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DIFFERENCES IN THE FUNDING PATTERNS BETWEEN PLATFORM AND NON-PLATFORM BUSINESS MODELS

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ABSTRACT

With the emergence of digital environments, the relevance of multi-sided platforms (MSPs) became increasingly important. The ability to leverage on network effects both direct and indirect, allowed companies to disrupt industries by achieving scalability. Consequently, they can be a great threat to traditional business. In the early-stage part of the life cycle, traditional and MSPs may compete for the same investing opportunities, while in the later stages, they may compete on market share. Therefore, one of the focuses of the present studies is to highlight the main differences and similarities among these businesses' models. The success of companies with platform business models such as Google, Facebook, Airbnb and Uber might signal potential of high returns to early-stage investors. However, since these ventures face peculiar challenges such as the chicken-and-egg paradox and achieving critical mass, they represent overly complex and high-risk investing opportunities. Additionally, as any other early-stage company, they also face funding gaps since they rely on external financing to conduct their activities. From the investors' perspective, information asymmetries raise doubts regarding the financing of companies. Therefore, they rely on strategies such as syndication and staging as mechanisms to decrease risk of investment and information asymmetries. Hence, this thesis aims to investigate the investment patterns in multi-sided platforms versus traditional business models. The current study begins with an extensive literature review on multi-sided platforms and equity financing to better understand the factors that influence attractiveness and risk of these companies. To assess these assumptions, we retrieve a sample of 9,524 companies, both platforms and traditional businesses, from VICO and Pitchbook data sources. Then, we performed descriptive statistics and multivariate regression analyses to describe the investment patterns in platforms vs. non-platforms. The results show statistically significant differences among platform business and traditional companies regarding investments by BVCs, CVCs and GVCs, staging, number of rounds and total amount of investment, however they did not present significant differences in terms of the remaining types of investors, syndication and syndication size. Thus, empirical evidence showed that platforms receive a higher amount of investment in more rounds with higher probability of staging than pipeline business.

Keywords: Multi-sided Platforms, Equity Financing, Staging, Syndication.

RESUMO

Com o surgimento de ambientes digitais, a relevância das plataformas multilaterais (PMLs) cresceu. A capacidade de alavancar os efeitos de rede, tanto diretos quanto indiretos, permitiu que empresas revolucionassem setores, alcançando escalabilidade. Consequentemente, elas podem ser uma grande ameaça para os negócios tradicionais. No estágio inicial, empresas tradicionais e as PMLs podem competir pelas mesmas oportunidades de investimento, enquanto em estágios posteriores, eles podem competir em participação de mercado. Portanto, um dos focos do presente estudo é destacar as principais diferenças e semelhanças entre estes modelos de negócios. O sucesso de plataformas como Google, Facebook, Airbnb e Uber pode sinalizar potencial de altos retornos para investidores. No entanto, como esses empreendimentos enfrentam desafios peculiares, como o paradoxo da galinha e do ovo e a obtenção de massa crítica, elas representam investimentos complexos e de alto risco. Além disso, como outras empresas em estágio inicial, elas enfrentam lacunas de financiamento, pois dependem disso para realizar suas atividades. Do ponto de vista dos investidores, as assimetrias de informação levantam dúvidas quanto ao financiamento das empresas. Os investidores contam com estratégias como *syndication* e *staging* como mecanismos para diminuir o risco de investimento e assimetrias de informação. Assim, esta tese tem como objetivo investigar os padrões de investimento em plataformas multilaterais versus modelos de negócio tradicionais. O presente estudo começa com uma revisão de literatura sobre plataformas e financiamento de capital para aprofundamento nos fatores que influenciam a atratividade e o risco de empresas. Para avaliar essas suposições, construímos uma amostra de 9.524 empresas com as fontes de dados VICO e Pitchbook. Em seguida, realizamos análises de estatística descritiva e de regressão multivariada para descrever os padrões de investimento em plataformas versus não plataformas. Os resultados mostraram diferenças estatisticamente significativas entre plataformas e empresas tradicionais quanto aos investimentos por BVCs, CVCs e GVCs, *staging*, número de rodadas e valor total de investimento, porém não apresentaram diferenças em termos dos demais tipos de investidores, *syndication* e tamanho da sindicação. Assim, a evidência empírica mostrou que plataformas recebem um valor de investimento maior em mais rodadas com maior possibilidade de *staging* quando comparadas a negócios tradicionais.

Palavras-chave: Plataformas Multilaterais, Financiamento de Capital, *Staging*, *Syndication*.

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SUMMARY

1. INTRODUCTION

Over the last years, digital platforms have become the largest and fastest-growing businesses, proliferating across different sectors, such as computers, video games, mobile phones, payment systems, e-commerce, and more. Platforms are a type of business model that connect distinct groups (individuals or organizations) by facilitating information exchange or transactions. They are a vital source of dynamism and innovation for diverse industries. By leveraging modularity and specialization, they reduced several market frictions and challenged incumbents with their disruption. The emergence of digital environments and internet technologies further broadened opportunities for the creation of these organizational forms. The fierce rivalry between platforms targeting the same user base is also a factor impacting the growth of this business model, for instance, Twitter outperformed the website Pownce, and Facebook has beaten the social network Orkut (ZHAO *et al*., 2020). It is evident that for every successful platform, there are numerous others that fail. This dynamic gives rise to a winner-takes-it-all scenario that highlights how platforms have potential high returns but severe risks.

The top four companies for market capitalization in 2020 were all digital platforms: Apple, Microsoft, Alphabet (Google) and Amazon (COMPANIES MARKET CAP, 2020). This accentuates the increasing relevance multi-sided platforms have been gaining in the last year. The COVID-19 pandemic further intensified the growth of these companies and of this segment, because, during the lockdown, the usage of platforms increased significantly (in the first half of 2020), especially in industries such as retail sales, restaurant delivery and mobile payments (OECD, 2021). To adjust to the "new normal", several businesses had to adapt themselves by shifting to online marketplaces.

Due to the pertinence and growing relevance that platform business had gained in the last years, this paper reflects on the distinctive features of platform business in comparison to traditional ventures that allowed the success of these companies. The research also deep dives on the main challenges encountered by these firms and the strategies adopted to cope with them.

According to Hagiu (2014), multi-sided platforms create value by primarily enabling direct interactions between two or more customers or participant groups. They also generate value by reducing search, transactions and product development costs. A main peculiarity of platform business models is the presence of network effects, which may give rise to the mentioned winner-takes-it-all dynamics (DUSHNITSKY *et al*., 2020). In short, it means that the more users a platform has, the more attractive it is for new users on the same-side or opposite-side of the platform to join. To benefit from it, however, business must overcome the chicken-and-egg paradox and achieve a critical mass of users. The literature review section will extensively explain these challenges. Consequently, the ventures need to establish a set of strategic choices to attract users of different customer groups to join the platform at (more or less) the same time and manage the complex relations in the platform.

As most new ventures, platforms businesses also need external finance to support their activities. Therefore, they must face the funding gap of the equity and debt market. In the funding process, the high-risk and high reward of investments shapes investor’s behavior. To decrease risk, they adopt control mechanisms such as staging and syndication to structure their investments and manage uncertainties and information asymmetries. Different players such as Crowdfunding, Business Angels and Venture Capitals can finance early-stage companies. Each type of investor has its own peculiarities and preferences when deciding their investments portfolio. Therefore, they may also have preferences among different business models. New ventures can also have debt financing, through banks and loans, however this thesis will not address this topic.

The purpose of this study is to understand how funding patterns differ for traditional companies and platform business in terms of timing, amount of funding, process of funding (staging and syndication) and types of investors. The following research question guides the present study: how funding patterns differ between platforms and traditional business?

This thesis addresses the question above by using a dataset built with VICO and Pitchbook’s databases. Specifically, the sample observed was composed of 9,524 companies founded in European countries from 1935 to 2018. By performing a descriptive statistical analysis, the thesis aims to contribute to the literature through a data-driven approach, besides with extensive literature research. The key results are: (a) identifying differences among platforms and non-platforms during the funding process, (b) how the peculiarities of platform-based business models influence the funding needs and patterns.

1.1. Outline of the thesis

The thesis contains four main parts: literature review, data and methodology, results and conclusion. The thesis begins with an extensive literature review on multi-sided platforms and equity financing. It contains the definition and typologies of platforms, the challenge they face, the possible strategic choices these companies take, the differences among MSPs and platform business and platform’s competitive landscape. Then, the equity financing part involves the main investor types, characteristics of the funding process (syndication and staging) and the main exit strategies adopted by investors. With the literature review, there will be enough information to understand the risk attached to platform businesses and what investors take into consideration when evaluating projects that they want to invest in.

Data and methodology section describes the dataset, the sample of companies and their characterization, the variables used, and the methodology applied for the round-level and company-level analysis. This section also presents a descriptive statistical analysis illustrating the distribution of investment rounds by years, the distribution of multi-sided platforms vs traditional companies by country, foundation year and industry, as well as explanatory and control variables.

Afterwards, the results chapter presents univariate analysis with t-test and chi-square models and multivariate statistics with Probit and linear regression models to underline the main differences among the business models in terms of the funding patterns, with focus on types of investors, staging, syndication and total amount invested. Finally, the conclusion analyzes and interprets the findings together with generalizable insights on how it supports platform literature. Also, the paper discusses the limitations of the study based on the sample size and methodological choices.

This research can contribute with an extensive literature review on platform business and equity financing, as well as, with an empirical analysis on the funding patterns for platform and non-platform ventures. There is, however, great room for improvement due to the limitations of this thesis.

2. LITERATURE REVIEW

The objective of this section is to introduce Multi-Sided Platforms and its key features to support an in-depth investigation of platforms and how they affect investor behavior. The second part will focus on the possible funding channels and their main advantages and disadvantages. Followed by a discussion of syndication and staging as strategies of risk dilution.

2.1. Multi-sided platforms (MSPs)

Companies with a *platform* business model are those that connect individuals and organizations to share information or facilitate transactions, allowing the multiple sides to innovate and interact, potentially escalating utility and value of the involved parts in a non-linear way (CUSUMANO *et al*., 2019b). This definition covers from more traditional sectors such as the newspaper industry, which connects advertisers and readers, to newer digital platforms such as social networks, which connects advertisers, content creators and users. Well-known examples include (1) media markets, which sell content and advertising space, (2) payment cards markets, which sell the use of cards to buyers and point-of-sale terminals to stores, and (3) online intermediaries, which connect buyers and sellers (FILISTRUCCHI *et al*., 2014).

Multi-sided platforms also serve the function of acting as building blocks, that is, the foundation for other firms to build and offer their products and services (GAWER AND CUSUMANO, 2002). App Store and Google Play, for example, are platforms in which app developers display their products according to the specificities of each platform building block. In this context, *complementors* are the independent providers of the goods and services, also known as *complements* (BOUDREAU AND JEPPESEN, 2015). Another crucial concept regards *platform ecosystem* which refers to the combination of the platform and its network of complementors responsible for creating complements and guaranteeing the platform's value creation (CECCAGNOLI *et al*., 2012).

The core value proposition of platforms is to reduce search costs for customers to identify and compare service providers and to reduce marketing costs for the service providers, while making the transaction process with an unfamiliar party more comfortable and trustful (KRETSCHMER *et al*., 2020). A shopping mall, for instance, is a platform ecosystem. Customers have lower search costs because instead of having to drive to multiple locations and stores, they can find different offerings in just one place. Stores, on the other hand, do not need to invest so much in marketing, because the shopping mall itself already attracts potential customers.

The advent of internet, mobile technologies, analytics advancement, AI, Big Data and the shift of consumption patterns and consumer preferences fueled platform businesses (WIRTZ *et al*., 2019). Services such as Airbnb, Uber, Lyft, EatWith and RentMyWardrobe emerged in this value shift context and changed the way companies meet customer needs. By doing so, they surpassed established firms in traditional markets, also called pipeline businesses, which used to offer similar services such as hotels, taxi companies, restaurants and wardrobe rental businesses. When comparing traditional firms with digital platforms, there is empirical evidence that platform firms innovate faster, with fewer employees, achieving higher market values, despite having started later (WORLD ECONOMIC FORUM, 2019). Also, because platforms externalize their labor forces to complementors, they may enjoy the benefits of a smaller internal workforce.

While externalizing their labor forces, MSPs can also leverage on reduction of physical assets. Even though Airbnb, for instance, is in the hoteling industry, it does not own any properties offered in the platform, which decreases costs compared to the pipeline model. This asset-based disruption helps platforms go beyond physical limits, allowing a fast growth of these companies and gain in scale. Because of these peculiarities and the fast growth, platforms, mainly digital ones, are spreading across industries from social media, travel, books, and music to transportation, banking, healthcare, and energy (EVANS AND GAWER, 2016).

2.1.1. Typologies of multi-sided platforms (MSPs)

The literature classifies multi-sided platforms into digital and non-digital. Digitization regards the process of creating digital versions of products or services with an increasing gain on scalability and growth (BERTONI *et al*., 2021). Because of this performance gain, digital ventures receive increased attention by investors and are defining the business models of the companies which are emerging (MONAGHAN *et al*., 2020). In the financial industry, for instance, PayPal was a pioneer by transforming the payment market into digital. This led to the explosion of the Fintech market, which leverages on facilitated processes and lower bureaucracy.

By going digital, the ventures can surpass physical limits and reduce transactional and search costs for users of all sides, making them more attractive for potential investors. Shopping malls are an example of non-digital platforms, which connect vendors and stores with potential buyers. With digitization, marketplace firms emerged as the digital version of shopping malls but benefiting from more scalability and even lower embedded costs for the participants of the platform. With shopping malls, shoppers already have lower search costs for finding different offerings in just one place, with marketplaces, the buyers do not even have to leave home, minimizing this cost to zero. E-commerce platforms also have higher reach in comparison to their non-digital counterparts since they have no or exceptionally low geographical and physical barriers.

Cusumano *et al*. (2019a) suggests a typology, which is composed of two main categories and a mixture of them, as presented in Figure 1.

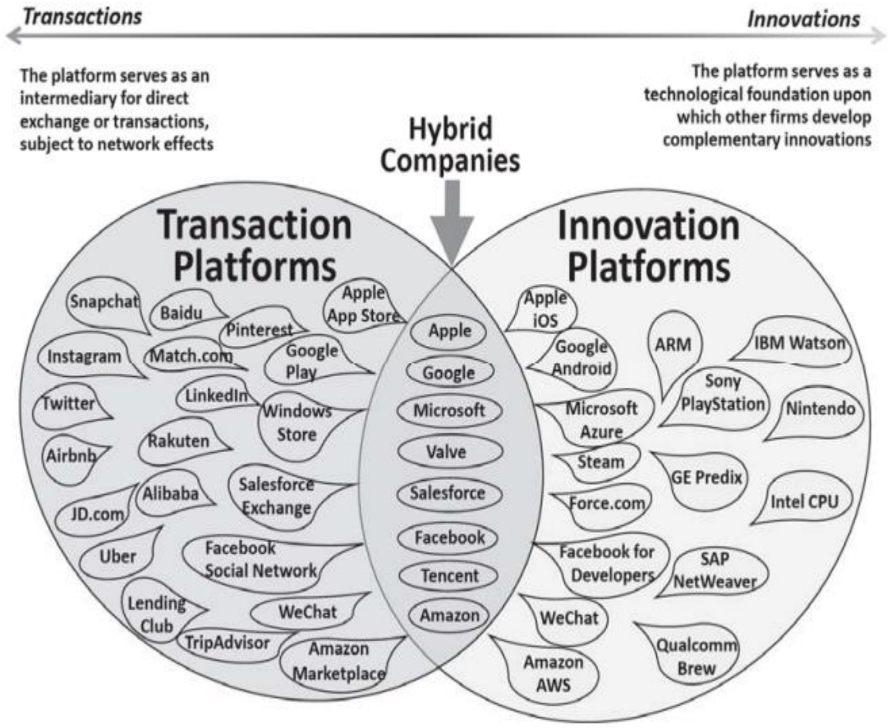

Figure 1 - Two basic platform types
Source: Cusumano *et al.* (2019a)

I. Innovation platforms: technological building blocks in which the platform owner and service providers share to create new complementary products and services, such as iTunes and Netflix. The complementary products are all the innovations that add functionality or access to assets that increase the platform value. These platforms create value by facilitating the development of complementary products and services supplied by the platform and mostly by third-party providers.

II. Transaction platforms: intermediaries or online marketplaces, in which parties can share information or buy and sell goods and services, such as Google Search, Amazon marketplace, Facebook and Mastercard. They create value by facilitating buying and selling of goods and services or allowing interactions.

III. Hybrid platforms: companies that support both types previously explained, such as Apple, Oracle, SAP and Salesforce.

Cusumano's classification, by adopting the concept of hybrid platforms, also considers the existence of overlap. Nevertheless, by doing so, they consider not only the strategies within the same platform infrastructure but also within the same company. These companies might have been born as one of the "pure" classifications and with time developed into a hybrid solution or could have already been from the start a hybrid.

Wirtz *et al*. (2019) proposes a further structure, which suggests that there are several types of platform business models as shown in Figure 2 such as search, communication, social media, matching, content and review, booking aggregator, retail, payment, crowdsourcing and crowdfunding, and development platforms. The most depicted one, however, are the sharing economy platforms, characterized by temporary access or no transfer of asset ownership. Amazon e-commerce or eBay, for instance, are not sharing economies once these platforms perform the sale of assets and the total transfer of ownership. Airbnb, on the other hand, is based on the temporary rent of a room, also called access-based, therefore is a sharing economy.

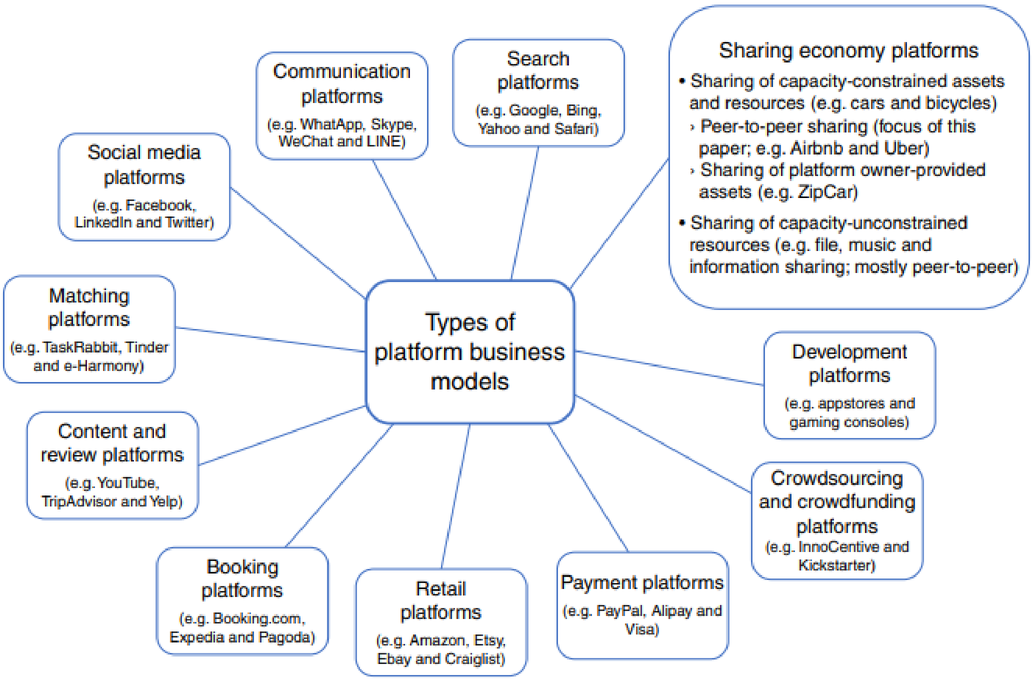

Figure 2 - Types of platform-based business models
Source: Wirtz *et al.* (2019)

He also delineates the differences among sharing economy platforms which differ in terms of capacity-constrained and unconstrained assets. The first refers to assets with spare capacity and relative reduced use and ecological impact, such as physical assets (cars, rooms and bicycles), experiences dependent on labor and shared assets (cooking or dining experience) and intangible assets (capital for loans). The latter refers to assets which different people can simultaneously consume without restraints, such as files, music and information.

Furthermore, these “pure” classifications proposed by Wirtz are combinable as presented by Cusumano’s models. A social media platform, for instance, can also have communications contents, retail and payment functions.

As presented, there are different typologies related to platforms, due to the complexity and peculiarities of the business model. They can help better understand the main challenges MSPs face and how to cope with them. With digitization and technological developments, however, new disrupted platforms will emerge and with that there is the need for new typologies and classifications.

2.1.2. Network effects

The MSPs share distinctive features such as the presence of direct (or same-side) and indirect (or cross-side) network effects. The first emerges when the benefits of participation depend on the quantity of other users in the network (EISENMANN *et al.*, 2008). In the video game industry, for instance, the players can benefit from the presence of other players, since it means greater positive feedback on the quality of the game but also allows an online multiplayer platform.

The direct network effects, however, are less relevant for capacity-constrained assets platforms, because, in these businesses, the service providers have limited inventory to offer. Hence, the participants benefit only up to a threshold level (WIRTZ *et al.*, 2019). In Uber, for instance, if there are too many people looking for drivers, some users may end up not getting a ride. So, unless there is a high enough number of drivers, there is a limit to the benefit of more same-side actors to join.

The indirect effects happen when different sides of a network can mutually benefit from the size of the other side (BOUDREAU AND JEPPESEN, 2015), which implies that a greater number of agents on one side generates greater value added to the other side (HAGIU, 2014). Still considering the video game industry, for game developers it is more advantageous to join a platform with a large customer base, because it offers a greater demand for their games in comparison with smaller platforms (VENKATRAMAN AND LEE, 2004). On the other hand, the availability of a larger set of games influences the adoption decision of users, which consequently increases the customer base (MCINTYRE *et al.*, 2017). These network effects favor the dominant platforms in a "winner takes it all" strategy (EISENMANN *et al.*, 2006). This outcome is especially true when platform specialization is low and multihoming costs (cost of joining multiple platforms) are high.

The network effects caused the shifting of the production logic from vertical integration to open orchestration (WORLD ECONOMIC FORUM, 2019), that is, instead of having an in-house production, companies outsource these working forces. By externalizing production, platforms can have null marginal costs and without costs of production, they can scale faster by adding new complementors. Therefore, they can manage value creation from its complementors while having a more concise internal working force. A further benefit from this shift is that the value of the platform's offerings appreciates with time due to the network exchanges. Since it is based on continuous feedback from the network, the platform benefits from a dynamic and increasing value proposition of exchange with its participants (WORLD ECONOMIC FORUM, 2019).

The impact of network effects, however, differs according to the industry, which implies there is a relative influence of network effects across different markets. On sectors such as ridesharing and credit cards, in which consumers are less worried with the total size of the network and give higher importance to participation of smaller networks of key complementors, the market presents multiple platforms which attend the customers' heterogeneous needs (MCINTYRE *et al.*, 2017). In these markets, users value more specialization than network size. Thus, users benefit from multi-homing, that is, being part of multiple platforms concurrently, which offer slightly diverse services and products. In streaming services, for instance, where the offering is diverse, subscribers practice multi-homing to have access to diverse contents on different platforms.

