

## **Employee Entrepreneurs of Platforms: Positioning and Performance**

### **ABSTRACT**

The growth of platform firms today leads to a great spillover effect in employee entrepreneurship. Previous literature has pointed out that employee entrepreneurs who leave the incumbent firms will enter the same industries and compete with their parent firms. Using a sample of new ventures founded by former employees from incumbent firms in the Chinese high-tech industries, we find that employee entrepreneurs from platform firms are more likely to enter different industries and become the platform complementors of their parent firms, rather than competitors. We further distinguish between employee entrepreneurs from innovation platforms and transaction platforms, and highlight that this complementary effect is more pronounced among those from innovation platforms. We also find that spinouts from transaction firms may face higher risks of entrepreneurial failure.

**Keywords:** platform and ecosystem; employee entrepreneurship; spinouts; platform complementor; innovation platform; transaction platform

## INTRODUCTION

Knowledge has been considered an important source of competitive advantages for firms (Coff, 1997; Teece, 1986). Employee mobility often facilitates knowledge transfer and diffusion across organizations, leading to great spillover and innovations (Agarwal, Campbell, Franco, & Ganco, 2016). Former employees will either join another existing company or establish new start-ups by themselves (Kim & Steensma, 2017). When employees leave their incumbent firms and start a spinout defined as a new venture founded by former employees from the incumbent firms, they become employee entrepreneurs (Franco & Filson, 2006; Garvin, 1983). In many high-tech manufacturing industries including automobile, chip, disk drive, laser, etc., spinouts are widespread and important innovators (Agarwal, Echambadi, Franco, & Sarkar, 2004; Franco & Filson, 2006; Klepper, 2009; Klepper & Sleeper, 2005; McKendrick, Wade, & Jaffee, 2009). One exemplary example is Fairchild Semiconductor, which spawned hundreds of successful ventures such as Intel and AMD, and greatly facilitated the development of Silicon Valley. Extant literature has revealed that the process of employee entrepreneurship is linked with knowledge inheritance and transfer from incumbent firms to the spinouts (Gompers, Lerner, & Scharfstein, 2005; Klepper & Sleeper, 2005), therefore leading to intra-industry competition (Garvin, 1983; Klepper, 2009).

The rapid development of digital technology has been continually driving transformations and innovations in the business world. New organizational patterns of platforms emerge, with different organizational architecture, interaction mechanisms and governance structures compared with traditional supply chain-based enterprises (Cusumano, Gawer, & Yoffie, 2019; Jia, Cusumano, & Chen, 2019; Parente, Rong, Geleilate, & Misati, 2019). The platform-based business model is adopted by a large number of digital firms. According to a Statista 2021 report<sup>1</sup>, seven out of the top 10 largest companies by market value – that is, Apple, Microsoft, Amazon, Alphabet (Google’s parent), Facebook, Tencent Holdings, Alibaba Group– have developed platform-based business models. Platforms attract and nurture a large amount of innovative human capital, as well as lead to increasing employee mobility and a great spillover effect in terms of talents (Cutolo & Kenney, 2020). These platforms also spawn

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<sup>1</sup> Source: The 100 largest companies in the world by market capitalization in 2021  
<https://www.statista.com/statistics/263264/top-companies-in-the-world-by-market-capitalization/>

many spinouts in different industries, which may open up a new research context. For instance, former Google employees have founded nearly 200 new ventures in various industries including the mobile industry, social media, health, etc.<sup>2</sup> Amazon even encourages employee entrepreneurs by announcing a new incentive plan for its employees to start their own package delivery businesses<sup>3</sup>.

Therefore, the phenomenon of platform-spawned startups may suggest theoretical gaps both in literature on employee entrepreneurship and platform strategy. First, Extant research on employee entrepreneurship mostly has adopted an intra-industry perspective and suggested that spinouts mostly compete with their parent firms within the same industry, putting pressure on the incumbent firms and bringing potential threats (Agarwal & Shah, 2014; Campbell, Ganco, Franco, & Agarwal, 2012). Meanwhile, these findings have been based on product innovation through entrepreneurship in industries including disk drive, automobile, etc. The context of platforms involving a higher degree of openness and complementarity has been rarely studied by far, and may provide new insights into the current research on employee entrepreneurship.

Second, extant platform research has explored the platform entry into new industries from multiple perspectives, including approaches such as M&A, diversification strategy, the effect when entering complementary markets, the possible monopoly consequences, all based on a platform-owner perspective (Eisenmann, Parker, & Van Alstyne, 2011; Garvin, 1983; Katz, 2020; Wen & Zhu, 2019). The external perspective is quite absent, which considers entry into new markets through third-party players such as employee entrepreneurs, external partners. Hence, this leads to an important research question to bridge the research gaps both in employee entrepreneurship research and platform research: how do employee entrepreneurs spawned by platforms differ from those from non-platforms?

To address this research question, we explore the entrepreneurial positioning and performance of platform spinouts. We build our theoretical framework on knowledge-based literature (Agarwal, Echambadi, Franco, & Sarkar, 2004; Garvin, 1983; Moore & Davis,

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<sup>2</sup> Source: Companies founded by ex-Google <http://startups.alecmgo.com/ex-google>

<sup>3</sup> Source: Employees Turned Entrepreneurs: New Amazon Initiative Helps Employees Start Their Own Package Delivery Business <https://press.aboutamazon.com/news-releases/news-release-details/employees-turned-entrepreneurs-new-amazon-initiative-helps/>

2004), and posit that due to the higher connectivity, complementarity and openness in platform businesses, employees from platform incumbents have higher chance to expose to diverse knowledge sets in different industries. Therefore, platform spinouts are more likely to be able to exploit cross-industry entrepreneurial opportunities and become complementors of their parent firms, rather than competitors in the same industry. Further, we distinguish between two types of platforms by how platforms organize their business and what core knowledge they rely on, based on definitions by Cusumano, Gawer, and Yoffie (2019). One type is the transaction platform which acts as an intermediary to connect multi-side product/service providers and buyers and facilitate the transaction, such as Amazon and YouTube. The other type is the innovation platform which provides a common technological foundation to support complementary innovations, such as ARM and AWS. Consequently, we posit that employee entrepreneurs from innovation platforms may develop a higher extent of complementarity with their parents, since they may inherit highly diversified knowledge of possible complementary innovations from innovation platform incumbents, and also encounter great difficulty in replicating parent firms' complementary assets. We also predict that employee entrepreneurs from transaction platforms may face a higher risk of failure because they are more likely to face the problem of knowledge decoupling, which means that their inherited knowledge is not matched with the operation and needs much complementary knowledge from other fields, such as marketing, supply chain management.

We test the hypotheses using a sample of entrepreneurs' information in China and collect the top 250 parent companies and their employee entrepreneurs. Our sample contains 7,823 entrepreneurs, a total of 9,781 entrepreneurial records. We classify the type of parent firms, and define the positioning of spinouts based on the field they and their parent firms operate in. Our empirical results suggest that compared with non-platform firms, employee entrepreneurs of platform firms are more likely to break the industry boundaries and become cross-industry complementors of their parent firm. Meanwhile, we find that among platform employee entrepreneurs, the extent of complementarity is higher for innovation platforms. As for the performance, we find that employee entrepreneurs from transaction platforms may face higher risks of failure.

Our research thus contributes to the literature on employee entrepreneurship by uncovering the new insights provided by platform firms. Compared with the conventional view that employee entrepreneurs compete with parent firms within the same industries, our research findings suggest a new entrepreneurial positioning that spinouts from platforms develop complementary relationships across various industries, which may help the incumbent platform develop a wider ecosystem. Our work also adds to the knowledge-based view of employee entrepreneurship, by connecting the literature on knowledge inheritance and exploration with platform theory. We explore the different knowledge patterns and complementary assets of platforms and non-platforms, as well as transaction platforms and innovation platforms, which shape the positioning and performance of their spinouts. Further, our research advances the understanding of platform entry and growth. Our findings reveal a new perspective that platforms can leverage external players such as spawning complementary employee entrepreneurs, to help enter new industries and build an ecosystem. The findings don't imply that we rule out the possibility for spinouts from non-platform incumbents to become complementors. Instead, the higher complementarity of platform spinouts suggests a new way for non-platforms to also benefit from spinouts, through organizational design and knowledge management.

## **THEORETICAL FRAMEWORK AND HYPOTHESES**

### **Literature on employee entrepreneurship**

Spinouts are defined as the new ventures created by employee entrepreneurs who leave their parent firm to start their own business (Agarwal, Echambadi, Franco, & Sarkar, 2004; Franco & Filson, 2006; Garvin, 1983). Over the past decades, previous literature has studied employee entrepreneurs from multiple perspectives, including their entrepreneurial motivation, positioning, performance, and influence on parent firms.

According to existing literature, employee mobility and entrepreneurship can be attributed to several motivations: frustration and disappointment with parent firms (Franco, 2005; Garvin, 1983; Klepper, 2002; Klepper, 2007; Shah, Agarwal, & Echambadi, 2019), learning from parent firms (Franco, 2005; Franco & Filson, 2006; Yeganegi, Laplume, Dass,

& Huynh, 2016), underexploited market opportunity or knowledge (Agarwal, Echambadi, Franco, & Sarkar, 2004; Christensen, 1993; Gambardella, Ganco, & Honoré, 2015; Ganco, 2013; Klepper & Sleeper, 2005), etc. Research also has found that employees from small firms in emerging industries are more likely to leave and start their own new ventures (Elfenbein, Hamilton, & Zenger, 2010; Eriksson & Kuhn, 2006; Gompers, Lerner, & Scharfstein, 2005; Sørensen, 2007). Most research has focused on the contexts in which spinouts and the incumbent firms operate in the same industry and found that employee-founded firms often develop a competitive relationship with parent firms (Agarwal & Shah, 2014; Klepper, 2007; Klepper, 2001). Consequently, their parent firms are likely to suffer a restrained performance due to losing important resources and facing new competitive pressure (Campbell, Ganco, Franco, & Agarwal, 2012; Phillips, 2002). But employee entrepreneurs do not always bring detrimental effects to parent firms (Kim & Steensma, 2017). A few research has pointed out that employee entrepreneurs can act as suppliers or complementors to parent firms, in terms of product, knowledge, social capital, etc. (Agarwal, Audretsch, & Sarkar, 2007; Moore & Davis, 2004; Somaya, Williamson, & Lorinkova, 2008). The creation of new ventures by former employees can encourage parent firms to reallocate their resources and routines, therefore becoming more adaptive to the current business dynamics (Ioannou, 2014; McKendrick, Wade, & Jaffee, 2009). Meanwhile, literature has suggested that CVC-active incumbents and their spinouts can build up a partnership through investment and further acquisition (Agarwal, Audretsch, & Sarkar, 2007; Kim & Steensma, 2017). Therefore the incumbents have the chance to enjoy the beneficial knowledge and technology spill-in back from the new ventures founded by their former employees, based on high familiarity and relatedness (Kim & Steensma, 2017).

