Three Essays On
Chinese SME Innovation Heterogeneity
From A Process Perspective

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Declaration of Co-authorship and Publications

This dissertation includes three individual articles, of which two were completed independently and one was written in collaboration with a co-author.

First article: **Non-R&D innovation in SMEs: is there complementarity or substitutability between internal and external innovation sourcing strategies?**

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Second article: **Does combining different types of innovation always improve SME performance? An analysis of innovation complementarity**

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Third article: **SME innovation patterns identified from a process perspective: linking innovation to SME performance**

- I am the first author and Hamdy Abdelaty is the co-author.
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Time flies by so fast that I can hardly believe it has been nearly five years since I started my PhD. Before this period, I had been studying finance for seven years. Due to the past educational experience, I had no knowledge about innovation research and did not realize the difficulties in accessing relevant data, until I set out to undertake the research. Despite limited research resources, I have achieved my PhD goal that is to publish at least two SSCI articles. My achievements would have been impossible without the help of the following people to whom I must express gratitude.

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Content

List of Figures

List of Tables

List of Abbreviations

2SLS	Two-Stage Least Squares
AC	Absorptive Capacity
CATPCA	Categorical Principal Component Analysis
EFA	Exploratory Factor Analysis
ES	Chinese Manufacturing Enterprise Survey
OI	Open Innovation
OLS	Ordinary Least Squares
R&D	Research and Development
RBV	Resource-Based View
RMT	Resource Management Theory
SMEs	Small- and Medium-Sized Enterprises
VRIN	Valuable, Rare, Inimitable, and Non-substitutable

Chapter 1 Introduction

1.1 Motivation and Research Objective

The effort into this dissertation is motived by the failures of China's current policies for small- and medium-sized enterprises (SMEs) and the research gaps identified from the literature. Accordingly, this dissertation aims to bridge the research gaps, producing results that have practical implications for innovation policy. The section 1.1 firstly outlines SME policies in China and then presents a brief literature review to account for the research motivations from both policies and literature. In response to the motivations, this section finally points out the research objectives.

1.1.1 Motivation from Policies

SMEs are the fundamental forces driving China's innovation, productivity, and economic growth. By the end of 2021, 48 million SMEs in China, accounting for around 99% of all active enterprises, play an important role in the development of technological innovation as they create 65% of invention patents, 75% of technological innovation, and 80% of new products.[1] At the same time, these SMEs contribute over 50% of national tax revenues, over 60% of gross domestic product, and over 80% of cities' and towns' employment.[2]

Chinese government has been aware of the central status of SMEs in national innovation development and the importance of innovation for strengthening SMEs' core competencies and improving their performance, and thus has designed and implemented specific innovation policies to promote and support innovation in SMEs (Zhao et al., 2021; Zhao and Ye, 2023). China's government departments and organizations involved in the SME innovation policy system include the national people's congress, the general office of the state council, and various ministries such as the national development and reform commission, the ministry of industry and information technology, the ministry of science and technology, and the ministry of

[1] The data is available at http://www.myasky.com/smes-positions.html (accessed on April 2023).
[2] The source of data is the ministry of industry and information technology of the people's republic of China.

finance (Li et al., 2017). According to topics, China's SME innovation policies can be classified into financial policies, commercial innovation support policies, human resource policies, and legal policy (Jia et al., 2020). Financial policies focus on taking advantage of financing guarantee, tax credit, listing services, and technology and innovation funds to meet the financial needs of innovating SMEs (Wonglimpiyarat, 2015; Wang and Kesan, 2022). Commercial innovation support policies aim at creating science and technology parks, incubation centers, and industrial clusters, providing well-functioning platforms for facilitating innovation activities in SMEs (Jia et al., 2020). Human resource policies concentrate on increasing the employment of university graduates, rewarding the entrepreneurship of students and researchers, and improving the assessment of employees' skills (Wang and Li, 2019). The only legal policy concerning SMEs is the SME promotion law implemented in 2003, which contains several provisions for supporting SME innovation (Du and Banwo, 2015).

Due to the massive number of SMEs and their differences in innovation capabilities, China's government decides to prioritize the development of SMEs with higher innovation capabilities and foster innovating SMEs at three levels: innovative SMEs (local level), specialized and sophisticated SMEs that produce new and unique products (local level), and little giants of the specialized and sophisticated SMEs that produce new and unique products (national level). The little giants consist of a group of SMEs with the highest innovation capabilities, which can offer a partial view of the innovation development of SMEs. Since 2019, China's government has been devoted to nurturing the little giants, and some targeted policies have been formulated and issued to support that particular group of SMEs in terms of funding, personnel, and intellectual property rights protection. As of 2021, China has recognized 4,762 national-level little giants, of which 74% in manufacturing and the rest in scientific research and technology services.[3] The little giants, who represent the most innovative group of Chinese SMEs, provide a lens through which to perceive the performance benefits of innovation in Chinese SMEs. In 2021, the little giants achieved 11.6 percent points higher increase

[3] The data is available at https://www.bworldonline.com/opinion/2022/04/04/440080/good-luck-trying-to-sanction-chinas-4762-little-giants/ (accessed on April 2023).

rate in revenues than SMEs above designated size and also earned 3.4 times the average profits of SMEs above designated size.[4] This implies that the little giants experience better economic performance, which can be attributed to the contribution of innovation to productivity.

The fact that innovative SMEs attain superior performance confirms the necessity of policies aiming at increasing the innovativeness of SMEs. As discussed above, a SME innovation policy system has been basically formed, in which various government departments put effort into supporting SME innovation by developing financial policies, commercial innovation support policies, human resource policies, and the SME promotion law. However, some SMEs may not be properly supported due to the policy biases as argued in the following. One bias is that China's government pays more attention to SMEs who perform research and development (R&D) and gives the policy preference to R&D-performing SMEs. For example, in preferential tax policies, the super deduction of R&D expenditures especially benefits R&D-performing SMEs, stimulating and expanding R&D activities in SMEs. Furthermore, the quantitative indicators of R&D expenditures are commonly used to determine the policy support objects, which results in the focus of corresponding policies on R&D-performing SMEs. For example, R&D expenditure to revenue ratio is one of the indicators that are used to identify the little giants. These R&D-centered policies neglect non-R&D-performing SMEs, accounting for the most of SMEs, who can innovate by learning by doing, using, and interacting. Another bias is that China's government puts particular emphasis on key manufacturing areas such as next-generation information technology, aerospace and aeronautical equipment, and new-energy vehicles, which receive highest priority in policy support. For example, China's SME development fund leads investments in strategic industries that are of high importance for national development. Another example is that SMEs with the priority technologies are in an advantageous position when recognizing the little giants. In these cases, SMEs in medium- and low-tech industries are ignored and they find themselves difficult to access policy resources

[4] The data is available at http://www.gov.cn/xinwen/2022-09/14/content_5709685.htm (accessed on April 2023).

albeit their innovation potentials. In addition to the biased policies, general policies applicable to all SMEs do not take individual SMEs' characteristics into account and may thus fail to meet their specific needs for innovation. Although Chinese government has grouped innovating SMEs by three levels of innovation capabilities, the indicators used to measure innovation capabilities are too limited to distinguish SMEs comprehensively, meaning that the corresponding policies do not address the characteristic differences among SMEs at the same level.

Overall, China's current SME innovation policy system lacks sufficient targeted policies to effectively support SMEs with different innovation characteristics. The policy biases towards R&D-performing and high-tech SMEs weaken the support for SMEs who innovate in non-R&D-based ways or in medium- and low-tech industries. On the other hand, the relevance of SME innovation policies is weak as they do not adequately reflect the differences in innovation characteristics among SMEs. These failures of China's SME innovation policies call for the research on Chinese SME innovation heterogeneity without emphasizing R&D and high-tech industries.

1.1.2 Motivation from Literature: Research Gaps

As mentioned earlier, China's SME innovation policy has a bias towards SMEs who undertake R&D activities, ignoring SMEs who innovate without formal R&D. The importance of R&D for innovation has been widely recognized (Mairesse and Mohnen, 2004; Ulku, 2007; Audretsch and Belitski, 2020). However, SMEs are less likely to invest in R&D because they suffer from resource constraints and scale limitation (Ortega-Argilés et al., 2009; Rammer et al., 2009). As a result, SMEs often introduce innovation without R&D and even R&D-based SMEs have to rely on non-R&D activities, suggesting that that non-R&D activities play a critical role in innovation (Raymond and St-Pierre, 2010; Hervas-Oliver et al., 2011; Moilanen et al., 2014; Thomä and Zimmermann, 2020). Although various non-R&D activities have been documented in the literature, including external knowledge sources (e.g., interfirm collaborations, technology acquisition, and inward technology licensing) and internal informal learning activities (e.g., training and experience-based learning) (Santamaría et al., 2009; Lee and Walsh, 2016), little fine-grained research has been carried out to investigate how non-R&D activities drive innovation in SMEs. In terms of the separate impact of non-R&D activities on innovation, little is known about the differences between R&D and non-R&D SMEs and few studies distinguish between product and process innovation (the exceptions are Santamaría et al., 2009; Barge-Gil et al., 2011; Hervas-Oliver et al., 2011). Similarly, in analyzing the combined impact of different activities on innovation, previous research rarely splits the sample of firms according to their R&D decisions and neglects the distinctions between product and process innovation. In particular, regarding the interplay between internal and external activities, empirical literature has concentrated on internal R&D as the only measure of internal efforts, without considering internal activities beyond formal R&D (Cassiman and Veugelers, 2006; Hagedoorn and Wang, 2012; Noseleit and de Faria, 2013), which increases research interests in the analysis of the relationship between internal and external innovation strategies composed of non-R&D activities. Therefore, additional research efforts are needed to focus on non-R&D activities to analyze how innovation activities individually and jointly affect innovation types by distinguishing innovation types and SMEs with different R&D decisions. Such research not only allows to identify the internal and external activities that lead to SME innovation heterogeneity on the dimension of innovation activities (innovation inputs), but also deepens our knowledge of heterogeneous importance of the activities for innovation, pointing out the critical activities for each group of SMEs.

The outputs of innovation activities are a multitude of innovation types that affect SME performance. A lot of attempts have been made to investigate the impact of innovation on firm performance (Gunday et al., 2011; Hashi and Stojčić, 2013; Wadho and Chaudhry, 2018; Ramadani et al., 2019). These studies, however, focus on technological types of innovation, i.e., product and process innovation, ignoring the role of organizational innovation (Damanpour and Aravind, 2012; Camisón and Villar-López, 2014). Another limitation of these studies is that they overemphasize the distinction between different innovation types and consider them distinct phenomena driving firm performance separately. In fact, technological innovation types are closely interrelated and can generate a joint impact on firm performance. Product innovation might trigger cost-reducing process innovation to satisfy consumer needs at a lower cost (Nahm and Steinfeld, 2014). In the same vein, process innovation might result in product innovation when manufacturing processes are significantly changed for the production of new products (Zhang et al., 2017). Hullova et al. (2016, 2019) show seven types of interplays between product and process innovation. Organizational innovation as the most important form of non-technological innovation favors the development of technological innovation (Camison and Villar Lopez, 2010; Mothe and Uyen Nguyen Thi, 2010; Anzola-Román et al., 2018). At the same time, technological innovation needs non-technological innovation in support of its implementation (Schmidt and Rammer, 2007; Radicic and Djalilov, 2019; Azar and Ciabuschi, 2017). A recent stream of empirical research has investigated how the simultaneous introduction of different innovation types shapes firm performance (Ballot et al., 2015; Guisado-González et al., 2017; Lee et al., 2019; Donbesuur et al., 2020), but Chinese SMEs have received little attention in the relevant literature. Taking account of the above, a further attempt should be made to analyze the effects on Chinese SMEs' performance of different combinations of technological and organizational innovation. In doing so, technological and non-technological types of innovation can be recognized that lead to SME innovation heterogeneity on the dimension of innovation types (innovation outputs) and the knowledge can be deepened on how SME performance varies with heterogeneous combinations of innovation types.

After elaborating innovation activities and innovation types, there has been an understanding of the sources contributing to SME innovation heterogeneity. As discussed before, China's current SME innovation policy system requires policies targeted towards addressing SMEs with different innovation characteristics in order to meet the specific needs of certain SMEs. This drives us to group SMEs into different innovation patterns to manage and interpret the SME heterogeneity in their innovation behavior. No work has been done to develop the innovation taxonomies of Chinese SMEs. In terms of SMEs in western countries, the existing research is limited to identifying their innovation patterns according to either innovation activities or innovation types (De Jong and Marsili, 2006; Evangelista and Vezzani, 2010; Brunswicker and Vanhaverbeke, 2015; Hervas-Oliver et al., 2016a; Hervas-Oliver et al., 2020; Thomä and Zimmermann, 2020; Runst and Thomä, 2022). SMEs' different innovation processes are shaped by innovation activities (the inputs) and innovation types (the outputs), which have been considered as the sources of SME innovation heterogeneity. Therefore, from the innovation process perspective, SME innovation patterns can be identified in a comprehensive way, indicating how SMEs conduct innovation activities and how SMEs introduce innovation types. These identified innovation patterns can be used to analyze the relationships between the patterns of innovation activities and innovation types and SME performance. The model proposed by Crepon, Duguet, and Mairesse (1998) is extensively used in empirical research to investigate to what extent innovation inputs relate to innovation outputs and productivity (Hall et al., 2009; Baumann and Kritikos, 2016; Wadho and Chaudhry, 2018; Edeh and Acedo, 2021). Most of the empirical literature uses R&D to represent the innovation inputs and focuses on different innovation outputs separately. Additional analysis of SME innovation process is needed to go beyond R&D and individual innovation types, using the identified patterns of innovation inputs and outputs. This analysis not only synthesizes SME innovation heterogeneity by providing a complete view of innovation patterns, but also derives the practical implications of innovation patterns from the link between innovation and SME performance.

1.1.3 Research Objective

The policy failures and the research gaps motivate the research to analyze and synthesize SME innovation heterogeneity. By taking a closer look at innovation activities and innovation types and grasping SME innovation heterogeneity from the process perspective, this dissertation guides targeted policy design and fills three research gaps identified in the aforementioned literature: (1) first, prior studies focus overly on R&D as the main driver of innovation, neglecting the role of non-R&D activities; (2) second, the productivity of different combinations of innovation types remains under-researched in the literature; (3) third, past research neither identifies

Chinese SMEs' patterns based on both inputs and outputs of the innovation process nor uses these patterns to examine the relationship between innovation and SME performance. This dissertation aims to analyze and synthesize SME innovation heterogeneity by exploring innovation activities and innovation types and their resulting patterns. This research aim is pursued with three empirical objectives: (1) the first is to analyze SME heterogeneity in innovation activities by highlighting a range of non-R&D activities and disentangling their respective and combined effects on technological innovation; (2) the second is to analyze SME heterogeneity in innovation types by exploring different combinations of innovation types and their effects on SME performance; (3) the third is to synthesize SME heterogeneity by identifying SME patterns of innovation activities and innovation types and use these patterns to explore the relationship between innovation and SME performance. The three empirical objectives and the research aims are outlined in Figure 1.1 in section 1.4.

1.2 Theoretical Background

The resource-based view (RBV) provides the theoretical basis for all three articles in this dissertation. The principal development of the RBV was under way in the last century (Kraaijenbrink et al., 2010). Starting with Wernerfelt's (1984) seminal work, the RBV has evolved into a substantial literature, contributed by many scholars, such as Barney (1986a, 1986b, 1991), Dierickx and Cool (1989), Conner (1991), Mahoney and Pandian (1992), and Peteraf (1993). The RBV has been widely applied to the strategy research and it has occupied a prominent position among the theories of strategic management.

According to the RBV, a firm consists of bundles of resources and capabilities that are specific to the firm (Wernerfelt, 1984). These resources and capabilities constitute the firm's tangible and intangible assets, including its physical and financial capital as well as employees' skills and organizational routines (Barney et al., 2001; Lockett et al., 2009). The RBV uses firm-specific resources and capabilities to explain the differences in firm performance. In this view, it is assumed that resources and capabilities are both heterogeneously distributed among firms and imperfectly mobile, leading to a firm's competitive advantage and in turn contributing to its performance (Newbert, 2008). Based on this assumption, the RBV argues that heterogeneous, immobile resources and capabilities have the attributes of being valuable, rare, inimitable, and non-substitutable (VRIN) and hypothesizes that valuable, rare resources and capabilities enable firms to attain a competitive advantage and inimitable, non-substitutable resources and capabilities allow firms to sustain this advantage (Barney, 1991; Newbert, 2008). The VRIN characteristics of resources and capabilities imply that a firm may attain a competitive advantage and improve its performance by combining resources and capabilities in a way that generates VRIN combinations (Barney et al., 2021). This thought is in line with the dynamic-capability view as an extension of the RBV. From the dynamic-capability view, a firm that has the ability to integrate, build, and reconfigure resources and capabilities can extract VRIN combinations from those resources and capabilities and thus obtain a competitive advantage (Teece et al., 1997; Eisenhardt and Martin, 2000). In short, a firm's competitive advantage not only comes from using VRIN resources on their own, but also from constructing VRIN resource combinations (Hervas-Oliver et al., 2015, 2018).

This dissertation takes a firm-level view of SME heterogeneity in the inputs and outputs of an innovation process. This innovation process starts with the use of innovation activities that results in the introduction of innovation types, consequently affecting overall firm performance. From the innovation process perspective, innovation activities facilitate a firm to access the resources required for introducing innovation types and innovation types are the resources exploited by the firm for enhancing its performance. Since the RBV posits that heterogeneous resources are useful for generating a competitive advantage that improves firm performance, it can be used as the basis for understanding how a firm conducts innovation activities to pursue innovation performance and how it introduces innovation types to achieve overall performance. In particular, the RBV and the dynamic-capability view highlight the combined use of innovation activities and the joint application of innovation types. As the RBV and the dynamic-capability view suggest, the integration of diverse innovation activities form complex combinations of innovation activities in which different innovation activities mutually complement and reinforce, strengthening a firm's innovation capabilities and thus innovation performance. Likewise, the combination of various innovation types constructs a complex system of complementary and mutually reinforcing innovation types, leading to higher-order innovation capabilities and thus superior firm performance. Therefore, the RBV offers a theoretical lens through which the existence of SME heterogeneity in innovation activities and innovation types and the differences in innovation performance and overall performance can be explained at the firm level: first, SMEs are thought to purposively adopt heterogeneous innovation activities and innovation types and combine innovation activities and innovation types in heterogeneous ways in order to experience better innovation performance and overall performance, showing the heterogeneity in innovation activities and innovation types; second, the use of heterogeneous innovation activities and innovation types and the heterogeneous combinations of innovation activities and innovation types are considered as the sources of the differences in innovation performance and overall performance.

1.3 Research Design

1.3.1 Methodology

This dissertation encompasses three article to address the research gaps identified from the literature and achieve three research objectives, respectively. All three articles are empirical research based on the phenomena of SME heterogeneity in innovation behavior. In order to describe SMEs' innovation behavior and measure the effect of innovation behavior, statistical and econometric approaches are chosen to quantitatively analyze a large amount of data.

The first article aims to achieve the first empirical objective by showing SME heterogeneity in innovation activities with an emphasis on non-R&D activities and exploring how innovation activities individually and jointly affect innovation types. In terms of quantitative methods used in the first article, this article firstly uses descriptive analysis to outline the heterogeneity in innovation activities conducted by R&D and non-R&D firms to introduce product and process innovation. Furthermore, considering some selectivity problems, this research applies heckprobit model to estimate the individual and joint effects of innovation activities on innovation types. To facilitate the estimation of the joint effect, the research especially uses a multivariate statistical method, namely categorical principal component analysis, to reduce a broad range of innovation activities to a limited number of composite variables that offer comprehensive coverages of the innovation activities. In summary, quantitative methods used in the first article include descriptive analysis, heckprobit regression, and categorical principal component analysis.

The second article attempts to achieve the second empirical objective by showing SME heterogeneity in the combinations of innovation types and exploring the impact of the heterogeneous combinations of innovation types on SME performance. Regarding the methodology of the second article, factor analysis is firstly used to capture different ways that SMEs combine innovation types, resulting in heterogeneous combinations of innovation types. The data on innovation types is then visualized to describe and summarize all combinations of innovation types, presenting the heterogeneity of combining innovation types among SMEs. The productivity of different combinations of innovation types is explored within a conditional supermodularity framework. More specifically, to overcome the endogeneity issue, a multinomial logistic regression and a two-stage least squares regression are jointly estimated to generate the coefficients of the combinations of innovation types, which are subsequently used to test the relationship between the innovation types of each combination based on the conditional supermodularity method. In short, the second article uses several quantitative methods, including factor analysis, descriptive analysis, multinomial logistic regression, two-stage least squares regression, and conditional supermodularity tests.

The third article tries to achieve the third empirical objective by identifying SME innovation patterns according to innovation activities and innovation types and applying these innovation patterns to analyze the link between innovation and SME performance. In the empirical analysis, factor analysis is firstly employed to condense the original variables on innovation activities and innovation types to corresponding factor scores. Using the factor scores as the clustering variables, hierarchical clustering procedures are carried out based on Ward's method with squared Euclidian distance to identify different typologies of innovation patterns. The identified innovation patterns are subsequently used in a structural model with two equations to analyze the relationship between innovation activities, innovation types, and SME performance. Due to the unordered nature of innovation patterns, this study applies a multinomial probit model to examine the relationship between patterns of innovation activities and of innovation types. The effects of the patterns of innovation types on firm performance are investigated by means of ordinary least squares regression. In a word, the third article uses factor analysis, cluster analysis, multinomial probit regression, and ordinary least squares regression.