In social networks, on the other hand, the users intensely value the size of the network more than specialization. After a social network achieves a certain critical mass, the value-added related to the size of the network is so high that new users will always prefer to join the dominant social platform instead of smaller ones. This is the "winner-takes-it-all" situation, in which the market converges to a single platform (MCINTYRE *et al.*, 2017). In these markets, users do not usually practice multi-homing since it is more attractive to join the dominant one.

Further studies discuss the existence of not only across, but within markets network effects. Microsoft, for example, leverages the network's effect both vertically (over multiple generations of products) and horizontally (on adjacent platforms). Consequently, there might be cross-platform network effects, if the membership in a certain platform such as Microsoft Windows might influence the likelihood of the adoption of an adjacent platform such as Xbox (MCINTYRE *et al.*, 2017).

Complementary products also play a key role in expanding the network size (MCINTYRE *et al.*, 2017). The success of the Windows platform, for example, is associated with the complementary productivity software products offered by Microsoft, such as Excel, Word and PowerPoint. Users who value the complementary products would opt to join the Windows network. A further driver to network size is the exclusivity of complements on a platform. iTunes, for example, is an exclusive product on iOS and, in previous times, was the only one which offered an easy single song download music service. Consequently, it was a competitive advantage for Apple, who would further attract users who wanted access to the app.

2.1.3. Achieving critical mass

Aiming to leverage the network effects of heterogeneous resources and user needs, platforms require a certain level of liquidity (transactions) to allow quality matching among the sides (WIRTZ *et al.*, 2019). A platform with high liquidity will deliver higher earnings to service providers and higher utility to users in comparison to platforms below the required level of liquidity. This is related to the critical mass constraint concept that prevents several businesses from succeeding (EVANS AND SCHMALENSEE, 2010). The MSPs need a minimum number of users to guarantee that transactions and interactions take place.

Evans and Schmalensee (2010) define critical mass as "the minimum sets of participants for the platform sides that are necessary for the platform to ignite – that is, have self-sustaining growth". In an e-commerce such as eBay, for instance, for the platform to thrive it needs to have enough buyers and sellers, which will further encourage more to join, otherwise, it will lose the ones it attracted. This concept is also known as the "tipping point" (PHILLIPS, 2007), which is reachable to an extensive length with initial advertising efforts (STRUBEN AND STERMAN, 2008). For a platform, achieving the critical mass is one of the first challenges. When companies achieve it, it can protect the firm from smaller competitors and be a source of competitive advantage (WIRTZ *et al.*, 2019).

According to Ruutu *et al*. (2017), there are three outcomes of platform development, illustrated by Figure *3*. The first scenario is the “Fragmented development” scenario. If there are several competing and non-interoperable platforms, there is the risk that no players reach critical mass. When a market has a short user reaction time, that is, if users can easily discard a platform, the platform owner cannot accumulate resources as effectively, which makes it more difficult to benefit from network effects. Hence, achieving critical mass is harder when user reaction timers are short.

The second is the “winner-take-all” competition scenario, that results on a single dominant platform. In this case, competing platforms develop similarly until a tipping point in which one of the platforms accumulates resources to the extent that there is no room for other competitors in the market. Thus, the market leader can harness increasing returns mechanisms and lock out potential competitors. This may negatively impact the innovativeness and development of an industry (GAWER AND CUSUMANO, 2014).

The last scenario is the “collaboration and competition” or coopetition, in which several platforms coexist in balanced competition. Collaboration between platforms can increase the size of the overall market and make it easier for platforms to achieve critical mass. For users, this scenario is the best outcome, because in the second scenario the market leader can reduce effort and still lock-in customers, while in the coopetition scenario, the rivalry ensures firms keep investing in platform development to attract users. Furthermore, open platforms decrease the risk of lock-in, which further increases platform adoption (EISENMANN *et al*., 2009).

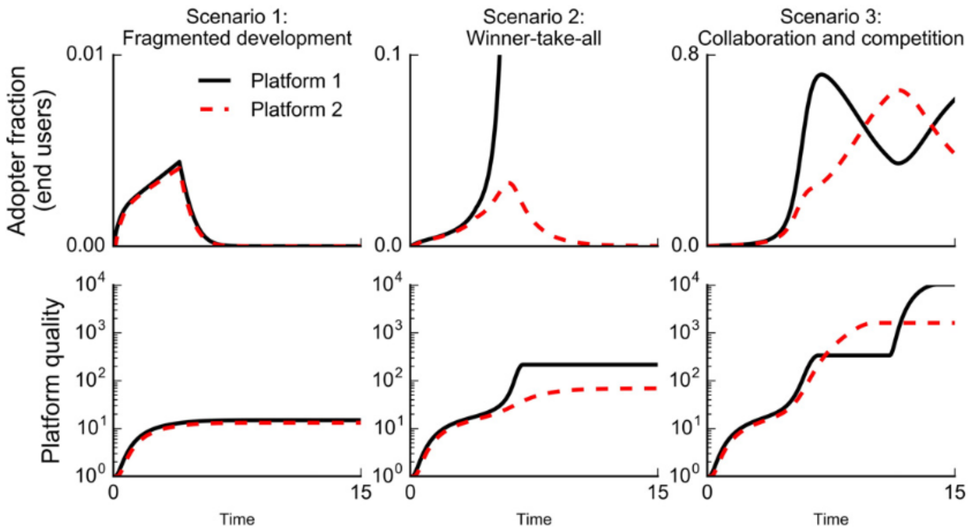

Figure 3 - Three scenarios of platform development
Source: Ruutu *et al.* (2017)

2.1.4. Chicken-and-egg paradox

Companies, therefore, have the challenge of gathering complementors and users to achieve the critical mass and succeed in the market. To attract buyers, the platform needs to have a large base of sellers, but to reach this large base of sellers they also need a sizable pool of potential customers (CAILLAUD AND JULLIEN, 2003). In this scenario, the chicken-and-egg paradox emerges, the MSPs need to simultaneously attract the different sides of the platform to reach critical mass and enjoy the benefits of the direct and indirect network effects.

To overcome the chicken-and-egg challenge, that is, for the platform to grow and become sustainable, it needs to design incentives for participants to join the platform. When participation is voluntary, the incentives should be higher than the opportunity cost the participants get from other forms of gaining income or passing time, compensating the low level of direct authority over participants' behavior (KRETSCHMER *et al.*, 2020). The literature presents different strategies to face this challenge, as presented below.

Evans (2011) proposes five strategies for overcoming the chicken-and-egg dilemma to reach critical mass that are non-exclusive.

I. The Basic Zig-zag strategy is the choice to continuously shift from one side of the platform to the other, to build participation incrementally. It starts with a small number of agents on both sides and then convince agents on either side to join, also relying on natural processes of product diffusion. eBilleMe, for instance, persuaded ToolKing to offer their service at checkout, so a small percentage of customers were using this payment alternative. Then, they turned to online retailers. For each subsequent merchant, they would get more users, incrementally increasing the platform value.

II. Pre-commitment to both sides is when platforms need to have multiple members of both sides to begin the zig-zag process, so they persuade a minimum number of early adopters on both sides to show credibility, by making them believe that when the platform opens for business there will be members of the other side. It is based on the capability of the firm to assure a promised customer base, through specific partnerships or favorable pricing structure, since participants make significant investments to receive the platform's offering. Sony's PlayStation 4, for instance, persuaded customers to invest a large amount on the console with a strong marketing campaign about future videogames and an exclusive partnership with Spotify. In this strategy, contingent contracts may emerge, when customers agree to join the platform under the condition that other customers on the same and other side also join. It takes only one agent to sign the contract, because that will have a domino effect on all other customers

III. Single and Double-Marquee strategies are another way to obtain enough members on both sides to begin the zigzag to critical mass. Marquee customers are the participants of a platform that enable the strongest cross-side positive network effects due to their influence and prestige. This strategy is based on focusing not only on the most profitable customers but also on the marquee customers. In shopping malls, for instance, they sign up a store (an anchor tenant) that attracts a large audience early on and that persuades smaller retailers to rent space at the mall, since they are interested in exploiting the traffic generated by the marquee shops.

IV. Two-step strategy consists of initially concentrating efforts on attracting customers on one side, which generates cross-side network effects. Then, as a second step, the focus is on the other side. This strategy works when the first side does not value access to the second side, which is the case for advertising-supported media. Search engines and social networks use this strategy since their first step is to attract users, and later they sell advertising space at higher prices due to the large user base.

V. Zigzag with self-supply is when the platform can start by providing one of the sides themselves at least initially. YouTube, for instance, is a three-sided platform: content creators, viewers and advertisers. They started by focusing on users and viewers, by generating content themselves and suggesting people from their personal social circles to check the content. Then applied alternating strategies of views and videos uploads to get both viewer and content creator on board at the same time.

According to Parkert *et al*. (2016), there are eight strategies for dealing with the chicken-and-egg dilemma. Some types intersect with the strategies presented by Evans.

I. Follow-the-rabbit strategy starts with an existing non-platform success to demonstrate the history of the company and reputation. Amazon, for instance, before becoming a platform business, operated as a pipeline business. After gathering a customer base, it converted into a platform with the marketplace.

II. Piggyback strategy is when the platforms connect an existing user base from a different platform to the offerings of your own. Justdial, an Indian marketplace, performed this by borrowing listings from existing yellow pages and collecting information going to business door-to-door, with this they created a phone directory service connecting users looking for service and merchants.

III. Seeding strategy is when the platform takes the task of value creation for themselves becoming the first producers. In video games, platform owners usually produce first-party content to overcome the chicken-and-egg paradox, since they cannot sell consoles without games and vice-versa.

IV. Marquee strategy, as already explained in Evans model, is when the platform provides incentives to attract specific members.

V. Single-side strategy is when businesses first create products or services benefiting one side and later convert into a platform. OpenTable, for example, started distributing booking management software to restaurants and once restaurant owners were on board, they built the customer side, connecting people who wanted to book dinners to the restaurants, which allowed OpenTable to collect fees for lead generation.

VI. Producer evangelism strategy involves attracting producers who can bring their own customers to become users of the platform. MasterClass is an example of a platform that brings influential teachers and lecturers on board that have the influence to convince their fans and followers to join the platform.

VII. Big bang adoption strategy involves traditional opportunistic push marketing to attract attention. Tinder's launch, for instance, happened during a frat party which dragged the interest of many young men and women and made it easier for them to reach critical mass.

VIII. Micro Market strategy targets small markets where members engage and prove its effectiveness. It starts from a market niche that allows it to concentrate on defined customers, with delimited requests and needs. This way the platform can better address the customer needs, making it easier to achieve critical mass, since the market is smaller, with the objective of making revenues soon and limiting risk for investors. Once the platform has already reached the critical mass, they can decide to enlarge the target and grow the platform. Facebook, for example, started in the closed Harvard community, which allowed to gather users concentrated in the university and ensured the later success of the community.

Another adopted solution to the chicken-and-egg problem is subsidization. To make it economically sustainable, platforms often adopt a "divide-and-conquer" strategy (CAILLAUD AND JULLIEN, 2001), which bases on subsidizing one of the sides of the platform, by providing discounts or even free use of the service to the most price-sensitive side, to attract the less price-sensitive group to join, which will pay for the service (MCINTYRE *et al*., 2017). In platform markets, giving away a product for free can maximize profit, which is a strategy used by free newspapers, payment cards and parties in which women enter for free (FILISTRUCCHI *et al*., 2014). Additionally, benefiting one side can discourage consumer use of competing platforms.

A further solution to the chicken-and-egg problem is to invest in one side of the market to lower costs for the participants of that side (WIRTZ *et al*., 2019). Microsoft, for example, invests in application developers by designing tools that help them write applications and giving assistance to the operating system. With this strategy, platforms can encourage one side to join, since they benefit from the tools and support provided by the platform, which further incentives the other sides to join leading to overall success of the platform (EVANS, 2003).

2.1.5. Differences between MSPs and traditional organizations

According to Wirtz *et al*. (2019), platforms and pipeline business models differ in terms of *market-level characteristics, market economics* and *firm-level characteristics*. Considering the *market-level* characteristics, traditional businesses are very consumer-focused, with weak aim to increase value to other participants of the value chain, which makes them a one-sided revenue generator. On the other hand, platforms thrive on a circular, iterative and feedback-driven process of value generation involving all agents of the whole value chain, which allows the platform to build multi-sided revenue models.

Regarding *market economics*, a platform's cost structure (fixed and marginal costs) is typically lower when compared to their pipeline counterparts. The latter have significant investments in production assets and stock. While platform's costs are composed mainly of system maintenance, since they have a near-zero marginal cost of production, with cost of serving one additional client and of adding one additional supplier also close to zero. Furthermore, traditional businesses manage supply based on demand. A car rental company, for instance, adjusts the fleet size based on predicted demand. Platforms can equilibrate supply and demand using pricing mechanisms and hence manage capacity constraints more effectively. In Uber, for example, pricing can attract a higher supply of drivers when there is increased demand in a specific region and time. Consequently, platforms are arguably faster and more flexible to respond to change on both supply and demand-side.

Additionally, pipeline businesses commonly offer standardized products and services to homogenous customer segments, opposed to platforms' heterogeneity. Due to this characteristic, platforms rely on sophisticated algorithms and analytics to mitigate the capacity constraints caused by heterogeneity. To better match heterogeneous assets to the heterogeneous user needs, platforms need high liquidity (i.e., transaction volume) to increase value for providers and users and benefit from indirect network effects. While traditional firms treat customers as the average member of an artificially created market segment and have lower requirements regarding liquidity.

Finally, in the *firm-level* aspect, the business models differ in terms of the leadership focus. Pipeline firms achieve competitive advantage by controlling inimitable resources that generate supply-side economies of scale and cost leadership. Doing so, they adopt internal systems of innovation. Oppositely, platform businesses emphasize on resource integration and orchestration for value creation. While pipeline businesses rely on controlling tangible and intangible resources, the platform's key asset is the orchestration of the network of producers and consumers. Consequently, they rely on rapid open innovation, enjoying the benefit of platform collaboration, such as finding new markets, enabling brand extension and overcoming supply constraints.

For Kretschmer *et al*. (2020), the MSPs contrast traditional organizations regarding other three main aspects: "authority", "motivation and incentives" and "governance and coordination". The *authority* of platforms comes from the technological architecture, which allows a centrality and coordination structure between the involved parts. The architecture controls the multi-sided parts, defines the rules of participation (e.g., terms and conditions) and allocates resources (user bases, feedbacks, fees and commissions). While in traditional organizations, the authority arises due to a hierarchical power structure.

Another difference among business models regards the *motivation and incentives*. In traditional business models, the motivation comes from wages payment, which is a low-powered incentive for the parties involved. In platforms, on the other hand, the incentives are indirect since they come from the exchange of value among participants, and they are high-powered since there is uncertainty involved. In Airbnb, for example, the hosts assume risk of non-payment, even though the platform can help solve disputes.

A further distinct feature relates to *governance and coordination*. In platform business models, the individuals or organizations are independent to make their decisions within the rules and limits of the platform. There is a split of control between the participants and the platform owners, differently from what happens in traditional organizations, in which decisions are hierarchical.

2.1.6. Competition with non-platform incumbents

When early-stage platforms are entering established markets and competing with non-platform incumbents, they need to compensate for their lack of power and authority by focusing on the autonomy and flexibility that participants can enjoy on the platform. The platform entrants offer a less restrictive arrangement in comparison with hierarchical incumbents, offering the complementors the opportunity to freely join and leave the platform easily (low entry and exit barriers). With this approach, the platform attracts the participants that prefer more autonomy on their own activities, making them leave the non-platform incumbents (KRETSCHMER *et al*., 2020). Under specific industry conditions (such as geographical, technological or institutional), entrants may even present more benefits in comparison to those incumbents, by offering modularity, loose coupling and flexibility of joining and designing complements to guarantee cooperation between the participants (KRETSCHMER *et al*., 2020).

Incentivizing complementors to join the platform, however, is a big challenge because there is great uncertainty in the takeoff which further increases with the lack of cases of success of platforms in a specific industry, leading to the chicken-egg problem (CAILLAUD AND JULLIEN, 2003). Without other platforms' benchmark, it is not known which incentives will work or not, so the platforms need to adapt themselves and make changes along the way (CLAUSSEN *et al*., 2013). The entrants need to design new incentives and push network effects to differentiate from traditional business models (KRETSCHMER *et al*., 2020) or implement strategies for complementors linkage as explained previously.

A further challenge new platforms may encounter is the fact that the heterogeneity in their available services may generate legitimacy problems, if they go against institutional norms (KURATKO *et al*., 2017). Incumbent unions against new entries can lobby for regulations and be a barrier for newcomers to compete (PAIK *et al*., 2018). Uber, for example, solved this problem with "liminal movement", when the venture tries to establish itself in between existing regulatory categories while intending to change the market environment (GARUD *et al*., 2020). New firms can achieve this by implementing market strategies (partnerships, economic incentives, high visibility events) and non-market strategies (circumventing regulation, fighting state and local labors, hiring lobbyists to influence regulators) (GARUD *et al*., 2020).

Platforms that compete with traditional companies arise faster in digital environments, where the design of the communication system is key to create value by enabling the matching and interaction between previously distant and unconnected parties (KRETSCHMER *et al*., 2020). The design of the communication system defines how transactions and interactions happen. Airbnb, for example, allows online direct communication among hosts and guests, but excludes off-platform communication to avoid offline transactions happening and its ability to get commission.

The incumbents can respond differently to the entries, whether it is by creating regulation barriers for entrants (PAIK *et al*., 2018) or by changing their strategies to differ from newcomers (SEAMANS AND ZHU, 2014, 2017). In Airbnb's case, for example, different hotels focused on diverse strategies: the high-quality hotels responded by increasing their customer service and experience while low quality ones tried to compete on price (CHANG AND SOKOL, 2020). In face of disruptive platform competition, incumbent firms are establishing their own platforms (EVANS AND GAWER, 2016). Hence, this theorizes that the platform entrants affect companies in diverse ways and may cause reshuffling of the industry structure instead of a fast replacement of incumbents (KRETSCHMER *et al*., 2020).

2.2. Equity financing

Among the challenges startups face, the lack of adequate level of funding is one of the main difficulties (TENCA *et al*., 2020). Early-stage ventures have many expenses from its initial phases, while they generate profits (if any) and positive cash flow only in the medium and long term. In this context, liquidity is critical for a startup’s early development, however personal funds and capital raised from friends and family are not enough to sustain the startup’s growth until the profits turn into significant cash flows. Consequently, funding becomes essential for startups to operate successfully in the market.

Nevertheless, young firms have difficulties in raising external capital due to lack of internal cash flow and collateral, asymmetric information, and agency problems (CARPENTER AND PETERSEN, 2002). Information asymmetries can be ex-ante or ex-post. The first one consists of adverse selection, that is, when investors or entrepreneurial finance institutions do not have all the information to select the best ventures, because they cannot distinguish superior and inferior quality startups. Early-stage investments often involve unproven technologies, unfinished products and services and unverified market demand (MURRAY AND MARRIOTT, 1998). This means that evidence certifying the startups’ quality is often unavailable. The second type of information asymmetry regards moral hazard, that is, when investors cannot monitor the behavior of the ventures, so firms can act with distinct objectives. Entrepreneurial firms can choose riskier projects in contrast to investors’ will, which can foster agency problems.

According to Tenca *et al*. (2020), early-stage ventures find it hard to access external finance due to three key concepts: uncertainty, complexity and lack of positive cash flows. Since new-founded firms never operated in the market, there is much uncertainty revolving around their performance, which makes it difficult for external financial providers to estimate the expected return of their investment. Mainly in technologically advanced sectors, the complexity of business models hinders investors from evaluating commercial potential of new developments. Lastly, new ventures hardly present stable and predictable cash flows, hampering to meet financial obligation for debt payment.

These information asymmetries and subsequent adverse selection, moral hazard and agency problems can lead to further market failure and financial gap (COLOMBO *et al*., 2016a). Hence, the relevance of entrepreneurial finance study has been growing and it is one of the key factors that influence quality and quantity of entrepreneurship (DELOOF *et al*., 2019; CHOWDHURY *et al*., 2019; POPOV AND ROOSENBOOM, 2013; SAMILA AND SORENSON, 2011).

Over the last years, many new players such as crowdfunding, accelerators and family offices emerged, as well as new entrepreneurial financing instruments, due to supply and demand factors (BLOCK *et al*., 2018). As a reaction to the 2008 economic crisis, the regulation of financial institutions, focused on banks, have intensified. As a response, banks introduced various risk measures that made it more difficult for small firms to obtain bank financing. Another reaction to the economic crisis was the cut of interest rates by central banks. As a result, investments in government and corporate bonds were less attractive which led investors to seek other investment opportunities, benefiting venture capital funds, incubators and crowdfunding providers.

On the demand-side, the rise of internet and social media as well as globalization fostered the environment for "winner-take-all markets", such as platforms. These business models need to grow fast to benefit from network externalities and to achieve that, they have high cash-burn rates in initial stages of the venture cycle, which further increases demand for funding.

2.2.1. Entrepreneurial finance ecosystem

Startups have common stages in their lifecycle as presented in Figure *4*. During the initial phases of the life cycle, also called "Valley of death", a startup operates without revenue, relying on initial invested capital. In this period, the startup began its operations and is expanding to launch its business and commercialize its products and services, which explains why they might not have yet generated cash flows. Surviving this first period is a great achievement for startups (TENCA *et al.*, 2020).

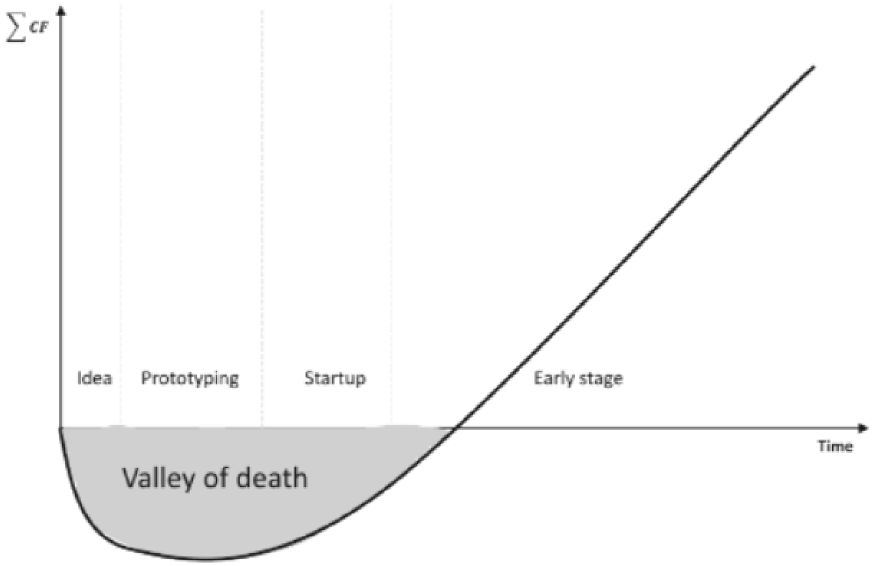

Figure 4 - Startup valley of death
Source: Tenca *et al.* (2020)

The entrepreneurs have the challenge of not only raising capital, but carefully choosing the channels available to raise money. Figure 5 and Table 1 show potential available channels for capital raising according to the stage of the lifecycle and the amount raised, which composes the entrepreneurial finance ecosystem. Among them, ventures can use debt or equity capital markets (TENCA *et al.*, 2020).

