The London School of Economics and Political Science

Contributions to a New Innovation Model: Evidence from China

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

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Abstract

Building on a body of new works (Fu, 2015; Greeven, Yip and Wei, 2019), this thesis focuses on three topics as critical parts of a new innovation model. The global digital economy grew to US$31.8 trillion in 2019 (CAICT, 2020) providing the basis for a new innovation model whose core includes 'Online Interactive Innovation' [OII]. The first study examines how OII constitutes 'virtual teamwork' where employees interact with millions of customers online. OII helps firms to collect and adopt many valuable suggestions from customers to design new functions, update appliances' operating systems, enhance customers' experience, file patent applications and increase product shipments. OII has advantages and works across different industries (e.g., Xiaomi in smartphones, Tesla in electrical vehicles and Haier in home appliances) and countries (e.g., India and Spain). Since the individual is the basic unit to create new ideas for innovation (Taylor and Greve, 2006), the second study analyses 2,078 employees joining 3,976 value engineering projects over 6.5 years and explores how education, via the chain relationship, influences employees' innovation performances measured by comprehensive indicators with triangulation. The third study focuses on how employee stock ownership plans [ESOPs] can activate employees, solve corporate governance problems and improve firms' innovation performance. Analysing 1,509 Chinese listed firms in 9 years, it finds that ESOP influence firms' innovation performance positively measured by annual patent application numbers and group effects exist at the level of industry. The impacts of ESOP in knowledge/talent-intensive industries are significant while not for other industries, which determines the different influences of various stock boards and locations of firms' headquarters. The impact of ESOP on innovation is more significant in SOEs than non-SOEs. These three studies rigorously demonstrate distinct features of innovation that have come to characterize leading practices. These hold implications for practice and future research.

Acknowledgements

The experience in PhD program is like to a journey to learn a lot of theories and research methods, then apply such theories and methods to explore the unknown world and create new knowledge or new theories. Since I like research and I know what I want clearly, this journey is full of interest and a lot of hard works! Many thanks to my supervisor, Dr Jonathan Liebenau, who taught me many theories in MG426 Organisations in the Economy and Society, one of the best courses I learned in LSE. Additionally, he supervised me how to conduct research and how to publish papers. Also, many thanks for many faculty members in Department of Management in LSE, including my second supervisor Dr Christopher Hughes, Dr Saul Estrin, Dr Lourdes Sosa, Dr Amitav Chakravarti and Dr. Carsten Sørensen, etc., from whom I learned a lot! Additionally, many thanks to the staff in the department who helped me a lot in the past four years! LSE is very strong in research methodology, since LSE has both Department of Methodology and Department of Statistics. I took about 8 courses from these departments and learned some tools to explore the unknown world. I should thank LSE to give me the offer with studentship which let me to concentrate in study and research in four years. I will prove that this studentship is a correct and valuable investment and I hope I can contribute to LSE in the future! I learned a lot from LSE and I love LSE! Finally, many thanks to my father, my mother and my brother, who give me endless love to support me to continue this journey to realize my dream!

Content

List of tables and figures

List of abbreviations

2G	Second generation (mobile communication standards)
3G	Third generation (mobile communication standards)
4G	Fourth generation (mobile telecommunication standards)
5G	Fifith generation (mobile communication standards)
AGE	Age of the employee
AI	Artificial intelligence
AIC	Akaike information criterion
BEPS	Basic earning per share
BEPSLG1Y	Basic earning per share in last year
BEPSLG2Y	Basic earning per share 2 years ago
BIC	Bayesian Information Criterion
BJI	Bgi Genomics Co., Ltd
BLUE	Best linear unbiased estimator
BMAJORID	The major for bachelor degree of the employee
C2M	Customer to manufacturing
CAT	Consensual Assessment Technique
CITIC	China International Trust and Investment Corporation
COE	collective-owned enterprises
Cp	Mallows's **C***p* to select models
CSRC	China Securities Regulatory Commission
DD	Difference-in-differences
DIDI	Didi Chuxing Co. Ltd.
DJI	Shenzhen DJ-Innovations Co. Ltd.
DV	Dependent variable
EDA	Electronic design automation software
EIMMLC	Equity Incentive Management Measures for Listed Companies
EIMPE	Extending incentives and managerial power to employees
EMUI	Operating system of Huawei's smartphones
EO	Employee ownership
ESOP	Employee stock ownership plans
FEG	Far East Group
FFAGE	The period in years when the employee has worked in Firm A
FIE	Foreigner invested enterprises
FIRMID	The id of firm which is the same as the id of firm listed in the stock markets.
GCM	Growth curve model
GPT	General Purpose Technology

HESTDEGR	Highest degree of the employee
HOMEPID	The home province of the employee
HQPID	The id of the province in which the firm's headquarter is actually located
ICC	Intra-class correlation coefficient
ICT	Information and Communication Technology
INDUID	The id of the industry which the firm belong to
IoT	Internet of things
IU	Interactive user
IV	Independent variable
KPI	Key Performance Indicator
LNAC1AUOF	The natural logarithm of the number of total suggestions from the firms' employees in all topics in every year
LNAC1AUOT	The natural logarithm of the number of total suggestions from interactive users (IUs) in all topics in every year
LNAC1AUSOF	The natural logarithm of the number of total suggestions from participative fans (PFs) in all topics in every year
LNAC1AUTT	The natural logarithm of the number of total suggestions from the firms' employees, PFs and IUs in all topics in every year
LNAC2OTR	The natural logarithm of the numbers of total replies from interactive users (IUs) in every year
LNAC2RT	The natural logarithm of the numbers of total replies from the firms' employees, PFs and IUs in every year
LNAC2SOFR	The natural logarithm of the numbers of total replies from participative fans (PFs) in every year
LNAC3ADD	The natural logarithm of the number of new functions added to the operating system in every year
LNAC3AM	The natural logarithm of the number of existing problems amended (repaired)in the operating system in every year
LNAC3OPT	The natural logarithm of the number of existing functions optimized in the operating system in every year
LNAC3TALL	The natural logarithm of the number of total changes in functions in the operating system in every year
LNACMC2OFR	The natural logarithm of the numbers of total replies from the firm's employees in every year
LNCHNSP	The natural logarithm of annual shipments of Chinese smartphones
LNCHNGDP	The natural logarithm of annual GDP in China
LNFALG1Y	Natural logarithm (ln) of total net fixed asset per firm per year in last year
LNFALG2Y	Natural logarithm (ln) of total net fixed asset per firm per year 2 years ago

LNGSP	The natural logarithm of annual shipments of global smartphones
LNIFNPDN	Natural logarithm (ln) of the project number of new products in all firms in each industry per year in official census
LNIFNPRV	Natural logarithm (ln) of the total sales of new products in all firms in each industry per year in official census
LNIFRIEM	Natural logarithm (ln) of the number of R&D employees in the R&D departments in all firms in each industry per year in official census
LNIFRIEX	Natural logarithm (ln) of the R&D budget in the R&D departments in all firms in each industry per year in official census
LNINUMFM	Natural logarithm (ln) of the number of all firms in each industry per year in official census
LNITLG1Y	Natural logarithm (ln) of total net intangible asset per firm per year in last year
LNITLG2Y	Natural logarithm (ln) of total net intangible asset per firm per year 2 years ago
LNITREV	Natural logarithm (ln) of the total revenue of all firms in each industry per year in official census
LNMAXPNUMB1	The natural logarithm of the number of total suggestions from the firms' employees, PFs and IUs in every week based on different categories of topics
LNMAXPNUMB2T	The number of total replies from the firms' employees, PFs and IUs in every week based on different categories of topics
LNMXAUGOF	The natural logarithm of the number of suggestions from the firm's employees in every week based on different categories of topics
LNMXAUGOT	The natural logarithm of the number of suggestions from interactive users (IUs) in every week based on different categories of topics
LNMXAUGSOF	The natural logarithm of the number of suggestions from participative fans (PFs) in every week based on different categories of topics
LNMXEPTVEWARD	The natural logarithm of the total award of the VEPs which the employee joined over 6.5 years
LNMXWKXMADD	The natural logarithm of the number of new functions added to the operating system in every week
LNMXWKXMAM	The natural logarithm of the number of existing problems amended (repaired) in the operating system in every week

LNMXWKXMOFRP	The natural logarithm of the number of replies from the firm's employees in every week based on different categories of topics
LNMXWKXMOP	The natural logarithm of the number of existing functions optimized in the operating system in every week
LNMXWKXMOTRP	The natural logarithm of the number of replies from interactive users (IUs) in every week based on different categories of topics
LNMXWKXMSOFRP	The natural logarithm of the number of replies from participative fans (PFs) in every week based on different categories of topics
LNNFIXA	Natural logarithm (ln) of total net fixed asset per firm per year
LNNITAS	Natural logarithm (ln) of total net intangible asset per firm per year
LNNPROF	Natural logarithm (ln) of total net profit per firm per year
LNPFLG1Y	Natural logarithm (ln) of total net profit per firm per year in last year
LNPFLG2Y	Natural logarithm (ln) of total net profit per firm per year 2 years ago
LNPFNPDN	Natural logarithm (ln) of the project number of new products in all firms in each province per year in official census
LNPFNPRV	Natural logarithm (ln) of the total sales of new products in all firms in each province per year in official census
LNPFRIEM	Natural logarithm (ln) of the number of R&D employees in the R&D departments in all firms in each province per year in official census
LNPFRIEX	Natural logarithm (ln) of the R&D budget in the R&D departments in all firms in each province per year in official census
LNPNUMFM	Natural logarithm (ln) of the number of all firms in each province per year in official census
LNPTREV	Natural logarithm (ln) of the total revenue of all firms in each province per year in official census
LNRDB	Natural Logarithm of Annual R&D Expense of Each Firm
LNTPATAP	Natural logarithm of annual number of patent application per firm
LNTPFG1Y	Natural logarithm (ln) of total profit per firm per year in last year
LNTPFG2Y	Natural logarithm (ln) of total profit per firm per year 2 years ago
LNTPROF	Natural logarithm (ln) of total profit per firm per year

LNTREVE	Natural logarithm (ln) of total revenue per firm per year
LNVEEMT	The natural logarithm of the total number of VEPs which the employee joined (either proposed as an applicant or took part in as a follower) over 6.5 years
LNVEEMTECN	The natural logarithm of the total economic value generated by VEPs which the employee joined over 6.5 years
LNVEEMTPAT	The natural logarithm of the total number of patent applications from the VEPs which the employee joined over 6.5 years
LNVEEROLETA	The natural logarithm of the total number of VEPs which the employee proposed as an applicant over 6.5 years
LNVEETACT	The natural logarithm of the total scores about activeness of the VEPs which the employee joined assessed by the firm over 6.5 years
LNVEETCREA	The natural logarithm of the total scores about creativity of the VEPs which the employee joined assessed by the firm over 6.5 years
LNVEETINVN	The natural logarithm of the total investment of the VEPs which the employee joined over 6.5 years
LNVEETTEAM	The natural logarithm of the total scores about teamwork of the VEPs which the employee joined assessed by the firm over 6.5 years
LNWDGDP	The natural logarithm of annual GDP in the world
LNXMAPATAP	The natural logarithm of annual number of patent applications
LNXMASP	The natural logarithm of annual shipments of Xiaomi's smartphone
LRTEST	Likelihood ratio test
LSDV	Fixed effect least square dummy variable
LTRVLG1Y	Natural logarithm (ln) of total revenue per firm per year in last year
LTRVLG2Y	Natural logarithm (ln) of total revenue per firm per year 2 years ago
MLM	Multiple level model
MIUI	Operating system of Xiaomi's smartphones
MUPS	Matching using the propensity score
NBSPRC	National Bureau of Statistics of the People’s Republic of China
non-SOE	non-State-owned enterprises
NSF	National Science Foundation of the U.S.
OECD	Organization for Economic Co-operation and Development
OII	Online interactive innovation

OLS	Ordinary least square
OWID	The id of the type of ownership of firm.
OWNSOEDV	ownsoedv =1 if firm is SOE ownsoedv=0 if firm is non-SOE
OWSODVTF2	The interaction between ownsoedv and teimpcf2
PF	Participative fan
POE	Private-owned enterprises
PS	Profit sharing
RDD	Regression discontinuity design
ROA	Return on Assets
RPRID	The id of the province in which the firm's headquarter is officially registered
RQ	Research question
SAFE	State Administration of Foreign Exchange of China
SEX	Gender of the employee
SOE	State-owned enterprises
STPID	The id of the stock board which the firm belong to
STPIDTF2	interaction of stpid and teimpcf2
T0	Stands for year, range from 0 to 8.
T0TEIMPCF1	The interaction between t0 and teimpcf1
T0TEIMPCF2	The interaction between t0 and teimpcf2
T0TEIMPCF3	The interaction between t0 and teimpcf3
T0TEIMPCF4	The interaction between t0 and teimpcf4
T0TEIMPCF5	The interaction between t0 and teimpcf5
T0TEIMPCF6	The interaction between t0 and teimpcf6
TEIMF	Dummy variable for teimpcf2, 1 if teimpcf2>0 in any year between 2007 and 2015, 0 if teimpcf2=0 in all year between 2007 and 2015.
TEIMPCF	Percentage point of ESOP which the employees keep ESOP to 2015.
TEIMPCF1	Percentage point of ESOP which the employees keep ESOP for 1 years.
TEIMPCF2	Percentage point of ESOP which the employees keep ESOP for 2 years.
TEIMPCF3	Percentage point of ESOP which the employees keep ESOP for 3 years.
TEIMPCF4	Percentage point of ESOP which the employees keep ESOP for 4 years.
TEIMPCF5	Percentage point of ESOP which the employees keep ESOP for 5 years.
TEIMPCF6	Percentage point of ESOP which the employees keep ESOP for 6 years.
TFLNIFNP	The interaction between teimpcf2 and lnifnpdn
TFLNIFNPR	The interaction between teimpcf2 and lnifnprv

TFLNIFRI	The interaction between teimpcf2 and lnifriex
TFLNIFRIEM	The interaction between teimpcf2 and lnifriem
TFLNIUM	The interaction between teimpcf2 and lninumfm
TFLNITRE	The interaction between teimpcf2 and lnitrev
TFLNPFRIEM	The interaction between teimpcf2 and lnpfriem
TFLNPFRIEX	The interaction between teimpcf2 and lnpfriex
TFLNPFNPDN	The interaction between teimpcf2 and lnpfnpdn
TFLNPFNPRV	The interaction between teimpcf2 and lnpfnprv
TFLNPNUMFM	The interaction between teimpcf2 and lnpnumfm
TFLNPTREV	The interaction between teimpcf2 and lnptrev
TPATAP	Annual patent application number per firm
VE	Value engineering
VEP	Value engineering project
VPC	Variance partition coefficient
WEEKSC0	The week beginning from March 16, 2012
YEAR	The natural year beginning from 2012

Chapter 1 Introduction

Schumpeter (1934) defined innovation as “new goods”, “an improved or better method of production”, “a new source of supply of raw materials or half-manufactured goods”, “the better organization of any industry”, “a new market” and more recently new business models (Foss, Nicolai and Saebi, 2017). Rothwell (1994) divides the development of innovation in the last 2 centuries into five generations based on their different features. The 1st generation rests on technology push in the early 19th century. The 2nd generation is characterized by market pull in the middle 19th century. The 3rd generation is a coupling model of innovation in the late 19th century and has since become common. The 4th generation is a model of integrated innovation invented by Japanese firms such as Nissan in the late 20th century.

The investment and applications of Information and communication technology (ICT) surged and shifted dramatically in two main periods in the U.S. which developed most of the ICT technologies and industry. In the first period between 1980 and 2006 in the U.S., the investment of ICT in firms and governments rose and shifted from mainframe computers to PCs and internet, and then many consumers bought PCs. The development of the internet connected by PCs provided the context for the 5th generation of innovation (Rothwell, 1994) and the 6th generation of innovation included ideas of disruptive innovation (Christensen, 1997) and open innovation (Chesbrough, 2003). During the decades since the policy of ‘Reform and Open’ beginning in 1979, China built the “open national innovation system” to learn from the Western countries (Fu, 2015), particularly from the U.S. In the late 1990s and early 2000s, Chinese internet firms copied business models from the U.S. and reproduced them in China, e.g., sina.com or sohu.com copied yahoo.com or American Online; Alibaba learned from Amazon, etc.

The second wave of ICT investment was triggered by the mobile internet and digital economy from 2007 when the iPhone was introduced by Apple. Global mobile-cellular telephone subscriptions increased over ten times from 739 million in 2000 to 7980 million in 2019 (ITU, 2021). Simultaneously, worldwide active mobile-broadband subscriptions increased from 20.67 million in 2007 to 5442 million in 2019, or about 27 times (ITU, 2021). Billions of consumers can afford cheap smartphones made by Chinese firms and cheap 3G or 4G services. The huge number of consumers attract and help innovators and entrepreneurs to invent many new technologies, new e-business models and to make them accessible and affordable for more potential consumers. Consequently, the global digital economy grew to US$31.8 trillion in 2019 (CAICT, 2020).

Since 2010, innovative Chinese firms developed rapidly by catching the opportunity of the mobile internet (Pony Ma of Tencent, 2017). Among the top 10 smartphone producers, 7 firms are from China, which constituted 45% of the global market in the 2nd quarter of 2019 (Counterpoint, 2019). With the cheap smartphones and affordable 3G and 4G services, there were 1.319 billion users of the mobile internet in China at the end of 2019, 32.17% of the world. The whole value of e-commerce in China soared from 6.09 trillion Chinese Yuan in 2011 to 34.81 trillion Chinese Yuan in 2019, constituting more than 40% of world spending (China Ministry of Commerce, 2020). This biggest market provides the largest space for innovations in many new application scenarios such as mobile commerce, mobile payments, digital security, social networking, 'sharing' bicycles, new media including Douyin or TikTok and other many creative uses of ICT. These provide voluminous data that push the development of big data, cloud computing, internet of things (IoT) and artificial intelligence (AI), etc. All of these contribute to a positive feedback cycle. The context of the innovations in the previous generations are quite different from the current large volume of digital activities with new technologies that consequently provide the new context for digital innovations.

An example of the new innovation models, which I refer to as the "Online Interactive & Integrated Innovation Model" [OIIIM], is illustrated in Figure 2.11 in Section 2.4. OIIIM combines both integrated product development [IPD] and online interactive innovation [OII] which reflect the open innovation system (Fu, 2015) and generates a series of important advantages. In this new innovation model OIIIM, there are three main parts:

First, earlier integrated innovation models (Rothwell, 1994) and integrated processes for product and cycle-time excellence (Mcgrath, 1986) evolved into the current integrated product development [IPD] approach. IPD clears internal barriers and integrates all departments in a firm into innovation processes to accelerate knowledge collaboration. This has been widely applied in the U.S. and other developed countries for decades because IPD can cut the time for new products to market, reduce waste in product development, and enhance the efficiency of product development. Huawei learned IPD from IBM in the context of a big consulting project between 1999 and 2007, which contributed to its success.

Second, leading innovative firms such as Xiaomi develop "online interactive innovation" [OII] which is analysed in Chapter 3 as the first study of this thesis. It focuses on how OII promotes innovation via the interaction between employees and customers. Previous publications have addressed related concepts about lead users (von Hippel, 1986), open innovation (Chesbrough, 2003), interactive innovation (Lundvall, 2009), online communities (Barrett, et al., 2016), word of mouth (Arndt, 1967a and 1967b) and innovation diffusion (Rogers, 1995). But new innovation practices for knowledge transfer from customers' suggestions to new products have become successful in innovative firms such as Xiaomi, Huawei, Haier in China and Tesla in the U.S. Unfortunately, the mechanism of the new practices has not been analysed. This study examines the 'virtual teamwork' connecting a firm's employees, participative fans (PFs) and interactive users (IUs) and knowledge sharing in the online communities.

This study uses panel data of Xiaomi' and puts it into the context of 10 other firms in smartphones and home appliances. Xiaomi was founded in 2010 and has been in the top 4 of the global smartphone market since 2014, entering the *Fortune* 500 in 2019 at an unprecedented speed (Fortune, 2020). Xiaomi invented OII in 2010 and Xiaomi's employees attract and cultivate millions of customers to act as interactive users (IUs). Then Xiaomi organises enthusiastic IUs to become participative fans (PFs) to help to attract and interact with more IUs in the online communities which provide millions of suggestions, comments and complaints. Xiaomi's employees supervise and manage PFs to evaluate and select useful suggestions. The creative, valuable and practicable suggestions are synthesised with the knowledge of Xiaomi's employees and are used to invent new functions, optimise or repair existing functions in the operating system of Xiaomi's smartphones. Creativity, usefulness and practicability are used to evaluate and select not only suggestions from customers, but also proposing new functions, optimising existing functions and suggesting patent applications. After being tested by about 100,000 PFs to find and fix any possible bugs, the new versions of the operating system are released every Friday for more than 200 million active users to update their smartphones. This study applies methods of growth curve modeling and multiple regressions to analyze Xiaomi's panel data between 2012 and 2018. It finds that the number of customers' suggestions is positively associated with the number of the replies from the firm's employees and other customers. Also, there are positive relationships among the suggestions, replies, functions changes in the operating system, patent applications and annual shipments of smartphones. OII and the consequent R&D works need a lot of engineers. Xiaomi and other Chinese firms can afford to hire sufficient engineers at relative low costs and motivate them by employee stock ownership plans [ESOPs], discussed in the third study of the thesis.

Furthermore, OII accelerates innovation diffusion drastically. One consequence of this is that the firm may underestimate such soaring demand from customers, which may surpass the existing supply if the firm does not have sufficient capability to manage their supply chain at a large enough scale. Evidenced by Huawei and Xiaomi, it is necessary, useful and important to combine both OII and IPD which are complementary, in order to avoid product shortage. OII breaks the wall at the border of the firm and connects millions of customers with the firm, while IPD clears barriers inside the firm and integrates all the internal departments for innovation. So that suggestions, complains or knowledge can flow easily from millions of customers to all the relevant internal departments of the firm to contribute to innovation, and vice versa.

Third, as the essential part of the "online interactive & integrated innovation model" [OIIIM], online interactive innovation [OII] has 13 advantages which are analysed and discussed in detail in Section 3.5.2. OII helps firms to enact fast iteration techniques, realise mass-customisation, enhance users' experience and trust, reduce costs, improve efficiency and productivity, etc. Additionally, both IPD and OII can help firms to keep low prices but high quality for hardware, e.g., Xiaomi cut smartphones' price and Tesla reduces price of electrical vehicles to catch the market quicker than their competitors, so that Xiaomi and Tesla can keep on growing at a speed faster than their competitors. But Xiaomi and Tesla enjoy high profit from interacting and internet services, evidenced by Xiaomi's financial report (Xiaomi, 2021c).

It is often asserted that "[t]alent is the bedrock of a creative society" (Yusuf, 2009: 1). Usually in idea creation, individuals were more effective than teams (Taylor and Greve, 2006). No matter if the individual works alone or in teams, the individual is usually the basic unit to create new ideas, which then contribute to innovation at levels of teams or firms. In existing theories about innovation and the "online interactive & integrated innovation model" [OIIIM] illustrated in Figure 2.11, one of the most important factors is individual innovation. Hence, this thesis explores and clears up confusions about three relevant topics, including the first study about online interactive innovation [OII] aforementioned, the second study about individual innovation and the third study about the relationship between incentives to employees in schemes such as

ESOP and firms' innovation performance.

The second study investigates "how does education influence individual innovation behavior?" There are many publications about the effects of education (Temple, 2000; Jia & Liu, 2018) and individual innovation (Scott & Bruce, 1994; Gruber, Harhoff and Hoisl, 2012) respectively, but none explores the mechanism of how education influences individual-level innovation performance particularly via creativity in details. This study analyses individual innovation activities of 2,078 employees who participated in 3,976 value engineering projects (VEPs) between January 2012 and June 2018 in a single listed manufacturing firm. The firm organises experts with relevant knowledge and expertise to review the results of VEPs every month and assess the performance of creativity, activeness and teamwork of each VEP. Also, the firm's accounting department figures out the investment and economic value of each VEP. This evaluation system has been tested and improved by evaluating 3,976 VEPs over 6.5 years. Hence the assessments are more realistic, accurate, reliable and practical than the measurement in academic laboratories in the relatively much shorter periods in some existing publications. This is much more convincing than existing studies that mainly experimented with students (Baas, DeDreu, and Nijstad, 2008) and may be significantly biased. The unit of analysis of this study is the individual. The data of all VEPs which every employee joined are summed to measure the innovation performance of the employee, which are not panel data but multilevel data within the firm's hierarchical organisation. Hence, the data are analysed by building a series of multilevel models. The independent variable is the education measured by the highest degree of each employee. It finds that education first influences the employee's creativity which acts at the middle of the chain of relationships. Then the employee's creativity contributes to enhance individual innovation performance, measured by three indicators. These are: 1) the total number of VEPs which the employee proposed as an applicant, 2) the total numbers of VEPs which the employee joined as either an applicant or a follower, and 3) the total number of patent applications from the VEPs which the employee joined over 6.5 years. This chain relationship is statistically significant in 2 models whose dependent variables (DVs) are the first and second indicators respectively and there is a direct association with statistical significance between education and the total number of patent applications in the third model. This triangulation proves that education has a positive relationship with individual innovation performance with reliability and validity. Furthermore, the first and second indicators about individual innovation have positive associations with the total economic value generated by VEPs with statistical significance. Simultaneously, there are strong group effects at the level of squads (teams) in all the models with statistical significance, which means the employees' innovation behavior influences each other significantly in squads. Other factors including employees' age, gender, majors of bachelor degrees, hometown by province, monetary awards and financial investment for VEPs, etc. are controlled in the models. If applying principal component analysis (PCA) to generate a composite index to measure the innovation performance of employees, the result is consistent with the previous findings with triangulation which prove the findings are robust.

The third study explores "how does employee share ownership activate employees and influence innovation?" This study focuses on 'activeness' and 'creativity' identified in the second study. Firms' innovation performance is measured by every firm's patent application number in every year and the unit of analysis is the firm. To be granted by the patent office, a patent application is required to be novel, unobvious (creative) and useful. Novelty and unobviousness are relevant to the creativity of employees. The separation of ownership and management is efficient for corporate governance (Fama, 1980). Stock options are awarded to managers to solve the principal-agent problem as the 1st type of corporate governance solution. However, more principal-principal problems appear in practice. Similarly, due to information asymmetry, different interests and incomplete contracts among employees, managers and shareholders, there are corporate governance problems relevant to R&D and innovation (Chen, et al., 2006).

Hence, in addition to stock options for mangers, ‘employee stock ownership plans’ [ESOPs] are awarded to key employees to solve the principal-agent and principal-principal problems (Koller, Goedhart and Wessels, 2010 and Rosen, 2013) as the 2nd type of corporate governance solution. ESOP is popular in European, Chinese and Japanese firms, but until now there has not been a study with a big sample and sufficient representativeness (Garrett, 2010) to test if ESOP can improve firms’ innovation performance or not. Furthermore, no studies have been done to analyse important possible influences, especially group effects of industries, locations of firms’ headquarters by provinces, stock boards and state ownership enterprises [SOEs] vs non-SOE on the impact of ESOP on innovation. The mixed design used here combines quantitative analysis and qualitative interviews. Some factors identified in interviews are tested by quantitative analysis and results from interviews help to explain the results of statistical models. This study builds growth curve models to analyse the panel data of 1,509 Chinese listed firms between 2007 and 2015. Six hypotheses about SOEs vs non-SOEs, industry, location (by province) of firms’ headquarters and stock boards are tested. Consequently, this study has three main contributions: First, it verifies the finding of Chen, et al. (2006) with a much bigger sample that ESOP can alleviate corporate governance problems and promote firms to increase R&D expense. Second, it finds that ESOP enhances firms’ patent application practices through a big sample with sufficient representativeness which fills the research gap identified by Garrett (2010). Third, the possible effects of various factors are analysed. The influence of ESOP on patent application numbers is bigger in SOEs than non-SOEs. SOEs are more prone to adopt ESOP to solve principal-agent and principal-principal problems and to attract or activate employees. But according to the interviews, private firms adopted ESOP to raise money from employees which was a priority in the early development period, e.g., Wens Group. Consequently, many senior employees in private firms have many stocks and the problems of “entrenchment” (Chang and Mayers, 1992) and “free riders” (Weitzman and Kruse, 1990) are much more serious in private firms than in SOEs as seen in interviews. There are also group effects at the level of the industry which influence the impact of ESOP on firms' annual patent applications. Usually knowledge-intensive industries are also talent-intensive industries. ESOP influences firms' innovation significantly in knowledge/talent-intensive industries while not significantly in non-knowledge/talent-intensive industries. Other factors that might be thought to have group effects do not, including stock boards and locations by provinces. The impact of ESOP on firms' innovation will be reflected only in provinces or stock boards where the knowledge/talent-intensive industries concentrate, e.g., eight provinces on China's Eastern coast or ChiNext. In summary, ESOP does help to solve the corporate governance problems relevant to R&D and innovation to improve the firms' innovation performance. Finally, suggestions for policy and management practice are provided, e.g., the Chinese government should continue the reform of mixed ownership and adopt ESOP to promote innovation particularly in SOEs.

In the following, Chapter 2 reviews the existing key literature shared by the three studies aforementioned. Chapter 3 investigates how OII helps firms to interact with millions of customers and promote innovations. Chapter 4 examines the relationship between education and individual innovation behaviour by analysing 2,078 employees. Chapter 5 explores the influence of ESOP on firms' innovation measured by the annual patent application numbers of 1,509 listed firms during 9 years. Chapter 6 draws conclusions and make recommendations for management practice, policy and future research.

Chapter 2 Critical Bibliography and Literature Review

A critical body of literature on innovation, knowledge creation and sharing forms a common foundation to the three studies in this PhD thesis. Literature specific to the three studies respectively are reviewed in the relevant chapters later. Chapter 3 about online interactive innovation reviews the literature about customers' input for innovation (Randall, Terwiesch and Ulrich, 2007), lead users (von Hippel, 1986), interactive innovation (Manley, 2003; Lundvall, 2009), online communities (Faraj, Jarvenpaa and Majchrzak, 2011), word of mouth (Arndt, 1967a), innovation diffusion (Rogers, 1995) and product scarcity (Shi, et al., 2020). Chapter 4 about individual innovation reviews the literature about individual innovation (Scott & Bruce, 1994; Shaker, Zeffane & Albaity, 2018), the influence of education on innovation (Kaneko, 1980; Temple, 2000), creativity (Udwadia, 1990), etc. Chapter 5 reviews publications about corporate governance (Fama, 1980), principal-agent and principal-principal problems (Shleifer and Vishny, 1997), employee ownership (Rosen, 2013), the relationship between employee stock ownership plan (ESOP) and innovation (Chen, et al., 2006).

2.1 Innovation theory over six generations

Innovation has been recognized as the base for competitiveness, efficiency and productivity (Griliches, 1990; Crepon, Duguet and Mairesse, 1998). "Innovation is the key driver of competitiveness, wage and job growth, and long-term economic growth" (U.S. Department of Commerce, 2012). Rothwell (1994) divided the development of innovation in the last 2 centuries into five generations, according to their different features. In each generation, there is a leading country with its dominant innovation model. I argue that the latent criteria of all these five generations of innovation are different sources of knowledge and different ways to apply knowledge.

2.1.1 Generation 1: Technology Push

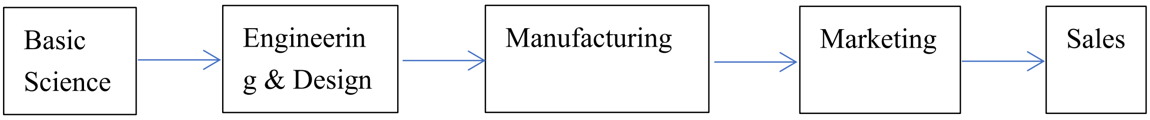

Figure 2.1 Technology Push (1st Generation, Rothwell, 1994: 10)

The 19th century was called the “century of science” with many breakthroughs in science and technology, but many products were not sufficient in the early 19th century. Products were developed by designers or researchers in firms with the help of universities which were the main source of novel knowledge, for example in the pharmaceuticals industries in the U.K. and U.S. (Liebenau, 1989 and 1990). This is similar to the closed innovation model described by Chesbrough (2003).

2.1.2 Generation 2: Market Pull

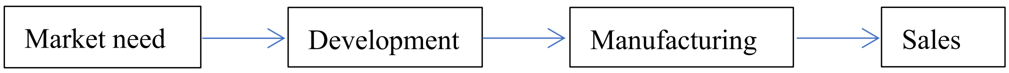

Figure 2.2 Market Pull (2nd Generation, Rothwell, 1994: 10)

In the middle 19th century, with abundant products supplied through intermediate markets, firms competed to attract consumers and paid more attention to their needs. This is consistent with the process perspective and suggests that innovation is a process with the knowledge, skills and commitment of multiple stakeholders mainly in the firms (Swan, Newell, and Robertson, 2000).

2.1.3 Generation 3: Coupling Innovation

The feature of this generation is a “coupling” model of innovation. Both knowledge and information about market needs, along with R&D in firms are combined in every stage of innovation. This dominated U.S. manufacturing in the late period of the 19th century and has since become common.

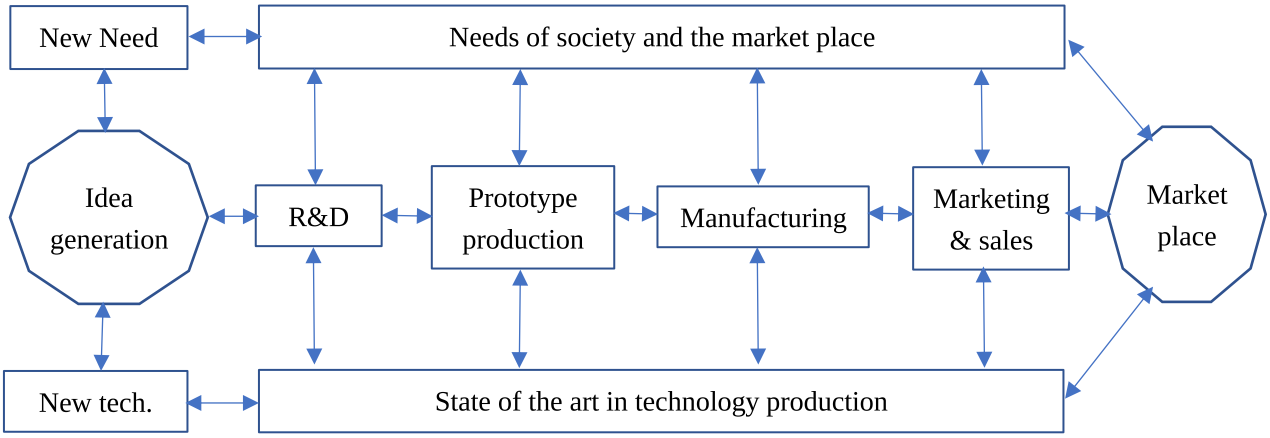

Figure 2.3 The Coupling Model of Innovation
(3rd Generation, Rothwell, 1994: 11)

2.1.4 Generation 4: Integrated Innovation

According to Imai, Nonaka and Takeuchi (1985), Japan improved the traditional development of innovation that was based on sequential and linear practices from development, design and manufacturing. For instance, creative design in the previous procedures met resistance in the later departments. To solve such problems, Japanese firms invented a new way, which is called the "Sashimi Model". Japanese companies "integrate" suppliers and most of internal departments into the new product development process at an early stage and work "on the project simultaneously (in parallel) rather than sequentially (in series)" (Rothwell, 1994: 12). This is better for knowledge sharing, synergy and synthetization and every step of knowledge advancement results in "incremental development" in products, so that they "achieved relatively rapid product cycles" (p.17) with high efficiency. The "incremental development" in the 4th generation was called 'iteration' later and become an element of the new innovation model, which will be discussed again in Chapter 3 about online interactive innovation.

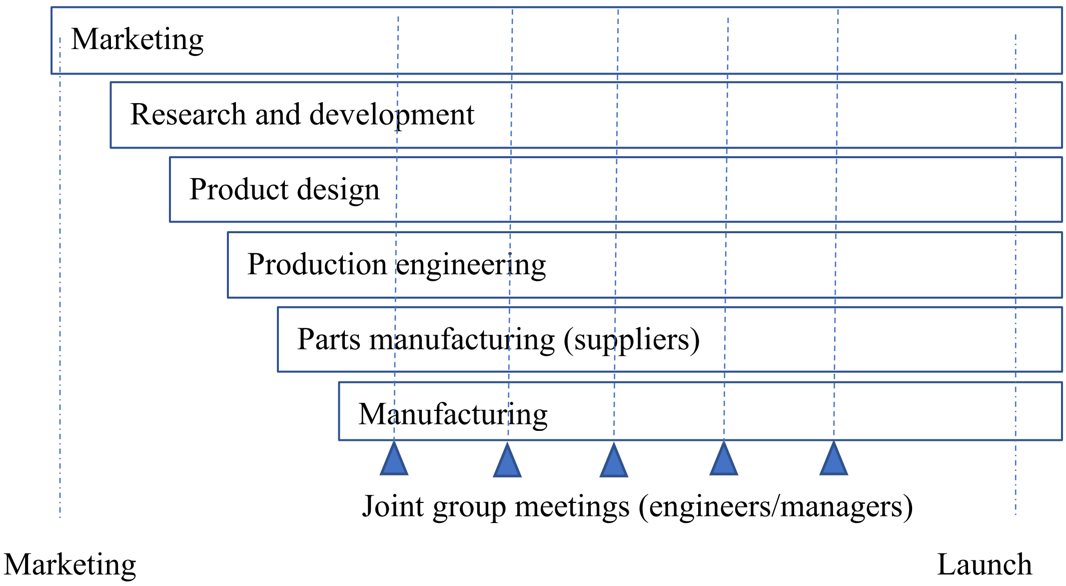

Figure 2.4 Integrated Innovation (4th Generation,
new product development process in Nissan, Rothwell, 1994: 17)

2.1.5 Generation 5: The U.S. "New Economy" in late 1990s

There were two main periods when the investment and applications of ICT surged and shifted dramatically. The first period was between 1980 and 2006 particularly in the U.S. The ICT investment shifted from mainframe computers to PCs and internet in firms and governments, followed by many ordinary consumers when the prices of PCs became affordable. After the heavy investment in ICT equipment, digital infrastructure was built up in most firms in the U.S. which accelerated the transmission of knowledge and information. Networking created "flatter and more flexible organizational structures" and integrated organizations and systems together at levels of firm, nation or globe. "Innovation is changing the structure and enhancing the capabilities of organizations" (Yusuf, 2009: 1). With the help of ICT, there were fully developed internal databases and electronically assisted product development in firms. Also, firms began to use networks to connect customers and suppliers (Rothwell, 1994; Sawhney, Verona and Prandelli, 2005). For instance, Dell asked customers to choose online what functions they want for their PCs, a fundamental practice of mass-customization, which laid the ground for mass-customization in the later generation of innovation and will be discussed again in Chapter 3 about online interactive innovation. The innovations and prosperity driven by ICT brough high growth rate of productivity and GDP, low inflation and unemployment rate to the U.S. (Mandel, 2000).

