Journal of Business Research 154 (2023) 113319

Contents lists available at ScienceDirect

Journal of Business Research

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

Growth, agglomeration externalities, and survival: Evidence from Chinese manufacturing start-ups

Ruiqi Cheng, Peng Yuan, Gongxiong Jiang *

Institute of Western China Economic Research, Southwestern University of Finance and Economics, China

ARTICLE INFO

Keywords:
Growth strategies
Firm survival
Specialization
Diversification
Related variety

ABSTRACT

Previous studies on the impact of firm growth on survival have paid little attention to agglomeration externalities. This study theoretically analyses how different agglomeration externalities affect the relationship between growth and survival. Using data from China's manufacturing start-ups, we confirm a U-shaped relationship between the growth and survival risks of start-ups. Moreover, we find that different agglomeration externalities have heterogeneous moderating effects on this U-shaped relationship. Specifically, specialization and diversification externalities have significantly negative and positive moderating effects, respectively. The positive moderating effect of diversification externalities comes from the moderating effect of related variety externalities, whereas unrelated variety externalities have no significant moderating effect. The robustness test results support the above conclusions and suggest that the moderating effect of specialization externalities is heterogeneous in terms of firms' resources.

1. Introduction

In strategic management, growth is believed to affect not only the success of a firm at a certain stage but also its survival. Regarding growth as a strategic choice and process facilitates a deep understanding of a firm's early survival process (Gjerløv-Juel & Guenther, 2019; Pe'Er, Vertinsky, & Keil, 2016). Many studies have discussed the relationship between growth and firm survival. The literature enriches our understanding of the survival outcomes of growth, but a consistent conclusion has not yet been reached.[1] Moreover, existing research on the relationship between growth and survival rarely considers the interactions between growth and external factors.

Recent studies have emphasized that exploring the underlying mechanism of business failure requires consideration of internal and external factors (Karabag, 2019; Zhang, Amankwah-Amoah, & Beaverstock, 2019). They argued that, although few studies have explained how the interaction of firms' external environment and managerial decisions (or strategic actions) contributes to business failure, interaction is not unimportant. Thus, when exploring the drivers of firm failure, we need an integrated framework that includes internal and external factors and considers the interaction of internal and external factors. Therefore, research on the survival outcomes of growth may need to be systematically reexamined to explore the role of the external environment.

As a critical local environmental factor, agglomeration has a significant impact on the performance outcomes of firm strategies (Pe'Er et al., 2016; Woo, Assaf, Josiassen, & Kock, 2019). Agglomeration may create external environmental conditions that interact with strategic choices and influence key processes such as firm growth. From a survival perspective, Pe'Er et al. (2016) explored the relationship between specialization agglomeration and performance outcomes of new firms' growth strategies. Specialization refers to the geographic concentration of firms in the same industry that can provide specialized labor, specialized input, technology spillover, and high demand (Marshall, 1920; Mccann & Folta, 2008). Although the relationship between specialization and the performance outcomes of firm strategies has been investigated, the relationship between diversification and the performance output of firm strategies remains to be explored. Diversification is another frequently mentioned type of agglomeration that differs from

* Corresponding author.
E-mail addresses: crqincd@163.com (R. Cheng), ypfeiyu@swufe.edu.cn (P. Yuan), 18217692671@163.com (G. Jiang).

[1] A strand of early research argued that rapid growth is beneficial for firm survival (Agarwal, 1997; Coad et al., 2013; Gjerløv-Juel & Guenther, 2019), while another study empirically found the opposite (Delmar et al., 2013). Some recent literature on entrepreneurship and strategic management, using the liability of smallness, the liability of newness, and Penrose's growth theory, has provided a more detailed demonstration of the relationship between growth and survival (Coad et al., 2020; Pe'Er et al., 2016; Zhou & van der Zwan, 2019).

https://doi.org/10.1016/j.jbusres.2022.113319
Received 24 August 2020; Received in revised form 5 September 2022; Accepted 12 September 2022
Available online 10 October 2022

specialization. It refers to the geographic concentration of firms in various industries that can increase opportunities for cross-sector (inter-sectoral knowledge spillover) ideas and applications to interact, generate, replicate, modify, and recombine (Beaudry & Schiffauerova, 2009; Jacobs, 1969).

The difference between specialization and diversification externalities is that the former operates mainly within a specific industry, whereas the latter operates across sectors. Many studies show that these two externalities may have different effects on firms, industries, regions, and even macroeconomics (Beaudry & Schiffauerova, 2009; de Groot, Poot, & Smit, 2016; Hu, Xu, & Yashiro, 2015; Zhu, Dai, & Jiang, 2017). Thus, the impact of different agglomeration externalities on the performance outcomes of firm strategies may be different. Inspired by the existing research, this study analyzes how different agglomeration externalities affect the survival outcomes of start-ups' growth. The analysis clarifies the roles of agglomeration externalities in the performance outcomes of firm strategies and provides guidance for firm strategies (Boschma, 2017; Lu et al., 2021).

Moreover, we distinguish between diversification externalities and discuss the roles of different diversification externalities. In recent years, the literature on evolutionary economic geography has pointed out that diversity does not necessarily produce cross-sector knowledge spillovers, mainly resulting from the exchange and collision of firms in industries with complementarity and technological relevance (Frenken, Oort, & Verburg, 2007; Guo, Zhu, & He, 2018; Neffke, Henning, & Boschma, 2011; Zhu, He, & Luo, 2019). Frenken et al. (2007) distinguishes diversity into related variety and unrelated variety, and defines unrelated variety as between-industry diversity and related variety as within-industry diversity.[2] They suggest that knowledge spillovers across sectors are best described by the concept of "related variety," which emphasizes that knowledge and technology reorganizations within "different but related" industries within a regional/local system are conducive to knowledge spillovers. They claim that only related variety will enhance knowledge spillovers, whereas unrelated variety will produce a portfolio-like effect, improving the ability of regional economies to resist external risks and protecting firms from special demand shocks. The distinction in diversity helps identify the main sources of diversification externalities (Boschma, 2017). Such a distinction also goes beyond the traditional dichotomy of specialization and diversification and provides new impetus to the debate on the relative importance of specialization and diversification to firm performance and regional development (Boschma & Iammarino, 2009; Lo Turco & Maggioni, 2016). Therefore, we continue to promote research on the role of diversification at the firm level and explore the impacts of different diversification externalities on the survival outcomes of firm growth.

After theoretically analyzing how different agglomeration externalities affect the relationship between growth and start-ups' survival risk, we conduct an empirical test based on the Chinese context. In terms of growth, agglomeration externalities, and start-up survival, exploration based on the Chinese background has two advantages. First, as the world's largest emerging market, China's rapid economic growth presents numerous market opportunities that encourage firms to pursue growth-oriented strategies. In particular, China is still in the process of industrialization, and the impressive expansion of manufacturing provides more market opportunities for manufacturing start-ups to pursue growth or attract key resources (Chen, Zou, & Wang, 2009). However, because of the lack of well-trained labor and high-quality management talent in emerging economies (Khanna & Palepu, 2000), high-growth firms may not be able to obtain sufficient support in terms of human resources, thus increasing the risks associated with growth. Moreover, the complex market environment and frequent institutional changes in emerging markets have increased firm growth uncertainty (He & Yang, 2016). To the best of our knowledge, no study has examined the relationship between firm growth and early survival in an emerging economy.[3] Our research fills this gap, deepening our understanding of start-ups' growth strategies and survival rules in emerging markets. Second, China has a nearly complete manufacturing industry system, and its manufacturing industry is experiencing obvious spatial agglomeration (Huang, Fang, & Gu, 2021; Lu & Tao, 2009), providing fertile ground for research on agglomeration externalities.

This study contributes to the literature in two ways: First, by integrating different agglomeration externalities into the research framework of growth and survival, we theoretically analyze the impact of different agglomeration externalities on the survival outcomes of growth. Based on the Chinese context, we confirm that the impacts of different agglomeration externalities on the relationship between start-up growth and survival risk are different. Specifically, specialization externalities have a significant negative moderating effect on the relationship between start-ups' growth and survival risk, whereas diversification and related variety externalities have a significant positive moderating effect, and unrelated variety externalities have no significant moderating effect on this relationship. Moreover, the moderating effect of specialization externalities on the relationship between growth and survival risk is heterogeneous in terms of firm resources. These findings not only confirm that the relationship between growth and survival is closely related to the industrial environment in which firms live but also suggest that research on strategic performance needs to carefully consider the differences in local industrial structure.

Second, it enriches our understanding of start-ups' growth strategies in emerging economies. We supplement the literature on the performance outcomes of growth strategies in emerging markets from a survival perspective and reveal a U-shaped relationship between growth and survival risks of start-ups. Our research not only confirms the universality and applicability of the "too-much-of-a-good-thing" effect in the context of emerging markets (Pierce & Aguinis, 2013) but also discovers the particularity of the "too-much-of-a-good-thing" effect—that is, a fast-growing emerging market is more able to tolerate and reward the growth of start-ups. Drawing on the distribution of observations, we find that the growth of start-ups is beneficial to their survival in most cases in China. Although the growth of start-ups in emerging markets faces high costs, growth can create higher returns, which, in most cases, makes the growth of start-ups in emerging markets conducive to their survival. Our research also indicates that under different socioeconomic contexts, there may be differences in the performance outcomes of the same strategies.

2. Literature review and hypothesis development

2.1. Growth and survival of start-ups

The view that large firms have a greater chance of survival seems widely accepted. Drawing on the passive learning theory (Jovanovic, 1982), firms do not know their potential production efficiency before entering the market, and only after entering the market can they know their potential production efficiency through the so-called "learning effect." This means that start-ups may enter the market at a suboptimal

[2] Grillitsch et al. (2018) further clarifies the concepts: "related variety captures the potential for diversification resulting from similarities in the knowledge base between industries that are not interwoven with such traded and untraded interdependencies…unrelated variety refers to the combination of non-similar knowledge.".

[3] Although studies on the relationship between growth and survival are becoming abundant, these have only focused on developed economies, including the United States (Agarwal, 1997), the United Kingdom (Coad et al., 2013; Coad et al., 2020), the Netherlands (Zhou & van der Zwan, 2019), Sweden (Delmar et al., 2013), Canada (Pe`Er et al., 2016), and Denmark (Gjerløv-Juel & Guenther, 2019). Overall, there is still a lack of empirical evidence from emerging economies.

scale instead of at an optimal scale (Audretsch & Mahmood, 1994). After a period of operation, relatively high-efficiency start-ups earn profits and achieve sustainable survival, whereas relatively low-efficiency start-ups can only maintain a small scale and lower market competitiveness and are eventually eliminated by the market. Therefore, passive learning theory implies that expansion may improve start-ups' survival prospects, which has already been confirmed in earlier studies (Audretsch, 1995).

However, with the advancement of research in this field, some scholars have found that given the same current size, start-ups with a larger initial size are more likely to exit the market. This is because start-ups with a smaller initial size have greater room for growth under a given minimum efficient scale. Thus, they need to grow faster to reach the minimum efficient scale, and rapid growth helps improve their survival possibility (Agarwal, 1997; Coad, Frankish, Roberts, & Storey, 2013; Mata, Portugal, & Guimarães, 1995). Over the past two decades, an increasing number of studies have shifted their attention from the impact of firm size on survival to the impact of growth on survival. Most of these studies have confirmed the assumption that growth can improve survival prospects (Agarwal, 1997; Coad et al., 2013; Gjerløv-Juel & Guenther, 2019), which is consistent with the conclusion of an early investigation in the United States (Phillips & Kirchhoff, 1989). However, more recently, conclusions on this issue have become more varied, with some studies reporting a negative (Delmar, Mckelvie, & Wennberg, 2013) or nonlinear relationship (Coad, Frankish, & Storey, 2020; Pe'Er et al., 2016; Zhou & van der Zwan, 2019)between growth and survival.

As mentioned, the results of empirical studies on the relationship between the growth and survival of start-ups are mixed. Growth may have both promoting and inhibitory effects on survival. Growth can help start-ups overcome the "liability of smallness" (Baum & Amburgey, 2002; Bruderl & Schussler, 1990; Pe'Er et al., 2016), and it can provide at least two benefits.[4]First, a fast growth rate can help firms accumulate resources, improve resource utilization, and reach the minimum efficient scale as soon as possible (Penrose, 1959). This makes it easier for them to obtain economies of scale and reduce production costs, eventually enabling them to increase their survival probabilities (Mata, 1993; Mata et al., 1995). Second, growth enhances legitimacy.[5] External stakeholders interpret firm legitimacy as a positive signal, particularly a measure of owners' and managers' confidence in their ability to compete and survive (Pe'Er et al., 2016). For example, start-ups can send positive signals to financial institutions through growth, thereby alleviating financing constraints (Coad, Frankish, Roberts, & Storey, 2016). Additionally, growth signals can help start-ups attract and retain qualified employees, thereby reducing their survival risk (Dahl & Klepper, 2015).

Although growth can provide advantages (Mata & Portugal, 2002), once the growth rate exceeds the optimal growth rate, entrepreneurs may lose control of growth, thereby increasing the possibility of business failure. An important reason is derived from the theory of Penrose (1959): The growth process of a firm entails the transformation of new resources into production opportunities, and this process often involves changes in adjustment costs. As a start-up grows, its internal organization becomes increasingly complicated, and new standards and routines must be established, which places strict requirements on managers. Insufficient managerial talent may lead to lower production and operating efficiency compared to competitors. For example, in terms of cash management, a successful operation requires sufficient cash, but excessive expansion may lead to imbalances in cash balances. Therefore, the rapid growth of start-ups requires managers to have the ability to manage fast-growing resources and balance cash flows (Churchill & Mullins, 2001). In terms of human management, start-ups that grow too fast are more likely to hire inappropriate employees because of hasty recruitment, leading to difficulties in their subsequent operations (Coad, Daunfeldt, Johanssony, & Wennberg, 2014). Further, the information asymmetry between start-ups and the market is likely to prevent start-ups from making appropriate growth decisions. This may lead fast-growing start-ups to invest more resources in their early stages and face higher costs in later strategic redeployment (Coad et al., 2020; Pe'Er et al., 2016), ultimately increasing survival risks.

Given that growth has both positive and negative effects on the survival of start-ups, its "net effect" is ultimately reflected as the sum of these two opposing effects (Coad et al., 2020; Haans, Pieters, & He, 2016). For positive effects, growth can provide benefits that reduce the survival risk of firms. However, these benefits disappear beyond a certain growth rate because of the limited benefits of economies of scale and positive signals. For the negative effect, beyond a certain growth rate, adjustment costs due to management inefficiencies and low-quality growth are incurred and increase with the growth rate, eventually leading to a high survival risk. A U-shaped relationship between growth and survival risk is established by adding these two effects, which suggests that the ultimate impact of growth on survival risk depends on the sum of the benefits and costs of growth. This U-shaped relationship validates the "too-much-of-a-good-thing" effect (Pierce & Aguinis, 2013).

Presently, the exploration of the relationship between growth and survival risk is mainly aimed at mature markets such as the United Kingdom, the Netherlands, and Sweden, and there is a lack of evidence from emerging markets. As the world's largest emerging economy, China has made tremendous achievements in rapid economic development over the past few decades. Such economic development practices provide excellent materials and rich nourishment for developing economic and management theories. This study focuses on start-ups in the Chinese manufacturing industry, which have many opportunities from the demand side. A larger market usually provides a more open environment in which more firms can coexist (Dollinger & Golden, 1992). Moreover, fast growth in emerging markets also plays an important role in attracting critical external resources, which in turn helps start-ups achieve a competitive advantage (Chen et al., 2009). However, pursuing growth in emerging markets is not without cost. A common feature of emerging markets is the lack of an effective labor market, which makes it impossible for start-ups to hire well-trained labor and high-quality management talent in the short term (Khanna & Palepu, 2000). Therefore, fast-growing start-ups in emerging markets may not be able to obtain sufficient human resource support, thereby increasing the risk of growth. In addition, the more complex market environment and frequent institutional changes in emerging economies have increased the uncertainty of the performance impacts of firm growth and brought challenges to firm survival (He & Yang, 2016). Therefore, the impact of growth strategies on the survival of start-ups in emerging economies requires further exploration.