Bank loans, overdrafts and other securities, such as minibonds, represent debt capital markets. In summary, companies must pay back debt finance with interest, and it does not mean ownership claim of the venture by the lender. Thus, there is a limit to the investor's upside. Interest is compounded and paid at maturity, so the company can have cash internally to invest in its own operation. There are two types of loans: secured, in case of the presence of collateral, or unsecured, in the absence of it. Collaterals are assets that borrowers offer the lender as a security of the loan payment (TENCA *et al.*, 2020).

Regarding the equity capital market (or risk capital), investors provide capital in exchange for ownership and control of the company. There are two types: private capital, such as venture capitalists, corporate investors and business angels, and public capital markets, such as IPOs (initial public offerings) and crowdfunding.

The different agents in the ecosystem specialize in distinct stages of the startup lifecycle (see again Figure 5 and Table 1). In the seed stage, the most typical source of financing comes from personal savings of founders and the 3Fs (Family, friends and fools). The first actual external investors are typically business angels, who provide from a few tens of thousands of euros to a few hundred thousand euros.

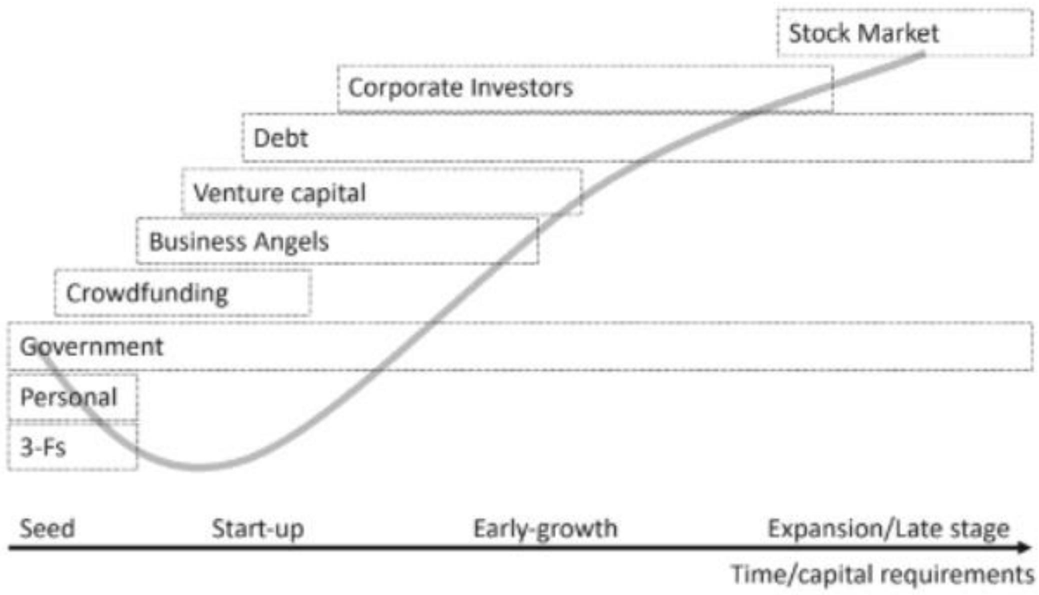

Figure 5 - Financial sources along the company lifecycle
Source: Tenca *et al.* (2020)

Table *1* - Stages of growth

Stages of growth	
Seed stage	A limited amount of capital is given to an entrepreneur as proof of concept. If the initial efforts are effective, next phases include product creation, market analysis and putting together a management team.
Startup stage	Capital is provided for developing the company. The products are usually in testing, pilot production or may be just commercialized. The company may be in the process of incorporation or may already be in business.
Early-growth stage	Capital is used to finance the initial expansion of the company. The company is producing and shipping and has growing working capital. It may or may not be showing a profit. Typically, the company has negative cash flows.
Expansion/late stage	Capital is used to finance a fairly stable growth of the company i.e., the company is still growing, but at a slower rate than in the early-growth stage. The company may or may not be profitable, but it is likely to be more profitable than in the early-growth stage. Typically, the company has positive cash flows. It may also be considering going through an IPO.

Source: Tenca *et al.* (2020)

Digitization has also paved the way for alternative financing channels such as crowdfunding and initial coin offerings (ICOs), which increased the complexity of the start-up financing ecosystem (BERTONI *et al*., 2021). These alternative financing platforms provide startups new types of value adding, such as market tests and feedback from consumers. These new channels can also be an option in seed and startup financing.

Finally, for startup and early-growth stages, venture capitalists and banks are the main options, followed by corporate investors and capital markets (e.g., IPOs). It is possible to consider all these alternatives as complementary forms of financing and not exclusive. A typical combination is Business Angels and Venture Capital, since having diverse skills, they are a heterogeneous combination of resources from which entrepreneurs can benefit (TENCA *et al*, 2020).

2.2.1.1. Crowdfunding

The launch of the first crowdfunding platform was in 2001 (WHARTON, 2010). In contrast to traditional fundraising methods, crowdfunding simplifies equity underwriting, which facilitates startups to obtain finance from a crowd of small investors (BERTONI *et al*., 2021). Crowdfunding is the act of collecting monetary contributions together with feedback and suggestions from a crowd of voluntary contributors through an open call on enabling web platforms (TENCA *et al*., 2020). Unlike other fundraising methods, crowdfunding requires the presence of an intermediary, that is, the crowdfunding platform. This platform is usually a website in which proponents can publish their campaigns within a defined period, and on which interest backers (crowd) can contribute. In a crowdfunding campaign, the project proponents are either individuals or companies and there is a limit to the average amount of finance in a successful campaign (BLOCK *et al*., 2018).

The platform intermediary allows not only the transactional monetary exchange among proponents and backers, but also the interaction which allows the fundraisers to receive feedbacks regarding their projects, understand customers' willingness to pay (BELLEFLAMME *et al*., 2014) and size potential demand (AGRAWAL *et al*., 2014). Backers are an important source of inbound open innovation for crowdfunding organizations, their cooperation makes an important contribution to both financial contribution and knowledge creation (STANKO, 2017). Furthermore, the outcome of a crowdfunding campaign can be an indication of the market response to the business idea, in such a way they can test and improve their products and business ideas. In case the reaction is negative, the entrepreneur can implement changes based on the received feedback (BROWN *et al*., 2017). Additionally, crowdfunding campaigns also serve marketing purposes, since a successful campaign brings public attention and awareness around the business (GERBER AND HUI, 2014). Finally, a successful crowdfunding campaign can be good signaling for other investors, since fundraisers can achieve legitimacy (COLOMBO AND SHAFI, 2019).

The crowdfunded projects in a platform can vary in terms of scope and across different fields and industries and the amount raised goes from a couple of dollars to over $10 million dollars (GERBER AND HUI, 2014). Researchers argue that backers invest in projects motivated by feelings of sympathy and empathy towards the cause in philanthropic campaigns (RICK *et al*., 2007) and for non-philanthropic projects, social identity and social status arises as greater motivations for the investors (GERBER AND HUI, 2014).

Gerber and Hui (2014) present two different funding models that crowdfunding platforms can apply:

I. All of nothing: all the funds return to the supporters if the creators do not achieve their stated goal. This is the model implemented by Kickstarter.
II. All and more: proponents can keep all funds even if they do not reach the goal. Rocket Hub implements this.

If the campaigns reach the goal, the crowdfunding platform requires the creators to pay a platform usage fee and a processing fee to established online payment processing systems, such as PayPal.

2.2.1.2. Business angels

Business Angels are commonly wealthy competent individuals (private investors) who invest in early-stage startups with intrinsic motivation since they often have previous managerial and entrepreneurial experience (TENCA *et al*., 2020). Usually, they provide equity and offer management support and network access, in exchange for a minority share and may also receive tax breaks to reduce investment risk. Due to their previous experience, they can fill potential knowledge gaps that the entrepreneurial team have (PARHANKANGAS AND EHRLICH, 2014).

Scholars agree that the entrepreneurial team is the crucial factor that influences BAs investment decisions, followed by market growth potential and attributes of the product or service (MASON *et al*., 2017). This is such a relevant factor that most rejection of investment opportunities are due to a perception of weaknesses in the entrepreneurial and management team and lack of confidence in the principals (RIDING *et al*., 1995).

The main BAs markets are Europe and the United States, however in recent years, BAs have a key role fulfilling the regional financial gaps, by investing in emerging economies such as China and Southeast Asia (TENCA *et al*., 2020). Therefore, due to political uncertainty, they tend to adopt different investment strategies related to prominent levels of informal networking and co-investments, by doing so, they are reducing financial, economic, legal, monetary, political and market risk (SCHEELA *et al*., 2015).

They are increasingly organizing themselves into angel groups or networks such as EBAN (European Business Angels Network) or IBAN (Italian Business Angels Network) to share information on research and pool their capital, as well as to advise each other regarding their portfolios (TENCA *et al*., 2020). By pooling their capital, they can provide higher amounts of financing than individual BA investors (BLOCK *et al*., 2018) and benefit from economies of scale in the selection and coaching of investment targets (TENCA *et al*., 2020). Also, they save time and cost in the pre-screening phase, reduce transaction costs and share risks.

2.2.1.3. Venture capitalists

Venture Capitalists are a further intermediary in financial markets that provides capital to young firms, by purchasing equity or equity-linked stakes (GOMPERS AND LERNER, 2001). The process of venture capital financing is composed of three stages: fundraising, investing and exit. They initially raise funds, proceed with the screening and selection of the investments, followed by the monitoring of the invested companies and allocation of additional capital to the most successful deals and end with the assisting to the successful exit of the ventures, which returns capital to its investors. This is called the “venture cycle”, that marks the venture capitals’ cyclical activities. VCs tend to finance high-risk firms with expectation of high returns (GROMPERS, 2018), consequently they help fill the finance gap for new ventures that face high uncertainties. Digital platforms are an example of business models that face high uncertainty and risks, due to the already mentioned chicken-and-egg paradox and the challenge to reach critical mass. However, due to its peculiarities, they also display enormous potential for fast growth in winner-takes-all markets, which turn them into attractive investments for VCs.

In the venture capital ecosystem as presented in Figure *6*, there are entrepreneurial firms or entrepreneurs who need funding and private investors who have capital but do not have time or capabilities to perform the investing activity. In this context, venture capitalists function as the intermediaries responsible for managing the cash raised from investors, selecting the best projects and ideas and investing the cash in these firms (BERGER AND UDELL, 1998). When the VC raises a fund, the limited partners (private investors) promise to provide a certain amount of capital during the fund lifetime called committed capital. Then the general partners (venture capitalists) are responsible for managing this capital and investing in different companies. In return for financing a startup for one to two years, they expect ten times return of capital over five years (ZIDER, 1998).

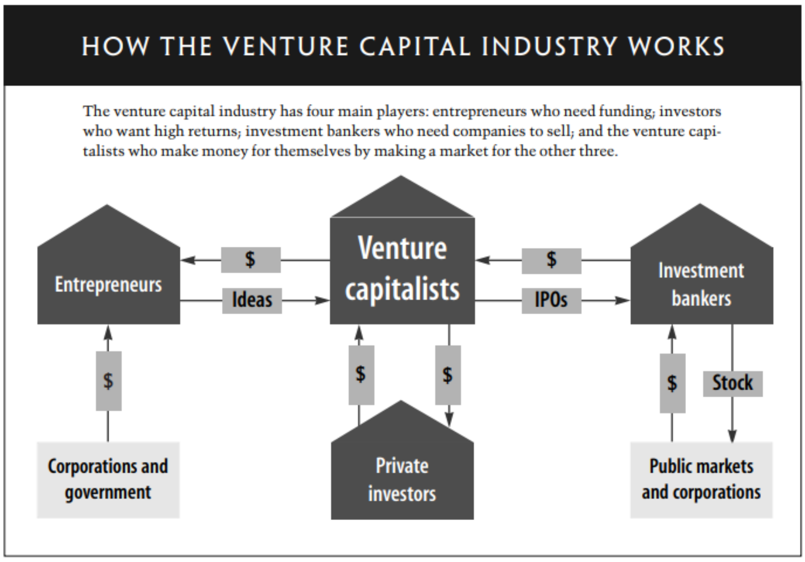

Figure 6 - How the venture capital industry works?
Source: Zider *(*1998)

VCs are responsible for monitoring firms, participating in board meetings and providing financing. After the investment period (usually of 5 years), the fund makes only follow-on investments in current portfolio companies. After a certain period, as startups grow, the general parts collect a percentage of the company's gains plus management fees. And the limited partners receive a percentage of the gains plus cost of capital. Since these investments represent a small part of their portfolios, VCs have great flexibility to screen projects. The VCs focus on investing in good industries and in the middle part of the industry S-curve. In other words, they avoid very early-stage firms, with uncertain technologies and unknown market needs, and later stages, with highly competitive stakes and low growth rates (ZIDER, 1998).

In comparison to the previous funding channels presented, Venture Capitalists are the ones that raise higher amounts of funding. Also, they can provide coaching and network which contributes to the improvement and growth of startups. On the other hand, by getting funding in VCs, ventures need to face the principal-principal agency problem and face agency costs. Besides the fact that the strategic objectives of VCs may diverge from the venture's founders.

Literature classifies venture capitalists in four distinct types: Independent venture capitalists (IVC), Corporate venture capitalists (CVC), Bank venture capitalists (BVC) and Government venture capitalists (GVC). There is also a further classification of university-based venture capitalists (UVC), in which academic institutions set-up funds, focusing, usually, in internal investments, that is, business projects and technologies developed inside the parent university (CROCE *et al*., 2014).

2.2.1.3.1. Independent venture capitalists

IVCs are those that operate independently through limited partnerships (DIMOV AND GEDAJLOVIC, 2010). A typical IVC firm manages more than one fund. These investors typically have purely financial motives, and this represents just one element of their diversified pool of investments (GOMPERS AND LERNER, 1998; JENG AND WELLS, 2000). The private investors in VC funds are typically large institutions, such as pension funds, financial firms, insurance companies, and university endowments, who put a small percentage of their funds into high-risk investments (ZIDER, 1998).

Several research compares behavior and strategies of independent venture capitalists and business angels. There are similarities between them, however VCs are mostly professional investors that invest in early-stage ventures providing mentorship. BAs, on the other hand, are individuals with high income that invest in seed-stage as a sideline activity, therefore do not have exclusive focus in the investing activity (ZIDER, 1998). Another difference is that IVCs are intermediaries between the entrepreneurial ventures and funds, while BAs invest their own money. Due to this difference, IVCs need to prove their competence to outside investors and thus stipulate performance requirements in contract to avoid ex-ante risks (EHRLICH *et al*., 1994; VAN OSNABRUGGE, 2000).

2.2.1.3.2. Corporate venture capitalists

In CVCs, large established firms invest into later or earlier stage startups, with an inclination towards early stage. These incumbents take minority stake in innovative new firms, which remain independent and help them further develop their technologies and markets (BLOCK *et al*., 2018). Besides financial objectives, such as profitable exits, CVCs focus on strategic goals that include exposure to innovative technologies (external R&D), potential to acquire companies, potential to license startups technologies, international business opportunities, demand enhancement due complementary products or services, learning how to do a Venture Capital, leveraging internal technological developments and corporate diversification. In comparison to IVCs, they tend to be more patient and less worried about financial returns since their goal is to have access to startup's innovation. The CVCs also provide network and capabilities related to the field and industry of the parent company.

They can be attractive partners due to the complementary resources and capabilities they offer due to the investor's parent company resources, such as access to labs, beta sites, network of customers and suppliers, marketing resources, distribution channels and insights on industry trends, market knowledge and competition. However, entrepreneurial firms face a big drawback in this type of partnership which is the knowledge misappropriation risk. Once a venture discloses information on its invention, there is a risk that the investor will exploit the information, imitate the invention and leave the investment (DUSHNITSKY AND SHAVER, 2009).

This risk raises awareness over the "swimming with sharks" dilemma, that is, when should entrepreneurs choose an investment partnership with established firms in the same industry (sharks) instead of less risky partners. According to Katila *et al*. (2009), entrepreneurs should take this risk when they need resources that incumbents uniquely provide and when they have defense mechanisms to protect themselves (secrecy and timing). Evidence shows that same industry ties between ventures and CVCs occur only in industries with strong intellectual property protection (DUSHNITSKY AND SHAVER, 2009). Besides legal defenses, ventures may also use timing defenses, such as postponing CVC partnership until later rounds, when protecting knowledge is easier (i.e., after obtaining a patent) (KATILA *et al*., 2009). A further strategy is social defenses such as receiving investments by a prominent IVC, who is central in a syndication network and can advertise misconduct of CVC investors and damage their reputation (HALLEN *et al*, 2014).

Different scholars have studied the performance of CVCs in comparison to IVCs, they found CVC-backed firms are at least as likely as IVCs to successfully exit, that is undergo an IPO or an acquisition at higher valuation, (GOMPERS AND LERNER, 1998) and to survive (HOCHBERG *et al*., 2007).

2.2.1.3.3. Bank venture capitalists

The BVCs are financial institutions' investment subsidiaries (DIMOV AND GEDAJLOVIC, 2010) that have the objective to raise demand for bank services and build relationships early (HELLMANN *et al*., 2008). Considering the possible financial channels that attend the demand for startups funding, they are involved with commercial bank services, such as loans, and investment bank services, such as bonds and exit decisions (IPOs and M&As). Commercial banks have immense potential of contribution to the venture capital market in terms of capital. If banks annually devoted 3 percent of their assets, investments would exceed that from all sources of VC (FIET AND FRASER, 1994).

Besides the fact that early-stage firms prefer equity financing to debt, it is also difficult for start-ups, which have volatile cash flow, less tangible assets and insufficient retained earnings to receive loans from banks (SUN AND UCHIDA, 2016). Therefore, banks started investing in shares of new firms to later provide loans when they become mature. The probability of a bank lending to a start-up increases when the bank previously invested in the firm whether directly or indirectly through its subsidiary BVC (HELLMANN *et al*., 2008).

Due to bank's reputation and visibility in the community, BVCs are very risk averse investors, which explains their tendencies to coinvest with similar types of investors and their investments to access risk-reducing information. Evidence shows that BVCs invest less in high-tech industries that may generate higher financial returns in comparison to IVCs because of the substantial risk attached (WANG *et al*., 2002).

2.2.1.3.4. Government venture capitalists

GVCs funds emerged to alleviate the financial gap problem and to yield social and political initiatives that generate positive externalities to society (COLOMBO *et al*., 2016a). These organizations can help fulfill the equity gap in underdeveloped seed and early-stage markets (BLOCK *et al*., 2018). Because, during the selection process, GVCs can consider investments that are not satisfactory in terms of return for risk if the venture generates enough social payoffs or public benefits. Additionally, they also fill the gap in underprivileged regions that only governmental intervention would attend.

Government programs can also provide training of good VCs and its awards can signal the potential of young firms to the VC market. Since GVCs can have quite different goals, there is great heterogeneity in the types of firms GVCs invest in. One of the specifically stated objectives is to promote innovation, since private investors are unlikely to fully appropriate the returns of R&D investments. Other goals involve job creation, investing in the local economy and supporting the development of national, regional and local technological hubs, besides addressing the equity gap and yielding social rates of return.

There are three allocation types for GVCs: direct public funds, hybrid private-public funds and funds-of-funds (BLOCK *et al*., 2018). The first includes investments done by government-supported VC schemes. The second emerges due to problems related to lack of skills or crowding-out issues. The latter consists of investing in other funds rather than directly in companies.

2.2.2. Equity financing strategies

Due to the elevated risk related to investing in seed and early-stage firms, VCs can use different strategies to dilute the risk such as staging and syndication and to reduce information asymmetries such as stock options as a way of monitoring (GOMPERS AND LERNER, 2001).

2.2.2.1. Syndication

Syndication is when different investors decide to invest together in the same startup with one of the VCs acting as lead investor to share risk, better screening and scale economies. Two empirical definitions of VC syndication appeared in the literature to date (TIAN, 2012). In the first, syndicated VCs are a group of two or more VC firms that share any round of financing. If, however, the entrepreneurial firm receives funds from only one VC firm per round and for all rounds, it is still an individual-backed firm even if different rounds involve different investing VCs. In the second view, if two or more VCs fund the entrepreneurial firm, authors classify the investment as syndicate backed. The first definition was adopted in this paper.

VC firms protect themselves from risk by coinvesting with other investors (ZIDER, 1998). Evidence shows that VC syndicates tend to invest in young, early-stage firms and in earlier financing rounds, when investments are riskier (TIAN, 2012). VCs prefer to have two or three groups involved in most stages of financing, which provides further portfolio diversification and the ability to invest in more deals per dollar of invested capital. Since investors join forces, they can provide higher amounts of funding than single VCs. By investing in more projects, investors can diversify away from firm-specific risk (GOMPERS AND LERNER, 2001).

They also decrease the workload of VC partners by getting others involved in assessing the risks during the due diligence period and in managing the deal (ZIDER, 1998). Furthermore, involving other ventures gives a “second” (or more) opinion on the investee, which limits the risk of funding a bad deal (GOMPERS AND LERNER, 2001) and improves the selection of high-quality ventures since there is double checking (COLOMBO *et al.*, 2016b).

Finally, considering that syndicate members have heterogeneous skills, specialization, and network linkages, they can provide more effective mentoring to entrepreneurs than individual VCs (COLOMBO *et al*., 2016b). Corporate VC firms, for example, may have more knowledge and expertise in specific industries compared to independent VC firms, so when they join forces, they can share knowledge to improve company performance. This allows VC syndicates to invest in more firms at distinct stages of their life cycle and in more R&D intensive and riskier firms than compared to single VCs (TIAN, 2012). By doing so, VCs foster innovation to their portfolio which results in better operating performance. Evidence shows that syndicated VC investments have greater average returns and add more value to entrepreneurial ventures than stand-alone investments, besides presenting higher innovative and post-IPO performances (BRANDER *et al*., 2002; TIAN, 2012).

Syndication also changes how financial markets perceive the quality of the company (TIAN, 2012). The presence of syndication is a positive signal to capital markets because it means that two or more VC firms were willing to co-invest in a single deal. This affects the probabilities of successful exits (IPO or acquisition), IPO underpricing and market valuation. Plus, the presence of several VC firms adds credibility to the investment (ZIDER, 1998).