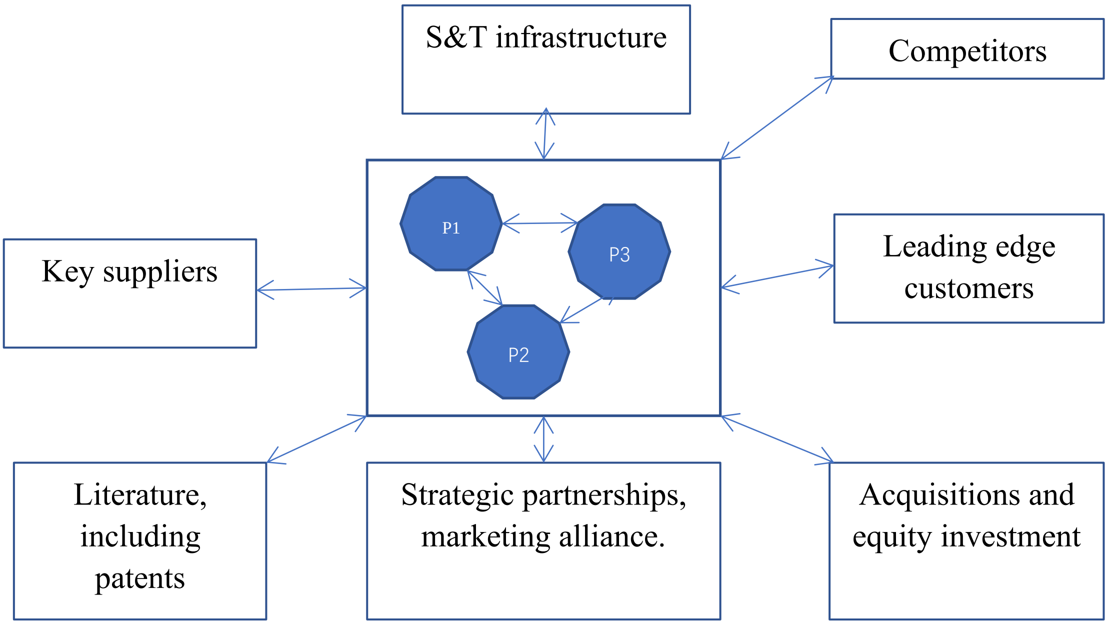

Figure 2.5 Innovation as a Process of Know-how Accumulation (5th Generation, initial mass-customization, Dell, Rothwell, 1994: 27)

2.1.6 Generation 6: Disruptive innovation and open innovation

Furthermore, the rapid development of ICT provides three main factors for innovation. First, more and more products became digitalized which make them amenable for fast iteration originated in the 4th generation of innovation. Second, ICT accelerating innovation provides the context for ‘disruptive innovation’. Christensen (1997) published *The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail* and advocated disruptive innovation. Christensen (1997) argued the disruptive innovators invented a new technology or new business model to win first in small niche markets other than the main stream market, which may be ignored by the big incumbent firms. But the disruptive innovators can improve the new technology or new business model quickly by fast iteration particularly accelerated by ICT, so that it can be used by more and more customers. Later, disruptive innovators enter the main stream market and supersede the incumbent firms.

Third, ICT networks and especially the internet help to transmit information and knowledge at much lower cost than before, which promotes ‘open innovation’. Additionally, ICT tools are used to improve knowledge management (KM) which contributes to promote innovation (Kodama, 2013). Similarly, Valdez-Juárez, et al., (2018: 1) found “ICT significantly influences KM, innovation and profitability. In addition, KM significantly influences innovation, and innovation and IP management significantly influence profitability.” Because the internet became more and more popular since the 1990s, firms can get access to more and more external knowledge in the digital world. These provided somewhat background for “open innovation” (Chesbrough, 2003).

Chesbrough (2003) advocated “Open Innovation” (OI) and redefined it “as a distributed innovation process based on purposively managed knowledge flows across organizational boundaries, using pecuniary and non-pecuniary mechanisms in line with the organization’s business model” (Chesbrough and Bogers, 2014: 1). The main concept of OI is illustrated as following. Fu (2015) argued that China adopted open innovation strategy at the national level and built “open national innovation system”. Following Rothwell (1994), Preez, Louw & Essmann (2017) described open innovation as the 6th generation of innovation.

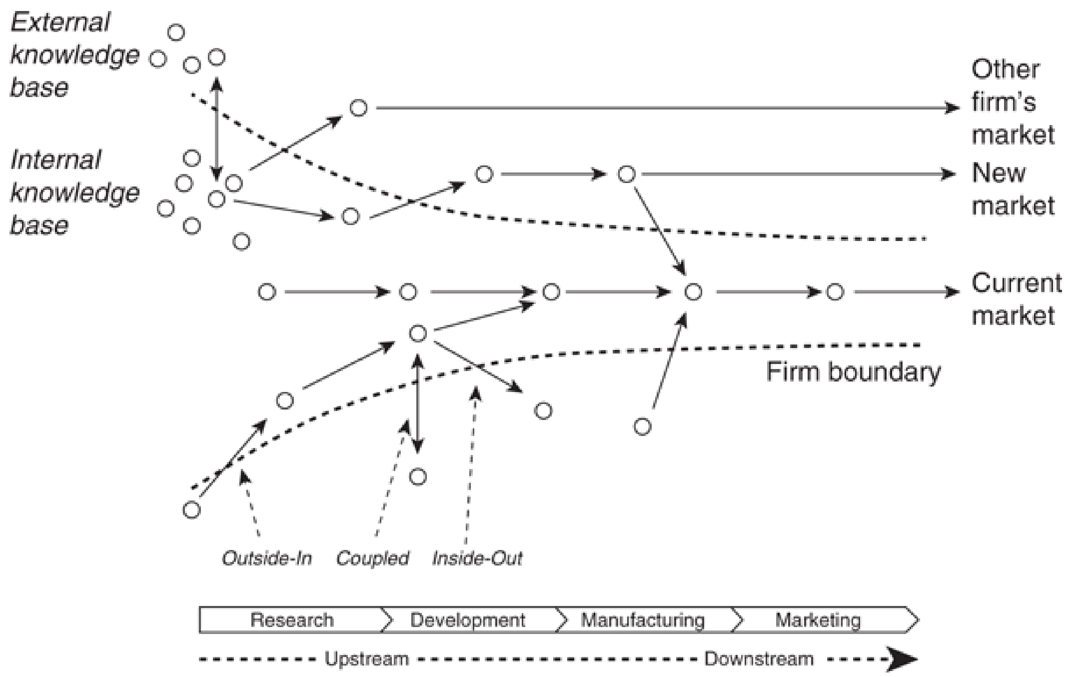

Figure 2.6 Open Innovation (Chesbrough, et al., 2014: 18).

In the digital world, the theory of dynamic capability may be suitable to explain some elements of innovation management. Dynamic capability is “the firm’s ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments” (Teece, Pisano and Shuen, 1997: 516). According to Eisenhardt and Martin (2000), it is difficult to be complicated in fast moving markets; modularization is good for products such as the smartphones of Apple and Xiaomi in high-velocity markets. But the theory of dynamic capability has mainly 3 drawbacks: it emphasizes actions in markets that are fickle and unpredictable; there is no sustainable and inimitable core capability for any firm; cooperation among firms is temporal and depends on projects. These three are not widely representative of the current business world.

From the first generation to the sixth generation, it can be seen that innovation becomes increasingly open and more stakeholders take part in the innovation process simultaneously, so that there is more knowledge sharing, synergy and synthetization among the various participants. Especially in the 4th and 5th generations of innovation, ideas and practices appear that presage some features of the new innovation model, such as iteration and mass-customization which will be discussed in details in Chapter 3 about online interactive innovation in this thesis. As innovation practices evolved from the 1st to 6th generation, the foundations of the new innovation model currently emerging in Chinese firms are being laid.

2.2 Innovation, knowledge creation and sharing

A clear and important relationship between knowledge and innovation has been found in many studies. “[I]n most cases, knowledge alone is not innovation: commercially valuable innovations are often created through the novel recombination of existing knowledge (Galunic and Rodan, 1998; Khilji, Tomasz, and Bernstein, 2006).” (West and Bogers, 2014: 29). According to Gibbons & Johnston (1974) and Faulkner (1998: 175), there are five types of knowledge used in innovation: “theories; properties of materials and components; design-based info, operating principals; test procedures & techniques; knowledge of knowledge”. In the studies about innovations in the late 1960s and 1970s, “[a]round two thirds of the knowledge used by companies in the course of innovation was found to derive from their own in-house R&D effort and expertise, the remaining third coming from external sources” (Faulkner, 1998: 173) which lay the ground for open innovation (Chesbrough, 2003).

Nonaka and Takeuchi (1995a and 1995b) described the 4 phases in Figure 2.7 including socialization (communication and sharing of tacit knowledge), externalization of tacit knowledge to explicit knowledge, combination of explicit knowledge, internalization of explicit knowledge into tacit knowledge. The knowledge creation process is illustrated in Figure 2.8.

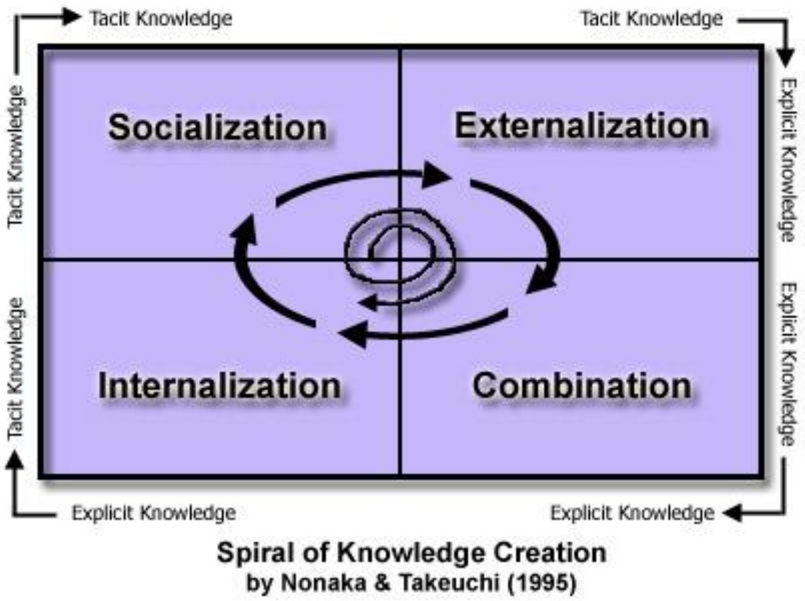

Figure 2.7 The Knowledge Spiral SECI (Nonaka & Takeuchi, 1995a).

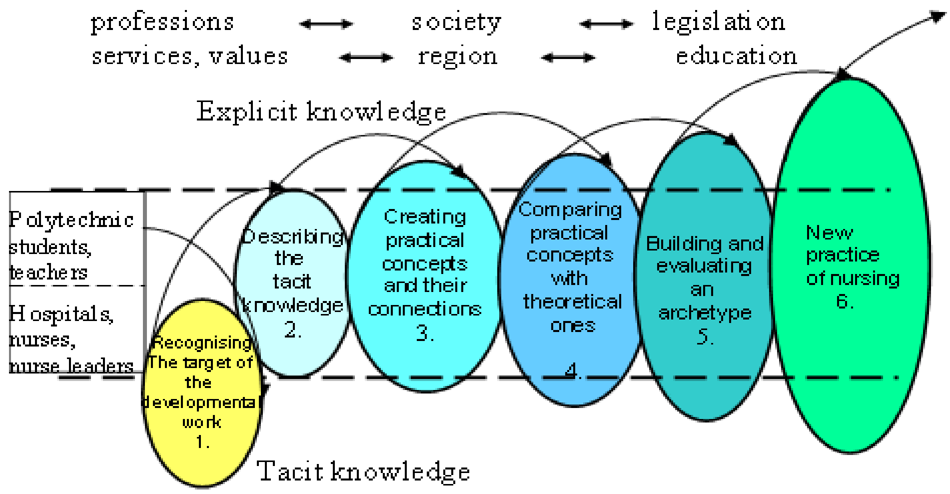

Figure 2.8 The Knowledge Creation Process (by Nonaka & Takeuchi 1995a; Kivisaari 2001; Astala & Ora-Hyytiäinen 2005; from Ora-Hyytiäinen and Rajalahti (2006))

"[I]innovations are seen to emerge in nonlinear processes, often combining very diverse knowledge bases" (Parjanen, Harmaakorpi & Frantsi (2010: 1). Hence, knowledge sharing in firms is important for employees to apply knowledge, innovate, and finally improve the firms' competitive advantage (Jackson, et al., 2006). There are some studies about knowledge sharing in firms which address: 1) environmental factors including organisational context, management support, culture, climate, team characteristics, etc., influence knowledge sharing inside firms (Ruppel & Harrington, 2001; Wang, 2004; Willem & Scarbrough, 2006). "The most effective way to disseminate knowledge and best practice is through systematic transfer. That is, to create a knowledge-sharing environment" (Lee and Yang, 2000: 783). This supports the study in Chapter 3 about online interactive innovation that shows how such "a knowledge-sharing environment" in the online community is created to foster the knowledge sharing among Xiaomi's employees and millions of customers. 2) individual characteristics such as education, work experience (Constant et al., 1994; Cabrera et al., 2006) which is discussed in Chapter 4; 3) motivational factors including awards, incentive such as ESOP (which is discussed in Chapter 5), benefit, cost, etc., influence knowledge sharing inside firms (Wang and Noe, 2010). Also, there are other publications about the three ways aforementioned for knowledge sharing between firms (Zhao, 2011).

However, there are apparently no studies about knowledge sharing and creation between employees and customers in online communities, e.g., how to collect and evaluate millions of suggestions and comments from many millions of customers at low cost. I will fill this significant gap by discussing Xiaomi plus10 other innovative firms in China. Furthermore, Nonaka and Takeuchi (1995a and 1995b) described the model qualitatively, but I examine every step of knowledge sharing and creation quantitatively by building growth curve models in Chapter 3.

2.3 The new context for the new innovation model

As discussed in Section 2.1.5, the first period of heavy ICT investment took place between 1980 and 2006 in the U.S. which provide the context for the 5th and 6th generation of innovations. The second wave of ICT investment took off since the mobile internet and digital economy developed from 2007. The mobile internet started in 2007 when the iPhone was introduced by Apple. Up to date, the mobile internet has been connecting billions of persons by 3G, 4G and 5G. As illustrated in Figure 2.9, global mobile-cellular telephone subscriptions increased from 739 million in 2000 to 7980 million in 2019 (ITU, 2021), more than global population as 7579 million since many individuals have more than one mobile phones. The number of individuals who use cellular telephone per 100 inhabitants increased from 12.4 in 2005 to 80.1 in 2019 in Africa where is the lowest in all continents, while from 52.1 in 2005 to 112.7 in 2019 in North America. According to interviews of managers at Huawei, the leading firm in the global telecommunication market, the cost to transfer every bit of information online by 5G decreased to only 0.01% of the cost by 2G. The costs of mobile phones and mobile services have been reduced drastically (ITU, 2020), so that most consumers can afford them. Consequently, the global active mobile-broadband subscriptions increased from 20.67 million in 2007 to 5442 million in 2019 (ITU, 2021) illustrated in Figure 2.10. The number of individuals who use active mobile-broadband per 100 inhabitants increased from 1.7 in 2010 to 32.1 in 2019 in Africa where is the lowest in all continents, while from 25.4 in 2010 to 99.1 in 2019 in North America.

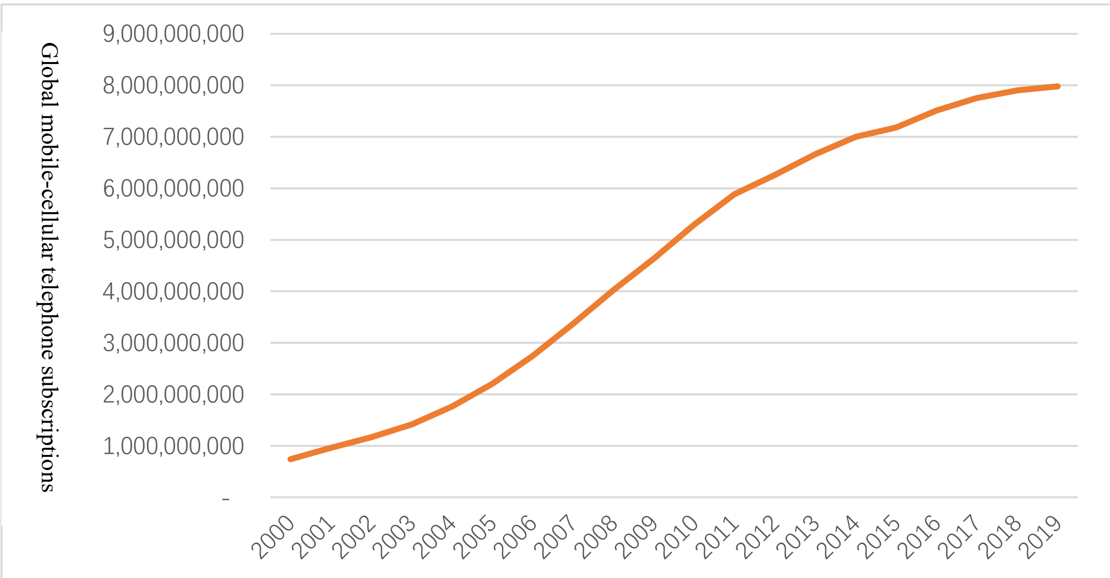

Figure 2.9 Global Mobile-cellular Telephone Subscriptions (Source: ITU, 2021)

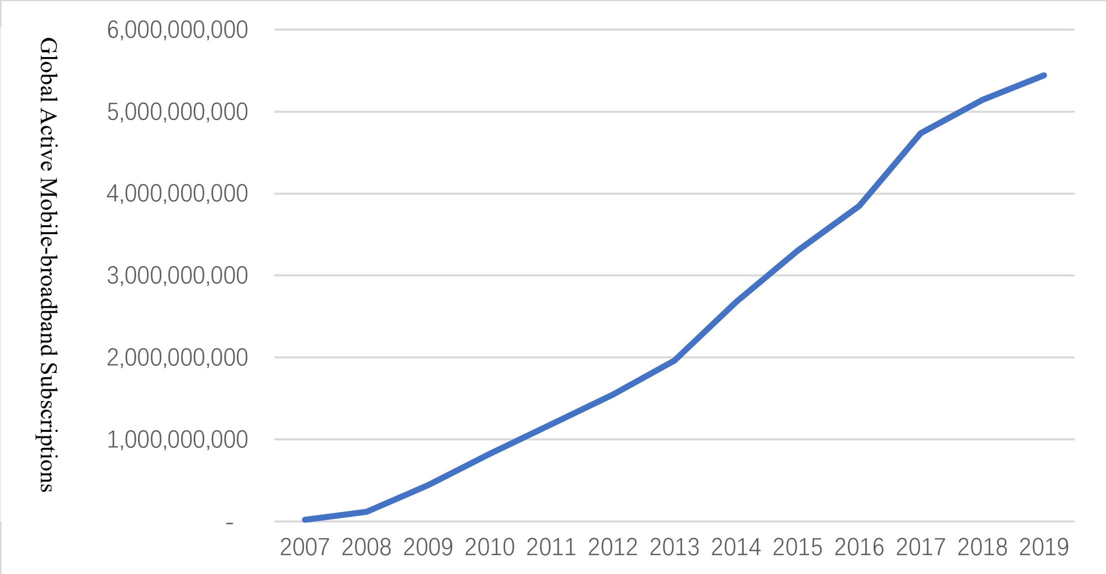

Figure 2.10 Global Active Mobile-broadband Subscriptions (Source: ITU, 2021)

Billions of people can buy cheap smartphones made by Chinese firms including Xiaomi whose innovation is explained in Chapter 3 and use cheap 3G or 4G services. These generate a huge digital market, which attracts and helps talented individuals to invent many new technologies, new e-businesses models and make them accessible and affordable for billions of potential consumers. The mobile internet and mobile digital economy including the new applications of internet of things (IoT), big data, cloud computing and AI have been changing the aspects of individuals, groups, organisations or firms, markets/economies and public societies. For example, the global digital economy soared to US$31.8 trillion in 2019 (CAICT, 2020). China's volume of e-commerce soared from 6.09 trillion Chinese Yuan in 2011 to 34.81 trillion Chinese Yuan in 2019 (China Ministry of Commerce, 2020). Particularly, the number of smartphones and tablets surpassed the number of laptops and PCs in 2011 (Chen, et al., 2012). Smartphones reduce the transaction costs for interactive innovation, which "presents a unique opportunity for businesses to treat the market as a conversation between businesses and customers instead of the traditional business-to-customer, one-way marketing" (Chen, et al., 2012: 1167). The context of the innovations in the previous generations are quite different from the current large volume of digital economy transactions with new digital technologies which consequently provide the new context for the new innovation model.

2.4 Online Interactive & Integrated Innovation Model

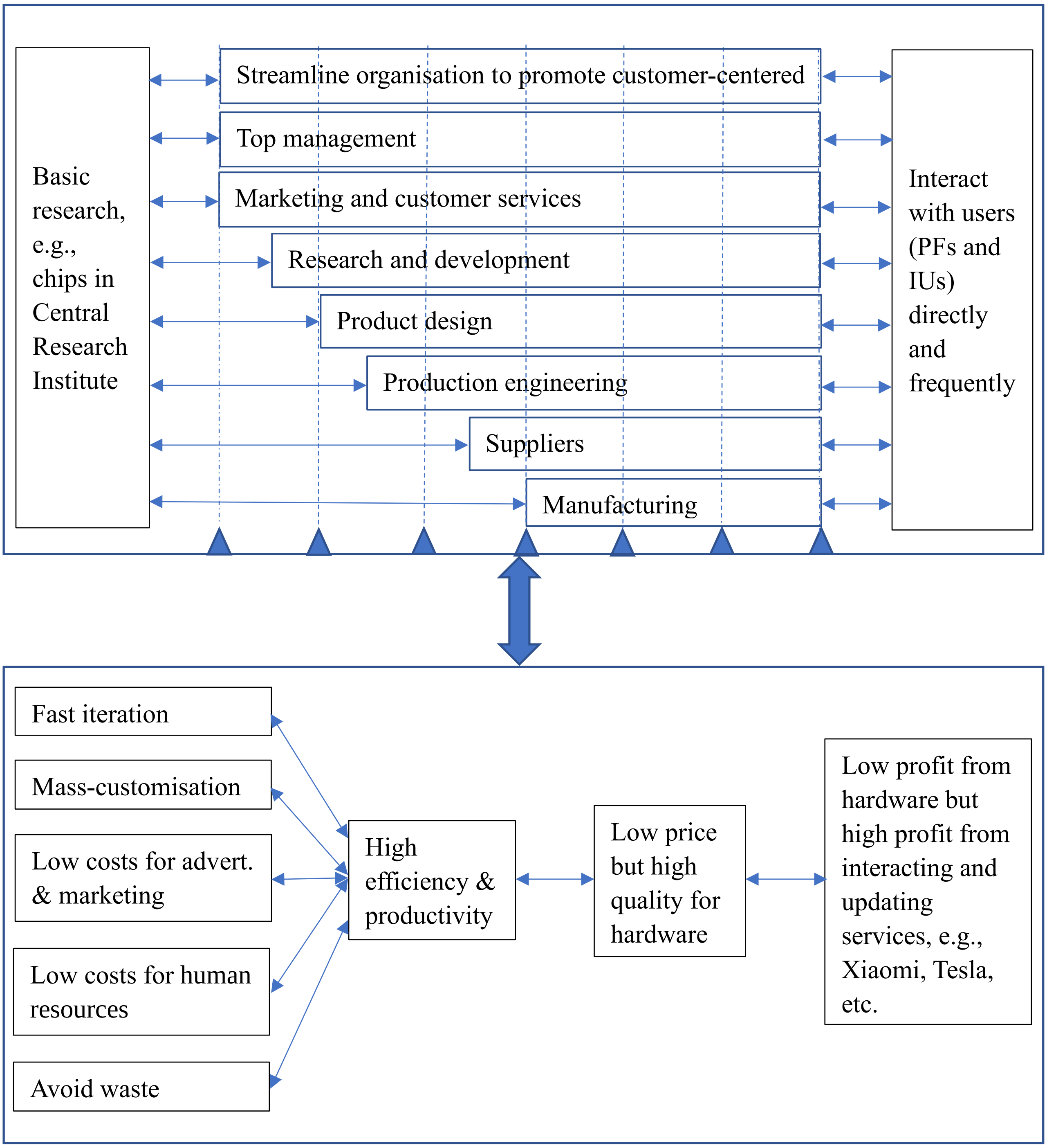

Figure 2.11 Online Interactive & Integrated Innovation Model [OIIIM]
(Combining OII and Integrated Innovation (Rothwell, 1994). OII connects users and firms' internal departments and/or external suppliers, which reflects open innovation (Chesbrough, 2003) and customer-centered of Huawei.)

Based on the previous innovation models particularly those in the 4th, 5th and 6th generation of innovations, a new innovation has been developing in the leading innovative firms such as Xiaomi, Huawei and Haier in China and Tesla in the U.S., which is called the 'Online Interactive & Integrated Innovation Model' [OIIIM] illustrated in Figure 2.11. In this new model, there are three main parts:

First, similar to the integrated innovation model (Rothwell, 1994), Mcgrath (1986) developed an integrated process for product and cycle-time excellence (PACE) which evolved into current integrated product development [IPD]. Before the previous integrated innovation model and current IPD, there were walls among the various departments in the same firm and only R&D department focus on the product development. Then R&D department sent their results to manufacturing or marketing to test the new products, followed by slow feedback linearly. But integrated innovation models and IPD clear such internal barriers and integrate all departments into the innovation and product development to accelerate the knowledge collaboration and 'open' inside the firm, while "Open Innovation" (Chesbrough, 2003) focuses on 'open' outside or the "knowledge flows across organizational boundaries". According to the consulting firm Pittiglio Rabin Todd & McGrath focusing on IPD, IPD can cut the time for new products to market by about 50%, reduce waste in product development by about 65%, and enhance the efficiency of product development by about 27%.

For instance, before Huawei applied IPD, Huawei had mismanagement and disorders in its product development projects. Ping Guo who used to be a project manager and now the rotating President recalled: "When I entered Huawei to work in R&D, Huawei had neither concept about product engineering nor scientific procedure and systems. The success of a project depended on the project managers and luck…The probability of product success seems random. Huawei's R&D depends on personal heroes" (Guo, 2014). IBM has gained plenty of experience to apply IPD in its management system successfully. Upon the request of Huawei, IBM taught Huawei

IPD as a big consulting project between 1999 and 2007. Huawei first implemented and then improved IPD in the Chinese context. IPD plays an important role for Huawei to develop its business and become the leading firm in global telecommunication industry. Attracting by the success of Huawei, more and more Chinese firms such as Xiaomi are learning IPD now (Lin, 2019).

Second, many employees in most internal departments of the leading innovative firms such as Huawei, Xiaomi and Haier interact with customers frequently, which is called “Online Interactive Innovation” [OII], reflecting open innovation (Chesbrough, 2003). For example, all the co-founders, managers, engineers and employees in Xiaomi are required to interact with customers regularly and to post their suggestions via OII as do ordinary customers (Fan, 2020; Li, 2014). Also, the basic technical problems are gathered and sent to the department of basic research, e.g., technology about chips to the Central Research Institute.

Additionally, firms apply big data and data mining techniques to explore the information provided by the interactive users and find what lies behind such information. This also can be a source of innovation and ideas for patent applications which is verified by the interviews in Lenovo’s Central Research Institute in Beijing in 2018. Its managers in R&D, design and patenting showed how they collect and analyze customers’ data and the comments from various social media and the platforms of e-commerce (Figure 2.12). The manager of patenting in Lenovo confirmed clearly: “All patents are influenced by information or knowledge from customers.” This is the triangulation from both qualitative interviews at Lenovo and quantitative research about Xiaomi in Chapter 3. These provide the strong evidences that customers are one of the main sources of R&D, innovation and patenting, and most departments of firms take part in and contribute to innovations as illustrated in the model in Figure 2.11. But it is not sufficient for firms such as Lenovo to only apply big data and data mining techniques to explore the information from consumers. Hence, Lenovo also followed

Xiaomi to adopt OII in its PC business in China since August, 2017 and OII helped Lenovo PC business to resurge in its market share (Yun, 2021).

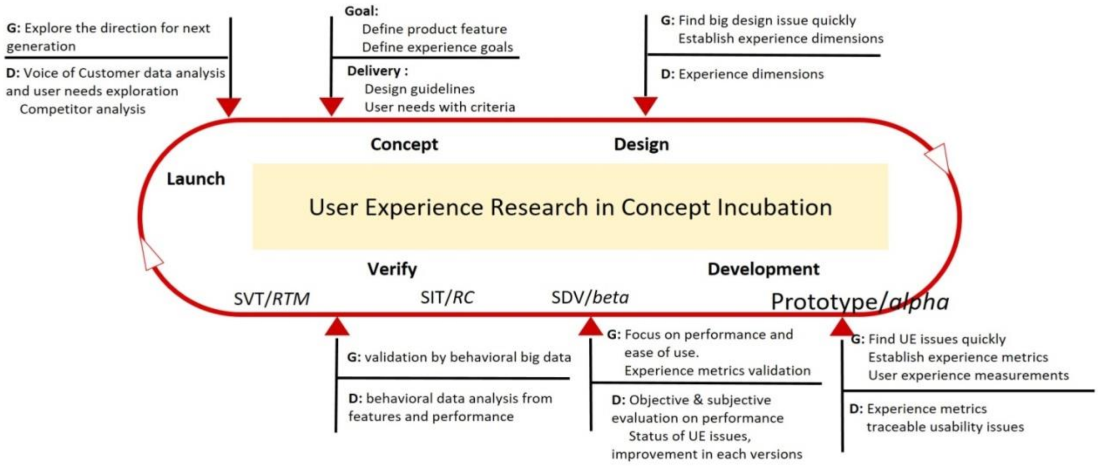

Figure 2.12 Lenovo's User Experience Research in Concept Incubation
(Source: Lenovo Institute of Research, 2018)

Third, as illustrated in the lower part of Figure 2.11, there are a series of advantages of 'Online Interactive & Integrated Innovation Model' [OIIIM]. As the essential part of OIIIM, online interactive innovation [OII] has 13 advantages which are analysed and discussed in details in Chapter 3. In summary, OII help firms to enact fast iteration techniques, realise mass-customisation, enhance users' experience and trust, reduce costs for advertisement (Chhabra and Metkar, 2020), marketing and human resources (e.g., participative fans are all volunteers in Xiaomi without monetary payment), avoid wasting in R&D, improve efficiency and productivity, etc. Furthermore, the firms with OII can keep low prices but high quality for hardware, e.g., Xiaomi cut smartphones' price and Tesla reduces price of electrical vehicles to catch the market quicker than their competitors, so that Xiaomi and Tesla can keep on growing at a speed faster than their competitors. Xiaomi and Tesla enjoy low profit from hardware but high profit from interacting and updating services. For instance, the gross profit margin is about 5% for Xiaomi's smartphones while 72.4% for Xiaomi's internet service in the first quarter of 2021, which is based on its smartphones used by about 368 million consumers (Xiaomi, 2021c).

As discussed in Section 3.4.2.6, OII changes innovation diffusion significantly and causes the product growth curve to rise much earlier and quicker. Consequently, using only OII but without IPD, Xiaomi used to have serious problems of unintentionally demand-induced product shortage because of underestimating the rising demand resulted from OII and supply-induced product shortage because of the mismanagement of the supply chain during the product launch (Shi, et al, 2020). The product shortage was misinterpreted by many that Xiaomi adopted a hunger marketing strategy purposively (Chen, et al., 2014; Zhang, et al., 2017; Feng, et al., 2020). But Huawei has both OII and IPD, hence Huawei has no problems of shortage in its supply chain before the U.S. sanctioned it in 2019. After Xiaomi noted this significant difference and learned IPD, Xiaomi improved its management system and solved its problems of shortages, which are discussed in detail in Section 3.4.2.7. The success of Huawei and later Xiaomi prove the necessity, usefulness and importance to combine both OII and IPD together, which are complementary. OII breaks the wall at the boarder of the firm and connects millions of consumers with the firm, while IPD clears the barriers inside the firm and integrates all the internal departments into innovation. So that after selection and evaluation, valuable and useful suggestions, complains or knowledge can flow easily from customers to all the relevant internal departments of the firm to contribute to innovation, vice versa.

This new innovation model ‘Online Interactive & Integrated Innovation Model’ [OIIIM], particularly online interactive innovation [OII] works well not only in China, but also other countries such as India (Chhabra and Metkar, 2020) and European countries, evidenced by Xiaomi reached No. 3 in the global smartphone market and No. 1 in some European countries (Xiaomi, 2021c). OII also works well in more industries including home appliances such as Haier, electrical vehicles such as Tesla, software such as Microsoft. Simultaneously, IPD has been developed and applied widely in many firms, e.g., IBM and 3Com with success in the U.S. and other countries for decades.

This new innovation model OIIIM combines both OII and IPD, and contributes to the success of particularly Xiaomi and Huawei in China and Tesla in the U.S. Particularly, both OII and IPD can improve the efficiency and reduce the costs, so that Xiaomi and Tesla can lower the prices of their hardware products drastically to catch market quickly, supported by the sufficient supply chain which are managed well. Hence, this new innovation model OIIIM has attracted many attentions by leading innovative firms. NVIDIA is the inventor of GPU and now the leader of global AI chips. Mr. Huang, its founder and CEO, said in an interview: “The business model of automobile manufacturers will fundamentally change. By 2025, many auto companies are likely to sell their cars at a price close to the cost, and provide value to users mainly through software” (Huang, 2021). This is exactly what Xiaomi is doing in smartphones and Tesla in electrical vehicles with the help of this new innovation model OIIIM.

This thesis analyses the new innovation model in Figure 2.11 from 3 aspects: Chapter 3 investigates OII in details, Chapter 4 examines individual innovation in firms since individual employee is the basic unit for firms’ innovation and Chapter 5 focuses on how ESOP influence firms’ innovation since ESOP is a popular incentive to employees in China currently.

Chapter 3. Online Interactive Innovation: How to Benefit from Customer Knowledge

ABSTRACT

New innovation practices for knowledge to transfer from customers' suggestions to new products have been successful in innovative firms such as Xiaomi, Huawei and Tesla, but the mechanism of these new practices has not yet been analysed. Previous studies have addressed related concepts about lead users (von Hippel, 1986) and user innovators (von Hippel & Euchner, 2013), open innovation (Chesbrough, 2003), interactive innovation (Lundvall, 2009), word of mouth (Arndt, 1967a and 1967b) and innovation diffusion (Rogers, 1995). What has been missing is an understanding of the process by which customers' suggestions and replies affect firms' abilities to bring about changes in products, file patent applications and increase product shipments. The new conception of 'online interactive innovation' [OII] examines how the new practice works in Xiaomi and Huawei, plus other 8 Chinese firms in the smartphone industry and Haier in home appliances. The model is tested in detail on Xiaomi, a company founded in 2010 in Beijing. Xiaomi became a highly influential firm that has been in the top 4 of the global smartphone market since 2014 and entered the *Fortune 500* in 2019 at an unprecedented speed. This study uses methods of growth curve modeling and multiple regressions to analyse the panel data of Xiaomi between 2012 and 2018. This study finds that the weekly number of suggestions is positively associated with the weekly number of the replies from the firm's employees and customers. Also, there are positive relationships among the weekly replies, weekly functions changes in the operating system, annual patent applications and annual shipments of smartphones. Also, this study finds that PFs and IUs in OII are totally different from lead users (von Hippel, 1986) or user innovators (von Hippel & Euchner, 2013). By using logistic modeling to compare the annual cumulative shipments of the firms with or without OII, it finds that OII changes innovation diffusion significantly as seen by shifting the product growth S-curve to the left, causing the product growth curve to rise much earlier and quicker than otherwise. OII also helps these firms to realise mass-customisation, enact fast iteration techniques, enhance users' experience and trust, reduce costs and improve productivity. OII can be generalised widely and OII works well for Xiaomi not only in China, but also in other countries, e.g., India (Chhabra and Metkar, 2020). Haier in home appliance and Tesla in electric vehicles also adopt OII and OII works very well. Finally, the misguided attribution of the shortage of Xiaomi's smartphones as a scarcity marketing or a hunger marketing strategy is explained, with integrated product development [IPD] as the practical solution which works well in Huawei since 1999 and Xiaomi after 2019.

Keywords: Online interactive innovation; interactive users; patent applications; innovation diffusion

3.1 Introduction

Consumer goods producers have routinely collected information about the needs of customers by questionnaires or from customer service hotlines. Early work by von Hippel (1986) found that lead users play an important role in inventing some new products by addressing their own needs as user innovators (von Hippel & Euchner, 2013). Since then many companies have experimented with customer feedback systems combining the advantages of them while avoiding their shortcomings. In rapidly growing Chinese electronics and appliances firms, new methods are being pioneered. This study refers to these new approaches as strategies that foster "online interactive innovation" (hereafter OII). The OII process can be described in a few steps, starting with firms attracting and cultivating customers to act as interactive users [IUs]. Then the firm organizes some enthusiastic IUs to become participative fans [PFs] to help to attract and interact with millions of IUs in the online communities. This generates many millions of suggestions, comments and complaints. With the help of volunteer PFs, the firm's employees reply, evaluate, screen and adopt valuable suggestions to improve products (adding new functions or optimizing existing functions, etc.). This becomes one of the main sources of R&D, as can be seen in the finding that these suggestions are positively relevant to patent applications. Some qualified PFs are privileged with the opportunity to test new versions of the operating system (OS) or new products internally. All of these aforementioned help to improve shipments and sales. OII can be complemented by interaction in offline shops and traditional customer services which make a relatively small contribution. The dynamic cycle of knowledge sharing and synthesis among the firm's employees, PFs and IUs, from online interaction to R&D and products with positive feedback is the core by which OII increases productivity and lowers costs. Since this form of online interactive innovation is relatively new, the existing theories can only indirectly illuminate part of the phenomenon. This analysis incorporates concepts of knowledge creation and sharing (Nonaka and Takeuchi, 1995a and 1995b), open innovation (Chesbrough, 2003), interactive innovation (Lundvall, 2009), word of mouth feedback (Arndt, 1967a and 1967b) and innovation diffusion (Rogers, 1995), etc.