Based on the above analysis, this study proposes the following hypothesis:

Hypothesis 1. ***A U-shaped relationship exists between Chinese start-ups' growth and survival risk.***

2.2. Roles of agglomeration externalities

2.2.1. Specialization and diversification externalities

Academics have been paying attention to the geographical concentration of industries for many years. Marshall (1920) asserted that the geographic concentration of a certain industry can provide external

[4] The propensity of small organizations to fail has also been argued in terms of liabilities of smallness, including "problems of raising capital, meeting a myriad of government requirements, and competing for labor with larger organizations." (Aldrich & Auster, 1986).

[5] Zimmerman and Zeitz (2002) argue that "legitimacy is a resource for new ventures—a resource at least as important as other resources, such as capital, technology, personnel, customer goodwill, and networks. Legitimacy, a social judgment of acceptance, appropriateness, and desirability, enables organizations to access other resources needed to survive and grow.".

benefits such as specialized intermediate inputs, specialized labor pools, and knowledge spillovers within the industry. External economies arising from the agglomeration of a single industry are typically called specialization externalities or Marshall externalities (Glaeser, Kallal, Scheinkman, & Shleifer, 1992). A recent study indicates that "specialization is theoretically not delineated by a single sector but by the interdependencies arising from complementary economic activities" (Grillitsch, Asheim, & Trippl, 2018). This interdependence includes functional interdependence in production (i.e., input/output linkages) and knowledge interdependence in learning or innovation. Functional interdependence means specialization provides more specialized customers and suppliers in value chain transactions and labor or other factors in market transactions. The interdependence of knowledge can lead to specialized knowledge spillovers that can promote improvements in production processes (Frenken et al., 2007). However, this implies less renewal and diversification, which can lead to technology lock-in (Crespo, Suire, & Vicente, 2014; Wang, Yang, & Qian, 2020). Consequently, specialization provides a stable environment and industry-specific information, which helps start-ups quickly replicate the networks and industry connections of firms within the industry, thus quickly establishing business contacts with specialized suppliers and customers (Shu & Simmons, 2018).

With the advancement of urbanization, the agglomeration of various industries in the same region has become increasingly common. Jacobs (1969) emphasizes that the variety of industries within a geographic region promotes knowledge externalities and, ultimately, innovative activity and economic growth. She claimed that a diverse local industrial structure fosters opportunities to imitate, share, and recombine ideas and practices across industries. The externalities generated by a diversified industrial structure are also called diversification externalities or "Jacobs externalities" (Glaeser et al., 1992). Most relevant research finds positive impacts of diversification externalities and points out that diversification externalities can lead to new product (or service) innovation and entrepreneurship (Beaudry & Schiffauerova, 2009; Tavassoli, Obschonka, & Audretsch, 2021). However, diversification is not always beneficial. With the intensification of urbanization, physical space has rapidly become scarce. This scarcity can lead to "congestion costs" (Nielsen, Asmussen, Weatherall, & Lyngemark, 2021; Saito & Wu, 2016), such as traffic congestion, environmental pollution, and high labor costs (Kosfeld & Mitze, 2020; Tomasz & Pawel, 2021).

The phenomenon of agglomeration externalities and their impact on economic growth, innovation, and firm performance has attracted widespread attention in academic circles. Despite substantial research on the relationship between agglomeration externalities and survival, empirical evidence remains mixed (Ebert, Brenner, & Brixy, 2019; He, Guo, & Rigby, 2017; Howell, He, Yang, & Fan, 2018; Power, Doran, & Ryan, 2019; Yi & Nam, 2019). For this reason, we do not make any prior hypotheses regarding this relationship. We mainly do not focus on the effects of agglomeration externalities on survival but their effects on the survival outcomes of growth strategies. Few survival analysis studies have incorporated the effects of agglomeration externalities on the survival outcomes of growth strategies. Thus, this area requires further investigation, as new evidence suggests that firm failure results from strategic decisions under different external factors (Karabag, 2019; Zhang et al., 2019). Moreover, firm strategic decisions have different impacts on firm survival or other firm performance under different levels of specialization (Pe'Er et al., 2016; Shu & Simmons, 2018; Woo et al., 2019). Therefore, will firm growth have different impacts on survival at different levels of diversification? Will the impacts of growth on survival vary due to different agglomeration externalities? We will discuss these issues in the next section.

2.2.2. Moderating effect of specialization externalities

The U-shaped relationship between growth and survival risk is due to the gradual reduction in marginal benefits and the gradual increase in marginal costs from growth. We argue that specialization externalities weaken this U-shaped relationship because they substitute for the benefits of growth and reduce growth costs.

We explain why specialization externalities can substitute growth gains from two perspectives. First, in a region with a high level of industrial specialization, specialized suppliers can better meet the demand of start-ups for intermediate inputs than non-specialized suppliers. Hence, start-ups can outsource production or services in place of the pursuit of internal-scale economies provided by growth (Pe'Er et al., 2016). This can also be understood as external-scale economies emanating from shared inputs between large concentrations of firms from the same industry, forming an alternative to internal economies of scale. Second, a high level of industrial specialization can provide legitimacy spillovers; thus, start-ups do not need to rely on the legitimacy benefits from growth for survival (Pe'Er et al., 2016). In locations with a high level of industrial specialization, start-ups can obtain high-quality supplies of specialized factors (e.g., labor) and establish close contacts with customers and specialized suppliers, thereby enhancing legitimacy (Zimmerman & Zeitz, 2002) and replacing the legitimacy benefits from growth.

There are two main reasons for the reduction in the cost of growth due to specialization. On the one hand, a high level of industrial specialization can provide a professional and high-quality start-up workforce, thereby reducing the administrative burden of excessive growth and the likelihood of hiring inappropriate employees (Churchill & Mullins, 2001; Coad et al., 2014; Penrose, 1959). On the other hand, a high level of industrial specialization is conducive to start-ups staying close to customers and specialized suppliers. As a result, start-ups can accurately predict market demand and reduce uncertainty in decision-making (Yli Renko, Autio, & Sapienza, 2001), thereby reducing the costs associated with redeployment due to excessive growth.

In summary, specialization externalities alleviate start-ups' need to rely on the benefits of internal growth for survival and reduce the cost of high growth rates. Therefore, we expect specialization to weaken the U-shaped relationship between growth and survival risk, thus making the U-shaped curve smoother. Thus, this study proposes the following hypotheses:

Hypothesis 2. ***Specialization externalities weaken Chinese start-ups' U-shaped relationship between growth and survival risks.***

2.2.3. Moderating effect of diversification externalities

Specialization and diversification represent two different characteristics of the local production structure: the former refers to the concentration of industrial activities in a region in a small number of industries, while the latter refers to the variety of industrial activities in a region (Beaudry & Schiffauerova, 2009). To some extent, the effects of specialization and diversification externalities on the business environment may be the opposite. Specifically, specialization provides specialized suppliers, labor, information, and customers, which enhances the stability of the business environment, whereas diversification provides many innovation and entrepreneurial opportunities as well as congestion costs, resulting in a relatively unstable business environment. We argue that diversification externalities have the opposite moderating effect on specialization externalities because diversification externalities push start-ups to rely more on the benefits provided by growth and increase growth costs.

First, we explain why diversification externalities push start-ups to rely on their internal growth benefits. First, high-level industry-diversified regions have many innovation and entrepreneurial opportunities, which means vast opportunities coexist with fierce competition (Tsvetkova, Thill, & Conroy, 2016). Due to this fierce competition, start-ups must rely on their internal growth to maintain their competitiveness, and start-ups that do not achieve sufficient growth rates have a higher risk of encountering failure. Second, diversification challenges fast-growing start-ups in collaboration with nonspecialized suppliers. In industry-diversified regions, start-ups can easily discover business opportunities such as new products or technologies, but they need to overcome some barriers in integrating non-specialized suppliers. For example, proprietary information may be intentionally or unintentionally revealed to competitors (Adner, 2006; Ragatz, Handfield, & Scannell, 1997). In this case, start-ups cannot easily replace their internal scale through supplier transactions. As a result, the diversified industrial structure motivates start-ups to pursue internal economies of scale to compensate for their disadvantages. Third, unlike start-ups in industry-specialized regions that rely on legitimacy spillovers from a large number of other firms in the same industry (Pe'Er et al., 2016), start-ups in industry-diversified regions cannot rely on these spillovers because these firms are dispersed across many different industries instead of being concentrated in only a few industries. Given the frequent business turnover and unstable external environment in industry-diversified regions, start-ups need to obtain legitimacy benefits from growth to demonstrate their competitive advantages to their stakeholders.

Next, we discuss the reasons for the increase in growth costs caused by diversification externalities. First, diversification makes it more difficult for fast-growing start-ups to collaborate with their suppliers. The development of new products and markets by start-ups requires matching new management talent and intermediate inputs (Adner, 2006; Audretsch, 1995; Ragatz et al., 1997). Although diversification brings a wide range of supplies to the local market, supplies are not industry-specific; that is, they are applicable to a wide variety of industrial contexts (Nielsen et al., 2021). Therefore, matching problems between fast-growing start-ups and non-industry-specific suppliers may lead to a decrease in management efficiency and an increase in growth costs. Second, diversification causes fast-growing start-ups to incur high operating costs. As mentioned earlier, the diversity of industries is often closely related to a city's size. Large-scale cities are not only densely populated but also home to diversified industries (Tavassoli et al., 2021). In such cities, start-ups need to pay higher direct costs for office space and higher wages to compensate employees for commuting or living costs (Nielsen et al., 2021). The high operating costs make it difficult for fast-growing start-ups to adjust for later redeployments.

Based on the above analysis, we propose the following hypothesis.

Hypothesis 3. ***Diversification externalities strengthen the U-shaped relationship between growth and survival risk of Chinese start-ups.***

2.2.4. Moderating effects of related and unrelated variety externalities

In recent years, with the development of evolutionary economic geography, academia has gained a deeper understanding of the diversification externalities. Many scholars believe that the spillover effect can be significant when complementarity and relevance exist among industries (Boschma & Iammarino, 2009; Boschma, Minondo, & Navarro, 2012, 2013; Frenken et al., 2007; Neffke et al., 2011). This view foreshadows the debate on the trade-off between diversity and similarity: although firms with non-overlapping capabilities and knowledge can provide new concepts that others can learn, only those with overlapping capabilities can communicate effectively (Content & Frenken, 2016; Neffke et al., 2011). According to this theory, Frenken et al. (2007) distinguishes between variety as a source of regional knowledge spillovers and variety as a portfolio protecting a region from external shocks, and claims that Jacobs externalities are best represented by related variety (within sectors), while the portfolio argument is better captured by unrelated variety (between sectors).[6]

Several studies have confirmed that related variety is relevant to regional innovation (Ascani, Bettarelli, Resmini, & Balland, 2020; Ejdemo & Ortqvist, 2020), employment or output growth (Boschma & Iammarino, 2009; Boschma et al., 2012; Content & Frenken, 2016), and entrepreneurship (Content, Frenken, & Jordaan, 2019). This also means that related variety is the main driver of urban prosperity, accompanied by high business costs. For example, studies have suggested that related variety can lead to high labor costs (Tomasz & Pawel, 2021) or increase the cost of valuable and rare resources (Lu et al., 2021). The role of unrelated variety is controversial in the literature (Karlsson, Rickardsson, & Wincent, 2021).[7] Some studies suggest that the reorganization of unrelated knowledge may lead to breakthrough innovation (Barbieri, Perruchas, & Consoli, 2020; Castaldi, Frenken, & Los, 2015).[8] However, other studies suggest that investment risk without related technologies is large; hence, the breakthrough innovation brought about by unrelated variety cannot occur spontaneously (Fagerberg & Srholec, 2022; Janssen & Frenken, 2019). Even if this breakthrough innovation is achieved, it may only give the innovation owner a global competitive advantage (Boschma, Coenen, Frenken, & Truffer, 2017) and may have little impact on regional innovation and economic development (Ascani et al., 2020; Content & Frenken, 2016). In addition, a greater unrelated variety means weaker technical linkages between firms, which may inhibit the restructuring and diffusion of ideas and inputs (Aarstad, Kvitastein, & Jakobsen, 2016).

In conclusion, based on existing theoretical and empirical studies on related and unrelated variety externalities, we believe that related variety externalities are highly representative of Jacobs externalities. Therefore, similar to the moderating effect of diversification externalities, we expect that related variety externalities result in a steeper U-shaped relationship between growth and survival risk because these externalities increase start-ups' reliance on the benefits of growth and increase the costs of such growth. Specifically, similar to diversification externalities (see Section 2.2.3), related variety externalities can promote knowledge spillovers, which can foster substantial innovation and entrepreneurial opportunities, ultimately triggering fierce competition (Tsvetkova et al., 2016). In regions with a high level of related variety, fierce competition motivates start-ups to rely on their internal growth to scale up, gain competitive advantage, and increase their probability of survival. In such regions, start-ups rely on gaining legitimacy from growth because they cannot enjoy the external benefits attributed to specialization agglomeration (Pe'Er et al., 2016). For fast-growing start-ups, an external environment with a high level of related variety introduces a challenge in matching these start-ups with non-specialized suppliers and human resources (Adner, 2006; Audretsch, 1995; Ragatz et al., 1997), thereby increasing growth costs.

Unlike related variety externalities, unrelated ones may hardly enhance opportunities or competition at the regional level because of the limited opportunities to generate knowledge spillovers in regions with a high level of unrelated variety (Fagerberg & Srholec, 2022; Janssen & Frenken, 2019). Recent studies have shown that knowledge spillovers and interactive learning are almost nonexistent in cities with a high level of unrelated variety because firms in such environments cannot easily transfer and share information and resources (Huang et al., 2021; Yang, Liu, & Qi, 2020). Therefore, regions with a high level of unrelated variety lack huge opportunities and face fierce competition due to the scarcity of knowledge spillovers. Although start-ups in these regions do not benefit from specialization agglomeration, they do not face high competition and are less pressured to grow to survive. Thus, we speculate that unrelated variety externalities have no significant moderating effect and that the moderating effect of diversification externalities primarily comes from the moderating effect of related variety

[6] In the classification of Frenken et al. (2007), two-digit industries are assumed to be unrelated, whereas four-digit industries belonging to the same two-digit industry are considered to share the same or similar knowledge base.

[7] Some studies even avoid the elaboration of unrelated variety. For example, Content et al. (2019) said that "*as for the effect of unrelated variety, the literature is more ambiguous*", "*we do not specify concrete hypotheses on the effect of unrelated variety, as it is not clear what the nature of this effect is*".

[8] An example is a new combination of technologies such as cars, sensor-based safety systems, communications, and high-resolution maps have been combined in self-driving cars (Boschma, 2017).

Table 1
Entry and survival of start-ups in each cohort.

Panel A:the number of surviving new entrants across cohorts									
entry year	firm age								
	1	2	3	4	5	6	7	8	9
1999	22,143	21,344	20,510	19,503	17,770	16,125	15,126	14,259	12,775
2000	27,763	27,157	26,222	24,333	22,244	20,965	19,750	17,699	
2001	31,752	31,017	29,236	26,836	25,350	23,928	21,390		
2002	34,667	33,335	30,798	29,251	27,631	24,680			
2003	35,974	33,701	32,121	30,336	26,972				
2004	29,242	28,191	26,773	23,856					
2005	26,103	24,955	22,087						
2006	18,855	16,816							
2007	6,316								
No. of firms	232,815	216,516	187,747	154,115	119,967	85,698	56,266	31,958	12,775
Panel B:average yearly survival rates across cohorts									
entry year	firm age								
	1	2	3	4	5	6	7	8	9
1999	98.65 %	95.09 %	91.37 %	86.89 %	79.17 %	71.84 %	67.39 %	63.53 %	56.91 %
2000	99.05 %	96.89 %	93.55 %	86.81 %	79.36 %	74.80 %	70.46 %	63.15 %	
2001	99.24 %	96.94 %	91.37 %	83.87 %	79.23 %	74.78 %	66.85 %		
2002	99.38 %	95.56 %	88.29 %	83.85 %	79.21 %	70.75 %			
2003	98.35 %	92.14 %	87.82 %	82.94 %	73.74 %				
2004	96.67 %	93.20 %	88.51 %	78.87 %					
2005	98.47 %	94.14 %	83.32 %						
2006	97.94 %	87.35 %							
2007	84.63 %								
total	96.93 %	93.91 %	89.18 %	83.87 %	78.14 %	73.81 %	68.93 %	63.53 %	56.91 %

externalities.

