign-assets-to-total-assets ratio (Cappa et al., 2020) were employed in previous research, these are not available for startups.

To build our model, we apply one-hot encoding, which transforms categorical variables into numerical form (Rao et al., 2023), converting "Yes" into "1″ and "No" into "0″. Summary statistics and the description of each variable, including target and independent variables, are shown in Table 2.

## 3. Results and discussion

### 3.1. Logistic regression

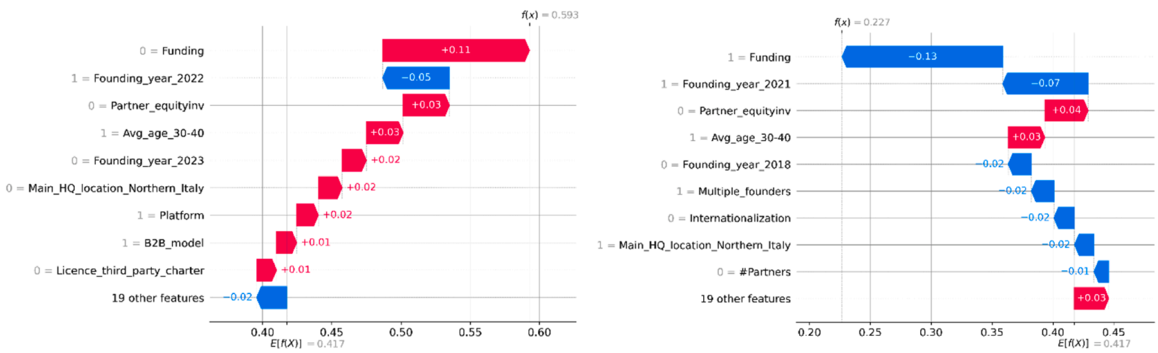
The logistic regression analysis reveals the factors affecting the likelihood of a FinTech reaching break-even (Table 3). The main finding is the negative impact of funding from external sources on profitability (coefficient of -2.106, *p*-value of 0.000), consistent with Kang (2020). Startups are disrupted by strategic pauses to align with new investors causing shifts in focus, by the need to respect investment clauses, and by loss of control in decision-making. They may also delay implementing stringent financial management

**Table 3**
Results of the logit model estimation (LLR p-value: 3.679e-05, 28 degrees of freedom). *** significant at the 1 % significance level, ** significant at the 5 % significance level, * significant at the 10 % significance level. *(Note: see Table 2 for a description of the variables).*

| | Coefficient | *p*-value |
|---|---|---|
| *Reg_activity* | -0.6949 | 0.194 |
| *Licence_working_on_it* | 0.0309 | 0.975 |
| *Licence_own_charter* | -0.0947 | 0.877 |
| *Licence_third_party_charter* | -1.0045 | 0.141 |
| *B2B_model* | -0.4001 | 0.317 |
| *B2C_model* | -0.0928 | 0.877 |
| *Platform* | -0.0247 | 0.958 |
| *Funding* | -2.1057*** | **0.000** |
| *Partner_equityinv* | -0.5025 | 0.260 |
| *Partnership* | 0.2946 | 0.593 |
| *#Partners* | 0.4707 | 0.284 |
| *Multiple_founders* | -0.1728 | 0.701 |
| *Avg_age_30–40* | 0.2902 | 0.521 |
| *Avg_age_40–50* | 0.6816 | 0.266 |
| *Avg_age_50+* | 0.7662 | 0.766 |
| *Founding_year_2016* | 0.1678 | 0.871 |
| *Founding_year_2017* | -1.1610 | 0.211 |
| *Founding_year_2018* | -0.1310 | 0.881 |
| *Founding_year_2019* | -1.5381* | **0.069** |
| *Founding_year_2020* | -1.7975* | **0.054** |
| *Founding_year_2021* | -1.6936* | **0.062** |
| *Founding_year_2022* | -1.4013 | 0.150 |
| *Founding_year_2023* | -20.9811 | 0.996 |
| *Internationalization* | 0.4545 | 0.297 |
| *Main_HQ_location_abroad* | -0.6449 | 0.480 |
| *Main_HQ_location_Northern_Italy* | -0.6669 | 0.279 |
| *Main_HQ_location_Southern_Italy_and_Islands* | -0.5889 | 0.523 |
| *Main_HQ_location_fully_online* | 12.1413 | 0.984 |
| *Constant* | 2.9741** | 0.034 |