Xiaomi has had particular success in developing and using OII. It was founded in 2010 as a smartphone producer and by 2014 led the Chinese smartphone market with revenues of US$ 10 billion and became one of the top 4 firms globally. In 2019 Xiaomi entered the *Fortune 500* list, an unprecedentedly rapid rise. OII sat at the core of Xiaomi's new business model between 2010 and 2018. Traditionally firms, especially those focusing on e-commerce including Amazon, Alibaba, Jindong and Meituan built online platforms mainly for customers to rate the services and chat in the online communities. Xiaomi adopted its OII at the start of business in 2010 and launched two specific panels to attract suggestions from IUs or PFs. One is the 'Panel of Suggestions for New Functions' (PSNF) [https://www.xiaomi.cn/board/558495]. Many millions of suggestions, comments and complaints are posted, discussed then ranked automatically and selected, evaluated in order to be adopted as the sources of new functions in the operating system of Xiaomi's smartphones ("MIUI") which is then updated weekly. All these contribute to patent applications and sales of smartphones, with a positive cyclical feedback to more suggestions and comments from IUs in that period. Some competitors, including Huawei, emulated Xiaomi's methods (see Huawei's 'Club' for suggestions: https://club.huawei.com/forum-455-1.html). To test its relative efficacy, this study discusses competing firms such as OPPO, VIVO, ZTE, Lenovo, Meizu, TCL, Gionee and Coolpad in the Chinese smartphone industry and Haier in home appliances.

By assessing 193,399 initial postings about suggestions (hereafter curve 1) and 734,750 replies (curve 2) from Xiaomi's employees, PFs and general IUs in PSNF, functions changes (curve 3) in the operating system, patent applications (curve 4) and annual shipments of smartphones (curve 5) between 2012 and 2018, this study tests 6 hypotheses concerning the relationships among curves 1 to 5 and the differences between firms with or without OII. Most of them have positive relationships with statistical significance. This study shows the internal structure of OII with the hypotheses whose results are statistically significant in Figure 3.9 in Section 3.5.1. Additionally, this study analyses the dynamics of how OII directly contributes to mass-customization, helps to accelerate the product iteration process, aids innovation and its diffusion, affects entry into foreign markets, enhances productivity, reduces costs and helps to maintain a high performance/price ratio, contributes to the development of new retailing processes and fosters internet of things (IoT) developments. OII is the first step for firms to be digitalized. Only after the users are connected online, other parts of firms including products, services, marketing, transactions and teams can become digitalized and online. This study assesses what are regarded as the significant advantages over preceding methods. Also, this study finds that PFs and IUs in OII are totally different from lead users (von Hippel, 1986) or user innovators (von Hippel & Euchner, 2013).

As more products become digitalized and their operating systems can be updated regularly to provide more functions and better services to customers, OII becomes more practicable for more products. This has fostered the deployment of OII to more industries including home appliances such as Haier, electrical vehicles such as Tesla, software such as Microsoft since 2015 (Ogawa and Nakai, 2015). OII works well not only in China, but also in other countries, e.g., India and Spain. Chhabra and Metkar (2020) in the Indian Institute of Management Studies and Research analysed why Xiaomi succeeded in India without advertisements. Although they did not use the term 'online interactive innovation' or 'OII', the method used by Xiaomi in India is the same as China. Hence, OII can be generalised which is important for management practice. According to the President of Haier, Mr. Ruimin Zhang (NWFE, 2015), in the production of intelligent goods, there are three key parts: the physical, intelligent and connecting parts which connect and interact with the IUs. OII provides a major means for firms to interact with IUs now and it is being developed as an element integral to Industry 4.0. This study also addresses some popular misunderstandings about the shortage of Xiaomi's smartphones such as the concept of 'scarcity marketing strategy' or 'hunger marketing strategy' and the practical solution to the shortage is provided.

This chapter is divided into 5 sections. Section 3.2 reviews the key literature on lead users, interactive innovation, knowledge sharing, online communities, word-of-mouth, logistic models and innovation diffusion, and develops hypotheses. Section 3.3 presents the research methods and case selection. Section 3.4 explains the data analysis and presents findings. Section 3.5 discusses more about OII. Section 3.6 concludes with suggestions for management practice and notes the limitations of this study.

3.2 Literature review and hypotheses development

3.2.1 Literature review

Traditionally, innovation was described linearly from basic research, through development and design of products, to manufacturing and selling, similar to the first generation of innovation addressed in Section 2.1.1. However, since the 1970s, researchers found the development, application and diffusion of innovation could not be explained sufficiently by linear models of innovations (Tuomi, 2002). It became more and more clear that innovation “cannot be analyzed in isolation.” On the contrary, “innovation capability depends in fact also on the amount of information that each firm is able to receive from the environment in which it operates” (Antonelli, 1996: 284). The external knowledge sources become as important as the internal R&D. Among the external sources of information, users or customers are the most important source which provides the signals of what the market needs. Rothwell (1994) paid attention to this and analysed the relationship between users and producers in all the five generations of innovations.

There are some previous theories about the role of users or customers in innovation. Lead users (von Hippel, 1986) have a significant influence on the development and adoption of new products and services. In an interview by the editor-in-chief of *Research Technology Management* (von Hippel & Euchner, 2013: 15), von Hippel clearly explained his concepts: “Users innovate in pioneering areas where the market is not clear. This is true in every field we have studied…User innovation is users innovating for themselves to make products and services they want without manufacturer assistance. It's an entirely independent activity; manufacturers can get involved, but users don't need them…User innovators are individuals or companies who develop something novel in order to use it.” In the 1980s, the cases of lead users concentrated in manufactured products for business. In recent years here are some examples of lead users strategically adopted by Motorola and then Lenovo. These producers provided parts for the smartphone Moto Z for lead users to develop special functions to meet their needs. This approach did not work well, as evidenced by the market share of Lenovo & Motorola falling to less than 1% in China in 2020. The lead users' strategy has significant limits. Most customers do not like to become such user innovators who develop new functions or products by themselves. Rather they prefer to suggest firms to develop new functions or products through blogs and other online procedures. The new concept of an "interactive user", coined in this study, has advantages in theory and practice, as discussed in Section 3.5.2 on the 'Advantages of OII', which can be applied more broadly than the concept of lead users (von Hippel, 1986) or user innovators (von Hippel & Euchner, 2013).

Chesbrough (2003) advocated "open innovation" and redefined it "as a distributed innovation process based on purposively managed knowledge flows across organizational boundaries, using pecuniary and non-pecuniary mechanisms in line with the organization's business model" (Chesbrough and Bogers, 2014:1). The open innovation concept is limited since it only focuses on knowledge sharing across the border of organizations. There are new features of Chinese innovation practices that go beyond those explained by open innovation theory.

Randall, Terwiesch and Ulrich (2007) found two methods for users to take part in product design and realise mass-customisation. The traditional "parameter-based" method is that designers list some parameters or functions and then users select them for the products they want. This method is used by Dell. Users select the various functions and parts of PCs they want and submit orders which are produced by Dell. The other method was "needs-based", which means that "the user expresses needs directly and leaves to the manufacturer the translation of needs into parameter choices" (p. 268). The authors found that if the users have sufficient knowledge about the products to be designed, the "parameter-based" method works well. If the users are neophytes, it will be better for them to use the "needs-based" method.

The third way to consider the customers' angle is to think and act as customers. For instance, Subaru, the Japanese car-maker, launched the Subaru Driving Academy (SDA) and built a testing infrastructure in which engineers are selected and trained to simulate what will happen in real driving conditions in all environments and possible situations. By doing this, the engineers will feel like the customers and become more sensitive to driving in order to design cars for the convenience, safety and environment of customers. As the results, Subaru has improved its models such as BRZ and Levorg, and they introduced the Subaru Global Platform (Da, 2016). However, there are endless scenarios about driving which cannot be simulated in an expensive test infrastructure. Tesla's approach is to welcome suggestions from many customers to update its electrical vehicles 'over the air' at low cost. For smartphones or other consumer goods, there are millions of applications which cannot be simulated or developed by firms. But many millions of users can make significant contributions through interactive innovation analysed in this study.

Beyond the three methods discussed above, there is the fourth method called 'online interactive innovation' where both users and producers take part in innovation together, which is becoming increasingly popular in business and needs more investigation. "Innovation is now seen as an interactive process requiring intense traffic in facts, ideas and reputational information within and beyond the firm…. Interactive innovation processes lie at the heart of success in the new economic circumstances" (Manley, 2003: 2). Interactive innovation evolves from the traditional innovation line, especially innovation systems, innovation networks, innovation value-chains and innovation clusters. These four key approaches were identified by Manley (2003), who developed a model incorporating their key features. But she did not go into detail about how interactive innovations work in firms. Interactive innovation between firms and customers can be one of the main sources to design and improve products. Interactive innovation plays an important role to influence the internal organization of firms and restructure the innovation system, innovation network, value-chain, cluster and/or ecosystem. This reciprocity is proved by the success of smartphone firms in China, with new business models and innovation strategies in past years.

Knowledge sharing is also important in interactive innovation. "[M]ultiple knowledge domains produce novel combinations that increase the variance of product performance and that extensive experience produces outputs with high average performance" (Taylor and Greve, 2006: 723). Similarly, "Research suggests new knowledge is created from the novel combination of existing knowledge (Fleming, 2001; Nelson & Winter, 1982)" (Phelps, Heidl, & Wadhwa, 2012: 1156-7). Creativity to create new knowledge is "embedded in relational networks of social and economic actors" (Kratke, 2011: 3) and the creative capital not only includes human capital, but also "organized interaction amongst creative workers in the innovation process" (p. 13). Knowledge sharing and intensive interaction among engineers and designers of firms and customers is important since all the knowledge from customers and R&D in firms will be combined, synergised, synthetised and applied by engineers and workers to design and manufacture the products. Nonaka and Takeuchi (1995a and 1995b) described four phases of knowledge development in firms, starting with socialisation (communication and sharing of tacit knowledge), externalisation of tacit knowledge to explicit knowledge, combination of explicit knowledge, and internalisation of explicit knowledge into tacit knowledge. They described the model qualitatively, but this study examines every step of knowledge sharing and creation quantitatively by growth curve models and multiple regression models.

There are many publications about online communities (OC) for e-commerce activities, e.g., ratings (Lu, Ba, Huang and Feng, 2013) and knowledge collaboration also occurs in OC (Faraj, Jarvenpaa and Majchrzak, 2011: 1224), e.g., "collaboration can occur among people not known to each other, who share different interests and without dialogue." Barrett, Oborn and Orlikowski (2016) analyzed an OC between

2009 and 2013 and examined the four stages to create value: rating, connecting, tracking and profiling. The data in such OC was applied to help pharmaceutical companies to attract patients for clinical trials and improve the efficiency of R&D only in the fourth stage in 2012. By comparison, OII in OC has been used for iteration and R&D purposively by Chinese firms such as Xiaomi since 2010. While much research has been done to analyze the ratings of customers, there are few studies about knowledge sharing and creation in online communities that link designers and customers. This study fills this significant gap by examining and discussing some typical firms.

Word-of-mouth (WOM) is “person to person communication between a receiver and a communicator whom the receiver perceives as non-commercial, regarding a brand, a product or a service” (Arndt, 1967a: 3). Positive WOM helped sales and vice versa (Arndt, 1967b). ICT, especially the internet, accelerates the diffusion of WOM significantly. Hence, the internet has accelerated the diffusion of digital products as well as non-digital products (Rangaswamy and Gupta, 1999). Both market promotion and e-WOM contribute to sales (Lu, Ba, Huang and Feng, 2013). Hennig et al. (2004) compared the traditional WOM and e-WOM online and found the new features of e-WOM in the digital platforms. Online e-WOM has greater power than traditionally offline WOM to determine the success or failure of new products or services (Craig, et al., 2015). For instance, Microsoft’s operating system Vista failed in China due to the initial bad reputation in e-WOM. Cho and Lau (2016) applied content analysis to examined the e-WOM in 126 weeks and found that “the weekly volume of posts, their relative number of positive (or negative) comments, especially regarding value for money and sound quality, and those posts from the earlier week impinged strongly on weekly sales of Shure products” (p. 927). However, there are significant gaps in existing publications about e-WOM. Almost all the existing studies just analyze the number of suggestions or focus on online ratings (Cho and Lau, 2016). But WOM in existing publications are ambiguous and few discriminate among the suggestions and replied postings from firms' employees, the fans organized by the firms and general customers. None of the existing literature has examined the relationship among the suggestions of customers, the replies, the changes in products' functions, patent applications and shipments, etc., which will be filled by this study.

According to Richardson (1991), the logistic model is one of the typical types of S-curve and innovation diffusion follows a logistic model (Rogers, 1995). This study addresses the ways the internet and especially OII can change the logistic model and the slope of an S-curve.

To summarize, there is much literature about lead users or user innovators, open innovation, interactive innovation, knowledge sharing, online communities, WOM, innovation diffusion and logistic models, but all of which are scattered in different bodies of literature. As a new innovation model, OII combines the advantages of interactive innovation, knowledge sharing, iteration, mass-customisation, e-WOM in online communities and innovation diffusion, etc. Few studies explain knowledge exchanges and syntheses between customers and firms, including suggestions provided by customers to firms, which may result in new functions of products and patent applications and finally contribute to annual shipments. The relationships among these factors construct the analytical framework of this study.

3.2.2 Hypotheses development

With the rapid development of smartphones and tablets, their number reached about 480 million units and surpassed laptops and PCs with about 380 million units for the first time in 2011 (Chen, et al., 2012). Smartphones help people to spend more time on social media and reduce the transaction costs for interactive innovation, which "presents a unique opportunity for businesses to treat the market as a conversation between businesses and customers instead of the traditional business-to-customer, one-way marketing” (Chen, et al., 2012: 1167). In online communities, there are many postings initiated by IUs, PFs or Xiaomi’s employees, which were commented on by other IUs, PFs or Xiaomi’s employees. It is not clear that if there are more postings of suggestions about one topic in every week, there will be more replies or comments about that topic from Xiaomi’s employees, PFs or IUs. This may or may not encourage more postings of suggestions. This is the “conversation” aforementioned and what needs to be examined in details. Here is the first hypothesis, which will be analyzed by growth curve models including different topics of suggestions. The time unit of this group of hypotheses is one week so that there are 337 weeks. In order to be parsimonious, the complicated relationships among the suggestions and replies from the firm’s employees, PFs and general IUs respectively are not examined here to avoid too many hypotheses.

Hypothesis H3.1: There is a positive relationship between the total weekly number of postings of suggestions from the firm’s employees, PFs, general IUs and the total weekly number of replies from the firm’s employees, PFs, general IUs in different categories of topics.

Second, Xiaomi requires all its managers and employees including President, co-founders, managers and engineers to interact with customers via OII periodically. On one hand, PFs and IUs post their suggestions in the online communities. Xiaomi’s employees may be inspired by such suggestions. Therefore, it is necessary to test the relationship between the number of postings of suggestions from IUs or PFs and the number of postings of suggestions from the firm’s employees.

Hypothesis H3.2A: There is a positive relationship with statistical significance between the weekly number of postings of suggestions from IUs and the weekly number of postings of suggestions from the firm’s employees.

Hypothesis H3.2B: There is a positive relationship with statistical significance between the weekly number of postings of suggestions from PFs and the weekly number of postings of suggestions from the firm’s employees.

On the other hand, Xiaomi's employees may synthesize suggestions from PFs and IUs with their own knowledge to create new suggestions which may be more practicable, similar to knowledge generation (Nonaka and Takeuchi, 1995a & 1995b). Furthermore, there is no internal channel for Xiaomi's employees to provide suggestions to the firm, but they have to post their suggestions via OII to be evaluated and selected as the suggestions from ordinary customers. They may use such suggestions to apply more patents. Hence, the more suggestions posted by Xiaomi's employees, probably the more new patent applications. Here is the relevant hypothesis:

Hypothesis H3.2C: There is a positive relationship with statistical significance between the annual number of postings of suggestions from the firm's employees and the annual number of new patent applications.

Hypothesis H3.2D: There is a positive relationship between the annual total number of postings of suggestions from the firm's employees, PFs and general IUs and the annual number of new patent applications.

There are about 100,000 enthusiastic PFs which is only 0.027% of about 368 million active users of Xiaomi's operating system MIUI (Xiaomi, 2021c). Some may misinterpret the role of PFs to be similar to lead users (von Hippel, 1986) and user innovators (von Hippel & Euchner, 2013). But there are some key differences between PFs and lead users or user innovators, as reviewed in Section 3.2.1. Although PFs provide their suggestions to Xiaomi, they do not develop the functions by themselves as do lead users or user innovators. Most of the 100,000 enthusiastic PFs do not have sufficient technical skills and Xiaomi cannot risk outsourcing software development to the PFs. Sometimes, if Xiaomi's programmers could not finish the works in time, Xiaomi borrowed more than 100 professional programmers from Kingsoft, since they share the same President. The programmers of Kingsoft flied from its headquarter in Guangdong Province to Xiaomi's headquarter in Beijing in a franchised airplane (Fan, 2020). Developers of opensource software may be user innovators (von Hippel &

Euchner, 2013) but the PFs and IUs in Xiaomi's online communities are not. The PFs mainly help Xiaomi to collect and evaluate the suggestions and comments of IUs in the online community and then test the new versions of operating systems internally as would ordinary customers without technical skills. Von Hippel & Euchner, (2013: 20) suggested that "what companies ought to do is to hire some embedded lead users. Hire users who know the communities the company is interested in and who can teach you how to work with them". But Xiaomi does not hire any PFs, they are entirely volunteers without payment from Xiaomi. As one consequence, the direct contributions of PFs to the firm's annual number of new patent applications should not be statistically significant, which is similar to IUs. Therefore, here are more hypotheses which help to make the roles of PFs and IUs clear. Since it takes time for the patent applications to be written and filed, the time unit of this group of hypotheses is one year.

Hypothesis H3.2E: There is no relationship with statistical significance between the annual number of postings of suggestions from PFs and the annual number of new patent applications.

Hypothesis H3.2F: There is no relationship with statistical significance between the annual number of postings of suggestions from IUs and the annual number of new patent applications.

Third, interactive innovation (Manley, 2003) and knowledge sharing (Taylor and Greve, 2006) reviewed in Section 3.2.1 help the firm to collect and adopt the valuable suggestions from customers and provide more new functions, or amend existing functions in the operating systems to realize fast iteration in order to meet the various needs of customers with mass-customization. Probably there are more replies from all three groups of authors to the postings, there will be more new functions about that topic. Hence, here is the third hypothesis, which will be analysed by the growth curve model including different topics. The time unit of this group of hypotheses is one week so there are 337 weeks.

Hypothesis H3.3: There is a positive relationship between the total number of replies from the firm's employees, PFs and general IUs and the total number of functions changes (including addition, optimization and amendment) in MIUI.

Fourth, there have been fierce patent wars in the smartphone industry among Apple, Google, Motorola, Samsung, Xiaomi, Nokia, etc. (Paik & Zhu, 2013). Xiaomi also used to be accused of patent infringement by Ericsson in India (Yu & Tu, 2014). In response, Xiaomi hired Xiang Wang, the former Vice President of Qualcomm, to be Xiaomi's Vice President (Guluwang, 2015), because Qualcomm is very good at patent strategy and is one of Xiaomi's key supplier of chips. Patent applications which are novel, useful and unobvious (creative) may be granted by the patent office. It is possible if there are more changes of functions of MIUI, Xiaomi will file more new patent applications to build its patent strategy. Hence, here is the fourth hypothesis. The time unit of this hypothesis is one year.

Hypothesis H3.4: There is a positive relationship between the annual total number of functions changes in MIUI including addition, optimization and amendment and the annual number of new patent applications.

Fifth, Steve Jobs of Apple had vowed to launch a nuclear patent war against Google to completely destroy the Android system (Elmer-DeWitt, 2012), an example of the sort of patent litigation that is an effective leading indicator of market growth (Tang & Huang, 2002; Li, 2017). In high-tech. industries, patents are widely used to protect not only core technologies, but also market positions (Paik & Zhu, 2013). Hence, it is possible that if there are more new patent applications, there will be more shipments of the firm's smartphone. Here is the fifth hypothesis:

Hypothesis H3.5: There is a positive relationship between the annual number of new patent applications and the annual shipments of the firm's smartphone.

Sixth, the annual cumulative data of smartphones' shipments follow a logistic model and the S-curve (Richardson, 1991 and Rogers, 1995). Firms can use OII to interact with customers, realise mass-customisation, enact fast iteration, enhance users' experience and trust, and attract more customers. It is reasonable to test if the annual cumulative shipments of firms with OII is faster than that of firms without OII. Therefore, here is the sixth hypothesis:

Hypothesis H3.6: The annual cumulative shipments of smartphones for the firms with OII is higher than that of the firms without OII.

3.3 Methods and cases selection

3.3.1 Methods

3.3.1.1 Panel data or longitudinal data

This study about OII analyses panel data of Xiaomi between 2012 and 2018. There are some advantages of panel data or called longitudinal data: Panel data has both the dimensions of time and cross section, which can provide more information than only time series data or cross section data (Hedeker and Gibbons, 2006). For example, cross section data cannot analyse the growth trend of suggestions, replies and weekly number of function changes in 337 weeks, and annual patent applications and shipments over 7 years in this study. "A major advantage of longitudinal data is that it allows comparisons to be made within subjects [topics in this study about OII], hence controlling for (possibly unknown) subject characteristics that are constant over time" (Rabe-Hesketh and Skrondal, 2012: 5). "[I]n a longitudinal study, each subject can serve as his/her own control" (Hedeker, and Gibbons, 2006: 1). Panel data analysis can help to "separate aging effects, from cohort effects. Such cohort effects are often mistaken for changes occurring within. Without longitudinal data, one cannot differentiate these two competing alternatives" (Hedeker, and Gibbons, 2006: 1-2). The panel data has bigger data volume with both dimensions of time and cross section, which can enhance the reliability and validity of research (Liu and Zhang, 2005). Similarly, the panel data helps to solve the problem of missing data. Missing data is popular in research, for example, the participants may disappear from the research called attrition or just typos in processing the large amount of data. Missing data is also resulted by the observable individual differences or heterogeneity. Panel data analysis is very helpful to solve such problems (Chen, 2014; Wang, Xie and Jiang, 2008). On the other hand, panel data has a few disadvantages. For instance, panel data need more time and cost to collect and process data (Chen, 2014), which is true in this study.

3.3.1.2 Growth curve models (GCMs)

Growth curve models (GCMs) are also called "latent-trajectory models or latent growth-curve models", which is "the most prominent … approach to longitudinal data [panel data]" (Rabe-Hesketh and Skrondal, 2012: 343). GCM has some advantages and it is suitable for this study: It "explicitly models the shape of trajectories of individual subjects over time [e.g., the weekly numbers of suggestions, replies and changes in functions in MIUI, and the annual numbers of patent application and shipments of Xiaomi between 2012 and 2018 in this chapter] and how these trajectories vary, both systematically, due to occasion-level and subject-level covariates, and randomly" (Rabe-Hesketh and Skrondal, 2012: 343). GCM is convenient to include new variables in the model and deal with missing data or data with different time spans. In this study, GCM can reduce and divide the total residual into 2 parts: residuals at the levels of week or year and functions or topics respectively. Hence, all the residuals can be independent and nearly normally distributed to meet the assumptions for the ordinary least square (OLS) regression to be the best linear unbiased estimator (BLUE). Otherwise, the model may be biased and misleading. This study also choses these methods after reviewing various criteria to select suitable models, especially AIC and BIC (Kutner, Nachtsheim and Neter, 2004; Agresti and Finlay, 2009).

Also, intra-class correlation coefficients (ICCs) or ρ are calculated for the GCMs to test any possible group effects. Intra-class correlation coefficients (ICCs) or ρ measures "the expected degree of similarity (or homogeneity) between responses within a given cluster" (Leckie, 2013: 20), e.g., functions or topics of suggestions in this study. If $\rho<0.059$, the correlation is relatively low and the variation across groups (functions or topics of suggestions in this study) can be ignored. But if $0.138>\rho\geqslant 0.059$, the correlation is relatively middle. If $\rho\geqslant 0.138$, the correlation is high. If $\rho\geqslant 0.059$, the variation across groups (functions or topics of suggestions in this study in Chapter 3) cannot be ignored (Cohen, 1988).

$0.059>\rho$ is low correlation

$0.138>\rho\geqslant 0.059$ is middle correlation

$\rho\geqslant 0.138$ is high correlation

3.3.1.3 Advantages to convert data into natural logarithm

There are some advantages to convert data into natural logarithm (Kutner, Nachtsheim and Neter, 2004), including:

- Reduce the absolute value of the number, e.g., Xiaomi's annual smartphone shipment increased from 7.19 million in 2012 to 119 million in 2018. It is more convenient if convert such data into natural logarithm.
- Some data cannot be fit by linear model, but can be fit by exponential model, e.g., the cumulative data of firms' annual shipment of smartphones follow S-curves. After converting such data into natural logarithm, the linear model can be used conveniently.
- The conversion of natural logarithm will not change the data's features and relationship, but will improve the reliability, stability and convenience to deal with residual, while reduce the collinearity and heteroscedasticity (Kutner, Nachtsheim

and Neter, 2004).

3.3.1.4 Criteria to select suitable models

First of all, the relevant theories, the findings and practices in existing publications are more important than the statistical indicators to choose the suitable models in this study. Additionally, here are some statistical criteria (Kutner, Nachtsheim and Neter, 2004; Agresti and Finlay, 2009) to help to choose the suitable models: 1) Even use software, e.g., stepwise in Stata, to select models, the human judgement is also necessary to keep the important IVs and CVs based on the relevant theories and practices. 2) Check if the residual is normally distributed and independent (Gujarati and Porter, 2009 and Rabe-Hesketh and Skrondal, 2012). 3) Cp is suitable for interpretation. PRESSp is suitable for prediction. AIC and BIC are suitable for model selection and they are applied in the study. The models with smaller values of AIC and BIC are better. 5) If the sign of a coefficient changes, there must be something wrong with model, which does not happen in the study. 6) Select the model supported by most criteria than fewer criteria because of triangulation. For instance, all of AIC, BIC and the results of likelihood ratio test (lrtest) are considered in the study.

3.3.2 Cases

3.3.2.1 Cases selection

In order to analyze OII comprehensively, most firms in the Chinese smartphone industry are discussed, including Xiaomi, Huawei, OPPO, VIVO, TCL, ZTE, Lenovo, Gionee, Meizu and Coolpad. Apple and Samsung are top firms in smartphones, but their annual growth rates were much lower than Xiaomi and Huawei between 2010 and 2018, and Samsung occupied only 1% of the smartphone market in China in 2019. Interviews were conducted in Xiaomi, Huawei and Lenovo including especially managers in relevant departments.

Xiaomi is the latest player to enter the fiercely competitive Chinese smartphone market. Xiaomi was founded in 2010 with the dream to “produce the best smartphone in the world, only sell for half the price, so that everyone can afford it” (Lei, 2020). Xiaomi built their market position with an unprecedented speed. Xiaomi designs its products by interacting with customers and outsources its manufacturing to Foxconn. The annual shipments of Xiaomi surged from 18.7 million in 2013 to 61.12 million in 2014, an increase of 227% in one year. Xiaomi caught the window of opportunity triggered by the dissemination of 4G services in China, while a long list of bigger incumbent firms, including Lenovo, Samsung, Meizu and Gionee suffered flat or declining market share in China, as illustrated in Figure 3.1. By 2015 Xiaomi led in market share in China with 15.4%, followed by Huawei with 14.2% and Apple with 11.3% (Strategy Analytics, 2016). The revenue of Xiaomi reached US$10 billion in 2014, only 4.5 years after it was founded. From year 0 to year 5, the annual shipments of Xiaomi rose quickly, similar to iPhone, as seen in Figure 3.2. Lenovo had not adopted OII in its smartphone business which mainly is Motorola in the U.S. now. The market share of Lenovo & Motorola fell to about 1% in China between 2017 and 2019. Hence, Lenovo is still classified in the group of smartphone firms without OII in China in this study between 2012 and 2018. Only since August, 2017, Lenovo also followed Xiaomi to adopt OII in its PC business in China and OII helped Lenovo PC to resurge (Yun, 2021).

Initially, the smartphones with the brand name of Xiaomi adopted the best components from foreign suppliers to keep high quality. In 2012, the Chinese government particularly Ministry of Industry and Information Technology asked Xiaomi to help the development of domestic supply chain of smartphones. With some hesitations, Xiaomi designed Redmi, a sub-brand name for smartphones with even lower prices. Redmi adopts most components from domestic smartphones suppliers to help them. The total shipment of the first version of Redmi with domestic components soared to 44.6 million. Since then, Xiaomi, particularly Redmi, boosted the Chinese domestic supply chain to grow and helped the whole Chinese smartphone industry to upgrade (Lei, 2020). According to the Junlin Research Center (2021), Redmi, whose price was as low as 799 Chinese Yuan, is a landmark in popular entry into the era of the mobile internet. Since the iPhone is too expensive for most consumers in the world, the much cheaper Redmi is affordable for most consumers in both developing and developed countries. Cheap smartphones and pervasive 4G mobile services attract consumers to use the mobile internet and provide the large market for new business models such as mobile commerce and social media, etc. Wei Cheng, the founder of Didi which acquired Chinese business of Uber, said: “Entrepreneurs of China’s mobile internet have to thank Xiaomi, since Xiaomi makes smartphones with high quality but low price, which are affordable to most of consumers and accelerate the development of the mobile internet. Currently, most of the digital firms including Didi, Meituan, ByteDance and Kuaishou benefit from the rapid development of the mobile internet” (Lei, 2020).

Huawei collects customers’ feedback via three main channels both online and offline: the ‘club of fans’ which is Huawei’s online community, service centers around the world and a hotline for customer service. Huawei adopts suggestions from customers and updates its operating system (“EMUI”) irregularly. They test the new version of EMUI in a few chosen PFs first. After bugs are no longer found, Huawei sends the new version of EMUI to all customers. In Huawei’s smartphones, there are plans for IUs to take part in improving the user experience. Many IUs adopt and test new functions in the new versions of EMUI or smartphones, a process similar to Xiaomi’s OII.

On the contrary, OPPO, VIVO, TCL, ZTE, Gionee, Meizu and Coolpad continued using traditional methods including advertisements or the standard 4P strategy. For instance, OPPO and VIVO are famous for spending a lot on advertisements, so that their logos are visible in most of the high streets in many small towns in China. Even more, OPPO beat VIVO in 2017 and paid US$ 160 million in their strategy to sponsor the Indian national cricket team, five times more than the previous sponsor (Zhao, 2018). Consequently, the price of OPPO and VIVO's smartphones are higher than Xiaomi's by 1000 Chinese Yuan despite similar hardware and functions since OPPO or VIVO has to include their huge expenditure in advertising in the price of their smartphones. Other firms such as TCL, ZTE, Gionee, Meizu, Coolpad and some minimal smartphone producers learned the "hunger marketing strategy" which they believe is the key for Xiaomi's success (Fan, 2020), as taught in Chinese business school and "proved" by many academic publications (Tolety, 2017; Zhang, et al., 2017). "Many have praised Xiaomi's 'hunger marketing' strategy' and attributed the firm's success to it" (Feng, et al., 2020: 1).

Figure 3.3 shows that by 2014 the total shipments of Chinese smartphone firms exceeded Samsung worldwide and continued increasing. Since 2014 Chinese smartphone firms have been growing rapidly to occupy about 80% of the Chinese market and about 45% of the global market in the 2nd quarter of 2019 (Counterpoint, 2019). Xiaomi played the key role to initiate this dramatic growth of Chinese smartphone firms.

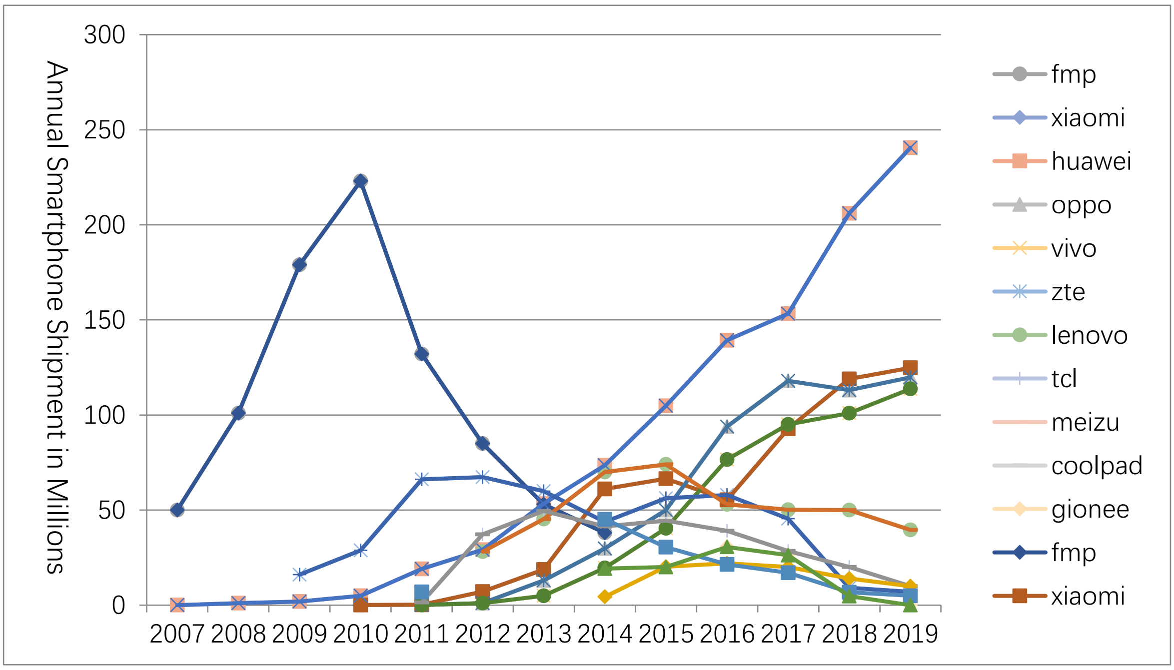

Figure 3.1 Shipments of Smartphones of Chinese Firms (fmp: knockoff cell phones.)
(Data source: Gartner, IDC, IC Insights, Strategy Analytics)

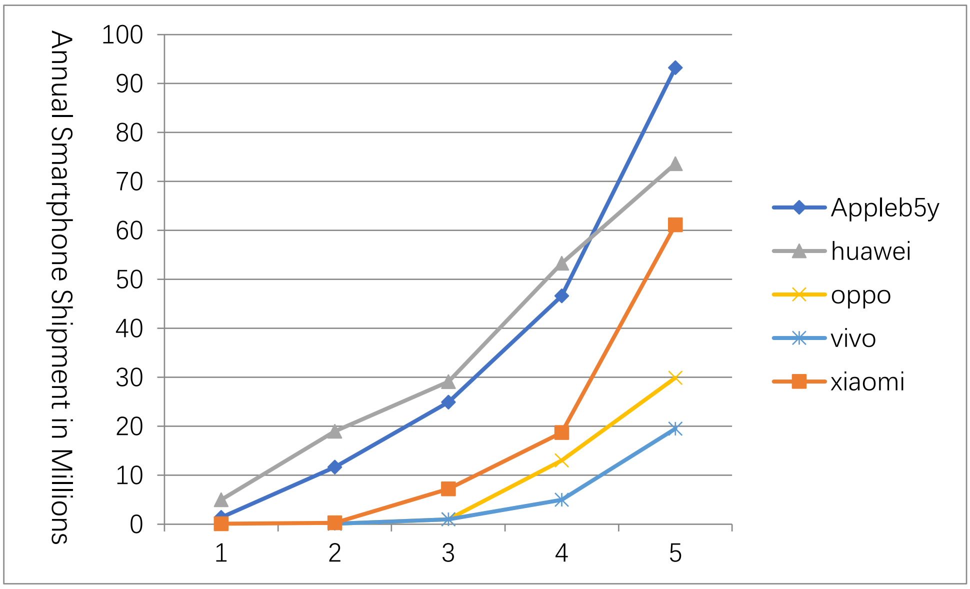

Figure 3.2 Annual Shipments of Smartphones of Apple, Huawei, Xiaomi, OPPO and VIVO in their Year 0 to Year 5
(Data source: Gartner, IDC, IC Insights, Strategy Analytics)

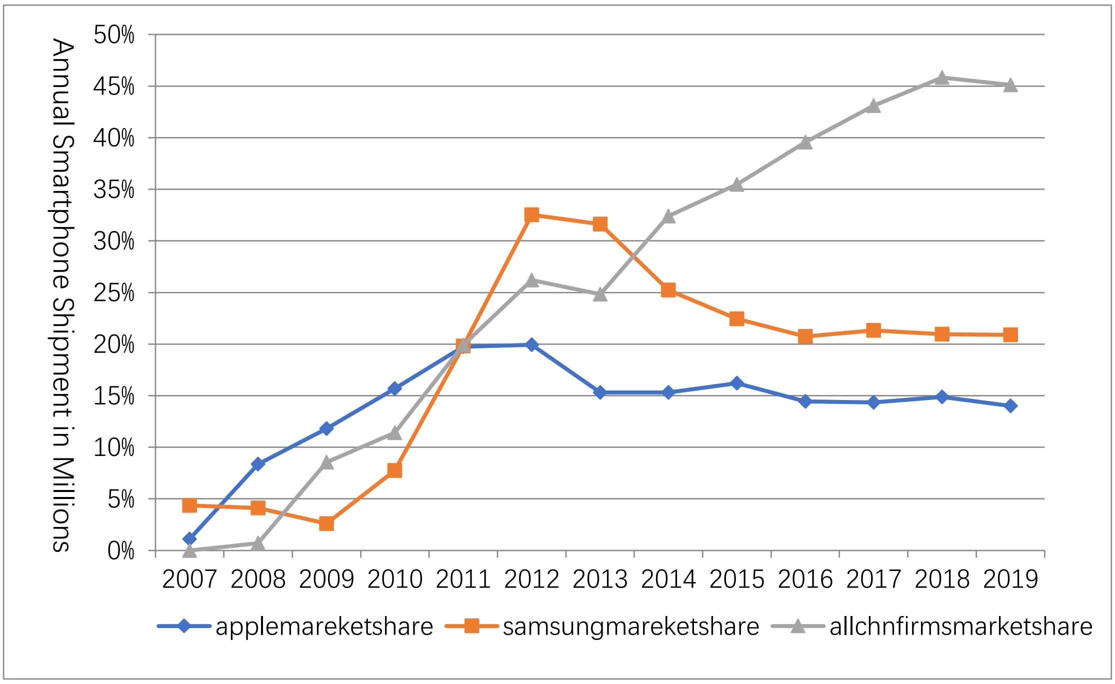

Figure 3.3 Global Market Shares of Smartphones of Samsung, Apple and Chinese Firms
(Data source: Gartner, IDC, IC Insights, Strategy Analytics)

To summarize, Xiaomi grew to become a top player in the global smartphone market using a set of strategies including a high performance/price ratio and applying the phrase "Focus, Extremeness and Fastness" whose key is OII, which will be explained in detail as the 4th advantage of OII in Section 3.5.2. Due to the advantages evidenced first by Xiaomi, OII has influenced significantly China's smartphones innovation practice since 2010. In response, ZTE launched its sub-brand 'Nubia' and Shanda launched its 'Bambook Phone' in 2012, Huawei launched 'Honor' and Gionee launched 'IUNI' in 2013, and VIVO launched 'IQOO' in 2019. OPPO introduced 'Realme' in 2018 and tried to learn and compete with Xiaomi's sub-brand 'Redme' which launched online in 2013. Similarly, Tim Cook of Apple said they took many suggestions from Chinese customers including QR code mode in digital camera in iPhone, evening mode and functions of 5G, etc. (Jinrongjie, 2021). Many entrepreneurs and CEOs visited Xiaomi to learn its methods (Lei, 2020). Some firms in home appliances also adopted OII. Haier, founded in 1984 based on a local refrigerator factory, focuses on product quality and customers' experience. As they adjusted to online practices and then IoT, Haier began using WeChat as the main platform to interact with its millions of customers and built a special portal to collect feedback and initial design ideas from fans.