Scholars have done studies regarding the performance of syndicated investment. Considering a European data set for high-tech entrepreneurial firms, both IVC and CVC investments improve portfolio firm's economic performance separately, however syndicates composed of both types of investors do not (COLOMBO AND MURTINU, 2016). Further studies found that ventures financed by a mix of IVC and GVC raised more money and had higher exit rates than IVC-backed only companies and GVC-backed only ones (BRANDER *et al*., 2015). Alternatively, studies show that the likelihood of successful exit is higher in IVC and GVC syndicated-backed firms, followed by IVC-backed only, further followed by GVC-backed only (CUMMING *et al*., 2014).

2.2.2.2. Staging

Staging is the stepwise provision of several rounds of finance to startups, instead of making a unique investment of all required capital (SAHLMAN, 1990). The investor decides to divide their investments in different rounds to minimize the risk, as with time, they will have more information about the ventures and less agency costs. There are two mechanisms for staged financing: milestones and round financing. In the first, the investor decides to inject new capital contingent to the investor's portfolio predefined targets, whereas, in the later, the negotiation of each new capital infusion happens separately.

By staging, the VC keeps the option to abandon the investment if the entrepreneur engages in opportunistic behavior or does not meet its milestones, thus decreasing agency costs (COLOMBO *et al*., 2016b). Also, by staging, the investors can learn more about the entrepreneur and venture's operations which allows them to make better informed decisions between each round (BERGEMANN AND HEGE, 1998). This is also referred to as the "learning hypothesis", which suggests staging creates value depending on what investors learn between rounds about the firm or the entrepreneur (TIAN, 2011). It implies that there is no relationship between the VC investor's ability to learn about the firm and the distance between them.

Entrepreneurial firms face two agency costs (GOMPERS, 1995) that arise from the principal-principal agency problem – that is the conflicts between controlling and minority shareholders when controlling shareholders disregard the interests of minority ones and expropriate them (BYUN AND KIM, 2013). The first agency costs happen when entrepreneurs (controlling shareholders) prioritize projects that give high personal returns but low payoffs to minority shareholders (such as venture capitalists). Second, entrepreneurs can undertake inefficient continuation when they have privileged information and choose to continue investing in negative NPV projects, because, for example, they receive private benefits from managing their own firm (GOMPERS, 1995). Entrepreneurs are more likely to invest in personally beneficial strategies at minority shareholders' expense when firm value depends on future growth opportunities. Therefore, firms with high market-to-book ratios are more susceptible to these agency costs, which further increases the value of monitoring and reduces the funding duration (GOMPERS, 1995).

To cope with these agency costs, ventures can recur to monitoring by VC investors and staging of capital infusions, also known as "monitoring hypothesis" (TIAN, 2011). An investor will engage in staging only if effective monitoring of the entrepreneur is too costly. Monitoring incurs in costs such as the opportunity cost of generating reports, contracting costs (lawyers and associated costs) and lost time and resources of entrepreneurs and investors. Even though VCs periodically "check-up" on the investees between the investment rounds, monitoring is highly valued once entrepreneurs still have privileged information about the projects they manage (GOMPERS, 1995). Monitoring can become too costly, for instance, if the geographic distance between the investor and the entrepreneur is too high (TIAN, 2011). Based on this, if the VC is located close to the entrepreneurial firm, then the investors will tend to reduce the number of financing rounds and rely on effective monitoring to deal with the agency costs.

On the other hand, staging incurs negotiation and contracting costs. Before each round of capital infusion, VC investors commit time and resources to negotiate and write new contracts. Also, staging can induce entrepreneurs to aim for short-term success rather than long-term (TIAN, 2011). Authors call this scenario “window dressing” since it secures a VC investor’s next round of investment. Furthermore, the division of capital infusions may increase costs for the entrepreneurial firm, thus, incurring in under-investment problems (WANG AND ZHOU, 2004)

The entrepreneur can hold-up a VC investor by threatening to leave the venture for a better career. The literature refers to this situation as the “hold-up” hypothesis (HART AND MOORE, 1994). With staging, the investors protect themselves since the reduced amount invested allows gradual embodiment of the entrepreneur’s human capital in the firm’s physical capital (build-up of collateral), which reduces the incentives for the entrepreneur to leave a firm (TIAN, 2011). Based on this, the investor is more likely to stage an investment if the entrepreneurial firm is in a close-knit community, with other firms clustered together. In this environment, the entrepreneur’s threat is more credible and his power to hold-dup the VC is higher, hence the investors rely on staging to reduce this risk.

Evidence shows that frequent staging is associated with lower industry ratios of tangible assets to total assets, higher market-to-book ratios, and greater R&D intensities (GOMPERS, 1995). There is also a correlation between the age of a venture and the probability for it to receive staged investments. Younger firms are more likely to receive investment in stages, since they lack history and have exceedingly high uncertainty attached (TIAN, 2011). Further research shows a positive relation between the number of financing rounds, for a firm located far away from the VC, and the propensity to go public, operating performance in the IPO and post-IPO survival rate. The opposite occurs for a firm located closer to a VC investor.

3. TESTED HYPOTHESIS

The previous chapters presented the challenges regarding digital platforms and new venture funding. However, the literature does not comprehend the relation between these two. This chapter, thus, introduces the research questions and related hypotheses that aim to fill the gap in the literature.

A fundamental concept that will be used as the base of the following hypothesis is the premise (P1) that platform businesses are risky investments. As presented in the literature review, there is a high risk involved in investing in platform businesses, since they must overcome several challenges. A first would be dealing with the chicken-and-egg paradox, followed by learning to leverage the direct and indirect network effects while trying to achieve critical mass. Platforms only generate value when they reach critical mass from both sides, differently from traditional business which can have a small share of the market without the need of reaching a critical mass to survive.

Additionally, competition in platform-based industries is characterized by a winner-takes-it-all dynamic which further increases the pressure of reaching critical mass. Specially for new ventures this scenario can be very challenging since users prefer the dominant platform to newcomers. Moreover, there are some platform-specific managerial challenges which include (but not limited to): coordination issues which are caused by the chicken-and-egg paradox at the early stages, problems regarding platform governance such as the decisions about the design of the platform (e.g., level of openness and exclusivity), and the platform strategies (i.e., pricing and non-pricing strategies), and also the issues regarding investments (i.e., sorting problems and agency costs). On top of these, there are some challenges caused by uncertainty and information asymmetries. The success and survival of the platform depend on their ability to manage these challenges.

3.1. Types of investors

The first defined hypotheses are related to the type of investors that fund platform businesses. Due to the need to achieve critical mass as early as possible to survive, it is expected that platforms receive their first investments in earlier years of their lifecycle. As well, business angels are usually the first external investors, investing in seed and startup phases. Business angels have also an intrinsic motivation when investing and they have the tendency of considering affinity in their funding decisions, which makes them more risk tolerant and, thus, they may invest in riskier projects, such as platforms.

H1a: MSPs are more likely to receive investment by BAs than non-platform businesses.

On the other hand, some types of investors may be more likely to invest in non-platforms businesses. It is expected that traditional (non-platform) firms tend to generate higher demand for financial services. Since some platforms have practically zero physical assets, it is harder for them to have collateral to ask for loans, which makes them less attractive to BVCs.

H1b: MSPs are less likely to receive investment by BVCs than non-platform businesses.

Another type of investor that could be considered with a higher chance of investing in platform businesses are CVCs, since they focus on innovative ventures and on strategic goals such as potential to acquire companies, demand enhancement due to complementary products and services and corporate diversification. So, investing in platforms can help diversify their operation and enhance their demand.

H1c: MSPs are more likely to receive investment by CVCs than non-platform businesses.

Regarding GVCs, platform businesses are usually not social businesses and they do not present enough payoff and public benefits. Besides that, since most of them are inherently digital, they are not present in underprivileged regions, in which GVCs tend to alleviate the funding gap.

H1d: MSPs are less likely to receive investment by GVCs than non-platform businesses.

IVCs are mainly influenced by financial motives, so they expect high returns with not so high risks. Platforms, when successful, can bring high performances due to peculiarities such as the chicken-and-egg paradox, however as explained before they are very risky investments. Therefore, there is an ambiguous expectation whether these types of investors would rather invest in platform or non-platform businesses. For the sake of the problem description, it will be assumed that they are less likely to invest in platform businesses, however this is not necessarily supported by the literature.

H1e: MSPs are less likely to receive investment by IVCs than non-platform businesses.

Regarding UVCs, they focus on internal projects, it is reasonable to conclude that their investments consist of innovative technology and product development ventures, which typically embodies traditional firms and not platforms.

H1f: MSPs are less likely to receive investment by UVCs than non-platform businesses.

Finally, in the present study we defined the category “Others” which, among different types of investors, crowdfunding platforms are included. Even though crowdfunding investors are less risk sensitive, they usually invest in projects motivated by feelings of sympathy and empathy towards philanthropic causes and/or social identity and social status with the campaigns. While platforms, as already detailed, are usually not social businesses with low focus on philanthropic causes. Assuming crowdfunding platforms are the major representative percentage of “Others”, it can be expected that MSPs are less likely to receive investments by “Others”.

H1g: MSPs are less likely to receive investment by Others than non-platform businesses.

3.2. Staging

From the investors’ point of view, it would be better if they did not have to compromise from the early stage of the venture, since all these challenges result in uncertainties. Nevertheless, by investing as early as possible, investors can benefit more if the investment succeeds. In this context, staging can be a solution since it allows the investors to abandon the investment after monitoring the results of an early-stage venture, giving an opportunity to exit in case of failure, which helps investors to minimize the risk of their investment portfolios.

Since the peculiarities of platform businesses presents risk in the earlier stages of a venture and staging is used as a mechanism to help with governance and monitoring of investees before they reach the critical mass and become self-sustaining, it can be hypothesized that staging is more frequent in platform-based companies than traditional businesses.

H2: MSPs are more likely to receive staged investment than non-platform businesses.

3.3. Syndication

Syndication is another strategy to minimize the impacts of their investments, since smaller shares of an investment means less to lose in case of failure. Also, syndicated deals help investors cope with managerial challenges since platform governance decisions can be better distributed among different investors who can contribute in terms of knowledge and capital. Therefore, it can be expected that platforms tend to receive syndicated investments

H3: MSPs are more likely to receive syndicated investments than non-platform businesses.

3.4. Total investment

It can be argued that digital platforms are more resource-consuming due to their unique requirements. In the start of their lifecycle, platforms incur in high costs due to strategies to overcome the chicken-and-egg paradox and achieve critical mass, such as subsidization (e.g., adoption of divide and conquer strategy), openness strategies (e.g., restriction of user access to minimize negative network effects) and marketing campaigns, which are all costly. However, since they externalize their workforce to complementors and can leverage on the reduction of physical assets (e.g., Uber) mainly in the case of digital platforms and peer-to-peer sharing economies, the contrary can also be argued. Nevertheless, considering their high return potential (winner-takes-it-all scenario), platforms may attract more equity financing than non-platform businesses.

H4: MSPs are more likely to receive a higher amount of equity financing than non-platform businesses.

A summary of the hypotheses is aggregated in Table 2.

Table 2 - Hypotheses to be tested

#	Topic	Hypotheses
H1a	Type of Investor	*MSPs are more likely to receive investment by BAs than non-platforms.*
H1b	Type of Investor	*MSPs are less likely to receive investment by BVCs than non-platforms.*
H1c	Type of Investor	*MSPs are more likely to receive investment by CVCs than non-platforms.*
H1d	Type of Investor	*MSPs are less likely to receive investment by GVCs than non-platforms.*
H1e	Type of Investor	*MSPs are less likely to receive investment by IVCs than non-platforms.*
H1f	Type of Investor	*MSPs are less likely to receive investment by UVCs than non-platforms.*
H1g	Type of Investor	*MSPs are less likely to receive investment by Others than non-platforms.*
H2	Staging	*MSPs are more likely to receive staged investment than non-platforms.*
H3	Syndication	*MSPs are more likely to receive syndicated investments than non-platforms.*
H4	Total Investment	*MSPs are more likely to receive a higher amount of equity financing than non-platforms.*

Source: Prepared by the author.

4. METHODOLOGY

This chapter shows a brief explanation of regression models and tests used to facilitate the understanding of the problem description and the results of the analysis. Since among the variables there are both qualitative and quantitative responses, OLS (Ordinary Least Squares) model and Probit model were used.

4.1. Linear models and ordinary least squares (OLS)

According to Wooldridge (2003), most econometric analyses aim to verify if the dependent variable y can be explained with the variations of an independent variable x, given that the two variables represent a population. A multiple regression model is considered when the research involves one dependent variable related to two or more independent variables (HAIR *et al*., 2005).

A standard way to represent linear multiple regression model, that is, with several explanatory variables, is given by Equation (1) (HEIJ *et al*., 2004):

$$y_i = \beta_0 + \beta_1 \times x_{1i} + \beta_2 \times x_{2i} + \cdots + \beta_k \times x_{ki} + \varepsilon_i \tag{1}$$

In Equation (1), y_i is the dependent variable that represents the answer to a given outcome question. While x_{ki} are the explanatory variables which can be both quantitative and qualitative. β_k are the parameters (constants) that we would like to estimate. ε_i is the unobservable random disturbance or error, which includes omitted variables and measurement error (WOOLDRIDGE, 2010).

Equation (1) can also be written in a matrix form as $Y = Xb + e,$ with the $n \times k$ matrix $X = (x_{ij})$, b as a $k \times 1$ vector of unknown parameters and e as an $n \times 1$ vector of unobserved disturbances (Heij *et al.*, 2004).

The purpose of linear regression is finding the β_k parameters for which the error is minimized. A common estimation method for multiple regression models is the ordinary least squares (OLS) method (BROOKS, 2008). Through this method, the best equation representing the relationship between the dependent variable y_i and the independent variables x_i is obtained by minimizing the sum of the squares of errors. It is possible to determine the least squares estimators as a function of the vector b, as shown in Equation (2) (HEIJ *et al*., 2004):

$$S(b) = \sum e_i^2 = e'e = (y - Xb)'(y - Xb) \tag{2}$$

The minimum of $S(b)$ is obtained by setting the derivatives of $S(b)$ to zero, as seen in Equation (3).

$$\frac{\partial S}{\partial b} = -2X'y + 2X'Xb = 0 \; \rightarrow \; X'Xb = X'y \; \rightarrow b = (X'X)^{-1}X'y \tag{3}$$

To perform a multiple regression model through the OLS method, seven assumptions are made to consistently estimate β_k (HEIJ *et al.*, 2004):

- Assumption 1: fixed regressors. All elements x_{ki} of the matrix Z are non-stochastic.
- Assumption 2: random disturbances, zero mean (in the population).
- Assumption 3: homoskedasticity – the covariance matrix of the disturbances exists.
- Assumption 4: no correlation. The off-diagonal elements of the covariance matrix of disturbances are all equal to zero.
- Assumption 5: constant parameters β and the scalar $\sigma > 0$ are fixed and unknown
- Assumption 6: linear model.
- Assumption 7: normality. The disturbances are normally distributed.

The performance of least squares can be evaluated by the coefficient of determination R², which is the fraction of the total sample variation $\sum(y_i - \bar{y})$ (HEIJ *et al.*, 2004). The coefficient of R^2 is calculated as presented in the Equation (4).

$$R^2 = 1 - \frac{SSR}{SST} = 1 - \frac{Sum\ of\ Squares\ Regression}{Sum\ of\ Squares\ Total} \tag{4}$$

Thus, a model with high prediction quality should have a coefficient R^2 close to 1, indicating that the predicted value is very close to the observed value (WOOLDRIDGE, 2003). On the other hand, if it is 0, the model does not explain any of the variation in Y (GUJARATI, 2011).

4.2.Probit model

Within the scope of econometrics, the class of models that study qualitative response variables is known as Models of Qualitative Response Regression. Among them, the Probit model. One in which the dependent variable Y_i is binary, therefore it can take two values: 0 and 1, as shown in Equation (5) (ALDRICH AND NELSON, 1984).

$$Y_i = \begin{cases} 1, if\ yes \\ 0, if\ no \end{cases} \tag{5}$$

This model is a statistical probability model with two categories in the dependent variable (Liao, 1994) and it is described as in Equation (6).

$$P = pr(y = 1|\, x) = \Phi(x\beta) \tag{6}$$

In Equation (6), P is the probability that $y = 1$, given a certain value of x, that is, it is a conditional probability. In most applications of binary response models, the primary goal is to explain the effects of x on the response probability $P(y = 1|\, x)$. In Equation (6), $\Phi(x\beta)$ is the cumulative distribution function of the standard normal distribution, with the following specification (DAVIDSON AND MACKINNON, 1993):

$$P(Y_i = 1) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x_i\beta} e^{-\frac{z^2}{2}}\, dz \tag{7}$$

The understanding of the Probit model and the interpretation of its β coefficients are facilitated with the representation of an unobservable latent variable (or utility index) I_i (GUJARATI, 2011) such as Equation 8.:

$$P(Y_i = 1) = \Phi(x_i\beta) \rightarrow I_i = x_i\beta \tag{8}$$

In Equation (8), the coefficients β represent the marginal effect of x_i over the latent variable. With the latent variable, it is possible to assume that there is a critical or threshold level of the index, call it I_i^*, such that if I_i exceeds I_i^*, the dependent variable Y_i will have the value of 1, otherwise it will be equal to 0 (GUJARATI, 2011). The value I_i^* is also not observable, but since we assume it is normally distributed with the same mean and variance, it is possible to estimate the parameters β of the index and I_i.

Once the Probit model is applied, several statistics are reported such as the values of β_i, their standard errors, and the value of the likelihood function (WOOLDRIDGE, 2010). The β_i give the signs of the partial effects of each x_i on the response probability. The statistical significance of x_i is determined by whether we can reject $H_0\colon \beta_i = 0$. This process is called the overall goodness of fit, which is tested based on the likelihood ratio on the null hypothesis (GUJARATI, 2011).

As a measure of goodness-of-fit for the Probit model, the statistic called McFadden's R^2, also called pseudo-R^2, defined as Equation (9) (BROOKS, 2008):

$$R^2 = 1 - \frac{LLF}{LLF_0} \tag{9}$$

In which LLF is the maximized value of the logarithm of the maximum function of likelihood for the Probit model. LLF_0 is the value of the logarithm of the maximum function of likelihood for a reduced model where all parameters are zero (the model contains only one intercept).

4.3.The *t*-test

To check whether the explanatory variables have a significant effect on y, we test the null hypothesis $H_0: \beta_i = 0$ against the alternative $H_1: \beta_i \neq 0$ (HEIJ *et al*., 2004). To test whether x_j has no effect on y ($\beta_j = 0$), we compute the t-value, calculating the test statistics as Equation (10) (HEIJ *et al*., 2008).

$$t_j = \frac{b_j}{s\sqrt{a_{jj}}} \tag{10}$$

In Equation (10), b_j are the estimates of the unknown parameters β_j; s is the unbiased estimate for the standard deviation σ and a_{jj} is the jth diagonal element of $(X'X)^{-1}$. The null hypothesis is rejected if t_j differs significantly from zero. Therefore, if $|t| > c$, where c is the significance level defined. In general, however, it is preferable to report the p-value of the test (HEIJ *et al*., 2004). In such a way that the null hypothesis is rejected only for small enough p-values of the test. The test statistics follows a t-Student distribution with $n - 1 - k$ degrees of freedom (where k is the number of estimated parameters). Thus, the p-value represents the area above the curve of an equivalent t-Student distribution from the test statistics on. The lower the estimated p-value, the lower the probability that the null hypothesis is true ($H_0: \beta_i = 0$). Commonly the significance level is α =5%, so the null hypothesis is rejected for $p < 0.05$.

4.4. Multicollinearity issue

Besides the first premise (P1) that platforms are risky businesses, we adopted another premise for the present study: that the dependent variables for the models are not correlated (P2), or else it could potentially cause multicollinearity issues for the multivariate analyses. This is an issue because multicollinearity means that the inputs are influencing each other and therefore there is a double counting in the model, which makes the variables not independent (O'BRIEN, 2007). Although it does not reduce a model's overall predictive power, it can produce estimates of the regression coefficients that are not statistically significant. When two or more independent variables are closely related or measure almost the same thing, then the underlying effect that they measure is being accounted for twice (or more) across the variables, which makes it impossible to say which variable is influencing the independent variable.

5. PROBLEM DESCRIPTION

After introducing the subject of study and the methodology used, this chapter aims at presenting the dataset used, the coding process of identifying platform-based companies, the variables, the model specification and a first look at the sample with an exploratory analysis.

5.1. The database

The VICO database (release 5.0) was the base to build the dataset for the present analysis. It was set up by the VICO project, a program of the European Commission with the objective of assessing the impact of VC investments on the economic performance of entrepreneurial firms in Europe (BERTONI AND MARTÍ, 2012). The sample of companies contains new ventures that operate in high-tech industries in Belgium, Finland, France, Germany, Italy, Spain, and the United Kingdom, independent from other corporations.

For the round-level data of this paper, we combined the VICO database with the PitchBook platform data. PitchBook is a financial data and software company that provides data on global business in private and public markets, investors, transactions, mergers & acquisitions, and funds, along with analytical tools to help interpret the data. The resulting dataset contained data on 14,243 ventures founded between 1935 and 2018 in three European countries (UK, Germany, and France) and invested until 2018.

5.2. Firm classification process

The PitchBook dataset containing the company name and the description of the businesses was the initial point to classify them into platform or non-platform businesses. We read, interpret, and manually classified the ventures according to the definition of CUSUMANO *et al*. (2019b) regarding platforms. Whenever a venture was a platform, we attributed it the value of 1, otherwise 0. We repeated the classification process for all the ventures in the dataset. The distribution of business models is in Table 3. In the end, out of 14,243 firms, it was possible to classify only 9,524 companies regarding the dummy variable 'platform', because we did not find all companies' definitions on PitchBook. As a result, approximately 12% of the classified companies are platform businesses.

According to the final dataset, 7,610 investors were responsible for a total of 19,599 investment rounds. Out of 7,610 investors, we classified 3,436 among seven types of investors categories (BA, IVC, CVC, BVC, GVC, UVC and Others). The subset "Others" includes crowdfunding platforms.

Table 3 - Business model distribution of the dataset

Type of Business Model	Frequency	%	Cumulative %
Non-platform	8,397	88.17	88.17
Platform	1,127	11.83	100.00
Total	9,524	100%	

Source: Prepared by the author.

5.3. Variables

To execute the analysis, we defined different variables as presented in Table 4. The key independent variable in this empirical analysis is the dummy variable "platform". The "TotalInv" contains the whole amount invested per company, so there is no detailed information on how much each investor invested when there is syndication in a particular round. The remaining variables characterize the companies and the investments.