As for entrepreneurial performance, employee entrepreneurs generally gain competitive advantages from their parents and outperform other entrants in the industry (Agarwal, Echambadi, Franco, & Sarkar, 2004; Chatterji, 2009; De Figueiredo, Meyer-Doyle, & Rawley, 2013; Eriksson & Kuhn, 2006; Franco & Mitchell, 2008; Simons & Roberts, 2008). Meanwhile, employee entrepreneurs possess a unique information advantage through learning from parent firms, helping them better identify and react to the market opportunity (Burton,

Sørensen, & Beckman, 2002; Garvin, 1983). Several studies have found that firms spawned by parent firms with superior performance have better performance as well (Boschma & Wenting, 2007; Dahl & Reichstein, 2007; Klepper, 2007; von Rhein, 2008; Wenting, 2008). Employee entrepreneurs from highly prestigious parent firms are more likely to get venture financing (Burton, Sørensen, & Beckman, 2002). However, some literature also has found that parent firms with smaller sizes spawn better-performing spin-offs, compared with larger firms (Elfenbein, Hamilton, & Zenger, 2010; Sørensen & Phillips, 2011).

To conclude, extant research on employee entrepreneurship in high-tech manufacturing industries including automobile, chip, disk drive, laser, etc., mainly has focused on product-side entrepreneurship (Agarwal, Echambadi, Franco, & Sarkar, 2004; Franco & Filson, 2006; Klepper, 2009; Klepper & Sleeper, 2005; McKendrick, Wade, & Jaffee, 2009). Meanwhile, existing literature mostly has adopted an intra-industry perspective, regarding intra-industry spinouts as the most common and best-performing type (Garvin, 1983; Klepper, 2009).

### **Platform entry literature**

This research also adds to existing research on platform entry. Firms enter new markets or industries through multiple approaches, including 1) acquisition of established firms, 2) diversification through new divisions or subsidiaries, 3) creation of new firms with/ by external stakeholders, such as third-party partners, former employees (Garvin, 1983). With the development of platform businesses, many platforms have implemented the above entry strategies and attracted the attention of a growing body of research.

First, literature on platform acquisition mainly focused on the possible monopolistic status, and its effect on consumer utility and social welfare (Argentesi, Buccirosi, Calvano, Duso, Marrazzo, & Nava, 2019; Axel & Joe, 2020; Bryan & Hovenkamp, 2020; Cabral, 2020; Kamepalli, Rajan, & Zingales, 2020; Katz, 2020; Katz, 2019; Koski, Kässi, & Braesemann, 2020; Motta & Peitz, 2020). Most studies have pointed out that platform acquisition may lead to excessive market power, which may damage social welfare. Therefore, restrictions on platform acquisitions should be placed (Axel & Joe, 2020; Bryan & Hovenkamp, 2020; Cabral, 2020). The kill zone effect is introduced, that is, innovation and entrepreneurship are inhibited in industries with strong platforms. Kamepalli, Rajan, and Zingales (2020) found

that large-scale acquisitions of platforms will reduce the entry rate of startups and venture capitals in the industry. Similarly, the analysis of Koski, Kässi, and Braesemann (2020) has found that the acquisitions of big tech platforms not only cause a kill zone effect on the platform-based market but may expand to traditional industries that provide complementary products. However, some studies have revealed that platform acquisitions do not necessarily cause damage to social welfare. This may be because when the acquired platform is at a significant disadvantage, being acquired can help improve the overall competitiveness, build a stronger ecosystem, and create more value for consumers (Katz, 2019).

Second, a branch of research has paid attention to the platform diversification strategy and the evolution from a single platform to a multi-platform. Multiplatform bundling refers to the strategy of a platform integrating multiple platforms on its own basis. Platforms can bundle with multi-platforms based on their users, data, etc. (Eisenmann, Parker, & Van Alstyne, 2006). The benefits of platform bundling strategy are diverse: the overlapping users on multiple platforms can be provided with attractive bundling prices, while non-overlapping users can be attracted as new users, leading to the economy of scope. Based on platform bundling, Eisenmann, Parker, and Van Alstyne (2011) proposed another platform diversification strategy: platform envelopment, which refers to platforms entering into a market, using similar components such as software and hardware infrastructure, platform rules, overlapping user groups, etc.

Finally, several empirical research examined the effect of platforms' entry into complementary markets. Li & Agarwal (2017) found that the integration of Facebook platform with Instagram causes a crowding-out effect on small third-party photo-sharing apps, but brings consumers additional value (Li & Agarwal, 2017). Foerderer, etc (2018) examined the influence of Google entering into photo applications, and found that the demand for third-party apps is increased, leading to a higher innovation motivation (Foerderer, Kude, Mithas, & Heinzl, 2018). However, the analysis of Wen & Zhu (2019) presented the opposite finding that the innovative effort of third-party app developers is restrained and the app price is also raised (Wen & Zhu, 2019). He, Peng, Li, and Xu (2020) focused on the impact of e-commerce platforms entering the market of third-party merchants and further studied the impact on



online and offline sales. The study found that the offline demand for third-party stores declines with the entry of the platform, but the online demand does not change significantly.

In a word, a growing body of literature has studied the platform entry strategies, but most are from a platform-owner perspective, disregarding one important approach concluded by Garvin (1983), which is creating new firms with/by external stakeholders. Meanwhile, research on platforms has emphasized that platforms involve higher cross-border complementarity and external dynamics (Boudreau & Jeppesen, 2015; Kapoor, 2013; Parker & Van Alstyne, 2018), which may lead to a higher level of external expansion, such as employee spinouts, as reflected in real business world.

To conclude, extant research on employee entrepreneurship has mainly focused on traditional the product-side, intra-industry spinouts, while the platform context has been rarely studied. This leads to a critical research gap in employee entrepreneurship theory, given the importance of platform firms today and their huge output of employee-founded new ventures. On the other hand, platform research now has focused on the entry strategies mostly by the platform owner, but disregards the external expansion driven by the spillover of platform employee entrepreneurship. Platform theory may provide important implications for extant research on employee entrepreneurship. Therefore, to address the theoretical gaps, this paper will explore the employee entrepreneurship of platforms.

### **Incumbent firm, knowledge inheritance, and entrepreneurial positioning**

Knowledge has been identified as one of the most important resources for a firm to generate competitive advantages (Barney, 1991). Knowledge is created and held by employees, especially the tacit knowledge which is hard to codify, is embodied in human assets (Kogut & Zander, 1992; Teece, 1986). Employee mobility often leads to knowledge diffusion and knowledge transfer among organizations. Knowledge transfer and knowledge breakthroughs have also been identified as important drivers of new firm formation (Agarwal & Shah, 2014). Therefore, as the main type of employee mobility, the process of employee entrepreneurship is greatly associated with knowledge transfer and knowledge inheritance from incumbent firms to new start-ups (Gompers, Lerner, & Scharfstein, 2005; Klepper & Sleeper, 2005). When employees leave their parent firms and start their new venture, the

knowledge they inherited from parent firms is transferred to the startup. The incumbent firms with abundant and cutting-edge knowledge are more likely to spawn employee entrepreneurs, because they provide their employees great knowledge endowment to learn, imitate and further exploit (Franco & Filson, 2006). Existing research also has identified the effect of different types of knowledge. Technological knowledge, including products, patents, or firm routines (Agarwal & Shah, 2014) is positively related to the probability of generating spinouts, as well as improving entrepreneurial performance (Franco & Filson, 2006; Ganco, 2013). More technologically advanced firms will generate more spinouts. Nontechnological knowledge, such as marketing, operational, and regulatory knowledge, also has a critical impact on the generation of spinouts (Agarwal, Echambadi, Franco, & Sarkar, 2004; Chatterji, 2009; Moore & Davis, 2004).

In addition to the new firm formation, the characteristics of parent firms also shape the initial strategy of their spinouts. Current literature has pointed out that employee entrepreneurs will transfer, imitate, and exploit the knowledge from their parents. Therefore, the initial knowledge endowment of the startup is greatly related with the incumbents' knowledge domain, which ultimately leads to a high degree of overlap in product and market strategy at birth of the startup (Klepper & Sleeper, 2005). Exploiting the similar knowledge domains as their parent firms help employee entrepreneurs better take advantage of the familiar knowledge and less risky opportunities, to better shape their competitiveness as a new entrant (Basu, Sahaym, Howard, & Boeker, 2015). As a result, spinouts mostly enter the same or highly similar industries as their parent firms, thus developing a competitive relationship with their parent firms (Agarwal & Shah, 2014).

Therefore, the knowledge that employee entrepreneurs can inherit and further exploit from their parent firms may determine their entrepreneurial positionings. In this research, we posit that the internal knowledge pattern that employees are exposed to, and the external opportunities for employees to exploit the knowledge of platform and non-platform companies, may differ, consequently leading to different entrepreneurial positions of their spinouts.

First, they are different in the business model, organizational structure, and therefore,

internal knowledge pattern. Non-platform firms generally sell products or services, with a dominant design and standard, and an established business model (Garvin, 1983). These firms may have more standardized operational processes and more closed organizational structures. Therefore, employees always get very systematical training and experience in the specific industries when working in the incumbent firms. The knowledge repository they are exposed to is more industry-specific. Therefore, as extant literature suggests, employee entrepreneurs who learn the industry-specific know-how from their parent firms generally compete in the same or similar industries with the incumbent firms (Franco & Filson, 2006).

Relative to non-platform firms, platforms are identified as organizations that “connect individuals and organizations for a common purpose or to share a common resource” (Cusumano, Gawer, & Yoffie, 2019). Platforms generally serve as an intermediary or a technological foundation, bringing together multi-side participants for interaction and innovation (Ceccagnoli, Forman, Huang, & Wu, 2012). Based on the nature of its connectiveness, platforms compete for a larger number, and higher diversity of participants, to improve their service quality. Thus the operation of platforms will require a greater degree of open interactions, continually breaking the industry boundaries (Parker & Van Alstyne, 2018). The employees in a platform company, therefore, are exposed to knowledge from participants from various industries that are brought together by the platform. They are also capable of identifying and capturing the under-exploited opportunities in other industries which are connected by the platform. Consequently, employees from platforms are equipped with knowledge in two dimensions. First, they possess the knowledge of the platform's core business, which is how to operate, manage and govern the platform. Second, they develop diverse knowledge access to various industries that are connected by the platforms. Consider the case of Amazon, an e-commerce platform selling all categories of products. The job of Amazon employees is not only to maintain an online platform, but they also need to be familiar with the knowledge and dynamics of various industries, to attract, connect with and manage sellers and buyers from a wide range of industries. Research has revealed that employees with less industry-specific knowledge and unrelated experience with the core business of parent firms may have a higher entrepreneurial motivation (Hellmann, 2007;

Yeganegi, Laplume, Dass, & Huynh, 2016). Therefore, for employee entrepreneurs from platforms, such as Amazon, the two-dimensioned knowledge base provides them with opportunities to step out of the same core business area as their parents, such as building another e-commerce platform. Instead, they can exploit the knowledge from various industries that are connected by the platform, while simultaneously leveraging the platform rules and platform resources they learned from prior employment. In this way, they don't have to compete with parent firms in the same market and may become complementors related with the incumbent platform.