3.3.2.2 How OII works at Xiaomi

OII was developed by Jun Lei who used to be the President of Kingsoft and Wanqiang Li who used to work in Kingsoft. Kingsoft is a software firm listed on the Hong Kong Stock Market in 2007, which produces office software to compete with Microsoft Office. In 2000, Wanqiang Li joined Kingsoft and launched the design team to interact with users and improve their experience. Jun Lei and Wanqiang Li improved the practice of monthly interactions in Kingsoft to daily interactions and weekly updates in Xiaomi from 2010. Earlier, Jun Lei channeled his enthusiasm for mobile phones by providing more than 100 suggestions to the Vice President of Nokia. This influenced his attitude about encouraging Xiaomi's fans to take part in designing products which will create real value for all stakeholders. In 2010, since Android did not fit the Chinese users' habits very well, Xiaomi decided to develop its own version of Android called 'MIUI'. Although building an operating system is complicated and needs a long commitment, Xiaomi learned from opensource code and devised MIUI, which can be updated weekly based on a flow of customers' suggestions (Li, 2014). Xiaomi released the first version of MIUI on August 16, 2010, only 4 months after its foundation and they built an online forum to attract voluntarily users. There were only 100 users in the first week, but it doubled in every week throughout the first year (Lei, 2019). When Xiaomi released its first smartphone in August, 2011, there were already half million PFs who had tested MIUI, found its bugs and volunteered suggestions to improve MIUI. Xiaomi also use social media including Weibo, WeChat and QQ to attract more PFs (Li, 2014).

According to Xiaomi, currently, there are about 100 key engineers who focus on the programming of MIUI, 1,000 privileged PFs who test MIUI daily, plus more than 100,000 PFs who are given the opportunity to test MIUI internally at various stages. Some privileged PFs also help to interact with IUs, collect and evaluate the suggestions from IUs. There are about 368 million IUs who are using smartphones and other IoT products of Xiaomi (Xiaomi, 2021c). In the online platform of Xiaomi, there are more than 10 million comments, feedback and complaints from millions of IUs or PFs online. The engineers of Xiaomi or privileged PFs collect and process such information daily. Usually there are polls in the online communities of Xiaomi, where IUs can vote and select which functions they want to be included in the new versions of MIUI. Often on Mondays, with the help of some privileged PFs, Xiaomi's engineers evaluate and adopt some popular suggestions to design new functions of MIUI, improve some existing functions or solve bugs in MIUI, followed by daily internal tests mainly by 1,000 privileged PFs. On Thursdays, more than 100,000 PFs test the new version of MIUI and provide feedback. Every Friday Xiaomi releases a new version of MIUI for about 368 million IUs to update easily. OII has been converting IUs into respected PFs as they feel their suggestions are noted and adopted by Xiaomi. They also play a role for product to be customized for them. In his book *The Long Tail: Why the Future of Business Is Selling Less of More*, Anderson (2006) argued that there used to be a clear division between professionals and amateurs. But this division almost disappeared for Xiaomi (Li, 2014), where customers have been cultivated to act in ways similar to citizen scientists (Horn, et al., 2015).

However, there are still many puzzles and misunderstandings about OII. This study examines every step of OII, and investigates why other explanations, such as scarcity marketing or hunger marketing strategy, are not suitable.

3.3.3 Dependent variables, independent variables and control variables

3.3.3.1 Dependent variables and independent variables

Electronic word of mouth [e-WOM] is commonly measured by the overall number of inclusive postings, which is full of misleading noise. This study focuses on the panel of suggestions for new functions [PSNF] in Xiaomi's online community, which is a special panel to encourage suggestions about MIUI. There are 118 categories with different functions between March 16, 2012 and June, 2018. In every category, e-WOM is divided and measured by the initial postings from three groups including Xiaomi's employees, PFs and IUs (curve 1) and replies from the three groups (curve 2) in PSNF to improve the functions of products including addition, amendment (repair), optimisation and deletion (curve 3) which is more concentrated and more meaningful with less noise. This is one of the main sources of creative ideas for R&D and the annual number of patent applications (curve 4), contributing to annual shipments of smartphones (curve 5). Since only 53 existing functions were deleted in 7 years which is relatively few, this type of change is not included in the study. This study examines the relationship among the variables in curve 1 to 5, therefore these variables are both dependent variables (DVs) and independent variables (IVs) in various models, as illustrated in Table 3.1.

Schumpeter (1934) defined innovation as "new goods", "an improved or better method of production", "a new market", "a new source of supply of raw materials or half-manufactured goods" or "the better organization of any industry", plus new business models in recent decades (Foss, Nicolai and Saebi, 2017), particularly as enabled by ICT. There are various indicators to measure innovations, e.g., budget and employees for R&D. In this study, the weekly number of changes to products' functions (curve 3) and the annual number of patent applications (curve 4) are indicators to measure the output of innovations.

3.3.3.2 Control variables

Chinese smartphones occupied about 45% of the global market in the 2nd quarter of 2019 (Counterpoint, 2019). The annual shipment of Chinese smartphone firms may be influenced by either Chinese or global smartphone market. Hence, the annual smartphones shipments of China and the world are control variables (CVs). Similarly, it is possible that the annual shipment of Chinese smartphone firms is influenced by the economy of China and the world, which may influence the consumers' willing to buy new smartphones and their purchase power. Therefore, the annual GDP of China and the world are CVs in the models in this study.

As discussed in Section 3.3.1.3, there are some advantages to convert some data into the natural logarithm (Kutner, Nachtsheim and Neter, 2004). This analysis uses the natural logarithm of all the variables in curves 1 to 5, so that its residuals are independent and normally distributed (Gujarati and Porter, 2009).

Table 3.1 Dependent Variables (DVs), Independent Variables (IVs) and Control Variables (CVs) for the Study in Chapter 3

	Order	DV or IV	Description
Time	1	weeksc0	the week beginning from March 16, 2012
	2	year	the natural year beginning from 2012
Curve 1 (suggestions)	3	lnmxaugof	the natural logarithm of the number of suggestions from the firm's employees in every week based on different categories of topics
	4	lnmxaugsof	the natural logarithm of the number of suggestions from participative fans (PFs) in every week based on different categories of topics
	5	lnmxaugot	the natural logarithm of the number of suggestions from interactive users (IUs) in every week based on different categories of topics

	6	lnmaxpnumb1	the natural logarithm of the number of total suggestions from the firms' employees, PFs and IUs in every week based on different categories of topics
	7	lnac1auof	the natural logarithm of the number of total suggestions from the firms' employees in all topics in every year
	8	lnac1ausof	the natural logarithm of the number of total suggestions from participative fans (PFs) in all topics in every year
	9	lnac1auot	the natural logarithm of the number of total suggestions from interactive users (IUs) in all topics in every year
	10	lnac1autt	the natural logarithm of the number of total suggestions from the firms' employees, PFs and IUs in all topics in every year
Curve 2 (replies)	11	lnmxwkxmofrp	the natural logarithm of the number of replies from the firm's employees in every week based on different categories of topics
	12	lnmxwkxmsofrp	the natural logarithm of the number of replies from participative fans (PFs) in every week based on different categories of topics
	13	lnmxwkxmotrp	the natural logarithm of the number of replies from interactive users (IUs) in every week based on different categories of topics
	14	lnmaxpnumb2t	the number of total replies from the firms' employees, PFs and IUs in every week based on different categories of topics
	15	lnacmc2ofr	the natural logarithm of the numbers of total replies from the firm's employees in every year
	16	lnac2sofr	the natural logarithm of the numbers of total replies from participative fans (PFs) in every year
	17	lnac2otr	the natural logarithm of the numbers of total replies from interactive users (IUs) in every year

	18	lnac2rt	the natural logarithm of the numbers of total replies from the firms' employees, PFs and IUs in every year
Curve 3 (function changes)	19	lnmxwkxmadd	the natural logarithm of the number of new functions added to the operating system in every week
	20	lnmxwkxmop	the natural logarithm of the number of existing functions optimized in the operating system in every week
	21	lnmxwkxmam	the natural logarithm of the number of existing problems amended (repaired) in the operating system in every week
	22	lnac3add	the natural logarithm of the number of new functions added to the operating system in every year
	23	lnac3opt	the natural logarithm of the number of existing functions optimized in the operating system in every year
	24	lnac3am	the natural logarithm of the number of existing problems amended (repaired)in the operating system in every year
	25	lnac3tall	the natural logarithm of the number of total changes in functions in the operating system in every year
Curve 4	26	lnxmapatap	the natural logarithm of annual number of patent applications
Curve 5	27	lnxmasp	the natural logarithm of annual shipments of Xiaomi's smartphone
Other CVs	28	lnchnsp	the natural logarithm of annual shipments of Chinese smartphones
	29	lngsp	the natural logarithm of annual shipments of global smartphones
	30	lnchngdp	the natural logarithm of annual GDP in China
	31	lnwdgdp	the natural logarithm of annual GDP in the world

3.4 Analysis and results

3.4.1 Analysis

In the next section, growth curve models (Rabe-Hesketh and Skrondal, 2012) are built to analyse the data. Since Xiaomi's data about OII is most complete, this study tests the hypotheses with Xiaomi's panel data. Huawei's OII data do not have functions in every week, which is relatively simple. Since the data about suggestions, replies and changes in functions are available in every week, so the relevant hypotheses (H3.1, H3.2A, H3.2B and H3.3) are analysed by growth curve models with the time unit as a week, which is about 337 weeks. Since the patent applications and shipment are available in every year, so the relevant hypotheses (H3.2C, H3.2D, H3.2E, H3.2F, H3.4 and H3.5) are analysed by growth curve models with the time unit as a year, which is about 7 years. Hypotheses H3.6 compared the firms with or without OII by building logistic models based on the data of the annual shipment between 2010 and 2019, which is 10 years. As reviewed in Section 3.3.1.4, the final model is chosen based on the relevant theories, management practice and the smallest value of AIC and BIC (Kutner, Nachtsheim and Neter, 2004; Agresti and Finlay, 2009). This study makes conclusions only when the p-value is less than 0.05, to be conservative. Multicollinearity and homoscedastic are tested for all models. There is no serious homoscedastic problem. The autocorrelation problem is solved by the growth curve models. The value of VIF to check multicollinearity are listed in the relevant tables.

3.4.2 Results

3.4.2.1 Data summary

Data in the online platform of Xiaomi in 337 weeks between March 16, 2012 (Week 82 from Xiaomi's foundation) and August 24, 2018 (Week 418) were downloaded. As illustrated in Table 3.2, there were 193,399 initial postings including 626 (0.32%)

postings from Xiaomi's employees (keyword in coding as augof, official), 55,128 (28.5%) postings from PFs organized and authorized by Xiaomi (keyword in coding as augsof, semi-official), plus 137,645 (71.17%) from IUs (keyword in coding as augot, others). There were totally 734,750 replies including 59,972 (8.16%) replies from Xiaomi's employees (keyword in coding as ofrp), 309,954 (42.18%) replies from PFs organised and authorised by Xiaomi (keyword in coding as sofrp), plus 364,824 (49.65%) from general IUs (keyword in coding as otrp). All these groups of data are measured in weeks, according to different functions such as phone directory, text, security, music, etc. Additionally, these three groups of data are measured in years, in order to be analysed with the annual number of patent application and Xiaomi's annual number of smartphone shipments.

Table 3.2 Summary of Data about Initial Postings and Replies

	From Xiaomi's employees	From PFs	From IUs	Sum
Initial postings	626	55,128	137,645	193,399
%	0.32%	28.50%	71.17%	100%
Replies	59,972	309,954	364,824	734,750
%	8.16%	42.18%	49.65%	100%

3.4.2.2 The models whose DVs are the natural logarithm of replies to others' postings

In order to explain how I construct the growth curve model (GCM) by Stata, the command for GCM is explained as following:

mixed lnmxc2tresp lnmxpnumb1t weeksc0 || folder: weeksc0, covariance(unstructured) mle

'mixed' is the command in Stata, lnmxc2tresp (natural logarithm of number of total replies from the firms' employees, PFs and IUs in every week based on different categories of topics) is the dependent variable (DV), lnmxpnumb1t (natural logarithm of number of total suggestions from the firms' employees, PFs and IUs in every week based on different categories of topics) is the independent variable (IV) and weeksc0 (the week beginning from March 16, 2012) is the control variable. The suggestions (IV) and replies (DV) about different functions of smartphones are listed by different categories of topics in the website of Xiaomi and they are downloaded to the relevant folders with unique folder ids, e.g., dial, text message, music, security, etc. Hence, 'folder' as the id to categorize DV and IV is included in the model. For random slope model, covariance(unstructured) is necessary in the model to set the nonzero covariance between random effects (Hamilton, 2009), otherwise the command 'mixed' will "set the covariance to zero by default" (Rabe-Hesketh and Skrondal, 2012: 196). In all the models, random slope models and random intercept models with the same DV, IV and CVs are compared, and usually the former fits the data better than the latter.

The results to test Hypothesis H3.1 are illustrated in Table 3.3. The coefficient for the total number of the postings of suggestions is 0.91 ($p<0.001$). Hence, Hypothesis H3.1 can be supported and there is a positive relationship between the total number of replies and the total number of postings of suggestions with statistical significance. There are group effects in the models since ICC is 0.23, in the range of $\rho \geqslant 0.138$ which is highly correlated (Cohen, 1988). This means that the weekly data in each category of topics are highly correlated. There are 337 weeks with 75 categories of topics. The VIF value is 1, lower than the threshold value 10, which means there is no multicollinearity. Also, the results of the original model and the model with robust regression are compared to prove that there is no serious homoscedastic problem. The autocorrelation problem is solved by the growth curve modelling. Multicollinearity and homoscedastic are tested for all models. This paragraph will not be repeated again for parsimony, but the VIF value for each model is listed in the relevant table.

Table 3.3 Results of Growth Curve Models with Natural Logarithm of Number of Total Replies from the Firms' Employees, PFs and IUs (lnmxc2tresp) in Every Week Based on Different Categories of Topics as DV Respectively

	lnmxc2tresp as DV
	coefficient
Intercept	1.55***
Weeksc0 (the week beginning from March 16, 2012)	-0.0002
lnmxpnumb1t (natural logarithm of number of total suggestions from the firms' employees, PFs and IUs in every week based on different categories of topics)	0.91***
AIC	17034.38
BIC	17086.48
ICC	0.23
VIF to check multicollinearity	1.0

(* *p* < .05 ** *p*< .01 *** *p*< .001)

3.4.2.3 The models whose DVs are the natural logarithm of the number of functions' changes in MIUI

As illustrated in Table 3.4, in the weekly updated versions of MIUI, there were 5,559 functions changed in MIUI, the operating system of Xiaomi, including 1,256 new functions, 1,665 optimisations, 2,585 amendments of bugs and 53 deletions of existing functions between 2012 and 2018. There were many new functions added, existing functions amended and optimised in early period such as 2012 and 2013. But when the products become increasingly mature and stable, there were fewer and fewer changes. This may be due to "low hanging fruit" problem and "better than Beatles" problem which will be discussed in Section 3.5.1 on the internal structure of OII.

Table 3.4 Types of Functions' Changes

New functions added	Existing functions Optimised	Existing functions amended	Existing functions deleted	Sum
1,256	1,665	2,585	53	5,559
22.60%	30.00%	46.50%	1%	100%

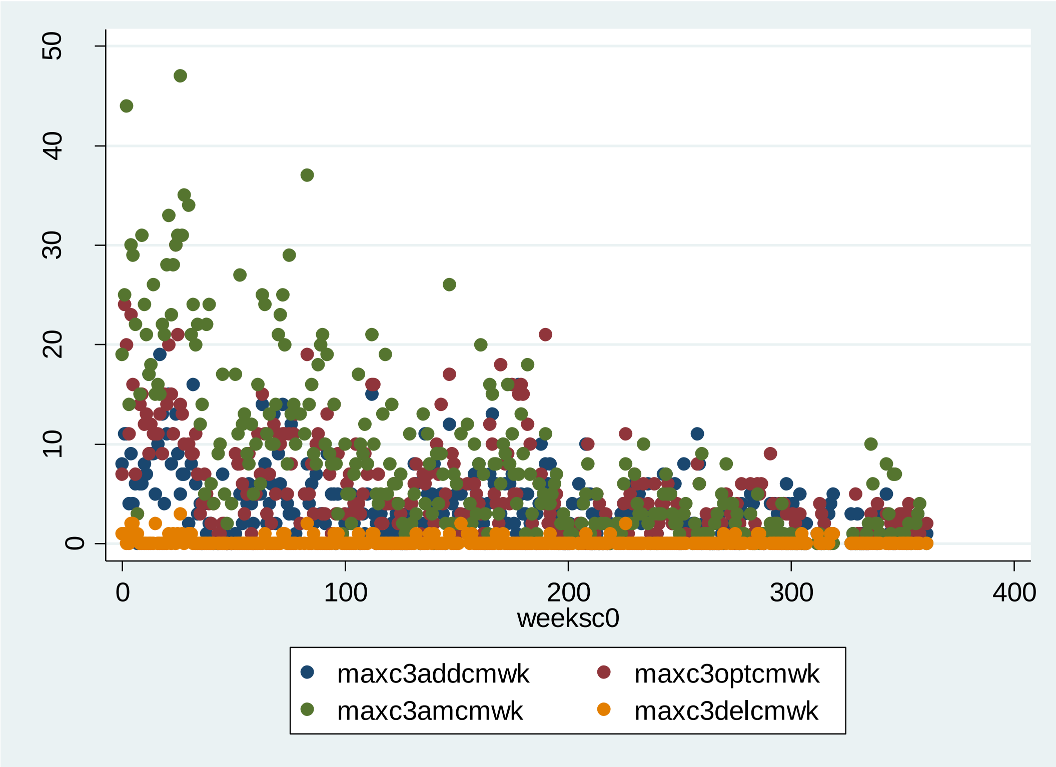

Figure 3.4 Weekly Numbers of Changed Functions in MIUI Between 2012 and 2018

(maxc3addcmwk: new functions added in the operating system of smartphone in every week

maxc3optcmwk: new functions optimized in the operating system of smartphone in every week

maxc3amcmwk: new functions repaired in the operating system of smartphone in every week

maxc3delcmwk: existing functions deleted in the operating system of smartphone in every week)

The relationship between the total number of the replies in every year (lnac2rt as IV) and the total number of functions changed in every year (lnac3tall as DV) is tested in Hypothesis H3.3, controlling the CVs including the total number of the suggestions in every year (lnac1autt) and annual smartphone shipments of China (lnchnsp) along with the Chinese annual GDP (lnchngdp). The coefficient of lnac2rt is 3.22 and the p-value is $0.01<0.05$. The coefficient of lnac1autt is -2.95 and the p-value is $0.009<0.05$, which are listed in Table 3.5. In the sensitivity analysis, the coefficients become less statistically significant if the total number of functions' changes is lower than 65. However, the VIF to check multicollinearity in this model is 57.42, much higher than the threshold 10. On the right of Table 3.5, the VIF to check multicollinearity is reduced to 1.78, but there is no significant relationship between the total number of the replies in every year (lnac2rt as IV) and the total number of the functions changed in every year (lnac3tall as DV). Hence, Hypothesis H3.3 is not supported. There may be three reasons: first, the total number of functions' changes keeps on decreasing, while the total number of postings and replies keep on increasing. Second, there are only 7 observations (for 7 years) in total. If this study limits the total number of functions' changes, the number of observations may be reduced and influence the results. Third, there may be a "low hanging fruit" problem and a "better than Beatles" problem, which will be discussed in Section 3.5.1 on the internal structure of OII.

Table 3.5 Results of the Model with Natural Logarithm of
Total Number of Functions Changed in Every Year (lnac3tall) as DV

	coefficient	coefficient
Intercept	13.69	17.97**
Lnac1autt (natural logarithm of annual number of total suggestions from the firms' employees, PFs and IUs in all topics)	-2.95**	
Lnac2rt (natural logarithm of annual numbers of total replies from the firms' employees, PFs and IUs)	3.22*	0.05
Lnchnsp (natural logarithm of annual shipments of Chinese smartphones)	1.97*	
Lnchngdp (natural logarithm of annual GDP in China)	-11.06**	-5.07**
AIC	-19.81	
BIC	-20.08	
VIF to check multicollinearity	57.42	1.78

(* p < .05 ** p< .01 *** p< .001)

3.4.2.4 The models whose DVs are the natural logarithm of the annual number of patent applications

First, there is a positive relationship between the natural logarithm of the annual number of suggestions from IUs based on different categories of topics and that of Xiaomi's employees with statistical significance (p<0.001) as illustrated in Table 3.6, which supports Hypothesis H3.2A. Similarly, there is a positive relationship between the natural logarithm of the annual number of suggestions from PFs based on different categories of topics and that of Xiaomi's employees with statistical significance (p<0.001) which supports Hypothesis H3.2B. If use the annual number of suggestions in the models, the results are similar, which are not illustrated to be parsimonious.

Table 3.6 Results of 2-level Model with Natural Logarithm of Annual Number of Suggestions from Firm's Employees based on Different Categories of Topics (lnmxaugof) as DV

	2-level Models with IVs in Curve 1 and lnmxaugof as DV	
	coefficient	coefficient
Intercept	-0.27***	-0.43***
Lnmxaugsof (the natural logarithm of the number of suggestions from participative fans (PFs) in every week based on different categories of topics)	0.23***	
Lnmxaugot (the natural logarithm of the number of suggestions from interactive users (IUs) in every week based on different categories of topics)		0.22***
AIC	416.77	423.98
BIC	423.1	442.97
VIF to check multicollinearity	1	1

Furthermore, there is a positive relationship between the natural logarithm of the number of suggestions from Xiaomi’s employees (Lnac1auof) and annual number of patent applications with statistical significance ($p<0.05$) as illustrated in Table 3.7, which supports Hypothesis H3.2C. Also, the coefficients of annual numbers of postings initiated by all of Xiaomi’s employees, PFs and IUs (Lnac1autt) in Table 3.7 are positive with statistical significance ($p<0.01$), which supports Hypothesis H3.2D. In the second model in Table 3.7, the coefficient for the natural logarithm of the annual number of total suggestions from PFs seems statistically significant, but it has multicollinearity since its VIF value is as large as 116.71, much larger than the threshold 10, hence this model is not valid.

To integrate these relationships, there is chain relationships as illustrated in Figure 3.5: PFs or IUs provide suggestions to Xiaomi’s employees with statistical significance and the annual suggestions of Xiaomi’s employees have statistically significant relationship with annual patent applications. But the annual numbers of suggestions of PFs or IUs has no statistically significant association with annual patent applications which support Hypothesis H3.2E and H3.2F. Additionally, as illustrated in Table 3.7, there is a positive relationship with statistical significance ($p<0.05$) between the annual total number of functions changes in MIUI including addition, optimization and amendment (Lnac3tall) and the annual number of new patent applications, which support Hypothesis H3.4.

Table 3.7 Results of the Model with Natural Logarithm of Annual Number of Patent Applications (lnxmapatap) as DV

	Model with IVs in Curve 1		Model with Total Numbers
	coefficient	coefficient	coefficient
Intercept	2.51*	1924.59	-20.52*
Year		-0.96	
Lnac1auof (natural logarithm of annual number of total suggestions from firms' employees in all topics)	0.47*		
Lnac1ausof (natural logarithm of annual number of total suggestions from PFs in all topics)	0.38	3.76*	
Lnac1auot (natural logarithm of annual number of total suggestions from IUs in all topics)		-1.86	
Lnac1autt (natural logarithm of annual number of total suggestions from the firms' employees, PFs and IUs in all topics)			0.81**
Lnac3tall (natural logarithm of annual number of total changes in functions in the operating system)			1.02*
Lnchngdp (natural logarithm of annual GDP in China)			5.74*
AIC	0.62	-2.27	-5.97
BIC	0.46	-2.49	-6.19
VIF to check multicollinearity	2.13	116.71	8.32

(* p < .05 ** p< .01 *** p< .001)

Xiaomi employees' have incentives from management metrics (such as key performance indicators) or as shareholders with ESOP. Also, they probably are enlightened by PFs or IUs through knowledge sharing, synergy or synthetization. Additionally, their ideas are reviewed by other colleagues, so that they keep on contributing creative ideas with high quality which contribute to more patent applications. However, some PFs have been fans in Xiaomi's online community for years. They probably have contributed their creative ideas to Xiaomi in their early periods, but they become less active or resistant to further changes, through inertia or entrenchment (Chang and Mayers, 1992). Also, the main works of PFs are to help Xiaomi's employees to manage the online communities, interact with millions of IUs, help to evaluate and select the suggestions and test the new versions of operating systems internally. IUs reflect the real and changing demand from the market and they are an original source of new and creative ideas. But IUs' suggestions may have much noise which needs the evaluation of Xiaomi's employees to take further for patenting. Hence, Xiaomi should keep on activating PFs and IUs or updating them, and continue encouraging employees. In a word, Xiaomi's employees are innovators who contribute to patent applications directly, but PFs and IUs are not lead users (von Hippel, 1986) or user innovators (von Hippel & Euchner, 2013).

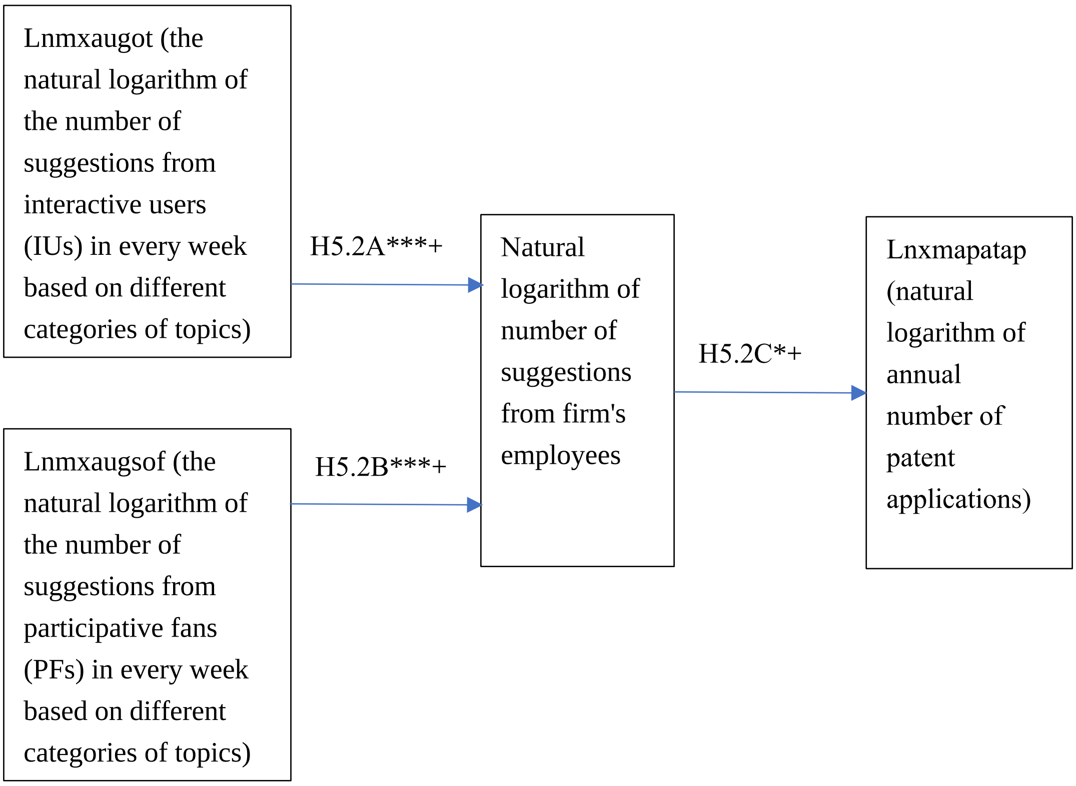

Figure 3.5 Chain Relationship Between the Numbers of Suggestions from IUs or PFs to the Suggestions from Firm's Employees to Patent Applications

3.4.2.5 The models whose DV is the natural logarithm of the annual shipments of Xiaomi's smartphones

Hypothesis H3.5 is tested and the results are illustrated in Table 3.8. There is a significant positive relationship between the number of patent applications and the shipments of smartphone in both models. Although there are many factors to influence the annual shipments of firms, the evidence from documents and analysis as following can prove OII with various advantages do help firms to enhance their annual shipments of smartphones. In the sensitivity analysis, the observation number is only 7 between 2012 and 2018. If this study reduces the number of patent applications to fewer than 5000, the observation number will be 6 or even smaller. But if I reduce the number of total postings of suggestions, the numbers of total replies and the numbers of functions' changes, the second model whose results are on the right of Table 3.8 still works well and the coefficient of the natural logarithm of annual number of patent applications (lnxmapatap) is still statistically significant. It is also interesting to note that the coefficients of the natural logarithm of annual GDP in the world are statistically significant in both models. This reflects the fact that Chinese smartphones occupied about 45% of the global market in the 2nd quarter of 2019 (Counterpoint, 2019), so it not surprised that the annual shipments of Chinese smartphones are influenced by the annual global GDP.

Table 3.8 Results of the Model with Natural Logarithm of Annual Shipments of Xiaomi's Smartphones (lnxmasp) as DV

	coefficient	coefficient
Intercept	-57.64***	-56.19**
Lnxmapatap (natural logarithm of annual number of patent applications)	1.11***	1.43**
Lnwdgdp (natural logarithm of annual GDP in the world)	12.11***	11.97**
Lnac1autt (natural logarithm of annual number of total suggestions from the firms' employees, PFs and IUs in all topics)		-0.33
AIC	-5.04	-9.86
BIC	-5.21	-10.07
VIF to check multicollinearity	1	4.63

(* $p < .05$ ** $p < .01$ *** $p < .001$)

3.4.2.6 Comparison of shipments of firms with and without OII

Among Chinese smartphone firms, only Xiaomi and Huawei have OII, while other firms did not have OII between 2012 and 2018. As illustrated in Figure 3.6, the sums of the annual shipments of Chinese firms are divided into 3 groups. The sum of Huawei and Xiaomi with OII (coded as HWXMOII in the following Figure 3.6 and 3.7) has been increasing faster than the sum of OPPO and VIVO without OII (coded as OPVInoOII), while others firms (coded as ELSEnoOII) are falling rapidly, including most of the incumbent firms such as Lenovo, ZTE, Meizu, TCL, Gionee and Coolpad, etc., whose initial annual shipments including featured mobile phones with existing customers and brand names. Huawei, Xiaomi, OPPO and VIVO all began their smartphone business around 2010 and they occupied 79% of the Chinese smartphone market in 2018. Hence, these four firms in 2 groups are comparable. The logistic models and S-curves are built for the sums of Huawei and Xiaomi to compare with the sum of OPPO and VIVO in Table 3.9 and Figure 3.7. When I use the coefficients and standard errors in Table 3.9 to calculate the t values about the differences of the slopes of two curves, the t values are larger than 10.46 and the p-values are less than 0.001. This means the coefficients of year (slope, annual growth rate) of the two curves are quite different with statistical significance. Hence, it can be concluded that Hypothesis H3.6 can be supported and the annual shipments of firms with OII increase more rapidly than the firms without OII with statistical significance. OII shifts the S-curve to the left and up, which means it increases earlier and faster than competitors. This is the main reason for the high demand of Xiaomi's smartphones in some periods especially when Xiaomi just released its new smartphones. In order to find out the true effect of OII more accurately, other characteristics of the four firms should be controlled for. Xiaomi mainly relies on OII in most of the period plus some offline shops later and Huawei has OII plus some offline shops. Oppo and Vivo totally depend on offline shops or dealers to promote their smartphones. It may be helpful to include their annual number of offline shops and the annual shipments in the offline shops vs online platforms respectively. But such data for these four firms are not available as they are regarded as business secrets, which is a limitation for this analysis.