1.3.2 Data

Three empirical articles in this dissertation share the same database, namely the latest Chinese Manufacturing Enterprise Survey (ES). This survey was carried out by the World Bank, spanning from November 2011 to March 2013. To best represent the entire population, the sample population was selected using stratified random sampling with three levels of stratification: industrial sectors, firm size, and geographic location. The industry stratification includes 11 specific manufacturing categories and one general manufacturing category.[5] The size stratification divides the sample population into three strata: small (5 to 19 employees), medium (20 to 99 employees), and large (more than 99 employees). The stratification by location is defined based on 25 main cities where the economic development is active.[6] The sample size for each level of stratification determines the overall sample size. With 7.5% precision in 90%

[5] The 11 specific manufacturing categories are food, textiles, garments, chemicals, plastics and rubber, nonmetallic mineral products, basic metals, fabricated metal products, machinery and equipment, electronics, and motor vehicles.
[6] The 25 main cities are Beijing, Chengdu, Dalian, Dongguan, Foshan, Guangzhou, Hangzhou, Hefei, Jinan, Luoyang, Nanjing, Nantong, Ningbo, Qingdao, Shanghai, Shenyang, Shenzhen, Shijiazhuang, Suzhou, Tangshan, Wenzhou, Wuhan, Wuxi, Yantai, and Zhengzhou.

confidence intervals, the sample size tends to 120 as population size increases.[7] To account for non-response problems, sample sizes were inflated by 25% and the sample size per manufacturing category was thus set to 150. The ES aimed to interview 3,000 of 20,616 manufacturing and service firms, but finally offers a total sample of 2,700 private sector firms and 148 fully state-owned firms in the manufacturing and service industries. I only use the dataset of 2,700 private sector firms, of which 1,690 are manufacturing firms. The research focus of this dissertation is on manufacturing SMEs. According to the Chinese national industrial classification, manufacturing SMEs in China refer to the manufacturing firms with less than 1,000 employees.[8] In the ES database, manufacturing SMEs are selected based on reported permanent full-time employees. As a result, out of a total 1,690 manufacturing firms, 1,619 firms are SMEs and only 71 firms are large ones. The data of 1,619 manufacturing SMEs serves as the empirical basis for all three articles in this dissertation.

The data from the ES is used for several reasons. First, the ES is particularly useful for the research focusing on SMEs because this database is skewed towards SMEs and includes a large number of manufacturing SMEs. Second, the survey data is still used in recent literature (e.g., Jin et al., 2022; Salike et al., 2022; Zhao and Zhang, 2023), which demonstrates its potential for this research. Third, innovation survey was directed only to manufacturing firms and provides detailed information on innovation in manufacturing firms. More specifically, the ES contains a broad set of data on innovation activities instead of restricting its focus on R&D activities. This allows for the research beyond formal R&D by considering the role of other innovation activities. On the other hand, the ES not only focuses on technological innovation but also on organizational innovation as the most important type of non-technological innovation. In terms of technological innovation, the ES distinguishes between different forms of product innovation and of process innovation. These advantages of the ES make it suitable for comprehensively analyzing innovation outputs by using more types of

[7] World Bank (2009), "Enterprise survey and indicator surveys: sampling methodology", available at: https://www.enterprisesurveys.org/content/dam/enterprisesurveys/documents/methodology/Sampling_Note.pdf (accessed on March 2023).

[8] The Chinese national industrial classification uses both size and revenue to define manufacturing SMEs. I do not use the indicator of revenue because this indicator is not available in the ES.

innovation. Fourth, the ES gives a detailed account of indicators of general firm characteristics, such as firm size and annual sales, which are useful for measuring firm performance. As such, firm performance can be considered in innovation research to investigate the effect of innovation on firm performance.

1.3.3 Variables

This dissertation, consisting of three articles, centres around SME heterogeneous innovation behavior and its performance implications, with the first article concentrating on innovation activities and innovation types, the second article on innovation types and SME performance, and the third article on innovation activities, innovation types, and SME performance at the same time. Therefore, among the different issues investigated by the ES, this dissertation pays attention to three groups of key variables. The first group covers a broad range of innovation activities: (1) Internal R&D is the R&D activities carried out by a firm itself; (2) External R&D is the R&D activities contracted out to other firms; (3) Use of new equipment and technology is the use of new equipment and technology for product/process improvements; (4) In-house development is the development of products/process innovation in-house; (5) Collaboration with suppliers is the development of products/process innovation in collaboration with suppliers; (6) Collaboration with clients is the development of products/process innovation in collaboration with clients; (7) Modification to existing products/Inward technology licensing is the changes to other firms' products for product innovation or the use of other firms' patented technology for process innovation; (8) Internal knowledge sourcing is the use of knowledge acquired from internal sources; and (9) External knowledge sourcing is the use of knowledge acquired from external scientific sources. The second group contains different types of innovation: (1) Quality innovation is the use of new quality control procedures in production or operation; (2) Organizational innovation is the use of new management/administrative procedures; (3) Product development is the introduction of new products or services; (4) Product improvement is the addition of new features to existing products or services; (5) Efficiency innovation is the use of new or significantly improved methods to reduce unit production costs; and (6) Flexibility innovation is the use of new or significantly improved methods to increase production flexibility. The third group includes firm size and total sales to measure firm performance by the natural logarithm of total sales per employee last year.

1.4 Overview of Main Chapters

This dissertation focuses on SME innovation heterogeneity from a process perspective. Most of the literature using survey data considers an innovation process in SMEs and frames the innovation process from innovation activities to innovation types and then from innovation types to SME performance (e.g., Hall et al., 2009; Baumann and Kritikos, 2016; Edeh and Acedo, 2021). Based on the innovation process, SME innovation heterogeneity appears when SMEs implement different innovation processes shaped by various innovation activities and types. In other words, the inputs and outputs of the innovation process constitute the foundation of the presence of SME innovation heterogeneity. From the perspective of innovation process, SME innovation heterogeneity can be analyzed and synthesized by exploring the input and output stages of innovation process and the process as a whole, leading to three articles of this dissertation. In terms of the relationship between the three articles, the first and second articles analyze SME heterogeneity in innovation inputs and outputs, respectively, and the third article complements the first two articles by synthesizing SME heterogeneity in both inputs and outputs of the innovation process through the identification of SME innovation patterns of innovation activities and types. The following paragraphs briefly introduce the research gaps addressed, theoretical background, and main findings of each of the three articles.

The first article is included in Chapter 2 entitled "*Non-R&D innovation in SMEs: is there complementarity or substitutability between internal and external innovation sourcing strategies?*". This article investigates innovation in SMEs based on a set of non-R&D activities. It sheds light on the differences between non-R&D and R&D SMEs in the separate and joint effects of non-R&D activities on product and process innovation. Consequently, it extends the literature by considering non-R&D activities and SME heterogeneity that have been largely ignored in the empirical research (e.g., Cassiman and Veugelers, 2006; Hagedoorn and Wang, 2012; Guo et al., 2017; Xie et al., 2019). A notable proportion of SMEs are considered to innovate without R&D activities as they lack financial and human resources to invest in formal R&D (Rammer et al., 2009). In particular, with the increasing complexity of innovation, SMEs hardly innovate alone and they may adopt inbound open innovation (OI) to acquire external knowledge (Chesbrough, 2003; Dahlander and Gann, 2010; Spithoven et al., 2013). To benefit from inbound OI, the concept of absorptive capacity (AC) suggests that SMEs should develop internal ability to value, assimilate, transform, and exploit the knowledge from external sources (Cohen and Levinthal, 1989, 1990; Zahra and George, 2002). Despite the importance of internal R&D for AC, SMEs can also create AC by undertaking non-R&D activities in-house (Muscio, 2007; Hervas-Oliver et al., 2012; Moilanen et al., 2014). However, compared to non-R&D SMEs, R&D ones generally have stronger AC with the additional R&D efforts (Hervas-Oliver et al., 2021). In addition to the difference in AC between non-R&D and R&D SMEs, process and product innovation differ in terms of their determinants, especially their reliance on R&D (Krzeminska and Eckert, 2016). Based on the differences between non-R&D and R&D SMEs and between product and process innovation, two sets of hypotheses are formulated, one assuming different individual effects of various innovation activities and the other assuming different joint effects of internal and external activities. Drawing on a sub-sample of 1,392 SMEs from the ES, the results show that product and process innovation in non-R&D and R&D SMEs are explained by different innovation activities. R&D SMEs with higher AC are more open to external sources of knowledge than non-R&D SMEs, implying the important role of AC in sourcing external knowledge. Among various external sources of knowledge, R&D SMEs rely on suppliers for process innovation and customers and scientific sources for product innovation, which indicates the importance of the distinction between product and process innovation for identifying key knowledge sources. In terms of the interaction between internal and external activities, substitutability is found for product innovation in non-R&D SMEs and process innovation in R&D SMEs. These findings highlight SME heterogeneity in innovation activities and provide insights into how SMEs choose and combine different innovation activities depending on their R&D decision and innovation types pursued.

After analyzing the input stage of the innovation process, the dissertation turns to innovation outputs and their impact on SME performance. The second article forms Chapter 3 that is entitled "*Does combining different types of innovation always improve SME performance? An analysis of innovation complementarity*". This article explores how SMEs combine different types of innovation and how the combinations of innovation types shape SME performance. It pays attention to under-investigated SMEs and includes some innovation types that have not been used, contributing to the empirical literature. Based on prior case studies, firms are observed that they can introduce highly interconnected innovation types simultaneously (Wu et al., 2009; Nahm and Steinfeld, 2014; Zhang et al., 2017). This article further uses the RBV to theoretically argue that the simultaneous introduction of different innovation types allows SMEs to gain performance benefits that are greater than additive benefits from individual innovation type, capturing complementarity in performance between different types of innovation. However, the various strands of extant empirical research are inconclusive about the complementarity or substitutability between different innovation types. This suggests that the relationships between innovation types may be nationally contingent (Ballot et al., 2015; Guisado-González et al., 2017), which calls for the evidence from an emerging economy within China. The empirical analysis of this article relies on a sub-sample of 1,139 Chinese SMEs from the ES. The results of factor analysis show two groups of strongly correlated innovation types, implying that SMEs have two tendencies of combining innovation types: some SMEs tend to combine product innovation, quality innovation, and organizational innovation and others tend to introduce efficiency innovation and flexibility innovation in combination. The pairwise complementarities are tested for each group of innovation types by using Ballot et al.'s (2015) conditional supermodularity method. Regarding the relationship between product, quality and organizational innovation, the results show that they are neither complements nor substitutes, but instead generate additive effects on firm performance. In terms of efficiency innovation and flexibility innovation, they present substitutability, indicating that the simultaneous introduction of efficiency and flexibility innovation decreases SME performance. With the addition of organizational innovation, no substitutability appears between efficiency and flexibility innovation, which means that organizational innovation benefits SMEs who pursue efficiency and flexibility innovation at the same time. The aforementioned findings point out SME heterogeneity in combinations of innovation types and its resulting SME performance, which improve our understanding of how SMEs combine different innovation types to achieve superior performance.

The analysis of the input and output stages of the innovation process in first two articles increases the awareness and knowledge of SME heterogeneity in innovation activities and innovation types. The third article tries to synthesize SME innovation heterogeneity into interpretable and manageable innovation patterns, which leads to Chapter 4 entitled "*SME innovation patterns identified from a process perspective: linking innovation to SME performance*". Unlike the literature that takes into account either innovation activities or innovation types, this article identifies patterns of innovation activities and of innovation types at the same time (Evangelista and Vezzani, 2010; Brunswicker and Vanhaverbeke, 2015; Hervas-Oliver et al., 2016a; Thomä, 2017; Hervas-Oliver et al., 2020; Thomä and Zimmermann, 2020). It also analyzes the link between innovation inputs, innovation outputs and SME performance by applying the identified innovation patterns rather than certain innovation activities (e.g., R&D) and types (e.g., technological innovation) that often used in the literature (Baumann and Kritikos, 2016; Wadho and Chaudhry, 2018). Based on the RBV, innovating SMEs are heterogeneous as they purposively develop heterogeneous innovation resources and combine them in heterogeneous ways, showing various innovation patterns. This article bases the empirical analysis on a sub-sample of 1,127 manufacturing SMEs from the ES. The third article builds on the first and second articles (Chapters 2 and 3) and it thus focuses on various innovation activities used in the first article (Chapter 2) and different innovation types used in the second article (Chapter 3). According to the innovation activities, three innovation sourcing patterns are identified, namely internal sourcing group, low sourcing group, and open sourcing group, which present different degrees of being active and open in terms of knowledge sourcing. According to the innovation types, three innovation introducing patterns are identified, namely production innovators, product innovators, and multifaceted innovators, which show the variety of innovation types introduced. Regarding the relationship between innovation sourcing and introducing patterns, the regression results suggest that being active in innovation activities increases the likelihood of introducing various innovation types and being open contributes most to capturing a variety of innovation types. The results for the impact of innovation introducing patterns on SME performance show that production innovators who combine efficiency and flexibility innovation suffer inferior performance, confirming one result of the second article (Chapter 3), while product innovators and multifaceted innovators experience better performance. The abovementioned findings offer the possibility of synthesizing SME heterogeneity in innovation activities and innovation types into different typologies of SME innovation patterns and reveal that SMEs innovate differently, showing different innovation patterns and thus performance differences.

Figure 1.1 depicts the connection between the empirical objectives of Chapters 2, 3, and 4 and the aims of this dissertation. The other aspects of the main chapters are summarized in Table 1.1.

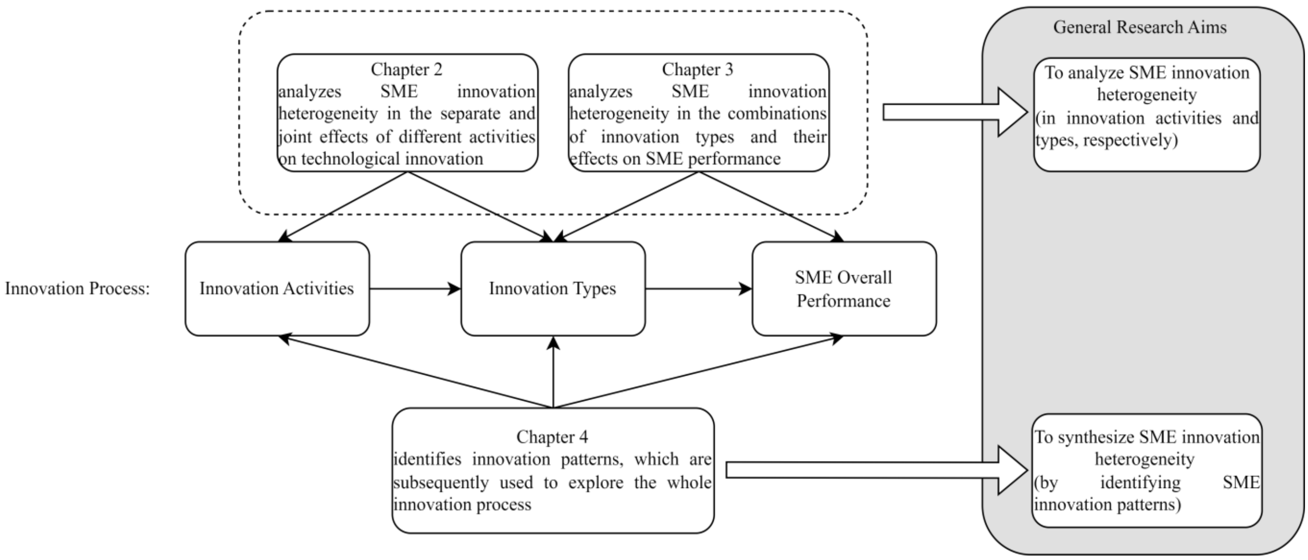

Figure 1.1 Empirical objectives of main chapters and general aims of the dissertation

Table 1.1 Overview of main chapters

Chapter 2	Chapter 3	Chapter 4
Title		
Non-R&D innovation in SMEs: is there complementarity or substitutability between internal and external innovation sourcing strategies?	Does combining different types of innovation always improve SME performance? An analysis of innovation complementarity	SME innovation patterns identified from a process perspective: linking innovation to SME performance
Main innovation aspects		
Innovation activities	Innovation types	Innovation activities and types
Main research question		
What are the differences between non-R&D and R&D SMEs in the separate and combined effects of non-R&D activities on product and process innovation?	How do SMEs combine different innovation types? How do different combinations of innovation types shape SME performance?	To what extent do SMEs show different patterns of innovation activities and of innovation types? What is the link between the two typologies of innovation patterns and SME performance?
Data		
A sub-sample of 1,392 SMEs from the ES	A sub-sample of 1,139 SMEs from the ES	A sub-sample of 1,127 SMEs from the ES
Quantitative method		
Descriptive analysis, heckprobit regression, and categorical principal component analysis	Factor analysis, descriptive analysis, multinomial logistic regression, two-stage least squares regression, and conditional supermodularity tests	Factor analysis, cluster analysis, multinomial probit regression, and ordinary least squares regression
Main findings		
Non-R&D and R&D SMEs rely on different non-R&D activities to introduce product and process innovation. Internal and external activities are substitutes for product innovation in non-R&D SMEs and process innovation for R&D SMEs.	There are two tendencies of combining innovation types. By combining product, quality, and organizational innovation, SMEs gain only additive benefits. By combining efficiency and flexibility innovation, SMEs gain no performance payoff without organizational innovation.	There are three patterns of innovation activities and three patterns of innovation types. SMEs show different likelihoods of transforming themselves from one pattern of innovation activities into one pattern of innovation types which results in the differences in SME performance.

Chapter 2 Non-R&D Innovation in SMEs: Is There Complementarity or Substitutability between Internal and External Innovation Sourcing Strategies?

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Chapter 3 Does Combining Different Types of Innovation Always Improve SME Performance? An Analysis of Innovation Complementarity

DOI link: https://doi.org/10.1016/j.jik.2022.100192

Abstract: Small- and medium-sized enterprises (SMEs) sometimes introduce different types of innovation simultaneously. However, the performance implications of simultaneous innovation practices remain under-researched in the literature. Therefore, this paper explores the combined use of six types of innovation and examines complementarity/substitutability in performance between these types of innovation. Data for the empirical analysis originates from a sample of 1,139 Chinese manufacturing SMEs. We identify two tendencies of simultaneous innovation by means of exploratory factor analysis (EFA), which are as follows: product-oriented and production-oriented. Using a conditional approach to supermodularity, we find no interplay between product-oriented types of innovation, but substitutability between production-oriented types of innovation. Based on organizational literature, we perform a supplementary test for the relationship between production-oriented types of innovation and organizational innovation. The result shows that substitutability between production-oriented types of innovation exists only in the absence of organizational innovation. These findings suggest that SMEs in China derive only additive benefits from a combination of product-oriented innovation, and gain no performance payoff from a combination of production-oriented innovation unless they introduce simultaneous organizational change.

Keywords: Manufacturing SMEs; Simultaneous innovation; Supermodularity; Complementarity; Substitutability

3.1 Introduction

Small- and medium-sized enterprises (SMEs) are generally considered to be the engines of innovation and technological change (Hall et al., 2009). In China, SMEs, accounting for 99% of total enterprises, have been extensively engaged in innovation, which is not only motivated by the increasing global competition (Cao et al., 2020) but also encouraged by Chinese government's innovation policies (Liu et al., 2017). There is evidence indicating that Chinese SMEs contribute to 70% of patents, 75% of technological innovation, and 80% of new products (Chen et al., 2017; Zhang and Merchant, 2020).

Despite their remarkable innovation success, SMEs in China still lag behind those in developed countries in terms of innovation capabilities and firm performance (Chen et al., 2020a). This has spawned a vast amount of research that explores the determinants of innovation in Chinese SMEs (e.g., Gu et al., 2016; Mei et al., 2019; Xiang et al., 2019) and the impact of innovation on Chinese SMEs' performance (e.g., Qiao et al., 2014; Zhang et al., 2018; Liu and Wang, 2022). These studies suffer from two main limitations. First, they concentrate on technology-based product and process innovation; in contrast, organizational innovation is under-researched empirically due to a lack of survey data, generic definitions, and measurement methods (Sapprasert and Clausen, 2012). Second, they consider innovation types as separate phenomena that drive firm performance individually, even though firms sometimes engage in different types of innovation simultaneously (Donbesuur et al., 2020). These two limitations constrain our understanding of the combined use of different innovation types in the context of China and the combinative effects of innovation types on Chinese firms' performance.

Recent evidence from developed countries shows that firms introducing more than one type of innovation outperform those introducing only one type of innovation at a time. In fact, the simple introduction of technological innovation alone does not allow enhanced competitiveness (Battisti and Stoneman, 2010). Technological innovation (product and process innovation) provides more performance benefits if it is accompanied by organizational innovation (Arranz et al., 2019). Furthermore, firms are better off if they introduce process, product, marketing, and organizational innovation at the same time (Tavassoli and Karlsson, 2016). These studies show that firms can derive synergistic gains from simultaneous innovation, indicating the existence of complementarities between innovation types. However, the complementary effects of innovation types on firm performance are still poorly understood. First, little research has been carried out on innovation complementarities in SME performance. The costs of innovation are high, especially for SMEs that are always resource constrained; thus, it is important for them to know how to leverage complementarities between different types of innovation (Donbesuur et al., 2020). The significance of investigating this gap in the innovation literature is that performance differences between SMEs may result from the use and the effectiveness of simultaneous innovation practices. Furthermore, different sub-types of product and process innovation are bundled together in most studies. In analyzing innovation complementarities, it is important to recognize that different pairwise complementary relationships exist among different forms of product and process innovation (Doran, 2012).