Second, the decisions of entrepreneurial positioning by employees also depend on the estimated potential and feasibility of transferring knowledge into an external market opportunity (Gambardella, Ganco, & Honoré, 2015). Relative to non-platform organizations, one of the most unique features is that platforms generate network effects, through the interaction of multi-side participants that are connected by the platform (Katz & Shapiro, 1985). Network effects lead to a positive feedback loop of platform growth, in which the larger the user base is, the more users will be further attracted to the platform (Cusumano, Gawer, & Yoffie, 2019; Rysman, 2009). Therefore, capturing the first-over advantage and establishing a large initial user base is very critical in platform competition. The strong network effect of incumbent platforms creates major barriers for new entrants (Evans, 2009; Zhu & Iansiti, 2012). The employee entrepreneurs from platform companies well understand the rules of platform businesses and the importance of network effects. They also may have direct access to market information, to help them evaluate the market dynamics and their potential. Even though they possess every knowledge needed to establish a new platform, exploiting the knowledge to compete with an incumbent is difficult, because of the existing network effect.

To conclude, from the knowledge-based perspective, two powers co-exist to determine the entrepreneurial positions of spinouts from platforms and non-platform firms. From the dimension of internal knowledge learning, employees from platform firms have greater chances to expose to and inherit knowledge in diversified industries that are connected by the platform, therefore, enabling their new ventures to enter these various industries and become

complementors of the incumbent platform. However, employees in non-platform firms receive a rather closed and industry-specific knowledge learning in their parent firms, limiting their entrepreneurial ideas within the same or similar industry as their parents. Further, from the dimension of external opportunity to exploit the inherited knowledge, employee entrepreneurs may avoid competing with parent firms, since they know the difficulty of competing with an incumbent platform with the established network effect. This leads to the following hypothesis:

*Hypothesis 1: Employee entrepreneurs from platform firms are more likely to become complementors of the parent firm, rather than competitors, relative to those from non-platforms.*

### **Heterogeneous entrepreneurial positioning of platform employees**

According to the definition by Cusumano, Gawer, and Yoffie (2019), there are two types of platforms. Transaction platforms, also called two-side platforms, serve as an intermediary for transactions or exchanges, such as Uber and Airbnb. Innovation platforms act as a technological foundation upon which other participants develop complementary innovations, such as ARM and Android (Cusumano, Gawer, & Yoffie, 2019). We posit that the knowledge that employees can inherit from the two platforms has a different pattern and market potential, determining heterogeneous positionings of the spinouts.

Relative to transaction platforms serving as an intermediary to facilitate transactions, innovation platforms generally are a fundamental technological base with common building blocks, where participants can develop complementary innovations. The nature of the innovation platform is intended for attracting a great diversity and number of complementors and enabling them to innovate based on the technological foundation in a quite independent way. Therefore, compared with transaction platforms, the way that innovation platforms interact with complementors is more open and autonomous, often with less degree of control and instruction, which accounts for their ability to support the innovation of an extremely wide range of stakeholders. Consider ARM as an instance, ARM provides the underlying technological foundation for the whole sector of embedded systems, including smartphones, tablet computers, etc., as well as for desktops and servers. ARM develops and licenses the IP

of ARM architecture to all types of chip design companies, such as Qualcomm and MTK, to support the design of their own products based on the ARM core. Consequently, the nature of nurturing complementary innovations in a wide range of industries provides a unique knowledge set for employees of innovation platforms. Employees are exposed to various complementary innovations supported by the platform, enabling them to inherit knowledge and identify possible opportunities in these complementary areas. Further, employees also gain a deep understanding of the innovation platform, such as what kind of complementary innovations are feasible and matched with the technological foundation, and how to leverage the platform resources and rules. To make the most of their knowledge both in innovation platform rules and various complementary industries, employee entrepreneurs from innovation platforms may be more likely to choose to become complementors of their parent firms.

Second, to compete with parent firms, employee entrepreneurs should not only transfer the core knowledge, but also transfer or replicate the complementary assets in the incumbent firms, such as physical assets, intellectual properties, to fully exploit the knowledge (Campbell, Ganco, Franco, & Agarwal, 2012; Teece, 1986). The complementary assets of an innovation platform include the highly advanced technological base and basic technological infrastructures, such as the ARM architectures for computer processors, Android operating systems and sets of software development kits (SDK), AWS cloud computing platforms and APIs (Cusumano, Gawer, & Yoffie, 2019). These complementary assets are highly firm-specific and almost impossible to transfer. Meanwhile, recreating these complementary assets requires both leading technological advantages and huge R&D inputs, causing very high barriers and discouraging new entrants to compete with the incumbents (Lofstrom, Bates, & Parker, 2014). For example, it is extremely hard to recreate another Android or another ARM. Further, with a basic technological foundation, an innovation platform generates a strong network since a wide range of industrial innovations are based on it. Therefore, competing with incumbent innovation platforms may become very difficult for new firms. In comparison, transaction firms often are characterized as business model innovations that act as an online intermediary to connect multi-side participants and enable transactions, such as Uber

connecting drivers and passengers. The complementary assets of transaction platforms may involve less technological complexity than innovation platforms, reducing the difficulty to recreate another platform. Meanwhile, the network effect of a transaction platform is highly related to the user demand and market pioneering knowledge (Agarwal, Echambadi, Franco, & Sarkar, 2004). Therefore, due to highly heterogeneous user preferences, employee entrepreneurs from transaction firms may still have chances to compete with parent firms, if they can identify and capture under-exploited market demand. One example is the establishment of Mogu, an e-commerce platform focused on fashion, which was by two former employees from Taobao, the biggest e-commerce platform in China.

In sum, we suggest that, given the more diversified knowledge of possible complementary innovations and higher difficulty to replicate parent firms' complementary assets, employee entrepreneurs from innovation platforms are more likely to become complementors of parent firms, compared with those from transaction platforms. This leads to the following hypothesis:

*Hypothesis 2: The extent of complementarity with parent firms is higher for employee entrepreneurs from innovation platforms, compared with transaction platforms.*

### **Inherited knowledge exploitation and entrepreneurial performance**

Existing literature has revealed that parent firm inheritance may determine not only the entrepreneurial positioning, but also have a long-term effect on the entrepreneurial performance of spinouts (Agarwal, Echambadi, Franco, & Sarkar, 2004). Spinouts inherit and transfer valuable knowledge from parent firms, which helps them perform better in terms of survival, venture financing and valuation (Agarwal, Echambadi, Franco, & Sarkar, 2004; Chatterji, 2009; Franco & Filson, 2006; Phillips, 2002). Meanwhile, employee entrepreneurs acquire critical resources, routines, and social capital such as social networks, consumer connections, etc., enabling them to outperform other new entrants (Ganco, 2013; Phillips, 2002; Yli-Renko, Autio, & Sapienza, 2001). In addition to how much knowledge can be inherited, extant research also has suggested that the performance of spinouts depends on the employees' ability to further exploit the inherited knowledge and connect it to the new

venture operation (Gambardella, Ganco, & Honoré, 2015).

Therefore, employee entrepreneurs have to closely combine knowledge and resources with their entrepreneurial targets, in order to achieve knowledge exploitation and value creation. We posit that the employee entrepreneurs from transaction platforms and innovation platforms may differ in matching their initial knowledge endowment with the subsequent venture operation and value creation, due to the different characteristics of their inherited knowledge from parent firms. When running a new venture, the founders usually need to seek and combine necessary complementary knowledge and recourse (Basu, Sahaym, Howard, & Boeker, 2015; Gambardella, Ganco, & Honoré, 2015; Shah, Agarwal, & Echambadi, 2019). The broader and more interdependent their knowledge endowment is with other fields, the more complementary resources are needed for further exploitation (Gambardella, Ganco, & Honoré, 2015). As we suggested, innovation platforms are highly technology-based and the platforms' technological foundation also forms the basis of the employees' knowledge systems. Meanwhile, employees from innovation platforms may be motivated by the complementary innovation opportunities provided by the platforms and start their own businesses in related fields. Their knowledge and entrepreneurial goals are all based on the technological foundation of the innovation platform, therefore well fit with each other. Consider the case of an employee from Android becoming an app developer, his knowledge of how to use Android SDK, and how to leverage the resources of Android matches greatly with his entrepreneurship. However, employee entrepreneurs from transaction platforms have higher chances to be motivated by some underexploited market demand to start a new venture, which may unexpectedly involve more complicated and interdependent factors in other fields, such as supply chain management and marketing. They need more complementary knowledge which may be beyond the knowledge set they directly inherit from transaction platforms. As a result, employee entrepreneurs from transaction platforms are more likely to face the problem of knowledge decoupling, which means their inherited knowledge from parent firms is not well fitted to what is needed to succeed as an independent firm, due to its higher interdependence with other needed complementary knowledge and recourse. Thus, the higher complexity and dynamics in terms of knowledge exploitation will increase the risks of



entrepreneurial failure (Strotmann, 2007). This leads to the following hypothesis:

*Hypothesis 3: Employee entrepreneurs from transaction platform firms face higher risks of failure.*

## EMPIRICAL APPROACH

### Sample

This paper aims to explore the positioning and performance of employee entrepreneurs from platform firms and non-platform firms. We examine this research question using data from ITJUZI, one of the largest databases that provide business information of high-tech start-ups in China<sup>4</sup>. Our research question focuses on the effect of parent firms, therefore our sample includes all entrepreneurs with prior employment information in ITJUZI, which includes records of 10894 entrepreneurs, including 1) entrepreneur information: name, profile, previous company, education experience; 2) start-up information: company name, company introduction, company location, time of establishment, number of employees, field, sub-field, registered capital; 3) financing information of start-up: time, round, amount, investor. We also collect some data of the incumbent firms such as financial performance from Osiris and Orbis databases to complement our dataset.