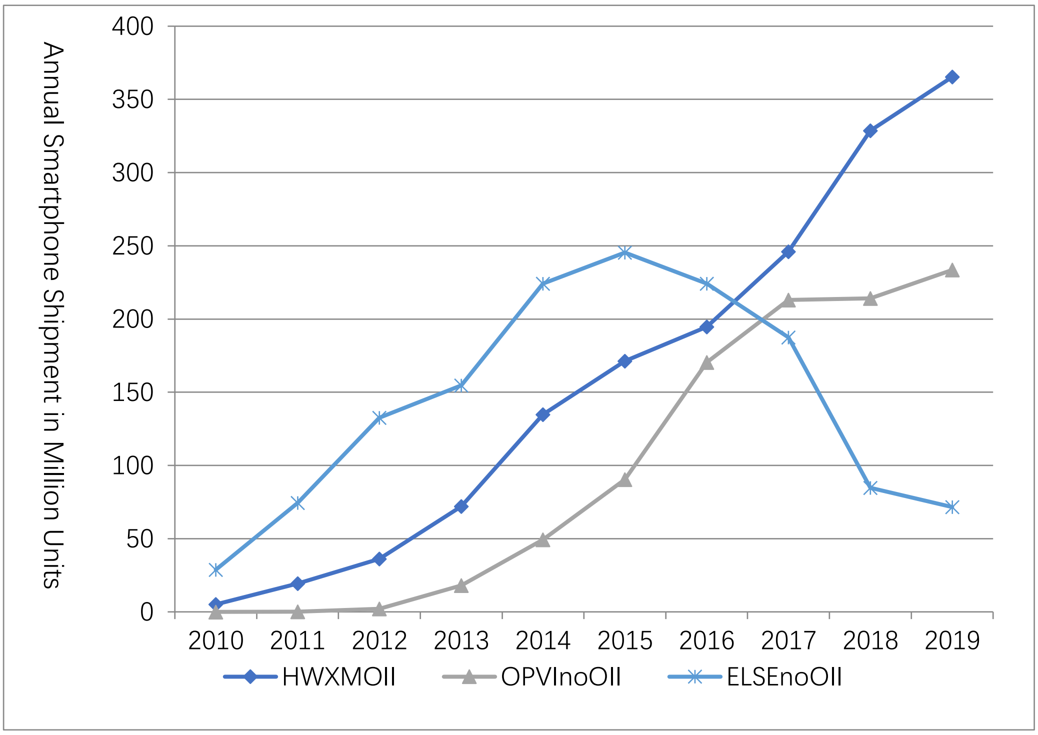

Figure 3.6 Three Groups of Firms in Chinese Smartphone Industry
(Data source: Gartner, IDC, IC Insights, Strategy Analytics)
(HWXMOII: The annual shipments of Huawei & Xiaomi with OII
OPVInoOII: The annual shipments of Oppo & Vivo without OII
ELSEnoOII: The annual shipments of other smartphone firms without OII)

Table 3.9 Coefficients about S-curves of Firms with or without OII

	coefficient
Huawei & Xiaomi with OII	
Intercept	1404.28***
Year	-0.7***
Oppo & Vivo without OII	
Intercept	2290.94***
Year	-1.14***

(* $p < .05$ ** $p < .01$ *** $p < .001$)

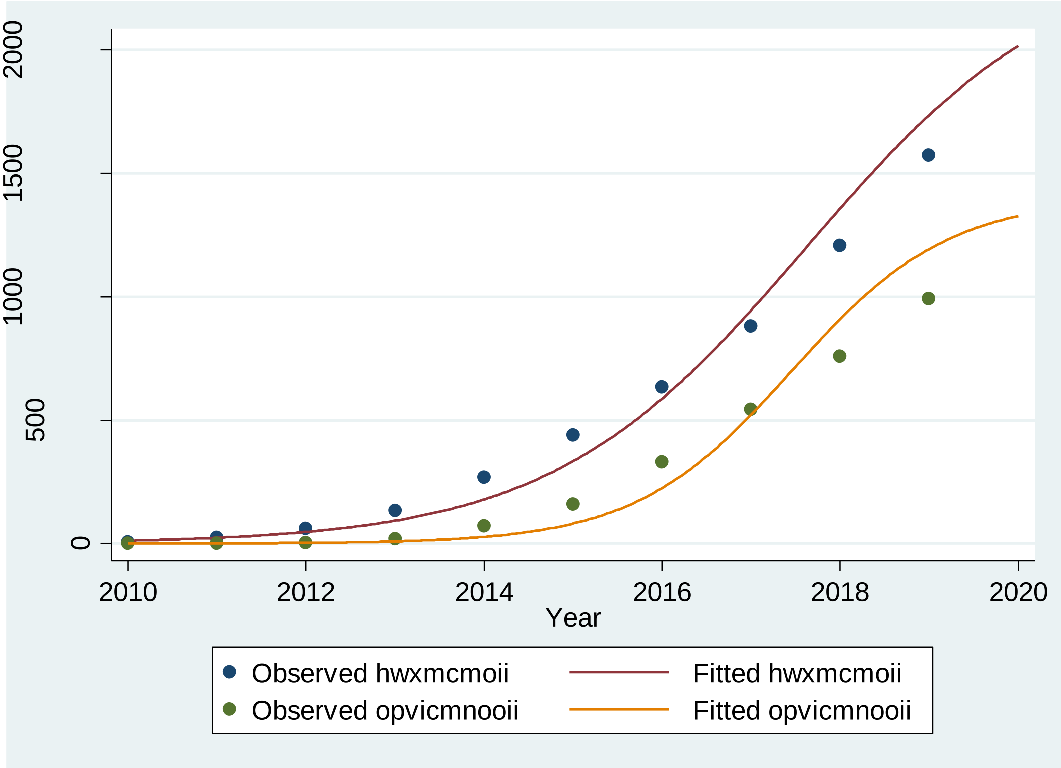

Figure 3.7 Two Groups of Firms with or without OII
(hwxmcmoii: The cumulative data of annual shipments of Huawei & Xiaomi with OII
opvocmnooii: The cumulative data of annual shipments of Oppo & Vivo without OII)

3.4.2.7 It is not hunger marketing strategy

As discussed above, OII increases the demand of customers dramatically but Xiaomi initially underestimated its significance. In 2011, Xiaomi's top management predicted that the total shipment for Xiaomi's first smartphone called 'Mi1' could be 0.3 million. However, consumers bought 7.9 million Mi1 in total (Fan, 2020). Second, successful new products commonly suffer supply-scarcity due to the initial difficulty in production and yield rate (Fekete, 2012). This kind of problem became worse since Xiaomi was a new firm in the smartphone industry in its early period. Xiaomi did not have sufficient talents and capability to manage the supply chain on such a large scale in its early period. For example, in the initial stage, three departments of Xiaomi including accounting, supply chain and sales used excel sheets to record their data respectively and had to bring 3 laptops together to check the data with each other (Fan, 2020). Also, few suppliers of smartphones knew about Xiaomi and there was no established and mature relationship between Xiaomi and suppliers. For instance, every big firm should have at least two suppliers ready for the same component for guarantees, but Xiaomi did not. In late 2014, right after Xiaomi released its 4th smartphone Mi4, Winteck which was Xiaomi's only supplier of OGS touch panels went bankrupt suddenly and pushed Xiaomi to find other suppliers urgently. This resulted in a serious shortage of Mi4s and gave big market opportunities to competitors (Fan, 2020). Even worse, Xiaomi's supply chain manager and his team irritated Samsung which is Xiaomi's key supplier of OLED displayers. Samsung consequently paused the delivery of OLED displayers to Xiaomi in 2015. As the result of such problems in the supply chain, the Xiaomi smartphone Mi5 was postponed from 2015 to 2016. During that tough period between mid-2015 and early 2016, Xiaomi's supply chain could not catch up with the release of new smartphones. Xiaomi painfully found that the two weeks after releasing new products were the best period for sales, but they had limited smartphones available for the market in those weeks (Fan, 2020). Xiaomi's shipment dropped from 66.5 million in 2015 to 55.4 million in 2016 and was surpassed by OPPO and VIVO. This disaster forced the President of Xiaomi to fire the Vice President of supply chain management and his direct leader in charge of Xiaomi's smartphone business, one of the eight co-founders of Xiaomi. Xiaomi's President then took responsibility for the smartphone business and supply chain management by himself and visited Samsung's headquarters in South Korea by four times to rebuild the supplier relationship (Lv, 2018; Fan, 2020). Xiaomi's President emphasised several times in Xiaomi's internal meetings: "We must provide sufficient smartphones and cannot make customers wait anymore, otherwise we always lose the best period to sell" (Gao, 2020: 280). Also, Xiaomi had to improve its internal management system to recover the employees' morale (Lei, 2020). Third, Xiaomi was a young firm and had to pay suppliers and manufacturers in advance for them to produce sufficient smartphones. But cash flow is important for Xiaomi especially in its initial stage before IPO. Also, the smartphones keep on changing and devaluing quickly, hence Xiaomi did not have the confidence to keep many smartphones in inventory (Custer, 2013).

These three main reasons resulted in the product shortage which was criticised by many customers. Customers complained that they had to compete to buy Xiaomi smartphones from Mi1 to Mi9, which were sold out in seconds. The first batch of Mi8 sold out in 97 seconds on June 8, 2018 and 53 seconds for Mi9 in March 5, 2019, e.g., around a million smartphones selling in less than two minutes. Xiaomi's management always promised they tried to provide as many smartphones as being demanded, but failed every time. Many customers complained and this triggered accusation of "deceptiveness" (Aguirre-Rodriguez, 2013) that Xiaomi adopted a scarcity or hunger marketing strategy deliberately. Many customers felt angry and bought similar products from other firms. Competitors noticed this phenomenon and reacted quickly to catch this opportunity. For instance, OPPO and VIVO provided sufficient smartphones similar to Xiaomi's to satisfy customers irritated by Xiaomi. According to big data analysis, in 2016 Xiaomi lost 18.23% of its customers to OPPO (Lv, 2018). In that period, there were rumors in the market that "Xiaomi may fall" which hurt the brand name and the confidence of customers and suppliers significantly (Fan, 2020). Xiaomi had not wanted to use a 'scarcity marketing' or 'hunger marketing' strategy to push itself into this dangerous situation (Fan, 2020 and Gao, 2020).

A similar problem happened earlier for i-mode in Japan. NTT DoCoMo in Japan launched i-mode in 1999 which was the first smartphone to surf online. NTT DoCoMo used a linear increment model instead of S-curves to predict the growth of subscribers, illustrated in Figure 3.8. Hence, NTT DoCoMo underestimated the number of subscribers and provided insufficient systems capacity, which resulted in multiple system failings and NTT DoCoMo lost about 2 million potential customers to its competitors.

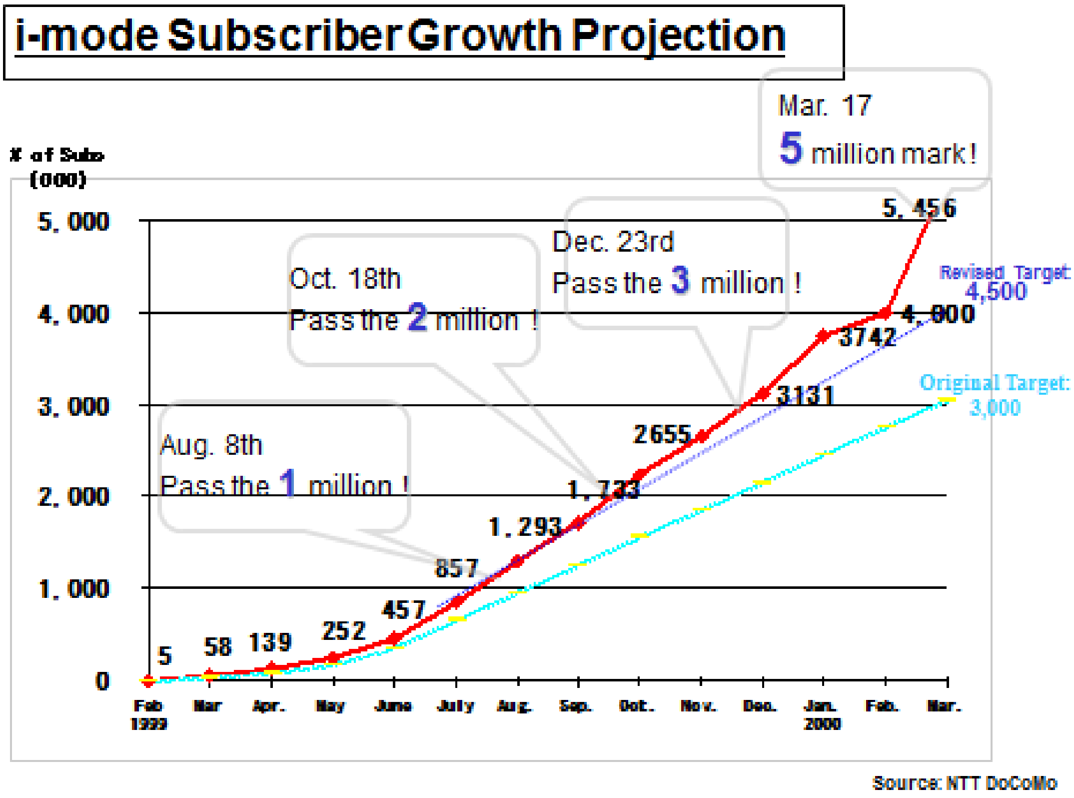

Figure 3.8 NTT DoCoMo Used Linear Increment Models
to Predict i-mode Subscribers Growth

In order to explain the reasons why Xiaomi's product shortage is not a 'scarcity marketing strategy' or 'hunger marketing strategy', it is necessary to review the relevant theories and publications about 'scarcity marketing strategy' or 'hunger marketing strategy' here. "Product scarcity is essentially the mismatch between actual demand and actual supply" (Shi, Li & Chumnumpan, 2020: 780). Scarcity happened in various products in history (Balakrishnan et al., 2014) and may be classified into demand-induced vs supply-induced (Roy & Sharma, 2015), deliberate vs unintentional, limited time vs limited quantity (Cialdini, 2008), only during the product launch vs throughout product cycle (Shi, et al., 2020). Different products such as utilitarian vs. hedonic products, functional vs. symbolic products also influence the effects of product scarcity (Shi, et al., 2020). Additionally, various characteristics of consumers including age, gender, education and income can also influence their behavior when they face scarcity marketing (Haugtvedt, et al., 1992; Ku, et al., 2012; Sharma, et al., 2012). Also, there are significant differences among various countries and cultures, e.g., Asia vs the U.S. (Shi, et al., 2020).

There are four main theories behind 'scarcity marketing' or 'hunger marketing' (Shi, et al., 2020). The first is based on commodity theory (Brock, 1968; Fromkin, 1970). Scarcity marketing utilises the consumers' psychology to buy something that is difficult to obtain. So that the consumer who has it seems unique (Belk, 1988; Wu, et al., 2012). The second is based on conformity theory (Bernheim, 1994; Eisend, 2008). Individuals want to have similar goods "when more people are buying it, which can be evidenced by the product's unavailability" (Shi, et al, 2020: 742). The third is based on regret theory (Loomes, et al., 1982; Gabler, et al., 2017). Consumers believe they should buy the product now or they will regret not buying it when it becomes unavailable in the near future. The fourth theory is based on psychologically reactant theory (Brehm, 1966). If consumers think their freedom to buy the products is restricted and the product is limited, they will be more likely to buy the product (Clee, et al., 1980).

It is important to emphasise that a 'scarcity marketing strategy' or 'hunger marketing strategy' means the firm plans and reduces the supply to create 'deliberate supply-induced scarcity'. Scarcity marketing strategy is popular in luxury products, as seen in a limited edition strategy throughout product cycle in luxury products (Jang, Ko, Morri and Chang, 2015). It is not suitable to include unintentional scarcity resulted from production mistakes or accidents.

As Xiaomi did not plan or adopt a 'scarcity marketing strategy', its shortage was unintentionally demand-induced because of underestimating the rising demand resulted from OII and was supply-induced because of the mismanagement of the supply chain during the product launch (Shi, et al, 2020). This almost pushed Xiaomi to disaster (Lei, 2020). On August 6, 2020, Jun Lei, the President of Xiaomi repeated in an interview that the shortage of smartphones was not due to a scarcity marketing strategy but problems in supply chain and manufacturing capability (Lin, 2020). After Xiaomi improved its management and alleviated the problems in supply chains and manufacturing, Xiaomi's shipment resurged to 91 million in 2017, 122 million in 2018 and 124.8 million in 2019. Lei Jun, the President of Xiaomi said: "No mobile phone company in the world could successfully recover after the decline in sales except Xiaomi" (Lv, 2018). In comparison, the long list of smartphone firms: Nokia, Blackberry, LG, Sony, ZTE, Lenovo, Meizu, TCL, Gionee and Coolpad, etc., all fell and never recovered. In the fiercely competitive smartphone market, a 'scarcity marketing strategy' or 'hunger marketing strategy' means losing customers to competitors. Unfortunately, Xiaomi's shortage is often misunderstood as a 'scarcity marketing strategy' or 'hunger marketing strategy' in Chinese business schools' teaching which resulted in many students' dissertations that misinterpreted Xiaomi, e.g., Zhao (2013), and many academic publications (Chen, et al., 2014; Zhang, et al., 2017). "Many have praised Xiaomi's 'hunger marketing' strategy and attributed the firm's success to it" (Feng, et al., 2020: 1). Ironically, some Chinese firms learned what is misinterpreted by academics and managers that Xiaomi applied a 'scarcity marketing strategy' or 'hunger marketing strategy' and applied such a strategy in their practice, but all lead to failure. This is evidenced by the fact that the market share of other smartphone firms continues decreasing to only 2.9% of Chinese smartphone market, while the market share of the top five firms without a 'scarcity marketing strategy' or 'hunger marketing strategy', including Xiaomi, reached 97.1% in the 2nd quarter in 2020 (IDC, 2020).

With painful lessons between 2015 and 2016, Xiaomi keeps on looking for solutions. Xiaomi had only OII without integrated product development (IPD), as reviewed in Section 2.4, while Xiaomi's main competitor Huawei has both OII and IPD. IPD streamlines the whole process from ideation, R&D to production and sales. In 1999, Huawei learned IPD from IBM to solve its many problems in product development and sales, which helped Huawei to avoid disorders in product development and shortages.

Since then, some Chinese firms have been following Huawei and learning IPD. Xiaomi noted this big difference in 2019 and thought IPD to be the solution that Xiaomi has been looking for. Bin Lin (2019), the senior VP and co-founder of Xiaomi, posted a picture on his Weibo site showing that Xiaomi's management were studying IPD on March 16, 2019. Under the picture he wrote:

> "It is too simple to attribute the shortage only to lacking the experience to manage supply chains and procedures. We should establish the whole system of integrated product development procedures to improve systematically our capabilities in product competitivity, technical innovation, quality control, costs, production and marketing. Only improvements in our procedure and capability can solve the problems including shortage systematically."

After Xiaomi learned and applied IPD, Xiaomi improved its management especially its supply chain. IPD helps Xiaomi and Huawei to break the barriers among various departments inside the firms and OII helps the firms to break the walls between the firms and a lot of interactive users. Consequently, Knowledge can flow fluently from millions of IUs to every department of firms, and vice versa. IPD and OII have different advantages which are complementary to each other. Since then, Xiaomi has seldom met problems of shortage. Even when there is a widespread shortage of chips for smartphones from late 2020, Xiaomi still has sufficient smartphones to sell, while other competitors encounter problems. On May 30, 2021, Xuezhong Zeng who is the manager of Xiaomi's smartphone said: "Since late 2020, Xiaomi has stored chips and some core chips are ready for the next year, or 2 to 3 years. Hence, Xiaomi's smartphones are available for market and there is no need for fans to worry about it" (Digital technology, 2021). As the result, Xiaomi's smartphone reached No. 3 in the global market with a market share of 14%, an increase of 62%, just behind Apple's 15% share based on an increase of 41%. It is likely Xiaomi will surpass Apple in the coming quarter to be No. 2 in the global smartphone market (Calalys, 2021).

3.5 Discussion

3.5.1 Internal structure of OII

After testing the hypotheses aforementioned, the internal structure of OII is illustrated in Figure 3.9. Most of the works to reply to the posting of suggestions and replies of millions of IUs are done by the PFs organised and authorised by the firm, which is consistent with the interviews and seen in internal document. The weekly total number of suggestions of the firm's employees, PFs and IUs is positively relevant to the weekly total number of replies by the firm's employee, PFs and IUs with statistical significance (Hypotheses H3.1).

Next, the suggestions and replies from IUs are very important, since they are the general users of the firm's smartphone and they may represent most of the new demand of the market. Li (2014: 31), the co-finder and Vice President of Xiaomi who designed and managed the OII system, stated that "there is an assistant function in the online communities to help users to submit their needs in forms. Especially when users see similar needs, they can just click on the button 'I need this function too'. Hence every week you can see the most urgent functions needed to be developed ranked at the top in the online communities." This statement and other documents prove that Xiaomi's employees really prioritize new ideas and update the functions according to the suggestions and replies of IUs. But PFs and IUs are not "user innovators" (von Hippel & Euchner, 2013), as proved in Section 3.4.2.4.

However, the regression models cannot find the relationship between the numbers of the replies by Xiaomi's employees, PFs and IUs and the numbers of functions' changes in MIUI updated weekly with statistical significance. This is the reason why dotted arrows are put between the box of the replies and the box of the functions' changes in Figure 3.9. This is due to the former increasing while the latter are decreasing, as illustrated in Figure 3.4 in Section 3.4.2.3. The first possible explanation for this may be the “low hanging fruit” problem that the easy improvements of functions from the suggestions of IUs were adopted in MIUI in the early period such as 2011 and 2012 when the numbers of functions’ changes were at the peak. The second explanation may be the “better than Beatles” problem that it becomes increasingly difficulty to develop a new function better than its predecessors. The third explanation may be that more and more suggestions can not only be realised easily by MIUI, but also need hardware improvements, which requires more R&D time. The improvement of the hardware and results from R&D are counted not by the number of functions changes in MIUI but by the number of new patent applications. This is consistent with the interviews in Huawei and Lenovo (Figure 2.9 Lenovo’s User Experience Research in Concept Incubation in Chapter 2). It is also proved by the statistically positively significant relationship between the number of patent applications and the numbers of suggestions from Xiaomi’s employees (Hypotheses H3.2C), and all of employees, PFs and IUs (Hypotheses H3.2D). PFs and IUs provide their needs or suggestions to Xiaomi’s employees with statistically significance (Hypotheses H3.2A and H3.2B). Then with the help of PFs, Xiaomi’s employees collect, evaluate and select some creative and practicable ideas to be synthesised with employees’ knowledge and are implemented for patent applications. Since patent laws do not protect abstract ideas but rather the embodiment of ideas, the intellectual property rights of such patents belong to the firm instead of PFs or IUs.

Similarly, there is a positive relationship between the annual total number of functions’ changes in MIUI including addition, optimization and amendment and the annual number of new patent applications (Hypothesis H3.4). All of these aforementioned prove that one of the main sources of iteration and improvement of the firm’s products is the interaction between Xiaomi and PFs or general IUs. This is the triangulation from both interviews at Lenovo and Huawei and quantitative research about Xiaomi.

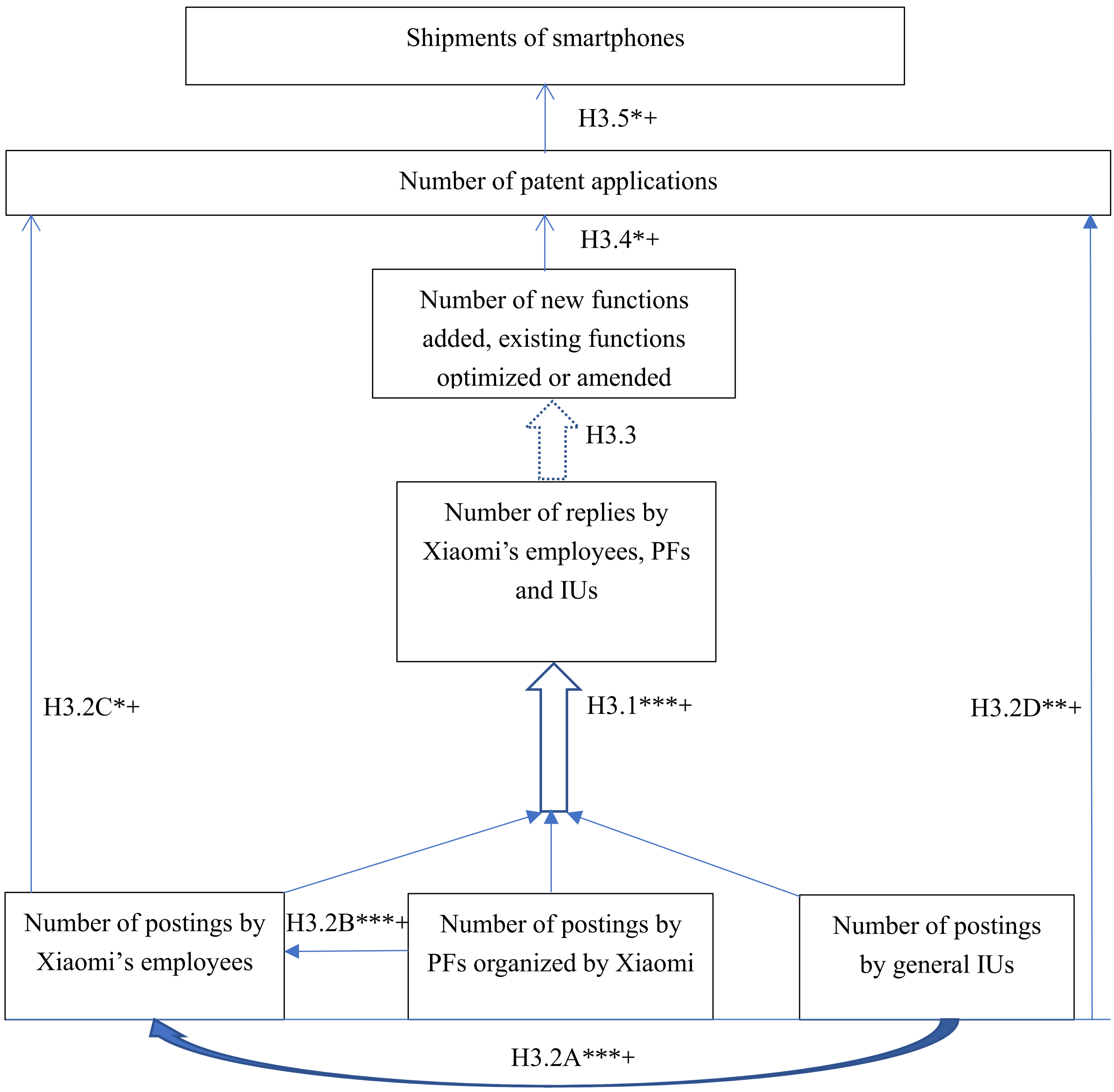

Figure 3.9 OII Internal Structure with Relevant Hypotheses Tested

(Note: PF: participative fans; IU: interactive users.

Two relationships are illustrated on the left and right of the figure:

On the left, there is a positive relationship between the annual number of postings of suggestions from the firm's employees and the annual number of patent applications with statistical significance (Hypothesis H3.2C).

On the right, there is a positive relationship between the annual total number of postings of suggestions from the firm's employees, PFs and general IUs and the annual number of patent applications with statistical significance (Hypothesis H3.2D).

(* $p < .05$ ** $p < .01$ *** $p < .001$)

3.5.2 The advantages of OII

In summary, here are 13 key advantages that Xiaomi and others enjoyed from OII:

1) OII can enlarge the sample, reduce the costs of transactions and processes and enhance the efficiency to collect opinions from millions of customers and help the firm to be sensitive to changes and to catch emerging opportunities. In 2016, Xuezhong Zeng, who was the Vice President in charge of the smartphone business in ZTE released a letter to his colleague and employees. Zeng (2016) confessed that Xiaomi was familiar with online marketing and noticed the changes in the market in time. Hence Xiaomi reacted much more quickly to catch the opportunity while ZTE fell behind. Similarly, OII is followed by Tesla which continues collecting suggestions from customers and updating software in its electrical vehicles (EVs) remotely. The Chinese management team of Tesla visited the clubs of Tesla owners around China to interact with them face to face. Also, they used the online community, Weibo, and announced an email box to receive suggestions and comments from customers. For instance, Tesla's Model S has been updated every few months remotely, adding to or improving more than 50 functions since 2012. Customers suggested on social media that Tesla should install bilibili (a Chinese video .com similar to YouTube) in EVs. After Tesla reviewed it, Tesla included the function of bilibili in the next update remotely. On June 21, 2020, the club of Tesla owners in Silicon Valley asked Elon Musk, the CEO, on Twitter: "Can we get screen mirroring from phone to the Tesla screen?" In one hour, Elon Musk replied: "Maybe, will look into it. We'd need to emulate a TV."

2) OII helps to create new knowledge as described by the SECI model of Nonaka and Takeuchi (1995a and 1995b) reviewed in Section 2.2, but this works more efficiently online. OII is very useful in the early stage for the ideation of new products. Usually, after a new product is produced, the firm has to spend some time to promote it for customers to become familiar with it and then accept it. But OII helps the firm to invite customers to take part in the design of the new product, which saves time and costs to promote it. This is one of the reasons why Xiaomi's new smartphones are always sold out quickly in seconds after they were released.

3) Currently, young consumers often do not want something uniform but prefer mass-customisation. Also, they like to interact with designers and take part in the design and evolution of products, which is called “interactive consumption” (Li, 2014; Yun, 2021) and only OII can realise this at large scale and effectively by reducing transaction costs drastically. Every Friday, about 368 million IUs of Xiaomi can update their smartphones easily and use new functions suggested by themselves or other IUs online. Similarly, some Chinese fashion firms including Bestseller interacted with young consumers in fans club and Shein adopted mass-customisation which achieved success.

4) OII sits at the core of Xiaomi’s strategy in the early period illustrated in Figure 3.10 and in the current period illustrated in Figure 3.11. OII uses the internet to collect suggestions from millions of customers, which are then applied to iterate the software (the operating system) weekly imbed and run in the hardware (smartphones). On the contrary, Samsung’s smartphones update much slower and less frequent than Xiaomi’s. For instance, Android released its Android 10 version in September 2019. Xiaomi updated its MIUI in October 2019 (‘fast’) for both high- and low-end smartphones, while Samsung updated its operating system of smartphones only in 2020. Samsung provides updates during the first 3 years after purchase; Xiaomi updates its MIUI every week for free and forever (‘extreme’ in time period). Hence, fast and much more frequent iteration enhances Xiaomi’s competitiveness over Samsung. One customer praised online: “Xiaomi’s engineers listen to customers’ suggestions and update MIUI frequently. Therefore, Xiaomi’s MIUI is most humanised and friendly. The atmosphere in the MIUI platform is so nice. But Samsung’s operating system is not good and not humanised.” Similarly, “Samsung definitely has better hardware than Huawei, but worse management than Huawei. Huawei’s engineers look at the fans club and improve its system according to customers’ suggestions.” Xiaomi’s current strategy is the extension of Xiaomi’s strategy in its early period. In Xiaomi’s strategy in the current period, the core is still users who interact with Xiaomi via OII. OII is not only applied to interact with users who bought Xiaomi's smartphones, but also with users who bought all Xiaomi's products and services including TVs in their ecosystem, entertainment and e-commerce services, illustrated in Figure 3.11.

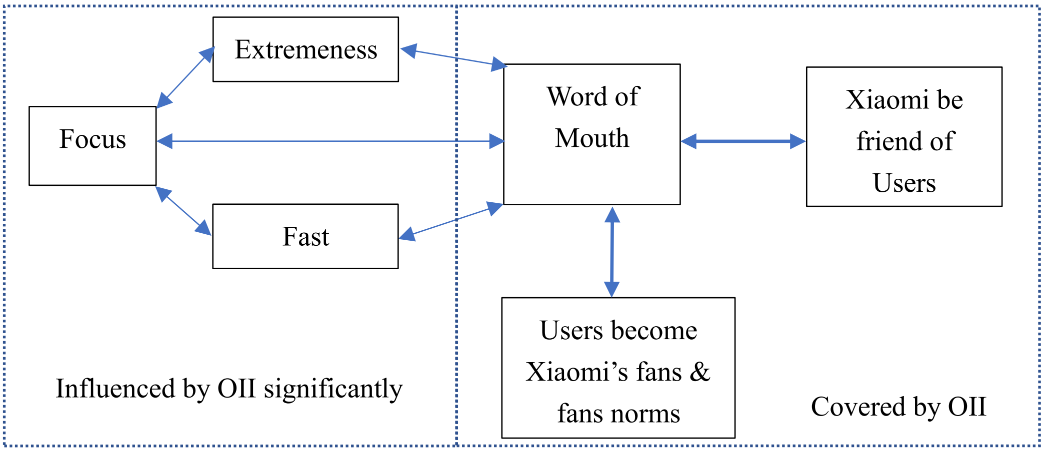

Figure 3.10 The Core Strategy of Xiaomi in Early Period

(amended from Lei, 2019 & 2020 and Gao, 2020)

"The essence of a business model is in defining the manner by which the enterprise delivers value to customers, entices customers to pay for value, and converts those payments to profit" (Teece, 2010: 172). Business model innovation is the "designed, novel, nontrivial changes to the key elements of a firm's business model and/or the architecture linking these elements" (Foss and Saebi, 2017: 201). From the external view, Xiaomi's fast success seems dazzling and its business model seems to be a novel and radical innovation. Careful and thorough analysis shows how online interactive innovation with millions of customers including fast iteration and mass-customization is at the core of Xiaomi's business model, which follows the philosophy of Xiaomi particularly its founder Jun Lei: "Xiaomi wants to be the friend of customers and create value for customers" (Lei, 2019 and 2020), consistent with Teece (2010). This also reflects the power of systematic innovation in new business models that the cumulatively minor improvements may result into a radical innovation. For instance, the first iPhone did not have any novel and radical breakthroughs in technologies, but iPhone 1 opened the era of mobile internet, which triggered the huge wave of digital economy.

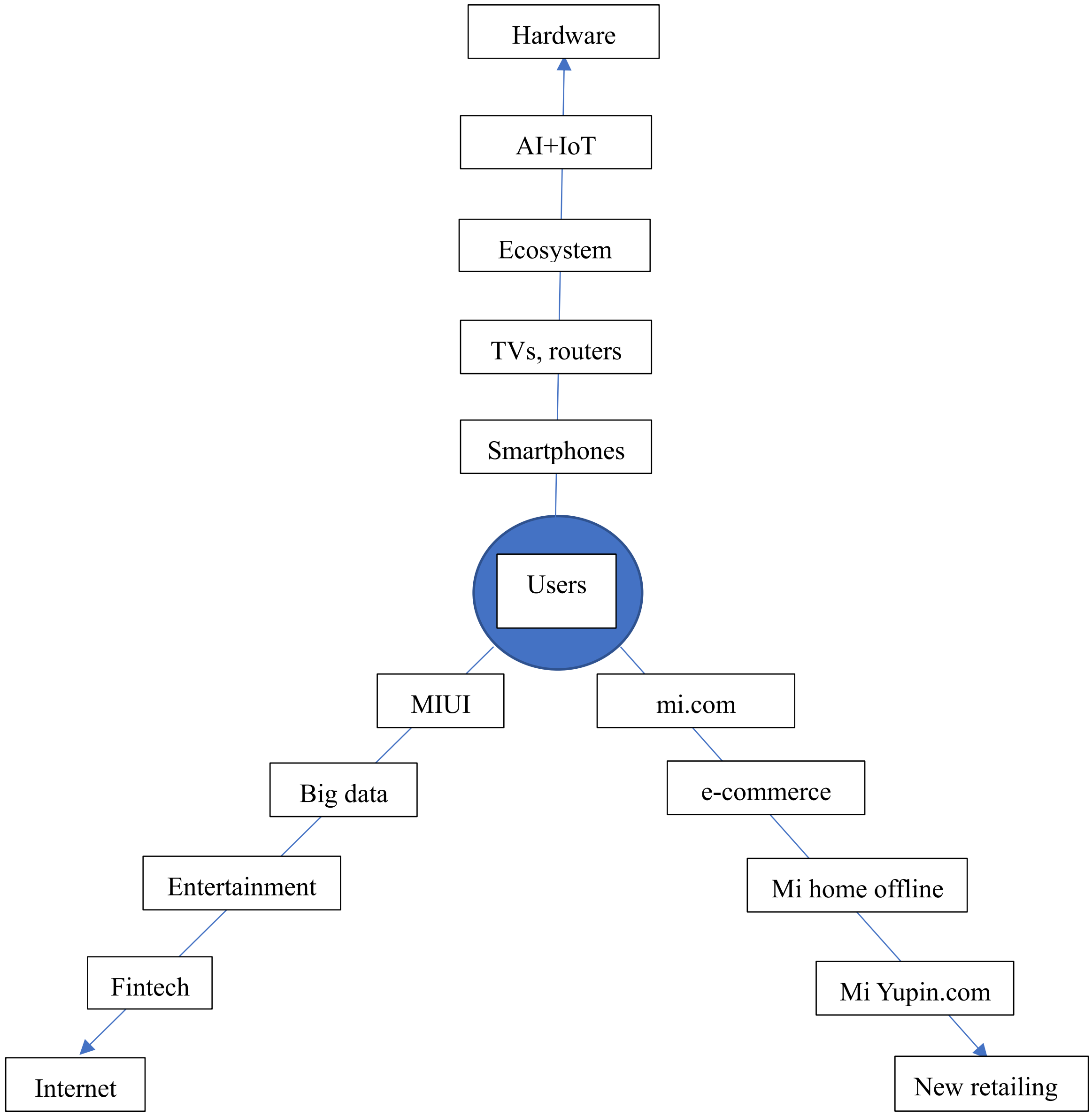

Figure 3.11 The Core Strategy of Xiaomi in Current Period (Source: Gao, 2020)

5) OII helps firms to realise the value of their IUs and their network, including economic value and noneconomic value such as being respected by Xiaomi and their suggestions are adopted by Xiaomi, etc. which can improve users' experience. OII helps to improve the service and enhance trust and loyalty between the firm and interactive users (Li, 2014). Interaction, mass-customisation, rapid iteration, trust and loyalty attract more potential customers and even lock extant users to firms and also increase their switching costs to change to other smartphones (Li, 2014; Gao, 2020).

Xiaomi's strategy is to produce a good product with mass-customisation and iteration and then attract more and more customers by creating and diffusing positive WOM, illustrated in Figure 3.10 (Gao, 2020). This is exactly the same strategy as Elon Musk uses in Tesla. Similarly, Jeff Bezos, the founder of Amazon, wrote: "The balance of power is shifting toward customers and away from companies" (Cunningham, 2017: 9).

6) OII helps Xiaomi to save costs for advertisements since Xiaomi uses positive WOM from OII (Fan, 2020), in contrast to the expensive advertisements of competitors, especially OPPO and VIVO, which spend a great deal on advertising in China and India. For example, OPPO beat VIVO in 2017 to win the sponsorship of the Indian national cricket team, reaching 62% of the Indian population for 5 years. OPPO paid US$ 160 million, five times more than the previous sponsor. But OPPO failed to convert this expenditure into shipments of smartphones in India (Zhao, 2018). Xiaomi occupied 30.9% of the Indian smartphone market in the second quarter of 2020, higher than the 21.3% for VIVO, 16.8% for Samsung and 12.9% for OPPO (Calalys, 2020a). Ironically VIVO, OPPO and Samsung spent large budgets for advertising in India, while Xiaomi did not (Chhabra and Metkar in Indian Institute of Management Studies and Research, 2020).

OII helps Tesla to save costs in public relationship building. Tesla cancelled its pubic relationships offices in the U.S. in 2020 but asked managers to interact with the public by social media such as Twitter or blogs and respond to the concerns of customers. When Gary Black, a former manager in Goldman Sachs suggested Tesla to hire an employee in pubic relationship. Elon Musk replied on Twitter: "Other companies spend money on advertising & manipulating public opinion, Tesla focuses on the product. I trust the people" (Musk, 2021). Simultaneously, Tesla's fans voluntarily produced and posted videos or comments online to support Tesla.

7) Xiaomi organised PFs to help each other, reply to questions and to manage themselves. This can save much human resources and time for Xiaomi. For instance, "Xiaomi sold 61 million smartphones in 2014 and obtained the largest market share in China with less than 300 employees in Xiaomi's department of smartphones, while other firms had thousands or more than 10 thousand employees with smaller shipments of smartphones" (Fan, 2020: 171). Also, OII helps firms to pinpoint the real needs of IUs and concentrate the attention and resources to satisfy the real needs of IUs efficiently, while lowering the risk to waste costs about R&D and human resources, etc. (Fan, 2020). Also, OII provides convenience for designers and manufacturers to 'focus' on improving products and enhancing customers' experience, continues fast iteration and customisation to realise Xiaomi's strategy. OII helps to enhance the productivity of Xiaomi.

8) All the cost reduction and high productivity aforementioned help Xiaomi to keep the price of smartphones at a relatively low level but with high quality, resulting into a high performance/price ratio, to attract more customers and sell Xiaomi's smartphone quickly (Lei, 2020). This is evidenced by the annual financial report of Xiaomi. The profitability rate of Xiaomi's smartphones is low, but its cash flow ability and its asset turnover rate is very good (Xiaomi, 2021b).

9) OII helped to attract about 368 million active users to Xiaomi's e-commerce platform which cut the transaction costs dramatically and brought Xiaomi to initiate new retailing in offline shops (Fan, 2020) and AI+IoT (Artificial Intelligence + internet of things). OII is the first step for firms to be digitalized. Only after the customers are connected online, other parts of firms including products, services, marketing, transactions and teams can become digitalized and online.

10) OII helps Xiaomi to enter foreign markets with much faster speed and much lower costs than its competitors. On September 20, 2010, the first version of MIUI was praised highly in the global conference of XDA-Developers Android Forums. Since then, MIUI became popular among enthusiastic fans globally (Lei, 2020). Many foreign fans have voluntarily translated Xiaomi's MIUI into other languages and diffused positive WOM about Xiaomi into many foreign online communities, e.g., India (Chhabra and Metkar, 2020). In July, 2011, fans in 24 countries translated MIUI into local languages voluntarily (Fan, 2020). This mass movement planted the seeds of Xiaomi's internationalization (Lei, 2020). Consequently, in the first quarter in 2021 even when the pandemic continued in Europe, Xiaomi's smartphone increased by 85% in European markets to be the second and Xiaomi's market share reached 23% in Europe, higher than Apple whose market share was 19% (Calalys, 2021).