practices through over-reliance on future funding rounds to cover any shortfall. Startups that place growth above immediate profitability can be guilty of inefficient spending and unsatisfactory cost control (Greenwood et al., 2022). The time-consuming process of securing VC funding (which involves extensive negotiations, due diligence, and compliance with various legal and financial requirements) sidetracks startups from core business operations, product development, and customer engagement.

Another finding is linked to when the startup was established. Startups founded in 2019, 2020, and 2021 are less likely to be at break-even than those founded in 2015. Survivorship bias may be a factor here, with longer-lasting startups having inherent qualities that contribute to their survival, including better management and market adaptability. Additionally, the Covid-19 pandemic probably disrupted startups created during this period, hindering their ability to test products and engage with stakeholders.




**(a)** **(b)**

**Fig. 1.** Local explainability plots for two startups where the predictions are "Break-even (Yes) - $f(x) > standardcutoff(0.5)$" (startup (a), left panel) and "Break-even (No) -$f(x) \leq standardcutoff(0.5)$" (startup (b), right panel). $E[f(x)] = 0.417$ represents the average value of f(x). Startup (a) has a high likelihood ($f(x) = 0.593$) of being at break-even. Additionally, we can also say that this result is primarily driven by the absence of funding from external sources (+0.11 on $E[f(x)]$). Conversely, startup (b) yields $f(x) = 0.227$, receiving a negative prediction for the target variable Break-even. *(Note: $f(x)$ = base value + sum (SHAP values) and $E[f(x)]$ = average value of $f(x)$; see Table 2 for a description of the variables).*

### 3.2. Random forest

The random forest model evaluates the impact of each variable on the likelihood of being at break-even by calculating the effect of the selected variables on observed values. The practical application of the random forest model explained through SHAP values is illustrated in Fig. 1, where we present the outcomes of two different startups, following Alabi et al. (2023). Using SHAP, each

**Table 4**
Summary of the random forest model. Overall prediction accuracy = 73 %.

| | Precision | Recall | F1-score | Accuracy |
|---|---|---|---|---|
| 0 – Break-even (No) | 0.80 | 0.73 | 0.76 | |
| 1 – Break-even (Yes) | 0.65 | 0.73 | 0.69 | |
| | | | | 0.73 |