The aim of this paper is to empirically analyze the existence of complementarities in use and in performance between six innovation types: product development, product improvement, quality innovation, efficiency innovation, flexibility innovation, and organizational innovation. Based on a sample of 1,139 Chinese manufacturing SMEs, we identify two tendencies of simultaneous innovation practices using factor analysis techniques. With reference to these two tendencies, we implement a new supermodularity approach developed by Ballot et al. (2015) to test for conditional complementarity/substitutability in performance between different types of innovation. We find that there is no interplay between product (measured by product development and product improvement), quality, and organizational innovation, but substitutability between efficiency and flexibility innovation that can be eliminated by organizational innovation. This study contributes to the micro-level evidence on innovation complementarities in three ways. First, we make an empirical and contextual contribution by using firm-level data from an emerging economy, China. To the best of our knowledge, this is the first work that addresses the complementarities between various types of innovation in the context of China. Second, we particularly focus on SMEs to enrich our knowledge about how they combine different innovation types and how their performance is shaped by such innovation combinations. Third, we use a broader range of innovation types, some of which are used for the first time in this area (e.g., efficiency and flexibility innovation), thus enabling us to explore more potential innovation combinations and their effects on firm performance.

The remainder of this paper is structured as follows: section 3.2 deals with the review of theoretical and empirical literature related to innovation complementarity; section 3.3 presents our econometric framework; section 3.4 shows the database, variables, and a preliminary analysis based on descriptive statistics; section 3.5 reports on the econometric results; and finally, section 3.6 concludes with a discussion of the results, implications, and limitations of our work.

3.2 Literature Review on Innovation Complementarity

Over the last several decades, many efforts have been made to measure the effects of innovation on firm performance. Substantial empirical evidence exists that strongly suggests that innovation plays a critical role in enhancing firm performance (Hall et al., 2009; Evangelista and Vezzani, 2010). Innovation, as an output, takes a multitude of types (OECD Oslo Manual, 2005), and thereby can be transformed into superior performance via different channels. Product innovation enables firms to gain a competitive advantage by developing new products to attract new customers or introducing significantly improved products to current markets (i.e., new product development and existing product improvement). Alternatively, process innovation provides firms with a competitive advantage by decreasing unit production costs or increasing market share associated with higher-quality products and flexible production (i.e., efficiency innovation, quality innovation, and flexibility innovation).

Most studies have focused on analyzing the adoption of single innovation types in isolation (e.g., Damanpour, 2010, Evangelista and Vezzani, 2010; Gunday et al., 2011).

However, recent research has found that firms tend to simultaneously undertake certain innovation practices that are linked. A multiple case study of Chinese nanotechnology companies conducted by Zhang et al. (2017) demonstrates the simultaneous adoption of product and process innovation. They argue that nanotechnology is a process-based technology in which a significant change in manufacturing processes results in a simultaneous change in the products. Nahm and Steinfeld (2014) also observe the concurrence of product and process innovation based on case studies drawn from Chinese renewable energy sectors. They identify that new product development triggers cost-reducing process innovation. These instances exemplify complementarities in use between product and process innovation: the introduction of one creates possibilities for introducing the other (Ballot et al., 2015). Hullova et al. (2016) developed a classification that includes seven unique types of complementarities in use between product and process innovation. Wu et al. (2009) and Chen et al. (2020a) further consider organizational innovation. They use many examples to show that organizational innovation is beneficial for technological innovation. In this paper, we explore complementarities in use employing possible innovation combinations generated by a wide range of innovation types.

The fact that firms combine different innovation types has further complicated the study of innovation and its impact on firm productivity. Complementarities in performance occur when the joint execution of innovation types produces greater economic effects than individual innovation types on their own (Ballot et al., 2015). Firms could derive synergistic gains from introducing different types of innovation in tandem (Hullova et al., 2019). This is theoretically supported by the resource-based view (RBV). The RBV uses firms' internal characteristics to explain their differences in performance. According to the postulate of RBV, a firm's valuable, rare, inimitable, and non-substitutable (VRIN) resources contribute to competitive advantage and therefore lead to superior performance (Barney, 1991; Peteraf, 1993). A firm's capability of integrating resources further underlines the importance of its VRIN elements as the determinant of its competitiveness. Due to the characteristics of VRIN resources, well-integrated firms can be protected against imitation and achieve distinctive competencies by effectively extracting competitive combinations from their resources (Lin and Wu, 2014; Hervas-Oliver et al., 2015). Therefore, the notion of complementarity is in line with the main assumption of the RBV that competitive advantage is a function of the unique bundling of resources and capabilities that increases complexity and inimitability of organizational practices (Rivkin, 2000; Colbert, 2004; Sok et al., 2016). The importance of complementarity is also reflected in Teece's framework (1986), which argues that the commercial value of an innovation crucially depends on whether it is used in conjunction with complementary assets (Christmann, 2000). The implication of these theories for this study is that the simultaneous adoption of different types of innovation reflects the complexity of innovative resource and capability interactions where value exists in the interrelationships. From this perspective, complementarities between innovation types allow firms to achieve better performance outcomes. Although each type of innovation may be beneficial for firm performance in isolation, complementarities between innovation types provide extra benefits generating multiplier effects rather than simple additive effects. Therefore, complementarities-in-performance can be interpreted as firms combining innovation types to achieve superior performance.

The complementary role that innovation types play in improving firm performance has opened a new sub-field of empirical research on innovation. Complementarities in performance have been examined using either interaction terms or the supermodularity approach. The analysis of interaction terms in a performance equation is a common practice in the literature. Lee et al. (2019) explore the combinative effects of product, process, marketing, and organizational innovation for a sample of Korean firms. They find that organizational and process innovation and marketing and product innovation have a synergistic effect on firm performance, but that the effect is contingent on industrial categories. Chen et al. (2020b) investigate Chinese manufacturing firms and find that organizational innovation enables firms to better leverage technological innovation capabilities to increase firm performance, indicating the existence of complementarity between organizational and technological innovation. Donbesuur et al. (2020) focus on international performance of SMEs in Ghana and also find a significant complementary relationship between organizational and technological innovation. In order to avoid severe multicollinearity problems, the supermodularity approach is an alternative methodology frequently used to analyze complementarities between more than two innovation types. Doran (2012), using Irish firm-level data, tests for strict complementarities between new-to-firm product, new-to-market product, process, and organizational innovation within the supermodularity framework. The study shows a strong complementary relationship between organizational and technological innovation, at least one complementary relationship exhibited by each type of innovation, and no evidence for substitutability. The strict supermodularity test used in Doran's (2012) research is based on critical values for the Wald test and is often inconclusive. Ballot et al. (2015) propose a conditional approach to supermodularity that tests for pairwise innovation complementarities conditional on the presence/absence of a third type of innovation. They use two samples of French and UK manufacturing firms to capture their differences in the complementarities between product, process, and organizational innovation. Their study suggests that the existence of innovation complementarities depends on the national context and firm characteristics. Guisado-González et al. (2017) apply the new supermodularity method proposed by Ballot et al. (2015) to test for complementarities in performance between product, process, and organizational innovation for a set of Spanish firms. They find stable complementarity between product and process innovation, and conditional substitutability between process and organizational innovation in the absence of product innovation.

The aforementioned empirical studies have generated mixed results about complementarities in performance and have limited our understanding for two reasons. First, complementarity appears to be a contingent relationship between different innovation types in shaping firm performance, which may depend on the technological capabilities of firms (Doran, 2012) and the technological complexity of a national production structure (Guisado-González et al., 2017). The distinct characteristics of SMEs (e.g., restricted access to resources) and the specific context of China (e.g., labor intensive and low-end production) raises the question of whether SMEs in China can obtain economies of scope across innovation types (Laforet and Tann, 2006; Li, 2018). Second, the existence of complementarity may be dependent on the types of innovation investigated. For example, Doran (2012) distinguishes new-to-firm and new-to-market product innovations, which exhibit different pairwise complementary relationships. This suggests the need to disentangle different forms of the same typology of innovation in order to facilitate a more comprehensive analysis of the relationship between some sub-types of innovation (e.g., efficiency and flexibility innovation are the sub-types of process innovation). Therefore, to further explore innovation complementarity, we attempt to provide evidence from Chinese SMEs to verify the theoretical arguments and existing findings, which have generated much empirical ambiguity.

3.3 Econometric Methodology

In order to overcome multicollinearity problems of the interaction approach and inconclusive interpretations of unconditional supermodularity tests, we decide to implement Ballot et al.'s (2015) conditional supermodularity procedure. We need to pool exclusive innovation combinations and then regress firm performance on them. Before estimating the final regression model, we are aware of the potential endogeneity of innovation. Unobservable factors (e.g., management quality and entrepreneurship) that have an influence on innovation could impact firm performance (Chudnovsky et al., 2006). Following the approach by Fu et al. (2018), access to external finance can be used as an exclusion restriction in the innovation equation. The variable is believed to affect firm performance only through innovation. Therefore, we apply a two-step estimation procedure that corrects the endogeneity of exclusive innovation combinations.

In the first step, we conduct a multinomial logistic regression to estimate the innovation equation (3.1).

$$P_{ij} = \text{Prob}(w_i = j \mid X_{1i}) = \frac{\exp(X_{1i}\alpha_{1j})}{\sum_{k=1}^{j} \exp(X_{1i}\alpha_{1k})} \tag{3.1}$$

where P_{ij} is the probability that firm i adopts innovation combination j. X_{1i} is a vector of firm characteristics, including access to external finance, and α_{1j} is the corresponding vector of parameters relating to innovation combination j.

In the second step, the performance equation (3.2) is specified as a Cobb-Douglas function with constant returns to scale. The equation is estimated using a two-stage least squares (2SLS) regression approach, where the predicted probabilities from equation (3.1) are used as the instruments of exclusive innovation combinations $w_k\,(k = 1, \dots, j)$.

$$y_i = \sum_{k=1}^{j} \beta_k w_{ki}^{*} + \alpha_2 X_{2i} + \varepsilon_i \tag{3.2}$$

where y_i is the indicator of firm performance. X_{2i} denotes a vector of firm characteristics and ε_i is an error term. Estimated coefficients of exclusive innovation combinations, $\beta_k\ (k = 1, \dots, j)$, are used to test for complementarity/substitutability between different types of innovation based on the conditional supermodularity method.

Beginning with a simple example to illustrate supermodularity tests, suppose there are two dichotomous choices of innovation, which implies that a vector of innovation combinations, W, consists of four elements that are as follows: $W = [w_{00},\ w_{10},\ w_{01},\ w_{11}]$ [9]. An objective function is given by equation (3.2), where $[\beta_{00}, \beta_{10}, \beta_{01}, \beta_{11}]$ is a vector of estimated coefficients corresponding to W. Then, the objective function is supermodular and the two types of innovation are complementary if:

$$\beta_{11} + \beta_{00} - \beta_{10} - \beta_{01} > 0$$

Alternatively, the objective function is submodular and the two types of innovation are substitutes if:

[9] The subscripts denote exclusive innovation combinations. For example, w_{00} indicates that neither of the two types of innovation is introduced, and w_{11} indicates that both types of innovation are introduced together.

$$\beta_{11} + \beta_{00} - \beta_{10} - \beta_{01} < 0$$

Ballot et al.'s (2015) conditional approach to supermodularity is applied when there are more than two dichotomous choices of innovation. For example, we focus on three innovation types that are INNO1, INNO2, and INNO3. The conditional supermodularity test implies examining separately pairwise complementarities conditional on the absence of the third innovation type and then on the presence of the third type. The restriction constraints to be tested for complementarity between INNO1 and INNO2 are as follows:

$$\begin{cases}\beta_{110} + \beta_{000} - \beta_{100} - \beta_{010} = 0 \text{ (absence of INNO3)} \\ \beta_{110} + \beta_{000} - \beta_{100} - \beta_{010} > 0 \text{ (absence of INNO3)}\end{cases}$$
$$\begin{cases}\beta_{111} + \beta_{001} - \beta_{101} - \beta_{011} = 0 \text{ (presence of INNO3)} \\ \beta_{111} + \beta_{001} - \beta_{101} - \beta_{011} > 0 \text{ (presence of INNO3)}\end{cases}$$

For complementarity between INNO1 and INNO3, the tests are as follows:

$$\begin{cases}\beta_{101} + \beta_{000} - \beta_{100} - \beta_{001} = 0 \text{ (absence of INNO2)} \\ \beta_{101} + \beta_{000} - \beta_{100} - \beta_{001} > 0 \text{ (absence of INNO2)}\end{cases}$$
$$\begin{cases}\beta_{111} + \beta_{010} - \beta_{110} - \beta_{011} = 0 \text{ (presence of INNO2)} \\ \beta_{111} + \beta_{010} - \beta_{110} - \beta_{011} > 0 \text{ (presence of INNO2)}\end{cases}$$

For complementarity between INNO2 and INNO3, the tests are as follows:

$$\begin{cases}\beta_{011} + \beta_{000} - \beta_{010} - \beta_{001} = 0 \text{ (absence of INNO1)} \\ \beta_{011} + \beta_{000} - \beta_{010} - \beta_{001} > 0 \text{ (absence of INNO1)}\end{cases}$$
$$\begin{cases}\beta_{111} + \beta_{100} - \beta_{110} - \beta_{101} = 0 \text{ (presence of INNO1)} \\ \beta_{111} + \beta_{100} - \beta_{110} - \beta_{101} > 0 \text{ (presence of INNO1)}\end{cases}$$

Following Guisado-González et al. (2017) and Serrano-Bedia et al. (2018), for each pair of restrictions we begin by performing the Wald test for the first one to test if a significant relationship exists between two types of innovation. If the test indicates that the relationship is statistically significant, then we perform a test for inequality to determine whether the two types of innovation are complements or substitutes.

3.4 Data, Variables, and Descriptive Analysis

3.4.1 Sample and Data

Our empirical analysis is based on firm data from the Chinese Manufacturing Enterprise Survey (ES) collected by the World Bank between November 2011 and March 2013. The ES captures information on multiple aspects of a firm (e.g., sales, employees, and industry sector) as well as its innovation behavior (e.g., R&D, technology acquisition, and innovation outputs). This allows us to consider various innovation types and ascertain firm performance. Despite the cross-sectional nature of ES dataset, some data (e.g., sales) shows a partial view of firm dynamics during a three-year period.

The sample is representative of the population of manufacturing firms in China, which is randomly selected based on three levels of stratification: firm size, industrial sector, and regional location. According to the definition of manufacturing SMEs in China, we restrict our focus to firms with less than 1,000 employees. The ES database containing a total of 2,848 firms is skewed toward manufacturing SMEs and 1,619 firms (56.85% of the total sample) are SMEs operating in 25 Chinese cities and 19 manufacturing sectors. After excluding firms with missing values, the number of manufacturing SMEs available for further analysis reduces to 1,139.

3.4.2 Variables and Measures

The dependent variable is firm performance. In order to mitigate simultaneity problems, we use the natural logarithm of total sales per employee in the last year covered by the ES to measure productivity as the proxy for firm performance. This measure of performance is widely used in research studying the effects of innovation on firm performance (Ballot et al., 2015; Fu et al., 2018).

We select six innovation types according to the OECD Oslo Manual (2005), some of which are new for the literature as previously mentioned. These innovation types are measured on a dichotomous scale (0 = No, 1 = Yes) and are listed as follows: (1) Quality innovation is the use of new quality control procedures in production or operation; (2)

Organizational innovation is the use of new management/administrative procedures; (3) Product development is the introduction of new products or services; (4) Product improvement is the addition of new features to existing products or services; (5) Efficiency innovation is the use of new or significantly improved methods to reduce unit production costs; and (6) Flexibility innovation is the use of new or significantly improved methods to increase production flexibility. The independent variables include individual innovation types and their exclusive combinations.

Following prior literature (Hall et al., 2009; Baumann and Kritikos, 2016), we include a set of control variables for other production inputs. Specifically, we set controls for firm size, physical investment, and human capital. As Hsieh and Klenow's (2014) research shows a significant effect of firms' life-cycle dynamics on productivity, we include firm age to control life-cycle effects. We also set controls for government and foreign ownership. In transitional economies like China, private-owned, government-owned, and foreign-invested firms coexist, and they differ in terms of their resource endowments, technological opportunities, and business environment, which lead to variations in their performance (Jiang et al., 2013). Finally, we use industry dummies and city dummies to capture unobservable differences across industries and cities.

Table 3.8 in the Appendix shows a detailed description and the measurement of all variables. Table 3.1 contains the summary statistics of these variables. In terms of our performance measure, its mean value is 12.444 and standard deviation is 1.042, suggesting interfirm differences in performance. When looking at the occurrence of the six types of innovation, we observe that efficiency innovation is the most frequent innovation type, followed by flexibility innovation. This reflects the fact that Chinese SMEs primarily leverage cost advantage to compete on price to build market share (Tang and Hull, 2012; Chen et al., 2017). In contrast, product-related types of innovation and organizational innovation occur less often in our sample.

Table 3.1 Descriptive statistics

Variable	Mean	Std. Dev.	Minimum	Maximum

Firm performance (log)	12.444	1.042	9.433	17.770
Quality innovation	0.444	0.497	0	1
Organizational innovation	0.428	0.495	0	1
Product development	0.494	0.500	0	1
Product improvement	0.447	0.497	0	1
Efficiency innovation	0.756	0.430	0	1
Flexibility innovation	0.617	0.486	0	1
Size (log)	4.241	1.110	1.609	6.856
Age (log)	2.434	0.478	0	4.828
Investment intensity (log)	5.004	4.696	0	15.356
Human capital	10.084	1.936	1	18
Government ownership	0.048	0.214	0	1
Foreign ownership	0.051	0.051	0	1
External finance	0.438	0.496	0	1

N = 1,139

3.4.3 A Preliminary Complementarity Analysis

The main interest of our research is the extent to which the sample firms introduced different innovation types simultaneously. We report the tetrachoric correlation matrix for the six innovation types in Table 3.2. For all the variables, the pairwise correlation coefficient is positive and higher than 0.4, showing that the adoption of one innovation type is correlated with the adoption of another innovation type and that the correlation exists between all innovation types. However, correlation coefficients differ from pair to pair of innovation types. The positive correlation is strongest between quality and organizational innovation. Strong correlations (coefficient value > 0.8) can also be found between product development and product improvement as well as between efficiency and flexibility innovation. These findings reflect the actual practices of firms where they adopt innovation types simultaneously, and there is the possibility that firms use multiple innovation types to gain higher performance.

Table 3.2 Matrix of tetrachoric correlations.

Variable	1	2	3	4	5	6
1 Quality innovation	1.000					
2 Organizational innovation	0.846	1.000				
3 Product development	0.708	0.683	1.000			
4 Product improvement	0.773	0.739	0.821	1.000		
5 Efficiency innovation	0.617	0.618	0.405	0.671	1.000	
6 Flexibility innovation	0.687	0.681	0.527	0.624	0.827	1.000

(Table 3.2 Continued)

N = 1,139

The complementarity testing procedure is overly tedious if all the six innovation types are included within a supermodularity framework.[10] Exploratory factor analysis (EFA) can provide analytical advantages by reducing a set of innovation types to a smaller number of uncorrelated factors. Each factor is represented by variables that are strongly correlated with each other and that are weakly correlated with variables representing other factors. Therefore, we concentrate on the analysis of complementarity between the innovation types that define each factor.

Bartlett's test of sphericity ($\chi^2(15)$ = 6,510.798, significant at p < 0.001 level) and the Kaiser-Meyer-Olkin test (overall measure of sampling adequacy = 0.76) indicate the suitability of our data for EFA. To determine the number of factors to retain, we use parallel analysis, resulting in a two-factor solution. Varimax rotation is performed to make the structure simpler to interpret. The two retained factors explain 80.6% of the total variance in the six innovation variables and the communalities are all higher than 0.5, indicating that the two-factor EFA model is desirable (see Table 3.3).

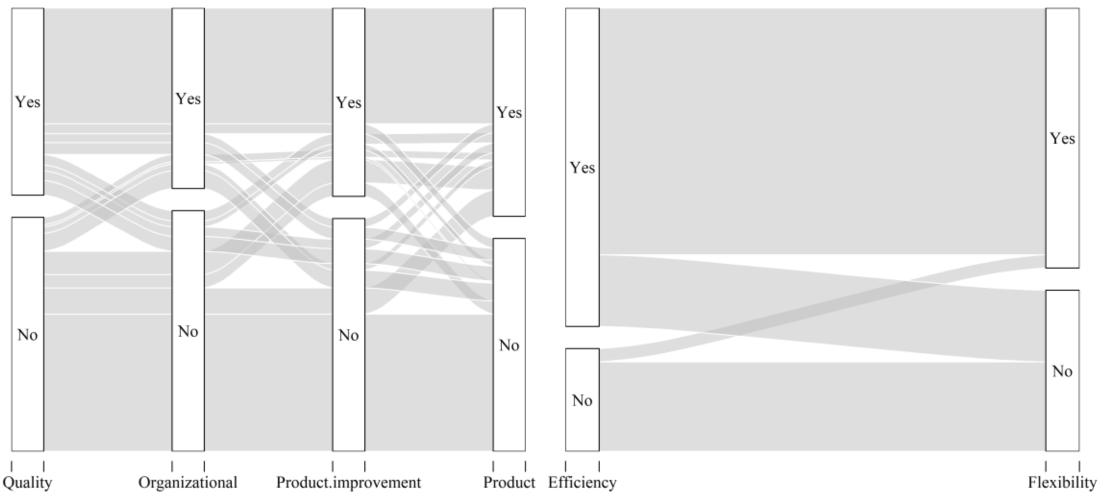
Table 3.3 VARIMAX rotated loadings of innovation variables on two factors

Variable	Factor 1	Factor 2	Communality
Quality innovation	**0.756**	0.469	0.791
Organizational innovation	**0.722**	0.477	0.749
Product development	**0.869**	0.184	0.789
Product improvement	**0.790**	0.430	0.809
Efficiency innovation	0.275	**0.932**	0.945
Flexibility innovation	0.427	**0.757**	0.756
Explained variance (%)	45.5	35.1	80.6

Table 3.3 shows the factor structure matrix, where loading values higher than 0.7 are in bold. Factor 1 contains mainly quality innovation, organizational innovation, product development, and product improvement, which are labeled as product-oriented innovation. Factor 2 focuses mainly on efficiency innovation and flexibility innovation,

[10] It can be shown that the number of constraints to be tested is equal to $2^{k-2}\sum_{i=1}^{k-1} i$, where k is the number of innovation types. With six innovation types, there are a total of 240 constraints for the supermodularity test.

which are labeled as production-oriented innovation. The first factor reflects the propensity to adopt product-oriented types of innovation simultaneously. The second factor captures the propensity to adopt production-oriented types of innovation simultaneously. This is a particularly relevant insight, considering that firms tend to introduce different types of innovation simultaneously. The exclusive combinations of innovation types are visualized using alluvial diagrams, as shown in Figure 3.1.[11] These exclusive innovation combinations suggest complementarities in use between innovation types to some extent. In terms of the firms introducing at least one type of product-oriented innovation, the majority of them adopt all four innovation types simultaneously (see Figure 3.1(a)). The most frequent exclusive combination in production-oriented innovation types is the simultaneous adoption of both efficiency and flexibility innovation (see Figure 3.1(b)). Thus, we distinguish between the two groups of innovation types that are combined most frequently and attempt to test for pairwise complementarities by groups.



