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Are financial technology firms more likely to receive equity funding?

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Declaration of Authorship

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Management Summary

Startup funding become an important topic in the corporate finance area since the technology driven, innovative companies has seen a dramatic increase recently. These companies are newly founded ventures without a financial performance history or credit payment record. Therefore, it is unlikely to use traditional borrowing options, bank loans or debt financing since they lack collateral or liquid assets necessary to make interest payments regularly. It is more common for startups to receive funding from venture capitalists, angel investors or their close circle, internally. In this type of funding, the startup sells a portion of their equity and ownership in exchange for investment. There are many determinants to understand the equity funding pattern and their impact on funding amount and number of funding rounds. However, it is difficult to find relevant studies which makes a comprehensive analysis of the factors that affect equity funding for Fintech companies specifically.

This research paper reviews the current literature both for startup and Fintech companies separately to sustain the theoretical baseline for the funding mechanisms in corporate finance. Second, a descriptive statistical definition is framed to understand the collected dataset. Third, an OLS regression analysis is conducted to analyze each model with different combination of independent variables. The results of the regressions show that Fintech companies are more likely to receive equity funding. Likewise, empirical study also illustrates that the headquarter location that the startup is based plays an important role both in the equity funding amount, number of funding rounds and the equity funding turnaround. In the emerged markets like US or highly growing markets like China startups are more likely to receive equity funding compared to emerging markets like India. On the other hand, micro, small and medium size firms are negatively correlated with equity funding amount. However, as the employee size increase the magnitude of this effect decreases.

The results are hence relevant to executives, investors and stakeholders of Fintech companies to evaluate if their investment strategies align with these criteria and determinants. Based on the limitations of this paper, further research can be expanded to investigate other determinants by integrating them into the regression models and combine with qualitative surveys or interviews with Fintech industry experts, founders and cofounders.

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Abbreviations

Fintech - Financial Technology

OLS - Ordinary Least Square

VC – Venture Capital

PE – Private Equity

M&A – Merger and Acquisition

FF – Family and friends

IPO – Initial Public Offering

EU – European Union

R&D – Research and Development

AI – Artificial Intelligence

POT – Pecking Order Theory

DV – Dependent Variable

FI – Financial Inclusion

3F – Family, Friends and Fools

DLT – Distributed Ledger Technology

Abstract

This study examines if the Fintech companies are more likely to receive equity funding compared to the other companies and other startups. The purpose of the research is to analyze if selected determinants (age, headquarters location, employee size, estimated revenue and operating industry) affect equity funding received. A sample of 59,429 startup companies across 130 countries on a cross sectional data is analyzed by using OLS regression in Python. The null hypotheses that these factors do not have an impact on equity funding to the alternative was tested. The results show that, among the selected determinants; age, employee size and estimated revenue have a positive relationship on equity funding and being a Fintech company and having a headquarters location in US have a negative relationship on equity funding. The impact of the headquarter location on equity funding is weaker in an emerged market compared to emerging markets.

Keywords: Venture Capital, Startups, Equity Financing, Fintech, OLS Regression

1. Introduction

Startups have been the main source of interest for the market, media and stakeholders with their high potentials for growth (Chang, 2004). These startup companies can generally be defined as *highly innovative* microbusinesses that are driven by new and unconventional, technology-intensive business models or ideas with a substantial growth potential. Although these recent innovative businesses are mainly associated with technology intensive companies, they can provide goods and services in various sectors including consumer goods, healthcare as well as IT, financial services and e-commerce (Kaya, 2016).

Among these highly innovative sectors in the ecosystem, financial technology (Fintech) companies have become significantly popular. This is because these companies disrupt the position of incumbent banks, quickly steer innovation in the financial industry, build new and effective business models without the liability for following the regulatory boundaries that are usually unfavorable to the incumbent banking sector (Lee & Shin, 2018), (BIS, 2017). Fintech companies play a crucial role in the improvement of financial services industry. They operate in a wide range of different areas, as shown in Figure 1 below, (Chemmanur et al., 2020). These companies boost innovation, competition and employment with their growing market share in the economy. Compared to the traditional finance institutions, Fintech companies promise a better service quality, lower costs, personalized and user-friendly customer experience, which leaves the current market share of these traditional finance institutions into a risky position due to the changing dynamics in the market competition. For example, according to a study by PwC in 2016, 83% of financial institutions assume that Fintech companies are likely to threaten several components of their operations (Lines, 2016). Hence, financial sector are poised to change their strategies to implement, invest or merge with the activities of this new, impactful and challenging business phenomena (Lee & Shin, 2018). In order to change the spending, saving, borrowing and lending behavior in the financial world in addition to new offerings and products for cryptocurrency, AI and sustainable investments, these companies need source of investment on the global level to keep up with the competition and continue to provide innovative solutions to their target client groups.

Figure 1 - Sectors of Fintech

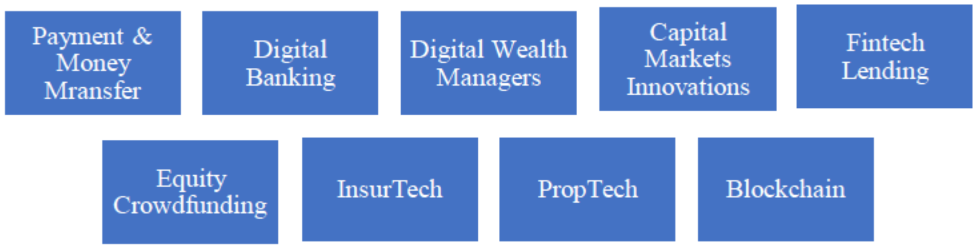


Figure Source: The figure is adopted from (Chemmanur et al., 2020).

Two main funding sources are essential in the early growth phase of the Fintech companies: 1) venture capital and 2) direct equity funding. First, venture capital has played a significant role in allowing the growth of today's big technology companies such as Yahoo and eBay since early 1990s, as the highly demanded type of equity financing (Gompers & Lerner, 2001). Venture capital owners can inject funds from investors to the innovative companies while securing a certain percentage of the future profits in return as in the equity form (Chang, 2004). Fintech companies are likely to benefit from the venture capital as the companies such as Yahoo and eBay did in early 1990s from the same funding alternative (Chang, 2004). Second, direct equity funding is an external financing method more pronounced with entrepreneurial stage companies since they possess intangible assets such as a business idea rather than tangible assets (Gompers & Lerner, 2003). Such a funding alternative can be useful for Fintech companies as the institutional investors not only help the companies with capital injection but also with management expertise and enhancing corporate value of the company (Chang, 2004).

All the startups at the early phase of their growth carry a high level of economic risk. Fintech companies are not exception to this risk factor since there is uncertainty in their return forecasts at the initial phase of their economic cycle (Hoenig & Henkel, 2015). It is rather difficult for startups to expand their borrowing limits due to negative earning anticipation, their innovative yet unconventional ideas and projects which can be categorized as intangible assets. Although total global investments to Fintech companies reached to US$210 billion with the number of deals amounting to 5,684 as of 2021 (O'Neill, 2022), it is still challenging for Fintech companies to receive funding since Fintech companies need an easy access to loans and well developed financial markets to succeed before their financial performance is identified (Haddad & Hornuf, 2019).

To alleviate such funding challenges at any stage of Fintech companies, it is essential for these companies to manage their funding sources and sustain their competitive position in the market. Throughout the lifecycle of any company, different funding alternatives and solutions may be relevant for a continuous financial growth (Davila et al., 2003). For example, at the early stages, venture capital and crowdfunding solutions may be more valid whereas equity financing may take place in the further development stages of companies (Kaya, 2016). For startup businesses that are unlikely to be approved for a bank loan, private equity (PE) and venture capital (VC) organizations provide a financing option (Gompers and Lerner 1998). While PE/VC invests funds by buying equity holdings, bank loans often offer a debt against the future payment of a principal plus interest. They normally only hold onto the equity for a short time—generally around 10 years—in an effort to boost the company's worth before they left (Tykvová, 2018). PE/VC firms act as middlemen, investing money from investors like pension funds, family offices, and insurance companies to finance start-up businesses with strong growth potential (Hoenig & Henkel, 2015).

Although Fintech companies can utilize the well-studied strategies for raising funding, it is likely that Fintech companies may require strategies and funding alternatives that are specifically tailored for their financial conditions and needs.

1.1. Research question

Funding requirements of Fintech companies deviate from the other recent and highly innovative companies in two ways. First, due to the strong link with the regulatory framework; the funding and the growth performance of a Fintech is associated with regulatory quality and the level of financial inclusion in the market (Aghion et al., 2018) (Cornelli et al., 2021). Second, as the most dominant players in traditional financial service industry, incumbent banks change their position in being the primary lender in the form of debt financing to being the stakeholder in the form of equity financing which differentiates the Fintech funding (Hommel & Bican, 2020). Understanding the tailored strategies based on the specific funding requirements of Fintech companies has the potential for improving their growth even at their initial startup phase. Hence, funding rounds, types and the determinants that affect the funding are necessary to understand the driving forces behind Fintech companies' growth. It is likely to identify a connection between funding amount, funding type, location, size, number of employees and actual or estimated revenue of the Fintech companies. In this study, we would like to find the connections between these dependent variables. The number of independent variables that may have an impact on the funding amount and consequently the growth of the Fintech companies is essential to analyze within the quantitative research design. Doing so, we aim to identify the following two questions. First, we aim to find if the Fintech firms are more likely to receive equity funding compared to other companies. This is important to understand because Fintech companies as digital newcomers will define the future financial market innovations, alter the competition with big banks and big techs and their easy access to funds triggers growth and potential revenues for the investors. Second, to quantitatively answer the first question, we also aim to find if the Fintech companies with a specific headquarter location have more equity funding turnaround which is a ratio to measure how many rounds can take place to reach a certain amount of funding. This investigation gives us the understanding if a given amount of funding is received on prolonged amount or one-shot capital injections.

The relevance and importance of this study stems from possible, valuable insights for managers, executives, investors and stakeholders of Fintech companies. This study aims to break down the funding alternatives, possible setbacks or challenges for startups and Fintechs that can cause funding and liquidity problems in early development stages (i.e., not having easy access to public funding market or bank loans due to lack of track record and prior financial performance which can be categorized as high-risk investment) and augmentation of methodologies for startup funding. Furthermore, the analysis of company factors with estimated revenues and employee size will be performed to support the findings and conclusions.

1.2. Research gap and methodology

Our goals in this thesis are to 1) methodologically understand the financial requirements of Fintech companies in addition to presenting the key determinants that have an impact on equity funding of Fintech companies, 2) analyze the funding alternatives, possible setbacks or challenges that can cause funding and liquidity problems in these companies and 3) determine the key mechanisms for enhancing the funding strategies at different stages of Fintech startups. The results of this study have the purpose to enhance the decision making and management of Fintech companies to further increase their high growth and contribution to economy. Depending on the possible results, there is room for further research in connecting different variables such as company's location, size, turnover rate, number of employees and age if the effect is significant among these independent variables. Moreover, within the sample of 66,996 firms if the industry they operate is related to financial technology, further conclusions can be drawn considering this concepts are more dominant in digital economy in the future.

Recently, startups, former big techs and small to medium size technology intensive companies are funded with equity funding mostly. However, to our current knowledge, there are limited studies examining the funding structure of Fintech companies with a link to company specific variables. There is room for research in which the industry characteristics, the size and the location of the Fintechs can be associated with the volume of funds received in a quantitative approach. We would like to fill in this research gap by applying an Ordinary Least Square (OLS) regression in Python to investigate the relationship between Fintech characteristics. For this purpose, the data platform for listed companies, namely Crunchbase, will be used. The dataset specifically produced for this study comprise 66,996 small to large size firms which receive equity funding at least for one round and their publicly available information. This raw dataset is collected and will be modified according to the purpose of this research to eliminate outliers as much as possible based on preset criteria. The outline of the methodological execution will be as following: First; the regression analysis including two dependent variable ('total funding amount' and 'number of funding rounds') and independent variables of the sample startup companies (size, age, turnover rate, in the sample of 66,996 small to medium size before data clearance) is conducted. Second, another set of regression to understand the impact of the interaction variables where size and industry variables are combined. Third, these factors' effect on the Equity Funding Turnaround is analyzed to differentiate companies that are located either in an emerged economy or an emerging economy to see if the results can variate. As our third and last dependent variable represents the ratio of how many funding rounds the company had to achieve the total equity funding amount, it will be calculated as the following formula:

$$Equity\ Funding\ Turnaround = \frac{Total\ Equity\ Funding\ Amount}{Number\ of Funding\ Rounds}$$

Lastly, the significance is checked to show the impact of the industry which is financial technology as a part of financial services in this case. Following the benchmark regression, further implications of specific characteristics of the Fintechs such as the age of the company, the turnover rate, size of the company can be effective in total equity funding volume that is used to fund the economic and innovative activity of the Fintech company.

1.3. Overview of the Research Paper

The research paper is consisted of seven main parts. In the first part, the background on the research question, research gap and methodology is given for identification and highlight of the research question and objectives of the study. Second, the literature review on current research studies on the topic is provided in a detailed way. The third part outlines the data and sample of companies selected before the application of the selected methodology. In the fourth part, the selected methodology is explained. The link between the Fintech companies' performance and their funding type is investigated with the help of Crunchbase data platform using multivariate regression models on our modified cross sectional data in the 'Methodology' section. In the fifth section, the results are discussed with a focus on equity funding, including summary statistics table. In the sixth part, the limitations that this work has been stated. Finally, the conclusion section posits the key findings, further improvements and the summary of the conclusion remarks.

2. Literature Review

2.1. Theoretical Framework

The following sections present a narrative synthesis of the current state of the literature. Our ground theory part is mainly governed by the nature of the newly founded companies which is linked to information asymmetry, risk and uncertainty for the funding provider of the startup companies, majorly VC firms and angel investors. Receiving VC funding represents the quality and success potential of the startup company (Davila et al., 2003). Nevertheless, it is an indispensable part of VC business to determine the risk characteristics of the newly founded firms to analyze whether there is a growth potential or not. Venture backed entrepreneurial firms and investment experts carry the risk of failing whereas venture capitalists carry the risk of losing investments, foregone capital gains when they cannot foresee the exit opportunity at the right phase. Therefore, venture capital investments require an expertise, a due diligence procedure to accurately assess the potential of growth by advising the inexperienced management. As a result of this, they allocate the necessary financial, managerial and strategic support to startups (D. Cumming & Johan, 2008). Further, venture capitalists must overcome and minimize the difficulties resulted from information asymmetry and the agency costs associated with the founded company. This is essential for them to be able to make valuation for the company.

Moreover, the theoretical framework for startup financing is mainly revolves around three paradigms explaining the nature of small, entrepreneurial businesses and their access to finance. One of them is Life Cycle Theory which explains the different stages of a startup in a detailed way and the second one is the pecking order theory which interprets the trade-off in deciding the capital structure of the firm. Further, according to Davila et al. (2003), and their grounding on signaling theory which will be further explored in Chapter 2.1.3, the uncertainty regarding the success/failure outcome of the startup and the information asymmetry among the market participants make certain variables such as founding rounds highly important signaling strategies of startup companies.

2.1.1. Life Cycle Theory

The first important theoretical aspect in startup financing is the Life Cycle Theory of small businesses. As the operational volume, revenue structure, size and growth trend of the company shifts the financing needs and alternatives may shift as well. Small businesses are not subject to information transparency which indicates a tendency to internal finance and angel investments. As the Figure 2 shown below (Salamzadeh, 2015) explains the first investors are defined as FF (family and friends) who are the individuals rely on the business idea, expect financial gains for the future and invest when the firm has mostly intangible assets and does not have a financial performance history. In this stage bootstrapping indicates the stage where entrepreneur allocate his/her personal funds or benefit from his/her personal connections such as FF to boost the investment activities of the newly emerging business when the economic gains are uncertain and risk level is high (Ebben & Johnson, 2006). There is an option pool dedicated to the potential employees for the future to be set aside.

Figure 2 - Lifecycle of Startups

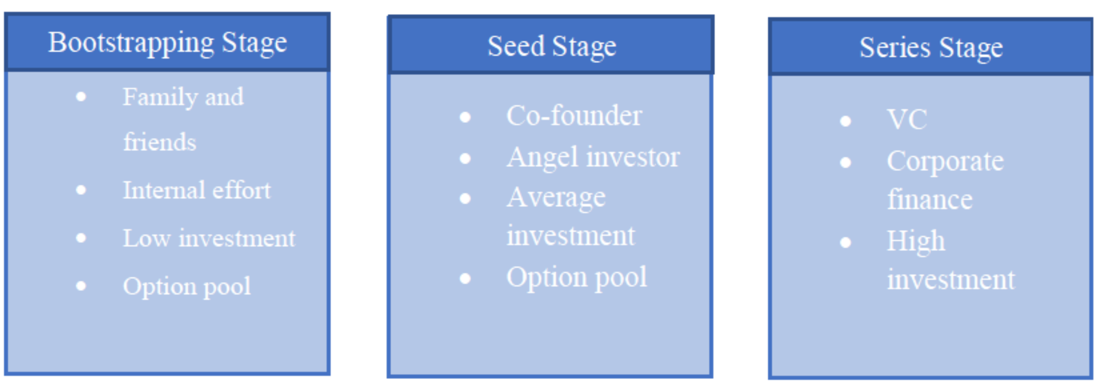


Figure Source: The figure is adopted from (Salamzadeh & Kawamorita Kesim, 2015).

In the second stage, seed financing which is higher in volume compared to bootstrapping stage is initiated to enhance additional costs arising due to the expansion of the business such as employment, prototype development, marketing, accelerators and incubators to boost further growth of the business. Seed funding is also called an early-stage funding where the product or the new technology is still in the development phase. Hence, seed funding can be considered as the temporary financing until the next cash inflow from VC is accessed or the business starts to make revenue (Halt et al., 2017). This stage is critical in terms of previously failed examples due to the lack of support (Salamzadeh & Kawamorita Kesim, 2015). Although, it may differ from one startup to the other, depending on which industry they operate in, the primary external funding source can be considered as the angel investment stage (Herck Giaquinto & Bortoluzzo, 2020). Despite seed money is more professional investment alternative for early-stage capital injection by investors, business angels are more accomplished entrepreneurs who allocate their personal wealth money in early stage entrepreneurial firms (Croce et al., 2018a). An investment initiated by an angel investor may be supported by other sources of investment; VC, PE of which may have additional rounds in the form of series A, B, and C, respectively.

According to Salamzadeh (2015), the third stage is where the company enters to the market and grows with the early employees in the team. The series funding brings higher volumes of investment followed by venture round which is the Series A funding and later on Series B, C, D (Salamzadeh, 2015). As the company expands its operations and the working prototype functions as expected, the access to equity side financing such as venture capital and external debt financing gets easier (N. Berger & F. Udell, 1998). Although, the order of the financing may change slightly across different industries, locations and sectors; Berger and Udell defines the initial startup stage as linked to the development of precise business plan which can serve as a guidance for accessing and angel investor. Usually, the second order belongs to venture capital where the products are tested for scalability and marketing has been completed. However, there are situations when major costs associated with product development, may be covered by VC. In businesses that have already obtained one or more rounds of angel funding, venture capitalists frequently make investments. Brewer and Genay (1994) and Brewer et al. (1996) suggests that intangible assets and idea testing operations are financed with venture capital (PE) whereas tangible assets that can further lead to collaterals in the form of accounts receivable, inventory and equipment financed with external private debt (Brewer & Genay, 1994), (Brewer et al., 1996).

2.1.2. Pecking Order Theory

Pledging collateral and accessing debt-based financing from external sources such as banks or intermediary financial institutions can differ for newly founded companies. The reason for this can be explained by another fundamental theory in corporate finance. Pecking order theory (POT) is one of the most prominent theoretical foundations in capital structure decisions and financing of firms. According to Myers, there is a pecking order implication when the firms need to provide for their financing needs. First of all, internal finance is preferred to external finance because of the adverse selection problem in which one party has a comparative advantage in terms of information power. This creates an imbalance and non-transparent situation for one of the transaction parties (Myers, 1984).