Considering the above arguments, we propose the following:

Hypothesis 4. ***Related variety externalities strengthen the U-shaped relationship between growth and survival risk of Chinese start-ups.***

Hypothesis 5. ***Unrelated variety externalities do not significantly moderate the relationship between growth and survival risk of Chinese start-ups.***

Although we speculate that unrelated variety externalities have no significant moderating effect on the relationship between growth and survival risk, we do not suggest that unrelated variety externalities be ignored in the empirical analysis. Although both related and unrelated variety externalities are normally associated with Jacobs externalities, the latter differs from the former; therefore, both externalities should be empirically separated (Boschma et al., 2012). In the later sections, to ensure the accuracy of our regression estimates, we need to include the moderating effect of unrelated variety in our empirical analysis, as has been done in previous studies(Content et al., 2019; Ejdemo & Ortqvist, 2020).

3. Methodology

3.1. Data sources and survival definition

The data used in this study were collected at the city and firm levels. City-level data were obtained from the *China City Statistical Yearbook* (which includes 278 cities at the prefecture level and above). Consistent with most of the literature on the survival of Chinese firms, the firm-level data used in this study come from the 1999 to 2008 *Annual Survey of Industrial Enterprises* (ASIE) compiled by the National Bureau of Statistics of China.[9] This database is one of the most comprehensive Chinese enterprise-level datasets available for academic use and has been used by many papers published in high-level journals (He & Yang, 2016). The firms recorded in the ASIE account for approximately 90 % of China's total industrial output value and approximately 70 % and 97 % of employment and exports, respectively (Ma, Qiao, & Xu, 2015). Therefore, these data reflect the operating conditions of Chinese industrial firms. We deleted firms with fewer than eight employees, a gross industrial production value less than zero, current assets greater than total assets, fixed assets greater than total assets, and non-manufacturing firms.

According to He and Yang (2016) and Howell (2017), firm exit may be interpreted as firm failure; that is, a firm cannot meet the minimum sales threshold in year t and fails to do so in year $t + 1$ or any other subsequent period. Thus, we define the survival duration as the period in which a firm appears in the ASIE before it exits. If a firm exits, then a failure event occurs. The dependent variable in this study is expressed in detail as follows. If the firm does not exist in the database in year $t + 1$, then the value of the firm's survival state variable for year t is 1. However, if the firm exists in the database in year $t + 1$, the value of the firm's survival state variable for year t is 0. Thus, the observations in 2008 are used only to measure the exit status of start-ups in 2007 in the following year, and the samples used in all regressions only include observations from 1999 to 2007.

When studying the issue of firm survival, it is also necessary to address the problems of "left censoring" and "right censoring" in the sample. "Left censoring" means that for firms that existed before the study period, we cannot obtain their survival conditions before the study period. If the left censoring is ignored, the estimation result will be biased. Thus, to avoid this problem, our sample included only new entrants during the study period. The advantages of choosing new entrants as research objects are that they will not be affected by the decisions made before the observation period (Howell, 2015) and are more motivated to seek external knowledge (Audretsch & Lehmann, 2005). Meanwhile, "right censoring" means that if the firm is still operating at the end of the study period, its survival status after the study period is not known. The right-censoring problem can be effectively solved using survival analysis methods (Hess & Persson, 2012).

In addition, given that non-state-owned enterprises (non-SOEs) must reach a sales value of RMB5 million to enter the ASIE, if the sales value of a non-SOE in a certain year is lower than the threshold, it will not be recorded by the ASIE in that year. As a result, some non-SOEs, whose sales value is around RMB 5 million, may have discontinuities in their survival status during the study period. We excluded these firms from

[9] Although the ASIE's data have been updated to 2013, our research can only use observations before 2009. This is because, in 2009, the database did not include new firms established that year, and since 2011, its statistical caliber has undergone major changes.

the sample because they could interfere with the analysis of survival issues.

Panels A and B in Table 1 report the number of survivals and survival rates of Chinese manufacturing start-ups after entering the market during the study period. The survival rate in the sample showed a downward trend every year. Overall, 96.93 % of these start-ups survived for more than one year; 78.14 % were still alive in the fifth year, but only 56.91 % were alive in the ninth year. This is comparable to prior studies on new firm survival in the Chinese manufacturing sector (Guo et al., 2018; Qu & Harris, 2019; Zhang & Xu, 2019).[10] Generally, manufacturing firms have a higher survival rate than firms in other industries. An important reason is that manufacturing firms often require significant investment in fixed assets, which form sunk costs, leading to higher barriers to entry and exit. Moreover, our sample mainly includes start-ups with annual sales revenues of RMB5 million (approximately US $600,000) and above, which have a survival advantage over micro firms (Guo et al., 2018).

Compared to some developed countries, the survival rate of start-ups in China is higher.[11] As an emerging economy, China experienced rapid economic growth during the research period, and its domestic market expanded rapidly, providing more market opportunities for new entrants. Moreover, China's accession to the WTO in 2001 created great convenience for Chinese firms to enter foreign markets. Finally, we observe a higher exit rate in 2008, which may have resulted from the global financial crisis.[12]

3.2. Model specification

In the relevant literature on survival, the Cox proportional hazard and discrete-time models are common survival analysis methods.[13] According to Hess and Persson (2012), compared to the Cox proportional hazard model, the discrete-time model can more effectively solve the problems of successive failures of firms at discrete time nodes and unobservable individual heterogeneity, and it does not need to satisfy the proportional hazard assumption. Thus, the discrete-time model is more suitable for the data structure in the current study. T_i denotes the survival duration of firm *i*. The discrete-time model estimates the probability of business termination in a given time interval $[t_k, t_{k+1}]$, *where* $k = 1,2\ldots,k_{max}$, and $t_0 = 0$. The probability of firm *i* ending in the time interval $[t_k, t_{k+1}]$ is called the discrete-time hazard rate. Its basic form is expressed as.

$$h_{ik} = P(T_i < t_{k+1} | T_i \geqslant t_k \geqslant X_{ik}) = F(X'_{ik}\beta + \gamma_k) \tag{1}$$

where h_{ik} $(0 \le h_{ik} \le 1)$ can be understood as the survival risk faced by firm *i* in period $[t_k, t_{k+1}]$ conditional on survival until time t_k; X_{ik} is a vector of time-dependent covariates; β is the parameter vector to be estimated; and γ_k is the interval benchmark risk rate. In the cloglog model, γ_k can be expressed as the integral of the continuous benchmark risk rate in $[t_k, t_{k+1}]$ in log. Generally, γ_k can be set as a dummy variable. To simplify the model, it can also be set as a specific functional form that depends on lifetime (Hess & Persson, 2012). The conditional survival risk faced by firm *i* in period *t* can be expressed as Equation (2):

$$\begin{aligned}\log(-\log(1-h_{i,t})) = \beta_0 + \beta_G GR_{i,t-1} + \beta_{G^2} GR^2_{i,t-1} + \beta_A \vec{A}_{i,t-1} + \beta_C \vec{C}_{i,t-1} \\ + INDU + PROV + \varepsilon_{it-1}\end{aligned} \tag{2}$$

In Equation (2), the explanatory variables include both the linear term (*GR*) and quadratic term (GR^2) of the growth rate to test the possible U-shaped relationship between growth and survival risk. In addition, $\vec{A}$ is a vector of aggregation variables, $\vec{C}$ is a vector of the control variables, *INDU* and *PROV* represent the industrial (at the two-digit level) and provincial dummy variables, respectively, and ε is the random error term. Given that a firm's survival time is equivalent to its age, the introduction of an appropriate functional form of firm age can also control the interval benchmark risk rate (γ_k) in Equation (1). This study introduces linear and quadratic terms of firm age to control γ_k.

One of the main purposes of this study is to test the moderating effects of agglomeration externalities on the relationship between growth and survival risk; therefore, we add the interaction terms of growth variables (*GR* and GR^2) and agglomeration variables based on Equation (2). Thus, we obtain Equation (3), which can be used to estimate the moderating effects:

$$\begin{aligned}\left(\log(-\log(1-h_{i,t})) = \beta_0 + \beta_G GR_{i,t-1} + \beta_{G^2} GR^2_{i,t-1} + \beta_A \vec{A}_{i,t-1} + \beta_{G,A} GR_{i,t-1} \times \vec{A}_{i,t-1}\right) \\ + \beta_{G^2,A} GR^2_{i,t-1} \times \vec{A}_{i,t-1} + \beta_C \vec{C}_{i,t-1} + INDU + PROV + \varepsilon_{it-1}\end{aligned} \tag{3}$$

In a nonlinear survival analysis model, even if unobservable heterogeneity is not correlated with the explanatory variable, it will still lead to inconsistent estimates (Heckman & Singer, 1984). To control for unobservable heterogeneity as much as possible, this study uses random effects to estimate the above equations. In panel cloglog models, fixed effects are usually not considered. As Statacorp (2013) pointed out, because a sufficient statistic allowing the fixed effects to be conditioned out of likelihood does not exist, conditional fixed-effects cloglog models cannot be estimated. If $\beta_{G^2,A}$ is significant, it indicates that agglomeration variables may play moderating roles in the U-shaped relationship between growth and survival risk.

3.3. Growth and agglomeration variables

The main explanatory variables in this study are firm growth and the different agglomeration. The most common measures of firm growth are the employment growth rate and output (sales) growth rate. Although employment growth can reflect firm growth strategies to a certain extent (Gilbert, Mcdougall, & Audretsch, 2016), some newly established firms (generally small- and medium-sized firms) have fewer employees in the early stages, and the trend of employee changes is not obvious. Therefore, using the employment growth rate may make it difficult to measure the growth of these firms. In this case, the output growth rate can be a

[10] A study in Portugal showed that nearly 76% of new manufacturing firms established during 2006–2010 have survived more than 5 years (Patel et al., 2019). This is similar to the 5-year survival rate of new entrants in China's manufacturing industry in our sample.

[11] A research report based on the OECD DynEmp v.2 database containing data on start-ups in 16 countries (13 of which are developed countries) showed that the survival rate of start-ups is on average equal to about 50% after 5 years from entry and to just over 40% after 7 years (Calvino, Criscuolo, & Menon, 2015).

[12] Taking start-ups that entered the market in 2007, the survivors of these start-ups accounted for only 84.63% in the next year after entering, which is much lower than the overall 1-year survival rate (96.93%) during the study period.

[13] The discrete-time models mainly include the logit, probit, and cloglog models, to name a few.

useful supplement to the employment growth rate. Owing to data limitations, most existing literature selects one measurement indicator. This study first uses the employment growth rate for baseline regressions and then uses the output growth rate for robustness analysis. In addition, E_{it} represents the average number of employees of firm i in year t, and the employment growth rate ($GR_{i,t}$) of firm i in year t can be calculated using equation (4):

$$GR_{i,t} = \frac{E_{i,t} - E_{i,t-1}}{E_{i,t-1}} \tag{4}$$

We can now measure agglomeration variables. Following Howell et al. (2018), we use the localization quotient to measure specialization. For four-digit industry l located in city j, its standard localization quotient $LQ_{j,l}$ can be expressed as.

$$LQ_{j,l} = \frac{E_{j,l}/\sum_j E_{j,l}}{\sum_l E_{j,l}/\sum_l \sum_j E_{j,l}} \tag{5}$$

where $E_{j,l}$ is the total number of employees in four-digit industry l in city j. The higher the value of LQ, the higher the level of specialization agglomeration.

Many studies measured industry diversity based on information entropy and decomposed it into related variety and unrelated variety (Boschma, 2015; Frenken et al., 2007). Given that entropy "captures variety by measuring the uncertainty of probability distributions" (Castaldi et al., 2015), we also use standard information entropy to measure related variety and unrelated variety, as well as overall variety (i.e., diversification). In line with Content et al. (2019), we assume that firms belonging to different four-digit industries are related to each of their two-digit industries, whereas those belonging to different two-digit industries are unrelated. The respective equations for unrelated variety (UV), related variety (RV), and overall variety (TV)are as follows:

$$UV_j = -\sum_{L=1} P_{j,L} \log_2(P_{j,L}) \tag{6}$$

$$RV_j = \sum_{L=1} P_{j,L}\left(\sum_{l \in L} \frac{p_{j,l}}{P_{j,L}} \log_2\left(\frac{P_{j,L}}{p_{j,l}}\right)\right) \tag{7}$$

$$TV_j = RV_j + UV_j = -\sum_{l=1} p_{j,l} \log_2(p_{j,l}) \tag{8}$$

In the above equations, $p_{j,l}$ represents the ratio of the number of employees in the four-digit industry l of city j to the number of employees in all manufacturing industries in the city (i.e., $p_{j,l} = E_{j,l}/\sum_l E_{j,l}$); $P_{j,l}$ represents the ratio of the employment of the two-digit industry L in city j to the employment of all manufacturing industries in the city (i.e., $P_{j,L} = (\sum_{l \in L} E_{j,l})/(\sum_l E_{j,l})$); and UV_j refers to the unrelated variety level of city j, which is the entropy between the two-digit sectors. In addition, RV_j refers to the related variety level of city j and is measured by the sum of entropy within each two-digit sector, weighted by employment shares $P_{j,L}$. The overall variety or diversification in city j (TV_j) can be measured by summing RV_j and UV_j.

3.4. Control variables

In addition to the above explanatory variables, this study considers control variables at the firm, industry, and regional levels.

(1) Firm age and its quadratic term (AGE and AGE^2): Firm age is expressed by the year of observation minus the year of establishment. Bruderl and Schussler (1990) revealed an inverted U-shaped relationship between age and survival risk, calling it the "liability of adolescence.".

(2) Firm size ($SIZE$): Firm size is expressed as a logarithm of the number of employees. Generally, large firms have strong risk resistance because of their rich experience and resources, ability to obtain economies of scale, and financing advantages (Bruderl & Schussler, 1990). In addition, with the expansion of firm size, the willingness of firms to exit decreases as their decision-making structure becomes more complicated, and entrepreneurs need to fulfill their commitments to more stakeholders (Wennberg, Delmar, & Mckelvie, 2016).

(3) State ownership ($STATE$): State ownership is expressed as the share of state-owned capital in paid-in capital. In transition economies, state-owned firms may face lower operating efficiency because of the non-market orientation of business objectives, soft budget constraints, and other reasons (Audretsch, Guo, Hepfer, Menendez, & Xiao, 2016).

(4) Foreign ownership ($FOREIGN$): Foreign ownership is expressed as the share of foreign capital in paid-in capital: many studies have confirmed that foreign participation is beneficial to firm survival (Baldwin & Yan, 2011; Esteve-Pérez & Mañez-Castillejo, 2008; Qu & Harris, 2019). This is because foreign-invested firms can generally obtain funding, technology, market channels, and management experience through parent firms and, thus, have higher production efficiency, market competitiveness, and less possibility of failure (Manova, Wei, & Zhang, 2015).

(5) Export behavior ($EXPORT$): If the firm exhibits export behavior during the study period, $EXPORT$ is equal to 1, and otherwise 0. Exporting can help firms diversify the risk of demand fluctuations in a single market, provide conditions for the development and diffusion of advanced technology, and extend their survival time (Guo et al., 2018).

(6) Innovative behavior ($INNO$): If a firm's new product output during the observation period is greater than 0, $INNO$ equals 1; otherwise, it is 0.[14] Although innovation can also bring uncertainty to a firm's operations, it can generally enhance its advantage in market competition and increase its survival probability (Howell, 2015).

(7) Government subsidies ($SUBSIDY$): If a firm receives government subsidies during the study period, it is assigned a value of 1, and otherwise 0. Government subsidies increase the funds available to firms and reduce the possibility of firms being financially restricted, thereby increasing their possibility of survival (Zhang & Xu, 2019).