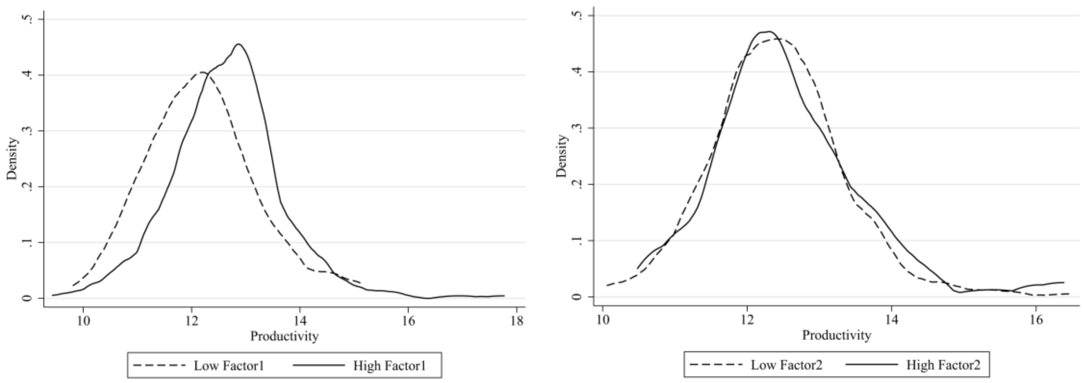
(a) Product-oriented types of innovation (b) Production-oriented types of innovation

Figure 3.1 Alluvial diagram summarizing the exclusive combinations of innovation types

The two factors can be interpreted as the extent of adopting multiple product-oriented/production-oriented innovation types. To substantiate our interpretation of the factors, we investigate how the predicted factor scores correspond with the number of

[11] The descriptive statistics of the exclusive combinations are available upon request.

innovation types. Figure 3.3 in the Appendix shows that Factor 1 is positively correlated with the number of product-oriented types of innovation introduced, and Factor 2 is positively correlated with the number of production-oriented types of innovation introduced. Hence, we use the factors to measure the usage intensity of both product-oriented and production-oriented innovation types. Figure 3.2 presents the kernel density of productivity, our performance measure, at low and high levels of each factor. One standard deviation below/above the mean represents a low/high level. The distribution for high-level Factor 1 is skewed toward the right as shown in Figure 3.2(a). Thus, firms introducing more product-oriented innovation types experience greater productivity. Moreover, only these firms have the highest productivity and can be found at the upper end of the spectrum. Since Figure 3.2(b) shows near perfect overlapping distributions, the joint adoption of production-oriented innovation types may not allow firms to achieve higher productivity. These preliminary results provide suggestive evidence for the combinative effects of product-oriented innovation types, but no evidence for production-oriented innovation types. A strict econometric analysis is needed to verify the existence of complementarity/substitutability in performance between innovation types.



(a) (b)

Figure 3.2 Distribution of productivity by level of factors

3.5 Econometric Results

3.5.1 Complementarities in Performance between Product-oriented Innovation Types

In a broad sense, product innovation includes new product development and existing product improvement (OECD Oslo Manual, 2005). In order to reduce the computational burden, a single variable (product innovation) is used in the following analysis, which takes 1 if product development and/or product improvement takes 1.

Model Ⅰ in Table 3.4 is estimated using the 2SLS method,[12] where the dependent variable is firm performance proxied by productivity, and exclusive innovation combinations are instrumented by their predicted probabilities from a multinomial logit model.[13]

Table 3.4 Performance regression: determinants of firm performance by exclusive combinations of product-oriented innovation types

	Model Ⅰ	
Variable	Coef.	Robust Std. Err.
(1,0,0)	1.445***	0.550
(0,1,0)	0.646	0.661
(0,0,1)	0.942	0.782
(1,1,0)	0.998**	0.438
(1,0,1)	2.154**	0.850
(0,1,1)	0.269	1.075
(1,1,1)	1.724***	0.501
Size (log)	−0.116**	0.054
Age (log)	0.062	0.080
Investment intensity (log)	−0.007	0.013
Human capital	−0.024	0.024
Government ownership	0.367	0.278
Foreign ownership	0.253	0.175
Constant	12.583***	0.529
Industry dummies	Yes	
City dummies	Yes	
Wald χ^2	162.36***	
Observations	1,139	

(i, j, k) denotes the exclusive innovation combinations, where i, j, and k represent product innovation, quality innovation, and organizational innovation, respectively. *, ** and *** indicate significance at 10%, 5% and 1% levels.

12 The first-stage results of 2SLS regression model are available upon request.

13 The multinomial logit model includes external finance as an exclusion restriction. Its results are available upon request.

Compared with the base combination (0,0,0), introducing product innovation only (1,0,0) and combining product innovation with any other innovation types, (1,1,0), (1,0,1), and (1,1,1), lead to higher performance. In contrast, introducing quality and/or organizational innovation in the absence of product innovation, (0,1,0), (0,0,1), and (0,1,1), does not make firms more productive. The individual coefficients of these exclusive combinations cannot directly reveal whether interaction relationships exist, but they are needed for the complementarity/substitutability tests (Mohnen and Röller, 2005).

Conditional supermodularity tests are based on the estimated coefficients of exclusive innovation combinations and the results are summarized in Table 3.5. We do not find any significant relationships between product, quality, and organizational innovation. However, these types of innovation individually have a significantly positive effect on firm performance (see Models 2, 3, 4, and 5 in Table 3.9 in the Appendix). Further, in Model 1 in Table 3.9 in the Appendix, a positive and statistically significant coefficient of Factor 1 indicates that firms introducing more product-oriented innovation types have higher performance, which is consistent with our previous finding shown in Figure 3.2(a). In summary, our results suggest that the simultaneous introduction of product-oriented innovation types favors firm performance merely by generating additive effects.

Table 3.5 Testing complementarity/substitutability in performance between product-oriented innovation types

	Chi^2	*P*-value
Product innovation - quality innovation		
Organizational innovation= 0		
(1,1,0) + (0,0,0) − (0,1,0) − (1,0,0) = 0	1.16	0.2817
Complements/substitutes/no relation	No relation	
Organizational innovation = 1		
(1,1,1) + (0,0,1) − (0,1,1) − (1,0,1) = 0	0.03	0.8654
Complements/substitutes/no relation	No relation	
Product innovation - organizational innovation		
Quality innovation = 0		
(1,0,1) + (0,0,0) − (1,0,0) − (0,0,1) = 0	0.07	0.7974
Complements/substitutes/no relation	No relation	
Quality innovation = 1		
(1,1,1) + (0,1,0) − (1,1,0) − (0,1,1) = 0	0.62	0.4301

(Table 3.5 Continued)

	Chi^2	*P*-value
Complements/substitutes/no relation	No relation	
Quality innovation - organizational innovation		
Product innovation = 0		
(0,1,1) + (0,0,0) − (0,1,0) − (0,0,1) = 0	0.64	0.4225
Complements/substitutes/no relation	No relation	
Product innovation = 1		
(1,1,1) + (1,0,0) − (1,1,0) − (1,0,1) = 0	0.00	0.9842
Complements/substitutes/no relation	No relation	

(i, j, k) denotes the exclusive innovation combinations, where i, j, and k represent product innovation, quality innovation, and organizational innovation, respectively.

3.5.2 Complementarities in Performance between Production-oriented Innovation Types

The exclusive combinations of efficiency and flexibility innovation are used to estimate the performance function. The results are shown in Model Ⅱ in Table 3.6. Firm performance increases due to the introduction of flexibility innovation (0,1), and subsequently decreases due to the addition of efficiency innovation (1,1).

Table 3.6 Performance regression: determinants of firm performance by exclusive combinations of production-oriented innovation types

	Model Ⅱ		Model Ⅲ	
Variable	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
(1,0)	−0.635	0.555		
(0,1)	2.303***	0.876		
(1,1)	−0.294	0.423		
(1,0,0)			−0.802	0.494
(0,1,0)			2.540***	0.705
(0,0,1)			−0.582	0.744
(1,1,0)			−1.116***	0.414
(1,0,1)			−0.665	1.178
(0,1,1)			0.326	1.603
(1,1,1)			0.039	0.508
Size (log)	−0.002	0.043	−0.041	0.054
Age (log)	0.061	0.076	0.037	0.080
Investment intensity (log)	0.037***	0.010	0.030**	0.012
Human capital	0.012	0.018	0.008	0.022
Government ownership	0.403	0.336	0.334	0.309
Foreign ownership	0.511***	0.145	0.430***	0.163

(Table 3.6 Continued)

Variable	Model Ⅱ Coef.	Robust Std. Err.	Model Ⅲ Coef.	Robust Std. Err.
Constant	12.841***	0.490	13.235***	0.516
Industry dummies	Yes		Yes	
City dummies	Yes		Yes	
Wald χ^2	185.25***		207.65***	
Observations	1,139		1,139	

(i, j) denotes the exclusive innovation combinations, where i and j represent efficiency innovation and flexibility innovation, respectively. (i, j, k) denotes the exclusive innovation combinations, where i, j, and k represent efficiency innovation, flexibility innovation, and organizational innovation, respectively. *, ** and *** indicate significance at 10%, 5% and 1% levels.

Based on the estimates of Model Ⅱ, the results in Table 3.7 show evidence of substitutability between efficiency and flexibility innovation. It appears that better performing firms tend to focus on flexibility innovation rather than introducing efficiency and flexibility innovation together. This could be explained by a flexibility-efficiency tradeoff. Efficiency innovation results in a more bureaucratic form of organization with improvements in standardization, formalization and specialization, which has a greater detrimental effect on the more fluid process of mutual adjustment achieved by flexibility innovation (Adler et al., 1999). SMEs pursuing both efficiency and flexibility innovation experience difficulties in achieving consistent organizational attributes due to "the liability of smallness" and thus suffer inferior performance (Ebben and Johnson, 2005).

O'Reilly III and Tushman (2008) argue that firms can benefit from the simultaneous adoption of efficiency and flexibility innovation as long as they construct an appropriate organizational context. Organizational innovation is intended to facilitate intra-organizational coordination and cooperation, which helps build organizational contexts conducive to the simultaneous pursuit of efficiency and flexibility innovation (Úbeda-García et al., 2020). Therefore, we conduct an additional analysis to determine whether organizational innovation plays a moderating role in the substitutability between efficiency and flexibility innovation. In Table 3.6, Model Ⅲ shows that firms introducing three types of innovation (1,1,1) outperform those merely introducing efficiency and flexibility innovation (1,1,0).

Table 3.7 reports the results of the complementarity/substitutability tests based on the estimates of Model Ⅲ. Efficiency and flexibility innovation are conditional substitutes if firms do not introduce organizational innovation. We find that the conditional substitutability disappears with the additional introduction of organizational innovation. These results suggest that the introduction of organizational innovation can defuse the conflict between efficiency and flexibility innovation. We also find conditional complementarity between efficiency and organizational innovation in the presence of flexibility innovation.

Model 6 in Table 3.9 in the Appendix shows that efficiency innovation has a significantly negative coefficient, which may be misleading due to its interaction with flexibility innovation. Model 1 in Table 3.9 in the Appendix shows an insignificant effect of Factor 2 on firm performance, which is in line with what was envisaged in Figure 3.2(b). The positive effect of flexibility innovation (see Model 7 in Table 3.9 in the Appendix) offsets the negative effect of the conflict between efficiency and flexibility innovation, thus leading to an insignificant combinative effect on firm performance. The majority of the sample firms tested in this research (58.56%) pursue both efficiency and flexibility innovation, but 37.93% of them without simultaneous organizational change are stuck in the middle and receive no performance payoff.

Table 3.7 Testing complementarity/substitutability in performance between production-oriented innovation types

	Chi^2	*P*-value
Supermodularity test based on the estimates of Model Ⅱ		
Efficiency innovation - flexibility innovation		
(1,1) + (0,0) − (1,0) − (0,1) = 0	3.19	0.0739
(1,1) + (0,0) − (1,0) − (0,1) > 0		0.0369
Complements/substitutes/no relation	Substitutes	
Conditional supermodularity tests based on the estimates of Model Ⅲ		
Efficiency innovation - flexibility innovation		
Organizational innovation = 0		
(1,1,0) + (0,0,0) − (0,1,0) − (1,0,0) = 0	10.05	0.0015
(1,1,0) + (0,0,0) − (0,1,0) − (1,0,0) > 0		0.0008
Complements/substitutes/no relation	Substitutes	
Organizational innovation = 1		
(1,1,1) + (0,0,1) − (0,1,1) − (1,0,1) = 0	0.01	0.9335
(1,1,1) + (0,0,1) − (0,1,1) − (1,0,1) > 0		

(Table 3.7 Continued)

	Chi^2	*P*-value
Complements/substitutes/no relation	No relation	
Efficiency innovation - organizational innovation		
flexibility innovation = 0		
(1,0,1) + (0,0,0) − (1,0,0) − (0,0,1) = 0	0.26	0.6074
(1,0,1) + (0,0,0) − (1,0,0) − (0,0,1) > 0		
Complements/substitutes/no relation	No relation	
Flexibility innovation = 1		
(1,1,1) + (0,1,0) − (1,1,0) − (0,1,1) = 0	3.12	0.0772
(1,1,1) + (0,1,0) − (1,1,0) − (0,1,1) > 0		0.9614
Complements/substitutes/no relation	Complements	
Flexibility innovation - organizational innovation		
Efficiency innovation = 0		
(0,1,1) + (0,0,0) − (0,1,0) − (0,0,1) = 0	0.63	0.4277
(0,1,1) + (0,0,0) − (0,1,0) − (0,0,1) > 0		
Complements/substitutes/no relation	No relation	
Efficiency innovation = 1		
(1,1,1) + (1,0,0) − (1,1,0) − (1,0,1) = 0	0.62	0.4310
(1,1,1) + (1,0,0) − (1,1,0) − (1,0,1) > 0		
Complements/substitutes/no relation	No relation	

(i, j) denotes the exclusive innovation combinations, where i and j represent efficiency innovation and flexibility innovation, respectively. (i, j, k) denotes the exclusive innovation combinations, where i, j, and k represent efficiency innovation, flexibility innovation, and organizational innovation, respectively.

3.6 Discussion and Conclusions

There is very little micro-based literature on the relationship between different types of innovation in emerging economies. This paper presents one of the first attempts to investigate complementarities in use and in performance in the context of Chinese SMEs. It also extends previous literature about innovation complementarity by including a wider range of innovation types, some of which are scarcely used in the literature as stated earlier. A significant feature of this research is that our estimation procedure deals with problems of multicollinearity and endogeneity that are identified as important to consider in innovation studies. In order to simplify the analysis of the relationships between six types of innovation, we use EFA to delimit two important aspects of these innovation types: the first captures product-oriented types of innovation that are strongly intercorrelated, and the second captures production-oriented types of innovation. The resulting factors are used to estimate the effect of innovation intensity on firm performance. Moreover, the approach enables the complementarity/substitutability tests by two groups, thus, largely reducing the computational burden.

Our results reveal some important insights into innovation behavior in Chinese SMEs. First, in our special case of the relationship between product, process, and organizational innovation, there is no interplay between product, quality (a type of process innovation), and organizational innovation. This is inconsistent with the evidence from developed countries. Ballot et al. (2015) find one complementarity and two substitutions for SMEs in the UK, and two complementarities and one substitution for SMEs in France. Guisado-González et al. (2017) find two complementarities and one substitution for Spanish manufacturing firms. These results suggest that the existence of complementarity/substitutability depends on the firms' national context. China has been dependent for a long time on the imitation and acquisition of existing technologies to rapidly promote technological progress and achieve economic growth (Hou and Mohnen, 2013; Liao et al., 2020). Chinese firms tend to directly exploit acquired knowledge with little internal effort, which in turn impedes the development of their own capabilities to absorb that knowledge (Petti et al., 2019). Internal innovation capability is key for the emergence of innovation complementarity because only firms that possess adequate capabilities can transfer knowledge and other resources from one innovation type to another, leading to economics of scope (Guisado-González et al., 2018; González-Blanco et al., 2019). Therefore, a possible reason for different patterns of innovation complementarity between developed countries and China may be attributed to the varying levels of firms' capabilities. Due to a lack of abilities to transfer and integrate knowledge, Chinese firms appear less able to profit from the combination of product, process, and organizational innovation than firms in developed countries. This may be particularly true for Chinese SMEs with weaker capabilities because these SMEs generally refrain from R&D activities and have difficulty recruiting qualified technical personnel (Chung and Tan, 2017). As a result, Chinese SMEs gain only cumulative benefits from the combination of product, process, and organizational innovation.

Second, we find substitutability between efficiency and flexibility innovation. The simultaneous pursuit of efficiency and flexibility innovation reflects that Chinese SMEs relying on a low-cost strategy attempt to increase their competitiveness by providing customized products. However, firms introducing efficiency and flexibility innovation simultaneously suffer from two conflicting goals, which explains the absence of enhanced performance. This finding provides empirical support for prior research on the efficiency-flexibility tradeoff (Tan and Wang, 2010; Phillips et al., 2019) and on the innovation ambidexterity paradox (Ngo et al., 2019). Our work goes one step further by additionally investigating organizational innovation as a contingency of the relationship between efficiency and flexibility innovation. The result shows that substitutability between efficiency and flexibility innovation exists only in the absence of organizational innovation. In addition, the relationship between efficiency and organizational innovation is complementary in the presence of flexibility innovation. These results suggest that the addition of organizational innovation is beneficial for the firms that wish to excel in both efficiency and flexibility. We interpret our findings from a knowledge-based perspective. The tradeoff between efficiency and flexibility innovation arises largely from contradictory knowledge processes (Soto-Acosta et al., 2018). Efficiency innovation exploiting existing knowledge and flexibility innovation exploring new knowledge generate tensions within firms (Solís-Molina et al., 2018). Organizational innovation involves the use of new knowledge management systems to reconcile the inherent contradictions, which enables firms to maintain both efficiency and flexibility innovation (Simao and Franco, 2018).

3.6.1 Practical Implications

The main implication of this study is that managers of Chinese SMEs can decide to introduce product, quality, and organizational innovation simultaneously, since these innovation types are neither complements nor substitutes, which means that their joint application does not additionally increase or decrease firm performance. It would be more appropriate to encourage managers to commit additional efforts to developing internal innovation capabilities. Such capabilities can improve firms' potential to capture complementarities and thus reap the maximum economic benefits from simultaneous innovation practices. R&D activities are very important determinants of a firm's innovation capabilities. For SMEs struggling to conduct R&D in-house, a more plausible way to build up internal innovation capabilities is through informal modes of learning, such as learning by doing, using, and interacting (Lee and Walsh, 2016). It is also feasible to enhance innovation capabilities by implementing better recruitment, training, incentives, and compensation packages to attract, leverage, and retain a competent workforce (Petti et al., 2019).

Another important implication is that Chinese SMEs who combine efficiency and flexibility innovation have a wrong perception of the effectiveness of the efficiency-flexibility combinatorial strategy, since there is substitutability between efficiency and flexibility innovation. This is particularly striking considering the efficiency-flexibility innovation combination as the most frequently used one by Chinese SMEs (58.56% of our sample firms). The preferred efficiency-flexibility innovation combination has not generated the expected positive results in terms of firm performance. Instead, Chinese SMEs should consider simultaneous organizational change, as suggested by us, or avoid combining efficiency and flexibility innovation, as argued by Ebben and Johnson (2005).

3.6.2 Limitations and Future Research

Our study is subject to some limitations, which suggest possibilities for future research. First, although cross-sectional data is used in many studies of innovation complementarity (e.g., Ballot et al., 2015; Serrano-Bedia et al., 2018), future availability of panel data would allow us to capture unobserved individual heterogeneity, and thus help improve the econometric analysis. Second, firm performance is a multidimensional construct. Gunday et al. (2011) define firm performance as four dimensions: innovative performance, production performance, market performance, and financial performance. The complementarities between different innovation types could be prolifically examined by employing a wide range of firm performance measures. Finally, we tested for complementarities between product-oriented types of innovation and also between production-oriented types of innovation. Further efforts could be made to explore the relationship between product-oriented and production-oriented innovation.