For the simplicity of the assumption, the three funding sources which are debt, equity and retained earnings are accessible to firms. Among these funding sources, the latter has no adverse selection problem whereas the former ones have adverse selection problem, majorly on the equity financing source. Equity funding has potentially the greater risk for the investor with a larger adverse selection risk premium. The tradeoff for selecting a riskier founding alternative brings a higher return for equity. Therefore, POT suggests that firms tend to use retained earnings in priority from a risk perspective. As an addition to the retained earning amount, debt financing is used in the second order when there is a shortfall on the retained earnings. Lastly, the final order is the equity financing which is used by the firms since the actual activities of a corporation and the related accounting structures are more complex than the POT alone (Frank & Goyal, 2003).

On the other hand, according to trade-off theory, there are two components affecting the capital structure of the firms. The first one is the bankruptcy cost which derives from the higher possibility to fail for young firms and more cost associated with bankruptcy (Cressy, 2006). However, the second component which is the tax advantage is more influential in the trade-off compared to the bankruptcy cost since paying debt plays a more crucial role than tax advantage, in the perspective of the founder (Poutziouris et al., 1999). Hence, POT has more explanatory power in capital structure of the young firm (Fourati & Affes, 2013).

However, whether there is a valid reverse POT for entrepreneurial firms or not has been a research question for the literature investigating the financing decision. In the reverse version of the POT, the equity finance is preferred prior to the debt financing when the entrepreneur or the founder believe that the value of the current debt is lower than the future return of their firm. In that case, debt financing is favored over equity financing (Vivian & Xu, 2018). In order to contribute to this research, Fourati and Affes (2013), investigate the business startup data and analyze statistics on their dataset to see by what percentage founders use internal finance sources and by what percentage they use the external debt when financing their firms. Based on the POT developed by Myers and Majluf, the authors achieved their first key finding. Internal funds which are comprised of equity contribution and personal debt are preferred more compared to external funds which can be considered as debt and VC by the entrepreneurial firms (Fourati & Affes, 2013). Second, an altered POT which redefines the priority order of financing for innovative firms is suggested by the academic literature because retained earnings and external equity are not applicable to the financing needs of startups (Atherton, 2009). This altered POT arrays the financing alternatives as the following, shown in Figure 3: New Pecking Order for Innovative Firms (Sau, 2007): 1) Internal source of Capital, informal private equity and seed financing; 2) Financing received from VC; 3) Self-financing, credit received from financial institutions; 4) Bond issuance and receiving public equity (Sau, 2007). Finally, the authors also found out that, in order to decide the existence of POT for the business startups; specific characteristics take important role. Since startups are lack of historical track record available to the public and have no transparent information regarding company's internal operations, it is challenging for startups to be funded with external financing (Paulson & Townsend, 2004). In this situation, it is plausible to mention POT in which the preference of funding can be ordered as the internal funding is the first, short term debt the second, long term debt the third and external funding as the last order (Cosh & Hughes, 1994). Also, agency problems within the startups makes it difficult to assess the validity of POT for them. The investor's role is associated with the principal and the founder's role is associated with the agent after the funding transaction occurred (Cherif, 1999). The agency problem of the funding providers is the cause of moral hazard problem since they have tendency to select riskier projects over the ones with a positive net present value. It decreases the use of external debt sources from banks because traditional banks and associated financial institutions aim to minimize the risks linked to adverse selection.

All in all, if new entrepreneurial activities have more tangible assets that serve as collateral and if they have a legal form in incorporation, they are more likely to have some external debt in their capital structures. The entrepreneurial operations with greater human capital are less likely to have some external debt and more likely to be supported by internal finance since human capital has the lowest value. Home-based businesses are more likely to be financed internally rather than externally to draw the attention of the fewer outside investors. Entrepreneurs with higher levels of education which can be associated with overconfidence bias and overestimation of future revenue stream, borrow more money from investors and take on more debt. Indeed, there are transaction costs associated with external debt (Vivian & Xu, 2018), (Fourati & Affes, 2013).

Figure 3 – New Pecking Order for Innovative Firms

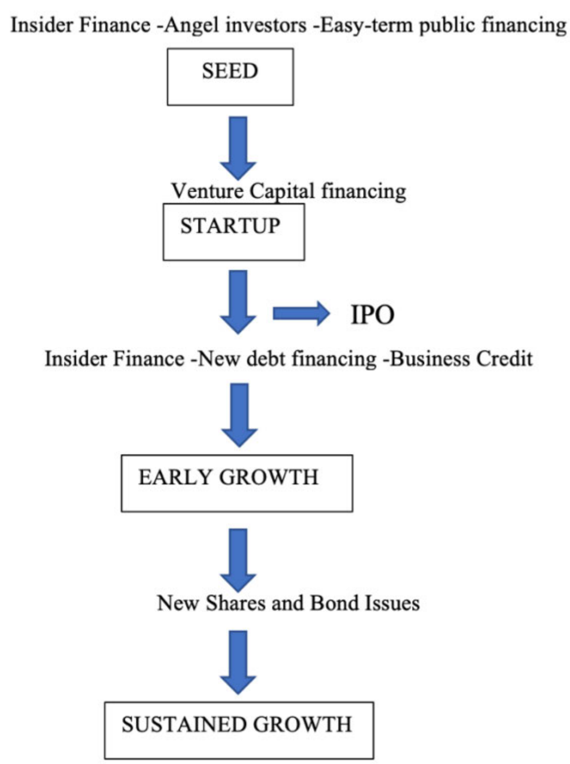


Figure Source: The figure is adopted from (Sau, 2007).

2.1.3. Signaling Theory

The signaling theory is based on information asymmetry and uncertainties inherited into the nature of a newly founded venture and utilized in order to evaluate if a firm is likely to receive funding to become successful or not. Signaling theory uses cash dividends as a measurement indicator since cash dividends signal positive cash flows in the future. This inference weakens the effect of imperfect information on the investor side (Bhattacharya, 1979).

The process that is used to identify the signals depends on the interpretation of the actions performed by the firms and how these actions are perceived by the investors in financing decisions. The signaling theory has a bilateral aspect where the investor and the firm have initially different levels of information and different understandings or motives for the signals (Connelly et al., 2011). First, as the IPO date approaches, investors become more attentive to company news, change in the board of management, the demand of investment from other angel investors or whether an interested VC exists or not. For instance, when a young firm in the early stages of their growth intends to have an IPO soon, reorganizes its management team with experienced set of executives to send a message about the resilient organizational structure of the firm (Certo, 2003). Likewise, according to the previous studies, if the angel investors who usually invest to the startup at the earlier stages, namely seed financing type of investment, compared to the VC investors are approached by the entrepreneurs and startup owners; this indicates that the firm has a positive cash out value (Elitzur & Gavious, 2003). If a startup is able to receive angel or seed financing, this gives a favorable signal that the company is likely to achieve the success by positive return generation and the deal is classified as a high quality (Croce et al., 2018). Second, the signal needs to be categorized either as positive or negative regarding the return characteristic on the firm's value or prospects for the investor. Both intentionally and unintentionally firms communicate with the public and with the people who will invest them through their signals. For example, when founder is committed to the firm and engage in operating activities, this gives a positive signal to the investor. On the contrary, when the firm issue new shares, the investors can understand that the current share price is overvalued and interpret this as a negative signal. Moreover, the investors categorize firms as high quality and low quality since only high-quality firms are financially capable of paying the interest of their debt and paying off dividends whereas low quality firms do not have this kind of capability (Connelly et al., 2011). Although there are different representations used in the literature for the meaning of quality, it is referred as the expectation of a positive cash flow from a firm in the future (Ross, 1973).

It is noteworthy that, there is an information imbalance between entrepreneurs and public when the firm is private because the entrepreneur is well informed about unofficial intelligence, e.g., development phase success of an idea, market research for an upcoming product, that is usually not transparent for the public view and can affect the future revenue, cash flow and share price. Sometimes, the unshared information may belong to the negative category such as lawsuits that can harm company image. When business owners have better access to unobservable information about their own companies' prospects than the public, they can manipulate the funding decision. The predictions regarding the founders' plan for the company can be revealed if he or she seeks and exit opportunity by selling his part of the shares to an investor or remain in the company for the longer time period (Connelly et al., 2011). By this way, the signals help investor to circumvent the effects of asymmetric information and adverse selection in their funding decision.

A fundamental tenet about signaling theory is that there is a conflict of interest between the entrepreneurs and investors. This tenet helps us to explain the motivation behind why the entrepreneurs' not retaining all the information to themselves. When the investors who are the receivers of the signals in this case, had access to the entrepreneur's private information, they might make better decisions. However, this brings another effort with it since having access to this information is attached to a cost along with. The "perfect information" assumption of economists is particularly challenged by signaling theory ("Signaling Theory and Entrepreneurship: What Is the Signaling Theory of Entrepreneurship?," n.d.).

2.2. Sources of Funding

All the firms aim to maximize the growth by leveraging capital and innovation. However, it is particularly difficult for the determine the main drivers behind funding sources for the young and innovative companies. As we discussed in the previous chapter, Life Cycle model, Pecking Order Theory and Signaling Theory are frequently employed to explain the selection between accessible funding alternatives for startups in which equity financing is majorly preferred due to various reasons. In order to gain a deeper understanding of the reasons why equity financing preferred, we investigate the different views provided by the current literature both for the startup and the Fintech companies as a special type of startup.

2.2.1. Funding of Startup Companies

Startup financing, especially with the recent expansion in venture capital initiatives, startup accelerator programs and public policy updates has grown over the last decade. Startup or private enterprises need to obtain private equity capital, in contrast to major corporations that can obtain financial resources through public stock markets. Family and friends, as well as experienced "accelerators" or "incubators" that offer mentorship to start-up enterprises, are some of the many sources of startup enablers (Bhatt, 2022). VC and PE are the funding alternatives to conventional loans from financial institutions for the purpose of combatting disincentivized investor due to high risk. Being an investor of either one of these two categories requires a specific skillset to assess the risk-return character of the firm which brings a cost along with it.

Firstly, VC is a funding option highly associated with companies with a great growth potential (Janeway et al., 2021). VC backed firms constitute the 50% of the whole revenue of publicly traded US companies and 75% of the market cap, bolstering innovation in the market (Lerner & Nanda, 2020). The potential of the new firms working on the development of a new technology, product or a business idea is assessed with the notion of high level of uncertainty at the early stage by the VC throughout sequence of series investments. Evaluation of the profitable ventures for the investor increase the number of trials of innovative initiatives and leads a promising development in early-stage investment. Due to the high risk and sensitivity to change in expectations of the new product outcome, VC investing requires a subject matter of expertise to select the startup with the potential to grow and sustain the investment in consecutive rounds. All venture capitalists must choose between ownership and diversification of the risk. A few extremely successful ventures tend to drive the majority of returns, so VC investors also want to have enough ownership in the firms that ultimately succeed to generate the returns they need. Due to the idiosyncratic risk, the possibilities among new ventures need to be allocated with the framework of risk management. However, only a few profitable businesses generate positive returns. When investing in early-stage companies since the likelihood of success is poorly guaranteed, this trade-off may be even more prominent. As a result, there needs to be a cooperation between early-stage investors and later-stage investors to keep funding the startup until it generates revenue. It is plausible for early-stage investors to predict which ventures will be funded by later stage investors. Moreover, it illuminates the rationale behind VC investors' desire to link their investments to different sectors and time frames (Nanda & Rhodes-Kropf, 2017). Early-stage investors' sensitivity to boom-or-bust signals can also be explained by the need to anticipate the preferences of later-stage investors and act accordingly, even though herding may have both rational and irrational aspects (Scharfstein & Stein, 1990), (Goldfarb et al., 2007).

Second, startup accelerating programs are another support mechanisms to provide funding for the startups. When there is lack of representativeness and guidance for newly developing or undeveloped areas, these initiations can fasten the growth especially in technology-based sectors. Accelerators are programs that aim to provide not only seed financing but also mentorship and training support in addition to aid in creating a demo or pitching their idea. The accelerator institution receives a percentage of equity in return to this effort and funding (Dempwolf et al., 2014). According to Smith et al. (2013), receiving support from accelerator programs increase the possibility of accessing funding faster in the later stage for a startup. These programs expands the business network and connections, founder experience and overall success rate of the startup (Winston Smith et al., 2013) as the successful examples such as Reddit, Airbnb and Dropbox show. The main focus of an accelerator program is to obtain the highest return from a given startup in a given time by selecting the most promising company. To achieve this goal, policymakers take into consideration the following elements: 1) startups needs to be invested more regionally, 2) startup funding allocation should not be centralized. First, the regions with business activity on various scale tends to lead more innovative environment compared to the economies dominated by large, multinational firms. The investment to these regions reinforces innovation and startup growth. Second, financial needs of small size enterprises and startups may be overlooked and focused in specific locations and business lines (Kymn, 2014). For instance, according to Bloomberg (2022), Silicon Valley and software companies receive more than half of the total funding volume allocated to other regions of the country ("Startups Raked In $621 Billion in 2021, Shattering Funding Records," 2022). Uneven concentration to certain components affects funding decision criteria of the investors. Accelerator programs can be used as an alternative solution to decentralized distribution of the available investments for startup companies (Porat & ECONOMIST, 2014).

The third funding enhancement for the startups is the policy amendments to trigger growth and enhance these firms access to their financial needs. As Kaya (2016) explains, Capital Markets Union project targets startups and young firms at the initial phase of their lifecycle to reach out the necessary finance they require. There are different financing alternatives for different type of startups based on their development stages. An overview for the VC structure and possible challenges for startup financing i.e., equity financing in public markets, bank lending, crowd funding. The paper directly relates to difficulties and advantages of equity financing for startups. There are possible enhancement measurements to overcome setbacks in equity financing such as difficulty for early startups to reach equity funding in public markets, bank loans, low volume in venture capital investments especially in Europe and platform consolidation as an augmentation of crowdfunding options to increase it (Kaya, 2016).

Furthermore, there are other challenges that hinder the potential of the digital startups. Kaya (2017) investigates the challenges that startups need to overcome to present potential value. To achieve this, the author uses the statistical data from German startup companies and explores the reasons in addition to suggesting the policy amendments that needs to be applied. The first reason is that there is a complex regulatory structure that makes it difficult to launch a new firm. With the help of scalable business model and product, previous startup success rate and well-developed examples such as Microsoft or Amazon which are today's giants, they have a growth potential. However, unlike US, German market has different regulatory system since it is exposed to EU laws which are more restrictive than UK or US which justifies low survival rate for technology-based startup companies in Germany. Second, due to lack of financial track record, startups have access constraint to bank loans or other traditional finance sources. Third, political authorities provide tax advantage for VC investors to ramp up startup financing. Fourth, German business culture that is more risk averse compared to US, posits a difficult environment for founders where failure may not be tolerated and loss cannot be compensated. Lastly, the room for improvement in technological infrastructure can slow down the innovative trend (Kaya, 2017).

2.2.2. Funding of Fintech Companies

According to a recent study by KPMG, there has been a considerable increase in funding of Fintech companies globally amounting to USD 210 billion across VC, PE and M&A with 5,684 deals in 2021, according to recent insights (KPMG, 2021). However, according to Nofsinger and Wang, asymmetric information and moral hazard are challenges that restrain the funding of entrepreneurial firms. As the business grows, the firms need the additional capital for expansion. On the other hand, the external investors may not rely on the future earning potential or the success rate because of the moral hazard risk of the startup owners' exploiting the capital for personal use (Nofsinger & Wang, 2011). Therefore, angel investors, seed stage investors and venture capitalist analyze diligently for the expected financial performance (Herck Giaquinto & Bortoluzzo, 2020).

The measures that enhance Fintech companies access to funding can be better clarified with understanding the main drivers of Fintech investment across different market characteristics. Cornelli, Doerr, Franco and Frost analyze the Fintech companies' main growth drivers and diversification of equity funding according to different parameters such as geographical location of the company, segmentation of the market, service and the product. The authors have several key findings. First, the enhanced quality of regulatory framework, level of financial development, capacity for innovation are positively correlated with the growth of the Fintechs. Second, there are country-based differences in Fintech investments. United States, United Kingdom, China and some European countries with advanced financial market structures and innovative technology capacity have higher Fintech investment/GDP ratios. Third, regulatory sandboxes where the financial products have the option to be tested when they operate with a new technology boost innovation and financial technology providers in developed markets (Cornelli et al., 2021).

In addition to the previous research, there are other studies stating that the financial market that Fintech companies operate and regulatory frameworks are impactful on equity investment rounds received by the Fintechs. Kostin, Fendel and Wild investigate the difference in level of economic development between German and Russian Fintech market over equity investments. To reach this goal, the authors apply and exponential growth model to the sample of companies with data provided by Crunchbase platform. They reach a conclusion that the economic and technological determinants behind Fintech startups determine the success rate of the company. Likewise, policies can actively contribute the emergence of the industry (Kostin et al., 2022).

Another study conducted by Rupeika-Apoga and Wendt (2022), examines the dependencies in Fintech development and the impact of regulation on the growth pattern of these firms. The authors investigate the shift in paradigm in financial service technology which is performed by the Fintechs that provides the same service and product range as the incumbent financial institutions but expect to find a leeway from the rigid regulatory framework. Also, until very recently the technology and infrastructure were relatively new and unknown. However, this phenomenon is subject to change as mergers between traditional financial organizations and Fintechs become more common and regardless of their size and scale of their operations compared to big banks, they are still required to be regulated by the authorities. From the perspective of the Fintech firms, they are eager to comply with the legislation since the ambiguity in legal framework creates a disadvantage for them. Before founding the new ventures, the Fintech entrepreneurs are not certain about the possible limitations to their operations and business activities. Therefore, the regulatory authorities took initiative to circumvent the imbalances in financial law and sustain a more solid legal base for Fintech companies (Zaidi & Rupeika-Apoga, 2021). To investigate the perception of the Fintech companies, the authors conducted a survey and comprehensive qualitative research in order to identify what is the position of regulations among the factors that hinder economic growth of Fintechs, specifically operating in Latvia market. The authors investigate the mindset of Fintech companies toward regulatory scrutiny, regulatory risks and the potential impact of regulation and enforcement on the profitability of their operations, for example due to costs associated with the implementation and compliance with regulation. They observed two key findings as a result of the analysis of their survey answers. First, the Fintech owners or entrepreneurs are willing to collaborate with the authorities and utilize tax benefits, flexible regulations for employment of international talent and improvement of the conditions for their future profit. Second and most importantly for the further interpretations of our results, equity funding receives the third place when the respondents are asked to make an order of importance between different funding options. Although majority of them agree that having different funding alternatives is important, they state that seed financing is more important than the others followed by VC (Rupeika-Apoga & Wendt, 2022).

As the importance of VC funding has been justified also with qualitative research, another research with a different methodology is conducted recently. Giaquinto and Bortoluzzo investigate the effect of private equity and venture capital funding on Fintech companies compared to Fintech companies which do not receive this kind of funding. To achieve this goal, the authors use a sample of over 2,500 companies covering a timeline from 2008 to 2018 by estimating with the Logit model in Stata software. They find two key results. First, seed financing has a bigger impact on the performance of Fintech companies from developed economies compared to the impact on the emerging economies in the sample. Second, the Fintech companies in the sample that provide products and services under different categories such as payment, financing, asset management and cryptocurrency, however these factors produce insignificant results on the PE/VC financing amount. Also, the study investigates which line of service in Fintech industry is more likely to receive funding and they conclude that payments and financing companies in their sample from 76 countries have a higher chance to receive funding. In order to further expand the results, the authors also use Crunchbase data platform to analyze PE/VC financing in a framework more concentrated around the angel investor and the distinction between having a single founder or multiple cofounders and the impact of this on financing. The authors conclude that payment and financing companies frame more significant results in the regressions and these companies are more likely to receive funding (Herck Giaquinto & Bortoluzzo, 2020).

According to Hommel and Bican, the criteria to decide funding is associated with the digital entrepreneurship, banking, technology and most notably scalability. The authors conduct 12 expert interviews to interpret important considerations in Fintech funding for equity investors. They reached the following key results: First, different than majority of the industries, the following factors are key for Fintech companies; to be managed by experienced executives, to be steered by a complete vision and increase their survival rate among competitors. Second, scalability is the most important determinant since it is forecasted to be the highest revenue generator by the investors. In addition to the business plans of a Fintech and investor is interested in the prototype of the scalable product to assess customer volume. Lastly, the authors conclude that cost reduction is an aspect that cannot be overlooked by the investors in Fintech funding since the value proposition is built on competition with traditional banks and possible acquisition by the big banks (Hommel & Bican, 2020).