(8) Labor productivity ($PROD$): This is measured by gross industrial output value per employee. Existing research suggests that market competition accelerates the exit of low-efficiency firms and promotes resource reallocation from low-efficiency to high-efficiency firms (Jovanovic, 1982). Therefore, firms with higher productivity can respond better to market competition and increase their survival probability (He & Yang, 2016).

(9) Debt-to-asset ratio ($DEBT$): This is measured as the ratio of total liabilities to total assets. The higher *the DEBT*, the less collateral a firm can use for further financing. Simultaneously, a higher $DEBT$ can also cause firms to face unreasonable financing costs in the financial market (Harrison & Mcmillan, 2003; Love, 2003) and intensify their financing constraints, thereby increasing the risk of firms exiting the market (Bougheas, Mizen, & Yalcin, 2006).

(10) Per capita wages at the city level ($CITY\_WAGE$): Generally, regions with high per capita wages have high human resource costs (Moretti, 2004) and high human capital (Dumais, Ellison, & Glaeser, 2002). High human capital in a region helps improve a firm's survival possibilities (Acs, Armington, & Zhang, 2007).

(11) Localized competition ($LCOMP$): The survival risk of firms increases with the intensification of localized competition (Low & Brown, 2017). In cities with higher levels of localized competition, competition among firms for resources and the market is more intense, thereby reducing the survival probability of new ventures (Pe'Er et al., 2016). We employed a widely used indicator created by Glaeser et al. (1992) to measure the degree of localized competition at the four-digit industry level. Specifically, localized competition in the four-digit industry l of city j is defined as the ratio of the number of firms per worker in industry

[14] "New product output" is one of the main statistical indicators of Chinese industrial firms. It refers to the output value of new products within the validity period recognized by relevant government departments.

Table 2
Baseline regression results.

Variables	1	2	3	4	5	6
GR		–0.4020***	–0.6593***	–1.0172***	–0.8593***	–0.6595***
		(0.0162)	(0.0178)	(0.0169)	(0.0174)	(0.0178)
GR^2			0.4400***	0.5855***	0.5329***	0.4403***
			(0.0160)	(0.0156)	(0.0157)	(0.0160)
LQ	0.0055**	0.0051**	0.0047*	–0.0122***	–0.0079**	0.0040
	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0033)	(0.0026)
RV	–0.0420**	–0.0376*	–0.0336*	–0.0270	–0.0167	
	(0.0203)	(0.0201)	(0.0200)	(0.0196)	(0.0197)	
UV	0.0737***	0.0747***	0.0723***	0.0646***	0.0628***	
	(0.0198)	(0.0196)	(0.0195)	(0.0192)	(0.0192)	
TV						0.0204**
						(0.0097)
AGE	0.0848***	0.0760***	0.0873***	0.0711***	0.0904***	0.0866***
	(0.0161)	(0.0160)	(0.0160)	(0.0158)	(0.0159)	(0.0160)
AGE^2	–0.0040***	–0.0039**	–0.0048***	–0.0043***	–0.0057***	–0.0047***
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
SIZE	–0.6835***	–0.6356***	–0.6140***			–0.6136***
	(0.0081)	(0.0081)	(0.0080)			(0.0080)
SIZE_D					–0.7862***	
					(0.0159)	
SIZE_D × *LQ*					0.0122***	
					(0.0045)	
STATE	0.5026***	0.4659***	0.4609***		0.4213***	0.4587***
	(0.0396)	(0.0390)	(0.0387)		(0.0377)	(0.0387)
FOREIGN	0.0324*	0.0276	0.0250		–0.0628***	0.0211
	(0.0194)	(0.0192)	(0.0192)		(0.0191)	(0.0191)
EXPORT	–0.1840***	–0.1994***	–0.2056***		–0.2924***	–0.2070***
	(0.0211)	(0.0209)	(0.0209)		(0.0207)	(0.0208)
INNO	–0.1573***	–0.1517***	–0.1517***		–0.2117***	–0.1525***
	(0.0239)	(0.0238)	(0.0238)		(0.0235)	(0.0237)
SUBSIDY	–0.1645***	–0.1668***	–0.1649***		–0.2578***	–0.1643***
	(0.0196)	(0.0195)	(0.0194)		(0.0193)	(0.0194)
PROD	–0.4400***	–0.4302***	–0.4266***		–0.3227***	–0.4259***
	(0.0071)	(0.0070)	(0.0070)		(0.0063)	(0.0069)
DEBT	0.1083***	0.0913***	0.0823***		0.0622***	0.0797***
	(0.0168)	(0.0167)	(0.0167)		(0.0172)	(0.0168)
DENSITY	–2.8336***	–2.7797***	–2.8491***	–3.0536***	–2.9220***	–2.9559***
	(0.3074)	(0.3053)	(0.3045)	(0.3037)	(0.3041)	(0.3039)
CITY_WAGE	0.3995***	0.4069***	0.4197***	0.3232***	0.4380***	0.3971***
	(0.0244)	(0.0242)	(0.0241)	(0.0234)	(0.0238)	(0.0230)
LCOMP	0.0037*	0.0039**	0.0038**	0.0251***	0.0172***	0.0040**
	(0.0019)	(0.0019)	(0.0018)	(0.0011)	(0.0014)	(0.0018)
INDU_GR	–1.3336***	–1.3145***	–1.3109***	–1.2092***	–1.2618***	–1.3102***
	(0.0210)	(0.0206)	(0.0205)	(0.0174)	(0.0180)	(0.0204)
INDU_COMP	–0.0001***	–0.0002***	–0.0001***	–0.0002***	–0.0001***	–0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MES	0.0344***	0.0323***	0.0321***	–0.0337***	0.0085	0.0322***
	(0.0064)	(0.0063)	(0.0063)	(0.0061)	(0.0062)	(0.0063)
Constant	–1.9532***	–2.1788***	–2.4908***	–5.4255***	–5.1501***	–2.1687***
	(0.2581)	(0.2557)	(0.2552)	(0.2462)	(0.2485)	(0.2328)
Rho	0.0663***	0.0392***	0.0301***	2.41e–05	0.00298	0.0292***
Log_likelihood	–111474	–111146	–110817	–115897	–112601	–110822

Note: The total number of firms in all models was 161,984, and the number of observations was 443,354. The numbers in parentheses are standard errors, and rho is used to measure whether the model is necessary to control for unobservable heterogeneity. ***, **, and * represent significance levels at 10%, 5%, and 1%, respectively.

l in city j relative to the number of firms per worker in industry l in China—that is , $LCOMP_{j,l} = (N_{j,l}/E_{j,l})/(\sum_l N_{j,l}/\sum_l E_{j,l})$, where $N_{j,l}$ is the number of firms in industry l in city j and $E_{j,l}$ is the number of employees in industry l in city j. As Plummer and Acs (2014) argued, this method of measuring localized competition is based on the viewpoint of Jacobs (1969) that firms compete for ideas embodied in individuals.

(12) Population density at the city level (*DENSITY*): This is expressed by the logarithm of the ratio of the city's population to its area (10,000 people per square kilometer). An increase in population density can result in increased local demand and productive services (Ciccone & Hall, 1996). Simultaneously, the increase in population density increases the supply of qualified local labor, reduces the transportation costs of the firm, improves the efficiency of the supplier-customer relationship, and increases the efficiency of the firm's production and operation (Aarstad et al., 2016).

(13) Level of industry competition (*INDU_COMP*): This is represented by the reciprocal of the Herfindahl–Hirschman index (HHI) calculated by the four-digit industry at the national level.[15] Unlike *LCOMP*, which measures the degree of competition at the regional (city) level, *INDU_COMP* measures the degree of competition at the national level. Given that manufactured goods are often traded nationwide (Glaeser & Kohlhase, 2003), controlling market competition at the national level is necessary.

[15] HHI is often used to measure the market concentration of an industry. A higher HHI means that the industry comprises a small number of large companies, and the degree of market competition is typically low.

(14) Industry growth (*INDU_GR*). This is measured by the employment growth rate at the four-digit industry level. New entrants entering fast-growing industries may have a survival advantage because they benefit from favorable market conditions and lower direct competition.

(15) Industry's minimum efficient scale (*MES*): This is measured by the average output (logarithm) of the top 50 % of firms at the four-digit industry level (Comanor & Wilson, 1967). The larger the *MES*, the more difficult it is for a firm to achieve economies of scale (Audretsch, 1995) and the greater the exit risk.

3.5. Descriptive statistics

To mitigate the effect of extreme values on the regression analysis, the growth variable is predominantly winsorized at the 0.5 % and 99.5 % levels. However, we found that some start-ups still had annual growth rates exceeding 300 %, even after the growth variable was winsorized. To reduce the estimated errors caused by extreme values, according to the data processing method of Zhou and van der Zwan (2019), we excluded start-ups with a growth rate greater than 200 %. Finally, the number of observations was 443,354, and the number of start-ups was 161,984 in the study sample. During the study period, 35,098 start-ups withdrew from the market.

Table A1 reports the descriptive statistics and correlation coefficients of the dependent, independent, and control variables (excluding the regional and industrial dummy variables). Table A1 shows that *LQ* has weak negative correlations with *RV* and *UV,* whereas *RV* has a strong positive correlation (over 0.5) with *UV*. We discuss the potential multicollinearity issues in Section 4.

4. Result analysis

4.1. Baseline regressions

Table 2 reports the estimation results of the cloglog model. Model 1 only includes control variables and three agglomeration variables. Model 2 adds the growth variable (*GR*) based on Model 1. Model 3 adds the quadratic term of growth variable (GR^2) based on Model 2. The coefficients of *GR* in Models 2 and 3 are significantly negative, whereas the coefficients of GR^2 in Model 3 are significantly positive. Further, Equation (9) can be used to calculate the marginal effect of growth on survival risk:

$$\frac{\partial h_{i,t}}{\partial GR_{i,t-1}} = f(\overrightarrow{X}\alpha')(\beta_G + 2\beta_{G^2} GR_{i,t-1}) \tag{9}$$

where $\overrightarrow{X}$ is the vector of covariates, α is the vector of the coefficient of covariates, and $f(\overrightarrow{X}\alpha')$ is the probability density function. Given that β_{G^2} is significantly greater than 0 in the estimated results of Model 3, the marginal effect of growth on survival risk increases with *GR*. In addition to checking the signs and significance of the quadratic term, two other steps can be used to verify whether the U-shaped relationship is true (Haans et al., 2016). First, given that other covariates are at the average value and *GR* takes the corresponding maximum and minimum values, the calculation results of the growth margins to survival risk are –0.1743 (Z = –21.18) and 0.0785 (Z = 11.25), respectively. These two marginal values eliminate the possibility that the survival risk is a logarithmic or exponential function of firm growth. Second, by calculating the turning point and its confidence interval (CI), we obtained GR^*=0.7492 (95 % CI = [0.7064–0.7920]). This turning point is in the GR range, confirming a U-shaped relationship between growth and survival risk. In the sample, 93.19 % and 6.81 % of the observations were located on the left and right of the turning point, respectively. Thus, growth mainly plays a role in reducing the survival risk. Although the growth of start-ups in emerging markets faces high costs, the high costs are not sufficient to offset the high benefits of growth. Therefore, the growth of start-ups in emerging markets may be conducive to their survival in most cases.

Model 4 excludes other firm-level control variables, except for firm age, to eliminate interference by potentially poor control variables (Whited, Swanquist, Shipman, & Moon, 2021), and its estimated results show that the coefficient signs of *GR* and GR^2 do not change compared to Model 3. These results show that controlling variables at the firm level do not fundamentally impact the U-shaped relationship between growth and survival. Thus, Hypothesis 1 was confirmed.

According to the estimated results of Models 1–3, we obtain the direct impact of agglomeration externalities on survival risk. In Models 1–3, the coefficients of *RV* are all significantly negative, suggesting that related variety externalities can help reduce the survival risk. Moreover, the coefficients of *LQ* and *UV* are all significantly positive, indicating that the externalities of unrelated variety and specialization increase survival risk.[16]

However, in Model 4, the coefficient of *LQ* is significantly negative, contrary to the estimation results of Models 1–3, with firm-level control variables included. This means that omitting firm-level control variables may result in an estimation bias. By performing a stepwise reduction of the control variables in Model 3, we find that controlling for firm size is the only factor affecting the direction of the coefficient of *LQ*.[17] Thus, when discussing the role of specialization externalities on survival, it is necessary to control for the impact of firm size. Therefore, we hypothesize that the impact of specialization externalities on survival risk is heterogeneous in terms of firm size.

To test whether the above estimation is true, we divided the sample used in Model 3 into two groups according to the average size of start-ups, after which we set up a dummy variable *SIZE_D*. If the start-up size is larger than the average size, *SIZE_D* equals 1; otherwise, it is 0. We replaced *SIZE* with *SIZE_D* in Model 3 and added the interaction term between *SIZE_D* and *LQ* ($SIZE\_D \times LQ$) to obtain Model 5. The estimated results of Model 5 are listed in Table 2. As can be observed, the coefficients of *LQ* and $SIZE\_D \times LQ$ are significantly negative and positive, respectively, and the sum of the coefficients of *LQ* and $SIZE\_D \times LQ$ is greater than 0. Therefore, specialization externalities can provide more survival benefits to relatively small start-ups. This finding confirms the hypothesis that the impact of specialization externalities on survival risk is heterogeneous in terms of firm size.[18]

The results in Table 2 reveal that related variety externalities are beneficial for survival, whereas unrelated variety externalities may increase survival risk. This is because many formal and informal communication opportunities are available for firms in a region with a high level of *RV*, and the cost of obtaining knowledge spillovers from related industries is low. This condition increases firms' learning opportunities and improves the possibility of innovation and success, thereby improving production efficiency and market competitiveness. In a region with a high *UV*, the degree of technological correlation among firms in different industries is low, and the input factors among firms lack complementarity; hence, knowledge spillovers among firms are hindered (Boschma, 2005; Nooteboom, Van Haverbeke, Duysters,

16 A recent study found that although unrelated variety increases the survival risk of manufacturing firms, it reduces the survival risk of service firms. This is because service industries mainly respond to local demand, while manufacturing has a higher international market orientation. In regions with a high level of unrelated variety, there are many unrelated sectors that provide sufficient local demand for service firms, which may benefit service firms more than manufacturing firms.

17 The estimated results are not reported, but can be obtained from the authors if necessary.

18 This conclusion is consistent with the view of Shaver and Flyer (2000) and Lin, Li, and Yang (2011). They argued that small firms generally bear higher unit costs in finding qualified workers and input transactions, but specialization externalities can greatly reduce the transaction costs of small firms in labor and intermediate input markets; large firms benefit less from specialization externalities due to their own high-quality resources and capabilities and may face risks, such as knowledge leakage caused by competition.

Table 3
The estimated results of the moderating effects.

Variables	7	8	9	10	11
GR	–0.5735***	–0.5780***	–0.5732***	–0.5789***	–0.5754***
	(0.0161)	(0.0161)	(0.0161)	(0.0161)	(0.0161)
GR^2	0.4397***	0.4432***	0.4399***	0.4439***	0.4414***
	(0.0160)	(0.0160)	(0.0160)	(0.0160)	(0.0160)
$GR \times LQ$	0.0098			–0.0007	–0.0027
	(0.0069)			(0.0073)	(0.0073)
$GR^2 \times LQ$	–0.0225***			–0.0171**	–0.0157**
	(0.0075)			(0.0078)	(0.0078)
$GR \times RV$		–0.1889***		–0.2301***	
		(0.0275)		(0.0361)	
$GR^2 \times RV$		0.1279***		0.1507***	
		(0.0283)		(0.0377)	
$GR \times UV$			–0.1172***	0.0839*	
			(0.0378)	(0.0501)	
$GR^2 \times UV$			0.0767**	–0.0831	
			(0.0385)	(0.0517)	
$GR \times TV$					–0.1052***
					(0.0184)
$GR^2 \times TV$					0.0568***
					(0.0185)
TV					0.0001
					(0.0106)
LQ	0.0087***	0.0043*	0.0044*	0.0069**	0.0058**
	(0.0029)	(0.0026)	(0.0026)	(0.0030)	(0.0029)
RV	–0.0339*	–0.0702***	–0.0344*	–0.0770***	
	(0.0200)	(0.0209)	(0.0200)	(0.0214)	
UV	0.0719***	0.0686***	0.0477**	0.0897***	
	(0.0195)	(0.0195)	(0.0213)	(0.0225)	
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	443,354	443,354	443,354	443,354	443,354
Rho	0.0309***	0.0291***	0.0289**	0.0303***	0.0282**
Log likelihood	–110812	–110792	–110812	–110787	–110800

Note: "Yes" means that all control variables are included in the model. The numbers in parentheses are standard errors, and rho is used to measure whether the model is necessary to control for unobservable heterogeneity. ***, **, and * represent significance levels at 10%, 5%, and 1%, respectively.