Table 4 - Variable descriptions

Variable	Definitions
platform	Type of business model that equals 1 if platform-based and 0 otherwise.
BAdummy	Dummy that equals 1 when the firm was invested by a BA and 0 otherwise.
BVCdummy	Dummy that equals 1 when the firm was invested by a BVC and 0 otherwise.
CVCdummy	Dummy that equals 1 when the firm was invested by a CVC and 0 otherwise.
GVCdummy	Dummy that equals 1 when the firm was invested by a GVC and 0 otherwise.
IVCdummy	Dummy that equals 1 when the firm was invested by an IVC and 0 otherwise.
UVCdummy	Dummy that equals 1 when the firm was invested by an UVC and 0 otherwise.
Othersdummy	Dummy that equals 1 when the firm was invested by "Others" and 0 otherwise.
d_staging	Dummy that equals 1 when the firm has more than 1 round and 0 otherwise.
nrounds	Each round is considered if the investments were done in the same year with the same "Total Amount Invested per round"
d_syndication	Dummy that equal 1 when at least one of the rounds was funded by more than one investor and 0 otherwise
syndsize	The number of different investors in the same round
TotalInv	Total Equity Invested (per company) in Euros
ageatinv	Age at First Investment Received was calculated by subtracting the InvestmentYear by the FoundationYear
industry	Company Industry (according to Pitchbook)
country	The Country of the Company (UK, Germany and France)
FoundationYear	Foundation Year of the Company
InvestmentYear	The year the investment happened

Source: Prepared by the author.

5.4. Model specification

From the hypotheses established in Table 2 at the end of section 3, it was possible to develop the model to answer the research questions. When dealing with the hypotheses related to the type of investors (H1a, H1b, H1c, H1d, H1e, H1f and H1g), staging (H2) and total investments (H4), the level of analysis is the company. While for syndication (H3) is the round of investment. STATA was used to perform the analyses. Y_{ni} represents a different dependent variable for each hypothesis. The subscript i represents the companies and the subscript n represents the round. In such way that for company level analysis $Y_{ni} = Y_i$. The variable Y_{ni} can be a dummy or continuous variable. For example, for H2a it represents whether the investment was staged or not (dummy). While for H4 it represents the total investment amount the company received (continuous).

The general model to test the hypotheses is described in Equation (11), where Y_{ni} is the dummy or continuous response variable, according to the n^{th} tested hypothesis.

$$Y_{ni} = f(platform, control\ variables) \tag{11}$$

The main specification for the analysis follows Equation (12). The variables used in the model are presented in Table 5.

$$Y_{ni} = \beta_0 + \beta_1 \times platform_i + \sum_{k=1}^{n} \beta_{ki} \times C_{ki} + \varepsilon_{ni} \tag{12}$$

Table 5 - Description of variables and parameters of the linear equation model

Variable	Description
β_0	Intercept coefficient
β_1	Coefficient of variable $platform_i$
$platform_i$	Dummy variable that represents the business model of venture i
β_{ki}	Vector of coefficients of each control variable
C_{ki}	Matrix of control variables, where each column is a different variable, and each line is an observation.
ε_{ni}	The standard error

Source: Prepared by the author.

The vector of control variables C_i changes according to the dependent variable. For all the H1 hypotheses it equals to $C_i = [ageatinv \quad FoundationYear \quad industry \quad country]$. For the H2 and H3 hypotheses it equals to $C_i = [ageatinv \quad industry \quad country]$. Finally, for the H4 hypothesis it equals to $C_i = [nrounds \quad d\_syndication \quad ageatinv \quad industry \quad country]$. The number of rounds ($nrounds_i$) and syndication ($d\_syndication_i$) are added to the list of control variables since the investment amount may increase due to the number of rounds and the existence of syndication.

As the type of investors, staging and syndication are dummy variables, Probit models are used to test H1, H2 and H3, according to Equation (13). $\Phi(x_i'\beta)$ is the cumulative distribution function of the standard normal distribution.

$$P = pr(y_i = 1|\ x_i) = \Phi(x_i'\beta) \qquad (13)$$

Binary dependent variables (Y_{ni}) used in the analysis vary according to the hypotheses tested as presented in Table 6.

Table 6 - Dependent variables per hypotheses

#	Dependent Variable	Description
H1a	$BAdummy_i$	Dummy that indicates whether the company has been invested by a BA
H1b	$BVCdummy_i$	Dummy that indicates whether the company has been invested by a BVC
H1c	$CVCdummy_i$	Dummy that indicates whether the company has been invested by a CVC
H1d	$GVCdummy_i$	Dummy that indicates whether the company has been invested by a GVC
H1e	$IVCdummy_i$	Dummy that indicates whether the company has been invested by a IVC
H1f	$UVCdummy_i$	Dummy that indicates whether the company has been invested by a UVC
H1g	$Othersdummy_i$	Dummy that indicates whether the company has been invested by "Others"
H2	$d\_staging_i$	Dummy that indicates whether the company has more than 1 investment round
H3	$d\_syndication_i$	Dummy that indicates whether at least one of the rounds was funded by more than one investor
H4	ln ($TotalInv_i$)	The natural logarithm of the total Equity Invested (per company) in Euros

Source: Prepared by the author.

This model is used to estimate the likelihood of being invested by each type of investor, of staged and syndicated investments for the sample of companies. The Probit model is estimated using the maximum likelihood method (Montgomery *et al.*, 2012). The marginal effects are used along with the coefficients to estimate the effect that the independent variables have on the dependent variables. Because the marginal effects display the change in the probability of $y = 1$ given a unit change in an independent variable x.

The level of analysis for H2 (i.e., staging) and H4 (i.e., the total amount of investments) is the company level and only the first-round characteristics are focused on. Including only the first round in the regressions is more appropriate because, after the first round, the characteristics of the venture become endogenous to the round (other specifications, such as averaging round characteristics over time, do not materially affect the main results and are available on request). The level of analysis for H3 (i.e., syndication) is at the round level. Because the unit of analysis at the round level involves several observations for the same company, standard errors are clustered by companies.

Finally, the dependent variable for H3 is $TotalInv_i$ which is the total amount of investment received by company i. H4 is tested using the OLS model showed in Equation 14:

$$\ln(Y_i) = \beta_0 + \beta_1 \times platform_i + \beta_2 \times nrounds_i + \beta_3 \times d\_syndication_i + \sum_{k=1}^{n} \beta_{ki} \times C_{ki} + \varepsilon_i \quad (14)$$

A linear regression model with syndication and the number of rounds as the control variables is performed for this hypothesis. We decided to perform a logarithmic transformation for this dependent variable to transform a highly skewed variable into a more normalized dataset. When modeling variables with non-linear relationships, the chances of producing errors are high. Therefore, we used logarithm in the $TotalInv$ variable to avoid overfitting the model.

5.5.The sample and exploratory analysis

The final sample of companies received their first investment rounds between 2008 and 2018. The number of first rounds of equity investments was stable until 2012, when it started increasing until it reached its maximum in 2017. Since almost 25% of the companies had their first investment year in the last two years of the dataset (2017 and 2018), there might not be enough subsequent data on further rounds of investments for these companies, which may compromise the analysis.

Table 7 - Descriptive statistics on the first investment round

	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Freq	1,031	759	1,021	1,041	1,044	1,186	1,391	1,563	1,678	1,807	1,722
%	7.24	5.33	7.17	7.31	7.33	8.33	9.77	10.97	11.78	12.69	12.09

Source: Prepared by the author.

Using the year of the first investment round and the foundation year of each company, we computed the age at first investment of each company, since the literature highlighted the impact of the age of firms with the type of investors that fund them. Analyzing the variable ageatinv against the Total Investment as presented in Figure *7*, there is not a big difference in the investment amount received regarding younger and older firms. However, there are more outliers in younger firms.

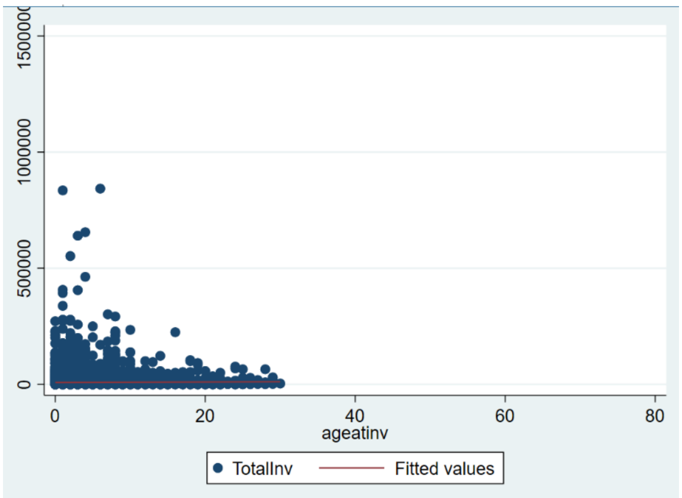

Figure 7 - Scatter plot TotalInv vs ageatinv
Source: Prepared by the author.

The results of the analyzed sample for company nation, foundation year, and industry are respectively $\chi^2(2) = 37.5873$, $\chi^2(33) = 217.6712$ *and* $\chi^2(210) = 2.2e+03$ and $p-value = 0.000$ for all of them. On the other hand, the test results of the full sample (considering missing value) for company nation, foundation year and industry are $\chi^2(4) = 139.7543$, $\chi^2(68) = 912.9796$ *and* $\chi^2(422) = 1.7e+04$, respectively and $p-value = 0.000$ for all. Therefore, the χ^2 test reveals a difference in distribution by country, foundation year and industry, due to the missing data.

The distributions of final sample companies by country are in Figure *8*. The distribution percentage of MSPs and traditional companies in the different countries are similar. The United Kingdom is the most representative country for both business models, with more than 40% of representation. However, France has a slightly higher percentage of traditional firms than multi-sided platforms, while the opposite occurs in Germany.

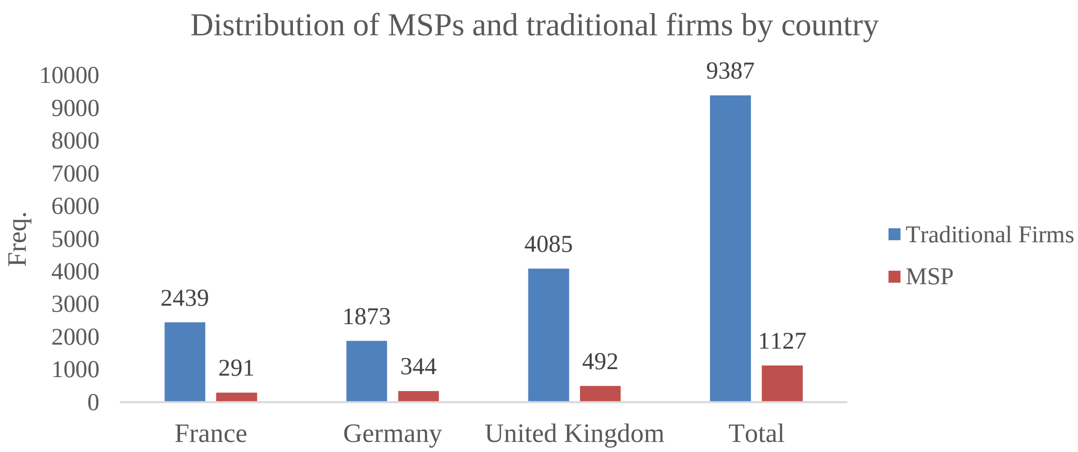

Figure 8 - Distribution of MSPs and traditional firms by country
Source: Prepared by the author.

In terms of foundation year, the peak for both pipeline business and platform companies occurred in 2014, with respectively 633 and 137 companies founded that year. Also, the distribution along the years follows the same tendency for both types of business, as presented in Figure *9*. After the peak in 2014, both the amount of founded traditional firms and MSPs dramatically decreased.

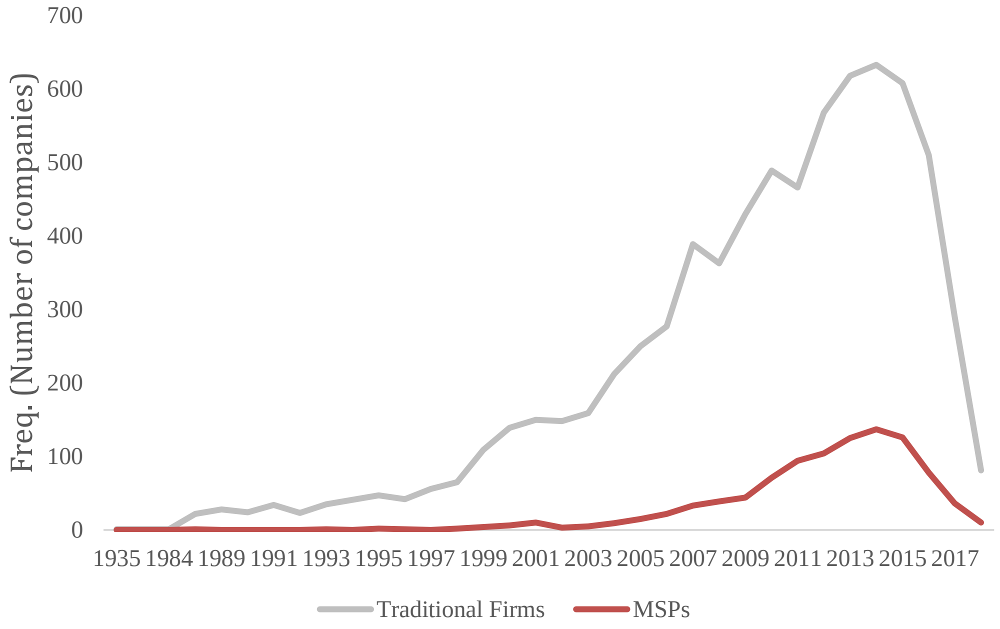

Figure 9 - Traditional *vs* platform business in terms of foundation year
Source: Prepared by the author.

The original dataset had more than 213 classifications for industry, so to facilitate the analysis, we manually grouped those industries according to the International Standard Industrial Classification (ISIC), as presented in Table 8.

The main representative industry for both pipeline and platform businesses was Information and Communication (38% and 42% respectively), which is related to the growth of digital products and services. It is noticeable that the other main industries in MSPs are related to well-known examples of platform business, such as e-commerce (Wholesale and retail trade, 11%) and cards and payments systems (Financial and insurance activities, 11%). On the other hand, it is rare to find platform businesses related to Professional, scientific, and technical activities and Manufacturing, which are the two other main sectors of pipelines business (14% and 10% respectively). Because platform businesses deal with dynamicity and, consequently, are present in industries where the velocity of information and flexibility are valued. The most traditional sectors such as Electricity, gas, steam, and air conditioning supply are most related to traditional firms. Also, MSPs lack governmental-related industries such as

“Public administration and defense; compulsory social security” and “Human health and social work activities”.

Table 8 - Distribution of MSPs and traditional firms by industry

	Traditional		MSP	
Industry	**N**	**%**	**N**	**%**
Accommodation and food service activities	84	1.00	49	4.35
Agriculture, forestry, and fishing	44	0.52	0	0.00
Arts, entertainment, and recreation	118	1.41	7	0.62
Construction	80	0.95	11	0.98
Education	232	2.76	34	3.02
Electricity, gas, steam, and air conditioning supply	374	4.45	1	0.09
Financial and insurance activities	573	6.82	120	10.65
Human health and social work activities	605	7.20	21	1.86
Information and communication	3,198	38.09	463	41.08
Manufacturing	1,208	14.39	96	8.52
Mining and quarrying	6	0.07	2	0.18
Other service activities	381	4.54	80	7.10
Professional, scientific and technical activities	829	9.87	73	6.48
Public administration and defense; compulsory social security	84	1.00	1	0.09
Real estate activities	101	1.20	34	3.02
Transportation and storage	107	1.27	9	0.80
Water supply; sewerage and waste management	6	0.07	0	0.00
Wholesale and retail trade	319	3.80	123	10.91
----	48	0.57	3	0.27
Total	8,397	100	1,127	100

Source: Prepared by the author.

6. RESULTS

This chapter presents the research results, data gathering, and analysis of the main differences of the funding process for the platform and non-platform business models. First, we present the univariate analyses of the main and control variables. Then, after verifying no multicollinearity issues, we present the multivariate analyses with more reliable data to investigate the relationship between the variables and to answer the study's questions.

6.1 Univariate analysis

6.1.1. Age at first investment

Ageatinv (age at first investment) is a control variable, used to capture the impact of young firms. Since companies invested in most recent years have a shorter time horizon, they may have lesser rounds of investments. Table 9 presents the summary statistic for the "ageatinv" variable and Figure *10* shows the box plot of the ageatinv variable grouped by the business model (where 0 represents traditional businesses and 1 represents MSPs).

Table 9 – Descriptive statistics for variable ageatinv

Ageatinv	*Obs*	*Mean*	*Std. dev.*	*Min*	*Max*	*t-value*	*P (two-tailed test)*
Traditional	7,309	4.240389	4.892140	0	78	11.8781	0.0000***
MSPs	978	2.349693	2.511877	0	22		
Total	8,287	4.017256	4.714265	0	78		

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.
Source: Prepared by the author.

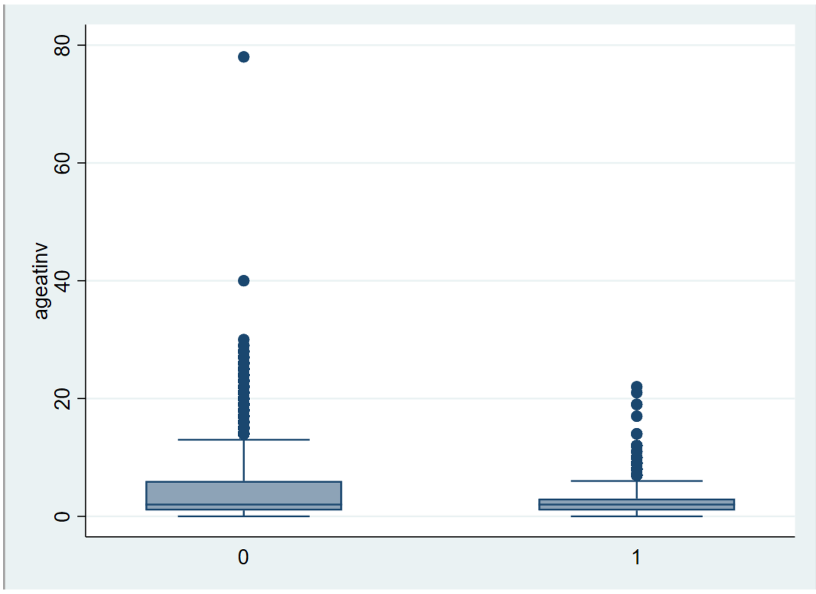

Figure 10 - Box plot age at first investment vs platform
Source: Prepared by the author.

For traditional firms, the average age of the first investments was 4.2 years ($\sigma = 4.9$) and for platform businesses, it was 2.3 years ($\sigma = 2.5$). There is a higher variance in traditional firms since there are more observations and a higher range of minimum and maximum values. When performing a t-test (mean comparison) between traditional and platform businesses, there is statistical difference in the mean age at first investment ($p - value = 0.00 < \alpha = 0.01$). We rejected the null hypothesis for a two-tailed test (H_0: $\mu_{np} - \mu_p = 0$), meaning that the difference in the age at first investment is statistically significant. Also, in the one-tailed test, we rejected the hypothesis that the difference between means is less than or equal to zero (H_a: $\mu_{np} - \mu_p \leq 0$) at 1% level ($p - value = 0.00 < \alpha = 0.01$). Therefore, platforms have a statistically and significantly lower age at first investment and thus receive their first investment before pipeline business, on average 1.9 years before.

This relates to platforms' need for early investments to address the chicken-and-egg problem. In winner-takes-it-all markets, firms have timing pressure to achieve the critical mass of users as early as possible. Therefore, they may look for external finance sooner than traditional businesses, since solving the chicken-and-egg can involve subsidizing, marketing expenses, contractual costs, and early technical developments.

Figure *11* presents the distribution of the variable "ageatinv". For both businesses' models, firms that received their first investment in less than 10 years represent around 80% of the sample of companies, with most companies receiving their first investment at age 1. Firms that received their first investment in less than 3 years represent 53% of the traditional firms and 70% of MSPs. This distribution supports the conclusion that platforms business models receive their first investment in average at earlier age when compared to traditional firms.

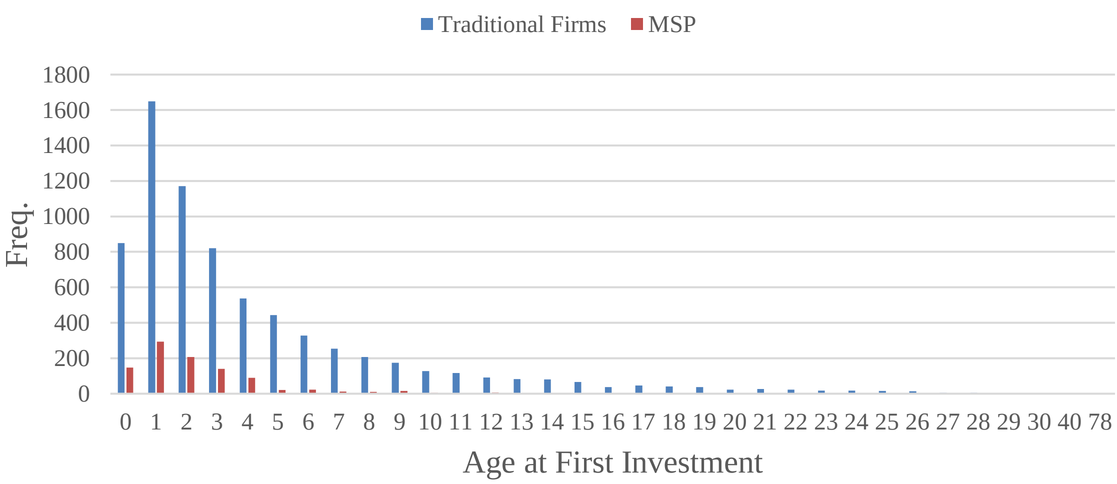

Figure 11 - Distribution of age at first investment for traditional firms and MSPs
Source: Prepared by the author.

6.1.2. Sources of investment

Regarding the types of investors, for both traditional firms and MSPs, Independent Venture capitalists are the main funding source, since more than 50% of the companies received at least one investment by IVCs, as presented in Table 10 and Figure *12*. Overall, the distribution of investor types as presented is similar among the business models. The result of Table 10 is preliminary evidence that digital platforms impact the sources of investment. There is statistical difference in the type of investors for Business Angels ($p - value < 1\%$), BVCs ($p - value < 0.1\%$), CVC ($p - value < 0.1\%$), GVC ($p - value < 1\%$) and UVC ($p - value < 5\%$). However further analysis is necessary before a conclusion of the relationship between platforms and the types of investors they attract.

Table 10 – Sources of investment for traditional firms and MSPs

	Traditional Firms		**MSP**		χ^2	**p-value**
InvestorType	**Freq**	**%**	**Freq**	**%**		
BA	484	6.05	89	8.46	7.9959	0.005**
BVC	625	7.81	51	4.85	12.8292	0.000***
CVC	774	9.67	159	15.11	26.8955	0.000***
GVC	841	10.51	77	7.32	11.5597	0.001***
IVC	4,752	59.39	605	57.51	3.4174	0.065
UVC	158	1.97	11	1.05	4.6751	0.031*
Other	368	4.60	60	5.70	2.0515	0.152
Total	8,002	100.00	1,052	100.00		

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.
Source: Prepared by the author.