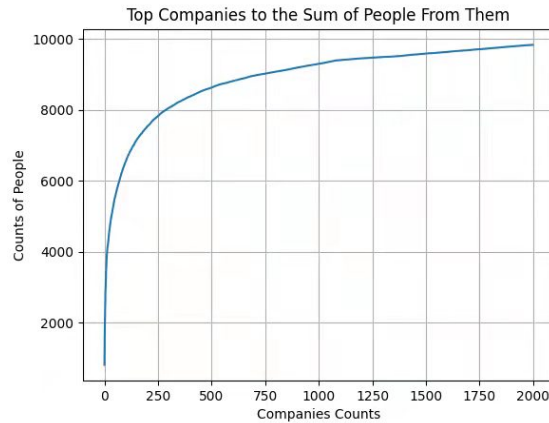
According to the statistical distribution of the number of employee entrepreneurs from top parent firms, as shown in Figure 1 and Table 1, we find the top ten companies contribute nearly 40% of all entrepreneurs. This research focuses on the top 250 parent companies and their employee entrepreneurs. The number of entrepreneurs spawned by the parent company after the 250th is less than 10 people and therefore may be relatively unrepresentative. The top 250 companies contribute about 80% of the total number of entrepreneurs. Our research sample contains 7,823 entrepreneurs, a total of 9,781 entrepreneurial records (part of the entrepreneurs have multiple entrepreneurial projects).

**Table 1. Top 10 parent firm and the numbe of employee entrepreneurs**

Rank	Parent firm	Number of employee entrepreneurs	Total employee (2019)
1	Alibaba	816	117600
2	Tencent	616	62885
3	Baidu	508	37779
4	Huawei	379	139000

<sup>4</sup> <https://www.itjuzi.com/>

5	Microsoft	355	144000
6	Sina	220	8300
7	IBM	218	352600
8	Shanda	183	2546 <sup>5</sup>
9	Sohu	171	7800
10	NetEase	160	20797



**Fig 1. Cumulative number of employee entrepreneurs from top 2000 parent firms**

### Measures

Next, we classify whether the parent firm is a platform company or not. Based on the definition by Cusumano, Gawer, and Yoffie (2019), there are two types of platforms: transaction platforms serve as an intermediary for transactions or exchanges, such as Uber and Amazon. Innovation platforms act as a technological foundation to support complementary innovations, such as ARM. Platforms that combine both innovation and transaction platform strategies are called hybrid platform (Cusumano, Gawer, & Yoffie, 2019). Based on the provided classification criterion and examples, our sample data of the top 250 firms yields to 102 platform firms including 33 innovation platforms and 76 transaction firms (7 hybrid platforms are identified as both innovation and transaction platforms), and 148 non-platforms. Table 2 shows the top 10 platforms and non-platforms.

**Table 2. Top 10 non-platform firms and platform firms**

Rank	Non-platform firm	Platform firm & platform type
1	Shanda	Alibaba (Hybrid)
2	Lenovo Group	Tencent (Hybrid)

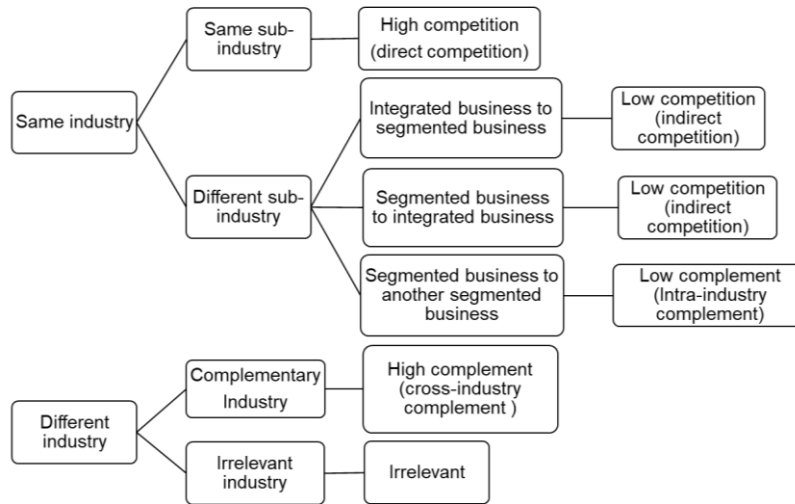
<sup>5</sup> Due to data availability, this data is from 2014

3	New Oriental	Baidu (Transaction)
4	China Mobile	Huawei (Innovation)
5	Ping An Insurance Company of China	Microsoft (Hybrid)
6	CCTV	Sina (Transaction)
7	Procter & Gamble	IBM (Innovation)
8	Motorola	Sohu (Transaction)
9	Hewlett-Packard	NetEase (Transaction)
10	Zhongxing Telecom Equipment	Google (Hybrid)

The next step is to define and classify the positionings of employee entrepreneurs, which is the spinouts' relationship with their parent firms. ITJUZI database provides a classification of industry and sub-industry of firms, including 19 industries, and 212 sub-industries. This enables us to pair each spinout with its parent firm, and match their industry tags. Figure 2 shows the matching rule, which leads to five types of positionings, including *High\_complement*, *Low\_complement*, *High\_competition*, *Low\_competition*, and *Irrelevant*<sup>6</sup>. *High\_complement* refers to the cross-industry complementary relationship in two different industries with a high level of complementarity, such as e-commerce and logistics. *Low\_complement* refers to the intra-industry complementary relationship, in which two companies are in the same industry but different sub-industries with complementarity. Consider the example of Facebook and WhatsApp. They all belong to the social networking industry but in different sub-fields. Facebook is a social sharing platform while WhatsApp is an instant messaging tool, and they complement each other. *High\_competition* refers to the direct competitive relationship where the spinout and its parent firm compete within the same sub-industry. If one of them is in a sub-industry with integrated businesses, and the other services in a narrow niche market, an indirect competitive relationship classified as *Low\_competition* is developed. Consider Amazon and Sephora. Amazon sells all types of products while Sephora focuses on personal care and beauty products. Competition exists in the personal care and beauty category but not others.

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<sup>6</sup> *Irrelevant* type refers to two companies in two irrelevant industries. We assume these employees may be motivated by unpredictable opportunities that not related with their experiences in parent firms, therefore we do not analyze this type in the empirical analysis.



**Fig 2. Matching rules of employee entrepreneurs and parent firms**

Table 3 summarizes the quantity and proportion of these types of entrepreneurial positionings. While existing literature has mostly focused on intra-industry competitive relationships, Table 3 reveals that complementary relationships exist extensively, especially for platform spinouts. Platform spinouts with cross-industry complementary positionings account for the highest proportion, reaching 73.0%, while only 3.0% of platform spinouts develop direct competitive positioning, which shows a very different trend relative to extant literature.

**Table 3. Number and proportion of entrepreneurial positioning types**

	Observation of platform parents	Proportion	Observation of non-platform parents	Proportion
High complement (Cross-industry complement)	4,549	73.0%	1,929	54.4%
Low complement (Intra-industry complement)	449	7.2%	264	7.4%
High competition (direct competition)	186	3.0%	213	6.0%
Low competition (indirect competition)	559	9.0%	559	15.8%
Irrelevant	492	7.9%	581	16.4%
Sum	6,235	100%	3,546	100%

### Empirical framework and variables

This research explores whether there are differences in entrepreneurial positioning (Hypothesis 1 and 2) and entrepreneurial performance (Hypothesis 3) for employee

entrepreneurs from different parent company types (platform & non-platform). The independent variable thus is the parent firm type, including *platform\_parent*, *transaction*, *innovation*, which are binary variables taking the value of 1 for parent firms that are platforms, transaction platforms, and innovation platforms.

The dependent variables for test of Hypothesis 1 and 2 is the entrepreneurial positioning, namely, *High\_complement*, *Low\_complement*, *High\_competition*, and *Low\_competition* as defined above. They are binary variables set to 1 if the positioning of the spinout belongs to this type. For Hypothesis 3, the survival time of a spinout is measured by its entry and failure date. We define a spinout as a failure if its operating status is closed, as of the date of data collection on February 10, 2021.

Because the experience of employee entrepreneurs and the size of the parent firms may also affect the startup's orientation and performance, this research controls the work experience, entrepreneurial experience, and education level of employee entrepreneurs, the size of the parent company in the previous year, including the age and total assets (the data is collected from Osiris and Orbis databases). Table 4 defines and explains the variables used in the measurement model.

**Table 4. Definition of variables in empirical models**

<b><i>Dependent Variable</i></b>	
<i>high_complement</i>	The value is 1 if the orientation is high_complement, 0 otherwise
<i>low_complement</i>	The value is 1 if the orientation is low_complement, 0 otherwise
<i>high_competition</i>	The value is 1 if the orientation is high_competition, 0 otherwise
<i>low_coopetition</i>	The value is 1 if the orientation is low_competition, 0 otherwise
<i>irrelevant</i>	The value is 1 if the orientation is irrelevant, 0 otherwise
<i>register_capital</i>	The register capital of the start-up
<i>survival</i>	The value is 1 if the start-up survives now, 0 otherwise
<i>survival_year</i>	Year of the start-up's survival time
<b><i>Independent Variables</i></b>	
<i>platform_parent</i>	The value is 1 if the parent firm is a platform, 0 if not.
<i>innovation</i>	The value is 1 if the parent firm is an innovation platform, 0 if not.
<i>transaction</i>	The value is 1 if the parent firm is a transaction platform, 0 if not.
<b><i>Control Variables</i></b>	
<i>job_experience</i>	The number of parent firms the entrepreneur worked for.
<i>mixed_experience</i>	The value is 1 if the entrepreneur worked both in platform and non-platform firms, 0 if not.
<i>multi_entrepreneur</i>	The value is 1 if the entrepreneur has more than 1 start-ups, 0 if not
<i>education</i>	The value is 1 if the entrepreneur graduated from famous universities, 0 if not

<i>asset</i>	The total asset of the parent firm in the year before the spinout year
<i>parent_age</i>	Age of parent firm in the year before the spinout year
<i>startup_age</i>	Age of start up
<i>finance_round</i>	Total number of rounds of getting investment
<i>Year</i>	The spinout year
<i>Region</i>	The region

### Summary statistics

In Table 5, we report summary statistics. Because the variables *asset*, *parent\_age*, *startup\_age* are highly skewed, we use the log transformations in the regression analyses.

**Table 5. Summary statistics**

Variables	(1) Obs.	(2) Mean	(3) SD	(4) Min	(5) Max
<i>high_complement</i>	9,781	0.662	0.473	0	1
<i>low_complement</i>	9,781	0.0729	0.260	0	1
<i>high_competition</i>	9,781	0.0408	0.198	0	1
<i>low_competition</i>	9,781	0.114	0.318	0	1
<i>irrelevant</i>	9,781	0.110	0.313	0	1
<i>ln_register_capital</i>	8,294	15.35	1.871	0	24.96
<i>survival</i>	9,781	0.852	0.355	0	1
<i>survival_year</i>	8,465	6.638	3.042	0.430	36.63
<i>parent_investment</i>	9,781	0.0235	0.177	0	4
<i>platform_parent</i>	9,781	0.637	0.481	0	1
<i>innovation</i>	9,781	0.354	0.478	0	1
<i>transaction</i>	9,781	0.490	0.500	0	1
<i>job_experience</i>	9,781	1.643	0.848	1	6
<i>mixed_experience</i>	9,781	0.243	0.429	0	1
<i>multi_entrepreneur</i>	9,781	0.194	0.396	0	1
<i>education</i>	9,781	0.481	0.500	0	1
<i>ln_asset</i>	7,085	16.34	2.479	0	21.97
<i>parent_age</i>	8,180	23.55	29.74	0	171
<i>startup_age</i>	8,475	7.080	2.955	0.430	36.63
<i>finance_round</i>	7,110	2.504	1.830	1	19

## RESULTS

### Entrepreneurial positioning of employee entrepreneurs

Logit models are adopted to explore entrepreneurial positioning. Table 6 shows the regression results for the entrepreneurial positioning of employees from the platform and non-platform firms, while Table 7 compares employees from transaction platforms and innovation platforms. The coefficients associated with *platform\_parenet*, *innovation* and

*transaction*, are positive and significant ( $p < .001$ ) in the *High\_complement* model, and are negative and significant ( $p < .001$ ) in the *High\_competition* model, providing support for Hypothesis 1. Since our empirical model is nonlinear, Figure 3 and Table 8 show the average marginal effects of the parent firm types with the other variables at their mean value (Hoetker, 2007).