Giarettaa and Chesinib explore the determinants of the debt financing of Fintech startups which gives another perspective to our research according to the capital structure puzzle between debt and equity financing. The relevancy of this study stems from the identification and analysis of the determinants that enable Fintechs to obtain long-term debt and grow by using Tobit regression model. The results from the empirical analysis demonstrate that unregulated Fintech startups are more likely to be financed with long-term debt. Asset structure, owner characteristics and the specific Fintech activity influence the funding source. Moreover, Fintech startups backed by equity investors receive less long-term debt funding than their peers (Giaretta & Chesini, 2021). Accessing external financing is a critical issue for startups due to information asymmetry and lack of collateral and the presence of information asymmetries. The use of debt, indeed, is associated with better performance prospects for startups which can be referred depending on the results of regression model. The results are relevant because they clearly explain which characteristics help firms to receive debt financing which can be used in the discussion as opposed to the equity funding. The findings provide evidence that Fintech startups that receive equity resources from financial investors seek less external debt funding.

Fintech startups in general has different factors that affect their funding process. One of the processes is fundraising which is defined as the sales of a business idea or a design to a portion of the market (Caselli & Negri, 2021). The other determinants which previously identified are the employee volume, revenues, investment, profit and the specific product status of a viable product. Also, the blueprint of Fintech financing and how many rounds did it take to receive funding are prominent parameters in deciding effect of the survival rate of the company. There are various parameters that are influential in fundraising activity such as the size of the company, estimated revenue and the R&D status of a product or technology in progress (Shelters, 2013). Apart from them, specifics of the market that the company is located, risk appetite of the founders or the owners (Ang et al., 2010), (Gastaud et al., 2019), the industry that the company operate (Harding & Cowling, 2006) and available product and service offerings (Roeder et al., 2018) are influential components of fundraising and financing activities of a firm (Khajehpour et al., 2020). As expected, receiving successive VC funding and performing better in subsequent rounds of fundraising are both positively correlated with a business angel's early fundraising experience (Croce et al., 2018a). Firms that through fewer conventional fundraising rounds (such as VC) have higher probability to receive equity-based crowd funding (Bui & "Neo" Bui, 2019). Khajehpour et al. investigate the patterns and the series of funding order for the analysis of the Fintech fundraising. Their goal is to specify the link between capital structure and the firm characteristics that was generalized by the previous literature, to focus more on the business models rather than owners related specifications, to dive deeper on Fintech funding structure, considering their role in development of the financial industry. To achieve this, the authors use the data including 100 Fintech companies from KPMG database by developing algorithms to assess group of investment rounds, so that the categorization of the firms by similar characteristics can create more accurate and inclusive funding patterns for startups. As a result, they achieved three key findings. First, unlike previous literature suggests, there can be venture capitalists even in the early stage of the startups along with the angel investment providers which was less preferred than VC. Second, in the cluster with relatively younger firms, the pattern's dominant funding was also the VC, however the angel investors lacked presence. Third, in general the equity funding was the most used in the last stage of the funding. The paper concludes that equity related funding rounds are sequenced with VC in the next round (Khajehpour et al., 2020).

3. Data and Sample Collection

The goal of this research paper is to find out if Fintech companies are more likely to receive equity funding and if other parameters such as location of the company, size of the company and age of the company have influence on the amount of round of equity funding. Therefore, this paper will be based on quantitative research which includes data collection, analysis, and interpretation. This is conducted with the OLS Regression methodology. First, the sample of companies from various sectors, namely Fintech, e-commerce, health, asset management, software development, biotechnology etc., which are either public or private and already funded via different funding alternatives such as VC, IPO, PE or M&A are chosen. This dataset includes 66,996 startup companies in total and downloaded from Crunchbase database. Crunchbase is a platform that is initiated as a startup itself and used as a reliable source for scholars in academic research of the startup/tech-based companies. It provides up to date financial information uploaded by the companies and accessed freely by the investors which made Crunchbase widely used major source of data with the help of machine learning algorithms based on AI technology (Dalle et al., 2017). This comprehensive dataset is obtained from the platform which is actively contributing to the academic research regarding young entrepreneurial businesses for over a decade. The sample companies' different variables are all reported in the database. These are; size class, headquarter location (city and region), industry, last funding type, number of employees (categorically from 1 to 10,000), IPO status (private or public), foundation date, number of founding rounds, estimated revenue range (categorically; <$1, $1-$10, $10-$50, $50-$100, $100-$500, >$500, in million), total equity funding amount, funding status and last funding type were created and updated, respectively. Regardless of these criteria, all entities are referred to in this context as "startup companies."

The sample companies' headquarters are located in different markets of the world and they operate in 140 countries which allows us to compare funding patterns based on geographic location and analyze differences with respect to different regulatory perspectives, considering continental Europe, India, China and US are the main distinction in the regulatory framework of funding a startup company, business environment and startup ecosystem. Moreover, the companies must have the accurate categorical variable classification which will constitute the dummy variables for the regression and at least one round of equity funding to specify the effect of this type of funding. To avoid static data as much as possible, limiting the data by specifying company age not to be older than 50 years, number of founding rounds not to be greater than 15 and equity funding in total to be less than USD 1 billion and more than USD 10,000 is applied as requirement criteria. To be clearer about the employee number and categorization of the firm size, the European Commission and OECD definition classifications can be used as a reference. According to their framework, small and medium size enterprises are categorized as follows: 1) If the employee size is from 1 to 9, the enterprise is a micro enterprise, 2) if the employee size is from 10 to 49, the enterprise is a small enterprise and 3) if the employee size is from 50 to 250, the enterprise is a medium enterprise (Publications Office of the European Union, 2003), (OECD Data, 2020). This generic threshold holds for majority of the companies and for some of the industries. However, due to the comprehensiveness of the dataset in terms of geographic location of the companies we used a slightly different categorization to name the categorical independent dummy variables. In our research, if the employee size range is 1-10 companies are called micro sized companies, if the employee size range is 11-50 companies are called small sized companies, if the employee size range is 51-100 companies are called medium sized companies. Since startups are more capital-intensive type of businesses rather than labor intensive, the classification size is decreased from 250 to 100 employees.

First, company age to be calculated based on the founded date shall be the indication whether the company can be classified as a young, startup company or not. Hence, we selected a criteria to choose companies founded 50 years ago latest. Second, we exclude the companies that receive more than 15 rounds of funding are excluded since the funding amount may be greater as the rounds increase which can be considered as an outlier in our results. Third, for the interpretation of our regression analysis, receiving a funding more than USD 1 billion can be considered as an outlier and affect the validity of our OLS regression model. After the data clearance is completed with respect to the aforementioned requirements, the dataset is collected. The filtered dataset is generated and 59,429 companies are generated as the final sample. Among these total number of startup companies, the distribution of categorical employee size is shown in Figure 4a, the categorical revenue distribution is shown in Figure 4b, the share of Fintech industry is shown in Figure 4c and the distribution of location of our selected countries is shown in Figure 5d relatively. First, as shown in 4a, approximately half of our filtered sample includes startups with employee size is from 11 to 50, which indicates a startup which is at the end of early growth stage. Second, Figure 4b represents the estimated revenue categorization of our sample startups where majority of them are classified as from USD 1 million to USD 10 million, meaning that the 49% of our sample can be considered as small to medium size startups. Also, the smallest share belongs to the startups with estimated revenue from USD 50 million to USD 100 million, which constitutes only 1,360 companies in total. Third, as we can see from Figure 4c, Fintech industry is only 3% of our total sample because the industry categorization on our raw dataset with 66,996 companies is ordered according to the three to four primary operation field of the company. Therefore, it can be said that there is a detailed decomposition to the subcategories of Fintech such as Blockchain, payments, lending and financial services which can decline the category falls under Fintech since we filter down by the selection of the keyword “fintech” in Python. A certain percentage of the companies can be grouped with a different keyword for their industry, although they could serve under Fintech industry. Lastly, Figure 4d shows the location wise distribution which is mostly in the US and this gives a baseline for our hypothesis and discussion that the startup ecosystem is more developed in the US market.

Figure 4a – The Distribution of Startups based on Employee Size

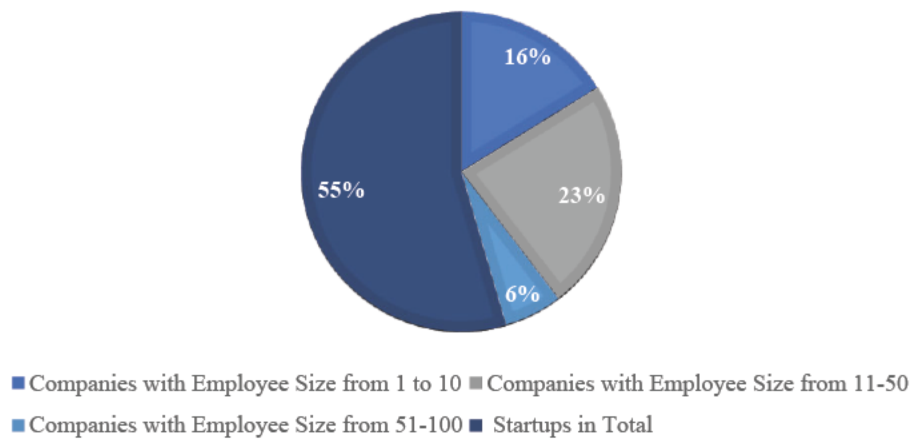


Figure 4b – The Distribution of Startups based on Estimated Revenue

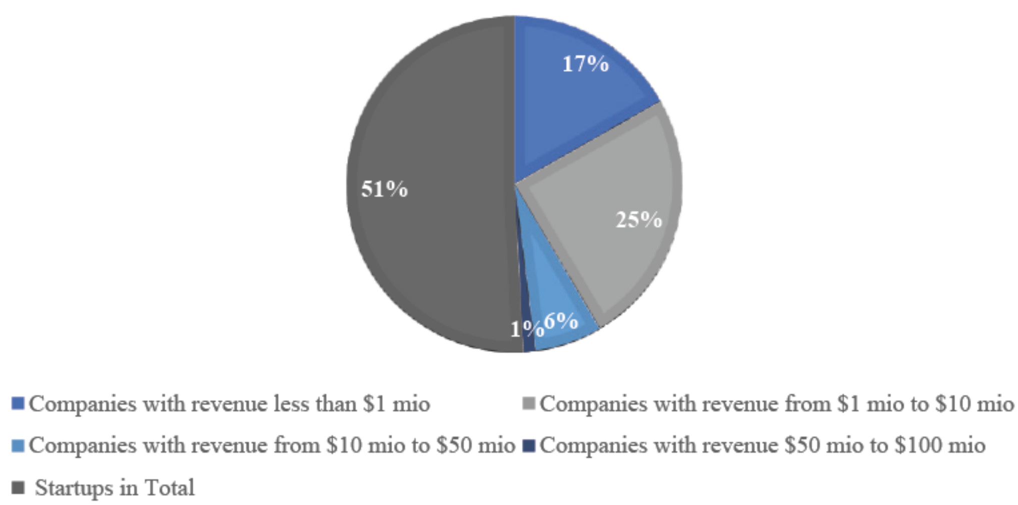


Figure 4c – The Distribution of Startups and Fintech Companies

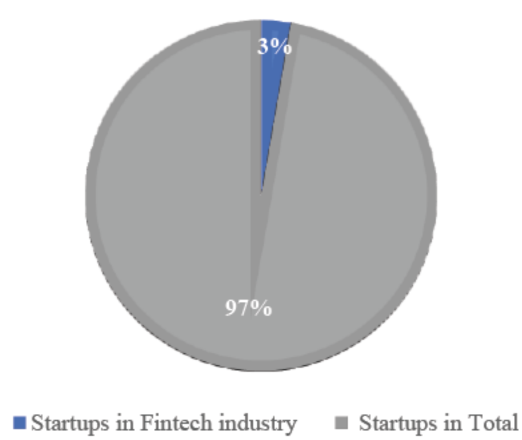
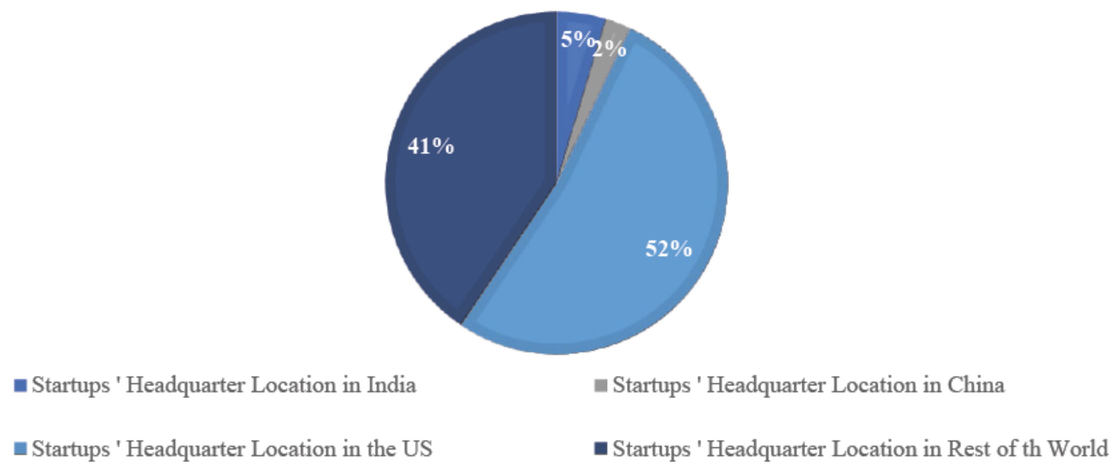
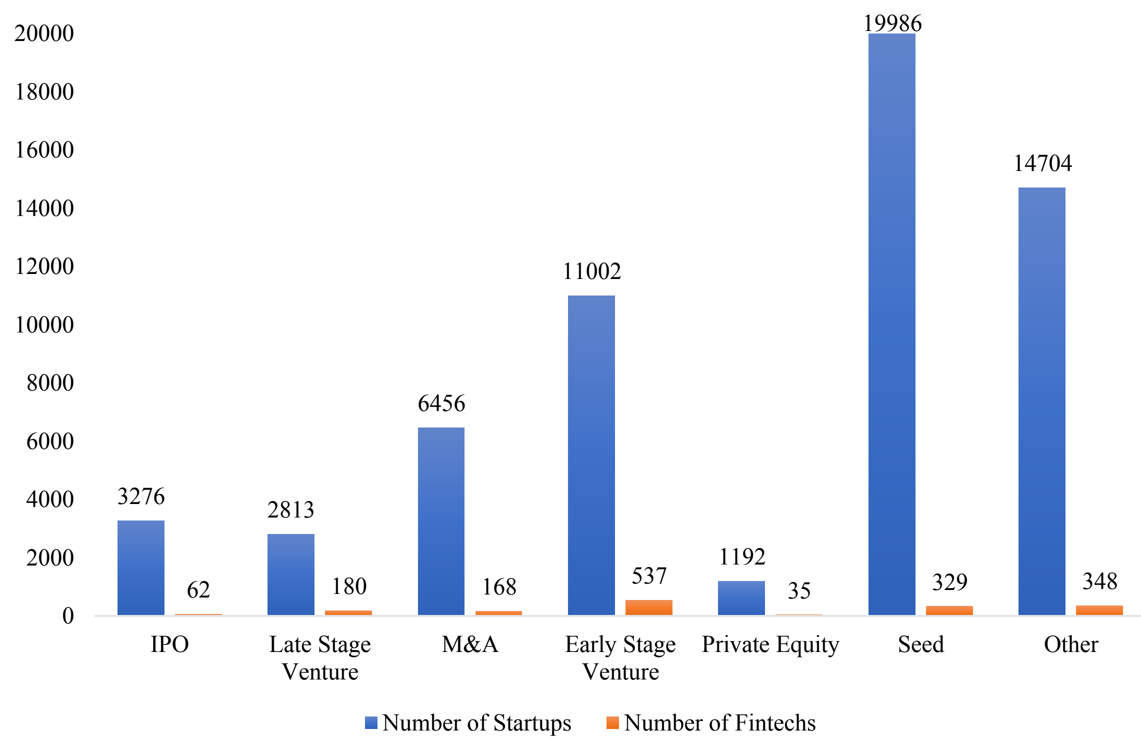


Figure 4d – The Distribution of Startups based on Headquarters' Location



Lastly, as we categorize our filtered data based on the funding status, shown in Figure 5, the majority of our sample is funded with seed financing and early-stage VC. Seed investing symbolizes the very early stage of the lifecycle of the startup which is the initial step of the external capital sources and paves the way towards a VC (Herck Giaquinto & Bortoluzzo, 2020). It is challenging for startups to match with the source of investment who is willing to buy out shares in exchange for capital. Aligned with our sample, majority of the startup companies are in the funding status "Early-Stage Venture". In the augmentation of a startup, the role of angel investors is very critical since they provide the management support, expertise, network and create a positive outcome on the performance and success rate of the startup (Lerner et al., 2018). With the guidance and support of the angel investor, the rounds of follow up investments can be obtained more easily (Werth & Boeert, 2013).

Figure 5 - The number of Startups Based on Funding Status



In the second parameter of the graph in Figure 5, the sample distribution belongs to the Fintech companies. Only 136 of the Fintech firms in our sample has "Debt Financing" as their last funding type since it is considerably difficult for early-stage firms to access typical bank loans which asserts long term interest payments. Therefore, it is more convenient for Fintechs to initiate financing process with the help of an angel investor until they are matched with a private equity and sequentially receive Series A, B, C type of funding options. Angel and seed investors are engaged in actively tracking investment strategy and investment choices to support startup growth. Due to this expertise, close relation to network of investors and entrepreneurs they experience less adverse selection problem resulted from asymmetric information bias. Both in the startup sample and Fintech subsample private equity and IPO has the least share of funding status. When the IPO takes place, PE funds typically own a fixed percentage of the shares of their portfolio businesses and they profit from any gains made after the IPO. The management team, strengthened by incentive compensation tools like stock options, is more likely to support a departure through an IPO than a sale to a third party (especially to a strategic buyer) (Sołoma, 2015). However, a considerable amount of entrepreneurial firms fails before they make it to the IPO stage since they need an established record of success to convince the external investors and public (N. Berger & F. Udell, 1998). The distribution in our dataset represents the challenges of access to PE and IPO funding status for a group of startups that are at the early stage of their growth cycle.

4. Methodology

To determine whether startups especially Fintech companies are more likely to receive equity funding or not and if the independent dummy variables have an influence on the funding amount of a company, an OLS Regression in Python is conducted. This test is specifically designed to show if the startup's or the Fintech company's employee size, estimated revenue, headquarters location and age react to any given funding amount concerning the company's financing need provided via equity funding. For example, the companies funded in US, the companies who operate in digitalized financial services or the companies operating for over 10 years can have an impact on the equity founding amount. Nevertheless, due to the nature of startups, pecking order theory may actually fail to recognize that some companies do not have to face debt-equity tradeoff since, they may be solely founded with equity funding and no debt financing is used (Atherton, 2012). The goal of this research paper is to use the regenerated dataset and analyze the determinants of their funding type, ideally equity funding, to determine what is the startups' and specifically Fintech companies' equity funding pattern. Therefore, the null hypothesis that is tested is that an independent variable has no effect on the equity or total funding amount or on the number of funding rounds or on the equity funding turnaround to alternative that it does:

$$H0: \beta 1 = \beta 2 = \cdots = \beta i = 0$$
$$H1: at\ least\ one\ \beta i\ \neq 0$$

In order to normalize the results of the regression on our large dataset which is relatively skewed and not to overfit our models which can affect our prediction on general pattern of the models, log transformation is applied to the following dependent variables; Equity Funding amounts in USD and Equity Turnover rate. As a result, log-linear model is generated.