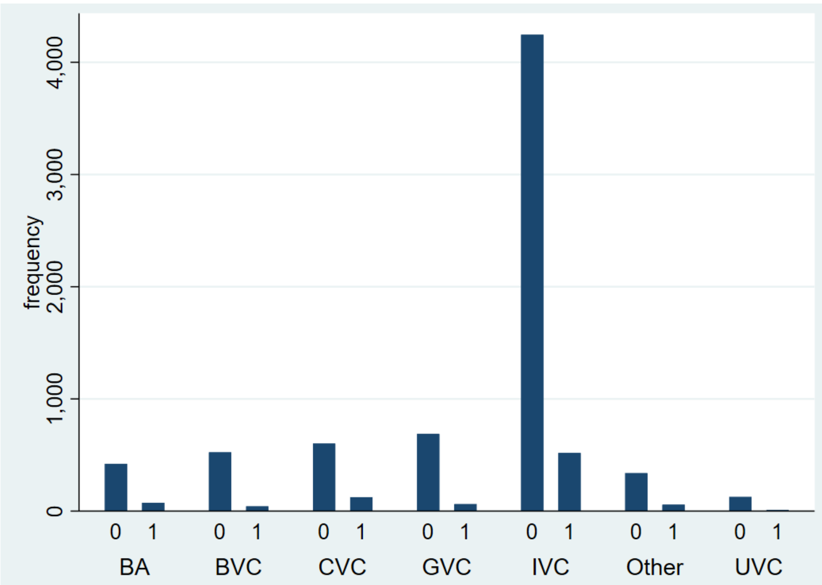

Figure 12 – Graph bar per type of investors and business model
Source: Prepared by the author.

When performing a chi-square (χ^2) test for Business Angels, there is a statistical difference between platforms and non-platform ($p - value = 0.005 < \alpha = 0.01$). The percentage of investments from business angels is significantly higher for platforms. Because, as presented before, multi-sided platforms tend to receive their first investments in earlier years of their lifecycle and business angels are usually the first external investors, investing in seed and startup phases. It can also be related to the intrinsic motivation business angels have when investing and their tendency of considering affinity in their funding decisions, which makes them more risk tolerant and, thus, they may invest in riskier projects, such as platforms, than other investors.

BVCs, on the other hand, have a statistically significantly higher percentage for traditional firms ($p - value = 0.000 < \alpha = 0.01$). Because traditional firms tend to generate higher demand for financial services. Since platforms have smaller cost structures, they may not need to recur to as many bank loans as pipeline businesses. Also, since some platforms have practically zero physical assets, it is harder for them to have collateral to ask for most loans.

CVCs have a higher representation of funding for platforms ($p - value = 0.000 < \alpha = 0.01$). This reflects their focus on innovative ventures and on strategic goals such as potential to acquire companies, demand enhancement due to complementary products and services and corporate diversification. As previously presented, the sampled platforms act mainly on “Information and communication” and “Wholesale and retail trade” industries, which are useful segments for incumbents to diversify their operation and enhance their demand.

GVCs, however, have a higher percentage of investments in pipeline business than MSPs ($p - value = 0.001 < \alpha = 0.01$). Because platform businesses are usually not social businesses and they do not present enough payoff and public benefits. Platforms have small internal workforce and thus tend to generate less jobs than traditional business. Besides that, since most of them are inherently digital, they are not present in underprivileged regions, in which GVCs tend to alleviate the funding gap. The industry “Human health and social work activities” represents only 1.86% of the platform sample companies, while it is higher (7.2%) in pipeline business.

UVCs have a higher percentage for traditional business ($p - value = 0.031 < \alpha = 0.05$). Since this type of investors focus on internal projects, it is reasonable to conclude that their investments consist of innovative technology and product development ventures, which typically embodies traditional firms and not platforms. Finally, there is no statistical significance for “IVCs” and “Other” since p-values are respectively 0.065 and 0.152, which are both higher than 5%.

6.1.3. Staging

In the sample, 25% of all companies received investments in stages. Comparing traditional firms and platforms, staging is more frequent in multi-sided platforms (30.5%) than pipeline business (24.5%) as presented in Table 11 and Figure *13*. When performing a chi-square (χ^2) test between traditional and platform business at company-level, there is statistical difference among staging ($p - value = 0.00 < \alpha = 0.01$) with $\chi^2(1) = 19.1411$. Therefore, platforms have a statistically and significantly higher probability to receive investments in staging than non-platform business.

Table 11 - Staging frequencies in traditional firms and MSPs

	Traditional Firms		**MSP**		χ^2	**p-value**
d_staging	**Freq**	**%**	**Freq**	**%**		
0	6,340	75.50	783	69.48	19.1411	0.000***
1	2,057	24.50	344	30.52		
Total	8,397	100.00	1,127	100.00		

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.
Source: Prepared by the author.

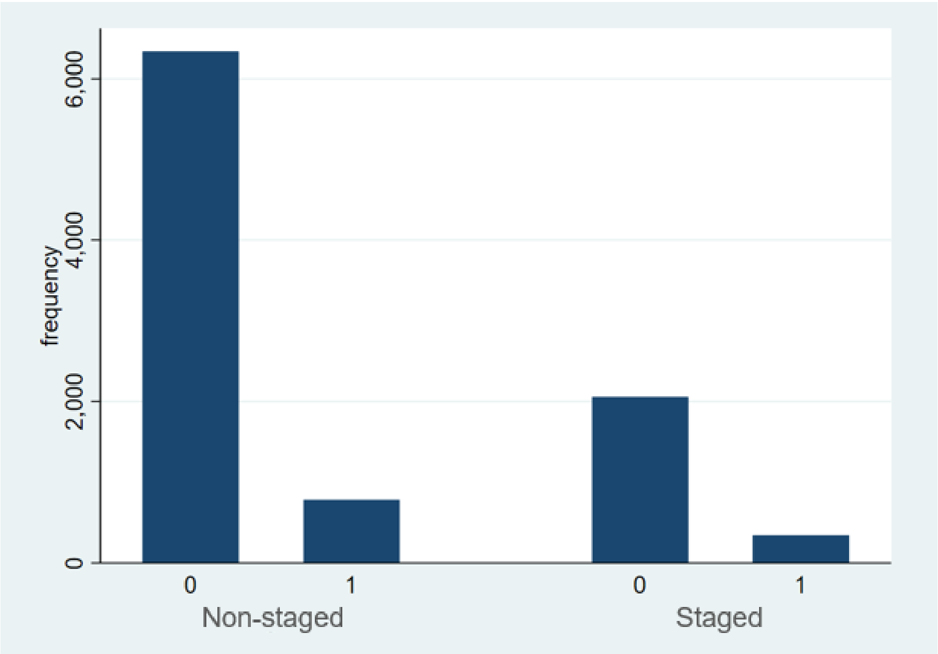

Figure 13 - Graph bar per staging and business model
Source: Prepared by the author.

This is due to the high risks that platforms incorporate. By staging, investors can dilute the risk in different rounds and gain more information on the performance of the venture. As previously seen, platforms tend to receive their first investment earlier, and as presented in the literature, younger firms are more likely to receive investments in stages, because they lack history and have high uncertainties. Since platforms go after external funding to cope with the chicken-and-egg problem, they still do not have a customer base and information asymmetries are remarkably high, which further increases the probability of staging.

Table 12 and Figure *14* show the summary statistics for the number of rounds variable, considering only the companies which received investments in stages. On average, platforms received 2.73 rounds of VC funding, while pipeline business received 2.63 rounds. When performing a t-test (mean comparison) between traditional and platform businesses that received funding in stages, there is no statistical difference among the number of rounds ($p-value = 0.11 > \alpha = 0.05$). We do not reject the null hypothesis for a two-tailed test (H_0: $\mu_{np} - \mu_p = 0$).

Table 12 - Descriptive statistics on number of rounds

Number of Rounds	***Obs***	***Mean***	***Std. dev.***	***Min***	***Max***	***t-value***	***P (two-tailed test)***
Traditional	2,057	2.630044	1.124857	2	12		
MSPs	344	2.735465	1.278811	2	11	-1.5763	0.1151
Total	2,401	2.645148	1.148489	2	12		

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.
Source: Prepared by the author.

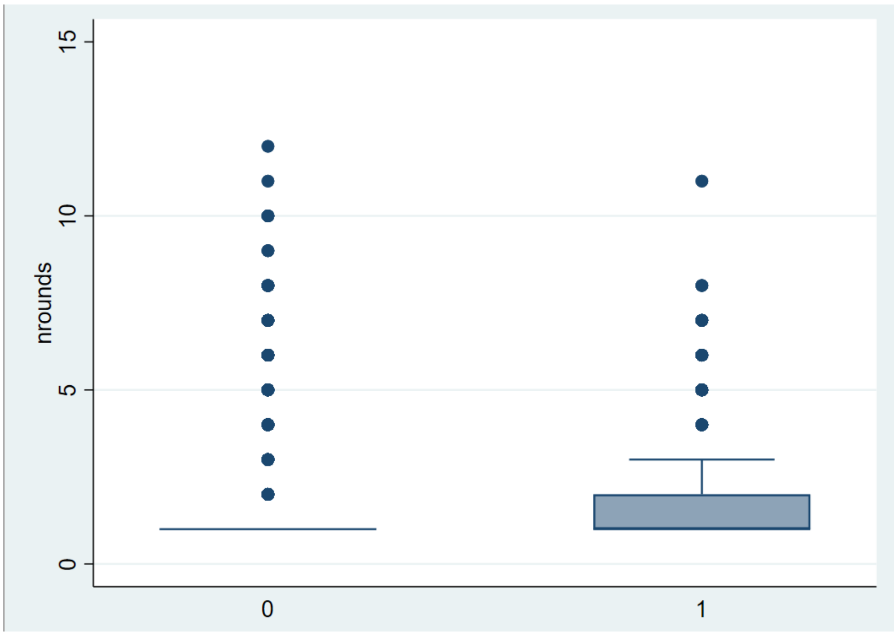

Figure 14 - Box plot nrounds grouped by business model
Source: Prepared by the author.

The initial results show statistically significant differences regarding the presence of staging on platforms and non-platforms. Yet, once these business models receive investments in stages, there is no distinction in the number of rounds received. Further analysis, however, is necessary before a conclusion of the relationship between platforms and the staging patterns.

6.1.4. Syndication

In the sample, 0.82% of all companies received syndication-backed investments. When performing a chi-square (χ^2) test between traditional and platform business at company-level, there is statistical difference among staging ($p - value = 0.006 < \alpha = 0.01$) with $\chi^2(1) = 7.4802$. Comparing traditional firms and platforms, syndication is significantly more frequent in MSPs (1.51%) than pipeline business (0.73%) as presented in Table 13 and Figure *15*.

Table 13 - Syndication frequencies in traditional firms and MSPs (company-level)

	Traditional Firms		**MSP**		χ^2	**p-value**
d_syndication	**Freq**	**%**	**Freq**	**%**		
0	8,336	99.27	1,110	98.49	7.4802	0.006***
1	61	0.73	17	1.51		
Total	8,397	100.00	1,127	100.00		

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.
Source: Prepared by the author.

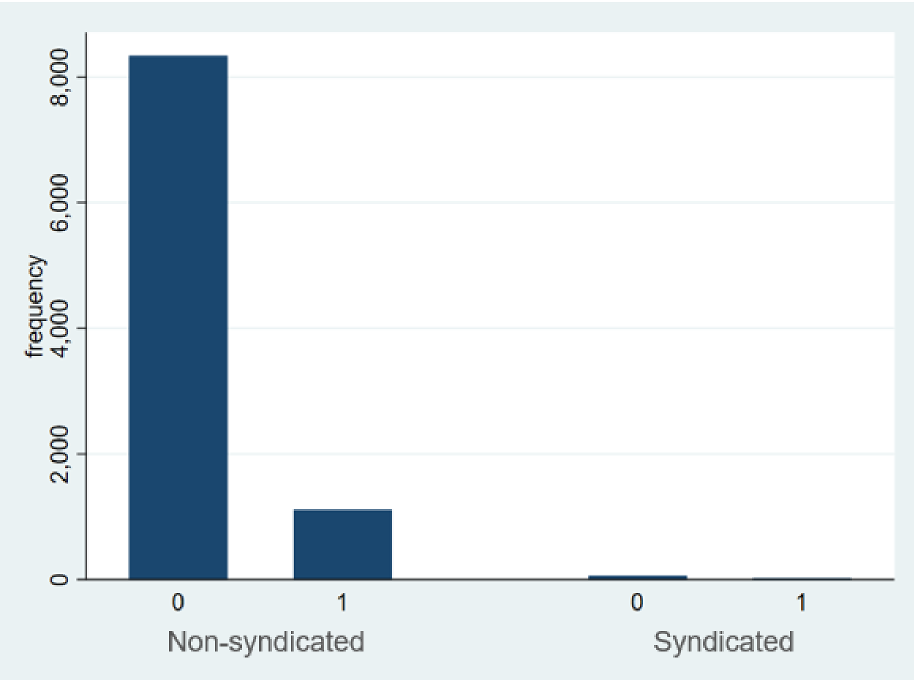

Figure 15 - Graph bar per syndication and business model (company-level)
Source: Prepared by the author.

This confirms the literature since syndication is a strategy used by investors to protect themselves from risky investments and platforms businesses have higher uncertainties and risks attached. Therefore, syndication allows investors to fund more deals which further diversifies their portfolio, limiting firm-specific risk. Also, by grouping with other investors, they have a "second" opinion regarding the investment, which improves the selection of high-quality ventures.

Table 14 and Figure *16* show that out of 13,474 investment rounds only 0.9% were syndicated investments. When performing a chi-square (χ^2) test between traditional and platform business at round-level, there is statistical difference among staging ($p - value = 0.02 < \alpha = 0.05$) with $\chi^2(1) = 5.4229$. Similarly, to the company-level analysis, syndication is significantly more frequent in MSPs (1.39%) than in traditional firms (0.83%) at round-level. The results are in line with the literature due to the same previous reasons.

Table 14 - Syndication frequencies in traditional firms and MSPs (round-level)

	Traditional Firms		**MSP**		χ^2	**p-value**
d_syndication	**Freq**	**%**	**Freq**	**%**		
0	11,653	99.17	1,700	98.61	5.4229	0.020*
1	97	0.83	24	1.39		
Total	11,750	100.00	1,724	100.00		

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.
Source: Prepared by the author.

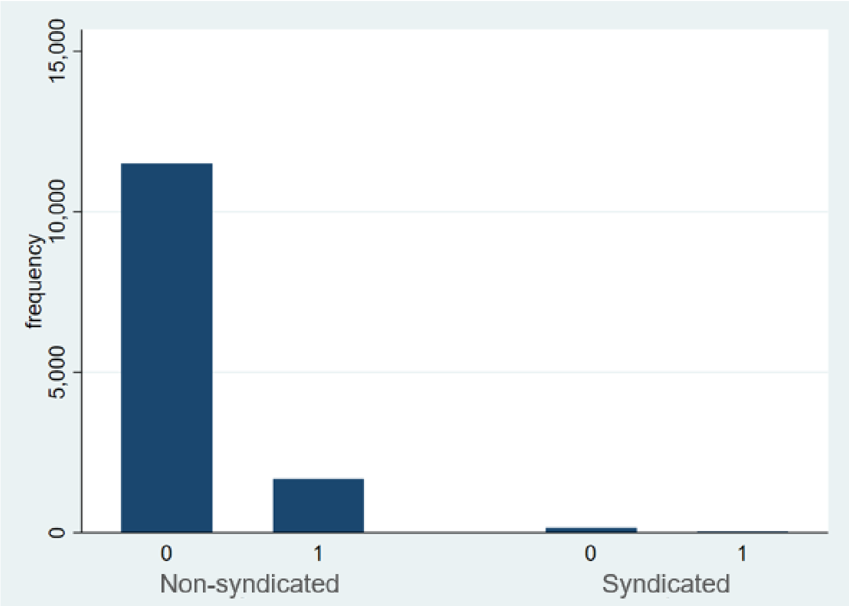

Figure 16 - Graph bar per syndication and business model (round-level)
Source: Prepared by the author.

Table 15 and Figure *17* show the summary statistics for syndication size considering only the rounds of investment with more than one investor. On average, platforms had a slightly higher syndication size 2.09, while pipeline business had 2.08. When performing a t-test (mean comparison) between traditional and platform business, there is no statistical difference among syndication size ($p-value = 0.8964 > \alpha = 0.05$). We do not reject the null hypothesis for the two-tailed test (H_0: $\mu_{np} - \mu_p = 0$), meaning that the difference of syndication size is not statistically significant.

Table 15 - Descriptive statistics on syndication size

Syndication Size	*Obs*	*Mean*	*Std. dev.*	*Min*	*Max*	*t-value*	*P (two-tailed test)*
Traditional	97	2.09278	0.325399	2	4		
MSPs	24	2.08333	0.282329	2	3	0.1305	0.8964
Total	121	2.09090	0.316227	2	4		

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.
Source: Prepared by the author.

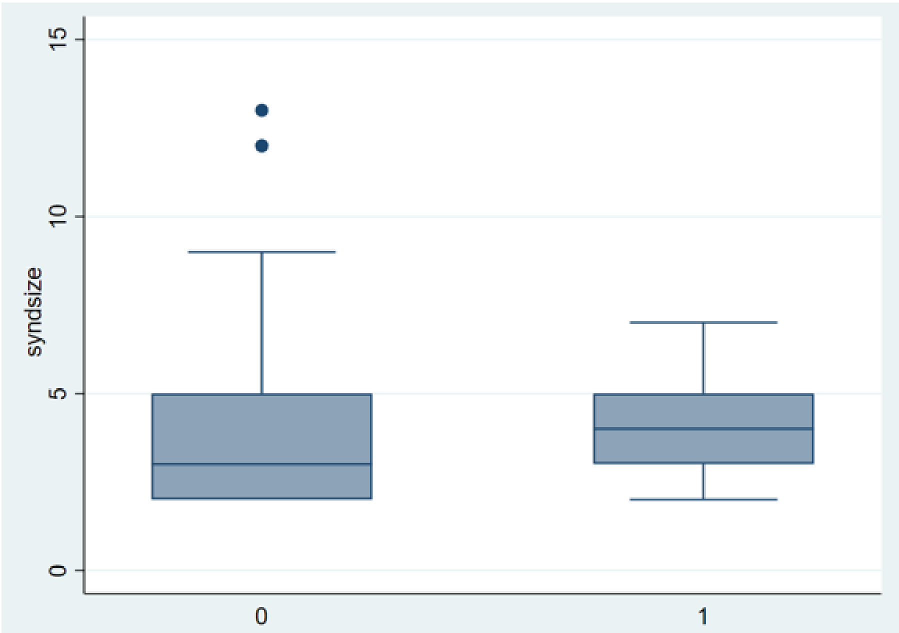

Figure 17 - Box plot syndsize grouped by business model
Source: Prepared by the author.

The initial results present statistically significant differences regarding the presence of syndication on platforms and non-platforms. Yet, once these business models receive syndicated-backed investments, there is no distinction in size of the syndication. Further analysis, however, is necessary before a conclusion of the relationship between platforms and the syndication patterns.

6.1.5. Investment amount

Table 16 and Figure *18* show the main descriptive statistics for the investment amount variable. On average, platforms received 11,974k€ as total investment, while pipeline business received 8,336k€. When performing a t-test (mean comparison) between traditional and platform business, there is statistical difference among the total investment amount ($p -$

$value = 0.0015 < \alpha = 0.01$). We reject the null hypothesis for the two-tailed test (H_0: $\mu_{np} - \mu_p = 0$), meaning that the difference of investment amount is statistically significant. Also, in the one-tailed test, we also reject the hypothesis that the difference between the average amount invested is greater than or equal to zero (H_a: $\mu_{np} - \mu_p \geq 0$) at the 1% level ($p - value = 0.0008 < \alpha = 0.01$). Therefore, platforms have statistically and significantly higher average investments than non-platform businesses.

Table 16 - Descriptive statistics on total investment amount per company

TotalInv	***Obs***	***Mean***	***Std. dev.***	***Min***	***Max***	***t-value***	***P (two-tailed test)***
Traditional	5,59	8,336.3	25,941.6	3.40	842,645.8		
MSPs	772	11,974.0	49,700.7	10.3	835,205.4	-3.1744	0.0015**
Total	6,363	8,777.6	29,867.5	3.40	842,645.8		

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.
Source: Prepared by the author.

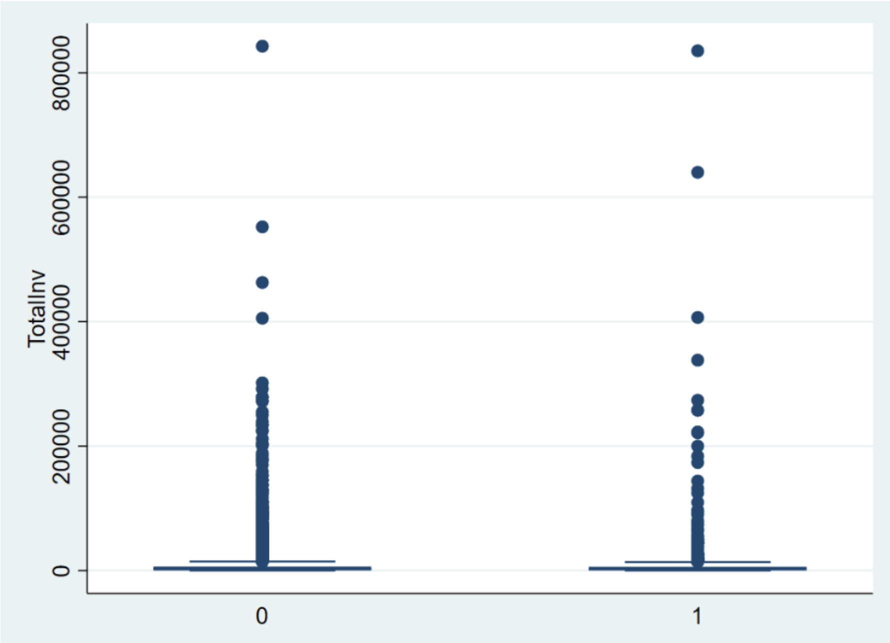

Figure 18 - Box plot investment amount grouped by business model
Source: Prepared by the author.

Platforms face specific problems such as the chicken-and-egg paradox and achieving critical mass, which makes them adopt costly measures such as subsidizing one of the sides or investing in marketing and publicity. Consequently, these businesses need higher amounts of funding to overcome these challenges than traditional firms. Further analysis, however, is necessary before a conclusion of the relationship between platforms and the total invested amount by investors.

Table 17 and Table 18 present the summary of the univariate tests performed.