**Table 6. Regression results of entrepreneurial positioning**

VARIABLES	(1)	(2)	(3)	(4)
	high_complement	low_complement	high_competition	low_competition
<i>platform_parent</i>	0.813*** (14.36)	0.163 (1.44)	-1.070*** (-7.11)	-0.700*** (-8.52)
<i>job_experience</i>	-0.004 (-0.11)	-0.025 (-0.42)	-0.110 (-1.03)	0.067 (1.38)
<i>mixed_experience</i>	0.079 (1.15)	0.220 (1.92)	0.000 (0.00)	-0.513*** (-4.49)
<i>multi_entrepreneur</i>	0.362*** (5.05)	-0.441** (-3.25)	0.031 (0.16)	-0.407*** (-3.59)
<i>education</i>	-0.019 (-0.35)	0.280** (2.99)	-0.392** (-2.71)	-0.031 (-0.39)
<i>foreign</i>	0.121 (0.32)	0.322 (0.52)	0.536 (0.53)	-0.725 (-1.03)
<i>ln_asset</i>	-0.016 (-1.37)	-0.075** (-3.22)	-0.166*** (-5.81)	0.198*** (10.10)
<i>ln_parent_age</i>	-0.007 (-0.21)	0.359*** (4.94)	0.096 (1.08)	-0.424*** (-11.68)
Constant	0.436* (2.24)	-2.578*** (-6.70)	-0.175 (-0.38)	-3.660*** (-10.23)
Observations	7,022	7,022	7,022	7,022
Pseudo R-squared	0.0312	0.0158	0.0510	0.0571

Robust z-statistics in parentheses

\*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$

**Table 7. Regression results of entrepreneurial positioning of platform employees**

VARIABLES	(1)	(2)	(3)	(4)
	high_complement	low_complement	high_competition	low_competition
<i>innovation</i>	0.680*** (11.93)	0.821*** (8.81)	-1.372*** (-6.49)	-1.148*** (-12.77)
<i>transaction</i>	0.613*** (10.74)	-0.813*** (-7.55)	-0.690*** (-4.53)	0.436*** (4.62)

<i>job_experience</i>	0.003 (0.09)	0.025 (0.41)	-0.134 (-1.25)	0.010 (0.20)
<i>mixed_experience</i>	0.079 (1.15)	0.140 (1.16)	0.027 (0.15)	-0.435*** (-3.99)
<i>multi_entrepreneur</i>	0.347*** (4.81)	-0.422** (-3.08)	0.038 (0.21)	-0.401*** (-3.53)
<i>education</i>	0.016 (0.30)	0.229* (2.40)	-0.404** (-2.81)	-0.006 (-0.07)
<i>foreign</i>	0.140 (0.37)	0.375 (0.59)	0.535 (0.53)	-0.797 (-1.13)
<i>ln_asset</i>	-0.057*** (-4.68)	-0.095*** (-4.49)	-0.125*** (-4.08)	0.298*** (12.27)
<i>ln_parent_age</i>	0.058 (1.67)	0.212*** (3.45)	0.051 (0.56)	-0.429*** (-10.59)
Constant	0.865*** (4.42)	-1.759*** (-5.22)	-0.635 (-1.34)	-5.539*** (-12.18)
Observations	7,022	7,022	7,022	7,022
Pseudo R-squared	0.0419	0.0498	0.0651	0.0763

Robust z-statistics in parentheses

\*\*\* p<0.001, \*\* p<0.01, \* p<0.05

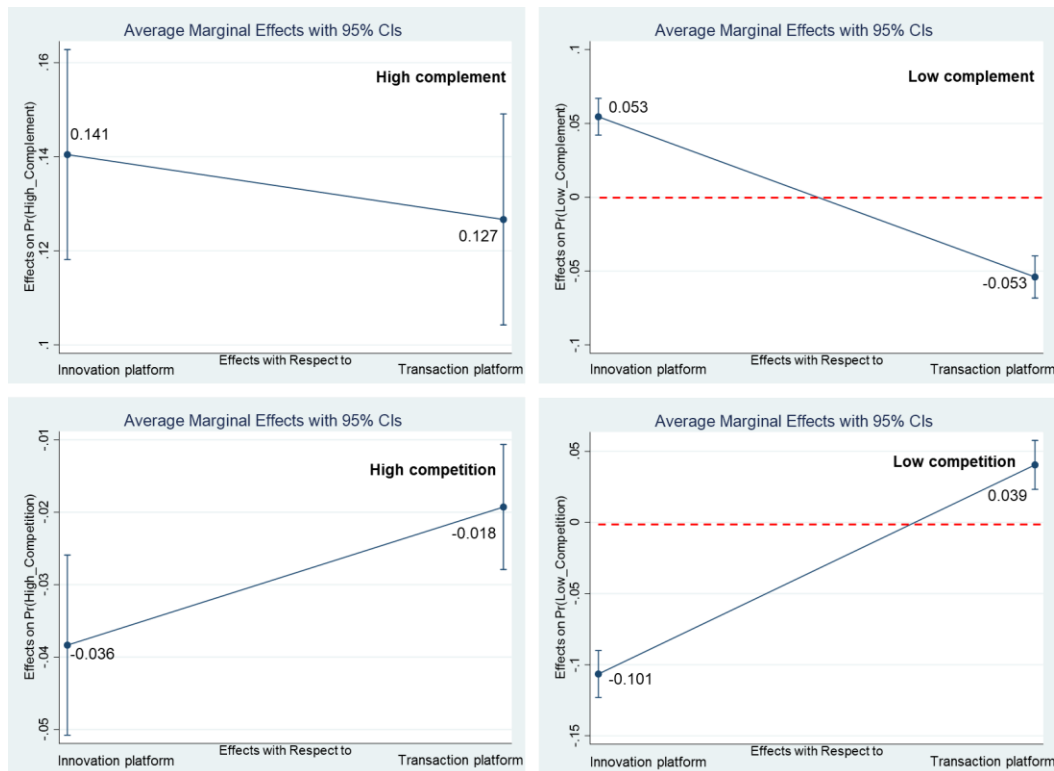
**Table 8. The marginal effect of parent firm types on employee entrepreneurial positioning**

	(1)	(2)	(3)	(4)
VARIABLES	high_complement	low_complement	high_competition	low_competition
<i>platform_parent</i>	0.171*** (15.28)	0.011 (1.45)	-0.028*** (-6.21)	-0.062*** (-8.30)
<i>innovation</i>	0.141*** (12.32)	0.053*** (8.48)	-0.036*** (-5.91)	-0.101*** (-12.08)
<i>transaction</i>	0.127*** (11.11)	-0.053*** (-7.28)	-0.018*** (-4.27)	0.039*** (4.68)

z-statistics in parentheses

\*\*\* p<0.001, \*\* p<0.01, \* p<0.05





**Fig 3. The marginal effect of platform type on entrepreneurial positionings**

The results in Column (1) of Table 8 show that employee entrepreneurs from platform parents can increase the probability of developing cross-industry complementary positioning by 17.1%, compared with non-platforms. Results in Column (3) and (4) shows the probability of becoming a direct and indirect competitor falls by 2.8% and 6.2% when spinouts are from platform parents. All the effects are statistically significant with  $p$  value smaller than .001. The results lead to the following findings:

- (1). Compared with non-platform parent firms, employee entrepreneurs from platforms are more likely to break the industry boundaries and become cross-industry complementors of parent firms.
- (2). Compared with non-platform parent firms, employee entrepreneurs from platforms are less likely to compete with parents.

These results are at variance with past literature on employee entrepreneurs which has focused on spinouts in the same industry with parent firms and develop competitive relationships. On the contrary, employee entrepreneurs from platform firms are more likely to develop cross-industry complementary relationships rather than competitive relationships with parents, which supports Hypothesis 1.

As we investigate different types of platforms, we find that employee entrepreneurs from innovation platforms and transaction platforms show different patterns. As shown in Table 8, among employee entrepreneurs from platforms, those from innovation platforms have a higher extent of cross-industry complementarity and a lower extent of direct competition. The impact of an innovation platform parent can increase the probability of cross-industry complement type by 14.1%, higher than the transaction platform with a marginal effect of 12.7%. The probability of direct competition type falls by 3.6% for innovation platform spinouts, which is more pronounced than that of transaction platform spinouts (-1.8%). All the effects are statistically significant with  $p$  value smaller than .001.

Meanwhile, results also reveal that spinouts from innovation platforms are more likely to become the intra-industry complement of parent firms, which is not the case for transaction platforms. Further, employee entrepreneurs of transaction platforms still show a positive tendency to develop an indirect competitive relationship with parents, while those from innovation avoid any type of competition. These lead to different entrepreneurial patterns regarding employees from innovation and transaction platforms. Employee entrepreneurs of innovation platforms show a higher extent of complementarity for both cross-industry and intra-industry, but avoid all competition, which supports Hypothesis 2 predicting that the extent of complementarity for employee entrepreneurs of innovation platforms is more pronounced relative to transaction platforms.

### **Survival of employee entrepreneurs**

This part analyzes the performance of employee entrepreneurs. We use Cox Proportional Hazards Model to examine the likelihood of failure of the employee-founded firms.