The effect of independent variables on two dependent variables which are equity funding amount in USD and number of funding rounds will be modelled with the combination of different dummy variables to see the specific effect of the most influential determinants on the equity funding. The estimation of the statistical impact of the independent continuous and categorical variables on the equity funding amount can be expressed as the following for our benchmark models:

$$log(\text{equity funding amount in USD}) = \alpha + \beta 1 * \text{age} + \beta 2 * employee\ size + \beta 3 * \text{estimated revenue} + \beta 4 * \text{country} + \beta 5 * \text{industry} + \varepsilon i$$

$$\text{Number of funding rounds} = \alpha + \beta 1 * \text{age} + \beta 2 * employee\ size + \beta 3 * \text{estimated revenue} + \beta 4 * \text{country} + \beta 5 * \text{industry} + \varepsilon i$$

$$log(\text{equity funding turnaround}) = \alpha + \beta 1 * \text{age} + \beta 2 * employee\ size + \beta 3 * \text{estimated revenue} + \beta 4 * \text{country} + \beta 5 * \text{industry} + \varepsilon i$$

Where:

α = intercept

ß1,2,3,4,5 = coefficient of each independent variable

employee size = dummy variable, 3 categories for micro, small and medium size of the companies

estimated revenue = dummy variable, 5 categories for revenue estimation up to USD 100 million

country= dummy variable, 1 for headquarters location in US and 0 otherwise

industry = dummy variable, 1 for operating in Fintech industry and 0 otherwise

εi= error term of startup i

4.1. Descriptive Statistics

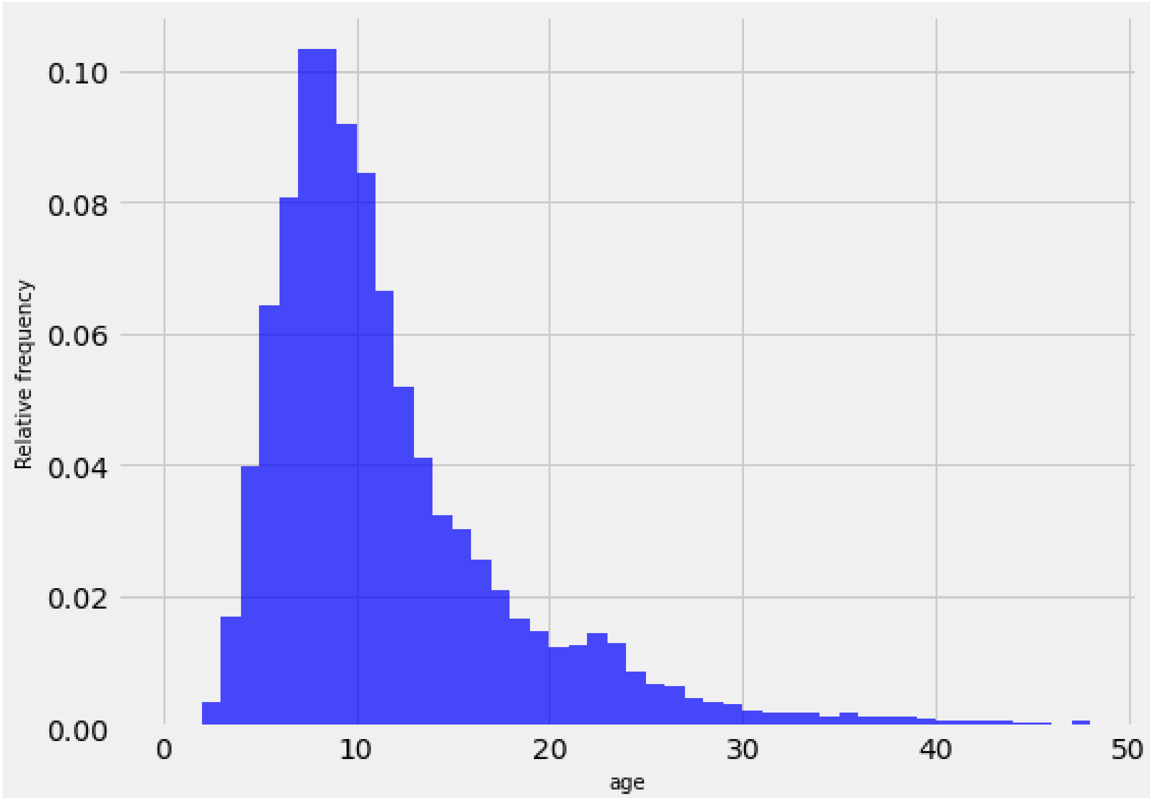
In the Table 1 the descriptive statistics for the variables are shown after the outliers based on the selected criteria has been eliminated. After the data has been filtered according to the criteria; 59,429 observations are generated for unique startup companies. Total Equity Funding Amount is USD 998,700,000 maximum whereas Equity Turnaround Rate is 920,000,000 which indicates that there may be high amount of funding received in a single round, although higher outliers are eliminated from the dataset. To conclude further results regarding the determinants of the equity turnaround rate, additional regressions are performed where ‘Equity Turnaround Rate’ is the dependent variable.

Table 1- Descriptive Statistics for Variables in the Analysis

	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Number of Funding Rounds	59,429	2.764	2.139	1.000	14
Total Equity Funding Amount in USD	59,429	26,262,016	73,957,780	10,134	998,700,000
Equity Turnaround Rate	59,429	904,271	30,515,174	2,272	920,000,000
Age	59,429	11.352	6.835	1	49

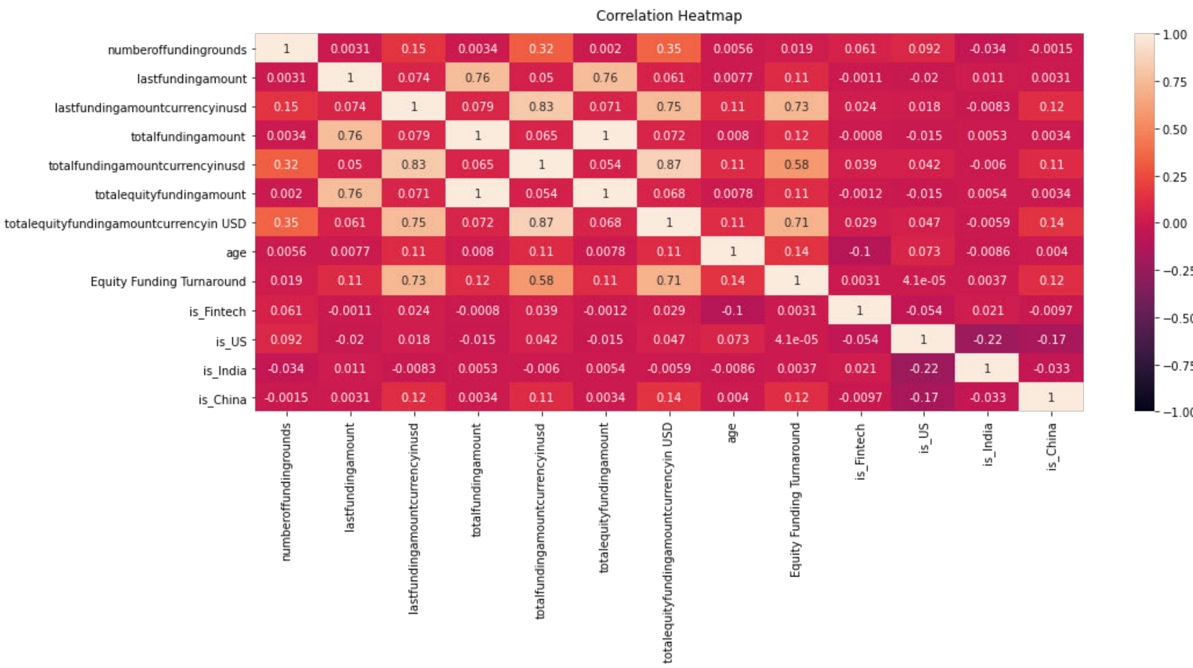
The age distribution of our sample is shown in the histogram in Figure 6 below, indicates the majority of our companies are centered around 10 years and the share of companies with age more than 30 is immaterial. This distribution aligns with Figure 5, where funding status is mostly consists of early-stage financing and less involving private equity or IPO since the latter is more valid for mature startups with a better financial performance forecast, revenue estimation and positive cash flow expectation.

Figure 6 – Distribution of Age within the Sample



The correlation heatmap is designed to identify the relationships and the strength level of the relationships between variables at a glance. As shown in Figure 7, the Pearson correlation coefficient between last funding amount and total funding amount or total funding amount and total equity funding amount is greater than 0.7 which implies a multicollinearity (Newbold, 2013). However, this does not necessarily mean a causal relationship in the model. Also, the equity amounts are not used mutually exclusive in any of the models. Besides the high coefficients for funding amounts and equity turnaround ratio derived from funding amount, which is expected, no strong correlation is observed. There is no strong negative correlation between any pair of variables. The maximum negative correlation value is -0.22 for startups in India and in the US. There are several variables that have no correlation and whose correlation is very small and correlation coefficient is close to zero.

Figure 7 – Correlation Heatmap



4.2. OLS Regression Details

In order to fully understand the interaction between equity funding, number of funding rounds and the aforenamed independent variables, OLS regression method is used for estimation as previous research applies (e.g. (Ewens & Townsend, 2020)). The integration of the dependent variables to the models is separated into three sections and each set of regressions categorized based on the dependent variable, as represented in Appendix A in a detailed way. We formulate five benchmark hypotheses, arranged in order below, and derive interaction terms as additional dummy variables, going forward.

First, the age of the sample companies is calculated as; current year date (2022) minus founded year. By using age, we decide the funding pattern of the young startup companies compared to old startup companies.

Hypothesis 1: *An old startup is more likely to receive* ***larger equity funding amount*** *from investors.*

Second, the employee size of the startup company is effective in equity funding amount. We use micro, small and medium size variables in terms of startup companies' number of employees. We hypothesize that number of employees that the startup has is negatively correlated with the equity funding received by the startup.

Hypothesis 2: *Micro size startups receive* ***less equity funding*** *compared to small and medium size startups.*

Third, the estimated revenue determined with the thresholds in the dataset has an influence on the equity funding amount. We set four thresholds for revenue estimation (estimated revenue less than USD 1 million, USD 1 to 10 million, USD 10 to 50 million and USD 50 to 100 million). It is expected that the estimated revenue up to USD 100 million affects the equity funding amount negatively.

Hypothesis 3: *The startups with lower estimated revenue amount receive* ***less equity funding*** *and lower number of funding rounds.*

Fourth, the geographic location of the headquarter of the startup company determines the equity funding amount. Due to the market conditions, the accelerators, the development level of the financial market which is highly correlated with the access to the funding for newly founded firms and distance to VC investors; we expect to see a positive relationship between the equity funding amount and where the startup is founded.

Hypothesis 4: *The startups with a headquarter in US receive* ***larger equity funding*** *amount and higher number of funding rounds.*

As the last one of our benchmark hypotheses, we include the industry of the startup company. We hypothesize a particular industry as more favorable compared to the others because of the high tendency to rapid applicability, innovative nature and closeness to the financial markets.

Hypothesis 5: *The startups operating in Fintech industry receive* ***larger equity funding*** *amount and higher number of funding rounds.*

There are two parts of our regression analysis; one is done with the variables that are already in our dataset. In this analysis, we aim to regress our dependent variables; total equity funding amount, number of funding rounds and equity turnover rate with our independent variables; age, location, employee size, revenue estimation and industry, Fintech specifically. In the second part, we aim to generate results with interaction terms. For this reason, we create dummy variables as a combination of two different dummy variables. In this way, we regress startups with a certain level of maturity, headquarter location, employee size or industry and integrate into our model as a separate independent variable. Hence, we can make interpretations and comparisons regarding our results.

5. Results

This chapter presents the results obtained from OLS regressions applied on the startup company dataset downloaded from Crunchbase platform and modified for the following reasons: 1) data clearance, 2) elimination of outliers, 3) better representation of young, innovative companies who received at least one round of equity funding with a predefined range of amount. As we formulate our null hypothesis and alternative hypothesis in the Methodology section, the independent variables' coefficients are regressed and evaluated based on them. We test the p-values by comparing in three significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. If the p value is smaller than one of the significance levels, the null hypothesis is rejected. Rejection of the null hypothesis indicates that at least one significant predictor variable is identified in the model (Newbold, 2013). Therefore, the smaller the p value, the more confidence level can be attributed to the validity of our models.

Our benchmark model includes firm age, employee size (micro, small, medium), estimated revenue, headquarters location and industry. The results are presented in Table 2 and Table 3 and divided into two panels, A and B. In the Panel A part of the Table 2, logarithmic value of total equity funding amount in USD currency is used as the dependent variable with different combinations of independent variables. Panel B of the Table 2 represents the four models with number of funding rounds as the dependent variable.

Age: According to the result of the model in Table 2A, Table 2B, Table 3A and Table 3B, the coefficient of the age is an economically insignificant variable on the equity funding amount and the number of funding rounds. However, the variable is statistically significant in all the models, meaning that there is a correlation between the firm's age and equity funding variables. Except Model 1A, the coefficient is negative and *Hypothesis 1* is rejected for this reason.

Employee size: Starting from the Model 1, the models predict the correlation by using age, micro, small and medium size firm variables. The results in Panel A of the Table 2 show that, the firms with employee size from 1 to 10 has highest negative effect in terms of magnitude in receiving equity funding compared to large firms (referred as the firms with more than 100 employees) and this magnitude shows a gradual pattern as the employee size increases. The firms with employee size from 11-50 receives also less equity funding compared to the large firms, the firms with employee size 51-100 receives equity funding amount less than large firms but more than micro and small size firms. The micro sized companies receive the least equity funding as expected. Hence, our results align with *Hypothesis 2*. In Panel B of the Table 2, as the employee size of the firm increase the funding rounds decrease relatively compared to firms with more than 100 employees. Firms with more employees receives the same amount of equity funding in less rounds, possibly in a shorter time.

Estimated revenue: We begin to incorporate estimated revenue variable with Model 2. As the estimated revenue increases up to USD 100 million, the coefficient becomes smaller and less negatively correlated with the equity funding amount. On the other hand, revenue is negatively correlated to funding rounds when revenue is estimated up to USD 10 million. The revenue threshold between USD 10-100 million indicates a positive correlation with the dependent variable. Since the estimated revenue can be decided based on many different parameters such as the industry, sales forecast or the revenue stream, regardless of the firm size, maturity as we previously tested, it is expected to have different correlation patterns. Therefore, we can partially agree to the statement in *Hypothesis 3*.

Headquarters location: The third model includes the headquarters location as US which gives us a positive correlation. When the startup is founded in the US, the equity funding amount is positively correlated, meaning that having a headquarter in the US gives the startup more equity funding and more rounds of funding. This result complies with the statement in *Hypothesis 4* but in order to lead to more comprehensive interpretation we can combine this result with the industry and interaction terms based on location with further regressions.

Industry: The benchmark model is generated with the industry in Model 4, Table 2. When only Fintech companies are added as a dummy variable to the models in Table 2, the results are still economically low. Especially, the results in Panel B of the same table can be explained with low R^2 and low predictable power. In the Model 4, a deeper understanding for Fintech sector can be gained through the additional dummy variable for sector categorization. The results of this final regression show that if the startup is operating as a Fintech, the equity funding amount is positively correlated. Model 3B and 4B show that being located in US and operating in Fintech industry is also positively influence the number of funding rounds, in line with *Hypothesis 5*.

If the predictor variables do not provide any useful information, the model specification has to be revised. In this case, in order to avoid the model misspecification; new and different variables have to be included. When two different dependent variables are compared together, the model better explains the correlation between the same independent variables and the total equity funding amount in USD currency than number of funding rounds. Hence, the Table 3 with interaction terms are created.

Table 2A: OLS Regression Results with Size Variables

Panel A: Dependent Variable: Equity Funding Amount (Log)

	(Model 1A)	(Model 2A)	(Model 3A)	(Model 4A)
Firm Age	0.0072***	-0.0052***	-0.0070***	-0.0056***
	(0.001)	(0.001)	(0.001)	(0.001)
Micro sized Firms	-3.683***	-3.0576***	-3.1082***	-3.0918***
	(0.024)	(0.026)	(0.026)	(0.026)
Small sized Firms	-2.1141***	-1.6026***	-1.6430***	-1.6345***
	(0.022)	(0.024)	(0.024)	(0.024)
Medium sized Firms	-0.8951***	-0.5683***	-0.6023***	-0.5991***
	(0.029)	(0.029)	(0.029)	(0.029)
Estimated Revenue				
< $1 million		-1.8953***	-1.8476***	-1.8433***
		(0.046)	(0.046)	(0.046)
>$1 million and <$10 million		-1.4555***	-1.4025***	-1.4006***
		(0.045)	(0.044)	(0.044)
>$ 10 million and < $ 50 million		-0.8063***	-0.8130***	-0.8105***
		(0.046)	(0.045)	(0.045)
>$ 50 million and < $ 100 million		-0.4215***	-0.4309***	-0.4296***
		(0.062)	(0.062)	(0.062)
Headquarters Location in US			0.3875***	0.3942***
			(0.014)	(0.014)
Industry of the firm: Fintech				0.3561***
				(0.033)
Other Controls				
Constant	17.1234***	18.2690***	18.0823***	18.0338***
	(0.025)	(0.045)	(0.045)	(0.046)
R^2	0.341	0.371	0.379	0.380
Adjusted R^2	0.341	0.371	0.378	0.380

Note: 1. Dependent variable is the log of the total amount of equity funding received.
*2. Standard errors are presented in parentheses and the levels of statistical significance are denoted as follows: * p < 0.1, ** p <0.05, *** p<0.01.*

Table 2B: OLS Regression Results with Size Variables

Panel B: Dependent Variable: Number of Funding Rounds

	(Model 1B)	(Model 2B)	(Model 3B)	(Model 4B)
Firm Age	-0.0257***	-0.0309***	-0.0328***	-0.0311***
	(0.001)	(0.001)	(0.001)	(0.001)
Micro sized Firms	-1.7565***	-1.5041***	-1.5579***	-1.5374***
	(0.027)	(0.030)	(0.030)	(0.030)
Small sized Firms	-1.0183***	-0.8152***	-0.8581***	-0.8476***
	(0.025)	(0.028)	(0.028)	(0.028)
Medium sized Firms	-0.3364***	-0.2286***	-0.2648***	-0.2609***
	(0.033)	(0.034)	(0.034)	(0.034)
Estimated Revenue				
< $1 million		-0.5218***	-0.4712***	-0.4658***
		(0.054)	(0.053)	(0.053)
>$1 million and <$10 million		-0.3565***	-0.3002***	-0.2978***
		(0.052)	(0.052)	(0.052)
>$ 10 million and < $ 50 million		0.0323	0.0252	0.0283
		(0.053)	(0.053)	(0.053)
>$ 50 million and < $ 100 million		0.1504**	0.1404*	0.1420**
		(0.072)	(0.072)	(0.072)
Headquarters Location in US			0.4114***	0.4199***
			(0.017)	(0.017)
Industry of the firm: Fintech				0.4431***
				(0.039)
Other Controls				
Constant	4.0519***	4.2746***	4.0763***	4.0160***
	(0.029)	(0.053)	(0.053)	(0.053)
R^2	0.076	0.082	0.091	0.093
Adjusted R^2	0.076	0.082	0.091	0.093

Note: 1. Dependent variable is the number of funding rounds.
*2. Standard errors are presented in parentheses and the levels of statistical significance are denoted as follows: * p < 0.1, ** p <0.05, *** p<0.01.*

Table 3A: OLS Regression Results with Interaction Variables

Panel A: Dependent Variable: Equity Funding Amount (Log)

	(Model 5A)	(Model 6A)	(Model 7A)	(Model 8A)
Firm Age	-0.056***	-0.0055***	-0.0056***	-0.0056***
	(0.001)	(0.001)	(0.001)	(0.001)
Micro sized Firms	-3.0917***	-3.0792***	-3.0901***	-3.0918***
	(0.026)	(0.026)	(0.026)	(0.026)
Small sized Firms	-1.6345***	-1.6334***	-1.6279***	-1.6344***
	(0.024)	(0.024)	(0.024)	(0.024)
Medium sized Firms	-0.5991***	-0.5987***	-0.5988***	-0.6065***
	(0.029)	(0.029)	(0.029)	(0.030)
Estimated Revenue				
< $1 million	-1.8433***	-1.8347***	-1.8441***	-1.8435***
	(0.044)	(0.046)	(0.046)	(0.046)
>$1 million and <$10 million	-1.4005***	-1.4008***	-1.4015***	-1.4007***
	(0.044)	(0.044)	(0.044)	(0.044)
>$ 10 million and < $ 50 million	-0.8105***	-0.8101***	-0.8112***	-0.8101***
	(0.045)	(0.045)	(0.045)	(0.045)
>$ 50 million and < $ 100 million	-0.4296***	-0.4295***	-0.4301***	-0.4294***
	(0.062)	(0.062)	(0.062)	(0.062)
Headquarters Location in US	0.3942***	0.3944***	0.3943***	0.3944***
	(0.014)	(0.014)	(0.014)	(0.014)***
Industry of the firm: Fintech	0.3607***	0.4181***	0.4081***	0.3400***
	(0.072)	(0.037)	(0.045)	(0.036)
Fintech firms, age less than 10	-0.0059			
	(0.081)			
Micro size Fintech firms		-0.2933***		
		(0.081)		
Small size Fintech firms			-0.1122*	
			(0.066)	
Medium size Fintech firms				0.1293
				(0.100)
Other Controls				
Constant	18.0339***	18.0286***	18.0310***	18.0344***
	(0.046)	(0.046)	(0.046)	(0.046)
R^2	0.380	0.380	0.380	0.380
Adjusted R^2	0.380	0.380	0.380	0.380