11) OII requires Xiaomi to restructure its organisation and streamline its processes in order to enhance efficiency and efficacy. Also, OII helps Xiaomi to cultivate the enterprise norm which put customers at the centre. If someone generates a bug which was commented on badly by users in the online community, that employee will be awarded a green cushion called the 'Pig Head Award' to be put on his/her chair in the office to warn him/her for one week (Fan, 2020). These also help Xiaomi to avoid a complicated big firm hierarchy. For instance, some engineers changed their jobs from Google China to Xiaomi and they compared Google and Xiaomi. In Google China, every new change in the interface for users has to be reported and permitted from a senior manager in Google's headquarters in the U.S. The fastest case they had took 2 weeks to convince Google's headquarters to agree to develop a function to greet Chinese New Year. But in Xiaomi, the procedure is simplified to be 'feedback from users—select what users feel inconvenient—design new functions or improve existing functions in the product—test and release' without any hierarchical delay. Also, the employees can eat lunch and discuss with the founder or co-founders about their relevant works (Fan, 2020).

12) OII helps to move the S-curve to the left to grow earlier and faster than otherwise, hence OII accelerates innovation diffusion. In a word, OII is one of the main reasons for Xiaomi to grow rapidly. At the end of 2013, the President of Xiaomi whose revenue was 26.6 billion Chinese Yuan bet they would surpass Gree in 5 years in a ceremony on Chinese Central TV. Gree is the largest firm in air conditioners globally with revenue of 120 billion Chinese Yuan in 2013. In 2019, Xiaomi's revenue reached 205.8 billion Chinese Yuan with 16,783 employees and surpassed Gree's revenue of 200.5 billion Chinese Yuan with 85,222 employees. The revenue per employee of Xiaomi is 12.3 million Chinese Yuan, much higher than the 2.4 million Chinese Yuan of Gree (data from their annual reports).

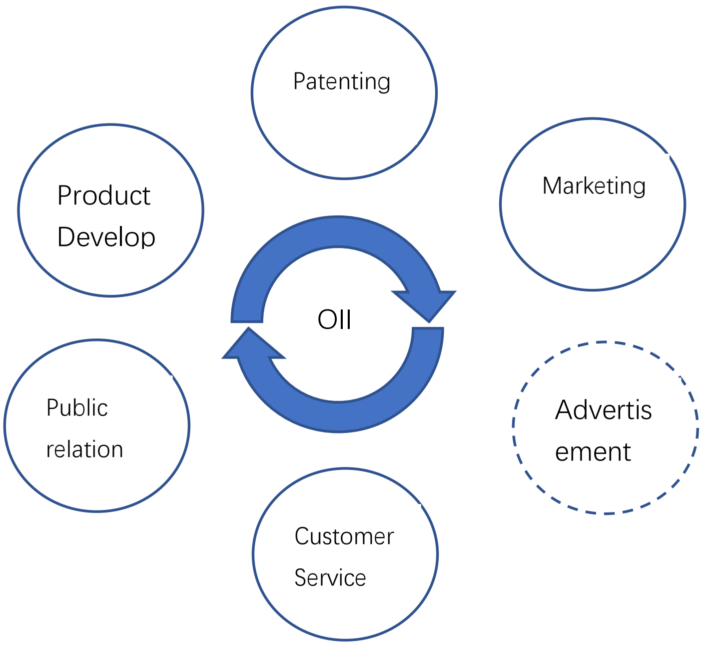

Figure 3.12 OII Integrates Six Parts by Accelerating Product Development, Patenting and Innovation Diffusion, Reducing Advertisement, Changing Marketing and Customer Service Dramatically

13) Usually in textbooks in any business schools, product development, patenting, marketing, advertisement, innovation diffusion, customer service and public relationships, etc., are separated in a firm. Now OII integrates all of them, reduces advertising, changes marketing and customer services dramatically and accelerates product development, patenting and innovation diffusion, as illustrated in Figure 3.12.

In a word, OII has a series of advantages evidenced by the successful practices of more and more innovative firms exemplified by Xiaomi in China and Tesla in the U.S.

However, no method is omnipotent including OII. OII is especially helpful for designers or producers to collect customers' suggestions to design new products or improve existing products at the early stage including ideation and iteration. In the later stage of Xiaomi, there are other strategies including AI+IoT for Xiaomi to develop sustainably. Also, there is another complementary method called 'customer to manufacturing' (C2M) at the later stage. Jingdong which is a top e-commerce platform firm developed a business model to connect customers and manufacturing directly by 'C2M'. Jingdong collects and analyses the data of 387 million active customers to find the real needs and niche markets. Then Jingdong provides the details of customers' demands and designs new products with manufacturers, followed by orders backed by guarantees. Hundreds of firms including Lenovo, HP, and Midea have been attracted to cooperate with Jingdong to produce C2M products.

3.6 Conclusion, limitations and future research

This study analyses the panel data about weekly suggestions and replies from customers and employees, weekly new functions in the operating system, annual patent applications and annual shipments of smartphones between 2012 and 2018 of Xiaomi, plus discussing ten other firms. It finds that the number of suggestions is positively associated with the number of replies with statistical significance and then the number of functions changed in the operating system. These are also associated with the annual numbers of patent applications and annual shipments with statistical significance. Also, there are group effects at the level of the different functions. This study suggests a new model about OII with 13 advantages, which are becoming increasingly popular in innovative firms in China, the U.S. and other countries. OII has been accelerating the speed of innovation and its diffusion drastically. This study clears some popular misunderstandings about "scarcity marketing strategy" or "hunger marketing strategy" and explains how the rapid success of Xiaomi between 2010 and 2018 can be ascribed to OII. Furthermore, there are significant implications about OII for new institutional economics. OII is important in management practice and it contributes to the understanding of innovation theory.

However, no method is omnipotent including OII and the effect of OII has a ceiling due to the “low hanging fruit” phenomenon and the “better than Beatles” problem. Because the size of Xiaomi’s data set is big, the standard error may become smaller resulting in bigger t and smaller p values. The data available in this study are not sufficient to find possible causal relationships. More case studies should be analysed to explore how OII might be generalised.

The next study will analyse the social network around innovation to explore individual innovative behaviours of firms’ employees, PFs or IUs. Innovators, earlier adopters, major adopters, late adopters and laggards will be identified and the differences among them will be compared to find methods to further accelerate product design and improvement. Also, if data about OII in different countries are available, it will be interesting to compare OII in different countries to see how the various institution, culture and customer’s habits will influence OII.

Chapter 4. How Does Education Influence Individual Innovation Behaviour? A Chain Relationship Model

Abstract

Individual innovation (Scott & Bruce, 1994; Hülsheger, et al., 2009; Gruber, Harhoff and Hoisl, 2012) and the economics of education (Temple, 2000; Jia & Liu, 2018) have been analysed in many publications separately, but the mechanism of how education influences individual innovation behaviour is still missing. By analyzing individual innovation activities of 2,078 employees who participated in 3,976 value engineering projects (VEPs) in one single company Firm A between January 2012 and June 2018, this study builds a series of multilevel models to explain how education measured by the highest degrees of employees improves individuals' innovation performance via creativity. Creativity acts at the middle of a chain of relationships and then contributes to enhance individual innovation performance, which is measure by three indicators. These are: 1) the total number of VEPs which the employee proposed as an applicant, 2) the total numbers of VEPs which the employee joined as either an applicant or a follower, and 3) the total number of patent applications from the VEPs which the employee joined over 6.5 years. This chain relationship is statistically significant in 2 models whose dependent variables (DVs) are the first and second indicator respectively and there is a direct association between education and the total number of patent applications in the third model. Furthermore, the first and second indicator have positive associations with the total economic value generated by VEPs with statistical significance. Also, there are strong group effects at the level of squads (or teams) in all models, which means the employees' innovation performance influences each other significantly in squads. Other factors including employees' age, gender, majors of bachelor degrees, hometown by province, monetary awards and financial investment for VEPs, etc. are controlled in the models. If apply principal

component analysis (PCA) to generate a composite index to measure the innovation performance of employees, the result is consistent with the previous findings. These triangulations prove that education has a positive relationship with individual innovation performance with reliability and validity.

Keywords: Education, Creativity, Individual innovation, Value engineering projects

4.1 Introduction

Innovation depends on the generation and commercialization of creative new ideas (Mumford, 2000) which first emerge in the mind of individuals and then are shared in teams (Crossan, Lane and White, 1999). "[I]nnovation at the organizational level depends critically on creativity at the individual level…Creativity originates in the individual" (Udwadia, 1990: 66-67). Since the individual is usually the basic unit to create new ideas, it is important to analyse individual innovation. There are many studies of individual innovation behaviour (Scott & Bruce, 1994; Shaker, Zeffane & Albaity, 2018) and the economics of education (Kaneko, 1980; Temple, 2000) separately. Among the long list of individual characteristics (Ford, 1996; Choi, 2004; Hammond, Neff, Farr, Schwall & Zhao, 2011), education plays an important role. But Hammond, et al., (2011: 90) conducted a meta-analysis including 303 correlations which were sampled from 1,820 publications between 1980 and 2008 and found that "[a] particular gap in the published literature is quantitative assessment of the predictors of employee or individual-level innovation." Furthermore, most of the existing publications focused on only one area and none has integrated the individual characteristics and creativity with the individual innovation performance. This study fills these significant gaps by analysing how education influences individual's creativity, and then improve individual innovation performance which contributes to create value for firms.

There are a few novel contributions of this research. First, many publications found education helps to promote economic growth at the national level or improve personal welfare at the individual level (Kaneko, 1980; Woodhall, 1987; Temple, 2000; Prais, 2012; Jia & Liu, 2018). But this study builds a series of multilevel models to explain the mechanism used to be in the black box: education improves the individuals' performance in creativity, which act as the variable in a chain relationship and then contribute to enhance individual innovation performance, measured by three comprehensive indicators. These are: 1) the total number of VEPs which the employee proposed as an applicant, 2) the total numbers of VEPs which the employee joined as either an applicant or a follower, 3) the total number of patent applications from the VEPs which the employee joined between 2012 and June 2018. This chain relationship is statistically significant in the two models whose DV are the first and second indicator aforementioned respectively and there is significant direct association in the third model whose DV is the total number of patent applications. This triangulation proves that education has a positive relationship with individual innovation performance with reliability and validity. Furthermore, the first and second indicators have positive associations with the total economic value generated by VEPs with statistical significance. Also, there are strong group effects at the level of the squad in all the models, which means the employees' innovation behavior influence each other significantly within squads.

The second contribution of the study is the comprehensiveness of measurements of individual innovation performance with high reliability and validity. As reviewed in Section 3.3.3.1, Schumpeter (1934) divided innovation into five categories, plus new business models in recent decades (Foss, Nicolai and Saebi, 2017). Existing publications commonly cover only one of these indicators: 1) the number of patents or patent applications; 2) the number of employees taking part in patenting and R&D which only covers a small proportion of total employees and reduces the representativeness of the sample; 3) the self-rating or rating by managers (Hammond, et al., 2011; Hülsheger, et al., 2009) which may be biased; 4) the rank of R&D

employees (Kim and Oh, 2002) which is skewed against those who prefer staying in laboratories to higher ranks with more administrative responsibility. 5) Data about sales and profits of every innovative product, which are useful to measure innovation performance and determine the financial compensation for R&D employees (Balkin and Gomez-Mejia, 1984) but are very difficult to access due to sensitive business secrets.

This study uses more comprehensive indicators as independent variables or control variables together, including the number of VEPs proposed or joined by employees, the number of patent applications, investments and net profits of every VEP, and awards from the firm to employees of every VEP. Additionally, employees' age, gender, the university major of employees' bachelor degrees, their working period in the firm, the home province, etc. are all controlled in the models. In this study, the results with comprehensive indicators are consistent with reliability and validity, better than single indicator such as annual patent application number or rating (Hülsheger, et al., 2009). If adopting principal component analysis (PCA) to generate a composite index to measure employees' innovation performance, the result is consistent with the findings with triangulation.

The third distinction of the study is the accuracy of measurement of individual creativity. Some extant studies measured individual creativity in laboratories in colleges. Those researchers designed some psychological, logical or mathematical questions to test students and marked the attitudes or answers of students or informants to measure their creativity. For instance, Baas, DeDreu, and Nijstad (2008: 795) conducted a meta-analysis on mood and creativity, including "66 reports with a total of 102 independent samples and over 7,000 research participants." "Experimental studies mostly involved students" (p. 796). Similarly, Hammond, et al., (2011: 91) reviewed publications about creativity and innovation and found "the majority of the included studies were laboratory experiments with student participants." This may be significantly biased, since creativity and novelty depend on different contexts and their meanings are different in various periods (Simonton, 1997, 2009, 2012; Tang & Werner, 2017). In contrast, this study analyses 2,078 employees who joined 3,976 value engineering projects (VEPs) between January 2012 and June 2018. The firm organizes senior experts to assess and mark the scores of creativity, activeness and teamwork of each VEP in every month and released the scores to all employees to welcome comments democratically, whose purpose is to build "fair performance evaluation systems" (Kim and Oh, 2002: 19). The benchmark to assess creativity is the knowledge and skills in the areas which they are very familiar with. Also, the knowledge and skills have been developed, tested, accumulated and improved in production in the high-tech. factories for years, so they are very objective and practical to measure and reflect the creativity of every VEP accurately. This is consistent with the measurement approaches of creativity proposed by Rhodes (1961) and developed by Kozbelt, Beghetto, & Runco (2010), Simonton (2012) and Tang & Werner (2017). The measurement is much better and more practical than studies in psychology laboratories with small samples usually composed of students over relatively short periods. Studies in this area previously used relatively smaller sample sizes compared to this study (Anderson, DeDreu & Nijstad, 2004).

Other contextual factors (West & Wallace, 1991; Shalley, Zhou and Oldham, 2004) including the extent of democracy in management, knowledge sharing between employees and teams, etc., are included in the answers to the questionnaires conducted in 2018. This reduces the large sample taken over 6.5 years to a smaller sample of one year. Hence, these contextual factors are separately analysed in the next study with the results of surveys conducted in 3 firms in 2018. This study focuses on the data aforementioned in Firm A between 2012 and 2018.

In the following sections, Section 4.2 reviews the existing publications about individual innovation, the factors influencing individual innovation, the relationship between education and individuals' creativity, various kinds of measurements of individual innovation performance and develops hypotheses. Section 4.3 covers the research design, case selection, dependent variables (DVs), independent variables (IVs) and control variables (CVs). Section 4.4 presents the results of models with various DVs, IVs and CVs respectively. Then the results are discussed in the following passages. Section 4.5 addresses the conclusions and limitations. In this chapter, "proposed as an applicant" refers to an employee who originally propose VEPs, while "join VEPs" includes the employee who either proposed as an applicant or took part in VEPs as a follower.

4.2 Literature review and hypotheses development

4.2.1 The importance of individual innovation

Innovation has been considered as the dynamic to drive economic growth for decades (Solow, 1957). Innovation consists of two broad stages: creativity and implementation (Patterson, 2002; Farr, Sin & Tesluk, 2003). Creativity focuses on the generation of novel ideas (Unsworth, 2001; Anderson, DeDreu & Nijstad, 2004). Innovation depends on the generation and commercialisation of creative and novel ideas (Mumford, 2000), which are invented by creative individuals in particular circumstances of time and place. Crossan, Lane and White (1999) emphasised that creative ideas first emerge in the mind of individuals and then are usually shared in teams. "Talent is the bedrock of a creative society" (Yusuf, 2009: 1). The individual is usually the basic unit to create new ideas, no matter if the individual works alone or in teams. Taylor and Greve (2006) found individuals were more effective than teams in idea creation. Hence, one of the main sources of innovation is employees, whose innovation behaviour can influence firms' performance and competitiveness significantly (Agars et al., 2008). Therefore, it is important to explore the factors which influence the individual innovation.

Similarly, "[h]uman capital, generally seen as a set of knowledge, abilities and skills of the individuals, …was considered to be a stimulus of the innovation process" (Popescu & Diaconu, 2008: 560). Human capital can be divided into three types: industry-specific, firm-specific and individual-specific human capitals. Industry-specific and firm-specific human capital focus on capabilities useful in a specific industry or firm, which influence innovation with limits. In contrast, "individual-specific human capital implies knowledge that is applicable to a large range of firms and industries [and has] a huge capacity of innovation induction" (Popescu & Diaconu, 2008: 560).

However, while there are many publications about innovation at national level, industry level, firm level or team level (West and Wallace, 1991), less research has been conducted at the individual level. After conducted a comprehensive meta-analysis, Hammond, et al., (2011: 90) noted that "[a] particular gap in the published literature is quantitative assessment of the predictors of employee or individual-level innovation." This study fills this gap by analysing the factors that influence individual innovation and how they contribute to create value for firms.

4.2.2 The factors influencing individual innovation

There are some existing publications about individual innovation. Farr, Sin & Tesluk (2003) found various individual, job and contextual factors may influence individual innovation, especially in the creation and implementation of ideas. Hammond, et al., (2011: 90) identified "four areas of particular importance for innovative performance (individual differences, motivation, job characteristics, and contextual influences)". Hülsheger, Anderson, Salgado and Jesus (2009) reviewed 104 independent studies about team-level innovation in the workplace between 1978 and 2008. They examined a series of variables at individual or team level including self-ratings vs. independent ratings of innovation, etc. Besides the 'big five' personality traits (Roberts & Delvecchio, 2000; Karwowski & Lebuda, 2016), Patterson (2002: 115) explored "eight important individual variables that predict innovation in the workplace… (1) intelligence [quotient], (2) knowledge, (3) motivation, (4) personality, (5) emotional intelligence, (6) mood states, (7) behaviours, and (8) values."

Among these extant publications, the kind and level of education is at the centre of individual innovation differences. Education is considered to influence the individual innovation and is studied (Hammond, et al., 2011; Hülsheger, et al., 2009). Education provides basic knowledge, skills and credit for individuals to become qualified employees (Tierney & Farmer, 2004). Individuals gain knowledge and skills via education which forms the background for them to think creatively and to solve problems in practice (Amabile, 1983). Firms offering formal training can improve innovation in developing countries including Kenya, Tanzania and Uganda (Uden, Knoben & Vermeulen, 2014) and patenting in China (Sun, Li & Ghosal, 2020). Hence, the highest degree of the employee which measures the education of employees is coded as hestdegr in Table 4.2 to be the independent variable in this study.

Different majors in education provide individuals with various expertise and advantages. Gruber, Harhoff and Hoisl (2012) found that inventors who majored in basic sciences can generate more patents than others with only engineering degrees. Tiwana and McLean (2005) analysed 142 participants in 42 information systems development projects and found if teams can integrate the expertise of individuals, they can achieve better performance. Also, they found that the expertise of employees should be complementary to each other and be integrated to achieve creativity especially at the team level. Hence, this study includes the majors of the employees when they obtain bachelor degrees. The majors are coded as bmajorid in Table 4.2 as the control variable.

Job characteristics also influence individual innovation (Oldham & Cummings, 1996). If the employee works in a special job which provides more opportunities for inventions and innovation, his/her innovation performance will be better than others. In factories, similar jobs are usually clustered in the same squad. Hence, squad codes which refer to job characteristics are included in this study. For instance, there are squads called 'wet etching', 'dry etching', 'film production', 'quality control', 'power supply', etc. in Firm A.

Contextual influences are also important for individual innovation (Udwadia, 1990; West & Wallace, 1991; Shalley, Zhou and Oldham, 2004), including "vision, task orientation, and external communication" (Hülsheger, et al., 2009: 1128). For instance, 3M integrated human resource management and strategic management and they built friendly and innovative institutional norms to encourage employees (Angle, Manz & Van de Ven, 1985). Scott & Bruce (1994) found that the climate for innovation in squads, divisions or departments should be open and safe for different opinions. The concept of "democracy of management" measures if the management welcomes different opinions and suggestions from employees or not (Choi, 2004). Madjar (2008) found that it is important for different teams to share experience and lessons. Usually, employees (level 1) are organised in different squads (level 2) in divisions (level 3) within departments (level 4), hence relationships between social structural context and behavioural outcomes are important (Spreitzer, 1995). Therefore, individual innovation is probably significantly influenced by the context of teams or departments (Scott & Bruce, 1994). This study builds multilevel models to test if there are group effects at the levels of squads or divisions or departments (Rabe-Hesketh and Skrondal, 2012). Hence, employees (level 1) are coded as empid, squads (level 2) are coded as sectid2, divisions (level 3) are coded as divisid and departments (level 4) are coded as deptid in Table 4.2, which are used in the multilevel models.

Incentives and motivational components are important and are analysed in most publications about individual innovation (Amabile, 1983; Ford, 1996; Scotchmer, 2006). Scott and Bruce (1994: 580) argued that "[s]ince the foundation of innovation is ideas, the study of what motivates or enables individual innovative behaviour is critical." Motivation includes the organisation payment such as compensation (Baer, Oldham & Cummings, 2003), systematic incentives and support from management (Axtell, Holman & Wall, 2006). Also, existing publications suggested the positive correlation between innovation and incentives (Scotchmer, 2006) including compensation (Amabile, 1996; George & Zhou, 2002). Balkin and Gomez-Mejia (1984) found financial compensation for employees in R&D based on sales volume and profitability is important to activate R&D employees. In this study, the compensation to motivate individual innovation in the firm is systematically examined. Hence, the financial award from Firm A to each VEP are included in this study. The natural logarithm of the total award of the VEPs which the employee joined over 6.5 years is coded as lnmxeptveward in Table 4.2 as the control variable.

Kim and Oh (2002: 19) conducted a survey covering more than 1,200 R&D scientists and engineers in R&D organizations in South Korea and found that although R&D employees paid attention to compensation, they cared more about that the "lack of fair performance evaluation systems could be the biggest obstacle towards implementing such a compensation scheme." In this study, Firm A organises senior experts to assess and mark the scores of creativity, activeness and teamwork of every VEP in every month and released the score to all employees to welcome comments democratically, in order to build "fair performance evaluation systems" (Kim and Oh, 2002: 19). Hence, the scores of creativity, activeness and teamwork of every VEP which the employees joined are included in this study and are coded as lnveetcrea, lnveetact and lnveetteam respectively in Table 4.2.

Another important factor which influences individual innovation behaviour is the resources provided by the organisation, including equipment, budget and information support (Udwadia, 1990; Madjar, 2008). For instance, the management of 3M allows employees to use 15% of their working time to invent what they want by using the equipment and resources of 3M, which helped 3M to become one of the most innovative firms. This study also includes the investment from the firm into every VEP conducted by employees. Therefore, the natural logarithm of the total investment of the VEPs which the employee joined over 6.5 years is coded as lnveetinvn in Table 4.2 as the control variable.

4.2.3 Integrating education with creativity, activeness and teamwork

Education plays an important role in individual innovation (Tierney & Farmer, 2004; Hammond, et al., 2011; Pisanu & Menapace, 2014) and is directly associated with creativity, activeness and teamwork. Without creativity, activeness and teamwork cultivated by education, the employee probably does not want, or have the capability to generate creative ideas or to overcome difficulties to generate, improve and apply any inventions.

Based on existing definitions, Ochse (1990: 2) regarded creativity as being both “original (new, unusual, novel, unexpected) and also valuable (useful, good, adaptive, appropriate).” Guilford (1950) began the modern research about creativity in 1950 and Rhodes (1961) suggested the 4P’s Model of Creativity. A new interdisciplinary science of creativity was named as creatology (Aleinikov, 2013). Udwadia (1990) argued that the important components of individual’s creativity are cognitive abilities and personality disposition. Cognitive abilities determine the potential of individual creativity, which include “intelligence [quotient], knowledge or expertise, and thinking style” (p. 68). Personality disposition helps individual creativity to generate useful outcomes, which include “curiosity, perseverance, high energy, intrinsic motivation, hard work, autonomy, independence of judgement” (p. 68). These are consistent with the findings of Barron (1969), Barron & Harrington (1981), Yusuf (2009) and Tang & Werner (2017). Creativity may be expressed in music or art, but the economy favours creativity to generate new knowledge which results into innovations with economic value (Yusuf, 2009). Creativity has been considered as one of the key factors influencing individual innovation (Rank, Pace & Frese, 2004). Udwadia (1990: 65) argued: "creativity… is the most basic and the most critical element in the process of innovation." Hence, lnveetcrea (the natural logarithm of the total scores about creativity of the VEPs which the employee joined assessed by the firm over 6.5 years) is included in the analysis of this study.

Heunks (1998) found the individual's education level influences the individual's creativity and innovation. The three components of cognitive abilities (Udwadia, 1990) aforementioned are directly relevant to education. Intelligence quotient (IQ) is a factor to influence individual creativity. Education is not a perfect but it is a popular social system with the relatively high reliability to screen talented individuals with high IQ. Simon (1988: 16) emphasised knowledge and expertise as "as the prerequisite to creativity". Knowledge from education helps the employee to generate creative ideas (Amabile, 1983). Bill Gates, the founder of Microsoft, is thought of as one of the most creative persons in the world and he worked with a lot of creative programmers and engineers in Microsoft. His view is that "[c]reativity is inspired by taking tests. I have never met a software developer who can't use multiplication. Who designed the most imaginative video game in the world? It's Japanese. I never thought they were people who worked on rote learning skills. Among the best software developers working for me are Japanese. You have to remember the original knowledge before you can expand to a wider field" (Friedman, 2006: 320). Education also trains students to learn and develop their efficient thinking style. Consequently, since education plays an important role to cultivate individual's creativity. Here is the first hypothesis:

Hypothesis H4.1: There is a significantly positive relationship between the education measured by highest degree of the employee and the scores about creativity.

The components of personality disposition (Udwadia, 1990) are also influenced by education. Intrinsic motivation is an important personal trait for creativity (Csikszentmihalyi, 1990, 2008; Gardner, 1993; Xu, Jiang & Wang, 2019). Activeness measures the individual's willingness and determination to think harder to generate creative ideas and work harder to overcome any possible difficulties in invention and the application of those inventions. It is important to consider that an employee who spends more time, money and effort than others to obtain higher degrees, he/she would be more active in work to harvest the benefits from their higher education. As part of this they are more likely to propose new ideas or join innovative teams. Invention is to explore the unknown world and create something that never existed before. Hence, invention is always full of trial and error with unpredictable difficulties. It is well known that Thomas Alva Edison tried more than six thousand kinds of materials to find the best one to be a suitable electric lamp filament. Hence, in this study, lnveetact (the natural logarithm of the total scores about activeness of the VEPs which the employee joined assessed by the firm over 6.5 years) is included as the control variable.

Knowledge has been growing at an exponential rate and everyone can only learn a minimal proportion of the ocean of human knowledge. The creative ideas and breakthroughs usually emerge by combining different knowledge from various disciplines. This results in the necessity of more and more interdisciplinary teamwork (Yusuf, 2009). For instance, most of the early breakthroughs in molecular biology were made by researchers not in traditional biology but in other disciplines. Erwin Schrödinger in physics published *What is Life? The Physical Aspect of Living Cell* in 1944, which led many physicists to change their research to biology. Former physicists including Rosalind Franklin, Francis Crick and Maurice Wilkins collaborated with the biologist James Dewey Watson to make significant contributions to find the structure of DNA, which opened the gate of molecular biology. Furthermore, original ideas are rarely mature or complete when they emerge. Commonly the inventor needs colleagues with complementary knowledge and skills to develop and improve their original idea and apply it to production. Therefore, teamwork is also important for individual innovation. Girotra, Terwiesch & Ulrich (2010: 591) compared two types of organisations: one where employees work together all the time in "team structures" vs employees who work independently and later together, which they called "hybrid structures". They found if employees work in "hybrid structures", they can generate more and better ideas and commercialize those ideas. Teamwork figures in most curriculums from primary school through university. Through formal education, employees learn that teamwork is necessary for success. Hence, in this study, lnveetteam (the natural logarithm of the total scores about teamwork of the VEPs which the employee joined assessed by the firm over 6.5 years) is included as the control variable.

Florida (2002) argued that creativity and innovation are the dynamics for economic growth and a new segment of labour "the creative class" has been increasing in developed countries, followed by "creative industries" (Hesmondhalgh, 2007) and "creative economy" in geographical regions (Howkins, 2007). In his book *The Creative Capital of Cities: Interactive Knowledge Creation and the Urbanization Economies of Innovation*, Kratke (2011) tried to prove that creativity is important for regional economic growth by analysing the share of employment in science and technology in different areas in Germany and in regional economic growth. However, he noted that his regional analysis "does not produce in-depth information on individual cooperation links" (p. 126). Similarly, economic research shows that education is important for individuals to improve their living standards and make contributions to firms (Woodhall, 1987; Kaneko, 1980; Jia & Liu, 2018), or improve productivity (Temple, 2000; Prais, 2012). However, little research has been done to explain the micro-mechanism about how education help individuals to improve their capabilities to foster creativity, to improve individual innovation performance and make contribution to firms and the economy.

This study fills these significant gaps by building a series of chain relationship models with triangulation, integrating education, associated personal factors of employees and creativity, to improve the individual innovation performance and make economic contributions to the firm.

4.2.4 Measuring individual creativity and innovation performance

It is not easy to measure creativity, novelty and originality, which are the keys to measure individual innovation performance. Creativity, novelty and originality depend on different contexts and their meanings vary in different periods (Simonton, 1997, 2009, 2012; Tang & Werner, 2017). In the 4P's Model of Creativity, Rhodes (1961) suggested four approaches to analyse and measure creativity: 1) a product-related approach assesses the creative product such as an idea, process, etc. A person is "considered creative if [he/she is] associated with the creative product (Tang & Werner, 2017: 54). Since the product approach measures the tangible objects, it is the most objective approach to measure creativity with reliability and validity (Kozbelt, Beghetto, & Runco, 2010). 2) A process-related approach addresses "how the creative process is organized" or "how thinking should be organized in order to achieve better result" (Tang & Werner, 2017: 57). 3) A personality-related approach addresses personal characteristics such as education, intrinsic motivation, independent judgement, industriousness, etc. 4) A press-related approach analyses environmental and contextual factors including job characteristics, atmosphere in teams, support from management, etc. These factors are accounted for in this study either directly or by proxy.

Amabile (1983 and 1996) developed the Consensual Assessment Technique (CAT) to measure creativity, novelty or originality. A group of experts in that area reach the consensus that it is creative or novel, so they mark it with different score. Hennessey, Amabile, & Mueller (2011) found the CAT could be validated in many settings and argued this method is usually reliable and valid. This method is adopted by Firm A to assess and mark the creativity, activeness and teamwork of the value engineering projects (VEPs) with reliability and validity.

There are numerous methods to measure individual innovation performance, each with different advantages and disadvantages. First, Balkin and Gomez-Mejia (1984) found that sales and profits of innovative products are important to calculate the financial compensation awarded by firms to R&D employees. However, successful products commonly used many different inventions, therefore it is difficult to identify the percentage contribution of each invention separately. Also, most accounting departments of firms do not calculate or record the cost and profits of each product which resulted from each invention generated by employees. Even if some firms assess such data, this is usually regarded as a business secret; hence few firms want to expose such data to academic research.

Second, some studies about individual innovations use the number of patents to measure the outcomes of innovation. However, most inventions and improvements are not qualified for patenting and it takes about 3 years for a utility patent to be granted. Some firms do not want to file patents to protect their most important breakthroughs, since the applications are exposed to the public and other companies can learn about what competitors are developing (Tang and Huang, 2002).

Third, Hammond, et al. (2011: 95) stated that "[m]ost studies of individual innovation that we found use either self- or supervisory-ratings as the outcome measure(s) of innovation". Such ratings including key performance indicator (KPI) will be biased by the perspectives of employees or their supervisors. Fourth, as a result, some researchers tried to use indirect indicators to measure and compare the output of R&D employees. For instance, some publications use the ranks of R&D employees in the firms to indicate the achievements of R&D employees (Kim and Oh, 2002). They assumed that the most successful R&D employees will be promoted to higher positions such as becoming a director of R&D or a department. This indicator is significantly biased, since many R&D employees do not want to be promoted to have more administrative responsibility but like to stay in their laboratories to continue their interesting R&D work. Fifth, most of the existing publications about individual innovation focuses on R&D employees only. But innovations in firms are not only the output of R&D employees, but also contributed by the employees in other departments including marketing and customer services who interact with customers frequently and collect the demands from customers, particularly in the open innovation and interactive innovation discussed in Section 2.1.6 and Chapter 3. Also, R&D employees are only a relatively small proportion, commonly 5-20%, of the total employees in technology firms, which may result in significant selection bias.

Value engineering (VE) was invented by Lawrence D. Miles at General Electric in 1947 to “provide the highest customer acceptance at the lowest cost” (Miles, 1961), which was then applied to many industries. Japan learned VE from the U.S. in the 1950s and introduced VE to China in 1979. VEPs are very popular and attract many employees to participate, e.g., 71% of total employees joined VEPs in the sampled firm in this study. This makes them sufficiently representative. In VEPs, the applicants propose projects by generating original ideas, organizing and leading team members to develop and apply the ideas to processes or production. Followers in the teams may also generate creative ideas and/or provide necessary knowledge or skills to solve problems in order to commercialize inventions or improve the original ideas.

Similar to CAT (Amabile, 1983 and 1996) aforementioned, Firm A organises a group of experts with sufficient knowledge and expertise in those areas and assess the creativity, activeness and teamwork of each VEP respectively in every month. The benchmark to assess creativity is the knowledge and skills that the experts have developed, tested and accumulated in production for years, so it is very objective and practical to measure and reflect the creativity of every VEP accurately. Hence, this study adopts such marks of the VEPs to measure the individual creativity of each employee who joined different VEPs. This is consistent with the product-related approach (Rhodes, 1961; Kozbelt, et al., 2010; Tang & Werner, 2017) aforementioned. The accounting department calculates the economic contribution of each VEP. Based on these, Firm A awards qualified teams periodically. All the details and data of VEPs and marks are released to all employees in the firm's intranet to welcome comments. This kind of assessment has been tested and improved with the democratic feedback of thousands of employees for more than 6 years. Hence, this method has high reliability and validity. This is also why the marks of the creativity, activeness and teamwork are coded in Table 4.2 as variables in the models.

Additionally, the data about VEPs and personal information of employees are accessed and analysed. Therefore, VEPs are a better index to analyse individual innovation. This study analyses a typical firm whose 2,078 employees (about 50% of total employees) took part in 3,976 VEPs between 2012 and June 2018 to examine individual innovation. Since each single indicator aforementioned probably measure only one aspect of individual innovation without comprehensiveness, this study uses four indicators to measure the output of individual innovation with comprehensiveness: the total number of VEPs which the employee proposed originally as an applicant (coded as lnveeroleta in Table 4.2), the total number of VEPs which the employee joined as either an applicant or a follower (coded as lnveemt in Table 4.2), the total number of patent applications (coded as lnveemtpat in Table 4.2) and the total economic value generated by VEPs (coded as lnveemtecn in Table 4.2) which the employee joined between 2012 and June 2018. The indicators are more comprehensive and complete than other indicators which focus one or two indicators only.

As discussed above, creative and novel ideas are important for innovation (Mumford, 2000). If the employee is more creative, he/she may have more novel ideas to propose and generate more VEPs. Also, they may be interested in others' creative ideas and join more VEPs advocated by others. These can generate more patent applications. Here are the second group of hypotheses.

Hypothesis H4.2A: There is a significantly positive relationship between the natural log of the total scores about *creativity* of the VEPs which the employee joined assessed by the firm over 6.5 years (lnveetcrea) and the natural logarithm of the total number of VEPs which the employee *joined* (lnveemt).

Hypothesis H4.2B: There is a significantly positive relationship between the natural log of the total scores about *creativity* of the VEPs which the employee joined assessed by the firm over 6.5 years (lnveetcrea) and the natural logarithm of the total number of VEPs which the employee *proposed* as an applicant (lnveeroleta).

Hypothesis H4.2C: There is a significantly positive relationship between the natural log of the total scores about *creativity* of the VEPs which the employee joined assessed by the firm over 6.5 years (lnveetcrea) and the natural logarithm of the total number of *patent applications* from the VEPs which the employee joined (lnveemtpat).

Finally, it is interesting to check if the natural logarithm of the total number of VEPs which the employee *joined* (lnveemt) or *proposed as an applicant* (lnveeroleta) or the natural logarithm of the total number of *patent applications* from the VEPs will contribute to the natural logarithm of the total economic value generated by VEPs (lnveemtecn) or not. Hence, here is the third group of hypotheses.

Hypothesis H4.3A: There is a significantly positive relationship between the natural logarithm of the total number of VEPs which the employee *joined* over 6.5 years (lnveemt) and the natural logarithm of the total economic value generated by VEPs (lnveemtecn).

Hypothesis H4.3B: There is a significantly positive relationship between the natural logarithm of the total number of VEPs which the employee *proposed as an applicant* over 6.5 years (lnveeroleta) and the natural logarithm of the total economic value generated by VEPs (lnveemtecn).

Hypothesis H4.3C: There is a significantly positive relationship between the natural logarithm of the total number of *patent applications* from the VEPs which the employee joined over 6.5 years (lnveemtpat) and the natural logarithm of the total economic value generated by VEPs (lnveemtecn).

4.3 Research design and cases selection

The key research question is: How does education influence the individual innovation behaviour via creativity to make contributions to the firm? Quantitative methods are adopted to analyse the factors about employees who took part in VEPs. In the real world and academic research, it is very popular to find observations in multiple levels or hierarchy structure. For example, the employees (level 1) work in different squads (level 2) in divisions (level 3) within departments (level 4) in this study in Chapter 4. Similarly, students are grouped in classes in schools in districts in cities in provinces. There are two main quantitative methods to analyze data with multiple levels or hierarchy structure: multilevel models (MLM) and structure equation models (SEM). MLM has some advantages as discussed in the following section which is applied widely (Gelman and Hill, 2007; Rabe-Hesketh and Skrondal, 2012; Snijders and Bosker, 2012). SEM usually is applied in the areas of psychology or sociology, etc. In psychology, there are latent variables which are difficult to measure and observable indicators have to be used to measure such latent variables (Acock, 2013; Qiu & Lin, 2009; Wang, Wang & Jiang, 2011). However, in this study, most of the variables are not latent variables and can be measured directly, e.g., Firm A uses the Consensual Assessment Technique (Amabile, 1983 and 1996) to measure creativity. Hence, SEM is not applied in this study.