**Table 9. Regression results of entrepreneurial survival**

VARIABLES	(1) failure	(2) failure
<i>platform_parent</i>	0.202 (1.93)	
<i>transaction</i>		0.313** (3.17)
<i>innovation</i>		-0.031 (-0.30)
<i>job_experience</i>	-0.051 (-0.91)	-0.060 (-1.07)
<i>mixed_experience</i>	0.137 (1.19)	0.149 (1.30)
<i>multi_entrepreneur</i>	0.215	0.207

	(1.93)	(1.85)
<i>education</i>	-0.203*	-0.188*
	(-2.13)	(-1.97)
<i>foreign</i>	-0.480	-0.517
	(-0.48)	(-0.51)
<i>ln_asset</i>	-0.009	-0.007
	(-0.48)	(-0.33)
<i>ln_parent_age</i>	-0.057	-0.030
	(-1.05)	(-0.50)
<i>finance_round</i>	-0.525***	-0.527***
	(-12.77)	(-12.77)
Constant		
Observations	5,192	5,192
R-squared		
Pseudo R-squared	0.0275	0.0283

Robust t-statistics in parentheses

\*\*\* p<0.001, \*\* p<0.01, \* p<0.05

Table 9 suggests that the transaction platform parent firm significantly increases the hazard of failure of their spinous by 36.8%<sup>7</sup> ( $p<0.01$ ). The results lead to the following findings: Employee entrepreneurs from transaction platforms face higher risks of failure.

### ROBUSTNESS CHECK

#### Year and region dummy

We check the robustness of the results in multiple ways (see appendix). First, we control the established year and region dummy of new ventures and get consistent results.

#### Sample selection biases

Our sample includes all entrepreneurs with prior employment information in ITJUZI database. However, this sample doesn't include those who have prior job experiences but didn't report them, which leads to the problem of sample selection bias. We assume that: whether entrepreneurs decide to report their employment experiences or not depends on how this employment experience contributes to expectational investment they can get.

$$Marginal\_Investment = \beta_0 + \beta_1 Parent\_Size + \beta_2 Parent\_Reputation + u$$

$$Report = \begin{cases} 1, & Marginal\_Investment > 0 \\ 0, & Marginal\_Investment \leq 0 \end{cases}$$

As we assumed, whether to report or hide their prior employment experience is related to the parent firm's size and reputation. If people worked for a small and unknown company

<sup>7</sup> The hazard ratio is calculated as  $e(\beta)$ , which is  $e(0.313) = 1.368$ .

before, they may choose to hide this experience because it brings negative effects on attracting investment. By controlling samples from top parent firms which are big and famous incumbents, we can assume that all employees from these top firms have incentives to report their job experiences. Therefore, we use observations from the top 200, top 150, and top 100 cutoffs for parent firms and find consistent results with our original findings. Therefore, we can say that our findings are robust even with possible sample selection bias.

### **Controlling for parent size**

Large incumbents tend to nurture more complementary spinouts because they may have multiple business lines. As a result, our original sample may be limited in terms of parent firm size. Therefore, we split the original sample into small firms and large firms according to the parent firm size (based on the median of assets), to re-explore the empirical model. The results show a consistent pattern in both subsamples.

### **Other robustness tests**

We use the probit model to explore entrepreneurial positioning and get similar results. For the survival analysis, we use Weibull proportional hazards model and AFT (accelerated failure-time) model to check the robustness of the results. As displayed in Table 15, We find consistent results that transaction platform type significantly increases the failure risk and decreases the survival time ( $p < .01$ ).

Meanwhile, we replace the binary variable *multi\_entrepreneur* with a continuous variable *entrepreneurial\_experience* measuring the number of total venture development experiences. We find consistent results that support the hypotheses. Finally, we conduct several exclusion tests to rule out alternative explanations. We excluded the outlier entrepreneurs who act as founders of multiple start-ups (>4, top 1st percentile). Meanwhile, considering the hybrid platform have attributes of both transaction and innovation platform, we tested the robustness using a sample that rules out the hybrid platform parents. These results remain consistent.

## **DISCUSSION**

Employee entrepreneurship often leads to cross-organizational knowledge transfer and industry dynamics. As suggested by existing literature, employee entrepreneurs mostly will pose competitive threats to parent firms by entering the same industries, which may conflict

with the interest of parent firms. With the development of information technology, platforms have grown rapidly and become a widely-adopted organizational form. Platform enterprises such as Google, Facebook, Amazon, Intel, ARM have been expanding their business scopes, continually driving profound changes in our economy. Platforms have shown tremendous ability to grow and expand, not only through their own strategic entry and diversification but also through external spillover effect by facilitating their employees to create new start-ups.

In this research, we aim to connect the literature in employee entrepreneurship with platform theory, and explore this research question: how do employee entrepreneurs in platforms and non-platforms differ? We empirically investigate this research question by using the data from entrepreneurs from top companies (both platform and non-platform enterprises) in China. Compared with extant literature suggesting that spinouts mostly will compete with their parent firms in the same industry, our main argument is that employees from platform companies are more likely to enter diverse industries and become the complementors for their parents. Our result also highlights the differences between transaction and innovation platforms, suggesting that innovation platforms are more likely to nurture complementary spinouts. Meanwhile, our results find that spinouts from transactions platforms may face higher risks of entrepreneurial failure.

### **Contributions**

Our research findings contribute to the literature on the positioning and performance of employee entrepreneurs. According to extant research, employee entrepreneurs mostly become competitors of their parent firms in the same industry, leading to interest conflict with the incumbents (Agarwal & Shah, 2014; Campbell, Ganco, Franco, & Agarwal, 2012; Phillips, 2002). Existing research has not yet explored the context of platform enterprises and the great numbers of spinouts founded by former employees. By introducing this new context of platform enterprises, our study takes a step forward to integrate the literature on employee entrepreneurship with platform theory. Unlike prior findings, we find that complementary relationships exist extensively among platform-spawned entrepreneurs. Employee entrepreneurs from platform companies are more likely to become complementors in diverse industries, rather than competitors in the same industry with their parent firms. The findings

provide new implications to help better understand the relationship between employee entrepreneurs and their parent firms in different contexts.

We also provide implications for the knowledge-based view of employee mobility and employee entrepreneurship. We add to the research on knowledge transfer and inheritance through employee entrepreneurship (Agarwal, Echambadi, Franco, & Sarkar, 2004; Franco & Filson, 2006; Ganco, 2013; Kim & Steensma, 2017), by suggesting that the inherited knowledge pattern and potential of knowledge exploitation of platforms differ from non-platforms. We show that platform employees may expose to highly diverse knowledge sets, due to the nature of connectivity and complementarity of platform businesses, which encourage them to break industry boundaries and become the complementors of platform incumbents. We also highlight the important role of entrepreneurs' ability to further exploit their inherited knowledge and imply that spinouts may face the problem of knowledge decoupling if their knowledge endowment is not well-matched with their entrepreneurial targets.

Meanwhile, our study has important theoretical extensions to the increasing body of literature exploring platform entry and expansion. Prior research has mainly focused on the entries and expansions by platform owners but paid less attention to the prevalent external spillovers by other stakeholders (Eisenmann, Parker, & Van Alstyne, 2011; Eisenmann, Parker, & Van Alstyne, 2006; Katz, 2019; Wen & Zhu, 2019). Our study focuses on the spillover through employee entrepreneurship from platform enterprises. We find that employee entrepreneurs from platforms are highly likely to develop a complementary relationship with parent firms. Thus, our research suggests that platform enterprises have both internal and external growing mechanisms to enter new industries, expand their businesses, and nurture complementors and partners.

Finally, our study addresses the differences between transaction and innovation platforms to help gain a deeper understanding of platform growth (Cusumano, Gawer, & Yoffie, 2019). We demonstrate that innovation platforms are characterized as a key technological base, while transaction platforms may involve more complicated and interdependent factors, which leads to the different patterns of knowledge their employees can inherit. Thus, employee

entrepreneurs from transaction and innovation platforms also show differences in terms of entrepreneurial positioning and performance. Our findings show that innovation platforms are most likely to encourage complementary spinouts, and nurture a highly cooperative, cross-industry ecosystem. Moreover, as for the performance of spinouts, we suggest that employees from transaction platforms may suffer a higher risk of failure, due to the high complexity and interdependence of knowledge needed for their venture operation.

Our research has managerial implications as well. While past literature has suggested that spawning competitors may hamper the performance of incumbent firms (Campbell, Ganco, Franco, & Agarwal, 2012; Phillips, 2002), our research findings offer a new perspective on platform-spawned firms and show that they may join the complementor networks of the incumbent firms. Therefore, our research suggests that platform employees with entrepreneurial orientations may provide a new approach to expanding the platform ecosystem externally through employee entrepreneurship. Managers should identify which complementary fields can be improved with employee entrepreneurs, and what type of employees are suitable, and then design and introduce relevant mechanisms. This implication resonates with the recent initiative by Amazon that supports its employees to start their own package delivery businesses, to complement Amazon ecosystem. For employee entrepreneurs, our research findings highlight the importance of exploiting initial knowledge endowment in the subsequent startup operations. We reveal the possible risks brought by knowledge decoupling, especially for spinouts from transaction platforms that may need a deep understanding of much complementary knowledge. Therefore, employee entrepreneurs should assess and identify their knowledge, and the need to combine other complementary knowledge before they start their own business.

### **Limitations and future research**

The limitations of our research provide an important avenue for future research. We define and classify the entrepreneurial positioning based on the fields of the spinout and parent firm, which may be rough to capture the actual relationship. One important direction is to refine the definition by using the detailed information of their products, or public information such as establishing cooperation or opening competition. Meanwhile, our

empirical results are based on data of start-ups in high-tech industries. The rapid innovation and frequent spinouts spillover in high-tech industries provide an important context, however, also leads to the limitation of generalizability of our findings. Therefore, more studies in various sectors and countries are needed to help extend our understanding of employee entrepreneurship.

Moreover, the mechanism of spinout formation should be further investigated. Our sample shows that big companies dominate in employee entrepreneurship, and the top 10 parent companies contribute nearly 40% of the total spinout formations. Therefore, even within the same company, employees from different departments or positions get very varied knowledge and experience, which determine their entrepreneurial ideas (Agarwal, Echambadi, Franco, & Sarkar, 2004; Dahl & Reichstein, 2007). Unfortunately, due to data availability, we are unable to investigate how the previous positions or experiences of employee entrepreneurs in parent firms influence their positionings. Future research should explore specific mechanism and determinants of spinouts' entrepreneurial positioning.

Finally, another interesting question not answered by our study is how the incumbent platforms are affected by employee entrepreneurship. Extant literature has suggested that most parent firms suffer knowledge loss and face competitive pressure from the intra-industry spinouts. If the employees tend to become complementors of their incumbent platforms as our study suggests, that could lead to a synergy effect and help the platforms build larger ecosystems. Therefore, studying the performance of incumbent platforms could provide new implications for current literature.