Note: 1. Dependent variable is the log of the total amount of equity funding received.
*2. Standard errors are presented in parentheses and the levels of statistical significance are denoted as follows: * p < 0.1, ** p <0.05, *** p<0.01.*

Table 3B: OLS Regression Results with Interaction Variable

Panel B: Dependent Variable: Number of Funding Rounds

	(Model 5B)	(Model 6B)	(Model 7B)	(Model 8B)
Firm Age	-0.0314***	-0.0309***	-0.0310***	-0.0310***
	(0.001)	(0.001)	(0.001)	(0.001)
Micro sized Firms	-1.5366***	-1.5188***	-1.5321***	-1.5376***
	(0.030)	(0.031)	(0.030)	(0.030)
Small sized Firms	-0.8463***	-0.8459***	-0.8264***	-0.8472***
	(0.028)	(0.028)	(0.028)	(0.028)
Medium sized Firms	-0.2598***	-0.2601***	-0.2596***	-0.2763***
	(0.034)	(0.034)	(0.034)	(0.035)
Estimated Revenue				
< $1 million	-0.4643***	-0.4663***	-0.4682***	-0.4663***
	(0.053)	(0.053)	(0.053)	(0.053)
>$1 million and <$10 million	-0.2961***	-0.2981***	-0.3006***	-0.2981***
	(0.052)	(0.052)	(0.052)	(0.052)
>$ 10 million and < $ 50 million	-0.0289	-0.0290	0.0263	0.0291
	(0.053)	(0.053)	(0.053)	(0.053)
>$ 50 million and < $ 100 million	0.1430**	0.1422**	0.1406*	0.1425**
	(0.072)	(0.072)	(0.072)	(0.072)
Headquarters Location in US	0.4190***	0.4201***	0.4200***	0.4201***
	(0.017)	(0.017)	(0.017)	(0.017)
Industry of the firm: Fintech	0.6555***	0.5352***	0.6082***	0.4093***
	(0.084)	(0.044)	(0.053)	(0.042)
Fintech firms, age less than 10	-0.2680***			
	(0.094)			
Micro size Fintech firms		-0.4353***		
		(0.095)		
Small size Fintech firms			-0.3554***	
			(0.077)	
Medium size Fintech firms				0.2733**
				(0.117)
Other Controls				
Constant	4.0185***	4.0083***	4.0072***	4.0172***
	(0.053)	(0.053)	(0.053)	(0.053)
R^2	0.093	0.093	0.093	0.093
Adjusted R^2	0.093	0.093	0.093	0.093

Note: 1. Dependent variable is the number of funding rounds.
*2. Standard errors are presented in parentheses and the levels of statistical significance are denoted as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

In Table 3 above, four different models are formulated to predict the correlation between equity funding and different variables specified for Fintechs as an addition to the benchmark model (Model 4). In Model 5, the young Fintech companies added as an interaction term filtered down from the dataset. 10 years benchmark is used to limit the young category for a startup, considering the oldest startup in our dataset is 49 years old with a relatively low share in total of the data sample (Figure 6). The results are insignificant since the p-value is 0.942, greater than all of the significance levels (0.01, 0.05 and 0.1). Young Fintech companies do not receive more equity funding compared to the aged Fintechs. Further, being a Fintech founded 10 or less years ago, does not have an additional influence on the equity funding amount. To deep dive into the impact of age determinant on the Fintech companies, an interaction term is created by the multiplication of Fintech dummy variable with age dependent variable only. The results are presented in the Appendix B.1. and Appendix B.2. which align with the results derived from young Fintech variable. Since the p-value is 0.236 for the model in Appendix B.1., the results are insignificant which implies that the Fintech industry combined with the age variable does not have a correlation with the equity funding amount. Also, Appendix B.2. confirms that the results are significant only in the significance levels 5% and 10% when the regression model with number of funding rounds as the dependent variable is run. With the justification from our supporting model with age variable interacted with Fintech industry, we can conclude that regardless of the years limit, age is not a significant determinant in equity funding amount.

In addition to that, when the independent variable is the number of funding rounds in Panel B of Table 3, the results confirm that the employee size is negatively correlated with the funding rounds. As employee size increase from one range to another, the decrease in number of funding rounds becomes smaller as we move from micro to medium size firms. In Model 5B, young Fintech variable has a relatively more significant result (p-value = 0.004 and coefficient = -0.2680). Young Fintech firms are negatively correlated to funding rounds whereas Fintechs alone are positively correlated, when we interpret together with our benchmark model, Model 4B (coefficient = 0.4431), for the same independent variable.

The results in Models 6, 7 and 8 show that the firms with employee size from 1 to 10 receives the least equity funding compared to large firms, the firms with employee size from

11-50 receives also less equity funding compared to the large firms (referred to the firms with more than 100 employees), the firms with employee size 51-100 receives equity funding amount less than large firms but more than micro and small size firms. In addition to that, as shown in the results of Model 6A, when a Fintech has maximum 10 employees, it is less likely to receive equity funding compared to micro sized firms from other industries, meaning that Fintech industry is discriminated in micro to medium size variable compared to others. The Model 7 indicates that, for the dependent variable equity funding amount, the results of the independent variable "Fintechs with employee size 11-50" is insignificant only at 1% level and insignificant at 5% and 1% levels. On the other hand, for the number of funding rounds as a dependent variable, the results are significant at all confidence levels, meaning that a small size Fintech firm is likely to receive less equity funding along with less funding rounds, although on a weak level. The Model 8A concludes that, this size effect on Fintech firms, the discrimination effect disappears when the employee size increase from 51 to 100 for medium Fintechs since the p-value is insignificant and there is no correlation between equity funding amount and the size of the Fintech. However, in Model 8B, on significance level 5%, approximately 0.3 more funding rounds are observable for medium size Fintech firms. This result along with the result of the age variable indicate that operating industry and the number of employees working in the startup play a more important role in funding than age characteristics role in startup funding and access to investments because the coefficients are greater. Also, the explanatory power is lower than expected and the coefficients are economically significant but statistically insignificant in general for number of funding rounds as a dependent variable than the equity funding amount. Therefore, the models for the first set of regressions on Panel A explains the results of the regressions on a greater level compared to the models on Panel B.

In addition, two first two set of regression models, the location wise differences need to be investigated to understand the impact of market dynamics of the funding patterns. Since the market characteristics can be associated with each amount given at a certain round, a robustness check is provided with a third dependent variable for the next set of analysis in Table 4. The results are placed in three separate panels into two panels, A, B and C. In the Panel A part of the Table 4, logarithmic value of total equity funding amount in USD currency is appended as the dependent variable, Panel B of the Table 4 depicts the three models with number of funding rounds as the dependent variable and Panel C shows the equity funding ratio as a measurement indicator in the dependent variable parameter.

Table 4A: OLS Regression Results with Location Variables

Panel A: Dependent Variable: Equity Funding Amount (Log)

	(Model 9A)	(Model 10A)	(Model 11A)
Firm Age	-0.056***	-0.0045***	-0.0062***
	(0.001)	(0.001)	(0.001)
Micro sized Firms	-3.0915***	-3.0369***	-3.1424***
	(0.026)	(0.026)	(0.026)
Small sized Firms	-1.6342***	-1.5823***	-1.6753***
	(0.024)	(0.024)	(0.024)
Medium sized Firms	-0.5992***	-0.5654***	-0.6274***
	(0.029)	(0.029)	(0.029)
Estimated Revenue			
< $1 million	-1.8439***	-1.7865***	-1.8462***
	(0.046)	(0.045)	(0.045)
>$1 million and <$10 million	-1.4014***	-1.3473***	-1.3872***
	(0.044)	(0.044)	(0.044)
>$ 10 million and < $ 50 million	-0.8112***	-0.7691***	-0.8072***
	(0.045)	(0.045)	(0.045)
>$ 50 million and < $ 100 million	-0.4303***	-0.4202***	-0.4328***
	(0.062)	(0.061)	(0.061)
Headquarters Location in US	0.3989***	0.4564***	0.3291***
	(0.015)	(0.015)	(0.015)
Industry of the firm: Fintech	0.3961***	0.3745***	0.3378***
	(0.043)	(0.033)	(0.034)
Fintech firms in US	-0.0972		
	(0.067)		
Headquarters Location in China		1.2071***	
		(0.048)	
Fintech firms in China		0.2027	
		(0.247)	
Fintech firms in India			-0.3210**
			(0.139)
Headquarters Location in India			-0.7650***
			(0.038)
Other Controls			
Constant	18.0319***	17.8664***	18.1367***
	(0.046)	(0.046)	(0.046)
R^2	0.380	0.387	0.384
Adjusted R^2	0.380	0.386	0.384

Note: 1. Dependent variable is the log of the total amount of equity funding received.
*2. Standard errors are presented in parentheses and the levels of statistical significance are denoted as follows: * p < 0.1, ** p <0.05, *** p<0.01.*

Table 4B: OLS Regression Results with Location Variables

Panel B: Dependent Variable: Number of Funding Rounds

	(Model 9B)	(Model 10B)	(Model 11B)
Firm Age	-0.0311***	-0.0313***	-0.0315***
	(0.001)	(0.001)	(0.001)
Micro sized Firms	-1.5369***	-1.5490***	-1.5703***
	(0.030)	(0.030)	(0.030)
Small sized Firms	-0.8471***	-0.8587***	-0.8739***
	(0.028)	(0.028)	(0.028)
Medium sized Firms	-0.2609***	-0.2681***	-0.2790***
	(0.034)	(0.034)	(0.034)
Estimated Revenue			
< $1 million	-0.4669***	-0.4779***	-0.4678***
	(0.053)	(0.053)	(0.053)
>$1 million and <$10 million	-0.2992***	-0.3091***	-0.2790***
	(0.052)	(0.052)	(0.034)
>$ 10 million and < $ 50 million	-0.0272	-0.0197	0.0305
	(0.053)	(0.053)	(0.053)
>$ 50 million and < $ 100 million	0.1408*	0.1405*	0.1402*
	(0.072)	(0.072)	(0.072)
Headquarters Location in US	0.4277***	0.4067***	0.3774***
	(0.017)	(0.017)	(0.017)
Industry of the firm: Fintech	0.5107***	0.4429***	0.4236***
	(0.051)***	(0.039)	(0.040)
Fintech firms in US	-0.1641**		
	(0.078)		
Headquarters Location in China		-0.2491***	
		(0.057)	
Fintech firms in China		-0.2471	
		(0.290)	
Fintech firms in India			-0.3378**
			(0.163)
Headquarters Location in India			-0.5062***
			(0.044)
Other Controls			
Constant	4.0127***	4.0513***	4.0834***
	(0.053)	(0.054)	(0.054)
R^2	0.093	0.093	0.095
Adjusted R^2	0.093	0.093	0.095

Note: 1. Dependent variable is the number of funding rounds.
*2. Standard errors are presented in parentheses and the levels of statistical significance are denoted as follows: * p < 0.1, ** p <0.05, *** p<0.01.*

Table 4C: OLS Regression Results with Location Variables

Panel C: Dependent Variable: Equity Funding Turnaround (Log)

	(Model 9C)	(Model 10C)	(Model 11C)
Firm Age	0.0086***	0.0086***	0.0081***
	(0.001)	(0.001)	(0.001)
Micro sized Firms	-2.5794***	-2.5780***	-2.6168***
	(0.023)	(0.023)	(0.023)
Small sized Firms	-1.3843***	-1.3822***	-1.4145***
	(0.021)	(0.021)	(0.021)
Medium sized Firms	-0.5452***	-0.5431***	-0.5660***
	(0.026)	(0.026)	(0.026)
Estimated Revenue			
< $1 million	-1.7158***	-1.7128***	-1.7176***
	(0.041)	(0.041)	(0.041)
>$1 million and <$10 million	-1.3376***	-1.3346***	-1.3273***
	(0.040)	(0.040)	(0.039)
>$ 10 million and < $ 50 million	-0.8247***	-0.8234***	-0.8219***
	(0.040)	(0.040)	(0.040)
>$ 50 million and < $ 100 million	0.4563***	-0.4591***	-0.4583***
	(0.055)	(0.055)	(0.055)
Headquarters Location in US	0.2610***	0.2608***	0.2107***
	(0.013)	(0.013)	(0.013)
Industry of the firm: Fintech	0.2287***	0.1832***	0.1958***
	(0.039)	(0.030)	(0.031)
Fintech firms in US	-0.0499		
	(0.060)		
Headquarters Location in China		1.2176***	
		(0.043)	
Fintech firms in China		0.2625	
		(0.220)	
Fintech firms in India			0.2190*
			(0.124)
Headquarters Location in India			-0.5627***
			(0.034)
Other Controls			
Constant	16.8947***	16.6815***	16.9264***
	(0.053)	(0.041)	(0.054)
R^2	0.365	0.374	0.368
Adjusted R^2	0.365	0.374	0.368

Note: 1. Dependent variable is the logarithmic value of Equity Funding Turnaround.
*2. Standard errors are presented in parentheses and the levels of statistical significance are denoted as follows: * p < 0.1, ** p <0.05, *** p<0.01.*

In Table 4, we represent the results of the second part of our regression models including interaction term with geographical categorical variables. The first interaction term is the Fintech companies located in the US in Model 9. We see that, the model fails to reject the null hypothesis which indicates that being a Fintech company founded in US does not imply a higher amount of equity funding, at 95% confidence interval. Although, the results are significant for both at the benchmark model, Model 3 and Model 4, showing that when the headquarter of the startup is located in the US, it is more likely to be funded with equity; there is no correlation between being a Fintech in the US and equity funding amount. Additionally, in Panel B where the dependent variable is the number of funding rounds, US Fintech companies has a negative relationship with number of funding rounds. Hence, for a further understanding of this result, we added Equity Funding Turnaround as an independent variable for the same model in Panel C and it represents how many rounds does it take for a firm to obtain a given amount of funding. Model 9C confirms that being a Fintech firm in US has no correlation with the equity funding turnaround, validating the Model 9A. In addition, the following set of models are built for the analysis of the emerging market economies to be accurately compared with the emerged US market. Model 10 where the Fintechs with a headquarter placed in China are added as a separate dummy variable shows that Fintechs in China variable is not correlated to equity funding amount, as shown in Model 10A, however being located in China as a startup from different industries shows significantly positive results (coefficient=1.2) for the same model. Panel B verifies that results for the other dependent variable where the results are insignificant for Model 10B which verifies Model 10A. Lastly, in Panel C, we cannot conclude if the investors are more likely to give out high levels of funding per round in China for Fintech companies or not since the results are also insignificant in Model 10C. It can be concluded from Model 10A, Model 10B and Model 10C that being a Fintech company whose headquarter is in China does not have any impact on equity funding amount, number of funding rounds and the equity funding turnaround.

Finally, to complete the comparative analysis based on headquarter location of the startup, Model 11 is integrated to show the impact momentum of Indian Fintechs, if there is any. First, a startup with a headquarter in India is less likely to be funded with equity.

Furthermore, a startup operating as a Fintech and located in India receives more equity funding at the significance levels 0.05 and 0.1, as shown in Model 11A. We can see that, being a Fintech in India provides a disadvantage to a startup in this market in terms of equity funding. When we expand the regression analysis to our second dependent variable, number of funding rounds, in Panel B, we see that the results of the Model 11A and the Model 11B are compatible. If a Fintech's or startup's headquarter is located in India the number of funding rounds and equity funding amount decrease. Furthermore, Panel C represents that the variable 'Fintech firms in India' has insignificant result at 1% and %5 levels and significant results at %10. We can conclude that the Fintech firms whose headquarter is India receives the same amount of equity funding in 0.2, (when the dummy variable is equal to 1) rounds fewer in 90% confidence interval which the total variability is explained by the regression model.

6. Discussion

6.1. Relevance of the Findings

The results have been stated under the light of our research question that asks if the Fintech firms are more likely to receive equity funding. To answer this question, we include different determinants as our independent variables throughout the various regression models to check the validity of our initial hypothesis and determine the overall effect of these determinants on equity funding amount, number of funding rounds and finally equity turnaround rate as a robustness check. For the relevance of our findings, it is noteworthy to mention four key determinants that have an impact on the discussion of our results.

First of all, we use firm's age as a measurement of how the startup is perceived in the market since the level of maturity is associated with the creditworthiness, reliability and financial rigidness for a company, we investigate the link with equity funding amount, if there is any (Abor & Biekpe, 2009), (Diamond, 1989). Age determinant has the same pattern in our results, indicating significant correlation in all of our models, except the first model 2A. In the remaining models, firm's age is negatively correlated with both the equity funding amount and number of funding rounds, when the age range of our sample companies is up to 50 years. The business risks of a new and young startup combined with uncertainty of the prospective growth pattern makes it challenging to find investors for their funding needs (Herck Giaquinto & Bortoluzzo, 2020). On the other hand, according to Cosh, Cumming and Hughes (2009), young and innovation driven firms have a tendency to ask for funding from external capital sources such as VC investors. Newly founded firms with high growth targets are preferred for investing by especially trade customer/suppliers compared to other companies that are tested (Cosh et al., 2009). Therefore, they have a potential for growth which gives them an advantage to receive funding. The older startups may prefer and have the capability to access more traditional financing alternatives such as bank loans. Previous literature supports this argument for firm age in general and aligns with POT that there is a positive relation between firms access to external financing options and maturity level (Quartey, 2003), (Osei-Assibey et al., 2012), (Hall et al., 2004).

Second, a size variable is critical for our analysis and our dataset includes eight different categories to classify the employee size (in various ranges from 1 to 10,000). There are other measurement types besides employee size to measure the business volume of the company such as value of the total assets or the total sales volume (Osei-Assibey et al., 2012) however our dataset is not extended to these variables. We categorize the employee size and regress them as three separate dummy variables to understand the effect on equity funding amount. All of our models verify that the employee size and equity funding amount and number of funding rounds are negatively correlated and the effect gets weaker as the number of employees expands up to 100 employees in medium firms' category. Startups are usually technology intensive firms and they do not require a load of workforce anymore because their intangible asset what their production relies on is the idea and a relatively small team of talent, skillset and technical know-how (Bhatt, 2022).

In our third hypothesis, revenue estimation which scales the future growth potential of the startup and affects how much equity funding will be received from the investors. The possibility to attract VC increase as the firm shows promising return capabilities (Koba, 2021). As the expectation of revenue growth improves, the business of the startup becomes more lucrative and receive more equity funding as confirmed by our results (Ramsinghani, 2014). The revenue estimation can be linked to the age of the startup as well. As the startup becomes more seasoned and the revenue growth estimation implies high returns, the possibility of VC investors or equity investors to be attracted increases (Hogan et al., 2017). One of the possible considerations when interpreting this result can be the significant assets value that is required by the banks in order to give out loans to the high-tech ventures. Small and newly funded startup firms do not have substantial profits, assets or capital that can lead them to external debt sources. However, they are likely to seek external finance preferably from VC although VC financing is difficult to obtain due to the limited funds to be assigned the most profitable startup (Cosh et al., 2009). Revenue as one of the key success determinants of the startups is found to be uncorrelated to VC investing and total funding whereas a positive relation is found between funding and annual sales (Hadley et al., 2018). Hence, estimated revenue as a dummy variable can be supported with other dependent variables integrated into our regression models, e.g., periodical sales (or any metric that contributes to the revenue stream of the startup).