Gilsing, & van den Oord, 2007). All of these factors can hinder an increase in firm productivity.[19]

In addition, we replaced *RV* and *UV* with *TV* based on the specifications of Model 3 and obtained Model 6 in Table 2. The estimated results for Model 6 show that the coefficient of *TV* is significantly positive. This result shows that *TV* has a negative effect on survival, which is similar to the effect of *UV* but opposite to the effect of *RV*, implying that the strength of the negative effect of *UV* exceeds the positive effect of *RV*.

As there is a high positive correlation between *RV* and *UV*, some questions need to be answered. Does potential multicollinearity affect the accuracy of the estimation results? In particular, does it affect the signs of the *RV* and *UV* coefficients? In response to these questions, we conducted additional tests and found that when *TV* is decomposed into *RV* and *UV*, incorrect conclusions may be obtained if both are not included in the model simultaneously. In Model 3, if *UV* is removed, the coefficient of *RV* changes from –0.0336 to 0.0049.[20] This is because the effect of *RV* is mixed with that of *UV* when the latter is not controlled. Similarly, in Model 3, although the sign of the coefficient of *UV* was not affected, the coefficient decreased from 0.0723 to 0.0555 if *RV* was removed. Therefore, if only *RV* or *UV* is included in the regression equation, it may lead to omitted variable bias. Recently, Lindner, Puck, and Verbeke (2020) stated that collinearity does not lead to estimation bias (except for extreme cases), whereas omitting variables with high collinearity can lead to endogeneity problems, leading to estimation bias. They suggested that researchers should add, rather than omit, potentially relevant collinear variables.[21]

In terms of control variables, the estimation results of Models 1–6 show that, except for *FOREIGN* and *MES*, the signs of the coefficients of all control variables remain the same, with only a slight change in the magnitudes of the coefficients. For control variables at the firm level, the coefficients of *AGE* and AGE^2 are significantly negative and positive, respectively, indicating that, as age increases, survival risk first rises and then decreases. The coefficients of *SIZE* are significantly negative, indicating that the larger the firm, the higher the survival probability. The coefficients of *STATE* and *DEBT* are both significantly positive, indicating that an increase in the proportion of state-owned capital and the debt ratio is detrimental to survival to some extent.

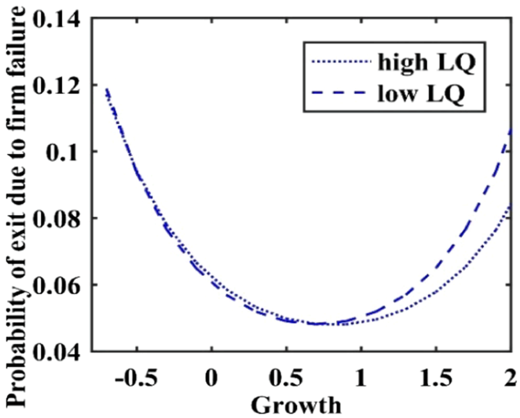
The coefficients of *EXPORT*, *INNO*, *SUBSIDY*, and *PROD* are always significantly negative, indicating that participation in export and innovation activities, the ability to obtain government subsidies, and increasing labor productivity can all reduce survival risks. The coefficient of *FOREIGN* is significantly negative in Model 5 and insignificantly positive in the other models (except Model 1). Therefore, although many studies have found that foreign investment is conducive to firm survival, the estimated results of this study fail to provide sufficient support for this conclusion.

Next, we report the estimated results for the control variables at the regional level. The coefficients of *DENSITY* are all significantly negative, indicating that the higher the population density, the greater the local

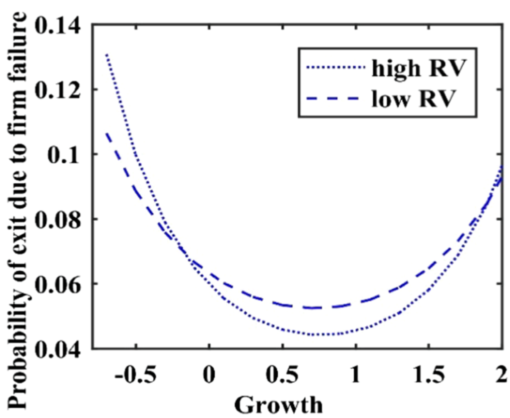
[19] Aarstad et al. (2016) asserted that a high level of unrelated variety, which is accompanied by a lower degree of proximity of organizations, society, and institutions, may reduce the efficiency of regional administrative routines. Additionally, a high level of local unrelated variety may mean that there is an unrelated and fragmented industry structure, which may further constrain regional economies of scale and localized competition. All of the above will eventually reduce firm productivity.

[20] To save space, the estimated results are not presented. However, the author can provide these as needed.

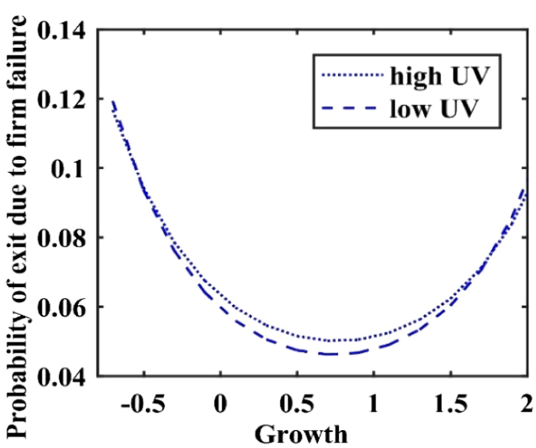
[21] Lindner et al. (2020) argued that if coefficients change when one or more potentially collinear variables are added to a regression model, it suggests that this model is incorrectly specified prior to addition of the collinear variables.



(a) The moderating effect of specialization externalities (*LQ*)



(b) The moderating effect of related variety externalities (*RV*)



(c) The moderating effect of unrelated variety externalities (*UV*)

Fig. B1. Moderating effects of Agglomeration externalities on growth and survival Note: The predicted hazard (probability of exit) is derived from Model 10 in Table 3 and holds all variables (except growth and agglomeration variables) at their mean.

market potential, and the higher the possibility of survival. The coefficients of *LCOMP* are always significantly positive, indicating that localized competition has a significant negative impact on survival. Contrary to our expectations, the coefficients of *CITY_WAGE* are all significantly positive, indicating that the higher the per capita wage, the higher the survival risk in the city. One possible explanation is that, although cities with higher per capita wages have higher levels of human capital, they also incur higher labor costs for local firms. In particular, during the study period, most of China's manufacturing firms were still at the low end of the industry chain as a whole, and the increase in per capita wage led to a sharp increase in their production costs, which increased survival risks.

Finally, we consider industry-level control variables. The coefficients of *MES* in the baseline regression results are significantly positive in most cases, whereas those of *INDU_GR* are always significantly negative. The increase in *MES* makes it more difficult for start-ups to achieve economies of scale, which may increase their survival risk. In fast-growing industries, start-ups benefit from favorable market conditions, endowing them with greater survival advantages. The coefficients of *INDU_COMP* are always negative, suggesting that industry competition helps reduce the survival risk. During China's economic transformation, for industries with a high degree of monopoly, new entrants are likely to be colluded with and attacked by a small number of incumbents. On the contrary, for industries with a high degree of competition, it is not only easier for new entrants to enter but also not easily boycotted by incumbents.

4.2. Estimated results of moderating effects

As shown in Table A1, certain correlations exist among the agglomeration variables. Therefore, to avoid potential multicollinearity problems, we separately added the interaction terms of *LQ*, *RV*, and *UV* with the growth variables into Models 7–9 based on Model 3 (see Table 3). For comparison, we combined the interaction terms of *LQ*, *RV*, and *UV* with the growth variables to obtain Model 10. Next, we replace *RV* and *UV* with *TV* in Model 10 to obtain Model 11, which considers the moderating effects of *LQ* and *TV*.

We first center the independent variables before constructing the interaction terms to avoid non-essential multicollinearity problems that an interaction item may generate (Dalal & Zickar, 2012). Table 3 shows that the coefficients of $GR^2 \times LQ$ in Models 7–11 are all significantly negative, indicating that specialization externalities may weaken the U-shaped relationship between growth and survival risk, which is consistent with the results of Pe'Er et al. (2016). Thus, Hypothesis 2 was confirmed. The coefficients of $GR^2 \times TV$ in Model 11 and $GR^2 \times RV$ in Models 8 and 10 are significantly positive, indicating that *TV* and *RV* strengthen the U-shaped relationship between growth and survival risk. Hypotheses 3 and 4 were thus confirmed.

The signs and significance of the coefficients of $GR^2 \times UV$ in Models 9 and 10 are different. In Model 10, the coefficient of $GR^2 \times UV$ is insignificant. However, the conclusion changes when considering the moderating effect of UV alone. As shown in the results of Model 9, the coefficient of $GR^2 \times UV$ is significantly positive without adding other moderating effects. In the previous section, we highlighted that the sign of the *RV* coefficient varies depending on whether *UV* is included. This is because, in the case of the relatively high correlation between *RV* and *UV*, if the moderating effect of *RV* (*UV*) is not controlled in the model, it will be mixed into the moderating effect of *UV* (*RV*) to some extent. Correct estimates can be obtained only when the moderating effects of

Table 4
Robustness test results (on the basis of the specification of Model 10).

Variables	12	13	14	15	16	17	18	19	20
GR	–0.4072***	–0.4069***	–0.4789***	–0.6416***	–0.3370***	–0.6299***	–0.5535***	–0.4850***	–0.6701***
	(0.0104)	(0.0175)	(0.0109)	(0.0176)	(0.0091)	(0.0301)	(0.0199)	(0.0210)	(0.0307)
GR^2	0.0449***	0.1428***	0.2736***	0.4944***	0.2618***	0.5687***	0.3958***	0.3977***	0.5343***
	(0.0011)	(0.0174)	(0.0077)	(0.0174)	(0.0090)	(0.0302)	(0.0198)	(0.0212)	(0.0292)
$GR \times LQ$	–0.0042	–0.0095	–0.0057	0.0022	0.0011	0.0199	–0.0061	–0.0078	–0.0090
	(0.0040)	(0.0076)	(0.0042)	(0.0080)	(0.0042)	(0.0143)	(0.0087)	(0.0101)	(0.0121)
$GR^2 \times LQ$	–0.0002	–0.0109	–0.0120***	–0.0232***	–0.0123***	–0.0249*	–0.0167*	–0.0274**	–0.0020
	(0.0005)	(0.0081)	(0.0033)	(0.0086)	(0.0044)	(0.0150)	(0.0094)	(0.0118)	(0.0118)
$GR \times RV$	–0.2402***	–0.2256***	–0.1549***	–0.2507***	–0.1246***	–0.2396***	–0.2175***	–0.2106***	–0.2886***
	(0.0215)	(0.0398)	(0.0221)	(0.0395)	(0.0204)	(0.0674)	(0.0443)	(0.0482)	(0.0654)
$GR^2 \times RV$	0.0236***	–0.0478	0.0285*	0.1678***	0.0886***	0.1871***	0.1143**	0.1563***	0.1742***
	(0.0024)	(0.0406)	(0.0168)	(0.0409)	(0.0211)	(0.0705)	(0.0462)	(0.0511)	(0.0653)
$GR \times UV$	0.1503***	0.1056*	0.0823***	0.1060*	0.0536*	0.1943**	0.0432	0.0654	0.1069
	(0.0297)	(0.0564)	(0.0301)	(0.0554)	(0.0289)	(0.0947)	(0.0605)	(0.0670)	(0.0912)
$GR^2 \times UV$	–0.0154***	0.0667	–0.0193	–0.1192**	–0.0671**	–0.1487	–0.0548	–0.1190*	–0.0492
	(0.0033)	(0.0568)	(0.0226)	(0.0572)	(0.0297)	(0.0962)	(0.0633)	(0.0715)	(0.0900)
LQ	0.0056*	0.0054*	0.0094***	0.0085***	0.0032*	0.0234***	0.0030	0.0035	0.0105**
	(0.0029)	(0.0028)	(0.0029)	(0.0032)	(0.0017)	(0.0057)	(0.0036)	(0.0041)	(0.0052)
RV	–0.1247***	–0.0499**	–0.0820***	–0.0720***	–0.0283**	–0.0626	–0.0934***	–0.0090	–0.0280
	(0.0213)	(0.0207)	(0.0213)	(0.0228)	(0.0113)	(0.0405)	(0.0262)	(0.0279)	(0.0400)
UV	0.1284***	0.0714***	0.0942***	0.0938***	0.0443***	0.1209***	0.0910***	0.0606**	0.0732*
	(0.0224)	(0.0209)	(0.0222)	(0.0240)	(0.0119)	(0.0415)	(0.0277)	(0.0297)	(0.0415)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	439,870	443,354	439,870	443,354	443,354	155,822	287,532	179,032	166,207
rho	0.0107	0.0333***	0.0285***	1.69e–05	7.69e–06	0.214***	0.0431**	0.0204**	0.0428***
log likelihood	–108842	–110890	–107674	–110756	–111008	–38365	–72084	–61094	–32439

Note: "Yes" means that all control variables are included in the model. The numbers in parentheses are standard errors, and rho is used to measure whether the model is necessary to control for unobservable heterogeneity. ***, **, and * represent significance levels at 10%, 5%, and 1%, respectively.

Table 5
Robustness test results (on the basis of the specification of Model 11).

Variables	21	22	23	24	25	26	27	28	29
GR	–0.3828***	–0.4008***	–0.4676***	–0.6376***	–0.3352***	–0.6384***	–0.5464***	–0.4800***	–0.6689***
	(0.0101)	(0.0174)	(0.0105)	(0.0176)	(0.0091)	(0.0300)	(0.0197)	(0.0209)	(0.0307)
GR^2	0.0427***	0.1455***	0.2773***	0.4912***	0.2600***	0.5760***	0.3912***	0.3918***	0.5343***
	(0.0011)	(0.0174)	(0.0074)	(0.0174)	(0.0090)	(0.0300)	(0.0196)	(0.0211)	(0.0292)
$GR \times LQ$	0.0016	–0.0116	–0.0015	–0.0003	–0.0001	0.0164	–0.0077	–0.0095	–0.0115
	(0.0038)	(0.0076)	(0.0041)	(0.0080)	(0.0042)	(0.0143)	(0.0087)	(0.0101)	(0.0121)
$GR^2 \times LQ$	–0.0008*	–0.0109	–0.0128***	–0.0213**	–0.0112**	–0.0225	–0.0157*	–0.0260**	–0.0004
	(0.0004)	(0.0080)	(0.0032)	(0.0086)	(0.0044)	(0.0149)	(0.0094)	(0.0118)	(0.0118)
$GR \times TV$	–0.1045***	–0.1098***	–0.0956***	–0.1096***	–0.0546***	–0.0692*	–0.1128***	–0.1000***	–0.1318***
	(0.0196)	(0.0184)	(0.0189)	(0.0204)	(0.0107)	(0.0359)	(0.0221)	(0.0246)	(0.0340)
$GR^2 \times TV$	0.0644***	0.0582***	0.0632***	0.0537**	0.0269**	0.0535	0.0457**	0.0461*	0.0855***
	(0.0209)	(0.0203)	(0.0204)	(0.0209)	(0.0109)	(0.0362)	(0.0225)	(0.0256)	(0.0323)
LQ	0.0063**	0.0044	0.0096***	0.0074**	0.0027	0.0221***	0.0019	0.0181	0.0161
	(0.0029)	(0.0028)	(0.0029)	(0.0032)	(0.0016)	(0.0057)	(0.0036)	(0.0139)	(0.0197)
TV	–0.0008	–0.0001	–0.0008	0.0036	0.0044	0.0206	–0.0055	0.0181	0.0161
	(0.0105)	(0.0105)	(0.0106)	(0.0113)	(0.0057)	(0.0211)	(0.0126)	(0.0139)	(0.0197)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	439,870	443,354	439,870	443,354	443,354	155,822	287,532	179,032	166,207
rho	0.0158	0.0317***	0.0297***	2.15e–05	3.24e–07	0.213***	0.0399**	0.0189*	0.0414**
log likelihood	–108898	–110902	–107703	–110769	–111019	–38372	–72093	–61098	–32443

Note: "Yes" means that all control variables are included in the model. The numbers in parentheses are standard errors, and rho is used to measure whether the model is necessary to control for unobservable heterogeneity. ***, **, and * represent significance levels at 10%, 5%, and 1%, respectively.