## REFERENCES

- Agarwal, R., Audretsch, D., & Sarkar, M. 2007. The process of creative construction: knowledge spillovers, entrepreneurship, and economic growth. *Strategic Entrepreneurship Journal*, 1(3-4): 263-86.
- Agarwal, R., Campbell, B. A., Franco, A. M., & Ganco, M. 2016. What do I take with me? The mediating effect of spinout team size and tenure on the founder–firm performance relationship. *Academy of Management Journal*, 59(3): 1060-87.
- Agarwal, R., Echambadi, R., Franco, A. M., & Sarkar, M. B. 2004. Knowledge transfer through inheritance: Spinout generation, development, and survival. *Academy of Management Journal*, 47(4): 501-22.
- Agarwal, R. & Shah, S. K. 2014. Knowledge sources of entrepreneurship: Firm formation by academic, user and employee innovators. *Research Policy*, 43(7): 1109-33.
- Argentesi, E., Buccirossi, P., Calvano, E., Duso, T., Marrazzo, A., & Nava, S. 2019. Merger policy in digital markets: An ex-post assessment.
- Axel, G. & Joe, L. 2020. Mergers in the digital economy. *Information Economics and Policy*: 100890.
- Barney, J. 1991. Firm resources and sustained competitive advantage. *Journal of management*, 17(1): 99-120.
- Basu, S., Sahaym, A., Howard, M. D., & Boeker, W. 2015. Parent inheritance, founder expertise, and venture strategy: Determinants of new venture knowledge impact. *Journal of Business Venturing*, 30(2): 322-37.
- Boschma, R. A. & Wenting, R. 2007. The spatial evolution of the British automobile industry: Does location matter? *Industrial and Corporate Change*, 16(2): 213-38.
- Boudreau, K. J. & Jeppesen, L. B. 2015. Unpaid crowd complementors: The platform network effect mirage. *Strategic Management Journal*, 36(12): 1761-77.
- Bryan, K. A. & Hovenkamp, E. 2020. Antitrust limits on startup acquisitions. *Review of Industrial Organization*: 1-22.
- Burton, M. D., Sørensen, J. B., & Beckman, C. M. 2002. *7. Coming from good stock: Career histories and new venture formation*: Emerald Group Publishing Limited.
- Cabral, L. 2020. Merger policy in digital industries. *Information Economics and Policy*: 100866.
- Campbell, B. A., Ganco, M., Franco, A. M., & Agarwal, R. 2012. Who leaves, where to, and why worry? Employee mobility, entrepreneurship and effects on source firm performance. *Strategic Management Journal*, 33(1): 65-87.
- Ceccagnoli, M., Forman, C., Huang, P., & Wu, D. J. 2012. Cocreation of Value in a Platform Ecosystem: The Case of Enterprise Software. *MIS Quarterly*, 36(1).
- Chatterji, A. K. 2009. Spawned with a silver spoon? Entrepreneurial performance and innovation in the medical device industry. *Strategic Management Journal*, 30(2): 185-206.
- Christensen, C. M. 1993. The rigid disk drive industry: A history of commercial and technological turbulence. *Business History Review*, 67(4): 531-88.
- Coff, R. W. 1997. Human assets and management dilemmas: Coping with hazards on the road to resource-based theory. *Academy of management review*, 22(2): 374-402.

- Cusumano, M. A., Gawer, A., & Yoffie, D. B. 2019. *The business of platforms: Strategy in the age of digital competition, innovation, and power*: Harper Business New York.
- Cutolo, D. & Kenney, M. 2020. Platform-dependent entrepreneurs: Power asymmetries, risks, and strategies in the platform economy. *Academy of Management Perspectives*(ja).
- Dahl, M. S. & Reichstein, T. 2007. Are you experienced? Prior experience and the survival of new organizations. *Industry and Innovation*, 14(5): 497-511.
- De Figueiredo, R. J., Meyer-Doyle, P., & Rawley, E. 2013. Inherited agglomeration effects in hedge fund spawns. *Strategic Management Journal*, 34(7): 843-62.
- Eisenmann, T., Parker, G., & Van Alstyne, M. 2011. Platform envelopment. *Strategic Management Journal*, 32(12): 1270-85.
- Eisenmann, T., Parker, G., & Van Alstyne, M. W. 2006. Strategies for two-sided markets. *Harvard Business Review*, 84(10): 92.
- Elfenbein, D. W., Hamilton, B. H., & Zenger, T. R. 2010. The small firm effect and the entrepreneurial spawning of scientists and engineers. *Management Science*, 56(4): 659-81.
- Eriksson, T. & Kuhn, J. M. 2006. Firm spin-offs in Denmark 1981–2000—patterns of entry and exit. *International Journal of Industrial Organization*, 24(5): 1021-40.
- Evans, D. S. 2009. How catalysts ignite: the economics of platform-based start-ups. *Cheltenham, UK and Northampton, MA, US: Edward Elgar*.
- Foerderer, J., Kude, T., Mithas, S., & Heinzl, A. 2018. Does platform owner's entry crowd out innovation? Evidence from Google photos. *Information Systems Research*, 29(2): 444-60.
- Franco, A. 2005. Employee entrepreneurship: recent research and future directions. *Handbook of Entrepreneurship Research*: 81-96.
- Franco, A. M. & Filson, D. 2006. Spin-outs: knowledge diffusion through employee mobility. *The RAND Journal of Economics*, 37(4): 841-60.
- Franco, A. M. & Mitchell, M. F. 2008. Covenants not to compete, labor mobility, and industry dynamics. *Journal of Economics & Management Strategy*, 17(3): 581-606.
- Gambardella, A., Ganco, M., & Honoré, F. 2015. Using what you know: Patented knowledge in incumbent firms and employee entrepreneurship. *Organization Science*, 26(2): 456-74.
- Ganco, M. 2013. Cutting the Gordian knot: The effect of knowledge complexity on employee mobility and entrepreneurship. *Strategic Management Journal*, 34(6): 666-86.
- Garvin, D. A. 1983. Spin-offs and the new firm formation process. *California Management Review*, 25(2): 3-20.
- Gompers, P., Lerner, J., & Scharfstein, D. 2005. Entrepreneurial spawning: Public corporations and the genesis of new ventures, 1986 to 1999. *The Journal of Finance*, 60(2): 577-614.
- He, S., Peng, J., Li, J., & Xu, L. 2020. Impact of platform owner's entry on third-party stores. *Information Systems Research*, 31(4): 1467-84.
- Hellmann, T. 2007. When do employees become entrepreneurs? *Management science*, 53(6): 919-33.
- Hoetker, G. 2007. The use of logit and probit models in strategic management research: Critical issues. *Strategic management journal*, 28(4): 331-43.
- Ioannou, I. 2014. When do spinouts enhance parent firm performance? Evidence from the US automobile industry, 1890–1986. *Organization Science*, 25(2): 529-51.

- Jia, X., Cusumano, M. A., & Chen, J. 2019. An Analysis of Multi-Sided Platform Research Over the Past Three Decades: Framework and Discussion.
- Kamepalli, S. K., Rajan, R., & Zingales, L. 2020. Kill Zone: National Bureau of Economic Research.
- Kapoor, R. 2013. Collaborating with complementors: What do firms do? *Advances in Strategic Management*, 30: 3–25.
- Katz, M. L. 2020. Big Tech mergers: Innovation, competition for the market, and the acquisition of emerging competitors. *Information Economics and Policy*: 100883.
- Katz, M. L. 2019. Platform economics and antitrust enforcement: A little knowledge is a dangerous thing. *Journal of Economics & Management Strategy*, 28(1): 138-52.
- Katz, M. L. & Shapiro, C. 1985. Network Externalities, Competition, and Compatibility. *American Economic Review*, 75(3): 424-40.
- Kim, J. Y. & Steensma, H. K. 2017. Employee mobility, spin-outs, and knowledge spill-in: How incumbent firms can learn from new ventures. *Strategic Management Journal*, 38(8): 1626-45.
- Klepper, S. 2002. The capabilities of new firms and the evolution of the US automobile industry. *Industrial and Corporate Change*, 11(4): 645-66.
- Klepper, S. 2007. Disagreements, spinoffs, and the evolution of Detroit as the capital of the US automobile industry. *Management Science*, 53(4): 616-31.
- Klepper, S. 2001. Employee startups in high-tech industries. *Industrial and Corporate Change*, 10(3): 639-74.
- Klepper, S. 2009. Spinoffs: A review and synthesis. *European Management Review*, 6(3): 159-71.
- Klepper, S. & Sleeper, S. 2005. Entry by spinoffs. *Management Science*, 51(8): 1291-306.
- Kogut, B. & Zander, U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization science*, 3(3): 383-97.
- Koski, H., Kässi, O., & Braesemann, F. 2020. Killers on the road of emerging start-ups—implications for market entry and venture capital financing: ETLA Working Papers.
- Li, Z. & Agarwal, A. 2017. Platform integration and demand spillovers in complementary markets: Evidence from Facebook’s integration of Instagram. *Management Science*, 63(10): 3438-58.
- Lofstrom, M., Bates, T., & Parker, S. C. 2014. Why are some people more likely to become small-businesses owners than others: Entrepreneurship entry and industry-specific barriers. *Journal of Business Venturing*, 29(2): 232-51.
- McKendrick, D. G., Wade, J. B., & Jaffee, J. 2009. A good riddance? Spin-offs and the technological performance of parent firms. *Organization Science*, 20(6): 979-92.
- Moore, G. & Davis, K. 2004. Learning the silicon valley way. *Building High-tech Clusters: Silicon Valley and Beyond*, 7: 36.
- Motta, M. & Peitz, M. 2020. Big tech mergers. *Information Economics and Policy*: 100868.
- Parente, R., Rong, K., Geleilate, J.-M. G., & Misati, E. 2019. Adapting and sustaining operations in weak institutional environments: A business ecosystem assessment of a Chinese MNE in Central Africa. *Journal of International Business Studies*, 50(2): 275-91.
- Parker, G. & Van Alstyne, M. 2018. Innovation, openness, and platform control. *Management Science*, 64(7): 3015-32.

- Phillips, D. J. 2002. A genealogical approach to organizational life chances: The parent-progeny transfer among Silicon Valley law firms, 1946–1996. *Administrative Science Quarterly*, 47(3): 474-506.
- Rysman, M. 2009. The Economics of Two-Sided Markets. *Journal of Economic Perspectives*, 23(3): 125-43.
- Shah, S. K., Agarwal, R., & Echambadi, R. 2019. Jewels in the crown: Exploring the motivations and team building processes of employee entrepreneurs. *Strategic Management Journal*, 40(9): 1417-52.
- Simons, T. & Roberts, P. W. 2008. Local and non-local pre-founding experience and new organizational form penetration: The case of the Israeli wine industry. *Administrative Science Quarterly*, 53(2): 235-65.
- Somaya, D., Williamson, I. O., & Lorinkova, N. 2008. Gone but not lost: The different performance impacts of employee mobility between cooperators versus competitors. *Academy of Management Journal*, 51(5): 936-53.
- Sørensen, J. B. 2007. Bureaucracy and entrepreneurship: Workplace effects on entrepreneurial entry. *Administrative Science Quarterly*, 52(3): 387-412.
- Sørensen, J. B. & Phillips, D. J. 2011. Competence and commitment: employer size and entrepreneurial endurance. *Industrial and Corporate Change*, 20(5): 1277-304.
- Strotmann, H. 2007. Entrepreneurial survival. *Small Business Economics*, 28(1): 87-104.
- Teece, D. J. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research policy*, 15(6): 285-305.
- von Rhein, K. 2008. Heritage and firm survival: an analysis of German automobile spinoffs 1886-1939: Jena Economic Research Papers.
- Wen, W. & Zhu, F. 2019. Threat of platform-owner entry and complementor responses: Evidence from the mobile app market. *Strategic Management Journal*, 40(9): 1336-67.
- Wenting, R. 2008. Spinoff dynamics and the spatial formation of the fashion design industry, 1858–2005. *Journal of Economic Geography*, 8(5): 593-614.
- Yeganegi, S., Laplume, A. O., Dass, P., & Huynh, C.-L. 2016. Where do spinouts come from? The role of technology relatedness and institutional context. *Research Policy*, 45(5): 1103-12.
- Yli-Renko, H., Autio, E., & Sapienza, H. J. 2001. Social capital, knowledge acquisition, and knowledge exploitation in young technology-based firms. *Strategic management journal*, 22(6-7): 587-613.
- Zhu, F. & Iansiti, M. 2012. Entry into platform-based markets. *Strategic Management Journal*, 33(1): 88–106.