As the purpose of this study is to reveal the fundamental reasons that affect the equity funding pattern, it is essential to include market location-based differences and analyze their results since the market is directly related to startup culture and level of improvement of the startup ecosystem. It was previously investigated in the literature that access to external funding is critically important for the development of a startup ecosystem in a certain market (Gorman & Sahlman, 1989), (D. J. Cumming et al., 2017), (Bernstein et al., 2016). The first headquarter location is the US where the startup ecosystem has been ranking as the leader for many years and presence of VC investments is known to be advanced with an industry amounting to USD 63 billion market size (*Venture Capital & Principal Trading in the US - Market Size 2002–2028*, 2022). For our fourth hypothesis, we test if it has a substantial effect on the equity funding when the headquarter is located in the US. According to our results, which are significant at all significance levels, the null hypothesis is rejected. Due to the development level of the startup market, having a base in US gives the startup an advantage in terms of access to equity funding. For comparison, other locations such as China and India used as dummy variables where the economies are emerging and the financial markets have different nature and structure. In China, the results show that although, there is a positive correlation between equity funding amount, there is a negative relationship with number of funding rounds. In the case of India, we see that, location is a disadvantage and there is a significant negative correlation with the equity funding amount. We need to perform a robustness check to analyze these location-based results combined with the characteristic differences and industry specifics for further interpretation.

6.2. Robustness Check

The access to financing needs and external capital is essential for firms that are categorized as startups for their growth. As they grow in terms of size and economical capacity, these new firms tend to lead to employment and productivity via boost in innovation (Rajan & Zingales, 1996). For innovation and job creation to be stimulated and the sufficient ecosystem to be generated; it is essential for financial industry to be disrupted. The new paradigm in the finance world moves towards a technology driven, user friendly, outside of the rigid regulatory framework companies. Thus, Fintech firms create faster, cost efficient and resilient financial industry with the improvements which comes along within the developments in the Fintech sector to accelerate the service and product quality (Lee & Shin, 2018). Current bottlenecks experienced by both retail clients and corporate institutions can be reduced with the augmentation of the Fintechs. Hence, small loans can be more available as an offering to new ventures since the transaction cost is lower as a result of financial technology, for instance. This chapter clarifies the results to explain the characteristics that have an influence on the Fintech industry in selected markets in a detailed way and make inference with the additional dependent variable “equity funding turnaround”.

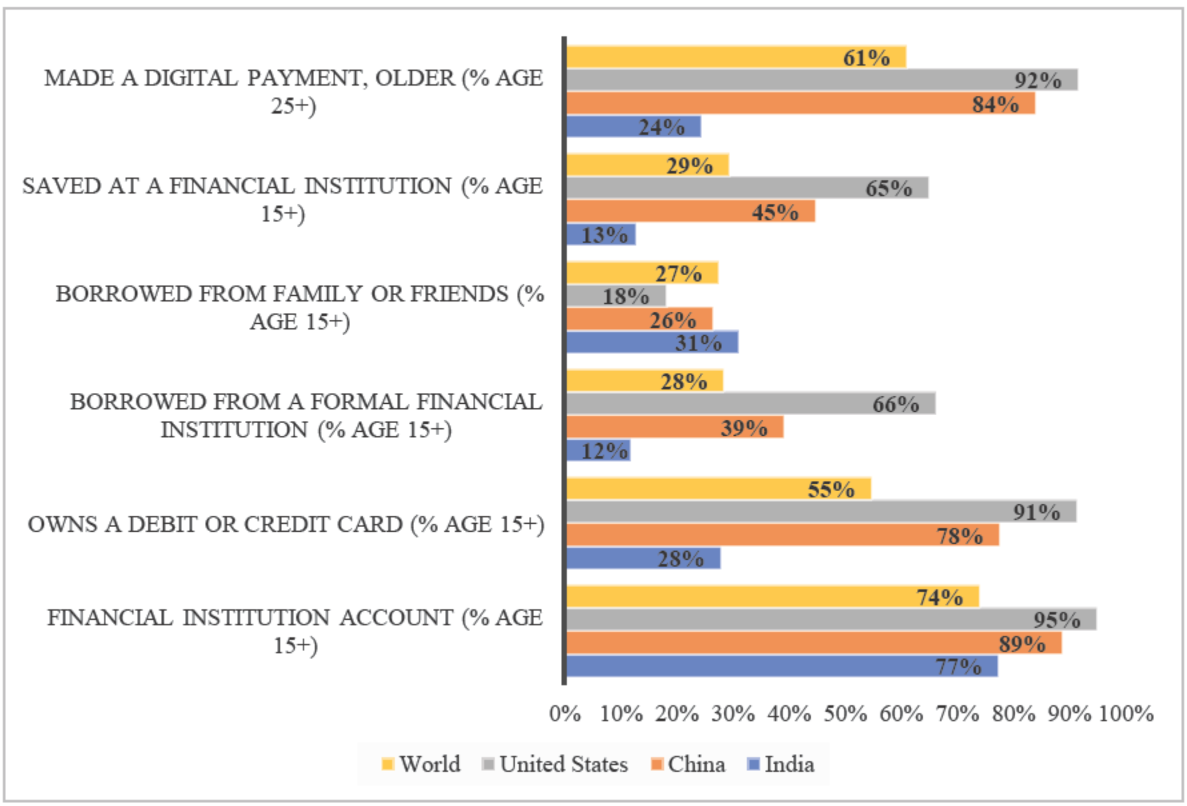
To associate the relationship between Fintech industries in different geographies which is believed to be effective in the financial growth and funding provision for innovative firms, related interaction terms are used in our dataset as a dummy variable. Thus, Fintech industry criteria which is the main focus of our research objective is integrated into our regression models. In all of our models, startups which are operating in the Fintech industry are positively correlated to both equity funding amount and the number of funding rounds. Further, when the employee size is combined with the Fintech firms as an interaction term, micro and small size variables are negatively correlated to equity funding amount and being a medium size Fintech is positively correlated to both dependent variables. This can be explained with the growth of employee size, the Fintech becomes more matured and may be more inclined to provide funding needs from traditional financing alternatives. Also from the investor side, when the risk is higher at the early stage of the financing, the expected return on investment is higher which makes the Fintech more attractive to be funded. This result is aligned with our model including the estimated revenue variable. As the estimated revenue gradually increase to USD 100 million, the momentum of negative correlation decreases.

Moreover, it can be concluded from the results that, operating in financial technology industry and providing technological financial solutions increase a startup's possibility to receive equity funding. This result is valid when the dummy variable is not subject to any interaction with another variable including geographic location of the headquarter, age or any of our size variables. Accordingly, the location of the headquarter affects our results as we test the hypothesis and present the result in Table 4. According to the Model 11, both total equity funding amount received and number of funding rounds are negatively correlated to headquarters of the Fintech being located in India. In all of our results, the negative correlation coefficient is greater on equity funding than number of funding rounds. To have a more comprehensive understanding of this result, we can analyze the results in Table 4 Panel C*,* which regresses the equity funding turnaround as dependent variable. According to the results of Model 11C, being a Fintech in India is negatively correlated to equity funding turnaround. On the other hand, the relation is only significant if we test the hypothesis at 10% confidence level. We can state that, Fintech firms in India receives on average 0.2% more equity funding turnaround and the targeted funding amount is reached faster. The same model gives the following result for the US: Being a startup in the US is positively correlated and being a Fintech in the US is not correlated to equity funding turnaround because the results are insignificant. When we test the model for China, startup location variable has an economically significant positive effect and when Fintech is combined with location variable in the interaction term has insignificant results. The difference between our empirical results suggests that the distinctions in level of development in these three different economies and Fintech sector can be substantial for our discussion under three main parts.

First of all, it is plausible to mention funding gaps that is lack of source of funding ready for enterprises to use for their financing needs. Due to the consequences of the funding gaps, some of the startups with promising growth prospects cannot get access to investment or capital boost especially, when they need to scale their business size with a funding more than 3F- family, friends and fools - is capable of (Fazekas & Becsky-Nagy, 2015). It is noteworthy that there is a funding gap in Fintech sector currently. Especially after Covid-19 pandemic, there has been a declining shift in VC investments since the investors prefer to stay more on the liquid side. In such an environment where the competition for funding among startup companies peaks due to the low risk appetite of investors, it can be challenging to access to the equity funding. Another setback that challenges the funding levels is the declining profitability and downside expectation in 2020 and onwards (Zachariadis et al., 2020). This could be an opportunity to become an early-stage investor for the potential high revenue generating Fintech firms and support the ecosystem because the incumbent banks minimize their physical existence recently due to the developments in digitalization. Particularly certain Fintech companies operating in certain areas such as open banking, crowdfunding and mobile payments can be an important source of return for the VC investors.

Second, financial inclusion can be a possible reason to explain why being located in India is not a favorable feature in receiving equity funding. Financial inclusion level indicates to what extend the integration to the banking or financial services is completed in the society. The lack of integration to these services and lack of alignment with the technological developments can pose a threat to possible economic growth particularly in emerging markets (Garg & Agarwal, 2014). Limited access to the technological solutions for the financial needs prevent financial inclusion level to rise and also development of the environment where financial institutions other than brick and mortar banks grow. India is one of the largest startup hubs in the world (Makai, 2021). On the other hand, it is known that compared to other countries used as a location dummy variable in our research, namely China and US, the level of financial inclusion is the lowest in India which may indicate a rationing for the results of the regression. As shown in Appendix C, we downloaded a set of data by utilizing the Global Findex, a database provided by World Bank, updated as of 2021 and selected six fundamental financial transaction criteria. These criteria include usage of payment services, digital financial solutions, borrowing/lending activity from financial institutions and informal sources and account holding ratios, in percentages for three different regions and comparison with the world average as a benchmark. They are shown for 2021 in Figure 8 below, as a summary of the current status. The data from China align with our results that indicate a significantly positive correlation with the equity funding and headquarters location in China. On the other hand, India has the least activity ratio and society interaction to financial systems even in the most fundamental banking and finance activities. For instance, borrowing money from the family and friends has the highest rate in India which complements the statistics that represents the low percentage of borrowing from a financial institution in that region. When we analyze the results from the US, we see that especially the ratio of mobile and digital payments and debit or credit card ownership are peaked in since 2014 that explains the extend of integration to financial markets and financial activities in every layer of the society (from age 15 and above) and high level of financial inclusion as shown in Appendix C. We aim to show that this comparison relates the differences in complexity level of market structures, various difficulty level of access to simple financial products, affordability of financial solution and services in different geographical regions.

Figure 8 – The Level of Financial Inclusion in India, China, US and World (2021)



Data Source: The Global Findex Database 2021 (World Bank, 2021).

In summary, in the emerging markets, a high portion of the society is still unbanked and it is a challenge for small size firms to reach out credit and alternative capital solutions (Zalan & Toufaily, 2017). These inefficiencies are frequently severe in emerging economies when the population has less access to financial products and small firms face more credit restrictions. For instance, The Global Findex, reveals that just 63% of individuals in emerging nations have an account, compared to 94% in affluent economies (World Bank, 2021). Financial services can stimulate growth by lowering the cost of receiving payment or by enabling individuals to save and invest in their health and education (Leong et al., 2017). The financial integration and knowledge level is lower in India which makes the country one of the largest financially illiterate society in the world. According to previous literature, there are four key reasons that can cause to this problem in India; geographical access, high cost, inappropriate banking products, and low level of financial literacy. The vast majority of the population in India lives in rural areas and this creates a physical distance combined with inadequate infrastructure. Although the percentage of account ownership for Indians in rural regions is increased with the financial inclusion accelerator programs, the ratio of active users is still not at the desired level. The most important reasons behind this situation are the unaffordability of the financial services or the products and product-client mismatch and physical access to financial institutions is a burden for the society (Schuetz & Venkatesh, 2020). Therefore, in order to be useful and to have an impact on personal financial management of the society, financial products must initially be adapted to their needs so that the financial inclusion can be fully realized. To promote and ensure consumer confidence in the legal financial system, protection and education on a financial service user level needs to be sustained. Basically, achieving the benefits of financial inclusion requires a sufficient financial infrastructure, a regulatory framework that supports innovation and a financial system that is solid, strong and dependable (Demirgüç-Kunt & Singer, 2017).

Lastly, the different regulatory and legislative structure along with policies effective in these regions can be a reason for lack of funding appetite or equity funding provision in longer time periods, with more funding rounds. According to our results, this case is especially valid in the startups with headquarter located in China since the results are the most significantly correlated to dependent variable “equity funding turnaround”, regardless of operating in the Fintech industry. The startup ecosystem policy implementations by the Chinese government, led the successful startup giants, Baidu, Alibaba, Tencent, in the country since 2015 thanks to the massive entrepreneurship and innovation targets to combat unemployment in the young portion of the society. Similar to incubators and accelerators, the support platform for the newly founded ventures boosted the culture as well as their financing needs via funds allocated by the government (Hyun et al., 2020). Also, the e-commerce, logistics and AI are the main focus of industries where revenue stream is more reliable compared to Fintechs which is influential in selecting which companies to be funded. Hence, in China, startup funding has a greater positive correlation and less funding rounds compared to the other countries in our sample.

6.3. Limitations, Challenges and Suggestions for Future Research

This study expands on the current literature with key findings and connection between multiple determinants of startups and equity funding amount. However, this research has room for improvement for further analysis and comparison of different funding determinants.

Even though this study makes a substantial contribution to the field of startup funding, it has some limitations. The limitations and challenges can be model related or dataset related. First, despite the dataset is comprehensive enough to include 66,996 startups' data in industry, headquarters location, IPO status, number of employees, estimated revenue, founding date and total funding amount, it can be expanded and/or filtered to clusters to make a comparative analysis with similar company groups. Startups are one of the two focus groups of this study together with the Fintechs regardless of the different characteristics of the content of financial technology used or the financial technology solution being provided. Consequently, it might be better to concentrate on a sample from a single industry's subsection of areas. For instance, a sample consist of Fintechs providing only mobile payment solutions or a sample of startups operating in Bioinformatics industry using AI algorithms can be composed as a cluster and same set of regressions can be run based on this grouping. Moreover, a thorough qualitative inquiry may be reckoned in order to give a more extensive portrait because a mere empirical study may not present a detailed grasp of the correlation of funding amount and startup characteristics. In our research, four independent, categorical variables together with one continuous numerical variable were included. Hence, it is advised that future studies can be based on additional factors such as the background and the gender of the founder/cofounder, perception of startup ecosystem in a given market, an additional dummy variable representing the financial inclusion. A complementary analysis using the survey methodology with startup founders or venture capitalists would also be interesting. They could provide additional input to specify the likelihood of receiving the equity funding and combine the results as quantitative and qualitative.

Second, other limitations and challenges of our research are model related ones. One of them is the relatively less explanatory power of the model on the number of funding rounds compared to equity funding amount. Although the outlier funding rounds which are more than 15 are eliminated, the model predicts the independent variables with only economically insignificant coefficients especially for the age. A plausible explanation for this can be the skewed distribution of the number of funding rounds data, as shown in Appendix D. We can conclude that even the oldest Fintech company received 0.05 additional round of funding in our dataset. When the model is tested with the new aforementioned dataset with additional determinants affecting the number of funding rounds, the result can be more material and the age variable can be better interpreted for understanding the equity funding mechanisms.

Third, we show the results of estimated revenue of the startups up to USD 100 million and analyze accordingly. However, combining this approach with other financial metrics which can be available on Crunchbase platform gives a better understanding in terms of understanding the external finance dynamics of the investors. Return on Investments (ROI) ratio, annual sales, funding and revenue turnaround ratio can reveal a pattern about how VC investments are transforming a startup into a positive return and enables success.

Fourth, in this analysis we try to estimate the regional discrepancies by comparing countries as comprehensive and as different as possible to identify the headquarter location impact. For this purpose, we integrate China, US and India to the models and limit this dummy variable to these three countries only. However, this impact can be expanded with other startup ecosystems from different regions and dissimilar to our current regions such as Nordic countries. When we take a look at the Nordic startup ecosystem, countries such as

Finland and Sweden have high rates of successful startups and an advanced ecosystem. The reasons and motivations that place these markets in a different position are the technological advancement level, digital integration, the government system that promotes social welfare and flexible and compatible entrepreneurship culture that allows boosting innovative ideas (Kaya, 2017). In order to take a deeper dive into the regional and governmental differences, these Scandinavian countries can be appended to our current models and OLS regression results can be compared to emerging ecosystems in China and India or with US which has advanced financial inclusion level but different political climate. This suggested study can produce interesting results in terms of location effect on startup equity funding and measurement of policy updates and incentives.

Fifth, due to the limitations of an empirical study, some models may produce puzzling or unpredictable results. As one of the pitfalls of our selected methodology, OLS, in case of a mispredicted error term, the remaining part of the data is impacted on a greater magnitude due to the square multiplication since the OLS' s main focus is to minimize the standard errors. Although, at the beginning when we clear out the raw dataset, the filtered data has still outliers and this affects the results of the model in a negative way. Moreover, the linearity is another bottleneck of this regression methodology. In our dataset, the funding amounts, estimated revenues and equity funding turnaround consist of large value numbers and when we run them with dummy variables in the model, the predicted variable has a tendency to give zero as a probability result. In order to tackle this limitation, we use logarithmic values for the equity funding amounts and run the models according to this new dependent variable value. After the logarithmic transformation both the explanatory power of our regression models and training of the data points produce better estimation. To deal with this problem, cross validation with a more complex regression method can be performed such as Kernel regression (ClockBackward, 2019).

6.4. Further Outlook on Fintech Funding

As mentioned in the result section of our research, the model where both China and India is added into the regression for an interpretation of the emerging economies, it has been observed that China received more investment compared to US, UK and India due to the policy update and support by the government to create a startup ecosystem. On the other hand, in recent years the restrictions and regulations regarding the cryptocurrencies in China (Riley, 2021) could have a larger effect on the results due to the discouraging environment for startups, especially Fintechs to grow and receive funding. Fintech funding is a relatively new topic with its upcoming consequences including regulatory framework, competition with traditional banks and large technology companies. Currently, there is a declining pattern in Fintech financing compared to last year as shown in the Figure 9 (*State of Fintech Q3'22 Report*, 2022). An additional study can be expanded to understand the severe drop in the deal numbers and funding amounts in the Fintech industry globally starting with the first quarter of 2022.

Figure 9 – Global Fintech Investment Volume

Data Source: CB Insights, State of Fintech Q3'22 Report, 2022 (*State of Fintech Q3'22 Report*, 2022).

Further important result that can lead to auxiliary research is the negative coefficient results in the model where Indian startup companies are included. Although India has the skillset, innovation hub and know how that is required to grow a startup, the results show that equity funding amount is negatively correlated to the geographical dummy variable for India. In this case, there can be room for improvement of the results with a study focusing specifically on startup funding in India and compare with other emerging economies to investigate the reasons. Moreover, a possible capital or talent outflow in India can be researched with a qualitative approach including expert and founder interviews.

Another aspect of the Fintech that can be associated with funding mechanisms and still limited is the effect of Blockchain technology on the growth of Fintech in different markets and regions. Blockchain and financial inclusion in emerging economies can be subject of another research. The results are expected to confirm the empirical results of our study. Moreover, the underlying reasons that lead to the financial exclusion such as high cost, geographical access, lack of compatible financial products, and financial illiteracy (Schuetz & Venkatesh, 2020). As an addition to physical and geographical challenges, the overall income level of the country is USD 110, according to the statistical data from 2017 (NABARD, 2018). Financial inclusion may be too overpriced for Indian households and informal practices in financing processes lacks the financial product range from a simple loan towards more complex ones. However, with its challenges and advantages Blockchain can alleviate some of the aforementioned bottlenecks resulted from financial exclusion in India for three key reasons.

First of all, the technology behind Blockchain enables transactions without intermediaries. Even though the nature of the transactions is still in a traditional, cash-based manner, the benefit of lack of intermediary individuals or institutions can be an important impediment to integrate the rural regions with more financial transactions without having the risk of dealing with an intermediary. In the further stage, the introduction of smart contracts which enable transaction protocol with automation without the need to guarantee of payment situation or check if there is sufficient fund available to complete the transaction. Also, for the lenders even if there is an uncertainty about the credit track record of the borrower, this technology brings reliability (Schuetz & Venkatesh, 2020). Considering trust is an important factor affecting the creditworthiness in an emerging market economy, financial exclusion can be eliminated on a substantial level. With the adoption of further technological advancements, financial inclusion as well as financial technology hub can lead to better outcomes for both Fintechs and other startups in terms of reaching out to investments.