Appendix

Table 3.8 Description of variables

Variable	Description and unit
Firm performance	Sales per full time equivalent (FTE) employee in the last survey year (in logs)
Quality innovation	Whether the firm introduced new quality control procedures in production or operation during the three-year period (dummy)
Organizational innovation	Whether the firm introduced new management/administrative procedures during the three-year period (dummy)
Product development	Whether the firm introduced new products or services during the three-year period (dummy)
Product improvement	Whether the firm added new features to existing products or services during the three-year period (dummy)
Efficiency innovation	Whether the firm introduced new or significantly improved methods to reduce unit production costs during the three-year period (dummy)
Flexibility innovation	Whether the firm introduced new or significantly improved methods to increase production flexibility during the three-year period (dummy)
Size	Number of FTE employees in the last survey year (in logs)
Age	Number of years since a firm was formally founded (in logs)
Investment intensity	Investment in physical assets per FTE employee in the last survey year (in logs)
Government ownership	Whether the firm is owned by government or state in the last survey year (dummy)
Foreign ownership	Whether the firm is owned by private foreign firms in the last survey year (dummy)
Human capital	Average number of years of education of FTE employees (in years)
External finance	Whether the firm had access to external finance (dummy)

Table 3.9 Performance regression: determinants of firm performance by factors or individual innovation types

	1	2	3	4	5	6	7
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
Factor 1	0.724*						
	(0.394)						
Factor 2	0.396						
	(0.356)						
Quality innovation		1.434***					
		(0.169)					
Organizational innovation			1.370***				
			(0.208)				
Product innovation				1.612***			
				(0.138)			
Product improvement					1.370***		
					(0.210)		
Efficiency innovation						−1.198***	
						(0.176)	
Flexibility innovation							1.231***
							(0.214)
Size (log)	−0.164***	−0.129***	−0.134***	−0.097***	−0.099**	0.064*	−0.084**
	(0.054)	(0.041)	(0.043)	(0.037)	(0.040)	(0.035)	(0.039)
Age (log)	0.018	0.032	−0.010	0.082	−0.013	0.067	0.046
	(0.087)	(0.077)	(0.079)	(0.079)	(0.078)	(0.075)	(0.076)
Investment intensity (log)	−0.015	−0.006	−0.001	0.003	−0.002	0.048***	0.002
	(0.014)	(0.009)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)
Human capital	−0.009	0.005	−0.012	−0.024	0.009	0.007	0.013
	(0.033)	(0.023)	(0.022)	(0.023)	(0.024)	(0.020)	(0.022)
Government ownership	0.364	0.371	0.236	0.362	0.257	0.319	0.520**
	(0.361)	(0.245)	(0.239)	(0.241)	(0.240)	(0.233)	(0.246)
Foreign ownership	0.185	0.265	0.163	0.288*	0.274*	0.497***	0.316**
	(0.174)	(0.171)	(0.175)	(0.165)	(0.158)	(0.143)	(0.155)
Constant	13.693***	12.755***	13.070***	12.731***	12.669***	13.382***	12.074***
	(0.577)	(0.519)	(0.465)	(0.520)	(0.509)	(0.502)	(0.482)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wald χ^2	3,082.75***	1,081.17***	1,016.28***	1,100.40***	882.37***	690.94***	740.60***
Log pseudolikelihood	−4,361.89	−2,148.19	−2,149.38	−2,150.43	−2,155.74	−1,993.86	−2,125.93
Observations	1,139	1,139	1,139	1,139	1,139	1,139	1,139

The conditional mixed process procedure is used to estimate innovation and productivity equations simultaneously. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels.

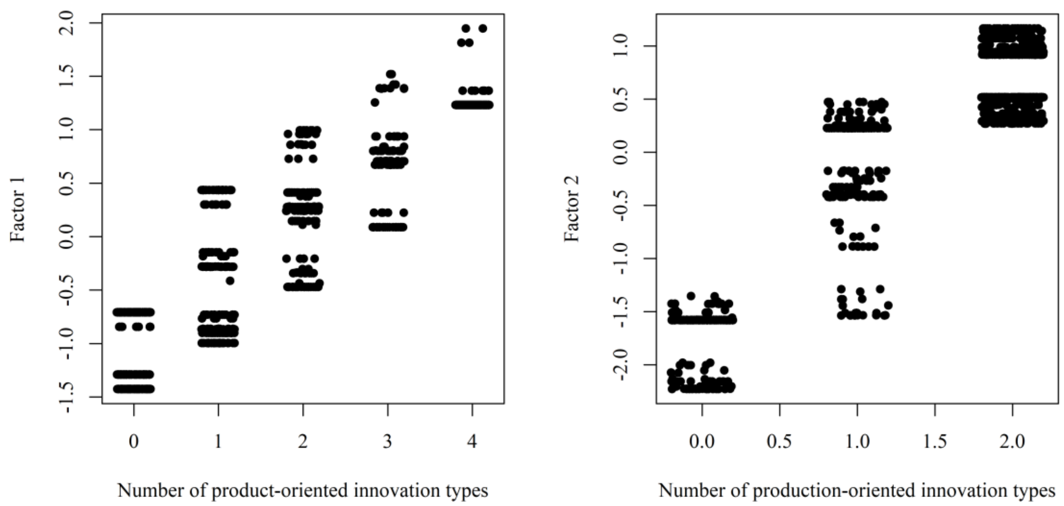


Figure 3.3 Jitter plot showing the relationships between factor scores and the number of innovation types

Chapter 4 SME Innovation Patterns Identified from a Process Perspective: Linking Innovation to SME Performance

Abstract: Little attention has been paid to the analysis of Chinese manufacturing SMEs' innovation patterns and their impact on the SMEs' performance. This paper develops two categories of SME innovation patterns and applies these innovation patterns to analyze the link between innovation and SME performance. Innovation patterns are identified based on the input and output stages of the innovation process. The innovation inputs covering internal and external sources of knowledge are used to identify innovation sourcing patterns which differ in the degree of being active and open in terms of knowledge sourcing. The innovation outputs involving technological and non-technological types of innovation are employed to identify innovation introducing patterns which show the variety of innovation types introduced. It is subsequently examined how innovation sourcing patterns relate to innovation introducing patterns that affect SME performance. Regarding the relationship between innovation sourcing and introducing patterns, we find that being innovation-active increases the likelihood of introducing various innovation types and being open is most likely to lead to a variety of innovation types. The results for the impact of innovation introducing patterns on SME performance show that a simultaneous adoption of innovation types related to the production process is detrimental to SME performance, while a pure introduction of product innovation and a combination of technological and non-technological innovation offer performance benefits. This paper has policy and research implications.

Keywords: Manufacturing SMEs; Innovation patterns; SME performance

4.1 Introduction

Small- and medium-sized enterprises (SMEs) are highly heterogeneous in their innovation behavior, which motivates the creation of innovation patterns to manage and interpret the heterogeneity among innovating SMEs (Peneder, 2003, 2010; Hervas-Oliver et al., 2021). In this study, SME innovation patterns refer to the grouping of SMEs with similar innovation characteristics. Awareness and understanding of different innovation patterns across SMEs are needed for Chinese policymakers who have neglected some SMEs' emphasis on experience-based learning and thus have failed to meet the specific needs of certain SMEs (Jia et al., 2020). Despite the high profile of innovation patterns in SME policy formulations, no work searches for regularities in Chinese SMEs' innovation behavior or taxonomies of innovating SMEs in China. By contrast, empirical evidence from western countries has showed a set of innovation taxonomies for SMEs (De Jong and Marsili, 2006; Brunswicker and Vanhaverbeke, 2015; Hervas-Oliver et al., 2016a; Hervas-Oliver et al., 2020; Thomä and Zimmermann, 2020; Runst and Thomä, 2022). However, the stream of literature provides a rather partial view of the innovation patterns of SMEs by taking into account either the innovation inputs or outputs of the firms (e.g., Evangelista and Vezzani, 2010). As a result, the empirical identification remains fragmented and inconclusive, limiting our knowledge of the diversity of SME innovation patterns. Due to the fundamental role that innovation inputs and outputs play in shaping an innovation process, the highly heterogeneous nature of SME innovation arises from innovation activities undertaken by SMEs and innovation types introduced by them, according to which SME innovation patterns can be identified in a comprehensive way. In this paper, we use "innovation sourcing patterns" to refer to the patterns indicating how SMEs undertake innovation activities and "innovation introducing patterns" to refer to the patterns indicating how SMEs introduce innovation types. Therefore, the first empirical goal of this study is to condense the vast heterogeneity of Chinese SMEs' innovation behavior into a set of typologies of innovation activities and innovation types, thereby producing innovation sourcing patterns and innovation introducing patterns.

After identifying and profiling the different patterns of innovation sourcing and introducing, it is subsequently examined how innovating SMEs transform from one innovation sourcing pattern to one innovation introducing pattern and what the economic performance of the innovation introducing pattern is, in order to deepen the practical implications of the innovation taxonomies for innovation policy. Two reasons account for the significance of such empirical analysis from the policymakers' perspective. First, the justification for policy intervention in support of innovating SMEs relates to the results of innovation activities and the productivity of innovation outputs (Storey, 2003; Thomä and Zimmermann, 2020). Second, this analysis is associated with a major concern of Chinese policymakers about how to catch up with leading countries, particularly to narrow technological and productivity gaps, by encouraging firms to innovate (Liu et al., 2017). Starting with the seminal work of Crepon, Duguet, and Mairesse (1998), a large and growing number of empirical studies use a structural approach to model the process from innovation inputs to innovation outputs and productivity (Hall et al., 2009; Conte and Vivarelli, 2014; Baumann and Kritikos, 2016; Wadho and Chaudhry, 2018; Shi et al., 2020). Most of this literature has limited inputs of the innovation process to R&D activities and has also concentrated on one innovation output at a time, but SMEs usually take advantage of innovation activities beyond formal R&D, in which way they may introduce different types of innovation at the same time (Rammer et al., 2009; Donbesuur et al., 2020; Zhang, 2022a, 2022b). Consequently, a research gap exists in the analysis of the innovation process, considering all possible innovation inputs and outputs for SMEs. Therefore, the second empirical goal of this study is to take a closer look at the innovation process in SMEs with the use of innovation patterns characterized by different mixes of innovation inputs and outputs.

The aims of this study consist of identifying SME innovation patterns and investigating how they relate to SME performance. In doing so, this study answers two key research questions: (1) to what extent do Chinese SMEs show distinct patterns in their innovation activities (innovation sourcing patterns) and in their innovation types (innovation introducing patterns)? and (2) what is the link between the two typologies of innovation patterns and SME performance? These issues are addressed by means of a quantitative analysis based on a sample of 1,127 Chinese manufacturing SMEs. Our analysis helps grasp the heterogeneity of Chinese SMEs' innovation behavior by grouping innovating SMEs according to their innovation activities and innovation types. It also contributes to understanding the complexity of the innovation process by using innovation patterns that offer comprehensive coverages of firm-level innovation inputs and outputs.

The remainder of this article is organized as follows: section 4.2 presents the theoretical background and literature review; section 4.3 describes the database and variables; section 4.4 reports on the empirical results; and section 4.5 summarizes the main findings and draws some implications for policymakers and researchers.

4.2 Theoretical Background and Literature Review

4.2.1 SME Innovation Patterns

In innovation research, the heterogeneity among firms has attracted intense interest in taxonomic work. The literature focusing on sectoral patterns of innovation has proved vastly influential (Pavitt, 1984; Castellacci, 2008). While the sectoral taxonomies were thought to be useful for making policies that support innovating firms, it has been growingly recognized that the sector-level analysis does not take into account the heterogeneity among firms in the same sector (Archibugi, 2001; Marsili and Salter, 2005). Over the last decade, there have been increasing efforts to investigate innovation patterns based on firm data, showing that firms within the same sector are dispersed across different patterns of the corresponding taxonomy (Filippetti, 2011; Trigo, 2013).

The firm-based innovation taxonomy can find its theoretical basis in the resource-based view (RBV) because the RBV posits that the differences in firm performance result from firms' unique resources and capabilities rather than the sectoral structural characteristics (Barney, 1986b; Donnellan and Rutledge, 2019). The RBV offers a theoretical lens through which the presence of firm heterogeneity and the formation of innovation patterns can be explained at the firm level. From the resource-based perspective, a firm is a bundle of resources and capabilities that are specific to the firm, which make it different from other firms, shape its particular pattern, and keep it competitive in the changing business environment (Wernerfelt, 1984; Barney, 1991). The traditional RBV addresses the attributes of individual resources and argues that valuable, rare, inimitable, and non-substitutable resources are the sources of a sustained competitive advantage (Barney, 1991; Nason and Wiklund, 2018). The dynamic-capability view complements the RBV underscoring the capabilities of integrating and reconfiguring resources, which allow firms to extract diverse combinations from those resources and thus enjoy new sources of competitive advantage (Eisenhardt and Martin, 2000; Lockett et al., 2009; Lin and Wu, 2014). As Hervas-Oliver et al. (2015, 2018) suggest, a firm's competitive advantage not only derives from developing each of resources on its own, but also from combining the resources in a unique way. The implications of the RBV for this study are: first, SMEs are heterogeneous, in terms of their resources or resource combinations, for the purpose of achieving a sustained competitive advantage; second, since resources are the fundamentals of SME innovation patterns, the use of heterogeneous resources and the heterogeneous combinations of resources lead to the variety of the patterns across innovating SMEs.

In this paper, we attempt to capture SME innovation patterns based on a linear and sequential innovation process. The innovation process starts with the decision to undertake innovation activities that result in various innovation types, consequently shaping the overall firm performance (Frank et al., 2016). This process perspective on SME innovation implies that innovation activities are the resources required for the introduction of innovation types and innovation types are the resources intended for superior firm performance. As mentioned earlier, resources constitute a precondition for SME innovation patterns to exist. Thus, we decide to use the indicators of innovation activities and of innovation types to separately identify the patterns indicating how SMEs conduct innovation activities and those indicating how they introduce innovation types, thereby comprehensively revealing SME innovation patterns. For the sake of brevity and distinction, we refer to the patterns of undertaking innovation activities as "innovation sourcing patterns" and the patterns of introducing innovation types as "innovation introducing patterns". Further in this section, we discuss key resources that construct SMEs' innovation sourcing patterns and their innovation introducing patterns.

4.2.1.1 Innovation Sourcing Patterns

Innovation sourcing patterns indicate how SMEs engage in various innovation activities to access different sources of knowledge. It is generally recognized that SMEs possess limited resources and capabilities and face difficulties in covering all the activities required for innovation success (Spithoven et al., 2013; Gimenez-Fernandez et al., 2020). Notably, SMEs lack financial and human resources to perform in-house R&D, which is a key driver of innovation success (Rammer et al., 2009). Furthermore, the complexity of innovation increases with technological progress, meaning that firms hardly innovate by themselves and relevant knowledge is distributed across multiple firms (Edwards et al., 2005; Lee et al., 2010). Therefore, SMEs have a strong incentive to adopt open innovation (OI) in order to benefit from inter-organizational knowledge flows (Chesbrough, 2003). OI is a broad concept involving inbound and outbound practices, but the focus of this paper is to investigate inbound ones through which SMEs may overcome the liability of smallness and lack of resources and competencies (Chesbrough, 2006; Usman et al., 2018). A variety of inbound OI practices have been documented, including R&D outsourcing, inward technology licensing, modification to existing products, purchase of new equipment, and collaborations with other firms or research institutes (Dahlander and Gann, 2010; Obradović et al., 2021; Zhang, 2022a). These inbound OI practices help SMEs acquire external knowledge and extend technological competencies, allowing them to shorten innovation time, reduce risks and costs, and increase access to the market (Parida et al., 2012; Brunswicker and Vanhaverbeke, 2015; Livieratos et al., 2022).

To substantially gain from inbound OI practices, SMEs need to develop internal capabilities in order to value, assimilate, transform, and exploit new knowledge from the external environment, suggested by the concept of absorptive capacity (AC) (Cohen and Levinthal, 1989, 1990; Zahra and George, 2002). In the literature, it is common to overemphasize the importance of internal R&D for AC (Laursen and Salter, 2006; Kale et al., 2019; Presutti et al., 2019). AC also builds on employee skills, organizational memory, and prior organizational experiments and experiences, meaning that internal R&D is not the only component of AC (Flatten et al., 2011). AC is less related to internal R&D in the SME context. As discussed earlier, few SMEs afford internal R&D activities due to inadequate financial or human resources. Moreover, R&D activities could be considered unnecessary for SMEs who are oriented to process innovation in low-tech industries (Hervas-Oliver et al., 2021). Therefore, SMEs tend to adopt informal activities internally, such as training and learning by doing, using, and interacting, which contribute to accumulating related knowledge to create AC (Muscio, 2007; Hervas-Oliver et al., 2012; Moilanen et al., 2014). These internal activities are indispensable for conducting external activities, implying that external activities are unlikely to characterize patterns alone without combining them with internal activities.

4.2.1.2 Innovation Introducing Patterns

Innovation introducing patterns, driven by the innovation sourcing patterns, emerge in the way SMEs introduce different types of innovation. The types of innovation can be classified as technological and non-technological, depending on whether they are technology-based (Schmidt and Rammer, 2007; Mothe and Nguyen-Thi, 2012). Technological innovation involves the development or use of new or improved technologies, which is traditionally perceived to encompass product and process innovation (Mothe and Nguyen-Thi, 2010; Geldes et al., 2017). Product innovation includes product development for the generation of new goods or services and product improvement for the significant improvements in the characteristics of existing goods or services. Process innovation refers to the implementation of new or significantly improved production methods and techniques, including quality innovation for assuring product quality, efficiency innovation for reducing production costs, and flexibility innovation for increasing production flexibility (Edwards-Schachter, 2018; Zhang, 2022b). In contrast to technological innovation, non-technological innovation does not relate to technologies, but affects an organization’s management systems (Pino et al., 2016). Following Evangelista and Vezzani, (2010), we concentrate on organizational innovation as it is the most crucial form of non-technological innovation. According to OECD (2005), organization innovation is the implementation of a new organizational method in the firm's business practices, workplace organization or external relations.

Although technological and non-technological types of innovation differ in nature, they indeed interact with each other (Schmidt and Rammer, 2007). Technological innovation demands non-technological innovation to support its implementation and exploitation (Azar and Ciabuschi, 2017). Non-technological innovation, in turn, provides more possibilities for the development of technological innovation (Mothe and Nguyen-Thi, 2012). Concerning organizational innovation, interactions with product and process innovation are both possible. Product innovation triggers organizational innovation when product innovation calls for the establishment of new divisions or departments, or the reorganization of workflows, knowledge management or external relations (Schmidt and Rammer, 2007; Radicic and Djalilov, 2019). From another point of view, organizational innovation enhances flexible and creative learning cultures that allow for the use of adaptive manufacturing systems and new ideas, thus facilitating product innovation (Camison and Lopez, 2010; Anzola-Román et al., 2018). Similarly, process innovation gives rise to organizational innovation when process innovation induces the reorganization of business routines that results in new business practices or new organizational models (Schmidt and Rammer, 2007). On the other hand, organizational innovation contributes to structural improvements, which lead to better intra-organizational coordination and cooperation mechanisms and thus create an appropriate environment for the adoption of process innovation (Gunday et al., 2011; Azar and Ciabuschi, 2017).

Coming back to the RBV, the concurrence of technological and non-technological innovation has been highlighted for the achievement of a sustained competitive advantage. Innovation introducing patterns characterized by combining various types of innovation configure a complex system of complementary and mutually reinforcing innovation types that derives higher-order innovation capabilities from the integration of technological and non-technological innovation capabilities, protecting firms against imitation and leading to superior performance (Hervas-Oliver et al., 2016b).

4.2.2 *Linking Innovation Patterns to Firm Performance*

The analysis of the relationship between innovation and firm performance has been intensively conducted during the last decades (Hall and Mairesse, 1995; Klomp and Van Leeuwen, 2001; Mohnen and Hall, 2013; Latifi et al., 2021). A popular approach is to use the CDM model which was presented in the seminal work of Crépon, Duguet, and Mairesse (1998). This model frames the process of transforming innovation inputs into innovation outputs and finally into firm performance by using four equations: the first two equations account for a firm's decision to engage in R&D and corresponding R&D investment, respectively; the third equation describes the knowledge production, namely the production of innovation outputs (patents/innovative sales) depending on R&D and other resources; the fourth equation is an innovation augmented Cobb-Douglas production function where innovation outputs affect firm performance. It is evident that the original CDM specification suffers from two main limitations: first, R&D underestimates the extent of a firm's innovation efforts, especially for SMEs who have many disadvantages in performing R&D activities (Hervas-Oliver et al., 2011). SMEs tend to undertake non-R&D activities to compensate for their lack of formal R&D. Second, not all innovation outputs are necessarily patented or can be measured by sales. Non-technological types of innovation, organizational innovation for example, do not directly generate marketable products or processes that may lead to patents or sales (Becheikh et al., 2006).

In more recent CDM literature, variants of the CDM model are used to examine the inputs and outputs of the innovation process as well as the link between the innovation process and firm performance. Hall et al. (2009) apply the CDM model to a sample of Italian SMEs and extend the knowledge production function of the CDM model to include product and process innovation. Conte and Vivarelli (2014) use not only multiple technological innovation outputs but also proxy innovation inputs by R&D and technology acquisition when they estimate the CDM model based on firm data. Instead of modifying the key variables originally used in the CDM model, Baum et al. (2017) employ a new methodology for the estimation of the CDM model to deal with the issues of selectivity and endogeneity. Despite many CDM research efforts, the heterogeneity of SMEs' innovation behavior has not been grasped. This is because many activities beyond R&D and firms' boundaries, and non-technological types of innovation outputs, especially organizational innovation, are under-investigated in the stream of empirical research. Therefore, we try to improve further on the CDM model by using innovation sourcing patterns and innovation introducing patterns, which allows us to take into account SME heterogeneity in innovation inputs and outputs to a large extent.