## APPENDIX

**Table A1. Regression results of entrepreneurial positioning with year and region dummy**

VARIABLES	(1)	(2)	(3)	(4)
	high_complement	low_complement	high_competition	low_competition
<i>platform_parent</i>	0.829*** (14.28)	0.170 (1.47)	-1.138*** (-7.45)	-0.784*** (-9.39)
<i>job_experience</i>	-0.001 (-0.03)	-0.047 (-0.79)	-0.136 (-1.25)	0.054 (1.08)
<i>mixed_experience</i>	0.090 (1.30)	0.194 (1.67)	-0.004 (-0.02)	-0.510*** (-4.45)
<i>multi_entrepreneur</i>	0.320*** (4.23)	-0.394** (-2.79)	0.062 (0.29)	-0.308** (-2.58)
<i>education</i>	-0.007 (-0.13)	0.246* (2.57)	-0.442** (-3.02)	0.015 (0.19)
<i>foreign</i>	-1.462 (-1.12)	1.230 (0.95)	0.836 (0.76)	1.981 (1.28)
<i>ln_asset</i>	-0.014 (-1.19)	-0.075** (-3.12)	-0.161*** (-5.46)	0.190*** (9.68)
<i>ln_parent_age</i>	-0.000 (-0.00)	0.366*** (5.14)	0.055 (0.61)	-0.452*** (-11.67)
<i>Year dummy</i>	Y	Y	Y	Y
<i>Region dummy</i>	Y	Y	Y	Y
Constant	-0.218 (-0.22)	-2.861** (-2.80)	1.354 (1.25)	-2.045 (-1.50)
Observations	6,998	6,819	6,743	6,761
Pseudo R-squared	0.0406	0.0401	0.0827	0.0719

**Table A2. Regression results of platform employees' entrepreneurial positioning with year and region dummy**

VARIABLES	(1)	(2)	(3)	(4)
	high_complement	low_complement	high_competition	low_competition
<i>innovation</i>	0.672*** (11.59)	0.898*** (9.29)	-1.338*** (-6.25)	-1.238*** (-13.46)
<i>transaction</i>	0.638*** (10.96)	-0.827*** (-7.52)	-0.795*** (-5.09)	0.414*** (4.21)
<i>job_experience</i>	0.003 (0.09)	-0.012 (-0.20)	-0.146 (-1.35)	0.004 (0.08)
<i>mixed_experience</i>	0.088 (1.27)	0.111 (0.92)	0.018 (0.10)	-0.433*** (-3.93)
<i>multi_entrepreneur</i>	0.308*** (4.05)	-0.354* (-2.46)	0.063 (0.30)	-0.366** (-3.03)
<i>education</i>	0.020 (0.37)	0.192 (1.96)	-0.440** (-3.03)	0.044 (0.54)
<i>foreign</i>	-1.356 (-1.00)	1.541 (1.26)	0.787 (0.70)	2.183 (1.46)
<i>ln_asset</i>	-0.054*** (-4.34)	-0.097*** (-4.43)	-0.123*** (-3.90)	0.295*** (12.00)
<i>ln_parent_age</i>	0.065 (1.84)	0.222*** (3.67)	0.013 (0.14)	-0.459*** (-10.72)

<i>Year dummy</i>	Y	Y	Y	Y
<i>Region dummy</i>	Y	Y	Y	Y
Constant	0.362 (0.36)	-1.961* (-1.99)	0.815 (0.75)	-4.484** (-3.21)
Observations	6,998	6,819	6,743	6,761
Pseudo R-squared	0.0504	0.0780	0.0935	0.0916

**Table A3. Regression results of entrepreneurial entry and risks with year and region dummy**

VARIABLES	dummy	
	(1) failure	(2) failure
<i>platform_parent</i>	0.180 (1.72)	
<i>transaction</i>		0.271** (2.76)
<i>innovation</i>		-0.006 (-0.06)
<i>job_experience</i>	-0.116* (-2.03)	-0.121* (-2.12)
<i>mixed_experience</i>	0.132 (1.14)	0.139 (1.20)
<i>multi_entrepreneur</i>	0.259* (2.20)	0.250* (2.13)
<i>education</i>	-0.198* (-2.03)	-0.187 (-1.92)
<i>foreign</i>	1.244 (.)	1.300 (.)
<i>ln_asset</i>	-0.008 (-0.41)	-0.009 (-0.39)
<i>ln_parent_age</i>	-0.059 (-1.05)	-0.033 (-0.55)
<i>finance_round</i>	-0.515*** (-12.30)	-0.516*** (-12.32)
<i>Year dummy</i>	Y	Y
<i>Region dummy</i>	Y	Y
Constant		
Observations	5,185	5,185
R-squared		
Pseudo R-squared	0.0432	0.0438

**Table A4. Regression results of entrepreneur employees from top 200, top 150 and top**

VARIABLES	100 parent firms				
	(1) high_comple ment	(2) low_comple ment	(3) high_competi tion	(4) low_competit ion	(5) failure
<b>Top 200</b>					
<i>innovation</i>	0.650*** (11.02)	1.032*** (10.27)	-1.194*** (-5.46)	-1.215*** (-13.14)	0.004 (0.04)
<i>transaction</i>	0.651*** (10.99)	-0.842*** (-7.45)	-0.849*** (-5.04)	0.414*** (4.12)	0.291** (2.90)
Observations	6,761	6,588	6,360	6,532	5,015

<b>Top 150</b>					
<i>innovation</i>	0.620*** (10.31)	1.071*** (10.38)	-1.122*** (-5.06)	-1.214*** (-12.86)	0.042 (0.39)
<i>transaction</i>	0.644*** (10.58)	-0.847*** (-7.22)	-0.783*** (-4.42)	0.429*** (4.06)	0.248* (2.42)
Observations	6,459	6,275	6,031	6,246	4,796
<b>Top 100</b>					
<i>innovation</i>	0.579*** (9.31)	1.263*** (10.88)	-1.140*** (-5.01)	-1.168*** (-11.75)	0.062 (0.55)
<i>transaction</i>	0.635*** (9.94)	-0.804*** (-6.34)	-0.720*** (-3.81)	0.455*** (4.10)	0.265* (2.52)
Observations	5,951	5,784	5,403	5,755	4,438

**Table A5. Regression results of entrepreneur employees from large and small parent firms**

VARIABLES	(1) high_comple ment	(2) low_comple ment	(3) high_competi tion	(4) low_competit ion
<b>Large</b>				
<i>innovation</i>	0.440*** (4.90)	0.974*** (6.22)	-0.938* (-2.40)	-2.019*** (-10.67)
<i>transaction</i>	0.652*** (6.31)	-0.518** (-3.00)	-0.918* (-2.10)	2.389*** (12.12)
Observations	3,500	3,370	3,301	3,349
<b>Small</b>				
<i>innovation</i>	0.838*** (7.80)	0.710*** (4.30)	-1.669*** (-4.56)	-0.725*** (-4.41)
<i>transaction</i>	0.441*** (5.20)	-0.917*** (-5.51)	-0.707*** (-3.66)	-0.004 (-0.03)
Observations	3,467	3,367	3,280	3,336

**Table A6. Regression results of changing model forms**

VARIABLES	(1) high_comple ment probit	(2) low_comple ment probit	(3) high_compet ition probit	(4) low_competi tion probit	(5) failure Weibull model	(6) survival time AFT model
<i>innovation</i>	0.410*** (11.79)	0.456*** (9.41)	-0.560*** (-6.74)	-0.650*** (-13.72)	-0.008 (-0.08)	0.022 (0.43)
<i>transaction</i>	0.386*** (11.02)	-0.422*** (-8.08)	-0.344*** (-5.02)	0.197*** (4.09)	0.276** (2.77)	-0.137** (-2.65)
Observations	6,998	6,819	6,743	6,761	5,185	5,185

**Table A7. Regression results of other robustness checks**

VARIABLES	(1) high_comple ment	(2) low_comple ment	(3) high_competi tion	(4) low_competit ion	(5) failure
<b>Control entrepreneur_experience</b>					
<i>innovation</i>	0.673*** (11.62)	0.896*** (9.27)	-1.338*** (-6.26)	-1.237*** (-13.47)	-0.005 (-0.05)
<i>transaction</i>	0.639***	-0.830***	-0.791***	0.409***	0.277**

	(10.98)	(-7.57)	(-5.04)	(4.15)	(2.82)
<i>Entrepreneurial_experience</i>	0.171***	-0.156	-0.025	-0.165*	0.054
	(3.78)	(-1.79)	(-0.24)	(-2.07)	(1.08)
Observations	6,998	6,819	6,743	6,761	5,185
<b><i>Exclude outliers of serial entrepreneurs</i></b>					
<i>innovation</i>	0.674***	0.896***	-1.341***	-1.243***	-0.001
	(11.61)	(9.24)	(-6.27)	(-13.46)	(-0.01)
<i>transaction</i>	0.638***	-0.845***	-0.797***	0.425***	0.266**
	(10.93)	(-7.65)	(-5.10)	(4.29)	(2.71)
Observations	6,956	6,777	6,707	6,724	5,161
<b><i>Exclude hybrid platform observations</i></b>					
<i>innovation</i>	0.598***	0.895***	-1.290***	-3.435***	-0.036
	(7.56)	(7.52)	(-4.97)	(-8.54)	(-0.23)
<i>transaction</i>	0.586***	-0.928***	-0.786***	-0.029	0.260*
	(7.97)	(-6.12)	(-4.61)	(-0.23)	(2.04)
Observations	5,280	5,150	5,081	5,056	3,840

Robust z-statistics in parentheses

\*\*\* p<0.001, \*\* p<0.01, \* p<0.05