RV and *UV* are considered simultaneously.[22] Therefore, we prefer *UV* to have no significant moderating effect on the U-shaped relationship. Thus, Hypothesis 5 is confirmed.

To intuitively observe the moderating effects, we drew graphs of these effects based on the estimated results of Model 10. Taking *LQ* as an example, according to Equation (9), we calculate the marginal effect of growth on survival risk at high (one standard deviation above the mean, i.e., *mean* + *SD*) and low (one standard deviation below the mean, i.e., *mean* – *SD*) values of *LQ* while keeping all other covariates at their mean value. Then, we have two U-shaped marginal effect curves: one is when *LQ* takes a high value, and the other is when *LQ* takes a low value. As shown in Fig. B1 in Appendix B, the U-shaped curve with high *LQ* is flatter than that with low *LQ* (especially in the high-growth phase), suggesting that *LQ* has a negative moderating effect on the relationship between growth and survival risk.

Similarly, we obtain two U-shaped marginal effect curves when *RV* (*UV*) takes high and low values. As shown in Fig. B1, the U-shaped curve with a high *RV* is steeper than that with a low *RV*, indicating that *RV* plays a positive moderating role. In addition, the U-shaped curve with high *UV* is flatter but very close to that with low *UV*. This means that *UV* had no significant moderating effect.

Although moderating effect graphs are intuitive, they are not sufficiently rigorous. This is because the values of the moderating effects of agglomeration externalities are affected by the values of all model variables. Thus, it is insufficient to observe the coefficients of the interaction terms to determine whether the moderating effects are significant (Wiersema & Bowen, 2009). To further test the moderating effects, this study refers to Haans et al. (2016) for testing, and the test results are shown in Appendix C. The results also show that *LQ* and *RV* have negative and positive moderating effects, respectively, while *UV* has no significant moderating effect.

4.3. Robustness tests

We performed several robustness tests to determine whether the conclusions drawn from the baseline regressions are robust. Based on the specification of Model 10, we perform several regressions in the following five steps: First, we use the growth rate of gross industrial output to replace the employment growth rate and obtain Model 12. To reduce the effect of extreme values, we winsorize the gross industrial output growth rate at the 0.5 % and 99.5 % levels and obtain 439,870 observations. Second, following Gjerløv-Juel and Guenther (2019) and Coad et al. (2020), we use a logarithmic growth rate instead of an annual growth rate to recalculate employment and gross industrial output growth rates. Thus, we obtained Models 13 and 14. Third, we test whether the distribution hypothesis of the hazard function affects the estimated results. As mentioned above, the most commonly used hazard function distribution forms include logistic and normal distributions, in addition to extreme-value distributions. Therefore, we replaced cloglog with logit and probit to obtain Models 15 and 16, respectively.

Fourth, we divide the sample into two sub-samples according to firm age and then regress them into sub-samples. Model 17 is for firms older than five years, and Model 18 is for firms younger than or equal to five years. Some studies consider firms younger than five years old as start-ups or new ventures (Dumont, Rayp, Verschelde, & Merlevede, 2016; Gjerløv-Juel & Guenther, 2019; Kim, 2018). However, other studies have relaxed the upper age limit for start-ups to eight years (Wennberg et al., 2016), nine years (Howell, 2015), or even ten years (Coad et al., 2016; Geroski, Mata, & Portugal, 2010; Patel, Pearce, & Guedes, 2019). In the baseline regressions, we regard firms aged nine years and under as start-ups, but the data allow us to define start-ups more strictly—that is, to treat firms five years old or younger as start-ups. Thus, we can test whether the conclusions drawn in the baseline regressions remain the same with a more rigorous definition of start-ups.

Fifth, we divide the sample into two subsamples according to firm resources and explore whether the moderating effects of agglomeration externalities exist for firms with different resource stocks. Prior studies have indicated resource heterogeneity in the relationship between agglomeration externalities and firm survival; that is, firms with relatively fewer resources benefit more from agglomeration externalities (Pe'Er & Keil, 2013; Shaver & Flyer, 2000). We follow this line of thought and aim to test whether the moderating effects of different agglomeration externalities are heterogeneous in terms of the resources held by start-ups. Meanwhile, we focus on the total assets that firms hold relative to competitors as a proxy for their tangible and intangible resources and define start-ups with total assets that have never reached the median level of those in the same industry during the research period as start-ups with relatively few resources. Start-ups with total assets that have always been larger than the median of those in the same industry during the research period are deemed start-ups with relatively abundant resources.[23] Models 19 and 20 are regression models for start-ups with relatively few and abundant resources, respectively.

The results for Models 12–20 are presented in Table 4. Similarly, based on the specification of Model 11, we perform the same five steps to obtain Models 21–29 and obtain the estimated results shown in Table 5. As mentioned above, we centralized the growth and agglomeration variables to alleviate the problem of multicollinearity. The estimated results of Models 12–29 show that the coefficients of *GR* are significantly negative, whereas those of GR^2 are significantly positive. This is consistent with the results estimated in Section 4. Thus, Hypothesis 1 is confirmed.

Next, we conduct robustness tests on the moderating effects of the agglomeration externalities. In Models 12–29, the coefficients of $GR^2 \times LQ$ were all negative and passed the significance test in most cases. The coefficients of $GR^2 \times RV$ in Table 4 are all significantly positive in the other eight models, except Model 13, and the coefficients of $GR^2 \times TV$ in Table 5 are all significantly positive in the other eight models, except Model 26. Therefore, the results of the robustness tests further confirm the negative moderating effects of *LQ* and the positive moderating effects of *TV* and *RV*. The coefficients of $GR^2 \times UV$ in Table 4 are all negative in the other eight models, except Model 13, but they are only significant in Models 12, 15–16, and 19. This finding indicates that the moderating effect of *UV* has not been sufficiently confirmed. Considering that the coefficient of $GR^2 \times UV$ is insignificant in most cases, we

[22] To resolve this suspicion, we sequentially remove the moderating effects of *LQ* and *RV* on the basis of the specification of Model 10, after which we observe whether the moderating effect of *UV* changes. The results show that removing the moderating effect of *LQ* does not affect the direction of the moderating effect of *UV*, while removing the moderating effect of *RV* changes the moderating effect of *UV* from negative to positive. This is similar to the results of Model 9, which contains only the moderating effect of *UV*. This means that considering the moderating effect of *RV* can fundamentally affect the judgment of the moderating effect of *UV*. If the significant and positive moderating effect of *RV* is not controlled in the model, it will be mixed in the moderating effect of *UV* to a certain extent, changing the sign and significance of the moderating effect of *UV*. Therefore, if the moderating effect of *RV* is not considered, misleading conclusions about the moderating effect of *UV* can be obtained.

[23] This classification enables us to exclude start-ups with total asset value exceeding the median level of those in the same industry in some years but not in other years during the study period.

believe that *UV* does not play a significant moderating role in the relationship between growth and survival risk.

Finally, we focus on whether the moderating effects of agglomeration externalities differ by firm age and resources. The regression results of Models 16 and 17 show that the moderating effects of agglomeration externalities do not differ by firm age.[24] However, the moderating effect of *LQ* differs by firm resources. The negative moderating effect of *LQ* is significant for start-ups with relatively few resources (see Models 19 and 28) but not for start-ups with relatively abundant resources (see Models 20 and 29). This is because start-ups with relatively few resources are the main beneficiaries of specialized labor, specialized suppliers, and local customers, whereas start-ups with relatively abundant resources often have sufficient resources to produce specialized supplies internally and seek a broader demand market outside the local area (Pe'Er & Keil, 2013). For start-ups with relatively few resources, resource fungibility assumes added importance because it lowers the cost of business failure and enables them to leverage limited resources across multiple capabilities (Sapienza, Autio, George, & Zahra, 2006). This situation also makes start-ups with relatively few resources the main beneficiaries of the moderating effect of specialization externalities. Moreover, the coefficients of $GR^2 \times RV$ and $GR^2 \times TV$ are significantly positive for start-ups with relatively poor or rich resources. In other words, the positive moderating effects of diversification externalities are not affected by the resources held by start-ups.[25]

5. Conclusions

In strategic management, scholars emphasize that firm survival results from the external environment and internal decision-making. In this study, we use China's manufacturing start-ups from 1999 to 2007 as a research sample to investigate the impact of growth on survival and analyze the moderating effect of different agglomeration externalities on the relationship between growth and survival. A U-shaped relationship exists between growth and survival risk for Chinese manufacturing start-ups. Given that most observations fall on the left side of the U-shaped curve, the positive effects of growth dominate.

Different agglomeration externalities have different moderating roles in the relationship between growth and survival. Specialization externalities play a negative moderating role because they provide benefits that are substitutes for growth benefits and reduce the costs of growth. Meanwhile, diversification externalities play a positive moderating role because they push firms to rely on their internal growth benefits to survive and increase growth costs. After decomposing diversification, we find that the moderating effect of related variety externalities follows the same direction as that of diversification externalities, whereas unrelated variety externalities have no significant moderating effects. Therefore, the positive moderating effect of diversification externalities arises from related variety.

5.1. Theoretical implications

This study focuses on the relationship between growth, agglomeration externalities, and the survival of start-ups in the context of emerging markets. We reconfirmed the finding of Pe'Er et al. (2016) that specialization externalities weaken the U-shaped relationship between growth and survival risk by replacing the survival benefits of growth and reducing the survival costs of growth, as well as the heterogeneity of the moderating effect of specialization externalities under the resource-based view. The empirical results suggest that the moderating effect of specialization externalities exists only for start-ups with relatively few resources. Thus, our study adds to the agglomeration literature (Pe'Er & Keil, 2013; Shaver & Flyer, 2000), bringing back firm-level heterogeneity into the research on agglomeration externalities, thereby helping to further integrate the resource-based view with agglomeration theory.

Moreover, we extend the agglomeration literature by linking firms' strategic behavior to other types of agglomeration externalities, thereby enriching our understanding of how different agglomeration externalities interact with start-ups' growth strategies, jointly affecting their survival. The existing literature has discussed the interaction of specialization externalities with firms' strategic choices (Pe'Er et al., 2016; Woo et al., 2019) but has not yet addressed diversification externalities in this topic. We analyze how diversification externalities affect the survival outcomes of start-up growth strategies. The empirical results suggest that diversification externalities strengthen the U-shaped relationship between growth and survival risk by pushing start-ups to rely more on the benefits of growth and the increasing survival costs of growth. Our study suggests fundamental differences between diversification and specialization externalities in creating environmental conditions that interact with strategic choices, leading to opposing moderating effects on the relationship between growth and survival. Although prior literature has focused on the direct effect of diversification externalities on firm survival (He et al., 2017; Howell et al., 2018; Power et al., 2019), we study the indirect effect of diversification externalities on firm survival (i.e., how industrial diversification creates environmental conditions that interact with growth strategies to affect the survival performance of start-ups). Furthermore, we confirm that the moderating effect of diversification externalities comes mainly from the related variety. An increasing number of studies have highlighted the importance of related varieties in the conceptualization of traditional diversification (Content & Frenken, 2016; Ejdemo & Ortqvist, 2020). Our study provides additional support to this strand of literature, confirming that related variety is a representative indicator of the concept of "Jacobs externalities." The preceding findings confirm that firm survival depends on the comprehensive results of the external environment and internal decision-making and also suggest that research on firm strategic performance requires careful consideration of the differences in the industrial structure of firms' locations.

In addition, our study enriches the understanding of start-up growth strategies in emerging markets. We reveal a U-shaped relationship between growth and survival risk of start-ups in the Chinese manufacturing sector. The reason for this relationship is that appropriate growth can improve survival probabilities by overcoming the "liability of smallness" and sending positive signals to stakeholders, whereas excessive growth may lead to business failure because of increases in adjustment costs and the degree of unreasonable resource allocation. This study demonstrates the rationality of treating growth as a strategic choice and process and confirms the universality and applicability of the "too-much-of-a-good-thing" effect in emerging markets (Pierce & Aguinis, 2013). Moreover, this study responds to the controversy in the literature on the relationship between growth and survival

[24] Although the coefficients of $GR^2 \times LQ$ and $GR^2 \times TV$ in Model 26 are not significant at the 10% level, their p-values are extremely close to 0.1 (0.133 and 0.140, respectively). Therefore, we are convinced that the estimation results of the model confirm the moderating effects of *LQ* and *TV*.

[25] The moderating effect of *UV* is negative and significant at the 10% level for start-ups with relatively fewer resources, but insignificant for start-ups with relatively more resources. Start-ups with relatively few resources are relatively more sensitive to fluctuations in the external environment due to their limited chance of surviving external competition, shocks, and other adversities (Pe'Er & Keil, 2013). In regions with a high level of *UV*, knowledge spillovers and interactive learning among firms are weak (Huang et al., 2021; Mi, Shang, & Zeng, 2022; Yang et al., 2020). This exposes start-ups to few external opportunities and weak competition. Therefore, *UV* can increase the stability of the business environment, which allows start-ups with relatively few resources to not rely too much on growth for survival benefits and also reduces the cost of their growth.

by considering the emerging market background. We discover the peculiarities of the relationship between growth and survival of start-ups in the context of China—that is, the positive effect of growth on survival dominates. Given that most observations fall to the left of the U-shaped curve, the growth of start-ups can procure more survival benefits in fast-growing emerging markets. This is because, in fast-growing emerging markets, start-ups must attract key external resources through growth and gain a competitive advantage in scale. Although the disadvantages of emerging markets in terms of institutions and market environments pose high costs and uncertainties for growth, the benefits of growth usually exceed the costs, thereby contributing to the survival of start-ups. Our findings prove that under different socioeconomic contexts, the performance outcomes of firm strategies may be different.

5.2. Practical implications

Our study has several practical implications. For business managers in emerging markets, the benefits and risks of growth should be balanced, and the growth rate must be adjusted in time to eliminate the cost of growth. Furthermore, entrepreneurs should focus on the interactions between different agglomeration externalities and firm growth strategies when making location choices. First, the effects of specialization externalities should be considered because specialization offers a broad range of strategic options for start-ups, particularly those with insufficient resources. Second, the focus should be on changes in the external environment brought about by diversification externalities, specifically related variety externalities. The interaction between related industries makes appropriate growth markedly important. Therefore, the implementation of growth strategies should consider local industrial environments.

Our research also provides inspiration for policymakers. First, our findings emphasize the importance of the coordinated development of industries with technological connections. Policymakers should emphasize the joint cultivation of technology-related industries in the long term. Second, the supply of resources for start-ups in regions with low-level specialization or high-level diversification (particularly the related variety) should be increased. Although immediately changing the existing industrial structure in a certain region in the short term is unrealistic, alleviating the resource constraints encountered by start-ups is feasible by providing subsidies and credits for start-ups. Obtaining additional external resources can help start-ups adjust their business strategies promptly, thereby increasing their chances of survival.

5.3. Limitations and future research

Although it makes several contributions to the existing literature, this study is not free from limitations, and there is vast room for future research. First, measurement errors may be present in agglomeration variables because ASIE does not include manufacturing firms with an annual sales revenue of less than 5 million RMB. Whether the conclusions of this study apply to small firms that are not recorded in the database needs further verification.