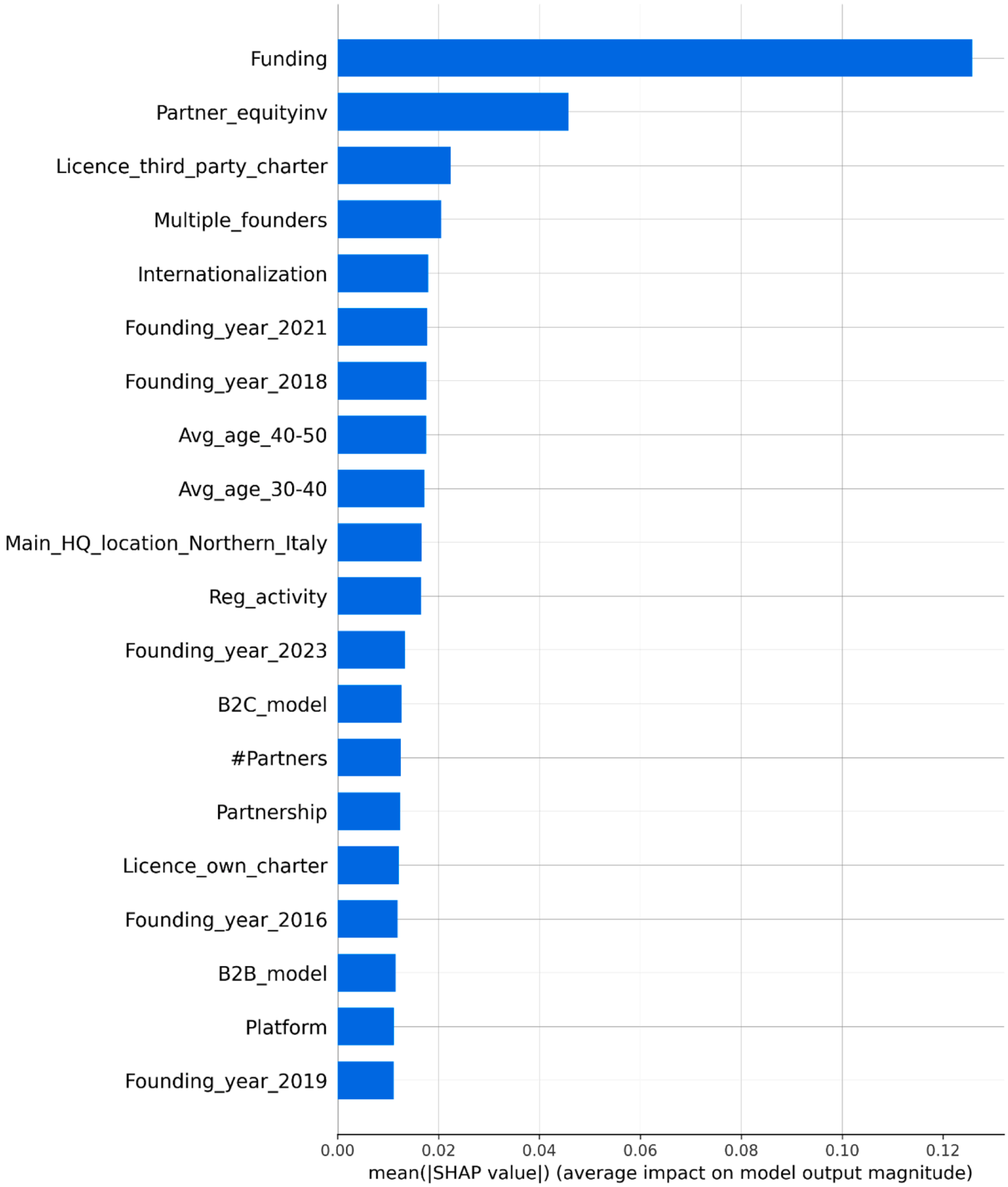



**Fig. 2.** Summary of the average SHAP values for the random forest model, ranked from largest to smallest. *(Note: see Table 2 for a description of the variables).*