4.3 Data and Variables

4.3.1 Sample and Data

We base our empirical analysis on the latest Chinese Manufacturing Enterprise Survey (ES) collected by the World Bank between November 2011 and March 2013. The survey data is still used in recent research (e.g., Jin et al., 2022; Salike et al., 2022; Zhao and Zhang, 2023), which demonstrates its potential. The ES includes a broad and interesting set of data on innovation activities as well as innovation types, allowing us to go beyond formal R&D and technological innovation and thus have a complete view of SME innovation patterns. Another advantage of the ES database is its detailed account of variables on general firm characteristics, such as sales and size, which can be used to ascertain firm performance. Due to these strengths, the data from the ES is particularly suitable for capturing the patterns of innovation activities and innovation types and analyzing the link between innovation patterns and firm performance.

The sample is representative of the population of Chinese manufacturing firms, which was randomly selected according to three levels of stratification: firm size, industrial sector, and geographic location. As a result, the ES offers a total sample of 2,848 Chinese firms in the manufacturing and service industries. Since the innovation survey was conducted only in the manufacturing industry, we restrict our focus to 1,690 manufacturing firms. Following the Chinese national industrial classification, we further concentrate on manufacturing firms with less than 1,000 employees belonging to manufacturing SMEs in China. It is noted that the ES database is skewed towards

SMEs and 1,619 firms (56.85%) of the total sample are SMEs operating in 12 Chinese administrative regions and 19 manufacturing sectors (See Figures 4.1 and 4.2). Excluding firms with missing values gives us a final sample of 1,127 manufacturing SMEs for the empirical analysis.

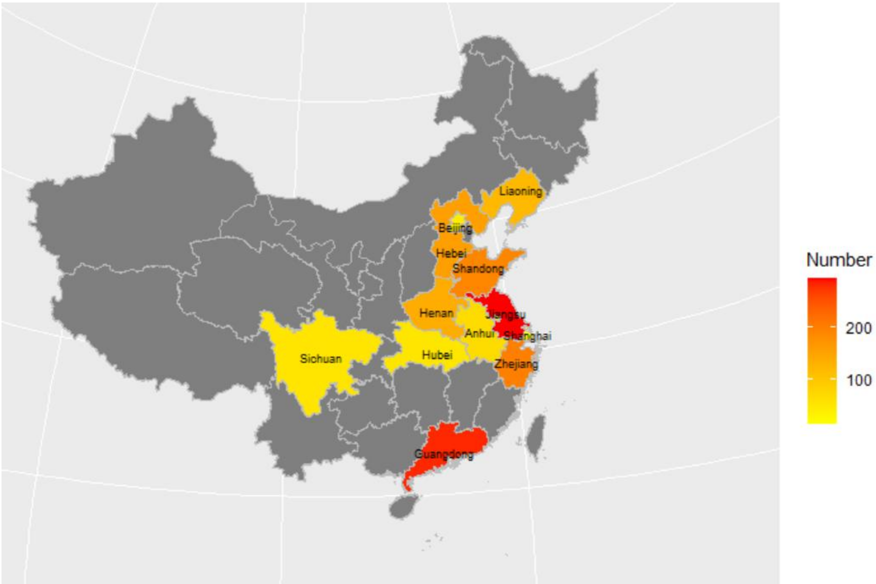


Figure 4.1 Regional distribution of SMEs surveyed by the ES

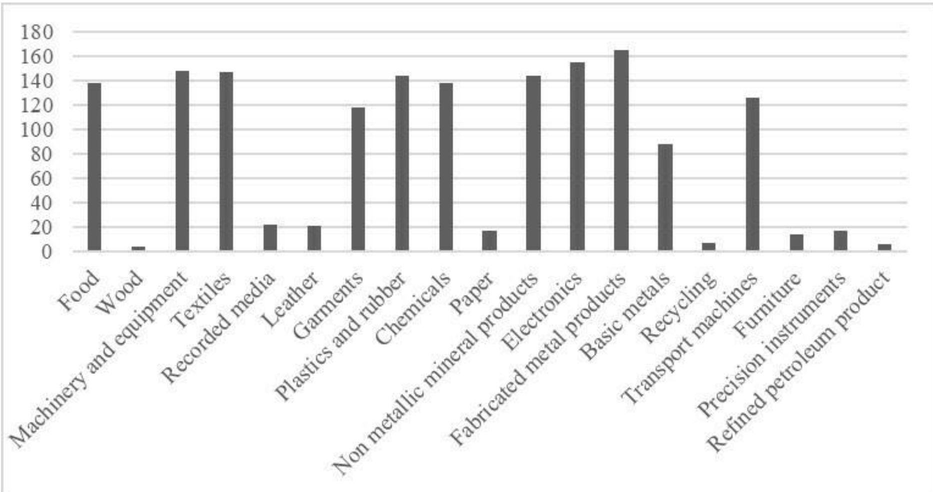


Figure 4.2 Sectoral distribution of SMEs surveyed by the ES

4.3.2 *Variables and Models*

As discussed earlier, we apply a modified version of the CDM structural model with two equations to analyze the relationship between innovation inputs, innovation outputs, and SME performance.

The first equation (4.1) is a knowledge production function in which innovation introducing patterns depend on innovation sourcing patterns. Due to the unordered categories of innovation introducing patterns (the dependent variable), we estimate equation (4.1) using a multinomial probit model.

$$P_{ij} = \mathrm{Prob}(pattern_i = j \mid X_{1i}) \tag{4.1}$$

where P_{ij} is the probability that firm i belongs to innovation introducing pattern j $(j = 1,2,3)$. The initial variables for identifying the innovation introducing patterns are related to different types of innovation. X_{1i} is a vector of an independent variable and control variables. The independent variable is the categorical indicator of innovation sourcing patterns that are derived from various innovation activities. With respect to control variables, we include a set of variables to control for firms' characteristics, including firm size, firm age, ownership, human capital, industry dummies and city dummies.

The second equation (4.2) is a productivity function specified as a Cobb-Douglas function with constant returns to scale. We conduct an ordinary least squares (OLS) regression to estimate equation (4.2).

$$Y_i = \alpha_1 pattern_i + \alpha_2 X_{2i} + \varepsilon_i \tag{4.2}$$

where Y_i is the indicator of firm performance. $pattern_i$ is a categorical variable denoting the specific innovation introducing pattern that firm i belongs to and α_1 is its coefficient. X_{2i} represents a vector of control variables with α_2 their corresponding coefficient vector. Specifically, we control for production inputs, including firm size, physical investment, and human capital, and also employ firm age, ownership, industry dummies, and city dummies as additional controls. ε_i is an error term.

In summary, we focus on three groups of key variables. The first group covers a wide range of innovation activities. The second group contains different types of innovation. The third group addresses firm performance, which is measured by the natural logarithm of total sales per employee last year. In addition, we control for some firms' characteristics. Table 4.9 in the Appendix shows a detailed description and the measurement of all variables. The descriptive statistics of these variables are summarized in Table 4.1. From our sample, we observe how innovation is a common phenomenon in Chinese manufacturing SMEs, where they undertake various innovation activities and introduce multiple types of innovation.

Table 4.1 Descriptive statistics

Variable	Mean	Std. Dev.	Minimum	Maximum
Internal R&D	0.411	0.492	0	1
External R&D	0.112	0.315	0	1
Use of new equipment and technology	0.688	0.464	0	1
In-house development	1.373	0.883	0	2
Collaboration with suppliers	0.579	0.854	0	2
Collaboration with clients	0.673	0.897	0	2
Modification to existing products/ Inward technology licensing	0.731	0.878	0	2
Internal knowledge sourcing	1.309	0.897	0	2
External knowledge sourcing	0.570	0.855	0	2
Quality innovation	0.525	0.500	0	1
Organizational innovation	0.500	0.500	0	1
Product development	0.562	0.496	0	1
Product improvement	0.519	0.500	0	1
Efficiency innovation	0.857	0.350	0	1
Flexibility innovation	0.708	0.455	0	1
Firm performance (log)	12.461	1.070	9.433	17.770
Size (log)	4.328	1.073	1.609	6.856
Age (log)	2.529	0.459	0	4.836
Government ownership	0.049	0.216	0	1
Foreign ownership	0.050	0.217	0	1
Human capital	10.100	1.949	1	18
Investment intensity (log)	5.132	4.691	0	15.356

N = 1,127

4.4 Empirical Analysis

4.4.1 *The Identification of SME Innovation Patterns*

4.4.1.1 Preparing Clustering Variables

Before undertaking cluster analysis, two separate factor analyses are employed to compress the original variables on innovation activities and innovation types into corresponding factor scores as the clustering variables. We use factor scores instead of original variables to perform cluster analysis for two reasons. First, factor scores are more robust clustering variables as they are linear combinations of the original variables. Second, condensing highly correlated variables into distinct factors overcomes the multicollinearity problem that negatively affects the cluster analysis results (Thomä, 2017).

Regarding the categorical variables on innovation activities, Bartlett's sphericity test shows a probability significance level < 0.001, lower than the required 0.05, and the Kaiser-Meyer-Olkin test gives a test statistic of 0.531, higher than the required 0.5, which ensure the appropriateness of factor analysis. To determine the number of factors to retain, we apply the latent root criterion (eigenvalues > 1) based on a polychoric correlation matrix, resulting in a two-factor solution. With varimax rotation, the two retained factors explain 81.35% of the total variance in the nine variables on innovation activities, indicating that the two-factor model is satisfactory (see Table 4.2). In Table 4.2, loading values higher than 0.5 are bolded. Factor 1 is marked by high loadings on external innovation activities, including external R&D, use of new equipment and technology, collaboration with suppliers, collaboration with clients, modification to existing products/inward technology licensing, and external knowledge sourcing. Internal innovation activities, including internal R&D, in-house development, and internal knowledge sourcing, have high loadings on Factor 2.

Table 4.2 VARIMAX rotated factor matrix for the variables on innovation activities

Variable	Factor 1	Factor 2
Internal R&D	0.044	**0.806**
External R&D	**0.504**	0.425

(Table 4.2 Continued)

Variable	Factor 1	Factor 2
Use of new equipment and technology	**0.534**	0.447
In-house development	0.227	**0.801**
Collaboration with suppliers	**0.775**	0.179
Collaboration with clients	**0.829**	0.191
Modification to existing products/Inward technology licensing	**0.700**	−0.034
Internal knowledge sourcing	0.175	**0.830**
External knowledge sourcing	**0.580**	0.395
Explained variance (%)	60.85	20.50

In the case of the dummy variables on innovation types, two factors are extracted (the significance of Bartlett's sphericity test < 0.001 and the Kaiser-Meyer-Olkin test statistic = 0.663). The bolded loading values in Table 4.3 show that quality innovation, organizational innovation, product development, and product improvement load significantly on Factor 1 and efficiency innovation and flexibility innovation on Factor 2.

Table 4.3 VARIMAX rotated factor matrix for the variables on innovation types

Variable	Factor 1	Factor 2
Quality innovation	**0.735**	0.421
Organizational innovation	**0.704**	0.434
Product development	**0.903**	−0.035
Product improvement	**0.814**	0.347
Efficiency innovation	0.081	**0.862**
Flexibility innovation	0.362	**0.725**
Explained variance (%)	79.66	21.13

4.4.1.2 Identifying Innovation Patterns

Based on two factor sets, hierarchical clustering procedures are carried out using Ward's method with squared Euclidian distance to identify different typologies of innovation patterns. Cluster stopping rules are used to decide the number of clusters.

The set of factors on innovation activities is used to perform a cluster analysis, yielding three innovation sourcing patterns. Table 4.4 reports the average values of each identified cluster for each original variable. All the means of original variables significantly differ across the three clusters, confirming the robustness of the three-cluster solution (see Chi2 values in Table 4.4). The first cluster, comprising 609 SMEs (54.04% of the total sample), is marked by above-average levels of internal R&D, in-house development, and internal knowledge sourcing. We interpret the strong reliance on internal innovation activities as an indicator that SMEs in the first cluster build up a high AC. However, their use of external knowledge sources is below average compared to the total sample. This drives us to assume that this cluster of SMEs has sufficient capabilities of handling innovation activities alone with a low propensity to open up these innovation activities to outside influences. Therefore, the first cluster is labeled the “internal sourcing group”. The second cluster consists of 297 SMEs (26.35% of the total sample) who show little interest in either internal or external innovation activities. SMEs in this cluster are not active in internal innovation activities and they thus lack critical internal capabilities needed to access external sources of knowledge. As a result, the second cluster of SMEs is characterized by a low involvement in innovation activities, as they neither actively develop internal innovation competencies nor do they intensively use external knowledge sources. Accordingly, the second cluster is named the “low sourcing group”. The third cluster, the smallest, is composed of 221 SMEs (19.61% of the total sample). The specific feature of SMEs in the third cluster is a marked combination of internal and external innovation activities. This cluster of SMEs attaches great importance to external sources of knowledge. At the same time, they also rely on in-house R&D and other informal internal activities, albeit less than SMEs in the first cluster. Along with the intensive engagement in internal innovation activities, extensive involvement in external innovation activities is observed in the third cluster. This feature of the third cluster justifies the assumption of AC that SMEs adopting an open innovation strategy have to develop AC through internal efforts to access external knowledge. Thus, we label the third cluster as the “open sourcing group”. Based on the number of innovation activities with above-average values, we observe that low, internal, and open sourcing groups show low, medium, and high degrees of being active in innovation activities, respectively, and only open sourcing group presents a high degree of being open to external activities while other two groups have a low degree of opening up.

Table 4.4 The characteristics of the three innovation sourcing patterns

	Cluster 1	Cluster 2	Cluster 3	Total	
Variable	N=609	N=297	N=221	N=1,127	Chi2
Internal R&D	54.19%	10.77%	45.70%	41.08%	157.8690*
External R&D	10.34%	2.36%	25.34%	11.18%	68.3303*
Use of new equipment and technology	68.64%	50.84%	93.21%	68.77%	105.9255*
In-house development	96.55%	11.78%	89.14%	72.76%	760.9817*
Collaboration with suppliers	20.69%	13.47%	96.83%	33.72%	494.6555*
Collaboration with clients	23.65%	21.55%	100.00%	38.07%	447.6590*
Modification to existing products/Inward technology licensing	29.23%	43.77%	87.33%	44.45%	221.7685*
Internal knowledge sourcing	88.18%	22.56%	85.97%	70.45%	444.7442*
External knowledge sourcing	26.44%	17.17%	71.04%	32.74%	190.8927*

* reports a significance level of 1%.

Besides identifying the innovation sourcing patterns, we apply the same clustering method based on the factor set on innovation types, generating three innovation introducing patterns. To closely inspect the characteristics of each cluster, the mean values of the original variables are provided in Table 4.5. The first cluster with 522 SMEs (46.32% of the total sample) constitutes the largest group in our sample. This cluster is profiled by a joint introduction of efficiency innovation and flexibility innovation. The significant high share of SMEs introducing efficiency innovation aligns with the fact that most Chinese SMEs reduce production costs to compete on price for seizing a market share (Tang and Hull, 2012; Chen et al., 2017). We label the first cluster as the "production innovators" due to its strong focus on production-related innovation types. The second cluster is the smallest, containing 206 SMEs (18.28% of the total sample) that greatly emphasize new product development. This reflects the fact that resource-constrained SMEs rarely develop new products, which requires abundant resources and brings risk exposures (Woschke et al., 2017). We refer to the second cluster as the "product innovators". The third cluster is made up of 399 SMEs (35.40% of the total sample) characterized by the simultaneous adoption of all six innovation types. SMEs in the third cluster develop non-technological innovation, while they introduce technological innovation, presenting a combination of non-technological and technological innovation. The third cluster is thus called “multifaceted innovators”.

Table 4.5 The characteristics of the three innovation introducing patterns

	Cluster 1	Cluster 2	Cluster 3	Total	
Variable	N=522	N=206	N=399	N=1,127	Chi2
Quality innovation	30.27%	24.27%	96.24%	52.53%	475.4276*
Organizational innovation	27.59%	20.87%	94.24%	49.96%	487.1022*
Product development	17.82%	68.45%	100.00%	56.17%	635.8433*
Product improvement	23.56%	30.58%	100.00%	51.91%	575.1957*
Efficiency innovation	98.66%	26.70%	99.25%	85.71%	717.0406*
Flexibility innovation	72.41%	15.05%	97.49%	70.81%	447.9637*

* reports a significance level of 1%.

4.4.2 *The Link to Firm Performance*

4.4.2.1 Innovation Sourcing Patterns and Innovation Introducing Patterns

To examine the relationship between innovation sourcing patterns and innovation introducing patterns, we perform a multinomial probit model to regress innovation introducing patterns on innovation sourcing patterns, with coefficients estimating the relative likelihood of falling into a particular innovation introducing pattern compared to the production innovators as the base category.

Table 4.6 provides the coefficients from the multinomial probit regression. Open sourcing group shows significantly positive coefficients for both innovation introducing patterns: product innovators and multifaceted innovators. The open sourcing group is thus more likely to be product innovators and multifaceted innovators instead of production innovators. This implies that an open innovation strategy that facilitates SMEs to enrich resources and extend capabilities increases the tendency to develop product innovation and introduce different innovation types simultaneously (compared to production innovation). In contrast, a negative and significant coefficient of low sourcing group indicates that this group has a lower relative likelihood of being found among multifaceted innovators compared to production innovators.

Table 4.6 Coefficient results from the multinomial probit (baseline dependent variable: production innovators)

Variable	Product innovators	Multifaceted innovators
Internal sourcing group	-	-
Low sourcing group	0.050	-0.800^{***}
	(0.181)	(0.188)
Open sourcing group	0.640^{***}	1.454^{***}
	(0.226)	(0.199)
Size (log)	−0.020	0.350^{***}
	(0.072)	(0.072)
Age (log)	0.102	0.035
	(0.167)	(0.164)
Human capital	0.133^{***}	0.125^{***}
	(0.045)	(0.042)
Government ownership	-1.097^{**}	-2.059^{***}
	(0.451)	(0.541)
Foreign ownership	−0.403	0.343
	(0.404)	(0.338)
Industry dummies	Yes	Yes
City dummies	Yes	Yes
Observations	970	970

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Some variables predict failure perfectly, thus reducing the corresponding observations.

The coefficients in Table 4.6 should be interpreted in comparison with the baseline dependent variable, whereas the marginal effects summarized in Table 4.7 demonstrate the absolute likelihood of falling into the corresponding innovation introducing pattern. Table 4.7 presents pairwise comparisons of the marginal effects across all three innovation sourcing patterns, leading to some findings. First, SMEs in the open sourcing group are more likely than those in the internal and low sourcing groups to be multifaceted innovators. However, compared to the other groups, the open sourcing group shows a lower likelihood of being found in production and product innovators (albeit no significant differences between the open and internal sourcing groups in the likelihood of being product innovators). This may offer a hint that SMEs adopt a widely diversified sourcing strategy in pursuit of different innovation types at the same time. Second, SMEs in the low sourcing group are least likely to transform themselves into the multifaceted innovators. On the other hand, being a member of the low sourcing group limits corresponding firms' attention to fewer types of innovation and thus increases their likelihood of introducing either production or product innovation. Third, the internal sourcing group occupies a middle position between the low sourcing group and the open sourcing group in terms of the possibilities of being production innovators and multifaceted innovators, but it shows a likelihood of being product innovators which is similar to the open sourcing group and lower than the low sourcing group. Overall, we find that the increasing the degree of SMEs being active in innovation activities, the higher the likelihood of them pursuing diversified innovation types, and an open sourcing strategy is especially linked to the greatest proficiency in achieving the variety of innovation types.

Table 4.7 Marginal effects from the multinomial probit

Variable	Production innovators	Product innovators	Multifaceted innovators
Low sourcing group vs. internal sourcing group	0.085^{**}	0.068^{**}	-0.153^{***}
	(0.035)	(0.031)	(0.030)
Open sourcing group vs. internal sourcing group	-0.254^{***}	−0.035	0.289^{***}
	(0.037)	(0.031)	(0.040)
Open sourcing group vs. low sourcing group	-0.339^{***}	-0.102^{***}	0.441^{***}
	(0.039)	(0.036)	(0.040)
Size (log)	-0.039^{***}	-0.032^{***}	0.070^{***}
	(0.012)	(0.011)	(0.012)
Age (log)	−0.014	0.015	−0.001
	(0.030)	(0.026)	(0.029)
Human capital	-0.027^{***}	0.013^{*}	0.014^{*}
	(0.008)	(0.007)	(0.007)
Government ownership	0.342^{***}	−0.027	-0.316^{***}
	(0.081)	(0.081)	(0.103)
Foreign ownership	−0.002	−0.098	0.100^{*}
	(0.066)	(0.063)	(0.059)
Industry dummies	Yes	Yes	Yes
City dummies	Yes	Yes	Yes
Observations	970	970	970

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Some variables predict failure perfectly, thus reducing the corresponding observations.