Table 17 - Summary of univariate analysis chi-square test

Variable	Observations		Test	
	Traditional	MSPs	χ^2	p-value
Type of Investor				
BA	484	89	7.9959	0.005**
BVC	625	51	12.8292	0.000***
CVC	774	159	26.8955	0.000***
GVC	841	77	11.5597	0.001***
IVC	4,752	605	3.4174	0.065
UVC	158	11	4.6751	0.031*
Other	368	60	2.0515	0.152
Staging				
Staged	6,340	783	19.1411	0.000***
Non-staged	2,057	344		
Syndication				
Syndicated (company level)	8,336	1,110	7.4802	0.006***
Non-syndicated (company level)	61	17		
Syndicated (round level)	11,653	1,700	5.4229	0.020*
Non-syndicated (round level)	97	24		

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.
Source: Prepared by the author.

Table 18 - Summary of univariate analysis p-value test of equality

Variable	Observations	Mean	P-value of Test of equality	
			t-value	Probability (two-tailed test)
Age at first investment				
Traditional	7,309	4.2403890		
MSPs	978	2.3496930	11.8781	
Total	8,287	4.0172560		0.0000***
Number of rounds				
Traditional	2,057	2.630044		
MSPs	344	2.735465	-1.5763	0.1151
Total	2,401	2.645148		
Syndication size				
Traditional	97	2.092784		
MSPs	24	2.083333	0.1305	0.8964
Total	121	2.090909		
Total Investments				
Traditional	5,591	8,336.27		
MSPs	772	11,974.00	-3.1744	0.0015**
Total	6,363	8,777.62		

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.
Source: Prepared by the author.

As a preliminary test result, the following variables presented statistical significance.

- Age at first investment: platforms have a statistically and significantly lower age at first investment and thus receive their first investment before pipeline business, on average 1.9 years before
- Business Angels: represent a higher percentage of platform`s investments than traditional ones
- BVCs: represent a higher percentage of traditional firms' investments than MSPs
- CVCs: represent a higher percentage of platform`s investments than traditional ones
- GVCs: represent a higher percentage of traditional firms' investments than MSPs
- UVCs: represent a higher percentage of traditional firms' investments than MSPs
- Staging: platforms have a higher probability to receive investments in staging than non-platform business
- Syndication: is significantly more frequent in multi-sided platforms than pipeline business
- Total Investment: platforms have higher average investments than non-platform businesses

However further analysis is necessary before a conclusion of how the funding patterns are impacted by the business model (platforms and non-platforms).

6.2. Multivariate statistics

To understand if the dependent variables (investor type, staging, syndication and total investment amount), independent variables (platform) and control variables have multicollinearity issues, we built the correlation matrix presented in Table 19 and Figure *19*. As expected, the number of rounds is highly correlated to the staging dummy (0,649) and syndication size is correlated to the syndication dummy (0,968). Another high correlation index is observed between the total investment amount and the number of rounds (0,478). Also, as expected, the foundation year is inversely correlated to the age at first investment (-0,833).

Other than that, there seems to be no concerns regarding multicollinearity issues as per the premises P2 previously explained. Thus, this section aims at investigating the relationships between the dependent variables and its list of control variables to understand whether the results of univariate analysis are conformant or not.

Table 19 - Correlation matrix

	platform	nrounds	d_staging	syndsize	d_synd	TotalInv	ageatinv	Found. Year	country	industry
platform	1.000									
nrounds	0.065	1.000								
d_staging	0.051	0.649	1.000							
syndsize	-0.004	0.097	0.066	1.000						
d_synd	-0.001	0.088	0.066	0.968	1.000					
TotalInv	0.124	0.478	0.212	0.031	0.027	1.000				
ageatinv	-0.123	0.069	0.029	-0.023	-0.023	0.054	1.000			
Found. Year	0.143	-0.107	-0.067	-0.046	-0.045	-0.042	-0.833	1.000		
country	-0.016	0.131	0.068	0.004	-0.002	0.083	-0.056	0.068	1.000	
industry	0.011	0.007	-0.003	0.026	0.027	-0.016	0.071	-0.094	-0.045	1.000

Source: Prepared by the author.

Figure 19 - Correlation graphs
Source: Prepared by the author.

6.2.1. Sources of investment (H1)

To analyze the relation between the sources of investment and the business models, we created seven dummy variables for each type of investor. If a company received any investment by that specific type of investor, it would be attributed the value of 1, otherwise 0. For each type of investor, we applied a Probit model of regression to make estimations at company-level, using the respective dummy variable as the dependent variable and equation 12 presented in the model specification section of the present dissertation: $Y_{ni} = \beta_0 + \beta_1 \times platform_i + \sum_{k=1}^{n} \beta_{ki} \times C_{ki} + \varepsilon_{ni}$, where $C_{ki} = [ageatinv_i \quad FoundationYear_i \quad industry_i \quad country_i]$. In short, the results found were:

- BAs: there is statistical significance for age at first investment, country and industry, but not for platform and foundation year. Therefore, H1a is not supported.
- BVCs: there is statistical significance for platform, age at first investment and industry, but not for country and foundation year. There is support for H1b "*MSPs are less likely to receive investment by BVCs than non-platform businesses*".
- CVCs: there is statistical significance for platform, age at first investment, foundation year and country, but not for industry. There is support for H1c "*MSPs are more likely to receive investment by CVCs than non-platform businesses*".
- GVCs: there is statistical significance for platform, age at first investment, foundation year and country, but not for industry. There is support for H1d "*MSPs are less likely to receive investment by GVCs than non-platform businesses*".
- IVCs: there is statistical significance for age at first investment, foundation year, country and industry, but not for platform. Therefore, H1e is not supported.
- UVCs: there is statistical significance for age at first investment, foundation year and country, but not for platform and industry. Therefore, H1f is not supported.
- Others: there is statistical significance for foundation year and country, but not for platform, age at first investment and industry. Therefore, H1g is not supported.

6.2.1.1 Business Angels (H1a)

Table 20 shows the results for Business Angels for which we tested hypothesis H1a. Due to the missing data of some explanatory variables, the initial sample size of 14,243 companies for this test is reduced to 8,136. The Probit model for BA is significant because the probability model is lower than the level of significance ($p - value = 0.0000 < \alpha = 0.01$). There is statistical significance for age at first investment ($p - value = 0.000 < \alpha = 0.01$), country and industry. However, there is no statistical significance for the platform and Foundation Year variables. Therefore, contrary to the initial insights of the univariate analysis, investments by BAs are not related to the business model and H1a is not supported.

Table 20 - Investor type BA results (Coefficients and standard errors)

Variable Names	BAdummy	Std. Err.	P>|z|
platform	0.05868	0.06930	0.397
ageatinv	-0.05174	0.01193	0.000***
FoundationYear	0.00856	0.00790	0.279
country			
Germany	0.08175	0.07064	0.247
United Kingdom	0.28341	0.06028	0.000***
industry			
Agriculture, forestry, and fishing	0.00000	(empty)	
Arts, entertainment, and recreation	0.06346	0.36155	0.861
Construction	0.64756	0.34127	0.058
Education	0.34100	0.29303	0.245
Electricity, gas, steam, and air conditioning supply	0.29003	0.28768	0.313
Financial and insurance activities	0.53022	0.26839	0.048*
Human health and social work activities	0.33365	0.27481	0.225
Information and communication	0.36908	0.26113	0.158
Manufacturing	0.43467	0.26592	0.102
Mining and quarrying	0.88832	0.65934	0.178
Other service activities	0.25495	0.28352	0.369
Professional, scientific and technical activities	0.02100	0.27580	0.939
Public administration and defense; compulsory social security	0.00000	(empty)	
Real estate activities	0.07263	0.34576	0.834
Transportation and storage	0.24103	0.35238	0.494
Water supply; sewerage and waste management	0.00000	(empty)	
Wholesale and retail trade	0.25261	0.28359	0.373
_cons	-19.15635	15.91481	0.229
N	8,136		
Chi-squared (χ^2)	156.65		
Pseudo R^2	0.0448		
df	19		
Prob > chi2	0.0000***		

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.

Source: Prepared by the author.

Country also affects the predicted probability of an investment by a business angel. Evidence shows that if a company is in the UK, it has a higher probability of funding by a BA ($p - value = 0.0000 < \alpha = 0.01$). Also, if the firm operates in the "Financial and insurance activities" industry, it also has a higher probability of receiving a BA investment ($p - value = 0.048 < \alpha = 0.05$).

The age of first investment, country and industry coefficients can only explain 4.48% (because $R^2 = 0.0448$) of the business angel dummy variable. The coefficient of "ageatinv" equals to -0.05174, which means that a decrease in “ageatinv” increases the predicted probability of an investment by a business angel. Thus, younger firms are more likely to receive investments performed by business angels. This result is in line with the literature, since BAs are investments of seed and startup phases, usually being the first external investors of ventures.

6.2.1.2 BVCs (H1b)

Table 21 shows the results for Bank Venture capitalists for which we tested hypothesis H1b. Due to the missing data for some explanatory variables, the initial sample size of 14,243 companies for this test is reduced to 8,242. The Probit model for BVC is significant because the probability model is lower than the level of significance ($p - value = 0.0000 < \alpha = 0.01$). There is statistical significance for platform ($p - value = 0.029 << \alpha = 0.05$), age at first investment ($p - value = 0.000 < \alpha = 0.01$) and industry. However, there is no statistical significance for country and foundation year variables. Therefore, in line with the initial insights of the univariate analysis, investments by BVCs are related to the business model and H1b is supported.

The platform, ageatinv and industry coefficients can only explain 5.2% (because $R^2 = 0.052$) of the BVC dummy variable. The coefficient of “platform” equals to -0.16607, which means that the predicted probability of an investment by a BVC decreases in case of platforms. As presented in the univariate analysis, platforms have smaller cost structures and do not recur to as many bank loans as non-platform businesses, which explains the greater interest of BVCs in funding pipeline companies.

The coefficient of “ageatinv” equals to 0.03674, which means that an increase in “ageatinv” increases the predicted probability of an investment by a BVC. Thus, the business model (traditional firms preferred) and the age of company at first investment (older firms) impact the investments performed by BVCs. Since BVCs have interest in performing investing activities to generate demand for financial services, they target older companies which display higher information and therefore represent lesser risks.

Industry also affects the predicted probability of an investment by a BVC. Evidence shows that if the firm operates in “Education” ($p - value = 0.0000 < \alpha = 0.01$), “Electricity, gas, steam and air conditioning supply” ($p - value = 0.001 < \alpha = 0.01$), “Financial and insurance activities” ($p - value = 0.027 < \alpha = 0.05$), “Human health and social work activities” ($p - value = 0.004 < \alpha = 0.01$), “Information and communication” ($p - value = 0.0000 < \alpha = 0.01$), “Manufacturing” ($p - value = 0.003 < \alpha = 0.01$), “Professional, scientific and technical activities” ($p - value = 0.000 < \alpha = 0.01$) or

"Wholesale and retail trade" ($p - value = 0.019 < \alpha = 0.05$) industries, it has a lower probability of being funded by a BVC.

Table 21 - Investor type BVC results (Coefficients and standard errors)

Variable Names	BVCdummy	Std. Err.	P>|z|
platform	-0.16607	0.07596	0.029*
ageatinv	0.03674	0.00800	0.000***
FoundationYear	-0.00845	0.00689	0.220
country			
Germany	-0.09144	0.06138	0.136
United Kingdom	-0.00822	0.04940	0.868
industry			
Agriculture, forestry, and fishing	-0.55541	0.35508	0.118
Arts, entertainment, and recreation	-0.28676	0.22036	0.193
Construction	0.02378	0.23364	0.919
Education	-0.90954	0.23445	0.000***
Electricity, gas, steam and air conditioning supply	-0.61992	0.18694	0.001***
Financial and insurance activities	-0.36939	0.16725	0.027*
Human health and social work activities	-0.48723	0.17034	0.004**
Information and communication	-0.54210	0.15357	0.000***
Manufacturing	-0.46893	0.15989	0.003**
Mining and quarrying	-0.01499	0.58818	0.980
Other service activities	-0.22787	0.17087	0.182
Professional, scientific and technical activities	-0.59955	0.16528	0.000***
Public administration and defense; compulsory social security	-0.31962	0.25065	0.202
Real estate activities	-0.35894	0.22623	0.113
Transportation and storage	-0.23639	0.22183	0.287
Water supply; sewerage and waste management	0.00000	(empty)	
Wholesale and retail trade	-0.40831	0.17452	0.019*
_cons	15.86336	13.88077	0.253
N	8,242		
Chi-squared (χ^2)	224.68		
Pseudo R^2	0.052		
df	21		
Prob > chi2	0.0000***		

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.

Source: Prepared by the author.

6.2.1.3 CVCs (H1c)

Table 22 shows the results for Corporate Venture capitalists for which we tested hypothesis H1c. Due to the missing data for some explanatory variables, the initial sample size of 14,243 companies for this test is reduced to 8,242. The Probit model for CVC is significant because the probability model is lower than the level of significance ($p - value = 0.0000 < \alpha = 0.01$). There is statistical significance for platform ($p - value = 0.000 << \alpha = 0.01$), age at first investment ($p - value = 0.006 < \alpha = 0.01$), foundation year ($p - value = 0.008 < \alpha = 0.01$) and country. However, there is no statistical significance for the industry variable. Therefore, in line with the initial insights of the univariate analysis, investments by CVCs are related to the business model and H1c is supported.

Table 22 - Investor type CVC results (Coefficients and standard errors)

Variable Names	**CVCdummy**	**Std. Err.**	**P>|z|**
platform	0.22846	0.05617	0.000***
ageatinv	-0.02169	0.00784	0.006**
FoundationYear	-0.01651	0.00619	0.008**
country			
Germany	0.38621	0.05254	0.000***
United Kingdom	0.11356	0.04808	0.018*
industry			
Agriculture, forestry and fishing	-0.19338	0.38407	0.615
Arts, entertainment and recreation	-0.16764	0.25600	0.513
Construction	0.12325	0.26438	0.641
Education	0.07517	0.20582	0.715
Electricity, gas, steam and air conditioning supply	0.12615	0.19331	0.514
Financial and insurance activities	-0.03739	0.18450	0.839
Human health and social work activities	-0.11324	0.18841	0.548
Information and communication	0.11947	0.17196	0.487
Manufacturing	0.05183	0.17739	0.770
Mining and quarrying	0.10239	0.62554	0.870
Other service activities	0.00546	0.19094	0.977
Professional, scientific and technical activities	0.03672	0.18053	0.839
Public administration and defense; compulsory social security	0.13914	0.26852	0.604
Real estate activities	0.18995	0.22693	0.403
Transportation and storage	-0.17213	0.26270	0.512
Water supply; sewerage and waste management	0.00000	(empty)	
Wholesale and retail trade	-0.00265	0.18996	0.989
_cons	31.74858	12.45551	0.011*
N	8,242		
Chi-squared (χ^2)	115.68		
Pseudo R^2	0.0214		
df	21		
Prob > chi2	0.0000***		

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.
Source: Prepared by the author.

The coefficients can only explain 2.14% (because $R^2 = 0.0214$) of the CVC dummy variable. The coefficient of "platform" equals to 0.22846, which means that the predicted probability of an investment by a CVC increases in case of platforms. Since corporate venture capitalists have many strategic goals that go beyond financial returns such as potential to acquire new companies, demand enhancement due to complementary products and services and corporate diversification, they focus on platforms, which are innovative and help incumbents to achieve the other strategic objectives.

The coefficient of "ageatinv" equals to -0.02169, which means that a decrease in "ageatinv" increases the predicted probability of an investment by a CVC. The coefficient of "FoundationYear" equals to -0.01651, which means that a decrease in the foundation year increases the predicted probability of an investment by a CVC. Thus, the business model (platforms firms preferred), the age of company at first investment (younger firms) and the foundation year (companies with earlier foundation year) impacts the investments performed by CVCs. Because CVCs often help their investees with technological knowledge and development, it can be expected that they engage in investments from the beginning. Consequently, the results are in line with the literature, once CVCs investments are related to firms that received their first investments earlier.

The country also affects the predicted probability of an investment by a CVC. Evidence shows that if a company is in Germany ($p-value = 0.000 < \alpha = 0.01$) or UK ($p-value = 0.018 < \alpha = 0.05$), it has a higher probability of a CVC funding it. This may be related to the strong presence of incumbents in both countries.

6.2.1.4 GVCs (H1d)

Table 23 shows the results for Government Venture capitalists for which we tested hypothesis H1d. Due to the missing data for some explanatory variables, the initial sample size of 14,243 companies for this test is reduced to 8,248. The Probit model for GVC is significant because the probability model is lower than the level of significance ($p-value = 0.0000 < \alpha = 0.01$). There is statistical significance for platform ($p-value = 0.000 < \alpha = 0.01$), age at first investment ($p-value = 0.000 < 0.001$), company foundation year ($p-value = 0.000 < \alpha = 0.01$) and country. However, there is no statistical significance for industry. Therefore, contrary to the initial insights of the univariate analysis, investments by GVCs are not related to the industry, but they are related to the company business model, supporting H1d.

These coefficients can only explain 6.91% (because $R^2 = 0.0691$) of the GVC dummy variable. The coefficient of "platform" equals to -0.27519, which means that the predicted probability of an investment by a GVC decreases in case of platforms. As explained in the univariate analysis section, platforms businesses do not have enough payoff and public benefits. They tend to generate less jobs and, since most of them are inherently digital, they are not present in underprivileged regions. Thus, governmental institutions have less interest in funding platforms than traditional businesses.

Table 23 - Investor type GVC results (Coefficients and standard errors)

Variable Names	GVCdummy	Std. Err.	P>|z|
platform	-0.27519	0.06996	0.000***
ageatinv	-0.04100	0.00794	0.000***
FoundationYear	-0.03465	0.00628	0.000***
country			
Germany	0.27749	0.04861	0.000***
United Kingdom	-0.47582	0.04866	0.000***
industry			
Agriculture, forestry and fishing	0.06704	0.36087	0.853
Arts, entertainment and recreation	-0.01130	0.26961	0.967
Construction	-0.06200	0.30154	0.837
Education	0.30278	0.22706	0.182
Electricity, gas, steam and air conditioning supply	0.20421	0.21560	0.344
Financial and insurance activities	-0.07279	0.21346	0.733
Human health and social work activities	0.24171	0.20896	0.247
Information and communication	0.08616	0.19818	0.664
Manufacturing	0.22558	0.20198	0.264
Mining and quarrying	0.36855	0.60610	0.543
Other service activities	0.06300	0.21599	0.771
Professional, scientific and technical activities	0.34613	0.20366	0.089
Public administration and defense; compulsory social security	0.19797	0.28924	0.494
Real estate activities	0.27775	0.25596	0.278
Transportation and storage	0.44453	0.24903	0.074
Water supply; sewerage and waste management	1.04325	0.55016	0.058
Wholesale and retail trade	-0.01360	0.21642	0.950
_cons	68.49235	12.64372	0.000***
N	8,248		
Chi-squared (χ^2)	373.88		
Pseudo R^2	0.0691		
df	22		
Prob > chi2	0.0000***		

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.

Source: Prepared by the author.

The coefficient of “ageatinv” equals to -0.04100, which means that a decrease in “ageatinv” increases the predicted probability of an investment by a GVC. The coefficient of “FoundationYear” equals to -0.03465, which means that a decrease in the foundation year increases the predicted probability of an investment by a GVC. Hence, the business model (traditional firms preferred), age at first investment (younger firms) and the foundation year (companies with earlier foundation year) impact investments performed by GVCs.

The predicted probability of an investment by a GVC is also affected by the country, evidence shows that if a company is in Germany, it has a higher probability of being funded by a GVC ($p - value = 0.000 < \alpha = 0.01$) and if it is in the UK, there is lower probability of being funded by a GVC ($p - value = 0.000 < \alpha = 0.01$). This is related to the governmental and cultural differences between the two countries, once in Germany, there are more government incentives into innovation and entrepreneurship.

6.2.1.5 IVCs (H1e)

Table 24 shows the results for Independent Venture capitalists for which we tested hypothesis H1e.

Table 24 - Investor type IVC results (Coefficients and standard errors)

Variable Names	IVCdummy	Std. Err.	P>|z|
platform	-0.01291	0.04468	0.773
ageatinv	-0.03937	0.00570	0.000***
FoundationYear	-0.03484	0.00461	0.000***
country			
Germany	-0.25897	0.03924	0.000***
United Kingdom	0.02764	0.03356	0.410
industry			
Agriculture, forestry and fishing	-0.10818	0.24101	0.654
Arts, entertainment and recreation	-0.03086	0.17532	0.860
Construction	-0.26792	0.19708	0.174
Education	0.01999	0.15184	0.895
Electricity, gas, steam and air conditioning supply	-0.10223	0.14287	0.474
Financial and insurance activities	-0.03555	0.13428	0.791
Human health and social work activities	-0.08607	0.13581	0.526
Information and communication	-0.18414	0.12594	0.144
Manufacturing	-0.26530	0.12965	0.041*
Mining and quarrying	-0.18183	0.49159	0.711
Other service activities	-0.13696	0.13946	0.326
Professional, scientific and technical activities	-0.16140	0.13185	0.221
Public administration and defense; compulsory social security	-0.36971	0.19654	0.060
Real estate activities	-0.13964	0.17145	0.415
Transportation and storage	-0.26874	0.17698	0.129
Water supply; sewerage and waste management	-0.43198	0.53254	0.417
Wholesale and retail trade	-0.05523	0.13927	0.692
_cons	70.59197	9.29398	0.000***
N	8,248		
Chi-squared (χ^2)	153.69		
Pseudo R^2	0.0137		
df	22		
Prob > chi2	0.0000***		

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.

Source: Prepared by the author.

Due to the missing data for some explanatory variables, the initial sample size of 14,243 companies for this test is reduced to 8,248. The Probit model for IVC is significant because the probability model is lower than the level of significance ($p - value = 0.0000 < \alpha = 0.01$). There is statistical significance for age at first investment ($p - value = 0.000 < \alpha = 0.01$), foundation year ($p - value = 0.000 < \alpha = 0.01$), country and industry. However, there is no statistical significance for platform. Therefore, as presented in the univariate analysis, investments by IVCs are not related to the business model and H1e is not supported.

These coefficients can only explain 1.37% (because $R^2 = 0.0137$) of the IVC dummy variable. The coefficient of "ageatinv" equals to -0.03937, which means that a decrease in "ageatinv" increases the predicted probability of an investment by an IVC. The coefficient of "FoundationYear" equals to -0.03484, which means that a decrease in the foundation year increases the predicted probability of an investment by an IVC. Thus, age at first investment (younger firms) and foundation year (companies with earlier foundation year) impacts investments performed by IVCs.

Country and industry also affect the predicted probability of an investment by an IVC. Evidence shows that if a company is in Germany, it has a lower probability of an IVC funding it ($p - value = 0.000 < \alpha = 0.01$). If a venture acts in the "Manufacturing" industry, it also has a lower probability of an IVC funding it ($p - value = 0.041 < \alpha = 0.05$).