Further research can be conducted on the specification of the different branches of Fintech industry. Our dataset is limited and selective in terms of the industry specification of the startup. However, there are different categories in terms of 1) the service provided by the

Fintech, 2) the level of financial regulation, 3) the customer segment, 4) traditional financial institutions and 5) the technology that is used to enable the financial service mechanisms (Lee & Shin, 2018). These different components can alter the result if they are used as a separate categorical determinant variables regressed on equity funding amount. The dataset can be expanded with these specifications. For instance, the Fintech may be developing its technology based on Big Data Analytics, Cloud Computing, Algorithmic Trading or Cryptocurrency. Likewise, the Fintech may be operating in Payment, Wealth Management, Lending or Crowdfunding fields. Currently the top deals are obtained by Payment and Insurtech categories, USD 3.9 billion and USD 2.3 billion respectively, as of Q3 2022 ("Global Fintech Funding Continues to Decline; Drops 38% QoQ," 2022). Similarly, traditional financial institutions that are also important players in the financial ecosystem such as incumbent banks, insurance companies, Stock Brokerage firms or VC firms itself can be tested to see if they correlated to funding methods and amounts for the future research.

7. Conclusion

Fintech startup finance is still a mostly untapped subject. Multiple regressions are applied to a hand-collected dataset on startup companies in different sizes, markets and from different industries. This study examines the financing of 59,429 start-ups and 866 Fintechs by analyzing the effects of their characteristics on equity-based funding. We first identify the correlated determinants with equity funding amount with a benchmark model. We found that, the five selected determinants; 1) firm's age, 2) location of the headquarters', 3) employee size, 4) status of operating in Fintech industry and 5) estimated revenue are correlated to equity funding amount and number of funding rounds. The results are relevant because they clearly explain which characteristics help firms receive equity financing and which do not. Second, we expand our benchmark models by adding interaction terms which are generated via summation of two selected categorical variables. Third, in order to deep dive and investigate our results that we derived in the benchmark model, we perform robustness check by running the regressions on equity funding turnaround variable.

As a result, we have concluded three key findings. First of all, there is an inverse relationship between the age of the startup and equity funding amount, however age is positively correlated with equity funding turnaround. Second, size and estimated revenue variables are negatively correlated to equity funding received but their effect gradually weakens as the estimated revenue buckets raise. Third, being in the Fintech industry has the impact to change the size variables momentum in terms of changing the equity funding status, however Fintech industry characteristic has no significant impact on location to be a determinant in equity funding amount. In terms of location, the most robust result is derived from the startup data filtered down to headquarter location in China. There is a strong link between equity funding and being founded in China. Further, when the startup is founded in India, all of our results indicate a negative correlation and a disadvantage in terms of receiving equity funding. Last but not the least, when we revisit our research objective regarding the assessment of likelihood of Fintech firms to receive equity funding, we found out that they have a tendency to receive equity funding and receive additional funding rounds due to their industry compared to the other industries.

For the second part of our research question, we investigate if there is a correlation between being a Fintech and equity funding turnarounds (Total Equity Funding Amount/ Number of Funding Rounds). We found that location has an effect on equity funding turnaround only when the headquarter of the Fintech is in China, when we test our models for the Fintech companies in China, India and the US. The unique position of Fintech firms among other startups, require investigation of the funding mechanisms with more scrutiny and it is not always simple to make substantive interpretations. With the development of alternative lending and borrowing solutions, classical theories like POT may fail to explain these patterns. New technologies such as DLT brings new sources of capital, new funding mechanisms and new investors along with it. Moreover, the uncertainty risk attached to the equity funding and longer-term return projection must be compensated with the excessive return which is challenging to assess at the early stages of the Fintech companies.

All in all, this study, aims to contribute to the gap in the literature by providing an empirical overview for the startup and Fintech funding with selected determinants. Considering there are many determinants affecting the funding type, amount, timeline, turnaround of the new ventures, further questions pertaining other determinants of the equity funding patterns, among other things, could prove to be a comprehensive study for future quantitative or qualitative research.

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Appendices

Appendix A – Variable Definitions Table

Variables	Definition	Model
Firm Age	Independent variable that has continuous value from 1 to 49	All
Micro Sized Firms	Dummy variable that takes 1 if the startup has 1 to 10 employee	All
Small Sized Firms	Dummy variable that takes 1 if the startup has 11 to 50 employee	All
Medium Sized Firms	Dummy variable that takes 1 if the startup has 51 to 100 employee	All
Estimated Revenue < $ 1 million	Dummy variable that takes 1 if the startup's estimated revenue is less than $ 1 million	All
Estimated Revenue $1-$10 million	Dummy variable that takes 1 if the startup's estimated revenue is from $1 to $10 million	All
Estimated Revenue $10-$50 million	Dummy variable that takes 1 if the startup's estimated revenue is from $10 to $50 million	All
Estimated Revenue $50-$100 million	Dummy variable that takes 1 if the startup's estimated revenue is from $50 to $100 million	All
Headquarters Location in the US	Dummy variable that takes 1 if the startup's headquarter is located in the US	3,4,5,6,7,8,9,10,11
Headquarters Location in China	Dummy variable that takes 1 if the startup's headquarter is located in India	10
Headquarters Location in India	Dummy variable that takes 1 if the startup's headquarter is located in China	11
Industry of the Firm: Fintech	Dummy variable that takes 1 if the startup is in the Fintech sector	4,5,6,7,8,9,10,11
Fintech firms age less than 10	Interaction term that takes 1 if the startup is in the Fintech sector and founded 10 years ago, latest	5
Micro size Fintech Firms	Interaction term that takes 1 if the startup is in the Fintech sector and has 1 to 10 employee	6
Small size Fintech Firms	Interaction term that takes 1 if the startup is in the Fintech sector and has 11 to 50 employee	7
Medium size Fintech Firms	Interaction term that takes 1 if the startup is in the Fintech sector and has 51 to 100 employee	8
Fintech firms in China	Interaction term that takes 1 if the startup is in the Fintech sector and has a hedquarter in China	10
Fintech firms in India	Interaction term that takes 1 if the startup is in the Fintech sector and has a hedquarter in India	11
Fintech firms in the US	Interaction term that takes 1 if the startup is in the Fintech sector and has a hedquarter in the US	9
Total Equity Funding Amount	Dependent variable that logaritmic transformation has been applied	All, Panel A
Number of Funding Rounds	Dependent variable that has continues value from 1 to 15	All, Panel B
Equity Funding Turnaround	Dependent variable that logaritmic transformation has been applied	9,10,11, Panel C

Appendix B.1. – OLS Regression Results with Interaction Term 'Age x Fintech' on Equity Funding Amount

Dep. Variable:	logtotalequityfundingamountcurrencyin USD	R-squared:	0.380
Model:	OLS	Adj. R-squared:	0.380
Method:	Least Squares	F-statistic:	3307.
Date:	Sun, 20 Nov 2022	Prob (F-statistic):	0.00
Time:	14:48:42	Log-Likelihood:	-1.1737e+05
No. Observations:	59429	AIC:	2.348e+05
Df Residuals:	59417	BIC:	2.349e+05
Df Model:	11		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	18.0325	0.046	394.613	0.000	17.943	18.122
age	-0.0054	0.001	-4.714	0.000	-0.008	-0.003
emp_1-10	-3.0922	0.026	-119.052	0.000	-3.143	-3.041
emp_11-50	-1.6352	0.024	-68.283	0.000	-1.682	-1.588
emp_51-100	-0.5997	0.029	-20.562	0.000	-0.657	-0.543
revenue_Less than $1M	-1.8436	0.046	-40.447	0.000	-1.933	-1.754
revenue_$1M to $10M	-1.4009	0.044	-31.621	0.000	-1.488	-1.314
revenue_$10M to $50M	-0.8108	0.045	-17.908	0.000	-0.900	-0.722
revenue_$50M to $100M	-0.4303	0.062	-6.992	0.000	-0.551	-0.310
is_US	0.3944	0.014	27.278	0.000	0.366	0.423
is_Fintech	0.4255	0.067	6.314	0.000	0.293	0.558
age&fintech	-0.0083	0.007	-1.185	0.236	-0.022	0.005

Omnibus:	1231.309	Durbin-Watson:	1.515
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1321.160
Skew:	-0.347	Prob(JB):	1.30e-287
Kurtosis:	3.230	Cond. No.	177.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Appendix B.2. – OLS Regression Results with Interaction Term 'Age x Fintech' on Number of Funding Rounds

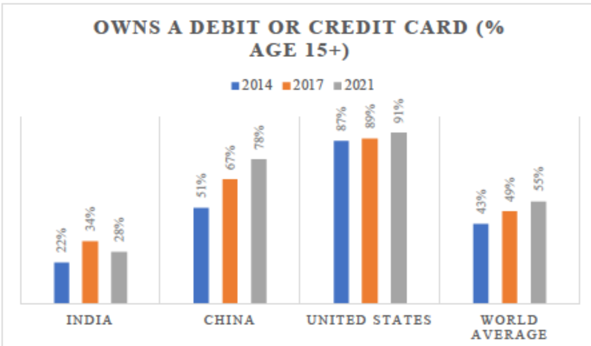
Dep. Variable:	numberoffundingrounds	R-squared:	0.093
Model:	OLS	Adj. R-squared:	0.093
Method:	Least Squares	F-statistic:	554.8
Date:	Sun, 20 Nov 2022	Prob (F-statistic):	0.00
Time:	14:52:55	Log-Likelihood:	-1.2661e+05
No. Observations:	59429	AIC:	2.532e+05
Df Residuals:	59417	BIC:	2.534e+05
Df Model:	11		
Covariance Type:	nonrobust		

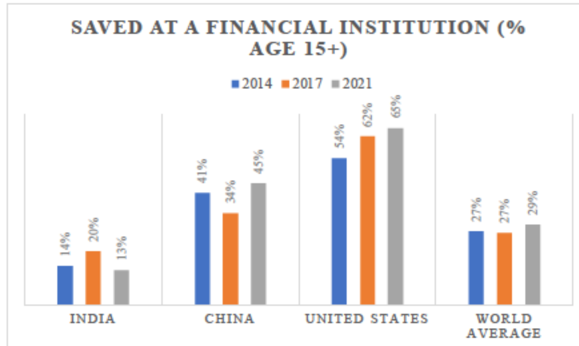
	coef	std err	t	P>|t|	[0.025	0.975]
const	4.0195	0.053	75.295	0.000	3.915	4.124
age	-0.0315	0.001	-23.463	0.000	-0.034	-0.029
emp_1-10	-1.5363	0.030	-50.632	0.000	-1.596	-1.477
emp_11-50	-0.8458	0.028	-30.233	0.000	-0.901	-0.791
emp_51-100	-0.2594	0.034	-7.612	0.000	-0.326	-0.193
revenue_Less than $1M	-0.4649	0.053	-8.732	0.000	-0.569	-0.361
revenue_$1M to $10M	-0.2968	0.052	-5.735	0.000	-0.398	-0.195
revenue_$10M to $50M	0.0290	0.053	0.548	0.584	-0.075	0.133
revenue_$50M to $100M	0.1436	0.072	1.998	0.046	0.003	0.285
is_US	0.4194	0.017	24.826	0.000	0.386	0.452
is_Fintech	0.2677	0.079	3.401	0.001	0.113	0.422
age&fintech	0.0209	0.008	2.563	0.010	0.005	0.037

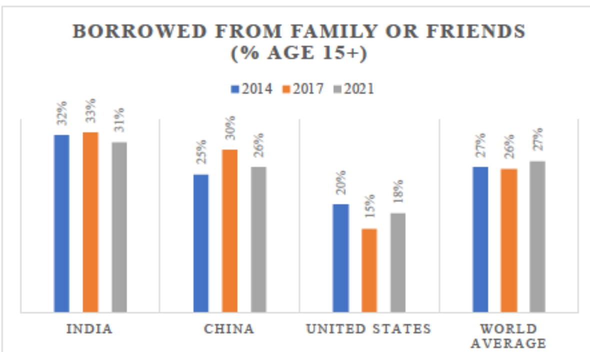
Omnibus:	18199.428	Durbin-Watson:	1.760
Prob(Omnibus):	0.000	Jarque-Bera (JB):	55599.256
Skew:	1.594	Prob(JB):	0.00
Kurtosis:	6.505	Cond. No.	177.

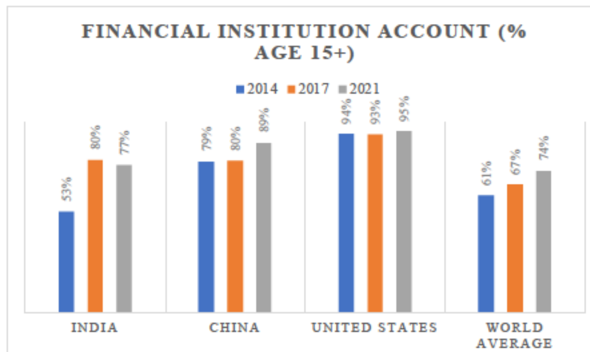
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

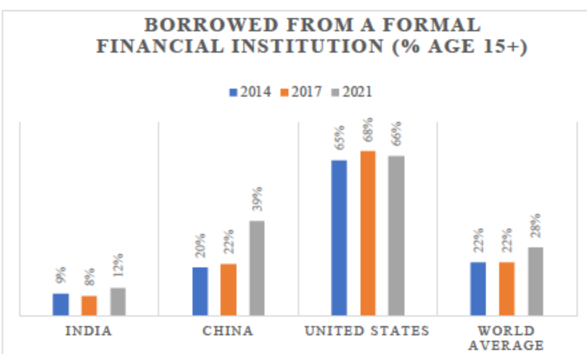
Appendix C – Financial Inclusion Parameters (2014, 2017 & 2021)

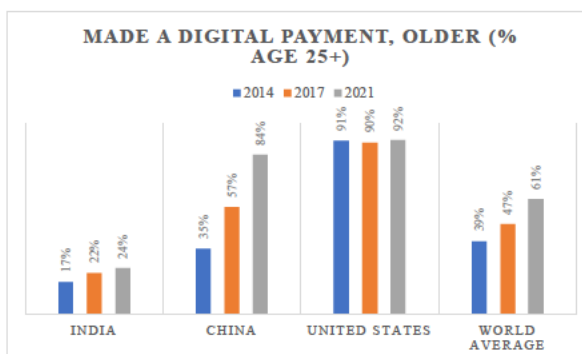






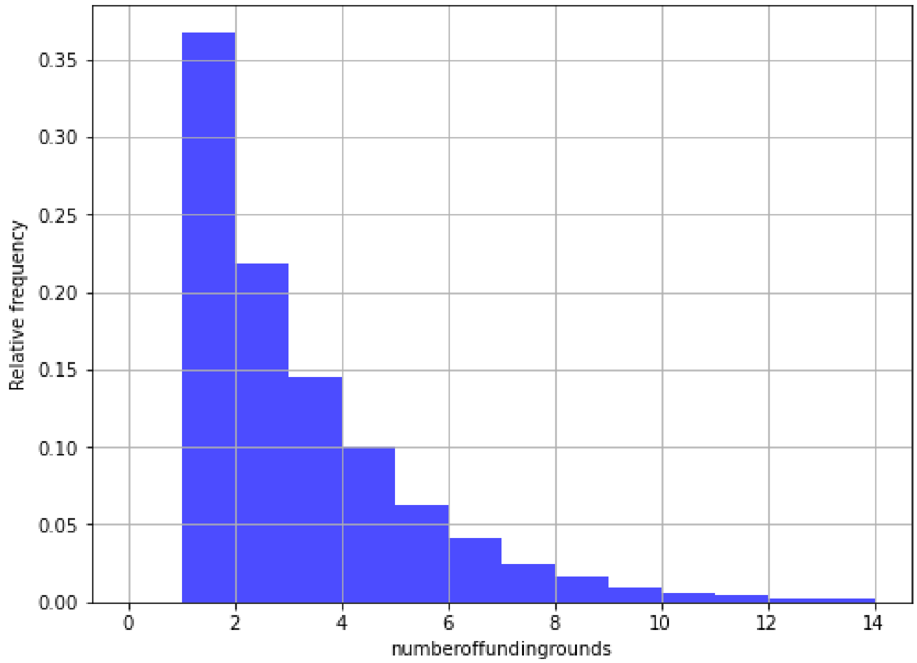






Data Source: The Global Findex Database 2021 (World Bank, 2021)

Appendix D – Distribution of Number of Funding Rounds



Appendix E - Python Codes Used in the Thesis

```
[ ]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import statsmodels.api as sm
from sklearn.preprocessing import
MultiLabelBinarizer import warnings
# Importing libraries to visualize the
correlation matrix import seaborn as sns
import matplotlib.pyplot as plt
warnings.filterwarnings("ignore")

pd.set_option('display.max_rows', 1000)
pd.set_option('display.max_columns', 1000)
pd.set_option('display.width', 1000)
pd.set_option('display.float_format', lambda x: '%.3f' % x)
r_data = pd.read_excel('DATA_RESEARCH2.xlsx')
```

```
[ ]: r_data['age'] = 2022 - pd.to_datetime(r_data['foundeddate'],
 format='%Y-%m-%d␣,→%H:%M:%S', errors = 'coerce').dt.year

#Delimiting headquarter location column based on the country that
 the startup␣,→is located
country = r_data['headquarterslocation'].str.split(", ",
expand=True)[2] temp = r_data['headquarterslocation'].str.split(",
") for rownum,rowitem in temp.iteritems():
        #some of the items were not list object. We first check
        #if temp[rownum] is list. If so, we check its length.
        #If the length is greater than 3, then the country
        #does not have the format City, State, Country (3 items)
        #Rather it is something like A, B, C, Country (4 items)
        #So we pick the last item in that case
        #Note: we checked if there are rows with
        length #longer than 4 items. There are none.
        if isinstance(temp[rownum], list):
            if len(temp[rownum]) > 3:
                country[rownum] = temp[rownum][3]
            # if len(temp[rownum]) > 4:
```

```
        #     print(rownum)

r_data['country'] = country

#first criteria for data clearance: age
r_data = r_data[r_data['age'] < 50]

# second criteria for data clearance: total equity funding less than
 USD 10.000␣,→and greater than USD 1.000.000.000 must be eliminated.
r_data = r_data[r_data['totalequityfundingamountcurrencyin USD'] > 10000]
r_data = r_data[r_data['totalequityfundingamountcurrencyin USD'] < 1000000000]

# third criteria for data clearance: number of funding rounds must not be␣
 ,→greater than 15 (which will create an immaterial drop (only 161 companies)␣
 ,→in number of observations)
r_data = r_data[r_data['numberoffundingrounds'] <15]

#Equity funding turnaround to be used as a dependent variable in the
later steps r_data['Equity Funding Turnaround'] =␣
 ,→r_data['totalequityfundingamountcurrencyin
 USD'] //␣,→r_data['numberoffundingrounds']

r_data.head()
```

```
[ ]:  filtered_data = r_data

#creating dummy variables for industries (this is a list of
 industries so we␣,→first convert it to list then dummy)
filtered_data['industries'] = filtered_data['industries'].str.split(', ')
inddummies = filtered_data['industries'].str.join('|').str.get_dummies().
 ,→rename(columns=lambda x: 'ind_' + str(x))

#creating a dummy variable only to check whether the company is in
 fintech or␣,→not. Other "custom sector" dummy variables can be added
 here in a similar␣,→fashion
filtered_data['is_Fintech'] = inddummies['ind_FinTech']

#Creating the dummy variables based on the selected
countries filtered_data['is_US'] = 0
filtered_data['is_US'] = np.where(filtered_data['country'] ==
 "United States",␣,→1, 0);

filtered_data['is_India'] = 0
filtered_data['is_India'] = np.where(filtered_data['country'] ==

"India", 1, 0); filtered_data['is_China'] = 0
```

```
filtered_data['is_China'] = np.where(filtered_data['country'] == "China", 1, 0);

#creating dummy variables for numberofemployees
empdummies = pd.get_dummies(filtered_data['numberofemployees']).
↪rename(columns=lambda x: 'emp_' + str(x))
filtered_data = pd.concat([filtered_data, empdummies], axis=1)

#creating dummy variables for estimatedrevenuerange
empdummies = pd.get_dummies(filtered_data['estimatedrevenuerange']).
↪rename(columns=lambda x: 'rev_' + str(x))
filtered_data = pd.concat([filtered_data, empdummies], axis=1)
```

```
[ ]: #creating estimated revenue range as a categorical dummy variable.
revenuedummies = pd.get_dummies(filtered_data['estimatedrevenuerange']).
↪rename(columns=lambda x: 'revenue_' + str(x))
filtered_data = pd.concat([filtered_data,
revenuedummies], axis=1) filtered_data.head()
```

```
[ ]: #Model 1A with dummy AGE, EMPLOYEE SIZE 1-100 AND
LOGTOTALEQUITYFUNDINGAMOUNT #define response variable
filtered_data['logtotalequityfundingamountcurrencyin USD'] = np.
↪log(filtered_data['totalequityfundingamountcurrencyin USD'])
y = filtered_data['logtotalequityfundingamountcurrencyin USD']
#define predictor variables
x = filtered_data[['age', 'emp_1-10','emp_11-50','emp_51-100']]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