Second, this study considers only the impact of the interaction between agglomeration and growth on the survival outcomes of growth. Future research could explore how agglomeration economies affect the performance outcomes of other strategic choices. In addition to growth strategies, firms make strategic choices, such as export and investment decisions (Shu & Simmons, 2018; Woo et al., 2019). These decisions may also interact with agglomeration externalities, and their effects on firm performance have not yet been explored. In addition, future research could consider more interactions between growth and other external factors, such as the industry life cycle and market competition.

Third, it is necessary to examine the impact of agglomeration externalities on a broad scale. The economic effects of agglomeration externalities may differ for countries or regions at different stages of development and industries with different characteristics. The ASIE records only industrial firms, which limits our research to manufacturing firms. Future research should consider including more countries and industries in the sample. This will not only help discover more interesting and novel conclusions but also help further explore the micro mechanism of agglomeration externalities.

Finally, exploring the long-term performance outcomes of growth strategies is a meaningful research direction. Our research has drawn some interesting conclusions about the short-term performance outcomes of growth strategies; however, we cannot generalize these conclusions to long-term scenarios. In fact, some factors that support the success of start-ups in the short term may discourage learning and technological capability building and thus cause firm failures in the long term (Gjerløv-Juel & Guenther, 2019; Karabag, 2019). Therefore, the impact of firm growth on long-term performance is worth investigating. Through such exploration, we can gain some novel and interesting conclusions.

CRediT authorship contribution statement

Ruiqi Cheng: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Peng Yuan:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Conceptualization. **Gongxiong Jiang:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

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

Acknowledgement

This paper was supported by the Science Foundation of Ministry of Education of China [grant number: 18XJA790008].

Appendix A. .

See Table A1.

Table A1
Descriptive statistics and correlation coefficients of all variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
1. *Exit*	1																			
2. *GR*	–0.07	1																		
3. *LQ*	0.00	0.01	1																	
4. *RV*	–0.01	0.02	–0.24	1																
5. *UV*	0.00	0.01	–0.29	0.59	1															
6. *AGE*	0.01	–0.06	–0.03	0.16	0.04	1														
7. *SIZE*	–0.12	0.18	0.10	–0.06	–0.09	0.02	1													
8. *STATE*	0.02	–0.02	0.00	–0.07	–0.03	–0.02	0.08	1												
9. *FOREIGN*	–0.03	0.04	–0.03	0.18	0.05	0.03	0.21	–0.05	1											
10. *EXPORT*	–0.04	0.02	0.04	0.11	0.02	0.06	0.23	–0.05	0.38	1										
11. *INNO*	–0.02	0.02	–0.01	0.01	0.00	0.04	0.10	0.04	–0.01	0.04	1									
12. *SUBSIDY*	–0.04	0.02	–0.01	0.03	0.01	0.04	0.14	0.04	0.04	0.07	0.10	1								
13. *PROD*	–0.03	–0.03	–0.06	0.13	0.09	0.04	–0.33	–0.04	–0.01	–0.18	0.03	0.03	1							
14. *DEBT*	0.01	–0.02	–0.03	0.09	–0.01	0.04	0.07	0.03	–0.07	0.03	–0.01	0.03	–0.07	1						
15. *DENSI*	0.00	0.02	–0.14	0.54	0.33	0.10	–0.02	–0.04	0.15	0.06	–0.01	0.03	0.08	0.02	1					
16. *CITY_WAGE*	0.01	0.01	–0.14	0.64	0.30	0.34	–0.07	–0.09	0.18	0.13	0.02	0.09	0.16	0.10	0.45	1				
17. *LCOMP*	0.06	–0.04	–0.09	–0.07	–0.01	–0.04	–0.25	0.00	–0.08	–0.08	0.00	–0.01	0.11	–0.02	–0.07	–0.05	1			
18. *INDU_GR*	–0.12	0.02	0.02	0.04	0.02	0.02	0.00	–0.03	0.04	0.04	0.00	0.00	0.00	–0.02	0.03	0.05	–0.03	1		
19. *INDU_COMP*	–0.02	–0.02	–0.03	0.02	0.01	0.02	0.10	–0.02	0.06	0.14	–0.05	0.00	–0.15	0.01	0.04	0.04	–0.12	0.05	1	
20. *MES*	0.03	0.01	0.00	0.05	–0.02	0.05	0.04	0.02	0.02	–0.12	0.05	0.03	0.24	0.04	0.00	0.10	0.20	0.00	–0.20	1
Mean	0.08	0.10	1.87	2.23	3.91	4.86	4.64	0.02	0.17	0.18	0.08	0.13	5.54	0.56	0.07	9.93	1.60	0.07	433.14	12.99
Std.Dev.	0.27	0.39	2.17	0.54	0.38	1.81	1.00	0.12	0.35	0.34	0.27	0.34	0.97	0.29	0.04	0.39	1.88	0.18	612.28	1.15
Min	0.00	–0.82	0.00	0.03	0.55	2.00	2.08	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	7.41	0.02	–2.00	1.00	8.34
Max	1.00	2.00	85.00	3.15	4.48	9.00	10.61	1.00	1.00	1.00	1.00	1.00	11.55	16.94	0.24	10.81	163.03	1.33	2889.5	18.36

Appendix B. .

See Fig. B1.

Table C1
Results of the moderating effect tests.

	High level (Mean + SD)		Low level (Mean + SD)		Difference	P
	GR	margin	GR	margin		
LQ	–0.3891	–0.0787	–0.5028	–0.1029	0.0242	0.0002
	–0.1891	–0.0556	–0.3028	–0.0708	0.0151	0.0001
	0.0109	–0.0389	–0.1028	–0.0483	0.0094	0.0001
	0.2109	–0.0262	0.0972	–0.0319	0.0057	0.0002
	0.4109	–0.0162	0.2972	–0.0194	0.0033	0.0134
	0.6109	–0.0077	0.4972	–0.0092	0.0015	0.3248
	TP1 = 0.8109		TP2 = 0.6972			
	1.0109	0.0077	0.8972	0.0092	–0.0015	0.5795
	1.2109	0.0162	1.0972	0.0194	–0.0033	0.3832
	1.4109	0.0262	1.2972	0.0319	–0.0057	0.2859
	1.6109	0.0389	1.4972	0.0483	–0.0094	0.2312
	1.8109	0.0556	1.6972	0.0708	–0.0151	0.1964
	2.0109	0.0787	1.8972	0.1029	–0.0242	0.1721
RV	–0.4335	–0.1099	–0.4758	–0.0718	–0.0380	0.0000
	–0.2335	–0.0742	–0.2758	–0.0518	–0.0224	0.0000
	–0.0335	–0.0498	–0.0758	–0.0367	–0.0131	0.0000
	0.1665	–0.0325	0.1242	–0.0251	–0.0075	0.0001
	0.3665	–0.0196	0.3242	–0.0156	–0.0040	0.0134
	0.5665	–0.0092	0.5242	–0.0075	–0.0018	0.3296
	TP1 = 0.7665		TP2 = 0.7242			
	0.9665	0.0092	0.9242	0.0075	0.0018	0.5781
	1.1665	0.0196	1.1242	0.0156	0.0040	0.3635
	1.3665	0.0325	1.3242	0.0251	0.0075	0.2413
	1.5665	0.0498	1.5242	0.0367	0.0131	0.1639
	1.7665	0.0742	1.7242	0.0518	0.0224	0.1126
	1.9665	0.1099	1.9242	0.0718	0.0380	0.0785
UV	–0.4394	–0.0836	–0.4606	–0.0972	0.0136	0.0724
	–0.2394	–0.0591	–0.2606	–0.0670	0.0079	0.0809
	–0.0394	–0.0412	–0.0606	–0.0457	0.0045	0.1016
	0.1606	–0.0277	0.1394	–0.0303	0.0025	0.1729
	0.3606	–0.0171	0.3394	–0.0184	0.0013	0.4026
	0.5606	–0.0082	0.5394	–0.0087	0.0006	0.7506
	TP1 = 0.7606		TP2 = 0.7393			
	0.9606	0.0082	0.9394	0.0087	–0.0006	0.8560
	1.1606	0.0171	1.1394	0.0184	–0.0013	0.7616
	1.3606	0.0277	1.3394	0.0303	–0.0025	0.6874
	1.5606	0.0412	1.5394	0.0457	–0.0045	0.6224
	1.7606	0.0591	1.7394	0.0670	–0.0079	0.5638
	1.9606	0.0836	1.9394	0.0972	–0.0136	0.5111

Note: The tests are based on the estimated results of Model 10.

Appendix C. .

We refer to the proposal in Haans et al. (2016) to test the moderating effects. For the convenience of expression, we consider specialization as an example. The following steps were carried out for testing:

The first step is to compute the turning point of the U-shaped marginal effect curve with high *LQ* (i.e., TP1) and the turning point of the U-shaped marginal effect curve with low *LQ* (i.e., TP2). The second step was to calculate the slopes (margin effects) at a given distance from each turning point. Specifically, assuming that the given distance is a, we obtain TP1–a and TP2–a, after which we separately calculate the slopes when $LQ = Mean + SD$ and $GR =$ TP1–a and when $LQ = Mean–SD$ and $GR =$ TP2–a. The third step is to change the distance to the turning points; that is, we take different values for a and then repeat the second step. The test steps for related variety and unrelated variety were the same as described above. Table C1 shows the test results for the moderating effects based on the estimated results of Model 10.

The results in Table C1 indicate that the absolute value of the slope calculated under high *LQ* is always lower than the absolute value of the corresponding slope calculated under low *LQ*. Moreover, for certain pairs of points, there are significant differences between the absolute values of the slopes calculated under high *LQ* and those calculated under low *LQ*. Even if these pairs of points are mainly located to the left of the turning point, we still have reason to believe that specialization externalities significantly weaken the marginal impact of growth on survival risk. This is because, as stated in the main text, many observations are distributed on the left side of the turning point, which means that greater attention should be paid to the difference between these pairs of points on the left.

For *RV*, at all selected points on either side of the turning point, the absolute values of the slopes calculated under a high *RV* were consistently higher than the corresponding slopes calculated under a low *RV*. Furthermore, there were significant differences between the slopes calculated under high *RV* and those calculated under low *RV* for certain pairs of points. These types of paired points with significant slope differences existed on both sides of the turning point. This proves that related variety externalities significantly strengthen the marginal effect of growth on survival risk; that is, related variety externalities play a significant positive moderating role.

For *UV*, at all selected points on either side of the turning point, the absolute values of the slopes calculated under high *UV* were lower than those calculated under low *UV*. However, for most of the selected points, the slopes calculated under high *UV* were not significantly different from the corresponding slopes calculated under low *UV*. Hence, the negative moderating effect of *UV* was generally insignificant.

References

Aarstad, J., Kvitastein, O. A., & Jakobsen, S. (2016). Related and unrelated variety as regional drivers of enterprise productivity and innovation: A multilevel study. *Research Policy, 45*(4), 844–856.

Acs, Z. J., Armington, C., & Zhang, T. (2007). The determinants of new-firm survival across regional economies: The role of human capital stock and knowledge spillover. *Papers in Regional Science, 86*(3), 367–391.

Adner, R. (2006). Match your innovation strategy to your innovation ecosystem. *Harvard Business Review, 84(4), 98–107*, 148.

Agarwal, R. (1997). Survival of firms over the product life cycle. *Southern Economic Journal, 63*(3), 571–584.

Aldrich, H., & Auster, E. R. (1986). Even dwarfs started small: Liabilities of age and size and their strategic implications. *Research in Organizational Behavior, 8*, 165–198.

Ascani, A., Bettarelli, L., Resmini, L., & Balland, P. (2020). Global networks, local specialisation and regional patterns of innovation. *Research Policy, 49*(8), Article 104031.

Audretsch, D. B. (1995). Innovation, growth and survival. *International Journal of Industrial Organization, 13*(4), 441–457.

Audretsch, D. B., & Lehmann, E. E. (2005). Does the knowledge spillover theory of entrepreneurship hold for regions? *Research Policy, 34*(8), 1191–1202.

Audretsch, D. B., & Mahmood, T. (1994). Firm selection and industry evolution: The post-entry performance of new firms. *Journal of Evolutionary Economics, 4*(3), 243–260.

Audretsch, D., Guo, X., Hepfer, A., Menendez, H., & Xiao, X. (2016). Ownership, productivity and firm survival in China. *Economia E Politica Industriale, 43*(1), 67–83.

Baldwin, J., & Yan, B. (2011). The death of Canadian manufacturing plants: Heterogeneous responses to changes in tariffs and real exchange rates. *Review of World Economics, 147*(1), 131–167.

Barbieri, N., Perruchas, F., & Consoli, D. (2020). Specialization, diversification, and environmental technology life cycle. *Economic Geography, 96*(2), 161–186.

Baum, J., & Amburgey, T. (2002). Organizational ecology. In J. Baum (Ed.), *Blackwell Companion to Organizations* (pp. 304–326). Malden, MA: Blackwell.

Beaudry, C., & Schiffauerova, A. (2009). Who's right, Marshall or Jacobs? The localization versus urbanization debate. *Research Policy, 38*(2), 318–337.

Boschma, R. (2005). Proximity and innovation: A critical assessment. *Regional Studies, 39* (1), 61–74.

Boschma, R. (2015). Do spinoff dynamics or agglomeration externalities drive industry clustering? A reappraisal of Steven Klepper's work. *Industrial and Corporate Change, 24*(4), 859–873.

Boschma, R. (2017). Relatedness as driver of regional diversification: A research agenda. *Regional Studies, 51*(3), 351–364.

Boschma, R., Coenen, L., Frenken, K., & Truffer, B. (2017). Towards a theory of regional diversification: Combining insights from Evolutionary Economic Geography and Transition Studies. *Regional Studies, 51*(1), 31–45.

Boschma, R., Minondo, A., & Navarro, M. (2012). Related variety and regional growth in Spain. *Papers in Regional Science, 91*(2), 241–256.

Boschma, R., Minondo, A., & Navarro, M. (2013). The emergence of new industries at the regional level in Spain: A proximity approach based on product relatedness. *Economic Geography, 89*(1), 29–51.

Boschma, R., & Iammarino, S. (2009). Related Variety, Trade Linkages, and Regional Growth in Italy. *Economic Geography, 85*(3), 289–311.

Bougheas, S., Mizen, P., & Yalcin, C. (2006). Access to external finance: Theory and evidence on the impact of monetary policy and firm-specific characteristics. *Journal of Banking & Finance, 30*(1), 199–227.

Bruderl, J., & Schussler, R. (1990). Organizational mortality: The liabilities of newness and adolescence. *Administrative Science Quarterly, 35*(3), 530.

Calvino, F., Criscuolo, C., & Menon, C. (2015). Cross-country evidence on start-up dynamics. OECD Science, Technology and Industry Working Papers, No. 2015/06.

Castaldi, C., Frenken, K., & Los, B. (2015). Related variety, unrelated variety and technological breakthroughs: An analysis of US state-level patenting. *Regional Studies, 49*(5), 767–781.

Chen, X., Zou, H., & Wang, D. T. (2009). How do new ventures grow? Firm capabilities, growth strategies and performance. *International Journal of Research in Marketing, 26* (4), 294–303.

Churchill, N. C., & Mullins, J. (2001). How fast can your company afford to grow? *Harvard Business Review, 79*(5), 135–143.

Ciccone, A., & Hall, R. E. (1996). Productivity and the density of economic activity. *American Economic Association, 86*(1), 54–70.

Coad, A., Daunfeldt, S., Johansson, D., & Wennberg, K. (2014). Whom do high-growth firms hire? *Industrial and Corporate Change, 23*(1), 293–327.

Coad, A., Frankish, J. S., Roberts, R. G., & Storey, D. J. (2016). Predicting new venture survival and growth: Does the fog lift? *Small Business Economics, 47*(1), 217–241.

Coad, A., Frankish, J. S., & Storey, D. J. (2020). Too fast to live? Effects of growth on survival across the growth distribution. *Journal of Small Business Management, 58*(3), 544–571.

Coad, A., Frankish, J., Roberts, R. G., & Storey, D. J. (2013). Growth paths and survival chances: An application of Gambler's Ruin theory. *Journal of Business Venturing, 28* (5), 615–632.

Comanor, W. S., & Wilson, T. A. (1967). Advertising market structure and performance. *Review of Economics and Statistics, 49*(4), 423–440.