6.2.1.6 UVCs (H1f)

Table 25 shows the results for University Venture capitalists for which we tested hypothesis H1f. Due to the missing data for some explanatory variables, the initial sample size of 14,243 companies for this test is reduced to 5,759. The Probit model for UVC is significant because the probability model is lower than the level of significance ($p - value = 0.0000 < \alpha = 0.01$). There is statistical significance for age at first investment ($p - value = 0.000 < \alpha = 0.01$), foundation year ($p - value = 0.000 < \alpha = 0.05$) and country. However, there is no statistical significance for the platform and industry variables. Therefore, contrary to the initial insights of the univariate analysis, investments by UVCs are not related to the business model and H1f is not supported.

The coefficients ageatinv, Foundation Year and country can only explain 8.04% (because $R^2 = 0.0804$) of the UVC dummy variable. The coefficient of "ageatinv" equals to -0.09118, which means that a decrease in "ageatinv" increases the predicted probability of an investment by an UVC. The coefficient of "FoundationYear" is equal to -0.05016, which means that a decrease in the foundation year increases the predicted probability of an investment by an UVC. Thus, the age of company (younger firms) and their foundation (companies with earlier foundation year) impacts investments performed by UVCs. Country also affects the predicted probability of an investment by an UVC. Evidence shows that if a company is in Germany, it has a lower probability of an UVC financing it ($p - value = 0.0000 < \alpha = 0.01$).

Table 25 - Investor type UVC results (Coefficients and standard errors)

Variable Names	**UVCdummy**	**Std. Err.**	**P>|z|**
platform	-0.18220	0.13723	0.184
ageatinv	-0.09118	0.01691	0.000***
FoundationYear	-0.05016	0.01193	0.000***
country			
France	0.00000	(empty)	
Germany	-0.80259	0.11382	0.000***
United Kingdom	0.00000	(omitted)	
industry			
Agriculture, forestry and fishing	0.00000	(empty)	
Arts, entertainment and recreation	-0.15849	0.53072	0.765
Construction	0.23616	0.55985	0.673
Education	-0.21283	0.46549	0.648
Electricity, gas, steam and air conditioning supply	0.12744	0.41232	0.757
Financial and insurance activities	-0.21325	0.40391	0.598
Human health and social work activities	0.16271	0.39192	0.678
Information and communication	0.07445	0.37490	0.843
Manufacturing	0.23262	0.38223	0.543
Mining and quarrying	0.00000	(empty)	
Other service activities	-0.02366	0.41583	0.955
Professional, scientific and technical activities	0.32641	0.38307	0.394
Public administration and defense; compulsory social security	-0.07185	0.57429	0.900
Real estate activities	0.00000	(empty)	
Transportation and storage	0.27963	0.49541	0.572
Water supply; sewerage and waste management	0.00000	(empty)	
Wholesale and retail trade	0.07908	0.41675	0.850
_cons	99.25827	24.02136	0.000***
N	5,759		
Chi-squared (χ^2)	113.49		
Pseudo R^2	0.0804		
df	17		
Prob > chi2	0.0000***		

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.

Source: Prepared by the author.

6.2.1.7 Others (H1g)

Table 26 shows the results for “Others” sources of funding for which we tested hypothesis H1g. Due to the missing data of some explanatory variables, the initial sample size of 14,243 companies for this test is reduced to 8,013. The Probit model for “Others” is significant because the probability model is lower than the level of significance ($p - value =$

$0.0000 < \alpha = 0.01$). There is statistical significance for foundation year ($p - value = 0.000 < \alpha = 0.05$) and country. However, there is no statistical significance for platform, age at first investment and industry. Therefore, in line with the initial insights of the univariate analysis, investments by "Others" are not related to the business model and H1g is not supported.

Table 26 - Investor type "Others" results (Coefficients and standard errors)

Variable Names	Others	Std. Err.	P>|z|
platform	0.01838	0.07856	0.815
ageatinv	-0.01265	0.01440	0.380
FoundationYear	0.06204	0.00964	0.000***
country			
Germany	0.43986	0.08844	0.000***
United Kingdom	0.54439	0.07995	0.000***
industry			
Accommodation and food service activities	0.00000	(empty)	
Agriculture, forestry and fishing	0.26218	0.39599	0.508
Arts, entertainment and recreation	0.26546	0.26923	0.324
Construction	-0.24087	0.43213	0.577
Education	0.08116	0.21745	0.709
Electricity, gas, steam and air conditioning supply	-0.21237	0.24254	0.381
Financial and insurance activities	-0.09917	0.18100	0.584
Human health and social work activities	0.08563	0.18434	0.642
Information and communication	0.25408	0.15487	0.101
Manufacturing	0.17196	0.16609	0.301
Mining and quarrying	0.00000	(empty)	
Other service activities	0.26573	0.19050	0.163
Professional, scientific and technical activities	-0.08312	0.18135	0.647
Public administration and defense; compulsory social security	-0.19381	0.45458	0.670
Real estate activities	0.00000	(empty)	
Transportation and storage	0.15042	0.29074	0.605
Water supply; sewerage and waste management	0.00000	(empty)	
Wholesale and retail trade	0.00000	(omitted)	
_cons	-127.029	19.41342	0.000***
N	8,013		
Chi-squared (χ^2)	248.84		
Pseudo R²	0.0882		
df	18		
Prob > chi2	0.0000***		

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.

Source: Prepared by the author.

These coefficients can only explain 8.82% (because $R^2 = 0.0882$) of the "Others" dummy variable. The coefficient of "FoundationYear" is equal to 0.06204, which means that an increase in the foundation year increases the predicted probability of an investment by

"Others". Hence the foundation year (companies with more recent foundation year) impacts the likelihood of investments by GVCs. The country also affects the predicted probability of an investment by "Others". Evidence shows that if a company is in Germany or the UK, it has a higher probability of "Others" funding it ($p-value = 0.0000 < \alpha = 0.01$). Since, "Others" category covers a range of different investors (crowdfunding included), it is not possible to bring insights on the reasons behind the results, because these investors are heterogeneous and therefore have distinct characteristics and strategic goals.

6.2.2. Staging (H2)

For this analysis, the staging dummy is the dependent variable at the company-level. Since it is a binary variable, we used the Probit model of regression with the equation 12: $Y_{ni} = \beta_0 + \beta_1 \times platform_i + \sum_{k=1}^{n} \beta_{ki} \times C_{ki} + \varepsilon_{ni}$, where $C_{ki} = [ageatinv_i \quad industry_i \quad country_i]$. The results for testing H2 are presented in Table 27. Due to the missing data of some explanatory variables, the initial sample size of 14,243 companies for this test is reduced to 8,248. In short, there is statistical significance for platform and age at first investment, but not for country and industry. Therefore, there is support for H2 "*MSPs are more likely to receive staged investment than non-platform businesses*".

The probit model for staging is significant because the probability model is lower than the level of significance ($p-value = 0.0000 < \alpha = 0.01$). The coefficient for the "platform" variable is significant ($p-value = 0.012 < \alpha = 0.05$) and the coefficient for the control variable "age at first investment" is significant ($p-value = 0.0000 < \alpha = 0.01$). Therefore, in line with the initial insights of the univariate analysis, staging investments are related to the business model. Country and industry do not have significance for this dependent variable. Platform and age at first investment coefficients can only explain 1.5% (because $R^2 = 0.0151$) of the staging dummy variable.

The coefficient of "platform" equals to 0.117, which means that platforms increase the predicted probability of staging. As already explained, staging is a risk reducing strategy, therefore it is more likely in case of platforms since they represent higher uncertainties in comparison to pipeline businesses.

The coefficient of "ageatinv" is equal to -0.036, which means that a decrease in "ageatinv" increases the predicted probability of staging. Thus, companies that received their first investments at younger age are more likely to receive investments in stages. This conclusion is reasonable since the younger a firm is, the higher the uncertainties and information asymmetries attached. By staging, investors can wait to have more information about the investees instead of investing the total amount in just one milestone.

Table 27 - VC staging results (Coefficients and standard errors)

Variable Names	Staging	St. Err.	P>|z|
platform	0.117	0.05	0.012*
ageatinv	-0.036	0.00	0.000***
country			
Germany	0.043	0.04	0.303
United Kingdom	0.025	0.04	0.476
industry			
Agriculture, forestry and fishing	0.027	0.26	0.917
Arts, entertainment and recreation	-0.093	0.19	0.628
Construction	0.009	0.22	0.968
Education	0.044	0.16	0.789
Electricity, gas, steam and air conditioning supply	0.208	0.15	0.173
Financial and insurance activities	0.089	0.14	0.534
Human health and social work activities	0.231	0.15	0.112
Information and communication	0.086	0.14	0.526
Manufacturing	0.047	0.14	0.737
Mining and quarrying	0.900	0.49	0.067
Other service activities	0.151	0.15	0.312
Professional, scientific and technical activities	0.226	0.14	0.110
Public administration and defense; compulsory social security	-0.076	0.22	0.734
Real estate activities	0.199	0.18	0.274
Transportation and storage	0.050	0.19	0.795
Water supply; sewerage and waste management	0.463	0.57	0.414
Wholesale and retail trade	0.143	0.15	0.336
_cons	-0.611	0.14	0.000***
N	8,248		
Chi-squared (χ^2)	146.82		
Pseudo R^2	0.0151		
df	21		
Prob > chi2	0.0000***		

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.

Source: Prepared by the author.

6.2.3. Syndication (H3)

For this analysis, the syndication dummy is the dependent variable in round-level. Since it is a binary variable, we built the Probit model of regression for estimations with the equation 12: $Y_{ni} = \beta_0 + \beta_1 \times platform_i + \sum_{k=1}^{n} \beta_{ki} \times C_{ki} + \varepsilon_{ni}$, where $C_{ki} = [ageatinv_i \quad industry_i \quad country_i]$. The results for testing H3 are presented in Table 28. Due to the missing data for some explanatory variables, the initial sample size of 19,599 investment rounds for this test was reduced to 11,860. In short, there is statistical significance for country and industry, but not for platform and age at first investment. Thus, there is no support for H3.

Table 28 - VC syndication results (Coefficients and standard errors)

Variable Names	Syndication	St. Err.	P>|z|
platform	0.085	0.10	0.398
ageatinv	-0.015	0.01	0.134
country			
Germany	0.579	0.11	0.000***
United Kingdom	0.095	0.11	0.396
industry			
Accommodation and food service activities	0.000	(empty)	
Agriculture, forestry and fishing	0.000	(empty)	
Arts, entertainment and recreation	-0.012	0.27	0.965
Construction	-0.397	0.41	0.336
Education	-0.149	0.22	0.500
Electricity, gas, steam and air conditioning supply	-0.508	0.24	0.036*
Financial and insurance activities	-0.424	0.18	0.017*
Human health and social work activities	-0.340	0.18	0.059
Information and communication	-0.445	0.13	0.001***
Manufacturing	-0.315	0.15	0.038*
Mining and quarrying	0.000	(empty)	
Other service activities	-0.166	0.18	0.362
Professional, scientific and technical activities	-0.630	0.20	0.001***
Public administration and defense; compulsory social s..	0.000	(empty)	
Real estate activities	-0.187	0.30	0.527
Transportation and storage	-0.191	0.30	0.529
Water supply; sewerage and waste management	0.000	(empty)	
Wholesale and retail trade	0.000	(omitted)	
_cons	-2.211	0.15	0.000***
N	11,860		
Chi-squared (χ^2)	80.88		
Pseudo R^2	0.0654		
df	16		
Prob > chi2	0.0000***		

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.
Source: Prepared by the author.

The Probit model for syndication is significant because the probability model is lower than the level of significance ($p - value = 0.0000 < \alpha = 0.01$). The coefficients for "platform" and "ageatinv" are not significant. Therefore, the platform dummy or the age at first investment do not affect the likelihood of receiving investments in a syndicated deal. However, "country" and "industry" have significant impact on the probability of syndication. These coefficients can only explain 6.54% (because $R^2 = 0.0654$) of the syndication dummy.

The control variables show that companies located in Germany have higher probability to receive syndicated investments. In terms of industry, companies that act on "Electricity, gas, steam and air conditioning supply", "Financial and insurance activities", "Information and communication", "Manufacturing" and "Professional, scientific and technical activities" have a lower probability to receive syndicated investments.

Therefore, the business model and the age at first investment do not have an impact on the probability to receive syndicated investments, but the country of the company and the industry do. Hence, contrary to the initial insights of the univariate analysis, syndicated investments are not related to the business model.

6.2.4. Total investment amount (H4)

For this analysis, the logarithm of the total amount of investment (TotalInvLog) is the dependent variable at the company-level to avoid skewed results as discussed in the model specification section. We applied a linear regression, more specifically a multiple regression model, with the equation 14: $\ln(Y_i) = \beta_0 + \beta_1 \times platform_i + \beta_2 \times nrounds_i + \beta_3 \times d\_syndication_i + \sum_{k=1}^{n} \beta_{ki} \times C_{ki} + \varepsilon_i$ where $C_{ki} = [ageatinv_i \quad industry_i \quad country_i]$. The results for testing H4 are presented in Table 29. Due to the missing data for some explanatory variables, the initial sample size of 14,243 companies for this test is reduced to 5,568. In short, there is statistical significance for number of rounds, age at first investment, country and industry, but not for platform and syndication. However, it can be argued that there is indirect support for H4 "*MSPs are more likely to receive a higher amount of equity financing than non-platform businesses",* since number of rounds is correlated to staging which is influenced by platform businesses.

This multiple regression model is significant because the probability model is lower than the level of significance ($p - value = 0.0000 < \alpha = 0.01$). In short, there is the statistical significance of the number of rounds (nrounds), age at first investment (ageatinv), country and industry on the total amount of investments. The platform and syndication dummies do not have significance for this dependent variable. The significant coefficients can explain 31.1% (because $R^2 = 0.311$) of the total amount of investments variable.

Table 29 - Total investments results (Coefficients and standard errors)

TotalInv	Total Inv	St. Err.	P>t
platform	-0.04	0.06	0.473
nrounds	0.78	0.02	0.000***
d_syndication	-0.08	0.20	0.670
ageatinv	0.09	0.00	0.000***
country			
Germany	0.21	0.06	0.001***
United Kingdom	-0.26	0.04	0.000***
industry			
Agriculture, forestry and fishing	-0.87	0.32	0.006**
Arts, entertainment and recreation	-0.64	0.24	0.008**
Construction	-0.15	0.27	0.589
Education	-1.10	0.20	0.000***
Electricity, gas, steam and air conditioning supply	-0.32	0.19	0.095
Financial and insurance activities	-0.15	0.18	0.417
Human health and social work activities	-0.60	0.18	0.001***
Information and communication	-0.67	0.17	0.000***
Manufacturing	-0.72	0.17	0.000***
Mining and quarrying	0.28	0.66	0.668
Other service activities	-0.42	0.19	0.025*
Professional, scientific and technical activities	-0.14	0.18	0.439
Public administration and defense; compulsory social security	-0.46	0.27	0.089
Real estate activities	-0.20	0.23	0.389
Transportation and storage	-0.79	0.24	0.001***
Water supply; sewerage and waste management	-0.66	1.03	0.521
Wholesale and retail trade	-0.32	0.18603	0.086
_cons	6.71	0.1742	0.000***

N	5,568
F-value	108.79
R^2	0.311
df	23
Prob > F	0.000***

Note: In all models; *, **, or *** indicate statistical significance at the 5%, 1%, 0.1% level, respectively.
Source: Prepared by the author.

Since this analysis uses a linear regression model, marginal effects are not necessary to understand the total impact of explanatory variables because coefficients alone can display the effects of independent variables. If the number of rounds increases by one unit, the total amount of investments will increase 78%. If the age at first investment increases by 1 year, then the total amount of investments increases by 9%. Hence, higher number of rounds and older firms at investment receive higher volume of funding. Since later investments means that investors have more information on the venture, they may also be more comfortable investing higher funding amounts. Also, a higher number of rounds means more milestones for the ventures to receive capital.

The control variables show that companies located in Germany receive higher investment amounts, while those located in the UK receive lower. In terms of industry, companies that act on “Agriculture, forestry and fishing”, “Arts, entertainment and recreation”, “Education”, “Human health and social work activities”, “Professional, scientific and technical activities”, “Information and communication”, “Manufacturing”, “Other service activities” and “Transportation and storage” receive lower amounts of investments. Therefore, the business model and syndication do not have an impact on the investment amount, but the number of rounds, country of the company and the industry do.

Even though platform results showed not to be statistically significant, previous findings of the positive impact of platforms on the number of rounds is an argument to defend that platforms increase the total amount of investments indirectly. Since platforms positively impact staging, which is correlated to the number of rounds ($r = 0.649$) and the number of rounds increase the total amount of investments.

The results of the multivariate analysis were consolidated in Table 30, indicating the main differences between traditional businesses and platforms in their funding patterns.

Table 30 - Summary results of multivariate analysis

	Traditional	MSPs
BAs	No statistical significance	
BVCs	+	-
CVCs	-	+
GVCs	+	-
IVCs	No statistical significance	
UVCs	No statistical significance	
Others	No statistical significance	
Staging	-	+
Syndication	No statistical significance	
Total Investment		+ (Indirect)

Note: + means more likely and – less likely

Source: Prepared by the author.

7. DISCUSSIONS AND CONCLUSION

The purpose of this thesis was to determine the differences and similarities of the funding patterns between platform and non-platform business models, especially in terms of sources of investment, syndication, staging and total amount of investments. The univariate analysis showed a significant difference between multi-sided platforms and traditional business in terms of age at first investment, sources of investment, staging, syndication and total amount of investment.

With the multivariate analysis, only a few of these claims found support. The results indicate a direct positive relation between platforms and staging and an indirect positive relation between platforms and the total amount of investment, once platforms are related to staging, which is correlated to the number of rounds and a higher number of rounds is attached to a higher investment amount. The results befit the literature, because platforms are substantial risk investments and staging is a strategy to reduce uncertainty and information asymmetries. Also, staging allows the gathering of higher capital amounts since the ventures receive capital infusion in more milestones than firms that only have one round of funding. Additionally, in the start of their lifecycle, platforms incur in high costs due to strategies to overcome the chicken-and-egg paradox and achieve critical mass, such as subsidization and marketing campaigns. So, platform ventures require higher amounts of funding than non-platform businesses.

The analysis also revealed that the age at first investment affects staging, that is, younger firms have higher probability of receiving staging investments, that syndication is related to the country and industry of a company and that age at first investment, country and industry influences the total investment amount.

Considering the sources of investment, the business model of the companies affects only BVCs, CVCs and GVCs. The results revealed that traditional businesses have a higher probability of receiving funding by bank and governmental institutions than platforms. Regarding BVCs, traditional companies have more physical assets and therefore higher probability of having collaterals to sustain the demand for financial services, therefore, they are more attractive for BVCs. In relation to GVCs, because platforms have a small internal workforce, they tend to generate less jobs than traditional businesses. Also, since most of them are inherently digital, they are not present in underprivileged regions, in which GVCs tend to alleviate the funding gap. Therefore, on average, platform businesses do not present enough payoff and public benefits to be invested by GVCs.

On the other hand, platform businesses are more likely to receive funding by CVCs than pipeline firms. By investing in (and potentially acquiring) platforms such as those related to e-commerce and information and communication services, corporate venture capitalists can enhance their demand with complementary products and services and corporate diversification.

Age at first investment also affects the sources of investment, younger firms have higher probability of receiving funding from BAs, CVCs, GVCs, IVCs and UVCs while older companies are more likely to receive BVCs investments. Ventures with earlier years of foundation are more likely to receive funding by CVCs, GVCs, IVCs and UVCs. On the other hand, firms with more recent years of foundation are more likely to be funded by "Others". Regarding the geographical location, those located in Germany have lower probability to receive financing by IVCs, and UVCs and higher probability to receive funding by CVCs, GVCs and "Others". Those located in the UK are more likely to receive financing by BAs, CVCs and "Others" and less likely by GVCs. Industry also significantly affects investments by BAs, by BVCs and IVCs.

Comparing the types of business models, MSPs are more likely to receive funding in stages than traditional businesses. They are also less likely to receive funding by BVCs and GVCs and more likely to receive funding from CVCs. Nevertheless, they do not seem to receive more syndicated investments or have significantly higher syndication size than pipeline firms. Finally, platforms can have an indirect influence on the total amount of investments that firms receive, since they have higher probability of staging which is correlated to the number of rounds and higher investment rounds are related to higher funding volumes.

The literature supports the relation between platform business and staging. Scholars suggest that MSPs face higher uncertainty and complexity than other ventures, making this business model riskier to invest and harder to manage. As a response, investors rely on staging strategy to dilute the risk and have more information on the performance of the venture, reducing agency costs.

Regarding the total amount of funding, different studies present different points of view. Considering WIRTZ *et al*. (2019) platform's typologies, there can be capacity-constrained and unconstrained platforms. The capacity-constrained platforms can be peer-to-peer sharing (e.g.: Airbnb and Uber) and platform owner-provided assets (e.g.: Zipcar). The latter involves a more robust cost structure. Thus, this type of platform business may require higher amounts of funding. However, capacity-unconstrained and peer-to-peer sharing have simpler cost structure and practically null physical assets. Therefore, in comparison to pipeline counterparts they may require smaller amounts of funding. Due to the challenges platforms businesses face (network effects and critical mass achieving), there is a higher managerial complexity in platforms which make them more resource consuming.

Considering that most platform businesses require higher amounts of funding further supports the relation between staging and platforms, since costlier investments may explain the behavior of investors of dividing investments into different rounds.

The size of the sample (i.e., 9,524) limits the study's results. The analysis regarding syndication, for example, were inconclusive since out of the sample only 78 companies (0.82%) received syndication-backed investments. This is also related to the definition of syndication adopted. If the second definition presented in the literature was used (if the entrepreneurial firm receives funds from only one VC firm per round and for all rounds, it can still be classified as syndicated-back if different rounds are funded by two or more investors), the sample size would increase. Also, since the process of firm classification was manual, it is subject to human error. Furthermore, many of the descriptions found on the PitchBook database were not exhaustive and may not be enough data to perform the coding process. The missing data also impacts the outcome of the research, since the χ^2 test revealed differences in distribution by country, foundation year and industry when comparing the sample and the complete data (including the missing ones).

The univariate analysis, although gives first insights to the study, since t-test for mean comparison presents statistical differences between two groups, it does not evaluate cause-and-effect relationships between platform characteristics and investment patterns. Thus, the results of the descriptive statistics segment should be treated as empirical characterization of companies instead of causal relations.

Finally, the choices of models used such as Probit and linear regression model also limit the analysis. Regarding the analysis of total investment amount, a two-step model could have been more appropriate, however the use of more instruments complicates the analysis.

The present study can be further expanded horizontally, that is, with a broader sample, including more companies, countries, industries and/or investment years, or deepened vertically, with more focus variables, such as the typologies of the platform business, cost structure of the companies, exit strategies and reputation of investors. The analysis of a company's performance can be a future research avenue.

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