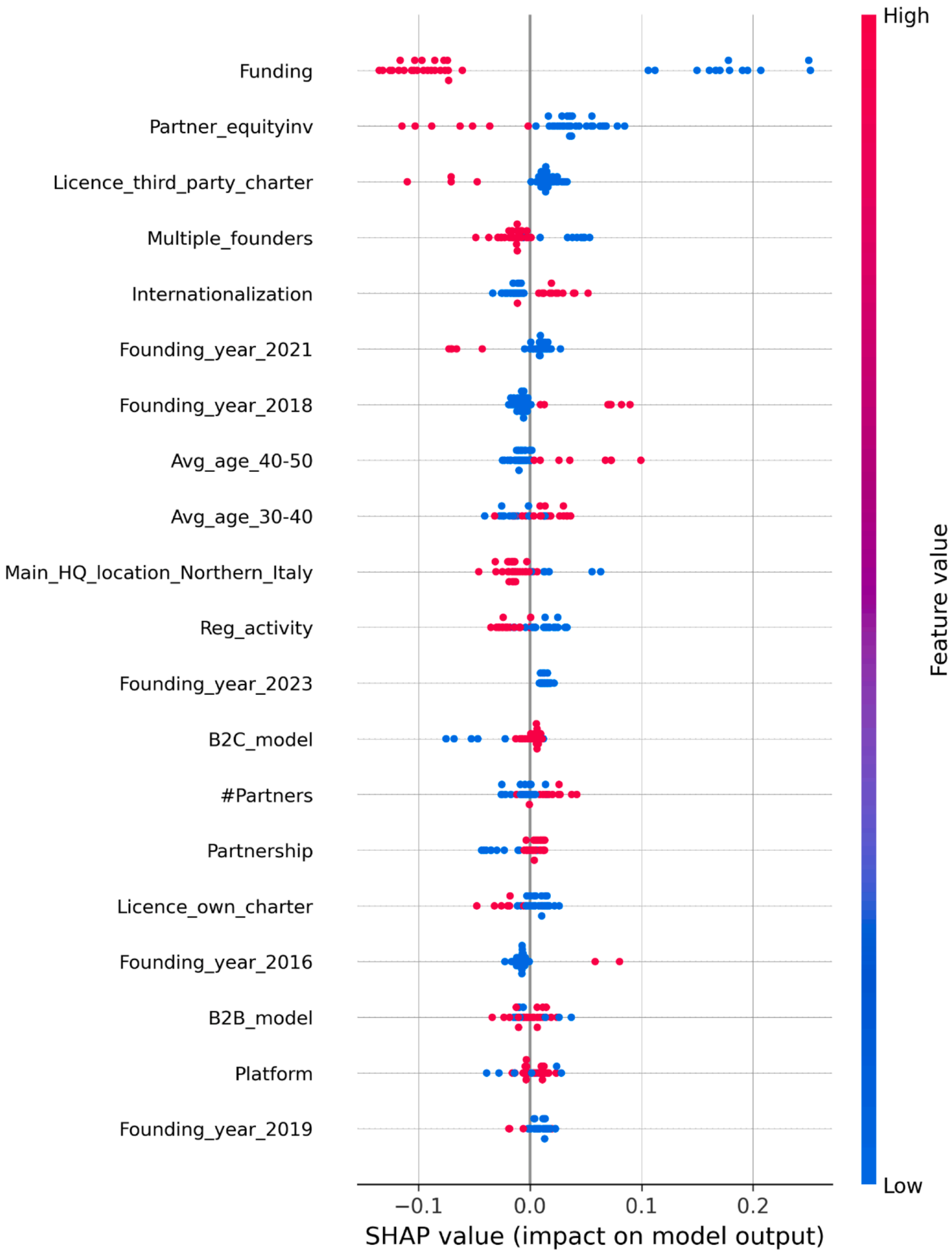



**Fig. 3.** Bee swarm plot of the SHAP values of the random forest model. The SHAP value for each variable in each startup is represented by a dot. *(Note: see Table 2 for a description of the variables).*

prediction is represented as $f(x)$ = base value + sum (SHAP values), where the base value = $E[f(x)]$ is 0.417 in our case.

The model, detailed in Table 4, is 73 % accurate in predicting whether a startup is at break-even. It is better at identifying startups that are not (0.80 for the "No" group) than those which are (0.65 for the "Yes" group), with F1-scores of 0.76 and 0.69, respectively. Recall, i.e. the share correctly identified in either group (Kovvuri et al., 2023), is 0.73 for both.

Absolute SHAP values are aggregated across all startups (Fig. 2), with each feature being ranked by importance. The SHAP analysis confirms that funding from external sources is the dominant factor, with an average impact exceeding 0.1. *Partner_equityinv* is also significant, with an impact of approximately 0.05. Other variables, such as third-party licences, multiple co-founders, and international reach, have less pronounced effects.