```
[ ]: #Model 1B with dummy AGE, EMPLOYEE SIZE 1-100 AND NUMBER OF
FUNDING ROUNDS #define response variable
y = filtered_data['numberoffundingrounds']
#define predictor variables
x = filtered_data[['age', 'emp_1-10','emp_11-50','emp_51-100']]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
#Model 2A: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
↪TO 500M AND LOGTOTALEQUITYFUNDINGAMOUNT
#define response variable
filtered_data['logtotalequityfundingamountcurrencyin USD'] = np.
↪log(filtered_data['totalequityfundingamountcurrencyin   USD'])
y = filtered_data['logtotalequityfundingamountcurrencyin
USD'] #define predictor variables
      x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-100','revenue_Less
than␣ ↪$1M','revenue_$1M to $10M', 'revenue_$10M to $50M','revenue_$50M to $100M' ]]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
#Model 2B: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
↪TO 500M AND NUMBER OF FUNDING ROUNDS
#define response variable
y = filtered_data['numberoffundingrounds']
#define predictor variables
      x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-100','revenue_Less
than␣ ↪$1M','revenue_$1M to $10M', 'revenue_$10M to $50M','revenue_$50M to $100M' ]]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
#Model 3A: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
↪TO 500M, COUNTRY US AND LOGTOTALEQUITYFUNDINGAMOUNT
#define response variable
filtered_data['logtotalequityfundingamountcurrencyin USD'] = np.
↪log(filtered_data['totalequityfundingamountcurrencyin   USD'])
y = filtered_data['logtotalequityfundingamountcurrencyin
USD'] #define predictor variables
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-
 100','revenue_Less than␣↪$1M','revenue_$1M to $10M', 'revenue_$10M to
 $50M','revenue_$50M to $100M',␣↪'is_US' ]]

#add constant to predictor variables
```

```
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
#Model 3B: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
↪TO 500M, COUNTRY US AND NUMBER OF FUNDING ROUNDS
#define response variable
y = filtered_data['numberoffundingrounds']
#define predictor variables
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-
100','revenue_Less than␣↪$1M','revenue_$1M to $10M', 'revenue_$10M to
$50M','revenue_$50M to $100M',␣↪'is_US' ]]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
#Model 4A: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
↪TO 500M, COUNTRY US, FINTECH SECTOR AND LOGTOTALEQUITYFUNDINGAMOUNT
#define response variable
filtered_data['logtotalequityfundingamountcurrencyin USD'] = np.
↪log(filtered_data['totalequityfundingamountcurrencyin   USD'])
y = filtered_data['logtotalequityfundingamountcurrencyin
USD'] #define predictor variables
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-
100','revenue_Less than␣↪$1M','revenue_$1M to $10M', 'revenue_$10M to
$50M','revenue_$50M to $100M',␣↪'is_US', 'is_Fintech' ]]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
#Model 4B: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
↪TO 500M, COUNTRY US, FINTECH SECTOR AND NUMBER OF FUNDING ROUNDS
#define response variable
y = filtered_data['numberoffundingrounds']
```

```
#define predictor variables
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-
 100','revenue_Less than␣,→$1M','revenue_$1M to $10M', 'revenue_$10M to
 $50M','revenue_$50M to $100M',␣,→'is_US', 'is_Fintech' ]]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

```
[ ]: #Creating interaction terms for young fintech companies, age less
than 10 years condition = [(filtered_data['age']<=10) &
(filtered_data['is_Fintech']==1)] val= [True]
filtered_data['young_Fintech'] =
np.select(condition,val) filtered_data.head(15)
```

```
[ ]: #Model 5A: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣

 ,→TO 500M, COUNTRY US, FINTECH SECTOR, YOUNG FINTECH
 AND␣,→LOGTOTALEQUITYFUNDINGAMOUNT
#define response variable
filtered_data['logtotalequityfundingamountcurrencyin USD'] = np.
 ,→log(filtered_data['totalequityfundingamountcurrencyin   USD'])
y = filtered_data['logtotalequityfundingamountcurrencyin
USD'] #define predictor variables
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-
 100','revenue_Less than␣,→$1M','revenue_$1M to $10M', 'revenue_$10M to
 $50M','revenue_$50M to $100M',␣,→'is_US', 'is_Fintech', 'young_Fintech']]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

```
[ ]: #Model 5B: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣

 ,→TO 500M, COUNTRY US, FINTECH SECTOR, YOUNG FINTECH AND NUMBER OF
 FUNDING␣,→ROUNDS
#define response variable
y = filtered_data['numberoffundingrounds']
#define predictor variables
```

```
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-
 100','revenue_Less than␣ ↪$1M','revenue_$1M to $10M', 'revenue_$10M to
 $50M','revenue_$50M to $100M',␣ ↪'is_US', 'is_Fintech', 'young_Fintech']]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

```
[ ]: #Creating interaction terms for fintech companies with age
 variable␣ ↪(multiplication of two variables)
filtered_data['age&fintech'] = filtered_data['age']
 *␣ ↪filtered_data['is_Fintech']
filtered_data.head()
```

```
[ ]: #Appendix C.1: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED
 REVENUE USD␣ ↪1M TO 500M, COUNTRY US, FINTECH SECTOR, AGE&FINTECH AND␣
 ↪LOGTOTALEQUITYFUNDINGAMOUNT
#define response variable
filtered_data['logtotalequityfundingamountcurrencyin USD'] = np.
 ↪log(filtered_data['totalequityfundingamountcurrencyin  USD'])
y = filtered_data['logtotalequityfundingamountcurrencyin
USD'] #define predictor variables
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-
 100','revenue_Less than␣ ↪$1M','revenue_$1M to $10M', 'revenue_$10M to
 $50M','revenue_$50M to $100M',␣ ↪'is_US', 'is_Fintech', 'age&fintech']]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

```
[ ]: #Appendix C.2: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD␣
 ↪1M TO 500M, COUNTRY US, FINTECH SECTOR, AGE&FINTECH AND NUMBER OF
 FUNDING␣ ↪ROUNDS
#define response variable
y = filtered_data['numberoffundingrounds']
#define predictor variables
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-
 100','revenue_Less than␣ ↪$1M','revenue_$1M to $10M', 'revenue_$10M to
 $50M','revenue_$50M to $100M',␣ ↪'is_US', 'is_Fintech', 'age&fintech']]
```

```
#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
#creating interaction term for micro firms
condition = [(filtered_data['emp_1-10']==1) &
(filtered_data['is_Fintech']==1)] val= [True]
filtered_data['micro_Fintech'] = np.select(condition,val)
filtered_data.head()
```

[ ]:
```
#Model 6A: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
↪TO 500M, COUNTRY US, FINTECH SECTOR, MICRO FINTECH
AND␣↪LOGTOTALEQUITYFUNDINGAMOUNT
#define response variable
filtered_data['logtotalequityfundingamountcurrencyin USD'] = np.
↪log(filtered_data['totalequityfundingamountcurrencyin   USD'])
y = filtered_data['logtotalequityfundingamountcurrencyin
USD'] #define predictor variables
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-
100','revenue_Less than␣↪$1M','revenue_$1M to $10M', 'revenue_$10M to
$50M','revenue_$50M to $100M',␣↪'is_US', 'is_Fintech', 'micro_Fintech']]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
#Model 6B: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
↪TO 500M, COUNTRY US, FINTECH SECTOR, MICRO FINTECH AND NUMBER OF
FUNDING␣↪ROUNDS
#define response variable
y = filtered_data['numberoffundingrounds']
#define predictor variables
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-
100','revenue_Less than␣↪$1M','revenue_$1M to $10M', 'revenue_$10M to
$50M','revenue_$50M to $100M',␣↪'is_US', 'is_Fintech', 'micro_Fintech']]

#add constant to predictor variables
x = sm.add_constant(x)
```

```
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
#creating interaction term for small firms
condition = [(filtered_data['emp_11-50']==1) &
(filtered_data['is_Fintech']==1)] val= [True]
filtered_data['small_Fintech'] = np.select(condition,val)
filtered_data.head()
```

[ ]:
```
#Model 7A: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
↪TO 500M, COUNTRY US, FINTECH SECTOR, SMALL FINTECH
AND␣↪LOGTOTALEQUITYFUNDINGAMOUNT
#define response variable
filtered_data['logtotalequityfundingamountcurrencyin USD'] = np.
↪log(filtered_data['totalequityfundingamountcurrencyin   USD'])
y = filtered_data['logtotalequityfundingamountcurrencyin
USD'] #define predictor variables
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-
100','revenue_Less than␣↪$1M','revenue_$1M to $10M', 'revenue_$10M to
$50M','revenue_$50M to $100M',␣↪'is_US', 'is_Fintech', 'small_Fintech']]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
#Model 7B: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
↪TO 500M, COUNTRY US, FINTECH SECTOR, SMALL FINTECH AND NUMBER OF
FUNDING␣↪ROUNDS
#define response variable
y = filtered_data['numberoffundingrounds']
#define predictor variables
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-
100','revenue_Less than␣↪$1M','revenue_$1M to $10M', 'revenue_$10M to
$50M','revenue_$50M to $100M',␣↪'is_US', 'is_Fintech', 'small_Fintech']]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
```

```
#view summary of model fit
print(results.summary())
```

```
[ ]: #creating interaction term for medium firms condition
= [(filtered_data['emp_51-100']==1) &␣
↪(filtered_data['is_Fintech']==1)]
val= [True]
filtered_data['medium_Fintech'] =
np.select(condition,val) filtered_data.head()
```

```
[ ]: #Model 8A: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
↪TO 500M, COUNTRY US, FINTECH SECTOR, MEDIUM FINTECH
AND␣↪LOGTOTALEQUITYFUNDINGAMOUNT
#define response variable
filtered_data['logtotalequityfundingamountcurrencyin USD'] = np.
↪log(filtered_data['totalequityfundingamountcurrencyin   USD'])
y = filtered_data['logtotalequityfundingamountcurrencyin
USD'] #define predictor variables
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-
100','revenue_Less than␣↪$1M','revenue_$1M to $10M', 'revenue_$10M to
$50M','revenue_$50M to $100M',␣↪'is_US', 'is_Fintech', 'medium_Fintech']]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

```
[ ]: #Model 8B: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
↪TO 500M, COUNTRY US, FINTECH SECTOR, MEDIUM FINTECH AND NUMBER OF
FUNDING␣↪ROUNDS
#define response variable
y = filtered_data['numberoffundingrounds']
#define predictor variables
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-
100','revenue_Less than␣↪$1M','revenue_$1M to $10M', 'revenue_$10M to
$50M','revenue_$50M to $100M',␣↪'is_US', 'is_Fintech', 'medium_Fintech']]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
#Creating interaction term for Fintech firms in US
condition = [(filtered_data['is_US']==1) &
(filtered_data['is_Fintech']==1)] val= [True]
filtered_data['US_Fintech'] = np.select(condition,val)
filtered_data.head(15)
```

[ ]:
```
#Model 9A: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
,→TO 500M, COUNTRY US, FINTECH SECTOR, FINTECH IN US
AND␣,→LOGTOTALEQUITYFUNDINGAMOUNT
#define response variable
filtered_data['logtotalequityfundingamountcurrencyin USD'] = np.
,→log(filtered_data['totalequityfundingamountcurrencyin   USD'])
y = filtered_data['logtotalequityfundingamountcurrencyin
USD'] #define predictor variables
x     =     filtered_data[['age',     'emp_1-10','emp_11-50','emp_51-
100','revenue_Less␣,→than $1M','revenue_$1M to $10M', 'revenue_$10M to
$50M','revenue_$50M to␣,→$100M', 'is_US', 'is_Fintech', 'US_Fintech']]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
#Model 9B: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
,→TO 500M, COUNTRY US, FINTECH SECTOR, FINTECH IN US AND NUMBER OF
FUNDING␣,→ROUNDS
#define response variable
y = filtered_data['numberoffundingrounds']
#define predictor variables
x     =     filtered_data[['age',     'emp_1-10','emp_11-50','emp_51-
100','revenue_Less␣,→than $1M','revenue_$1M to $10M', 'revenue_$10M to
$50M','revenue_$50M to␣,→$100M', 'is_US', 'is_Fintech', 'US_Fintech']]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
#Model 9C: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
,→TO 500M, COUNTRY US, FINTECH SECTOR, FINTECH IN US AND EQUITY
FUNDING␣,→TURNAROUND
```

```
#define response variable
filtered_data['log9c_Equity Funding Turnaround'] =
 np.log(filtered_data['Equity␣,→Funding Turnaround'])
y = filtered_data['log9c_Equity Funding
Turnaround'] #define predictor variables
x     =     filtered_data[['age',     'emp_1-10','emp_11-50','emp_51-
 100','revenue_Less␣,→than $1M','revenue_$1M to $10M', 'revenue_$10M to
 $50M','revenue_$50M to␣,→$100M', 'is_US', 'is_Fintech', 'US_Fintech']]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
 # Creating interaction term for Fintech firms in China
condition = [(filtered_data['is_China']==1) &
(filtered_data['is_Fintech']==1)] val= [True]
filtered_data['China_Fintech'] = np.select(condition,val)
filtered_data.head(15)
```

[ ]:
```
#Model 10A: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
 ,→TO 500M, COUNTRY US, FINTECH SECTOR, FINTECH IN
 CHINA AND␣,→LOGTOTALEQUITYFUNDINGAMOUNT
#define response variable
filtered_data['logtotalequityfundingamountcurrencyin USD'] = np.
 ,→log(filtered_data['totalequityfundingamountcurrencyin   USD'])
y = filtered_data['logtotalequityfundingamountcurrencyin
USD'] #define predictor variables
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-100','revenue_Less
 than␣ →$1M','revenue_$1M to $10M', 'revenue_$10M to $50M','revenue_$50M to
 $100M',␣ →'is_China','is_US', 'is_Fintech', 'China_Fintech']]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
#Model 10B: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
 ,→TO 500M, COUNTRY US, FINTECH SECTOR, FINTECH IN CHINA AND NUMBER OF
 FUNDING␣,→ROUNDS
#define response variable
```

```
y = filtered_data['numberoffundingrounds']
#define predictor variables
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-100','revenue_Less
 than␣ →$1M','revenue_$1M to $10M', 'revenue_$10M to $50M','revenue_$50M to
 $100M',␣ →'is_US', 'is_Fintech', 'China_Fintech','is_China']]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
#Model 10C: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
 ,→TO 500M, COUNTRY US, FINTECH SECTOR, FINTECH IN CHINA AND EQUITY
 FUNDING␣,→TURNAROUND
#define response variable
filtered_data['log10c_Equity Funding Turnaround'] = np.
 ,→log(filtered_data['Equity  Funding Turnaround'])
y = filtered_data['log10c_Equity Funding
Turnaround'] #define predictor variables
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-100','revenue_Less
 than␣ →$1M','revenue_$1M to $10M', 'revenue_$10M to $50M','revenue_$50M to
 $100M',␣ →'is_US', 'is_Fintech', 'China_Fintech','is_China']]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
 # Creating interaction term for Fintech firms in India
condition = [(filtered_data['is_India']==1) &
(filtered_data['is_Fintech']==1)] val= [True]
filtered_data['India_Fintech'] = np.select(condition,val)
filtered_data.head(15)
```

[ ]:
```
#Model 11A: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
 ,→TO 500M, COUNTRY US, FINTECH SECTOR, FINTECH IN
 INDIA AND␣,→LOGTOTALEQUITYFUNDINGAMOUNT
#define response variable
filtered_data['logtotalequityfundingamountcurrencyin USD'] = np.
 ,→log(filtered_data['totalequityfundingamountcurrencyin  USD'])
y = filtered_data['logtotalequityfundingamountcurrencyin USD']
```

```
#define predictor variables
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-100','revenue_Less
 than␣ ↪$1M','revenue_$1M to $10M', 'revenue_$10M to $50M','revenue_$50M to
 $100M',␣ ↪'is_US', 'is_Fintech', 'India_Fintech','is_India']]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
#Model 11B: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
 ↪TO 500M, COUNTRY US, FINTECH SECTOR, FINTECH IN INDIA AND NUMBER OF
 FUNDING␣ ↪ROUNDS
#define response variable
y = filtered_data['numberoffundingrounds']
#define predictor variables
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-100','revenue_Less
 than␣ ↪$1M','revenue_$1M to $10M', 'revenue_$10M to $50M','revenue_$50M to
 $100M',␣ ↪'is_US', 'is_Fintech', 'India_Fintech','is_India']]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
#Model 11C: model with dummy AGE, EMPLOYEE SIZE 1-100, ESTIMATED REVENUE USD 1M␣
 ↪TO 500M, COUNTRY US, FINTECH SECTOR, FINTECH IN INDIA AND EQUITY
 FUNDING␣ ↪TURNAROUND
#define response variable
filtered_data['log11c_Equity Funding Turnaround'] = np.
 ↪log(filtered_data['Equity  Funding Turnaround'])
y = filtered_data['log11c_Equity Funding
Turnaround'] #define predictor variables
x = filtered_data[['age','emp_1-10','emp_11-50','emp_51-100','revenue_Less
 than␣ ↪$1M','revenue_$1M to $10M', 'revenue_$10M to $50M','revenue_$50M to
 $100M',␣ ↪'is_US', 'is_Fintech', 'India_Fintech','is_India']]

#add constant to predictor variables
x = sm.add_constant(x)
#fit regression model
model = sm.OLS(y,x, missing = 'drop')
```

```
results = model.fit()
#view summary of model fit
print(results.summary())
```

[ ]:
```
#detailed descriptive statistics of all of the dependent, independent
 and dummy␣ ,→variables, interaction terms generated.
filtered_data.describe()
```

[ ]:
```
 #Figure 6 - Distribution of Age within the Sample ( creating a histogram to␣
 ,→show the relative frequncy of the age distribution in the sample from
1 to 4) filtered_data['age'].plot(kind = 'hist',
            bins = range(0,49),
            density = True,
            color = 'b',
            grid = True,
            figsize = (8, 6),
            alpha = 0.7)
plt.xlabel('age', fontsize = 10)
plt.ylabel('Relative frequency', fontsize = 10)
```

[ ]:
```
# The correlation heatmap in a compressed
version r_data.corr()
sns.heatmap(r_data.corr())
```

[ ]:
```
 #Figure 7 - Correlation Heatmap
# Increase the size of the heatmap.
plt.figure(figsize=(16, 6))
# Setting the range of values to be displayed on the colormap from -
 1 to 1 and␣ ,→setting the annotation to True to display the correlation
 values on the␣ ,→heatmap.
heatmap = sns.heatmap(r_data.corr(), vmin=-1, vmax=1, annot=True)
# In order to give the title to the heatmap the following code is used.␣
 ,→adjusting pad to 12 to determine the title distance to the bottom of the␣
 ,→heatmap.
heatmap.set_title('Correlation Heatmap', fontdict={'fontsize':12}, pad=12);
```

[ ]:
```
# Appendix E - Distribution of Number of Funding Rounds (creating a
 histogram␣ ,→to show the distribution of the funding rounds from 1 to 15)
filtered_data['numberoffundingrounds'].plot(kind =
            'hist', bins = range(0,15),
            density = True,
            color = 'b',
            grid = True,
            figsize = (8, 6),
            alpha = 0.7)
plt.xlabel('numberoffundingrounds', fontsize = 10)
plt.ylabel('Relative frequency', fontsize = 10)
```