4.3.1 Multilevel analysis

In the following, multilevel models (MLM) is explained through the example of the firm, e.g., employee-level as level 1, squad-level as level 2, division-level as level 3 and department-level as level 4 in the study. The employees working daily in the same squads with the same context can influence each other by close knowledge sharing or collaboration, hence the data about their performance have significant correlations. If ignoring the correlations among such dada and run OLS model directly, the assumptions about independence for the models to be best linear unbiased estimator (BLUE) will be violated and the standard error may be wrong, which may result in a false p-value for decision-making (Gujarati and Porter, 2009). If there is only one simple model as following, ξ_{ijk} will be total residual which mixes all the residuals and may result in bias and become misleading.

$$y_{ijk} = \pi_{0jk} + \pi_{1jk}t_{ijk} + \xi_{ijk} \tag{3.1}$$

By only focusing on data at the employee level while ignoring IVs and CVs about the structure and influences of the squads, divisions or departments, there may be bias due to missing variables or structures of the squads, divisions or departments which may be influential. The standard error will be underestimated, resulting in a bigger z or t value and a bigger p-value. Hence the effect could be statistically significant which is actually false, resulting in Type I error (Steele, 2008 and 2013).

On the contrary, MLM has some important advantages which can avoid possible bias and solve the potential problems discussed above. 1) MLM helps to obtain correct standard errors of coefficients and p-value avoiding to be biased due to various problems discussed above. 2) MLM can “explore the effects of group-level [squad-level in this study] variables while simultaneously allowing for the possibility that y [the dependent variable] may be influenced by unmeasured group factors. Variables defined at level 2 are often called contextual variables and their effects on an individual's y-value are called contextual effects…If contextual effects are of interest, it is particularly important to use a multilevel modelling approach because the standard errors of coefficients of level 2 variables may be severely underestimated when a single-level model is used" (Steele, 2008: 33). 3) MLM helps researchers to "investigate the nature of between-group [between-squads in this study] variability (Steele, 2008: 2). 4) MLM can help "to distinguish within- and between-cluster effects of lower level covariates" (Rabe-Hesketh and Skrondal, 2012: 2). 5) MLM can process the cross-level interactions of independent variables in different levels. 6) MLM can help researchers to split the mixed residuals in single-level models into different parts and explain most of the residuals by IVs at different levels respectively. As a result, the residual left in the model will be independent and normally distributed, which obey the assumptions.

Furthermore, there are two methods to measure the variance components among different levels discussed above. The first one is variance partition coefficients (VPCs). "VPC statistics report the proportion of the response variance that lies at each level of the model hierarchy" (Leckie, 2013: 19). The range of VPC is from 0 (no differences between groups) to 1 (no differences within group). For instance, if the VPC is 0.3, variations for between groups occupy 30% and within-groups occupy 70%. (Leckie, 2013).

As reviewed in Section 3.3.1.2, Intra-class correlation coefficients (ICCs) or ρ measures "the expected degree of similarity (or homogeneity) between responses within a given cluster" (e.g. squads in this study in Chapter 4) (Leckie, 2013: 20). "For simple multilevel models, the VPC is equal to the intra-class correlation coefficient [ICC] which is the correlation between the y-values of two randomly selected individuals from the same group." However, "in more complex models, such as those including random coefficients", VPC will not be equal to ICC (Leckie, 2013: 21). As discussed above, MLM can divide the mixed residual into the residuals at different levels and figure out VPCs or ICCs, hence MLM is helpful to solve the possible problems about autocorrelation.

Based on the advantages, MLM is applied in this study in Chapter 4. The unit of analysis is each employee. The total number of VEPs which every employee joined as either an applicant or a follower between 2012 and June 2018 are summed together. Hence, it is not panel data, but the data with multiple levels since employees (level 1) work in different squads (level 2) in divisions (level 3) in departments (level 4).

4.3.2 Spurious association and chain relationship

There are various relationships among variables, especially spurious association and chain relationships, which have been carefully taken into account in this study. Problems arise if both X_1 and Y are associated with X_2. X_1 and Y are associated when not controlling X_2. But when controlled for X_2, X_1 and Y are not associated anymore. One possible explanation is that X_1 and Y have a spurious association (Agresti, 2009; Angrist and Pischke, 2009 and 2014). Spurious associations are very common. For instance, in the summer, there is both higher consumption of ice cream and a higher rate of crime in the evening in cities, because they are both influenced by the summertime temperature, which induces people to consume more ice cream and stay outside in the evening more frequently, as illustrated in Figure 4.1.

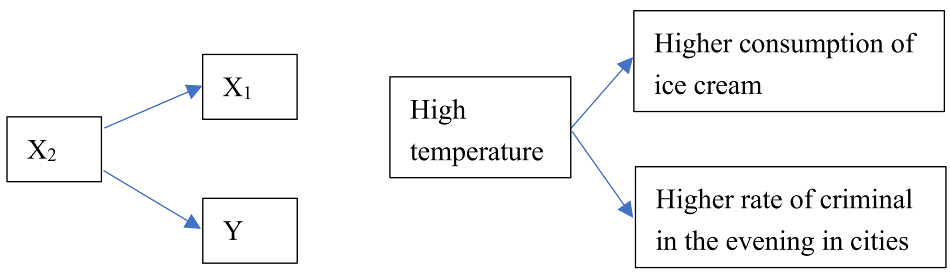

Figure 4.1 The Spurious Association
(Source: Amended from Agresti, 2009)

Another possible explanation is that X_1 and Y have the chain relationship. X_1 influences X_2, and then X_2 influences Y. For instance, higher education results into higher income, which results in longer life expectation, as illustrated in Figure 4.2.

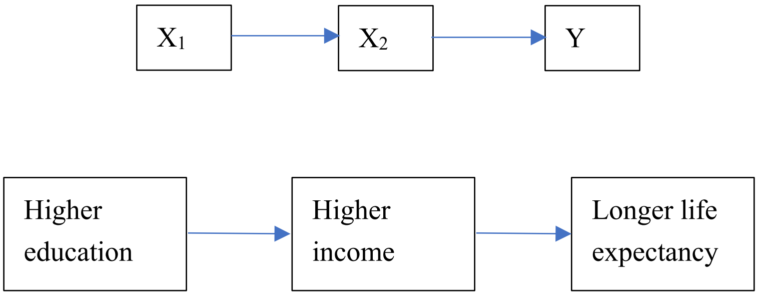

Figure 4.2 The Chain Relationship
(Source: Amended from Agresti, 2009)

4.3.3 Case selection and data collection

As discussed in Section 4.2.4, there are some quantified indices to measure individual innovation, such as KPI, patenting and the data about VEPs. Ratings including KPI are significantly influenced by the managers' personal opinions which may be biased. Usually only a small proportion of employees take part in patenting, and so this cannot cover most employees. But VEPs commonly attract most employees and are a better representative to analyse the individual innovation of employees. Therefore, a firm with extensive VEPs is selected. Firm A is a top firm in the Chinese electronics industry and is listed on a Chinese stock market. In 2018, Firm A had about 4,200 employees in total and about 3,000 employees took part in VEPs. After signed a strict Non-Disclosure Agreement (NDA), the data in Firm A were accessed during the Summer of 2018, including the data about 3,976 VEPs and all the personal data in the department of human resources about 2,551 employees who joined such VEPs. The personal data may be too private to be exposed and the VEPs data may be relevant to business secrets. Also, as a listed firm in the stock market, Firm A has strict rules on exposing information. So that I cannot release the name of Firm A.

Since Firm A is competing in the technology-intensive industry with intense international competition, it has been emphasizing innovation. Also, the minor innovations in process and product development influence its yield rate, profit and competitiveness. Hence, Firm A learned VEP from NEC which is a leading Japanese firm. Then Firm A released and continued iterating its management procedure about VEPs (MPVEP). According to MPVEP, the main purpose of VEPs system is to promote innovation and improve the firm's competitiveness. Firm A demarcates eight areas for VEPs and most of them focus on cost-cutting and enhancement of yield rate or productivity, which are the "improved or better method of production", among the categories of innovations defined by Schumpeter (1934). Firm A provides resources including budget, equipment and time for employees to work in VEPs. According to Firm A, most of the VEPs are proposed by employees as applicants which are relevant to their daily work in R&D or factories, plus only a few VEPs are proposed by managers. The applicant of each VEP can finish it by him/herself, or ask colleagues to self-organize team work if necessary.

In the 6.5 years between 2012 and June 2018, employees in Firm A had 3,976 VEPs. Firm A invested about 1.7 billion Chinese Yuan into these VEPs and the net profits were 895 million Chinese Yuan; their net profit rate is about 51% over 6.5 years. Firm A also provided about 37.8 million Chinese Yuan as monetary awards to employees who joined such VEPs or 9,507 Chinese Yuan per VEP, illustrated in Table 4.1.

Table 4.1 The Summary of VEPs in Firm A Between 2012 and June 2018

	Total value (Chinese Yuan)	Value (Chinese Yuan) per VEP	Total Number of VEPs
Award to employees	37,800,000	9,507	3976
Net profit from VEPs	895,000,000	225,101	3976
Investment for VEPs	1,737,949,000	437,110	3976

4.3.4 Dependent variables, independent variables and control variables

4.3.4.1 Dependent variables

As reviewed in Section 4.2.4, numerous methods with different advantages and disadvantages can be used to measure individual innovation performance but no single method is perfect and omnipotent. In order to measure the individual innovation performance of employees in VEPs from different aspects with comprehensiveness, four different DVs are used: the natural logarithm of the total number of VEPs which the employee joined (lnveemt), the natural logarithm of the total number of VEPs which the employee proposed as an applicant (lnveeroleta), the natural logarithm of the total number of patent applications from the VEPs which the employee joined (lnveemtpat). Additionally, profits of innovations can be another indicator (Balkin and Gomez-Mejia, 1984). Hence, the natural logarithm of the total economic value generated by VEPs which the employee joined (lnveemtecn) over 6.5 years is also adopted.

Firm A reviews the results of VEPs in every month and marks the performance of creativity, activeness and teamwork of each VEP. These scores of all VEPs which every employee joined are summed to indicate the performance of creativity, activeness and teamwork of the employee, which is not panel data but data with multiple levels. The evaluation system has been tested and improved by evaluating 3,976 VEPs over 6.5 years. These scores are based on the performance of the employee in their work in VEPs over 6.5 years which are more realistic, accurate, reliable and practical than measurements in laboratories over relatively much shorter periods in some previous studies. The limitation of this method is that it is difficult to differentiate the performance of each employee in the same VEPs. But another measurement can complement the former measurement, since lnveeroleta directly measures the natural logarithm of the total number of VEPs which the employee proposed as an applicant over 6.5 years. One VEP has only one employee as the applicant, hence lnveeroleta can indicate the creativity and activeness of the applicants.

4.3.4.2 Independent variables

As reviewed in Section 4.2.3, among the previous publications, education is widely considered to influence individual innovation (Hammond, et al., 2011; Hülsheger, et al., 2009). Education provides knowledge and skills for individuals to think creatively and to solve problems in practice (Amabile, 1983). Among the factors to measure the education received by individuals, the highest degree is the most prominent and practicable indicator. Hence, the highest degree of the employee which measures the education of employees is the independent variable and is coded as hestdegr in Table 4.2. Since there are chain relationships, some variables such as the natural logarithm of total scores of creativity of VEPs which the employee joined assessed by the firm (lnveetcrea), the natural logarithm of total number of VEPs of each employee (lnveemt) and the natural logarithm of total number of applicants in VEPs of each employee (lnveeroleta) are DVs in one model while IVs in the other model.

4.3.4.3 Control variables

As reviewed in Section 4.2.2, individual characteristics are the most important for both creativity and individual innovation, hence the control variables (CVs) especially relevant to individual differences are identified. There are various personal factors which probably influence the individual innovation of employees in value engineering projects (VEPs). All the data in the department of human resources are analysed after signing the NDA with Firm A, including employees' age, gender and the majors for bachelor, master and doctor degrees respectively, home provinces, the period in years when the employee has worked in Firm A, the employee's position in which squad, which division, which department, etc.

After the monthly review of VEPs, Firm A provides some monetary awards to employees based on individual innovation performance and the economic contributions of the VEPs that the employees joined respectively. These data are included in the study. As discussed in Section 3.3.1.3, due to the advantages to convert data into natural logarithm, some variables in this study are also converted into natural logarithm, including the natural logarithm of the total scores about creativity of the VEPs which the employee joined assessed by the firm (lnveetcrea), the natural logarithm of the total scores about activeness of the VEPs which the employee joined assessed by the firm (lnveetact), the natural logarithm of the total scores about teamwork of the VEPs which the employee joined assessed by the firm (lnveetteam), the natural logarithm of the total award from Firm A to employees according to the VEPs which the employee joined (lnmxeptveward) and the natural logarithm of the total investment of the VEPs which the employee joined over 6.5 years (lnveetinvn). All the variables are calculated according to each employee, which is the unit of analysis of this study.

Table 4.2 illustrates the DVs, IVs and CVs, which are all relevant to the factors reviewed in Section 4.2 and Section 4.3.

Table 4.2 Dependent Variables (DVs), Independent Variables (IVs) and Control Variables (CVs) for the Study in Chapter 4

Type	Group of factors	Order	DV or EV	Description
DVs	innovation performance	1	lnveemt	The natural logarithm of the total number of VEPs which the employee joined (either proposed as an applicant or took part in as a follower) over 6.5 years
		2	lnveeroleta	The natural logarithm of the total number of VEPs which the employee proposed as an applicant over 6.5 years
		3	lnveemtecn	The natural logarithm of the total economic value generated by VEPs which the employee joined over 6.5 years
		4	lnveemtpat	The natural logarithm of the total number of patent applications from the VEPs which the employee joined over 6.5 years
	intermediary	5	lnveetcrea	The natural logarithm of the total scores about creativity of the VEPs which the employee joined assessed by the firm over

				6.5 years
IV		6	hestdegr	Highest degree of the employee
CVs	individual differences	7	lnveetact	The natural logarithm of the total scores about activeness of the VEPs which the employee joined assessed by the firm over 6.5 years
		8	lnveetteam	The natural logarithm of the total scores about teamwork of the VEPs which the employee joined assessed by the firm over 6.5 years
		9	age	Age of the employee
		10	sex	Gender of the employee
		11	bmajorid	The major for bachelor degree of the employee
		12	homepid	The home province of the employee
		13	ffage	The period in years when the employee has worked in Firm A
	contextual factors	14	lnveetinvn	The natural logarithm of the total investment of the VEPs which the employee joined over 6.5 years
		15	lnmxeptveward	The natural logarithm of the total award of the VEPs which the employee joined over 6.5 years
		16	empid	The id of employee of Firm A
		17	sectid2	The id of squads of Firm A
		18	divisid	The id of divisions of Firm A
		19	deptid	The id of departments of Firm A

4.4 Analysis and discussion

4.4.1 Summary of data

In 2018, Firm A had about 4,200 employees and of those about 3,000 (71% of total employees) had joined VEPs. This study analyses the data between January 2012 and June 2018. Some data about VEPs are not complete for the period before 2012. This study covers the personal information of 2,551 employees in total, of whom 2,078 joined VEPs, covering about 50% of all 4,200 employees of Firm A. Among these employees, there were 155 who had been applicants of VEPs but never followers of

VEPs. There were 964 employees who used to be the followers of VEPs but never applicants of VEPs. There were 959 employees who had both been applicants and followers. The 2,078 employees in this study covers 100% of the employees who joined VEPs between January 2012 and June 2018. In this chapter, “proposed as an applicant” refers to an employee who originally propose VEPs, while “join VEPs” includes the employee who either proposed as an applicant or took part in VEPs as a follower. For the purpose of comparison in the sample, there were 473 employees who never joined any VEPs. The classification of employees is illustrated in Table 4.3.

Table 4.3 The Number of Employees about Value Engineering Projects (VEPs)

	Used to be an applicant of VEPs	Never be an applicant of VEPs
Used to be a follower of VEPs	959	964
Never be a follower of VEPs	155	473
Sum	1,114	1,437

Source: Provided from Firm A

As illustrated in Table 4.4, there were 3,976 VEPs between January 2012 and June 2018. There were fewer VEPs in 2012 and 2013, but the number of VEPs was relatively stable since 2014. There were 339 VEPs between January and June in 2018. Of the total, 315 VEPs which only one applicant without any followers. Other VEPs had one applicant and followers ranging from 1 to 9.

Table 4.4 Number of Value Engineering Projects (VEPs) in Year

Year	Number of VEPs
2012	400
2013	432
2014	698
2015	687
2016	726
2017	694
2018	339
sum	3,976

Source: Provided from Firm A

4.4.2 Multilevel models with different DVs

In the data analysis, the unit of analysis is each employee. The total number of VEPs which every employee joined as either an applicant or a follower between 2012 and June 2018 are summed together. Hence, it is not the panel data, but the data with multiple levels, since employees work in different squads in divisions in departments. This is the same for the total scores about creativity (lnveetcrea), activeness (lnveetact) and teamwork (lnveetteam) of the VEPs which the employee joined assessed by the firm, the total number of VEPs which every employee proposed as an applicant (lnveeroleta), the total number of patent applications (lnveemtpat) from the VEPs which the employee joined, the total economic value (lnveemtecn) generated by VEPs which the employee joined between 2012 and June 2018. Multicollinearity, homoscedastic and autocorrelation are tested for all models. Multilevel models are built and their residuals are tested to meet the assumptions and requirements for the models to be best linear unbiased estimator (BLUE) in the following sections (Rabe-Hesketh and Skrondal, 2012).

4.4.2.1 Models whose DVs are the natural logarithm of the total scores about creativity of the VEPs

First, the variables are tested to check if they have homoskedasticity or not. The p-value for White's test for Ho: homoskedasticity is 0.07 and the p-value for Breusch-Pagan / Cook-Weisberg test for Ho: Constant variance is 0.29, which all means they have homoskedasticity. Second, the variables are checked if they have multicollinearity or not. The value of VIF to check multicollinearity is 1.33, much lower than the threshold value of 10 (Zhang & Li, 2014). Multicollinearity, homoscedastic and autocorrelation are tested for all models. This paragraph will not be repeated again for parsimony, but the VIF value for each model is included in the relevant table.

From Table 4.5, it can be seen that the coefficients of the highest degree of the employee (hestdegr) are statistically very significant ($p<0.001$) when the DV is the natural logarithm of the total scores about creativity of the VEPs which the employee joined assessed by the firm over 6.5 years (lnveetcrea). The results support Hypotheses H4.1. The models also controlled other CVs including most of the individual characteristics from the Department of Human Resources of Firm A, such as the age (age), gender (sex) and the home provinces (homepid) of the employee, the period when the employee has worked in Firm A (ffage), the major for bachelor degree of the employee (bmajorid) and the natural logarithm of the total investment of the VEPs (lnveetinvn) which the employee joined over 6.5 years. The majors of the master or PhD degree of the employee are not included for two reasons: they are correlated with the major for bachelor degree of the employee and there are few employees who have master or PhD degree in the total employees.

The coefficients of the major for bachelor degree of the employee (bmajorid) are negative and statistically significant ($p<0.01$). The bmajorid is coded according to the standard codes of the majors in Chinese universities. The majors in science or engineering have small codes (e.g., 809 for electronics), while the majors in social science have larger codes (1204 for administration). Hence, the employees majored in science or engineering have higher scores in lnveetcrea ($p<0.01$) than the employees majored in social science such as administration or human resource management. The coefficient of sex is statistically significant; female is codes as 0 and 1 for male. There are many more male employees who majored in science or engineering, while more female employees majored in social science. The coefficient of ffage is statistically significant, since the longer the employees work in Firm A the higher the possibility they will join more VEPs. The coefficient of lnveetinvn is statistically significant, since the total investment of the VEPs from the firm is always important for employees to conduct research to find the optimal and practical solutions and apply inventions. The coefficients of these CVs are similar in other models as follows, hence the explanations will not be repeated to be parsimonious.

It can be seen that the ICC value at the level of squad is 0.84 in the model, much larger than 0.138, which means there is strong group effect at the level of squad (Cohen, 1988). But the ICC values at the levels of the division (divisid) and department (deptid) are 0.01 and 0.04 in the model, much smaller than 0.059, which means there is no group effect at the level of the division or department. This is reasonable, since employees work closely with their colleagues daily in squads.

Also, the residual is tested to be nearly normally distributed, as illustrated in Figure 4.3. This meets the requirement for the model to be the best linear unbiased estimator (BLUE). In the rest of the sections, all the models are tested in the same way and they all meet such requirement. Hence, the results will not be repeated again to be parsimonious.

Table 4.5 Results of 4-levels Random Slope Model with Natural Logarithm of Total Scores about Creativity of VEPs which Employee Joined Assessed by Firm (lnveetcrea) as DV

	coefficient
Intercept	1.6**
Age	0.01
Hestdegr (highest degree of the employee)	0.28***
Bmajorid (major for bachelor degree of the employee)	-0.001**
Homepid (home province of the employee)	-0.02
Sex	0.3**
Ffage (period in years when the employee has worked in Firm A)	0.05***
Lnveetinvn (natural logarithm of the total investment of the VEPs which the employee joined over 6.5 years)	0.13***
AIC	1800.14
BIC	1864.42
ICC at level of deptid	0.01
ICC at level of divisid| deptid	0.04
ICC at level of sectid2|divisid|deptid	0.84
Sample size (N)	729
VIF to check multicollinearity	1.33

* $p < .05$ ** $p < .01$ *** $p < .001$

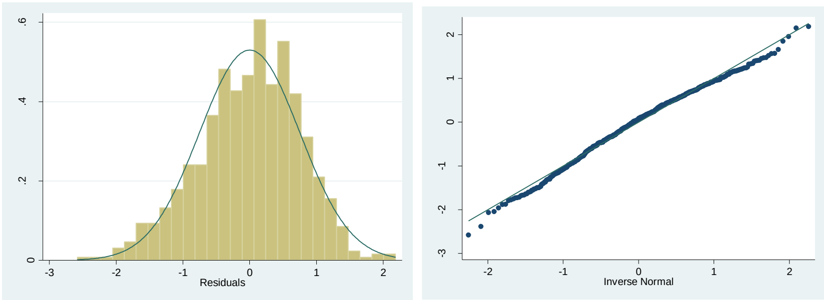

Figure 4.3 The Residue of the Model Whose DV Is the Natural Logarithm of the Total Scores About Creativity of the VEPs Which the Employee Joined Assessed by the Firm over 6.5 years (lnveetcrea)

4.4.2.2 Models whose DV is the natural logarithm of the total number of VEPs which the employee joined over 6.5 years (lnveemt)

Multicollinearity and homoskedasticity are checked here, similar to Section 4.4.2.1. There is multicollinearity in the models, but multicollinearity disappears if drop lnveetact, whose VIFs decrease from 51.58 to 5.45 respectively. There is homoskedasticity, but it does not influence the models significantly.

Table 4.6 shows the results of the models whose DV is the natural logarithm of the total number of VEPs which the employee joined over 6.5 years (lnveemt) and whose IVs include the natural logarithm of the total scores about creativity (lnveetcrea). In the first model, the coefficient of the natural logarithm of the total scores about creativity of the VEPs which the employee joined assessed by the firm over 6.5 years (lnveetcrea) is statistically significant ($p<0.001$). In the second model, the coefficient of the highest degree of the employee (hestdegr) is statistically significant ($p<0.001$) when the natural logarithm of the total scores about creativity (lnveetcrea) and teamwork (lnveetteam) of the VEPs are not controlled. But the coefficient of hestdegr becomes not statistically significant ($p=0.58$) when lnveetcrea and lnveetteam are controlled in the third model. Other CVs including the employee's age, gender, major, hometown by provinces, the length to work in Firm A, the total investment and awards in such VEPs are all controlled in the models. As discussed in Section 4.4.2.1, the coefficients of hestdegr are all statistically significant ($p<0.001$) in the model whose DV is lnveetcrea. These support Hypotheses H4.2A that there is a significantly positive relationship between the natural log of the total scores about *creativity* of the VEPs which the employee joined assessed by the firm over 6.5 years (lnveetcrea) and the natural logarithm of the total number of VEPs which the employee *joined* (lnveemt).

Furthermore, these prove there is a spurious direct relationship between highest degree of employee (hestdegr) and lnveemt reviewed in Section 4.3.2. But there is a chain relationship in Figure 4.4. The highest degree of employee (hestdegr) is strongly significantly associated with lnveetcrea ($p<0.001$) discussed in Section 4.4.2.1, which are then significantly associated with lnveemt ($p<0.001$). If an employee extends from a bachelor to master degree, his/her score of lnveetcrea will increase by 0.28, which raises the increment of lnveemt by 0.97 respectively. Furthermore, since ICC values at the level of sectid2|divisid|deptid are all larger than 0.138 (Cohen, 1988), there are strong group effects at the level of the squad.

Table 4.6 Results of Models Whose DV is lnveemt and IVs Including lnveetcrea and lnveetteam

	4-levels random slope model with the natural logarithm of the total number of VEPs of each employee (lnveemt) as DV and lnveetcrea as IV	4-levels random slope model with the natural logarithm of the total number of VEPs of each employee (lnveemt) as DV and hestdegr as IV	4-levels random slope model with the natural logarithm of the total number of VEPs of each employee (lnveemt) as DV and hestdegr & lnveetcrea as IVs
	coefficient	coefficient	coefficient
Intercept	-2.53***	-0.94	-2.47***
Age	0.001	0.01	0.001
Hestdegr (highest degree of employee)		0.28***	-0.002
Bmajorid (major for bachelor degree of the employee)		-0.001**	-0.0001*
Homepid (home province of the employee)		-0.01	0.001
Sex		0.29**	-0.005
Ffage (period in years when the employee has worked in Firm A)		0.05***	0.002
Lnveetinvn (natural logarithm of the total investment of VEPs which employee joined over 6.5 years)	-0.002	0.13***	-0.002
Lnmxeptveward (natural logarithm of the total award of the VEPs which the employee joined over 6.5 years)	0.005		-0.002
Lnveetcrea (natural logarithm of the total scores about creativity of the VEPs which the employee joined assessed by the firm over 6.5 years)	0.95***		0.97***
Lnveetteam (natural logarithm of the total scores about teamwork of the VEPs which the employee joined assessed by the firm over 6.5 years)	0.04**		0.03
AIC	-1950.03	1801.88	-1410.85
BIC	-1890.84	1866.17	-1332.8
ICC at level of deptid	0.08	0.02	0.1
ICC at level of divisid|deptid	0.1	0.04	0.11
ICC at level of sectid2|divisid|deptid	0.38	0.84	0.31

Sample size (N)	1,025	729	729
VIF to check multicollinearity	9.01	1.33	5.45

* *p* < .05   ** *p*< .01   *** *p*< .001

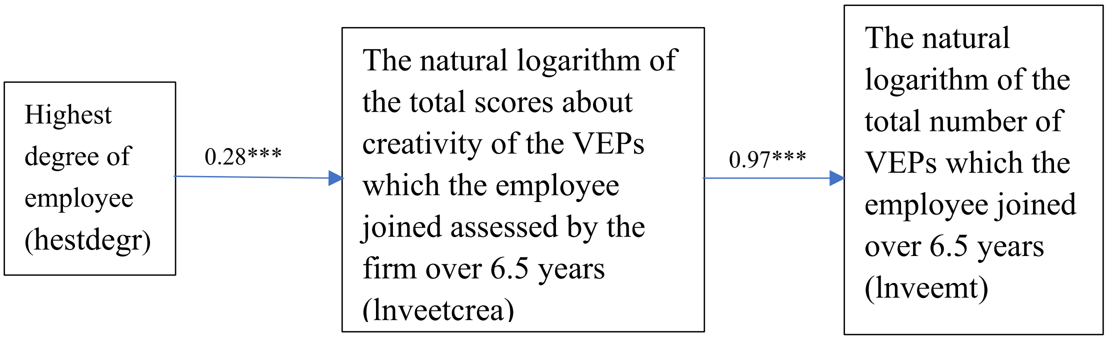

Figure 4.4 The Chain Relationship Between hestdegr and lnveemt
(* p < .05   ** p< .01   *** p< .001)

4.4.2.3 Models whose DV is the natural logarithm of the total number of VEPs which the employee proposed as applicants over 6.5 years (lnveeroleta)

Table 4.7 shows the results of the models whose DV is the natural logarithm of the total number of VEPs which the employees proposed as applicants over 6.5 years (lnveeroleta). Other CVs including the employee's age, gender, major, hometown by province, the length to work in Firm A, the total investment and awards in such VEPs are all controlled in the models. As discussed in Section 4.4.2.1, the coefficient of hestdegr is statistically significant (p<0.001) in the models whose DV is lnveetcrea. Also, in Table 4.7, the coefficient of lnveetcrea (p<0.001) is statistically significant in the model whose DV is lnveeroleta. This supports Hypothesis 4.2B. If the employee improves him/herself from bachelor degree to master degree, his/her natural logarithm of the total score about creativity (lnveetcrea) of the VEPs which the employee joined assessed by the firm will increase by 0.28, which results in the rise of lnveeroleta by 1.07. The chain relationship is illustrated in Figure 4.5.

lnveetteam has a negative association with lnveeroleta, which means applicants who have more creative ideas probably have worse capability to organize teamwork. This is consistent with the finding of previous publications. For instance, Udwadia (1990: 74) found “Creative individuals are generally more intrinsically motivated and less organization oriented.” Similarly, there is strong group effect at the level of the squad for the association between lnveetcrea and lnveeroleta.

Table 4.7 Results of Models Whose DV is lnveeroleta and IVs Including lnveetcrea and lnveetteam

	2-levels random slope model with natural logarithm of total number of applicants in VEPs of each employee (lnveeroleta) as DV and lnveetcrea as IV	2-levels random slope model with natural logarithm of total number of applicants in VEPs of each employee (lnveeroleta) as DV and hestdegr as IV	2-levels random slope model with natural logarithm of total number of applicants in VEPs of each employee (lnveeroleta) as DV and hestdegr & lnveetcrea as IVs
	coefficient	coefficient	coefficient
intercept	-0.29	-0.4	-0.48
age	-0.01	-0.01	-0.01
hestdegr (highest degree of the employee)		0.12	-0.02
bmajorid (major for bachelor degree of the employee)		-0.0001	0.0001
homepid (home province of the employee)		0.01	0.01
sex		0.48***	0.27**
ffage (period in years when the employee has worked in Firm A)		0.03**	0.01
lnveetinvn (natural logarithm of the total investment of the VEPs which the employee joined over 6.5 years)	-0.01	0.05*	-0.01
lnmxeptveward (natural logarithm of the total award of the VEPs which the employee joined over 6.5 years)	-0.28**		-0.28**
lnveetcrea (natural logarithm of the total scores about creativity of the VEPs which the employee joined	1.12***		1.07***

assessed by the firm over 6.5 years)			
lnveetteam (natural logarithm of the total scores about teamwork of the VEPs which the employee joined assessed by the firm over 6.5 years)	-0.32**		-0.3*
AIC	1478.25	1190.63	
BIC	1523.5	1241.03	
ICC at level of sectid2|divisid|deptid	0.59	0.69	
Sample size (N)	682	493	500
VIF to check multicollinearity	8.94	1.36	5.44

* *p* < .05 ** *p*< .01 *** *p*< .001

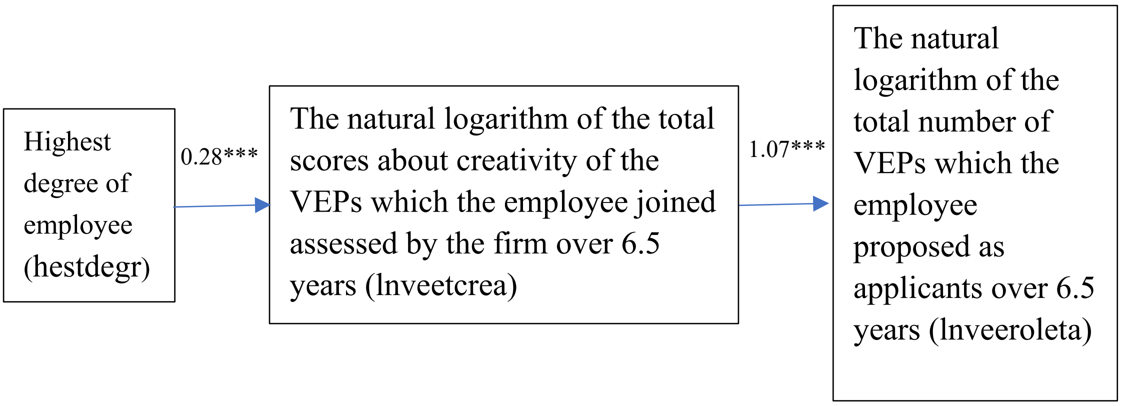

Figure 4.5 The Chain Relationship Between hestdegr and lnveeroleta via lnveetcrea
(* p < .05 ** p< .01 *** p< .001)

4.4.2.4 Models whose DV is the natural logarithm of the total number of patent applications from the VEPs which the employee joined over 6.5 years (lnveemtpat)

Table 4.8 shows the results of the models whose DV is the natural logarithm of the total number of patent applications from the VEPs which the employee joined over 6.5 years (lnveemtpat), controlling lnveetcrea and lnveetteam. The coefficients of the highest degree of the employee (hestdegr) are statistically significant (p<0.001) no matter if the natural logarithm of the total scores about creativity (lnveetcrea) and teamwork (lnveetteam) are controlled or not. Other CVs including the employee's age, gender, major, hometown by provinces, the length to work in Firm A, the total investment and awards in such VEPs are all controlled in the models. In Table 4.8, the coefficient of lnveetcrea is not statistically significant in the models whose DV is lnveemtpat. This does not support Hypothesis 4.2C. It is necessary to note that the sample size decrease from 1,025, 729, 682 or 493 in previous groups of models to 276 or 168 in this group of models whose DV is about patent applications number. This is consistent with that reviewed in Section 4.2.4 and there is only a small proportion of employees who take part in patenting.

Table 4.8 Results of Models Whose DV is lnveemtpat
and IVs Including lnveetcrea and lnveetteam

	2-levels random intercept model with natural logarithm of total number of patent applications of VEPs of each employee (lnveemtpat) as DV and scores as IVs	2-levels random intercept model with natural logarithm of total number of patent applications of VEPs of each employee (lnveemtpat) as DV and hestdegr as IV	2-levels random intercept model with the natural logarithm of total number of patent applications of VEPs of each employee (lnveemtpat) as DV and scores & hestdegr as IVs
	coefficient	coefficient	coefficient
intercept	-4.26***	-1.18	-3.7**
age	-0.01	-0.02	-0.003
hestdegr (highest degree of the employee)		0.52***	0.4***
bmajorid (major for bachelor degree of the employee)		-0.001	-0.0001
homepid (home province of the employee)		-0.04	-0.01
sex		-0.16	-0.16
ffage (period in years when the employee has worked in Firm A)		0.01	-0.02
lnveetinvn (natural logarithm of the total investment of the VEPs which the employee joined)	-0.02	0.05	0.01
lnmxeptveward (natural logarithm of the total award of the VEPs which the employee joined over 6.5 years)	0.4**		0.01
lnveetcrea (natural logarithm of the total scores about creativity of the VEPs which the employee joined assessed by the firm over 6.5 years)	0.26		0.21
lnveetteam (natural logarithm of the total scores about teamwork of the VEPs which the employee joined assessed by the firm over 6.5 years)	0.02		0.31
AIC	563.43	394.05	352.46
BIC	599.63	431.54	399.32
ICC at level of sectid2|divisid|deptid	0.65	0.75	0.83
Sample size (N)	276	168	168
VIF to check multicollinearity	7.98	1.41	5.25

* $p < .05$ ** $p < .01$ *** $p < .001$

4.4.2.5 Models whose DV is the natural logarithm of the total economic value generated by VEPs (lnveemtecn)

Finally, the relationship between the IVs analysed above and the natural logarithm of the total economic value generated by VEPs (lnveemtecn) are examined, whose results are illustrated in Table 4.9. It can be seen that there are positive relationships between lnveemt, lnveeroleta, lnveemtpat and lnveemtecn with statistical significance ($p<0.001$ or $p<0.05$) in the first model. There is a positive relationship between hestdegr and lnveemtecn with statistical significance ($p<0.01$) in the second model. However, the third model includes all of lnveemt, lnveeroleta, lnveemtpat and hestdegr as IVs and only lnveemt and lnveeroleta have positive relationships with lnveemtecn with statistical significance ($p<0.001$ or $p<0.01$). Hence, Hypotheses H4.3A and H4.3B can be supported, which means another chain relationship. But Hypotheses H4.3C cannot be supported. One of the reasons may be that the sample size is reduced from 728 in the second model to 207 and 123 if includes the data about lnveemtpat in the first model or lnveemtpat and hestdegr together in the third model in Table 4.9. This is consistent with the previous finding that only a small proportion of employees take part in patenting. Also, the values of VIFs to check multicollinearity are listed in the table, which are much smaller than the threshold value of 10. Heteroscedasticity is tested ($p>0.05$) and there is no heteroscedasticity problem. The holistic structure from highest degree of employee (hestdegr) to natural logarithm of the total economic value generated by VEPs (lnveemtecn) is illustrated in Figure 4.6 with chain relationships. In the figure, hestdegr has a positive relationship with score about creativity (lnveetcrea) ($p<0.001$). Then lnveetcrea has a positive relationship with natural logarithm of total number of VEPs of each employee (lnveemt) ($p<0.05$) and natural logarithm of total number of applicants in VEPs of each employee (lnveeroleta) ($p<0.001$) respectively. Finally, lnveemt has a positive relationship with lnveemtecn ($p<0.001$) and lnveeroleta has a positive relationship with economic value (lnveemtecn) ($p<0.01$) respectively.