The bee swarm plot (Fig. 3) illustrates the direction of impact for the features in each startup. Higher values of *Funding* and *Partner_equityinv* consistently reduce the likelihood of being at break-even. *Licence_third_party_charter* negatively affects profitability, suggesting that startups which use third-party charters face greater challenges. *Multiple_founders* negatively affects a startup's break-even status, possibly because the increased complexity in decision-making outweighs the potential benefits of broader networks and greater resource acquisition (Carbó-Valverde et al., 2022; Park and Kim, 2023). Conversely, *Internationalization* is associated with positive outcomes, indicating that market expansion and diversification benefit startups.

## 4. Conclusions

This study provides valuable insights into the determinants of break-even success among FinTech startups. Our analysis reveals that funding from external sources (mainly venture capital firms and other financial players) significantly decreases the likelihood of a startup having reached break-even. The likely causes are placing growth above immediate financial stability, diverting efforts to fundraising, and financial indiscipline as the result of excessive reliance on future funding rounds. Together, these factors present a dilemma, as, rather than being a positive signal, funding from external sources may reduce the chances of reaching break-even, increasing a startup's reputational risk and its business viability risk, as well as potentially limiting the incumbents' interest in industrial partnerships.

Our research contributes to the growing body of literature on startup performance, particularly in the under-explored FinTech sector. We apply signalling theory, and our use of logistic regression and random forest models coupled with the interpretation capacity of SHAP values is a further methodological contribution, enabling a nuanced understanding of how different factors (in our case, funding from external sources) impact on break-even success. Furthermore, the study adds to the discourse on startup funding by highlighting the paradox whereby external investment, commonly viewed as a driver of growth, may in fact delay financial independence.

For FinTech startup managers, these findings offer actionable insights into the financial management strategies that can help or hinder breaking even. Our results caution against over-reliance on funding from external sources, which often shifts the focus from disciplined financial management towards rapid growth. By identifying the associated strategic misalignments and operational distractions, managers are better placed to navigate the challenges of early-stage growth and concentrate on sustainable business practices.

For policymakers, our research highlights the role played by regulatory frameworks in shaping the operational paths of FinTech startups. As these startups operate in highly regulated environments, policymakers should consider how sandboxes, licencing processes, regulatory projects, and financial support mechanisms affect a startup's journey to profitability. Our findings on the adverse effects of funding from external sources suggest that initiatives designed to support startups should not hinge solely on growth but promote financial sustainability and long-term stability. Policymakers could also develop programmes to help startups achieve break-even, reducing the perceived risks for financial institutions seeking partnerships.

Our study has some limitations. First, the focus on Italian FinTech startups may restrict the generalizability of the findings. Second, the intrinsic complexity of startups and the complicated process of collecting data, especially under non-disclosure agreements, may introduce constraints. Third, we measured break-even as a binary variable based on self-reporting, limiting our ability to account for varying levels of profitability over time. Lastly, taking 2015 as the starting point could lead to survivorship bias. However, this reflects the real world where financial institution managers weigh up the various risks when deciding whether to establish partnerships and initiate strategic alliances. To double-check, we re-analysed the data, examining only startups established from 2020 onwards, obtaining similar results. *Funding* resulted significant in the logistic regression (coefficient of -3.1846, $p$-value of 0.004) and remained the prime variable in the random forest model (mean SHAP value of 0.11). Finally, future research should explore broader geographic contexts and employ more granular measures of profitability to ensure greater generalizability and wider understanding of this area.

## Funding

No funding was received.

## CRediT authorship contribution statement

**Claudio Garitta:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Laura Grassi:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

## Conflicts of interest/competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgments

The authors express their sincere gratitude to the Editor and the two anonymous Reviewers for their valuable insights and constructive feedback. Special thanks are extended to the Fintech & Insurtech Observatory at Politecnico di Milano for providing the data and to Anna Presciuttini for her assistance in auditing the model.

## Data availability

The authors do not have permission to share data.

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