4.4.2.2 Innovation Introducing Patterns and Firm Performance

The effects of the innovation introducing patterns on firm performance are investigated by means of OLS regression. To estimate the single effect of each introducing pattern on firm performance, we use dummy variables describing the introducing pattern as independent variables. In Table 4.8, Models 1-3 show the performance results of production innovators, product innovators, and multifaceted innovators, respectively. In Model 1, production innovators present a significantly negative coefficient, which indicates that production innovators experience decreased performance. In both Models 2 and 3, product and multifaceted innovators are positively and significantly associated with firm performance. This means that SMEs belonging to product and multifaceted innovators are able to increase their performance. In addition, Model 4 in Table 4.8 provides the pairwise comparisons of the estimates across all three innovation introducing patterns. The results indicate that the product and multifaceted innovators outperform the production innovators in terms of firm performance. In the case of the comparison between product and multifaceted innovators, the coefficient is not significant. The product innovators are thus similarly able to increase their performance compared with the multifaceted innovators.

Table 4.8 Results from the OLS regression

	Firm performance			
Variable	Model 1	Model 2	Model 3	Model 4
Production innovators	-0.265^{***}			
	(0.067)			
Product innovators		0.193^{**}		
		(0.088)		
Multifaceted innovators			0.148^{**}	
			(0.068)	
Product innovators vs. production innovators				0.308^{***}
				(0.095)
Multifaceted innovators vs. production innovators				0.244^{***}
				(0.073)
Multifaceted innovators vs. product innovators				−0.065
				(0.096)
Size (log)	−0.023	−0.006	−0.022	−0.020
	(0.033)	(0.033)	(0.033)	(0.033)

(Table 4.8 Continued)

	Firm performance			
Variable	Model 1	Model 2	Model 3	Model 4
Age (log)	0.011	0.011	0.012	0.011
	(0.072)	(0.073)	(0.073)	(0.073)
Investment intensity (log)	0.023***	0.026***	0.023***	0.023***
	(0.007)	(0.007)	(0.007)	(0.007)
Human capital	0.020	0.024	0.025	0.020
	(0.020)	(0.020)	(0.020)	(0.020)
Government ownership	0.119	0.065	0.066	0.120
	(0.220)	(0.222)	(0.221)	(0.220)
Foreign ownership	0.347**	0.377**	0.345**	0.353**
	(0.152)	(0.151)	(0.153)	(0.152)
Constant	13.024***	12.726***	12.749***	12.756***
	(0.430)	(0.436)	(0.440)	(0.435)
Observations	1,127	1,127	1,127	1,127

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.5 Discussion and Conclusions

This article tries to identify SME patterns of undertaking innovation activities and of introducing innovation types and how these innovation patterns are linked to SME performance. This study reveals that SMEs innovate differently depending on their innovation patterns, showing differences in their firm performance. This paper further advances our understanding on SME innovation patterns and their impacts on SME performance.

The contribution of this study to the literature is twofold. First, regarding contributions to the literature on innovation taxonomies, we focus our interest on under-investigated Chinese SMEs and enlarge the classifications of innovating SMEs by considering two stages of their innovation process: inputs (innovation activities) and outputs (innovation types). Although the variety of SME innovation patterns has been acknowledged (Brunswicker and Vanhaverbeke, 2015; Hervas-Oliver et al., 2016a; Hervas-Oliver et al., 2020; Thomä and Zimmermann, 2020), this study exhibits the huge SME heterogeneity in two dimensions, namely their use of innovation activities and their introduction of innovation types. The use of innovation activities characterizes innovation sourcing patterns, leading to “internal sourcing group”, “low sourcing group”, and “open sourcing group”. The internal sourcing group represents a strong reliance on internal activities and the open sourcing group shows the combined use of internal and external activities. To put it differently, internal activities occur either in their own form or in combination with external activities and external activities are unlikely to occur on their own. This is in line with the concept of AC, which suggests the importance of internal activities for enhancing a firm’s abilities to gain from external activities (Cohen and Levinthal, 1990). The introduction of innovation types profiles innovation introducing patterns, resulting in “production innovators”, “product innovators”, and “multifaceted innovators”. The production innovators and the multifaceted innovators are two different combinations of multiple innovation types and the multifaceted innovators particularly show a combination of technological and non-technological innovation. This finding supports existing evidence of the joint introduction of innovation types and sheds empirical light on the specific ways in which Chinese SMEs introduce innovation types simultaneously (Hullova et al., 2016, 2019).

Second, regarding contributions to the literature on the innovation-performance relationship, this study goes beyond a commonly used aggregated analysis of SME innovation process and its impacts on SME performance by using more comprehensive measures of innovation activities and types. Evidence is found that SMEs with a higher degree of being innovation-active show a stronger ability and propensity to generate a greater variety of innovation types. Although previous research suggests that openness offers performance benefits (Brunswicker and Vanhaverbeke, 2015; Hervas-Oliver et al., 2020), the present study finds an additional benefit of openness, measured by the number of external activities intensively undertaken by each innovation sourcing pattern, that increases the likelihood of grasping the variety of innovation types. We further find that the three innovation introducing patterns have a different impact on SME performances. The production innovators characterized by the simultaneous introduction of efficiency and flexibility innovation suffer inferior performance, which reinforces the findings of Zhang (2022b). The possible explanation is that efficiency and flexibility innovation result in a hybrid configuration with inconsistent organizational attributes and SMEs have such limited resources that they have to operate under a conflicting organizational environment and thus experience lower performance (Ebben and Johnson, 2005). Organizational innovation facilitates coordination and cooperation within the organization, allowing for the construction of an appropriate organizational context for the joint pursuit of efficiency and flexibility innovation (O'Reilly III and Tushman, 2008; Úbeda-García et al., 2020). Therefore, multifaceted innovators show that introducing both efficiency and flexibility innovation with the addition of organizational innovation leads to superior performance and no performance difference is observed compared with product innovators.

Our findings provide some implications for policymakers. In order to improve the performance of innovating SMEs, policymakers should be aware of SME heterogeneity and understand how SMEs transform themselves from one innovation sourcing pattern into one innovation introducing pattern and how different innovation introducing patterns shape SME performance. First, policymakers need to avoid the bias towards promoting R&D activities and instead recognize that SMEs of any innovation sourcing pattern strongly rely on non-R&D activities. It is important for policymakers to ensure that the specific sources of knowledge can be accessed by each innovation sourcing pattern of SMEs. Second, most of SMEs belong to the internal sourcing group and they occupy a middle position between low and open sourcing groups in terms of the likelihood of falling into any of innovation introducing patterns. Since this group of SMEs have stronger AC, policymakers can spur this group of SMEs to open up so that they are more likely to introduce various types of innovation to gain better performance. Third, production innovators constituting the largest group of SMEs should receive policymakers' concerns because they require policy measures aiming at increasing their performance. The measures for policymakers to address this may encourage production innovators to introduce simultaneous organizational innovation or avoid mixing efficiency and flexibility innovation.

This study suffers from limitations, which provide avenues for future research efforts. First, the current paper identifies innovation patterns according to a limited amount of innovation inputs and of innovation outputs. Future research may probe deeply into innovation taxonomies by using a broader range of SMEs' innovation behavior. Second, we use categorical variables to measure the innovation inputs and outputs. Future works could develop quantitative indicators, such as the expenditures in each innovation activity and the outcomes associated with each innovation type, to accurately evaluate the intensity of innovation activities and the achievements of innovation types. Third, the indicators of firm performance include sales growth, change in employment, and labor productivity (Thomä and Zimmermann, 2020). A more fine-grained analysis of the link between innovation and SME performance could be performed using multiple performance indicators.

Appendix

Table 4.9 Description of variables

Variable	Description and unit
Innovation activities	
Internal R&D	Whether the firm carried out R&D activities itself (dummy)
External R&D	Whether the firm contracted out R&D activities to other firms (dummy)
Use of new equipment and technology	Whether the firm introduced new equipment and technology for product or process improvements (dummy)
In-house development	The degree to which the firm developed new or significantly improved products/processes in-house (0-2)
Collaboration with suppliers	The degree to which the firm developed new or significantly improved products/processes in collaboration with suppliers (0-2)
Collaboration with clients	The degree to which the firm developed new or significantly improved products/processes in collaboration with clients (0-2)
Modification to existing products/Inward technology licensing	The degree to which the firm modified other firms' products for product innovation or obtained the rights to use other firms' technology for process innovation (0-2)
Internal knowledge sourcing	The degree to which the firm utilized knowledge acquired from internal sources (0-2)
External knowledge sourcing	The degree to which the firm utilized knowledge acquired from external scientific sources (0-2)
Innovation types	
Quality innovation	Whether the firm introduced new quality control procedures in production or operation during the three-year period (dummy)
Organizational innovation	Whether the firm introduced new management/administrative procedures during the three-year period (dummy)
Product development	Whether the firm introduced new products or services during the three-year

(Table 4.9 Continued)

Variable	Description and unit
	period (dummy)
Product improvement	Whether the firm added new features to existing products or services during the three-year period (dummy)
Efficiency innovation	Whether the firm introduced new or significantly improved methods to reduce unit production costs during the three-year period (dummy)
Flexibility innovation	Whether the firm introduced new or significantly improved methods to increase production flexibility during the three-year period (dummy)
Other variables	
Firm performance	Sales per full time equivalent (FTE) employee in the last survey year (in logs)
Size	Number of FTE employees in the last survey year (in logs)
Age	Number of years since a firm was formally founded (in logs)
Government ownership	Whether the firm is owned by the government or the state (dummy)
Foreign ownership	Whether the firm is owned by private foreign firms (dummy)
Human capital	The average number of years of education of full-time employees (in years)
Investment intensity	Investment in physical assets per FTE employee (in logs)

Chapter 5 Conclusion

After showing three individual articles in Chapters 2, 3, and 4, Chapter 5 pools the main findings of each article together to outline the contributions of this dissertation to innovation research, innovation policy, and innovation management. The last chapter also points out the limitations of this dissertation, which pave the way for future research.

5.1 Contributions

5.1.1 Contributions to Innovation Research

This dissertation aims to analyze SME heterogeneity in inputs and outputs of an innovation process and synthesize SME innovation heterogeneity by identifying innovation patterns from the innovation process perspective. To achieve the overall research objective, this dissertation takes SME innovation heterogeneity into consider when it examines the relationships between innovation activities and innovation types, between innovation types and SME performance, and between innovation activities, innovation types, and SME performance. These three relationships have spawned three streams of empirical research, which are contributed by this dissertation as follows.

Regarding contributions to the research on the relationships between innovation activities and innovation types, Chapter 2 of this dissertation tackles the role of non-R&D activities in SME innovation and disentangles the results of the literature about the impact of non-R&D activities on innovation. The focus on non-R&D activities is consistent with the fact that SMEs generally constrained with financial and human resources tend to refrain from R&D activities (Rammer et al., 2009; Hervás-Oliver et al., 2021). From the sample of Chinese SMEs, it is observed that most of them innovate without either internal or external R&D, but undertake heterogeneous non-R&D activities, such as interfirm collaborations, technology acquisition and licensing, and training. The regression results confirm the findings of Moilanen et al. (2014) and Guo et al. (2017) that non-R&D activities are crucial for explaining innovation in SMEs. This work goes beyond the literature by highlighting SME heterogeneity in R&D decision and innovation types pursued. Considering SME heterogeneity in R&D

decision, this research distinguishes between non-R&D and R&D SMEs, showing that non-R&D SMEs can introduce innovation without any R&D activities and R&D SMEs also need non-R&D activities for introducing innovation. However, these non-R&D activities are not equally important for non-R&D and R&D SMEs. The results show that, compared with non-R&D SMEs, R&D SMEs benefit from a wider scope of external networking. Further considering SME heterogeneity in innovation types pursued, the results show that R&D SMEs rely on suppliers for process innovation, and customers and scientific sources for product innovation, indicating that external networking actors are not of equal importance for product and process innovation. SME heterogeneity in R&D decision and innovation types also results in the substitutability effect between internal and external activities on product innovation in non-R&D SMEs and on process innovation in R&D SMEs. Taken together, this research sheds new light on how SMEs depend on their R&D decision and innovation types to choose and combine internal and external activities, complementing prior studies that overlook SME heterogeneity in R&D decision and innovation types pursued and thus produce fragmented evidence of SME innovation.

Regarding contributions to the research on the relationships between innovation types and SME performance, Chapter 3 of this dissertation extends the measures of innovation types to explore heterogeneous combinations of innovation types and their effects on SME performance. Previous research restricts attention to product, process, and organizational innovation (Ballot et al., 2015; Guisado-González et al., 2017), but this study includes a broad range of innovation types by distinguishing between different sub-types of product innovation and of process innovation. More specifically, this research focuses on six types of innovation, i.e., product development, product improvement, quality innovation, efficiency innovation, flexibility innovation, and organizational innovation. Based on the six types of innovation, it is observed that SMEs have propensities to introduce different combinations of product development, product improvement, quality innovation, and organizational innovation and also the combination of efficiency innovation and flexibility innovation, enlarging the combinations of innovation types beyond different combinations of product, process, and organizational innovation. These heterogeneous combinations of innovation types allow to investigate more pairwise relationships, avoiding generalization of the findings from only relationships between product, process, and organizational innovation. In terms of product (including product development and product improvement), quality, and organizational innovation, the results show that they are neither complements nor substitutes, indicating that SMEs gain no extra payoff but only cumulative benefits from the combination of product, quality, and organizational innovation. In terms of efficiency and flexibility innovation, a substitutability is found between them, meaning that the combination of efficiency and flexibility innovation reduces SME performance. The results of the relationships between efficiency, flexibility, and organizational innovation show that the substitutability between efficiency and flexibility innovation no longer exists with addition of organizational innovation, implying that organizational innovation favors the combination of efficiency and flexibility innovation. Overall, this research supports the presence of different combinations of innovation types and further adds potential combination forms, showing SME heterogeneity in the combinations of innovation types. Accordingly, the effects of heterogeneous combinations of innovation types on performance are examined for Chinese SMEs, providing a comprehensive and contextual understanding of the pairwise relationships between different innovation types.

Regarding contributions to the research on the relationships between innovation activities, innovation types, and SME performance, Chapter 4 of this dissertation improves the identification of innovation patterns as well as the analysis of the innovation-performance relationship. Most prior studies develop innovation taxonomies based only on the innovation activities undertaken by firms (Brunswicker and Vanhaverbeke, 2015; Hervas-Oliver, et al., 2016a; Thomä, 2017; Hervas-Oliver et al., 2020; Thomä and Zimmermann, 2020; Runst and Thomä, 2022) while a few studies group innovating firms according to only their introduction of innovation types (Evangelista and Vezzani, 2010). This research offers a comprehensive identification of SME innovation patterns based on both inputs and outputs of an innovation process and thus accounts for SME heterogeneity in innovation activities and innovation types.

Based on innovation inputs, three innovation patterns are identified that indicate how SMEs undertake innovation activities to access internal and external sources of knowledge, including “internal sourcing group”, “low sourcing group”, and “open sourcing group”. The open sourcing group shows the concurrent development of internal and external innovation activities, justifying Chapter 2 that examines the combined impact of internal and external activities on innovation. Based on innovation outputs, another three innovation patterns are identified that indicate how SMEs introduce different innovation types, including “production innovators”, “product innovators”, and “multifaceted innovators”. The production innovators show the combination of efficiency and flexibility innovation and the multifaceted innovators present the simultaneous introduction of technological innovation and organizational innovation, justifying Chapter 3 that examine the effects of different combinations of innovation types on SME performance. The identified innovation patterns as comprehensive measures of innovation activities and types are used to analyze the link between innovation and SME performance, responding to the call for a synthesis approach to the analysis of innovation and its economic effects (Evangelista and Vezzani, 2010). Regarding the relationship between the patterns of innovation activities and of innovation types, the results support that openness pays off (Brunswicker and Vanhaverbeke, 2015; Hervas-Oliver et al., 2020), especially by increasing the likelihood of introducing a variety of innovation types. The results for the impact of the patterns of innovation types on SME performance show that the combination of efficiency and flexibility innovation harms SME performance, but the combination of technological and organizational innovation offer performance benefits, which reinforce the findings of Chapter 3. In summary, this research provides a new process perspective for identifying SME innovation patterns, thereby comprehensively grasping SME innovation heterogeneity and analyzing innovation-performance relationship.

5.1.2 Contributions to Innovation Policy

This study contributes to improving China’s current innovation policies that have the biases identified in section 1.1.1. First, non-R&D activities should draw Chinese policymakers' attention. Although Chinese policymakers have acknowledged the importance of SME innovation and have designed innovation policies particularly for SMEs, they focus excessively on supporting R&D SMEs and encouraging R&D spending among SMEs. The results of Chapter 2 imply that R&D is neither necessary nor sufficient for SMEs to innovate. Non-R&D SMEs are not only active in various innovation activities beyond R&D but also successful in introducing different types of technological innovation. R&D SMEs even more frequently engage in non-R&D innovation activities than non-R&D SMEs do. In light of these results, the lesson for policymakers is that non-R&D activities rather than formal R&D are the general prerequisite for SME innovation, which calls for policy measures to trigger non-R&D activities among all innovating SMEs. More importantly, policymakers should take into account SME innovation heterogeneity and recognize that different non-R&D activities, especially external ones, are needed by non-R&D and R&D SMEs for product and process innovation. Non-R&D SMEs that rely heavily on the acquisition of existing technology can be stimulated with financial and tax incentives and favorable customs duties, while R&D SMEs require policies intended to create interorganizational collaboration and knowledge exchanges due to their extensive use of external sources of knowledge. At the same time, there is a need for support measures to strengthen non-R&D and R&D SMEs' internal ability to leverage external knowledge, e.g., by promoting human resources management and informal learning investment.

Second, organizational innovation should be promoted together with technological innovation. In emerging Chinese markets, an overemphasis on technological innovation neglects the significant role of organizational innovation, resulting in a lack of policy initiatives for organizational innovation (Chen et al., 2020b). Chapters 3 and 4 provide valuable learnings for policymakers from the fact that Chinese SMEs tend to introduce different types of innovation at the same time. The key finding that deserves policymakers' attention is that SMEs combining efficiency and flexibility innovation are likely to obtain higher performance only when they simultaneously adopt organizational innovation. Thus, in designing policies to promote innovation, it is necessary for policymakers to consider organizational innovation which allows for performance benefits from the combination of efficiency and flexibility innovation. Put differently, policymakers should promote innovation in a comprehensive way, facilitating the integration of technological and organizational innovation. This highlights the need for adequate policies that favor organization innovation. In support of organizational innovation, policymakers can encourage the training of employees (Arranz et al., 2019) and the use of new management tools (Hervas-Oliver et al., 2016b). Another useful finding for policymakers is that SMEs have difficulties in profiting additionally from the combination of product, process, and organizational innovation. Given the importance of knowledge management for integrating the knowledge from different types of innovation to lead to synergistic benefits, policymakers should enhance SMEs' capability of managing knowledge, e.g., by creating management talents (Hullova et al., 2019).

Third, SME innovation should be tackled considering distinct innovation patterns and their associated innovation behavior. It is noteworthy that SMEs show different patterns of undertaking innovation activities and of introducing innovation types and thus differ in their performance, as suggested in Chapter 4. This finding helps to question whether one-size-fits-all approaches to SME innovation policies provide the appropriate incentives for innovation in every SME. The one-size-fits-all policies do not take into account the characteristic diversity of SME innovation patterns and may fail to meet the specific needs of each innovation pattern of SMEs. Hence, an accurate understanding of SME innovation patterns is needed for policymakers to more properly support SME innovation by designing policies that are tailored to the needs of targeted patterns of innovating SMEs. According to the patterns of innovation activities, policymakers can support each pattern of SMEs in undertaking their specific activities. At the same time, policymakers should have the notion that SMEs capable of combining internal and external activities are likely to gain better innovation performance. Since internal sourcing group has established strong AC through internal efforts, policymakers can encourage them to engage in external activities. Considering the results of Chapter 2, there is a relevance of policy measures that aim to enhance the internal capacity to access external knowledge, especially in case of open sourcing group that is characterized by the extensive use of external sources. According to the patterns of innovation types, policymakers should recognize that SMEs often combine different types of innovation. Based on the results of Chapter 3, the suggested policies for knowledge management are useful for production and multifaceted innovators who present the combinations of different innovation types. The results of Chapter 3 also suggest the need for policy measures to promote organization innovation, which is particularly important for production innovators who combine efficiency and flexibility innovation.

5.1.3 Contributions to Innovation Management

A comprehensive understanding of innovation, how innovation activities explain innovation types and how innovation types affect overall performance, is necessary for SMEs that are influenced by constrained resources, limited market power, and fierce competition, which helps to increase their competitiveness and likelihood of survival (Amara et al., 2008; Madrid-Guijarro et al., 2009; Donbesuur et al., 2020). The findings of this dissertation provide managerial implications for practitioners who seek to improve innovation management in SMEs.

First, the results of Chapter 2 motive managers in SMEs to engage in innovation regardless of R&D activities. It is because there are more innovation activities than formal R&D and the activities beyond R&D are generally important for innovation and even determine innovation alone. Managers not investing in R&D can focus solely on non-R&D activities to introduce technological innovation. As for managers who decide to conduct R&D, they still need to consider non-R&D activities as the critical sources of innovation. In other words, managers in any innovating SMEs should put effort into non-R&D activities. Given the diversity of non-R&D activities, the findings of this dissertation suggest that managers should selectively develop and configure the activities that really matter according to their R&D decisions and types of innovation pursued. Considering open sourcing group of SMEs identified in Chapter 4, which attempts to integrate different activities to achieve higher innovation performance, the results of Chapter 2 highlight the need for managers in these SMEs to pursue a balance between internal and external activities. For this purpose, managers can choose a mix of external activities that fit with their internal capabilities; alternatively, they can increase investment in internal activities to provide a basis for better exploiting external activities.