Content, J., Frenken, K., & Jordaan, J. A. (2019). Does related variety foster regional entrepreneurship? *Evidence from European regions. Regional Studies, 53*(11), 1513–1531.

Content, J., & Frenken, K. (2016). Related variety and economic development: A literature review. *European Planning Studies, 24*(12), 2097–2112.

Crespo, J., Suire, R., & Vicente, J. (2014). Lock-in or lock-out? How structural properties of knowledge networks affect regional resilience. *Journal of Economic Geography, 14* (1), 199–219.

Dahl, M. S., & Klepper, S. (2015). Whom do new firms hire? *Industrial and Corporate Change, 24*(4), 819–836.

Dalal, D. K., & Zickar, M. J. (2012). Some common myths about centering predictor variables in moderated multiple regression and polynomial regression. *Organizational Research Methods, 15*(3), 339–362.

de Groot, H. L. F., Poot, J., & Smit, M. J. (2016). Which agglomeration externalities matter most and why? *Journal of Economic Surveys, 30*(4), 756–782.

Delmar, F., McKelvie, A., & Wennberg, K. (2013). Untangling the relationships among growth, profitability and survival in new firms. *Technovation, 33*(8–9), 276–291.

Dollinger, M. J., & Golden, P. A. (1992). Interorganizational and collective strategies in small firms: Environmental effects and performance. *Journal of Management, 18*(4), 695–715.

Dumais, G., Ellison, G., & Glaeser, E. L. (2002). Geographic concentration as a dynamic process. *Review of Economics and Statistics, 84*(2), 193–204.

Dumont, M., Rayp, G., Verschelde, M., & Merlevede, B. (2016). The contribution of start-ups and young firms to industry-level efficiency growth. *Applied Economics, 48*(59), 5786–5801.

Ebert, T., Brenner, T., & Brixy, U. (2019). New firm survival: The interdependence between regional externalities and innovativeness. *Small Business Economics, 53*(1), 287–309.

Ejdemo, T., & Ortqvist, D. (2020). Related variety as a driver of regional innovation and entrepreneurship: A moderated and mediated model with non-linear effects. *Research Policy, 49*(7), Article 104073.

Esteve-Pérez, S., & Mañez-Castillejo, J. A. (2008). The resource-based theory of the firm and firm survival. *Small Business Economics, 30*(3), 231–249.

Fagerberg, J., & Srholec, M. (2022). Capabilities, diversification & economic dynamics in European Regions. *The Journal of Technology Transfer*, 1–22.

Frenken, K., Oort, F. V., & Verburg, T. (2007). Relate variety, unrelated variety and regional economic growth. *Regional Studies, 41*(5), 685–697.

Geroski, P. A., Mata, J., & Portugal, P. (2010). Founding conditions and the survival of new firms. *Strategic Management Journal, 31*(5), 510–529.

Gilbert, B. A., McDougall, P. P., & Audretsch, D. B. (2016). New venture growth: A review and extension. *Journal of Management, 32*(6), 926–950.

Gjerløv-Juel, P., & Guenther, C. (2019). Early employment expansion and long-run survival. *Journal of Business Venturing, 34*(1), 80–102.

Glaeser, E. L., Kallal, H. D., Scheinkman, J. A., & Shleifer, A. (1992). Growth in cities. *Journal of Political Economy, 100*(6), 1126–1152.

Glaeser, E. L., & Kohlhase, J. E. (2003). Cities, regions and the decline of transport costs. *Papers in Regional Science, 83*(1), 197–228.

Grillitsch, M., Asheim, B., & Trippl, M. (2018). Unrelated knowledge combinations: The unexplored potential for regional industrial path development. *Cambridge Journal of Regions, Economy and Society, 11*(2), 257–274.

Guo, Q., Zhu, S., & He, C. (2018). Industry relatedness and new firm survival in China: Do regional institutions and firm heterogeneity matter? *Post-Communist Economies, 30*(6), 735–754.

Haans, R. F. J., Pieters, C., & He, Z. (2016). Thinking about U: Theorizing and testing U- and inverted U-shaped relationships in strategy research. *Strategic Management Journal, 37*(7), 1177–1195.

Harrison, A., & McMillan, M. S. (2003). Does direct foreign investment affect domestic credit constraints? *Journal of International Economics, 61*(1), 73–100.
He, C., Guo, Q., & Rigby, D. (2017). What sustains larger firms? Evidence from Chinese manufacturing industries. *The Annals of Regional Science, 58*(2), 275–300.
He, C., & Yang, R. (2016). Determinants of firm failure: Empirical evidence from China. *Growth and Change, 47*(1), 72–92.
Heckman, J., & Singer, B. (1984). A method for minimizing the impact of distributional assumptions in econometric models for duration data. *Econometrica: Journal of the Econometric Society, 52*(2), 271–320.
Hess, W., & Persson, M. (2012). The duration of trade revisited. *Empirical Economics, 43*(3), 1083–1107.
Howell, A. (2015). 'Indigenous' innovation with heterogeneous risk and new firm survival in a transitioning Chinese economy. *Research Policy, 44*(10), 1866–1876.
Howell, A. (2017). Marshallian sources of relatedness and their effects on firm survival and subsequent success in China. *Economic Geography, 93*(4), 346–366.
Howell, A., He, C., Yang, R., & Fan, C. C. (2018). Agglomeration, (un)-related variety and new firm survival in China: Do local subsidies matter? *Papers in Regional Science, 97*(3), 485–500.
Hu, C., Xu, Z., & Yashiro, N. (2015). Agglomeration and productivity in China: Firm level evidence. *China Economic Review, 33*, 50–66.
Huang, Y., Fang, Y., & Gu, G. (2021). Innovation effect and regional difference of related variety: An empirical study based on prefecture-level city data of China. *Applied Spatial Analysis and Policy, 15*(2), 441–454.
Jacobs, J. (1969). The economy of cities. New York: Random House.
Janssen, M. J., & Frenken, K. (2019). Cross-specialisation policy: Rationales and options for linking unrelated industries. *Cambridge Journal of Regions, Economy and Society, 12*(2), 195–212.
Jovanovic, B. (1982). Selection and the evolution of industry. *Econometrica, 50*(3), 649–670.
Karabag, S. F. (2019). Factors impacting firm failure and technological development: A study of three emerging-economy firms. *Journal of Business Research, 98*, 462–474.
Karlsson, C., Rickardsson, J., & Wincent, J. (2021). Diversity, innovation and entrepreneurship: Where are we and where should we go in future studies? *Small Business Economics, 56*(2), 759–772.
Khanna, T., & Palepu, K. (2000). The future of business groups in emerging markets: Long-run evidence from Chile. *Academy of Management Journal, 43*(3), 268–285.
Kim, J. D. (2018). Is there a startup wage premium? *Evidence from MIT graduates. Research Policy, 47*(3), 637–649.
Kosfeld, R., & Mitze, T. (2020). The role of R&D-intensive clusters for regional competitiveness. MAGKS Joint Discussion Paper Series in Economics, No. 01–2020.
Lin, H., Li, H., & Yang, C. (2011). Agglomeration and productivity: Firm-level evidence from China's textile industry. *China Economic Review, 22*(3), 313–329.
Lindner, T., Puck, J., & Verbeke, A. (2020). Misconceptions about multicollinearity in international business research: Identification, consequences, and remedies. *Journal of International Business Studies, 51*(3), 283–298.
Lo Turco, A., & Maggioni, D. (2016). On firms' product space evolution: The role of firm and local product relatedness. *Journal of Economic Geography, 16*(5), 975–1006.
Love, I. (2003). Financial development and financing constraints: International evidence from the structural investment model. *Review of Financial Studies, 16*(3), 135–161.
Low, S. A., & Brown, J. P. (2017). Manufacturing plant survival in a period of decline. *Growth and Change, 48*(3), 297–312.
Lu, J., & Tao, Z. (2009). Trends and determinants of China's industrial agglomeration. *Journal of Urban Economics, 65*(2), 167–180.
Lu, R., Song, Q., Xia, T., Lv, D., Reve, T., & Jian, Z. (2021). Unpacking the U-shaped relationship between related variety and firm sales: Evidence from Japan. *Papers in Regional Science, 100*(5), 1136–1157.
Ma, H., Qiao, X., & Xu, Y. (2015). Job creation and job destruction in China during 1998–2007. *Journal of Comparative Economics, 43*(4), 1085–1100.
Manova, K., Wei, S., & Zhang, Z. (2015). Firm exports and multinational activity under credit constraints. *Review of Economics and Statistics, 97*(3), 574–588.
Marshall, A. (1920). Principles of economics. London: Macmillan.
Mata, J. (1993). Entry and type of entrant: Evidence from Portugal. *International Journal of Industrial Organization, 11*(1), 101–122.
Mata, J., Portugal, P., & Guimarães, P. (1995). The survival of new plants: Start-up conditions and post-entry evolution. *International Journal of Industrial Organization, 13*(4), 459–481.
Mata, J., & Portugal, P. (2002). The survival of new domestic and foreign-owned firms. *Strategic Management Journal, 23*(4), 323–343.
McCann, B. T., & Folta, T. B. (2008). Location matters: Where we have been and where we might go in agglomeration research. *Journal of Management, 34*(3), 532–565.
Mi, Z., Shang, Y., & Zeng, G. (2022). The impact of knowledge base on technological innovation of emerging industries from the perspective of related variety: A case study of China's fuel cell industry. *Growth and Change, 53*(1), 57–75.
Moretti, E. (2004). Estimating the social return to higher education: Evidence from longitudinal and repeated cross-sectional data. *Journal of Econometrics, 121*(1–2), 175–212.
Neffke, F., Henning, M., & Boschma, R. (2011). How do regions diversify over time industry relatedness and the development of new growth paths in regions. *Economic Geography, 87*(3), 237–265.
Nielsen, B. B., Asmussen, C. G., Weatherall, C. D., & Lyngemark, D. H. (2021). Marshall vs Jacobs agglomeration and the micro-location of foreign and domestic firms. *Cities, 117*, Article 103322.
Nooteboom, B., Van Haverbeke, W., Duysters, G., Gilsing, V., & van den Oord, A. (2007). Optimal cognitive distance and absorptive capacity. *Research Policy, 36*(7), 1016–1034.
Patel, P. C., Pearce, J. A., & Guedes, M. J. (2019). The survival benefits of service intensity for new manufacturing ventures: A resource-advantage theory perspective. *Journal of Service Research, 22*(4), 352–370.
Pe'Er, A., & Keil, T. (2013). Are all startups affected similarly by clusters? Agglomeration, competition, firm heterogeneity, and survival. *Journal of Business Venturing, 28*(3), 354–372.
Pe'Er, A., Vertinsky, I., & Keil, T. (2016). Growth and survival: The moderating effects of local agglomeration and local market structure. *Strategic Management Journal, 37*(3), 541–564.
Penrose, E. T. (1959). The theory of the growth of the firm. New York: John Wiley & Sons.
Phillips, B. D., & Kirchhoff, B. A. (1989). Formation, growth and survival; small firm dynamics in the U.S. economy. *Small Business Economics, 1*, 65–74.
Pierce, J. R., & Aguinis, H. (2013). The Too-Much-of-a-Good-Thing effect in management. *Journal of Management, 39*(2), 313–338.
Plummer, L. A., & Acs, Z. J. (2014). Localized competition in the knowledge spillover theory of entrepreneurship. *Journal of Business Venturing, 29*(1), 121–136.
Power, B., Doran, J., & Ryan, G. (2019). The effect of agglomeration economies on firm deaths: A comparison of firm and regional based approaches. *Urban Studies, 56*(16), 3358–3374.
Qu, T., & Harris, R. (2019). Does support from government help firms survive? Evidence on financial and political assistance in China, 1998–2007. *Applied Economics, 51*(5), 528–541.
Ragatz, G. L., Handfield, R. B., & Scannell, T. V. (1997). Success factors for integrating suppliers into new product development. *Journal of Product Innovation Management, 14*(3), 190–202.
Saito, H., & Wu, J. (2016). Agglomeration, congestion, and U.S. regional disparities in employment growth. *Journal of Regional Science, 56*(1), 53–71.
Sapienza, H. J., Autio, E., George, G., & Zahra, S. A. (2006). A capabilities perspective on the effects of early internationalization on firm survival and growth. *Academy of Management Review, 31*(4), 914–933.
Shaver, J. M., & Flyer, F. (2000). Agglomeration economies, firm heterogeneity, and foreign direct investment in the United States. *Strategic Management Journal, 21*(12), 1175–1193.
Shu, C., & Simmons, S. A. (2018). Firm survival in traded industries: Does localization moderate the effects of founding team experience? *Small Business Economics, 50*(3), 643–655.
StataCorp, L. P. (2013). Stata glossary and index. Texas: Stata Press.
Tavassoli, S., Obschonka, M., & Audretsch, D. B. (2021). Entrepreneurship in cities. *Research Policy, 50*(7), Article 104255.
Tomasz, M., & Pawel, D. (2021). Related and unrelated variety vs. basic labour market variables-regional analysis for Poland. *European Planning Studies, 29*(2), 221–240.
Tsvetkova, A., Thill, J., & Conroy, T. (2016). Firm patenting activity, metropolitan innovative environment and their effects on business survival in a high-tech industry. MPRA Paper 75783.
Wang, J., Yang, Z., & Qian, X. (2020). Driving factors of urban shrinkage: Examining the role of local industrial diversity. *Cities, 99*, Article 102646.
Wennberg, K., Delmar, F., & McKelvie, A. (2016). Variable risk preferences in new firm growth and survival. *Journal of Business Venturing, 31*(4), 408–427.
Whited, R. L., Swanquist, Q. T., Shipman, J., & Moon, J. (2021). Out of control: The (over) use of controls in accounting research. *The Accounting Review, 97*(3), 395–413.
Wiersema, M. F., & Bowen, H. P. (2009). The use of limited dependent variable techniques in strategy research: Issues and methods. *Strategic Management Journal, 30*(6), 679–692.
Woo, L., Assaf, A. G., Josiassen, A., & Kock, F. (2019). Internationalization and hotel performance: Agglomeration-related moderators. *International Journal of Hospitality Management, 82*, 48–58.
Yang, N., Liu, Q., & Qi, Y. (2020). Does (un)-related variety promote regional innovation in China? Industry versus services sector. *Chinese Management Studies, 14*(3), 769–788.
Yi, C., & Nam, J. (2019). Interaction effects between the agglomerative externalities affecting the survival of small startups. *Growth and Change, 50*(4), 1311–1337.
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.
Zhang, D., & Xu, G. (2019). Does government subsidy affect firm survival? Evidence from Chinese manufacturing firms. *Emerging Markets Finance and Trade, 55*(11), 2628–2651.
Zhang, H., Amankwah-Amoah, J., & Beaverstock, J. (2019). Toward a construct of dynamic capabilities malfunction: Insights from failed Chinese entrepreneurs. *Journal of Business Research, 98*, 415–429.
Zhou, H., & van der Zwan, P. (2019). Is there a risk of growing fast? The relationship between organic employment growth and firm exit. *Industrial and Corporate Change, 28*(5), 1297–1320.

Zhu, H., Dai, Z., & Jiang, Z. (2017). Industrial agglomeration externalities, city size, and regional economic development: Empirical research based on dynamic panel data of 283 cities and GMM method. *Chinese Geographical Science, 27*(3), 456–470.

Zhu, S., He, C., & Luo, Q. (2019). Good neighbors, bad neighbors: Local knowledge spillovers, regional institutions and firm performance in China. *Small Business Economics, 52*(3), 617–632.

Zimmerman, M. A., & Zeitz, G. J. (2002). Beyond survival: Achieving new venture growth by building legitimacy. *Academy of Management Review, 27*(3), 414–431.

Ruiqi Cheng is a PhD student at Southwestern University of Finance and Economics. Her research is centered on business economics. She is particularly interested in firm growth and the role of policy.

Peng Yuan is a professor of industrial economics at Southwestern University of Finance and Economics. His research is centered on strategy economics and firm development. He is particularly interested in agglomeration economics.

Gongxiong Jiang is a PhD student at Southwestern University of Finance and Economics. His research interests include firm location strategy and regional innovation.