Second, as the findings of Chapters 3 and 4 imply, managers in SMEs that decide to adopt a combinatorial strategy of innovation types should note that not all combinations of innovation types allow for higher SME performance. It is important for managers to concentrate on the way in which SMEs are able to profit from different types of innovation. The results of this dissertation do not support the simultaneous introduction of efficiency and flexibility innovation in the absence of organizational innovation. This suggests that managers not interested in organizational innovation should decide not to introduce efficiency and flexibility innovation in combination. It is also appropriate to advise managers to be aware of the key role of organizational innovation in facilitating the combination of efficiency and flexibility innovation; that is to say, managers pursuing both efficiency and flexibility innovation need to develop organizational innovation, e.g., by investing in employees training. In addition to the combination of efficiency, flexibility, and organizational innovation, managers can consider combining product, process, and organizational innovation. The suggestion for these managers is to increase the capabilities of integrating knowledge from different types of innovation to achieve the joint potential of product, process, organizational innovation for reinforcing each other and consequently improving SME performance.

Third, the results of Chapter 4 point out performance benefits of the concurrent development of internal and external innovation activities, which in turn drives internally-innovating SMEs to be open to external activities. Managers in the internal sourcing group of SMEs need to know that limiting attention to internal activities hinders the potential performance advantages resulting from the simultaneous pursuit of internal and external activities. Given their internal efforts, they should adopt an integrative approach toward internal and external activities. Based on the results of

Chapter 2, the internal sourcing group of SMEs should not simply incorporate external activities but accordingly develop the internal capabilities to reinforce the exploitation of external activities, which enables them to achieve a variety of innovation types and thus experience increased performance.

5.2 Limitations and Future Research

This dissertation is subject to several limitations, which suggest new avenues for future research. Given that all three articles use survey data and quantitative methods, the limitations of this dissertation mainly involve the age of data, the type of data, and the variables used.

The first concern is about the age of data. This is firstly argued by presenting the following reasons for the use of the World Bank database. The main reason is that it is the only available database that contains a great deal of information on innovation activities, innovation types, and SME performance, allowing for empirical analyses to achieve the research goals of this dissertation. The second reason is that the survey data has the potential for this research as it is still used in recent literature (e.g., Jin et al., 2022; Salike et al., 2022; Zhao and Zhang, 2023). The third reason is that innovation is characterized by path dependency, which means that the future development of innovation depends on the path it followed in the past (Nieto, 2004; Thrane et al., 2010). From this view, a firm tends to search for new knowledge from the innovation activities familiar to the firm and focuses on developing the innovation types within its existing skills, showing historically stable innovation patterns. This implies that past data can be used to reflect the current state of firm innovation. For example, Weidner et al. (2023) assign the firms to one of the innovation patterns identified using the data collected ten years ago, which confirms the validity of previously identified innovation patterns and implies the path dependency of firm innovation. Above reasons for the use of the World Bank database suggest that, although the survey was carried out between November 2011 and March 2013, the survey data is useful for current research, leading to valid and reliable findings and thus providing implications for today's policies and management. As Robins (2004) argues, the age of data matters little to the generalization of research findings when models are appropriately and adequately specified. However, some may remain skeptical about the use of older data in studies as they are concerned about the possibility that SMEs' innovation behavior varies with the changes in the business environment. The effective response to the concern is to make research more convincing by updating the database and replicating empirical analysis with more recent data. In the future, researchers should look for latest available data or even collect new data by themselves. Since firms can produce a lot of new data over time, it would be helpful to adopt data management with regular updates, which not only provides the newest data any time for research but also offers a dynamic view of firm innovation. Using recent data, future research could reproduce this research carried out based on earlier database to validate and enrich the presented findings. The comparison between the results from future research and those from this work would contribute to an understanding of SME innovation development.

Another issue is related to the type of data that is cross-sectional by nature. It is a typical practice in the quantitative research to apply cross-sectional data. However, the prevalent use of cross-sectional data has brought about a discussion regarding its disadvantages. Due to a lack of time dimension, cross-sectional data cannot show that one variable precedes the other variables in time, thus providing information on the correlations rather than causality between two variables (Taris et al., 2021). On the other hand, cross-sectional data may have selection bias. The bias arises when certain groups included in the survey are different from other groups, resulting in a sample that cannot represent the entire population. Because of selection bias, it is difficult to derive accurate results from the study relying on cross-sectional data (Sedgwik, 2014). In contrast to cross-sectional data, longitudinal data indicating the chronological sequence of the variables allows to employ advanced modelling methods to capture unobserved heterogeneity, correct biased estimates, and make causality inferences (Stritch, 2017). This dissertation relying on cross-sectional data preliminarily establishes some interesting relationships among variables. This is a good start for researchers who are interested in studying causes and effects by setting up the longitudinal research, as the findings of this dissertation help these researchers to justify investing in collecting longitudinal data. Therefore, a future attempt could be made to conduct multi-wave surveys and construct longitudinal database. The aforementioned suggestion on a system for regularly updating data is useful for longitudinal data production. For the appropriate design and analysis of a longitudinal study, researchers need to deal with theoretical and methodological issues. In future longitudinal research, it is necessary to consider the theoretical role of time in conceptualizing how variables change over time and explaining why the change in a set of variables affects the change in another variable (Ployhart and Vandenberg, 2010). In the future, innovation management theory could be developed and refined by incorporating the time elements. Furthermore, as the variables and their relationships are likely to change in a nonlinear way, researchers should explore statistical methods intended to model the nonlinearity, which allows them to scrutinize the dynamics of SME innovation.

Thirdly, the findings of this dissertation are limited by the variables used. In the dissertation, innovation activities and innovation types are measured on a dichotomous scale, which loses fine-grained information on their intensity and thus limits the ability to grasp SME innovation heterogeneity (Nuzzo, 2019). The use of dichotomous variables also leads to reduced statistical power and inaccurate effect size in regression, failing to detect the true relationship between among variables (Irwin and McClelland, 2003). Therefore, continuous variables should be used instead of dichotomous ones, if available, and their dichotomization should be avoided as well. When looking for new database or conducting a survey for new data collection, researchers should select the databased with continuous data or design their survey around continuous data. In practice, they could develop and apply financial indicators for the investments in innovation activities and profits from the innovation types. In addition to improving the measurement of variables, research results could be enhanced by expanding the range of variables used. Some innovation activities, e.g., the collaboration with competitors, are not included in the analysis of their heterogeneous effects on technological innovation. Collaboration with competitors on technological innovation can be a way to acquire new technological knowledge, but may lead to problems of information leakage and hold-up (Gnyawali and Park, 2011; Fitjar and Rodríguez-Pose, 2013). This indicates that the indicator of collaboration with competitors is required for further research to explore the role of competitors in innovation in the context of Chinese SMEs. Moreover, marketing innovation, as one of four main types of innovation, is absent from the analysis of heterogeneous combinations of innovation types. In fact, marketing innovation is connected to technological innovation as new marketing methods are demanded to promote sales of new products or market the increased capacity and improved quality (Schmidt and Rammer, 2007; D'Attoma and Ieva, 2020). Future availability of the indicator to measure marketing innovation could extend the knowledge on the role of marketing innovation in China as well as its combination with other innovation types.

Finally, the use of more recent database, longitudinal data type, and supplementary continuous variables, as suggested above, can lead to new empirical findings. Based on these new results, innovation policy studies can be developed in the future. A promising direction for future policy research is to use the newly identified innovation patterns to design targeted policy measures for different groups of innovating SMEs.

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Abstract

Small- and medium-sized enterprises (SMEs) are an important force for promoting innovation in China as they represent the bulk of China's industrial fabric and have the most innovative vitality and potential due to entrepreneurial dynamism, organizational flexibility, and fast responsiveness. However, SMEs generally lack financial, technological, and human resources to develop innovation. Furthermore, innovation gives rise to externalities, which could reduce the incentive of SMEs to engage in innovation. Therefore, public aids are needed in support of SME innovation. In light of the variety of innovation behavior among SMEs, innovation policies should be designed to target certain SMEs and support them according to their specific characteristics. In addition, with a strong focus on formal R&D and main types of technological innovation (i.e., product and process innovation), prior research restricts a comprehensive understanding of diverse innovation activities, especially non-R&D activities, and different innovation types, especially non-technological innovation. Given the need for targeted innovation policies and the under-researched heterogeneity among innovating SMEs, this dissertation aims to deepen the understanding of SME innovation heterogeneity from a perspective of the following innovation process: innovation activities – innovation types – SME overall performance.

This dissertation is organized into five chapters. Chapter 1 introduces research motivations, theoretical background, research design, and an overview of the three articles presented in Chapters 2, 3, and 4. Three empirical articles in Chapters 2, 3, and 4 constitute the core of this dissertation and they are summarized as follows.

The first article in Chapter 2 empirically analyzes SME heterogeneity in innovation activities based on the input stage of the aforementioned innovation process (innovation activities – innovation types), especially by disentangling the varying effects of innovation activities on technological types of innovation. This article, focusing mainly on non-R&D sources of innovation, compares non-R&D and R&D SMEs with respect to the separate and combined effects of non-R&D activities on product and process innovation. Drawing on a database collected from 1,392

manufacturing SMEs in China, empirical result reveals heterogeneous importance of non-R&D activities to product and process innovation for non-R&D and R&D SMEs. Specifically, non-R&D SMEs rely mainly on embodied knowledge to introduce technological innovation, while R&D SMEs can access external knowledge from customers and scientific sources to develop product innovation and also from suppliers to introduce process innovation. In addition, substitutability is found between internal and external innovation strategies composed of non-R&D activities, which is limited to product innovation for non-R&D SMEs and process innovation for R&D SMEs.

The second article in Chapter 3 contributes to the empirical analysis of SME heterogeneity in innovation types based on the output stage of the process (innovation types – SME overall performance), especially by exploring different combinations of innovation types and their effects on SME performance. This article investigates SMEs' combined use of different innovation types as well as the effect of the combination of innovation types on SME performance. The empirical analysis is based on data from 1,139 Chinese manufacturing SMEs. The results of factor analysis imply a tendency of combining product, quality, and organizational innovation and the other tendency of combining efficiency and flexibility innovation. A conditional approach to supermodularity is used to test for the relationship between different types of innovation. The results show that product, quality, and organizational innovation are neither complements nor substitutes, meaning that their combination generates only additive effects on SME performance. It is also found that substitutability between efficiency and flexibility exists without organizational innovation but it disappears with organizational innovation, which suggests that simultaneous organizational innovation is required for better use of efficiency and flexibility innovation in combination.

The third article in Chapter 4 synthesizes SME innovation heterogeneity through the identification of SME innovation patterns according to the inputs and outputs (i.e., innovation activities and innovation types) of the innovation process. Based on a sample of 1,127 Chinese manufacturing SMEs, this article identifies SME patterns of innovation activities and of innovation types and uses the identified innovation patterns to analyze the relationship between innovation and SME performance, contributing to a comprehensive analysis of the whole innovation process. The innovation activities associated with internal and external knowledge sourcing characterize three innovation sourcing patterns, namely internal sourcing group, low sourcing group, and open sourcing group, which differ in activeness and openness of knowledge sourcing. The innovation types involving technological and non-technological types of innovation profile three innovation introducing patterns, namely production innovators, product innovators, and multifaceted innovators, which differ in the variety of innovation types introduced. Regarding the relationship between innovation sourcing and introducing patterns, being active in innovation activities increases the likelihood of introducing various innovation types and being open is most likely to capture a variety of innovation types. The results for the relationship between innovation introducing patterns and SME performance show that production innovators combining efficiency and flexibility innovation experience decreased performance while product innovators focusing on product innovation and multifaceted innovators combining technological and non-technological innovation achieve better performance.

Chapter 5 concludes by discussing the contributions to innovation research, innovation policy, and innovation management, along with the limitations of this dissertation and the directions for future research.

Zusammenfassung

Kleine und mittlere Unternehmen (KMU) sind eine wichtige Triebkraft für die Förderung der Innovation in China, da sie den Großteil der chinesischen Industrie ausmachen und aufgrund ihrer unternehmerischen Dynamik, organisatorischen Flexibilität und schnellen Reaktionsfähigkeit über die größte Innovationskraft und das größte Innovationspotenzial verfügen. Allerdings fehlt es den KMU im Allgemeinen an finanziellen, technologischen und personellen Ressourcen, um Innovationen zu entwickeln. Darüber hinaus führt Innovation zu externen Effekten, die den Anreiz für KMU, sich an der Innovation zu beteiligen, verringern könnten. Daher sind öffentliche Beihilfen zur Unterstützung der Innovation von KMU erforderlich. Angesichts der Vielfalt des Innovationsverhaltens von KMU sollten innovationspolitische Maßnahmen so gestaltet werden, dass sie auf bestimmte KMU abzielen und diese entsprechend ihrer spezifischen Merkmale unterstützen. Da sich die bisherige Forschung stark auf formale FuE und die wichtigsten Arten technologischer Innovationen (d. h. Produkt- und Prozessinnovationen) konzentriert, ist ein umfassendes Verständnis der verschiedenen Innovationsaktivitäten, insbesondere der Nicht-FuE-Aktivitäten, und der verschiedenen Innovationstypen, insbesondere der nichttechnologischen Innovationen, nur begrenzt möglich. In Anbetracht der Notwendigkeit einer gezielten Innovationspolitik und der unzureichend erforschten Heterogenität innovierender KMU zielt diese Dissertation darauf ab, das Verständnis der Innovationsheterogenität von KMU aus der Perspektive der folgenden Innovationsprozesse zu vertiefen: Innovationsaktivitäten - Innovationstypen - Gesamtleistung von KMU.

Die vorliegende Dissertation ist in fünf Kapitel gegliedert. In Kapitel 1 werden die Forschungsmotivation, der theoretische Hintergrund, das Forschungsdesign und ein Überblick über die drei in den Kapiteln 2, 3 und 4 vorgestellten Artikel vorgestellt. Die drei empirischen Artikel in den Kapiteln 2, 3 und 4 bilden den Kern dieser Dissertation und werden wie folgt zusammengefasst.

Der erste Artikel in Kapitel 2 analysiert empirisch die Heterogenität der Innovationsaktivitäten von KMU auf der Grundlage der Input-Stufe des oben erwähnten Innovationsprozesses (Innovationsaktivitäten - Innovationstypen), insbesondere durch die Entflechtung der unterschiedlichen Auswirkungen von Innovationsaktivitäten auf technologische Innovationstypen. In diesem Artikel, der sich hauptsächlich auf Nicht-FuE-Innovationsquellen konzentriert, werden Nicht-FuE- und FuE-KMU im Hinblick auf die separaten und kombinierten Auswirkungen von Nicht-FuE-Aktivitäten auf Produkt- und Prozessinnovationen verglichen. Auf der Grundlage einer Datenbank mit 1.392 KMU des verarbeitenden Gewerbes in China zeigen die empirischen Ergebnisse, dass die Bedeutung von Nicht-F&E-Aktivitäten für die Produkt- und Prozessinnovation bei Nicht-F&E- und F&E-KMU sehr unterschiedlich ist. Insbesondere verlassen sich KMU, die keine F&E-Aktivitäten betreiben, bei der Einführung technologischer Innovationen hauptsächlich auf verankertes Wissen, während KMU, die F&E betreiben, bei der Entwicklung von Produktinnovationen auf externes Wissen von Kunden und wissenschaftlichen Quellen sowie bei der Einführung von Prozessinnovationen auch auf Zulieferer zurückgreifen können. Darüber hinaus wird eine Substituierbarkeit zwischen internen und externen Innovationsstrategien festgestellt, die sich aus Nicht-FuE-Aktivitäten zusammensetzen, die sich bei Nicht-FuE-KMU auf Produktinnovationen und bei FuE-KMU auf Prozessinnovationen beschränken.

Der zweite Artikel in Kapitel 3 leistet einen Beitrag zur empirischen Analyse der Heterogenität von KMU bei den Innovationstypen auf der Grundlage der Output-Stufe des Prozesses (Innovationstypen - Gesamtleistung der KMU), insbesondere durch die Untersuchung verschiedener Kombinationen von Innovationstypen und ihrer Auswirkungen auf die Leistung der KMU. In diesem Artikel werden die kombinierte Nutzung verschiedener Innovationstypen durch KMU sowie die Auswirkungen der Kombination von Innovationstypen auf die Leistung von KMU untersucht. Die empirische Analyse basiert auf Daten von 1.139 chinesischen KMU des verarbeitenden Gewerbes. Die Ergebnisse der Faktorenanalyse deuten auf eine Tendenz zur Kombination von Produkt-, Qualitäts- und Organisationsinnovation und auf eine andere Tendenz zur Kombination von Effizienz- und Flexibilitätsinnovation hin. Ein bedingter Ansatz zur Supermodularität wird verwendet, um die Beziehung zwischen verschiedenen Arten von Innovationen zu testen. Die Ergebnisse zeigen, dass Produkt-, Qualitäts- und organisatorische Innovationen weder Komplemente noch Substitute sind, was bedeutet, dass ihre Kombination nur additive Auswirkungen auf die Leistung von KMU hat. Es wird auch festgestellt, dass die Substituierbarkeit zwischen Effizienz und Flexibilität ohne organisatorische Innovation besteht, aber mit organisatorischer Innovation verschwindet, was darauf hindeutet, dass gleichzeitige organisatorische Innovation für eine bessere Nutzung von Effizienz- und Flexibilitätsinnovation in Kombination erforderlich ist.

Der dritte Artikel in Kapitel 4 synthetisiert die Innovationsheterogenität von KMU durch die Identifizierung von KMU-Innovationsmustern nach den Inputs und Outputs (d. h. Innovationsaktivitäten und Innovationstypen) des Innovationsprozesses. Auf der Grundlage einer Stichprobe von 1.127 chinesischen KMU des verarbeitenden Gewerbes werden in diesem Artikel KMU-Muster für Innovationsaktivitäten und Innovationstypen identifiziert und die identifizierten Innovationsmuster zur Analyse der Beziehung zwischen Innovation und KMU-Leistung verwendet, was zu einer umfassenden Analyse des gesamten Innovationsprozesses beiträgt. Die Innovationsaktivitäten, die mit der internen und externen Wissensbeschaffung verbunden sind, charakterisieren drei Innovationsbeschaffungsmuster, nämlich die interne Beschaffungsgruppe, die Gruppe mit geringer Beschaffung und die Gruppe mit offener Beschaffung, die sich in der Aktivität und Offenheit der Wissensbeschaffung unterscheiden. Die Innovationstypen, die technologische und nicht-technologische Innovationstypen umfassen, beschreiben drei Muster der Innovationseinführung, nämlich Produktionsinnovatoren, Produktinnovatoren und vielseitige Innovatoren, die sich in der Vielfalt der eingeführten Innovationstypen unterscheiden. Was die Beziehung zwischen Innovationsbeschaffung und Einführungsmustern betrifft, so erhöht eine aktive Beteiligung an Innovationsaktivitäten die Wahrscheinlichkeit der Einführung verschiedener Innovationstypen, und eine offene Einstellung erhöht die Wahrscheinlichkeit, eine Vielzahl von Innovationstypen einzuführen. Die Ergebnisse für die Beziehung zwischen Innovationseinführungsmustern und der Leistung von KMU zeigen, dass Produktionsinnovatoren, die Effizienz- und

Flexibilitätsinnovationen kombinieren, eine geringere Leistung aufweisen, während Produktinnovatoren, die sich auf Produktinnovationen konzentrieren, und vielseitige Innovatoren, die technologische und nichttechnologische Innovationen kombinieren, eine bessere Leistung erzielen.

In Kapitel 5 werden abschließend die Beiträge zur Innovationsforschung, zur Innovationspolitik und zum Innovationsmanagement sowie die Grenzen dieser Dissertation und die Richtungen für künftige Forschungen erörtert.

Liste der Vorveröffentlichungen

Publikationen in referierten Fachzeitschriften

- Vorpublikation von Kapitel 2:

  Zhang, H. (2022). Non-R&D innovation in SMEs: is there complementarity or substitutability between internal and external innovation sourcing strategies?. Technology Analysis & Strategic Management, 1-15. doi: 10.1080/09537325.2022.2065979

- Vorpublikation von Kapitel 3:

  Zhang, H. (2022). Does combining different types of innovation always improve SME performance? An analysis of innovation complementarity. Journal of Innovation & Knowledge, 7(3), 100192. doi: 10.1016/j.jik.2022.100192

Publikationen als Konferenzbeitrag

- Vorpublikation von Kapitel 4:

  Zhang, H., & Abdelaty, H. (2022). SME innovation patterns identified from a process perspective: linking innovation to SME performance. The 9th annual World Open Innovation Conference (WOIC) 2022, Eindhoven, The Netherlands, November 2022. This article is currently under review at the Economics of Innovation and New Technology.

Rechtliche Erklärung

Erklärung gem. §4 Abs. 2 (Promotionsordnung)

Hiermit erkläre ich, dass ich mich noch keinem Promotionsverfahren unterzogen oder um Zulassung zu einem solchen beworben habe, und die Dissertation in der gleichen oder einer anderen Fassung bzw. Überarbeitung einer anderen Fakultät, einem Prüfungsausschuss oder einem Fachvertreter an einer anderen Hochschule nicht bereits zur Überprüfung vorgelegen hat.

Berlin, August 2023

Hailun Zhang

Erklärung gem. §10 Abs. 3 (Promotionsordnung)

Hiermit erkläre ich, dass ich für die Dissertation folgende Hilfsmittel und Hilfen verwendet habe. Auf dieser Grundlage habe ich die Arbeit selbstständig verfasst.

- Software: Microsoft Office 2016, Stata 15.0, RStudio 1.4.1103, SPSS 26.0.0.0
- Literatur: siehe Literaturverzeichnis
- Bei den verwendeten Daten handelt es sich um die Daten aus der Weltbank chinesischen Unternehmensumfrage 2012.

Berlin, August 2023

Hailun Zhang