Table 4.9 Results of Models Whose DV is lnveemtecn

	4-levels random slope model with natural logarithm of total economic value generated by VEPs (lnveemtecn) as DV and lnveemt, lnveeroleta & lnveemtpat as IVs	4-levels random slope model with natural logarithm of total economic value generated by VEPs (lnveemtecn) as DV and hestdegr as IV	4-levels random slope model with natural logarithm of total number of patent applications of VEPs of each employee (lnveemtpat) as DV and lnveemt, lnveeroleta, lnveemtpat & hestdegr as IVs
	coefficient	coefficient	coefficient
intercept	10.26***	6.58***	8.97***
age	0.02	0.02	0.03
hestdegr (highest degree of the employee)		0.3**	0.16
bmajorid (major for bachelor degree of the employee)		-0.0003	0.0001
homepid (home province of the employee)		-0.03*	-0.04
sex		0.5***	-0.15
ffage (period in years when the employee has worked in Firm A)		0.05***	-0.02
lnveetinvn (natural logarithm of the total investment of the VEPs which the employee joined over 6.5 years)	0.05	0.24***	0.08
lnveemt (natural logarithm of the total number of VEPs which the employee joined (either proposed as an applicant or took part in as a follower) over 6.5 years)	0.68***		0.58***
lnveeroleta (natural logarithm of the total number of VEPs which the employee proposed as an applicant)	0.17*		0.29**
lnveemtpat (natural logarithm of the total number of patent applications from the VEPs which the employee joined)	0.2*		-0.005
AIC	561.75	2385.27	346.33

BIC	601.75	2449.54	391.32
ICC at level of sectid2|divisid|deptid	0.89	0.8	0.97
Sample size (N)	207	728	123
VIF to check multicollinearity	1.21	1.33	1.42

* $p < .05$ ** $p < .01$ *** $p < .001$

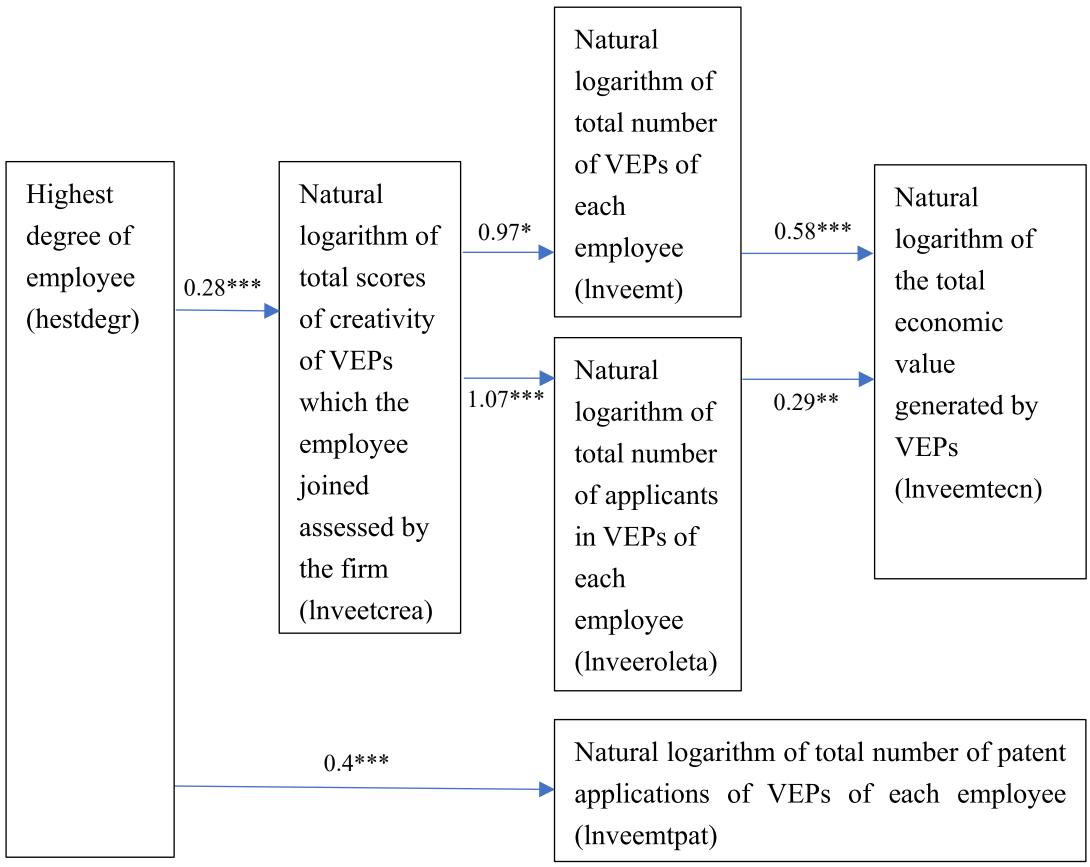

Figure 4.6 The Holistic Mechanism from Highest Degree of Employee (hestdegr) to Natural Logarithm of the Total Economic Value Generated by VEPs (lnveemtecn)
(* p < .05 ** p< .01 *** p< .001)

4.4.2.6 Composite indices from principal component analysis

As reviewed in Section 4.2.4, this study adopted some various index including the natural logarithm of total number of applicants in VEPs of each employee (lnveeroleta), the natural logarithm of total number of VEPs of each employee (lnveemt), the natural logarithm of total number of patent applications of VEPs of each employee (lnveemtpat) and the natural logarithm of the total economic value generated by VEPs (lnveemtecn) to measure the individual innovation of employees. It is necessary to adopt principal component analysis (PCA) to generate a composite index. Hence, these indicators are analysed by PCA and the new composite index "persinnovpca" is generated. Next, the similar multilevel model is built to test the relationship between the natural logarithm of total scores of creativity of VEPs which the employee joined assessed by the firm (lnveetcrea) and persinnovpca, whose results are illustrated in Table 4.10. The control variables in the model are similar to previous models in previous sections to make sure the models are comparable.

According to the result in Table 4.5 in Section 4.4.2.1, there is a positive relationship with statistical significance ($p<0.001$) between the highest degree of the employee (hestdegr) and the natural logarithm of total scores of creativity of VEPs which the employee joined assessed by the firm (lnveetcrea). According to the results in Table 4.10, there is a positive relationship with statistical significance ($p<0.001$) between lnveetcrea and persinnovpca, which constitute the chain relationship. Simultaneously, there is a positive relationship with statistical significance ($p<0.001$) between hestdegr and persinnovpca, probably because persinnovpca as a composite index includes the factor of the natural logarithm of total number of patent applications of VEPs of each employee (lnveemtpat). As illustrated in Figure 4.6, there is a positive relationship with statistical significance ($p<0.001$) between hestdegr and lnveemtpat. Also, there are group effects in squads as previous models. All of these prove the findings of this study are reliable and valid with triangulation.

Table 4.10 Results of 4-levels Random Slope Model with Composite Index "persinnovpca" (integrating all of lnveeroleta, lnveemt, lnveemtpat and lnveemtecn) as DV

	coefficient
Intercept	-4.94***
lnveetcrea (natural logarithm of total scores of creativity of VEPs which the employee joined assessed by the firm)	0. 85***
Age	-0.01*
Hestdegr (highest degree of the employee)	0. 26***
Bmajorid (major for bachelor degree of the employee)	0.0001
Sex	0. 03
Lnveetinvn (natural logarithm of the total investment of the VEPs which the employee joined over 6.5 years)	0.04**
AIC	1546.33
BIC	1606.25
ICC at level of deptid	0.04
ICC at level of divisid| deptid	0.05
ICC at level of sectid2|divisid|deptid	0. 23
Sample size (N)	742
VIF to check multicollinearity	1.09

* *p* < .05   ** *p*< .01   *** *p*< .001

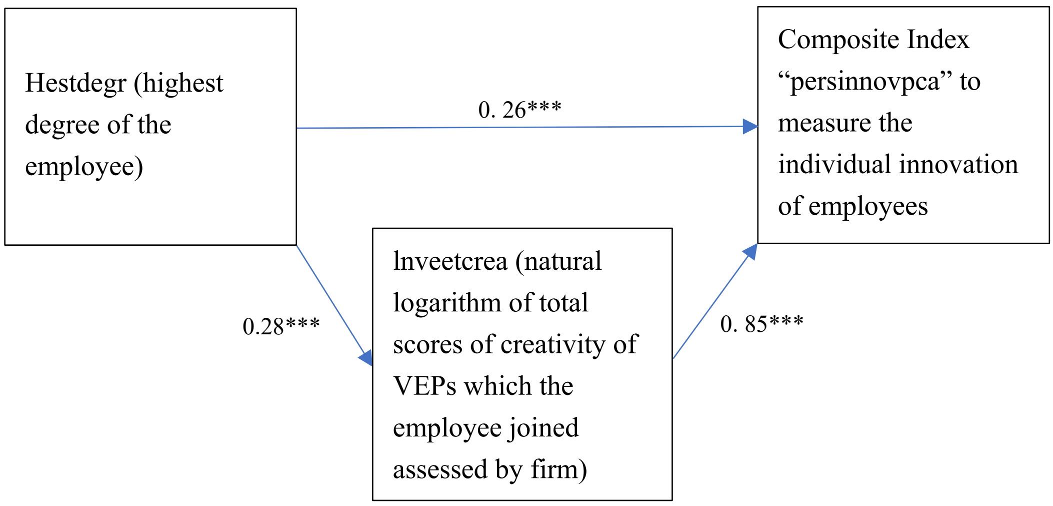

Figure 4.7 The Mechanism from Highest Degree of Employee (hestdegr) to Composite Index "persinnovpca" to Measure the Individual Innovation Performance of Employees (persinnovpca (integrating all of lnveeroleta, lnveemt, lnveemtpat and lnveemtecn)
(* p < .05   ** p< .01   *** p< .001)

Similarly, if adopting principal component analysis (PCA) to generate another composite index “creivpca”, integrating all of lnveetcrea, lnveeroleta, lnveemt, lnveemtpat and lnveemtecn. As illustrated in Table 4.11, there is a positive relationship with statistical significance (p<0.001) between hestdegr and creivpca. Also, there are group effects in squads as previous models. All of these prove the findings of this study are reliable and valid with triangulation.

Table 4.11 Results of 4-levels Random Slope Model with Composite Index “creivpca” (integrating all of lnveetcrea, lnveeroleta, lnveemt, lnveemtpat and lnveemtecn) as DV

	coefficient
Intercept	-4.18***
Age	0.03**
Hestdegr (highest degree of the employee)	0. 47***
Bmajorid (major for bachelor degree of the employee)	-0.0003
Homepid (home province of the employee)	-0.02*
Sex	0. 29**
Lnveetinvn (natural logarithm of the total investment of the VEPs which the employee joined over 6.5 years)	0.17***
AIC	2120.38
BIC	2180.3
ICC at level of deptid	0.01
ICC at level of divisid| deptid	0.03
ICC at level of sectid2|divisid|deptid	0.76
Sample size (N)	742
VIF to check multicollinearity	1.04

* $p < .05$ ** $p < .01$ *** $p < .001$

4.4.3 Discussion

Among all the models discussed above, it can be concluded that the employee’s education measured by the highest degree of the employee (hestdegr) influences the natural logarithm of the total scores about creativity (lnveetcrea) of the VEPs, which then impact on the indicators of individual innovation performance such as lnveemt and lnveeroleta respectively, and lnveemtecn finally. There is direct and positive association between hestdegr and the total number of patent applications (lnveemtpat). If applying principal component analysis (PCA) to generate a composite index "persinnovpca" to measure the employee's performance of innovation, the result is still consistent with the previous findings. This triangulation proves that education has a positive relationship with individual innovation performance with reliability and validity. This agrees with what Bill Gates experienced (Friedman, 2006). Also, there are strong group effects at the level of squads in all models, which is consistent.

Education provides individuals not only basic knowledge, but also the capability for them to continue learning by themselves in work. Additionally, education, especially post graduate education, trains individual to think critically, which helps them to understand the principles behind the phenomena of problems. Also, the knowledge and skills obtained in education and work help them to find creative and practical solutions to the problem. In this study, Firm A built a relatively complete system of continual education. Every new employee is assigned to a senior employee to guide him/her to become familiar with the job. Every week there are lectures in the firm open to all employees and some employees took part in more than 500 lectures in the past years to keep on learning and to refresh their knowledge and skills. Also, Firm A provides subsidies to encourage outstanding employees to register in universities to study for master or PhD degrees in subjects close to their job or to the business of the firm. The creative employees usually are very open to new technologies and like to think through problems, which is consistent with the findings of Feist (1998) and Karwowski & Lebuda (2016). As discussed in Chapter 5 about employee stock ownership plan (ESOP), incentives, especially monetary awards and financial support, are important to encourage employees.

In order to compare comprehensive indicators and single indicators, the ideal scenario is that different indicators are applied to analyse the same employees with the same data. In this study, the sample size is reduced from 728 without the data about patents to 207 if including data about patents, which eliminated many samples and their information. Hence, the comprehensive measurement using the number of VEPs proposed or joined by VEPs and the profit from such VEPs is better than the only indicator about patent. Even if adopting principal component analysis to integrate such 3 indicators and patents, the results are still consistent as in Section 4.4.2.6. Furthermore, different publications analysed different data in different scenarios which may be not comparable. It may be necessary to adopt meta-analysis to compare the publications with different indicators and different data, which exceed the scope of this thesis. But some existing meta-analysis already found interesting results. For example, the comprehensive indicators are better than the single indicator particularly ratings only, since rating may be influenced significantly by the personal relationships among teams. If adopting the only indicator such as self-ratings or independent ratings, the results may be quite inconsistent or misleading. Hülsheger, et al. (2009: 1128) applied meta-analysis to examine 104 independent studies between 1978 and 2008 and found: "[R]elationships differ substantially depending on measurement method (self-ratings vs. independent ratings of innovation) and measurement level (individual vs. team innovation). Team variables displayed considerably stronger relationships with self-report measures of innovation compared with independent ratings and objective criteria."

4.5 Conclusion, limitation and future research

This study fills the gap by building a series of multilevel models and finds the important mechanism for how education improves individuals' innovation performance particularly via creativity. First, education helps to improve employees' creativity, which then contribute to enhance individual innovation performance, measured by the total number of VEPs which the employee proposed as applicants and the total number of VEPs which the employee proposed as an applicant or took part in VEPs as a follower. Next, they contribute to create value for the firms with statistical significance. The education of employees influences directly and positively the total number of patent applications from the VEPs which the employee joined over 6.5 years. Also, there are strong group effects at the level of the squads in all the models, which means the employees' innovation behaviors influence each other significantly within squads. Other individual differences (age, sex, majors of bachelor degree, hometown, etc.) and the external factors such as awards to the employees and the investment to the different VEPs from the firm are controlled in this study. It may be better for firms to provide sources including subsidies to encourage employees to study for higher degrees with the majors relevant to the firm's business.

This study analyses the data only from one single firm which is a limitation. I tried to collect more data from other firms with similar VEP system, e.g., Fasten Group in Jiangsu Province. But the data about VEPs and the personal data about employees are too sensitive and Fasten Group did not want to provide the access. Also, there are other external factors which can influence individual innovation performance, which are not included in this study. Other contextual factors such as the level of democracy of management, knowledge sharing between employees and teams, inhibitors or enablers about knowledge sharing, etc., are only available in questionnaires already conducted in Firm A in 2018. Hence only the data about VEPs and employees in 2018 can be used. Since this will reduce the large sample size over 6.5 years drastically to the much smaller sample only in 2018, these contextual factors will be analyzed in the next study with the results of questionnaires already conducted in 2018. There were 904 copies of similar questionnaires received from Firm A, 387 copies from Far East Group in Jiangsu Province and about 200 copies from CITIC in Henan Province in China in 2018.

Chapter 5 Employee Share Ownership and Innovation: A Study of 1,509 Chinese Listed Firms

Abstract

Fama (1980) convincingly argued that the separation of ownership and management is efficient for corporate governance and extensive work has addressed this topic (Berle and Means, 1932; Chandler, 1977; Shleifer and Vishny, 1997 and Koller, Goedhart and Wessels, 2010). In order to solve the principal-agent problem, the stock option is commonly awarded to managers. However, more principal-principal problems appear in practice. Similarly, there are corporate governance problems relevant to R&D and innovation due to information asymmetry, differing interests among shareholders and incomplete contracts between employees and managers. Consequently, these problems make shareholders and top management hesitate to invest in R&D and innovation (Chen, et al., 2006), which will deteriorate the firm's competitiveness in the long term. As a result, in addition to stock options for mangers, 'employee stock ownership plans' [ESOP] are often awarded to key employees to solve principal-agent and principal-principal problems (Roe, 2004; Koller, Goedhart and Wessels, 2010 and Rosen, 2013). ESOP is helpful to attract and activate talented employees (Richte and Schrader, 2016) who are the main source of creative ideas and innovation (Yusuf, 2009) and improve productivity (Estrin and Shlomowitz, 1988). Although ESOP is popular in European, Chinese and Japanese firms, there is not a study with a big sample and sufficient representativeness to test if ESOP can improve firms' innovation performance or not (Garret, 2010). Furthermore, no studies have been done to analyse the possible influence including group effects of industries, the locations of firms' headquarters, stock boards and state-owned enterprises [SOE] vs non-SOE on the impact of ESOP on innovation. This study adopts the mixed design by combining

the quantitative analysis and qualitative interviews. Some factors identified in interviews are tested in statistical models and results from interviews help to explain the results of quantitative analysis. Panel data from 1,509 Chinese listed firms between 2007 and 2015 are analysed by using growth curve models. Six hypotheses about the factors including industries, locations of firms' headquarters by province, stock boards and SOE vs non-SOE are tested. Consequently, this study has three main contributions: First, it verifies the tentative finding of Chen, et al. (2006) with a much bigger sample that ESOP can alleviate corporate governance problems and prompt firms to increase R&D expenditure. Second, it finds that ESOP enhances firms' patent application practices with a big sample and sufficient representativeness, since the 1,509 firms covered 60.4% of all the 2,497 firms listed in Chinese stock markets in 2012. Third, the possible effects of various other factors are analysed. The influence of ESOP on patent application numbers is bigger in SOEs than non-SOEs. The possible reasons may be that SOEs are more prone to adopt ESOP to solve principal-agent and principal-principal problems and to attract or activate employees. But private firms adopted ESOP to raise money from employees, a priority in the early period. Consequently, many senior employees in private firms have many stocks and the problems of "entrenchment" (Chang and Mayers, 1992) and "free riders" (Weitzman and Kruse, 1990) are much more serious in private firms than in SOEs as seen in interviews. There are also group effects at the level of the industry which influence the impact of ESOP on firms' annual patent application numbers. Usually knowledge-intensive industries are also talent-intensive industries. ESOP influences firms' innovation significantly in knowledge/talent-intensive industries while not in non-knowledge/talent-intensive industries. Other factors that might be thought to have group effects do not, including stock boards and location by provinces. The impact of ESOP on firms' innovation will be reflected only in provinces or stock boards where the knowledge/talent-intensive industries concentrate. In a word, ESOP does help to solve the corporate governance problems relevant to R&D and innovation and improve the firms' innovation performance.

Keywords: ESOP, Innovation performance, Industry, SOE, non-SOE, Headquarter locations, Stock boards

5.1 Introduction

Fama (1980) argued that the separation of ownership and management is efficient for corporate governance. Shleifer and Vishny (1997) advocated that the main target of firms is to maximise the benefits of shareholders (the principle of shareholder primacy). According to Koller, Goedhart and Wessels (2010), firms' value is measured by the market value of the firms in the stock markets. Hence, Jensen & Meckling (1976) argued that the benefits of managers should be bound to the market value or stock price of the firms. Therefore, the main incentive mechanism for managers is that the stock option constitutes a significant proportion of the total payment of managers, which is the first type of corporate governance solution.

In contrast to the original expectations about solving principal-agent problems, more principal-principal problems appear in practice. Managers with share or stock options control the firms internally and can raise the stock prices by nefarious practices such as faking accounts. After scandals are exposed, stock bubbles collapse and disasters ensue in the stock market and in the economy more broadly. For instance, failures of corporate governance can be found in the Enron Corporation case in 2001, the subprime mortgage crisis in 2008 and the faked quality report of Kobe Steel in Japan in 2017. One of the effective solutions to solve such principal-principal problems may be ownership sharing with employees. "[E]mployee share ownership can be an effective interest-alignment mechanism" (Chen, et al., 2006: 382). Employees with ESOP will watch and encourage managers to avoid and/or solve principal-principal problems. If many employees keep silence and allow managers to misbehave, their interests will be hurt. This is the second type of corporate governance solution: in addition to stock options for mangers, awarding ESOP to some key employees helps solve principal-agent and principal-principal problems.

There is a long tradition and history of “worker cooperatives” in European countries, especially Italy and Spain (National Centre for Employee Ownership, 2018: 12). From the 1930s the Scanlon Plan was the most famous system of sharing ownership in the U.S. (Strauss and Sayles, 1960). Although Louis Kelso invented ESOP in the U.S. in 1956, it has withered there in recent decades except in Silicon Valley. However, ESOP is still common in Continental Europe and Japan and is becoming increasingly popular in Chinese firms. The foundation in China was set when the China Securities Regulatory Commission (CSRC) released ‘Equity Incentive Management Measures for Listed Companies’ (EIMMLC, Trial Implementation) in 2006 and a further formal version in 2016. Along with their ‘Guidance on the Pilot Implementation of Employee Stock Ownership Plans in Listed Companies’ by 2017, 1,549 listed firms adopted ESOP, constituting 43.7% of all listed firms (as of 2017 there were 3,546 firms listed in the Shanghai and Shenzhen stock exchanges).

ESOP is helpful to attract and activate talent (Richte and Schrader, 2016; Klein, 1987). ESOP also helps to build interest alignment among shareholders, managers and employees (Chang and Mayers, 1992) and to improve management (Estrin, Gerosk and Stewart, 1988), financial performance (Cin & Smith, 2010) and productivity (Estrin and Shlomowitz, 1988).

Similarly, there are corporate governance problems relevant to R&D and innovation. Usually, the individual is the basic unit to create new ideas (Taylor and Greve, 2006; Yusuf, 2009). Consequently, the activeness and creativity of employees in R&D are very important for innovation. However, with significant information asymmetry, employees in R&D have internal information and tacit knowledge that managers and shareholders do not know and this may cause mistrust among them (Chen, et al., 2006). Next, there may be different interests among employees in R&D, managers and shareholders. R&D and innovation are highly risky. If the interests of employees in R&D, managers and shareholders are not bound together, the untrustworthy among them will exacerbate the incredulity, which makes shareholders and top management hesitate to invest more for R&D and innovation (Chen, et al., 2006). Inadequate investment in R&D and innovation will deteriorate the firm's competitiveness in the long future.

While some previous studies have examined the relationship between ESOP and innovation (Garrett, 2010; Choi, Lee & Williams, 2011; Chang, at al., 2015; Brander & Zhang, 2017; Usman, Xiao & Li, 2018), few tested if ESOP can improve firms' innovation performance with big samples and sufficient representativeness (Garrett, 2010). Furthermore, no extant publication analysed the possible influence of group effects of industries, locations of firms' headquarters by provinces, stock boards and SOE vs non-SOE status on the relationship between ESOP and innovation. The 1st, 2nd and 3rd factors are important both in China and Western countries, while the 4th factor is particularly important in China. Hence, this study analyses the panel data of 1,509 Chinese listed firms and addresses the research question: Does ESOP influence firms' innovation performance? Since 1,509 firms can be grouped in different industries, locations of firms' headquarters by provinces, stock boards and SOE vs non-SOE, are there any possible influences, especially group effects, for these factors which impact on the relationship between ESOP and firms' innovation performance? Although these 1,509 firms can be grouped by the four factors, these factors are neither moderators nor mediators.

This study adopts a mixed design with the parallel combination of qualitative and quantitative methods (Creswell & Clark, 2011). Interviews are used to collect qualitative evidence (Hamilton and Bowers, 2006). Between 2017 and 2019, about 32 innovative firms in China were visited, which covered Northern, Central, Eastern and Southern China with representativeness. With the help of friends, about 100 interviewees in these firms were selected purposively and were conducted face to face. Thematic analysis (TA) (Attride-stirling, 2001) was adopted to analyse the transcripts of interviews. Some factors identified in the interviews such as the influences of industries, geographic areas and different types of ownership (SOEs vs non-SOEs) are examined by the quantitative analysis of panel data. The results of interviews also help to explain the results of quantitative analyses.

The panel data of 1,509 listed firms for the period 2007-2015 are gathered to analyze the effect of ESOP on innovation performance quantitatively. As one of the most important methods to protect new technologies, patent activities have been used to trace some key aspects of knowledge creation, innovation, spillover effects and to indicate other aspects of economic growth (Sanders, 1958; Pakes, 1984; Lanjouw, 1996; Kortum and Lerner, 1997). Hence, this study uses patent applications as the dependent variable (DV), which is the most practicable index. The main independent variable (IV) is the percentage point of ESOP in each firm in each year. Firms that achieved IPO after 2012 do not have sufficient panel data between 2007 and 2015 and are not included. After deleting the firms without patent applications and/or without sufficient financial data between 2007 and 2015, 1,509 firms are analyzed. These firms covered 60.4% of all the 2,497 firms listed in Chinese stock markets in 2012, which is sufficiently representative of established medium to large firms with patent applications. Some firms released their plans for ESOP between 2016 and 2019 and so have not had sufficient time for the effect of ESOP to be realized and/or become observable since it takes time for the patent application data to be released. They are not included in this research but will be in the follow-up studies in the near future. The main quantitative method is growth curve modeling (GCM) which is applied to analyze the panel data of firms in various industries, headquarters by provinces, stock boards and with different types of ownership (SOEs vs non-SOEs). GCM has some advantages that it can analyse the growth trend of patenting because of covariates at year-level, firm-level or industry-level and deal with missing data (Rabe-Hesketh and Skrondal, 2012).

Six hypotheses about the research question are tested, four of which can be supported while two cannot. Those that can be supported are as follows.

Hypothesis H5.1: There is a significantly positive relationship between ESOP and the annual R&D expense of firms. H5.1 can be supported only for firms in knowledge/talent intensive industries, but neither for all firms holistically nor for firms in non-knowledge/talent intensive industries.

Hypothesis H5.2: There is a significantly positive relationship between ESOP and the annual number of patent applications.

Hypothesis H5.3: The types of ownership (SOE or non-SOE) of firms influence the relationship between ESOP and the annual number of patent applications significantly.

Hypothesis H5.4: The industries which the firms belong to influence the relationship between ESOP and the annual number of patent applications significantly.

These hypotheses cannot be supported:

Hypothesis H5.5: The locations (by province) of firms' headquarters influence the relationship between ESOP and the annual number of patent applications significantly.

Hypothesis H5.6: Different stock boards influence the relationship between ESOP and the annual number of patent applications significantly.

There are three main contributions of this study. First, it verifies the finding of Chen, et al. (2006) with a much bigger sample with more representativeness that ESOP can alleviate corporate governance problems and promote firms to increase R&D expense. Second, based on the analysis of 1,509 Chinese listed firms with sufficient representativeness, it can be concluded that ESOP does influences firms' annual patent application number positively with statistical significance, filling the gap identified by

(Garret, 2010). Third, the possible effects of various factors are analysed respectively. In the relationship between ESOP and the firms' annual patent application number, there are group effects at the level of industry, which can be put on the third level of the growth curve model. Since there are group effect about industries, the industries are divided into 2 groups: 746 firms in 10 knowledge/talent-intensive industries vs 763 firms in 54 non-knowledge/talent-intensive industries. The effect of ESOP on patent applications is very strong for the group of knowledge/talent-intensive industries, consistent with Garrett (2010), but not for the group of non-knowledge/talent-intensive industries. This was ignored by Garrett (2010), since he analysed only 77 firms in high-tech. industries in the U.S.

In contrast, there are no group effects in various stock boards, types of ownership and provinces where the firms' headquarters are located respectively. Furthermore, province and stock board do not influence the effect of ESOP on the firms' annual patent application number holistically. But most firms in knowledge/talent-intensive industries concentrate in the 8 provinces of China's eastern coast, so the effect of ESOP in the group of the 8 provinces there is significant, while not for the other provinces. Similarly, some firms in knowledge/talent-intensive industries concentrate in the No. 3 stock board, called ChiNext. Consequently, the effect of ESOP in ChiNext is significant while not for the other 3 stock boards. Therefore, the effect of ESOP in different provinces or stock boards depends on the firms of knowledge/talent-intensive industries, which constitutes a triangulation test.

The SOEs have more patent applications than non-SOEs on average, which is consistent with the finding of Choi, Lee & Williams (2011). Also, the average annual growth rate of patent applications of SOEs is higher than non-SOEs. Similarly, the influence of ESOP on patent applications is bigger in SOEs than non-SOEs with statistical significance. According to the interviews, SOEs and non-SOEs have quite different original reasons to adopt ESOP. In SOEs, the main reasons for ESOP are to 1) solve the problems of principal-agent and principal-principals, 2) attract, keep and activate employees by economic compensations. But the original main reason for private firms to adopt ESOP particularly in the early period was to raise money from employees which is very common in private firms such as Far East Group, Wens Group and Hodo Group. Consequently, many senior employees in private firms have many stocks and the problems of “entrenchment” (Chang and Mayers, 1992) and “free riders” (Weitzman and Kruse, 1990) are much more serious in private firms than in SOEs, evidenced by the interviews. Hence, the effect of ESOP in private firms may be reduced by the problems of “entrenchment” and “free riders”. This distinction may explain why the influence of ESOP on patenting is higher in SOEs than non-SOEs.

In a word, ESOP does help to solve corporate governance problems and improve firms’ innovation performance. Finally, suggestions to management and government policy are provided: the Chinese government and firms should continue the reform of SOEs towards mixed ownership. However, according to the interviews, the reform should include not only the economic incentives such as ESOP, but also the non-economic incentives and sharing power with qualified employees, plus suitable management and fostering suitable institutional norms, etc. which is consistent with the finding of Brander & Zhang (2017).

The next sections are organized as following: Section 5.2 reviews the literature about principal-agent and principal-principal problems, ESOP in Europe, the U.S. and Asia, the relationship of ESOP and innovation, and develops the hypotheses. Section 5.3 introduces the research design including the mixed research design, cases selection and variables. Section 5.4 presents quantitative analyses and models. Section 5.5 discusses the results of both quantitative and qualitative analyses. Section 5.6 draws conclusions, identifies limitations and provides suggestions.

5.2 Literature review

5.2.1 Principal-agent problems and stock options for managers

Berle and Means (1932) analysed the dispersion of shares which resulted in the separation of ownership and management. Fama (1980) argued that the separation of ownership and management is efficient for corporate governance. Chandler (1977) assumed that managers preferred policies that favoured long term stability and growth of their enterprises to those that maximized current profits. Shleifer and Vishny (1997) advocated that the main target of firms is to maximize the benefits of shareholders (the principle of shareholder primacy). Koller, Goedhart and Wessels (2010) stated clearly that the management of firms should try their best to maximize the interests of shareholders in the well-known book *Valuation*: *Measuring and Managing the Value of Companies*, based on many cases of McKinsey & Company.

> "The book's messages are simple: Companies thrive when they create real economic value for their shareholders. Companies create value by investing capital at rates of return that exceed their cost of capital. And these two truths apply across time and geography. The book explains why these core principles of value creation are true and how companies can increase value by applying the principles to decisions, and demonstrates practical ways to implement the principles in their decision-making" (p. XII).

According to their theory, firms' value is measured by the market value of the firms in the stock markets. Hence, Jensen & Meckling (1976) argued that the benefits of managers should be bound to the market value or stock price of the firms. Similarly, Tosi & Gomez-Mejia (1994) suggested providing the stock option of the firm to managers to build the interest alignment between managers and shareholders. Therefore, the main incentive mechanism for managers is that the stock option constitutes a significant proportion of the total payment of managers. It seemed this could solve the principal-agent problems.

In contrast to the original expectation to solve the principal-agent problem, more principal-principal problems appeared in practice. Due to the contrasting incentives, information asymmetry and incomplete contracts, managers with shares or stock options control the firms internally and might raise the stock prices by faking an accounting sheet, etc. Another method is that the top management of U.S. listed firms used corporate bonds to borrow cash from the bond market. They did not invest the profit or cash borrowed in R&D or production, but use such cash to buy back stocks from the market to raise the stock prices in order to maximize their own interest. In 2018, 54% of the total profit of firms in S&P 500 Index were used to buy back stocks. Between 2008 and 2018, U.S. listed firms spent about UD$5.1 trillion to buy back stocks (Wei, 2019), when the Dow Jones Indexes rose from 8,776 in 2008 to 28,538 in 2019. But this bubble cannot be sustainable. After the scandals are exposed, the stock bubbles collapse and result in disasters in the stock market and the economy more broadly. For instance, the failures of corporate governance can be found in the Enron Corporation case in 2001, the subprime mortgage crisis in 2008 and the scandal of faked quality reports of Kobe Steel in Japan in 2017 which hurt 6,123 firms in Japan. This phenomenon repeats again and again, which is one of the main reasons for periodic crises.

5.2.2 Employee ownership in Europe and other countries except the U.S.

One of the effective solutions to solve such problems of principal-agents and principal-principals may be ownership sharing with employees. More than the function to let employees to benefit from shares or firms to benefit from tax cutting, there should be more purpose for ownership sharing to attract and activate employees (Rosen, 2013). "[E]mployee share ownership can be an effective interest-alignment mechanism" (Chen, et al., 2006: 382).

There is long tradition and history of "worker cooperatives" in European countries especially Italy and Spain (National Centre for Employee Ownership, 2018: 12). According to Estrin, Gerosk and Stewart (1988), there were some 300 schemes to share ownership or profits between 1865 and 1912. It became common again in Western countries in the 1980s due to two reasons: the increment of the labour force with good education and the success of Japanese firms in the 1980s (Estrin and Shlomowitz, 1988). Rosen (2013) compared the laws to encourage broad-based ESOP in some countries in Europe such as Ireland, the U.K., Poland, France, Denmark, Belgium, and Croatia and others including Canada, Australia, New Zealand and Korea. According to Rosen (2013), about 2011, employee ownership (EO) is common in the U.K. and Ireland, including large listed firms as well as smaller firms. The exemplary firms are John Lewis, Arup (a multinational engineering company), and Tullis Russell (a large paper producer). Around one million British employees joined some plans of employee ownership. The European Commission strongly supported employee ownership and the European Parliament approved a budget to build a Center for Employee Ownership in each member state of the EU. In countries in Continental Europe, the French government provided a discount or tax incentive and most of the plans were share purchase plans. Spain has specific laws to encourage worker cooperatives and tens of thousands of worker cooperatives exist in Spain and Italy (Rosen, 2013). Totally, the employees in all private sectors who join some kinds of employee ownership plan occupied only 1% to 3% in countries in Continental Europe around 2011 (Rosen, 2013). The countries of Eastern Europe and the former Soviet Union had different trajectories and extensive employee ownership was used to privatize former SOEs. Citizens bought shares very cheaply and later sold them to capitalists cheaply. As a result, the former SOEs were passed cheaply from the governments to private capitalists. About 2,500 of large European companies had 8.2 million employee owners whose held value of about 260 billion Euros (Kakabadse, Kouzmin, and Kakabadse, 2010).

According to Rosen (2013), 1.2 million workers took part in about 3,000 employee ownership plans in Korean public and private companies in 2012. The percentage was only 1.5% of the shares of each firm, no matter that Korea provided significant laws to encourage employee ownership. The percentage of ESOP in Japanese firms increased from 4.4% of all firms in 1960 to 95.9% in 1992. Japanese ESOPs have no tax incentives and are different from the U.S. or the U.K. (Kakabadse, et al., 2010). This is consistent with Jones & Kato (2010), who reported that more than 90% of Japanese listed firms had an ESOP, and about 50% of the employees in firms with ESOPs participated in the plan in 1988. But employee ownership plans are less popular in Australia and New Zealand (Rosen, 2013).

5.2.3 The Scanlon Plan, ESOP and the Silicon Valley model in the U.S.

"For much of American history, employee-owned companies were rare" (National Centre for Employee Ownership, 2018: 12). After the 1930s, the Scanlon Plan was the most common system of sharing ownership and profit in the U.S. (Strauss and Sayles, 1960). This originated in the context of the Great Depression with Joseph N. Scanlon, a union leader and later management reformer at MIT and has been improved over the subsequent 80 years. There are four rules to the Scanlon Plan: 1) Consistence, which means employees should take part in the decision-making and execution of plan of the firm. 2) Capability, which means the firm has high expectation of the employees' capability to take part in decision-making and improve performance. 3) A participation system which allows employees to provide more and better suggestions about management, production, etc. 4) Equality, which means the firm's success is not due to any one person but to all employees, clients, managers and investors (Scott, Davis and Cockburn, 2007; Markham, Scott and Walter, 1992; Scott, Floyd, Benson and Bishop, 2002).

Similarly, Louis Kelso invented the Employee Stock Ownership Plan (ESOP) in 1956. Kelso published a series of books to advocate and develop ESOP, including *The Capitalist Manifesto* (Kelso, 1958), *The New Capitalists* (Kelso, 1961), *Two-Factor*

Theory: The Economics of Reality (Kelso, 1968) and *Democracy and Economic Power: Extending the ESOP Revolution Through Binary Economics* (Kelso & Kelso, 1991). In 1973, Louis Kelso convinced Congressman Russell Long, to insert provisions relating to ESOP in the Employee Retirement Income Security Act, or ERISA, which was passed by Congress in 1974. Since then, more laws and policies were passed to "provide tax incentives for setting up ESOPs" (National Centre for Employee Ownership, 2018: 13), which have come to be seen as "a tax-exempt defined contribution retirement plan designed to facilitate employee ownership of a company" (Brill, 2013: 2). According to The National Centre for Employee Ownership (National Centre for Employee Ownership, 2018), about 7,000 U.S. companies have an ESOP which employed about 11 million employees, or 9% of private-sector workers in 2018.

Silicon Valley is another area where the sharing of ownership and/or profit with employees is very popular. The official webpage of Google used to say: "Silicon Valley needs to bring in great talent, and all of us benefit when great people and ideas come together to drive innovation." In Silicon Valley, start-ups commonly raise initial investment in 'round A' and allocate about 15-30% of the total shares to a pool, used to attract, keep and activate talent. For example, a board member from outside commonly needs 0.25%, a CEO needs 5% - 8%, a vice president needs 0.8% -1.3%, a manager needs 0.25%, an ordinary employee needs 0.1%, etc. The proportion of all the ESOP will be diluted to 5-10% of the total share before IPO. After IPO, the firm will launch a system of stock options for qualified employees. Triplebyte (2018) conducted an anonymous survey about the salary and stock options in some firms in Silicon Valley including Apple, Quora, Reddit, Coursera, OpenAI, etc. In the survey about employees' early options in start-ups, it found that 62% of employees could get more than 0.1% of the stock options if they joined the start-ups at the early stage. Nearly half of them could get 0.15%; 20% of them could get at least 0.5%; and the top 8% of people could get up to 1%. The denominator of the percentage is the market value of the start-up, e.g., Quora had a market value of US$1.8 billion.

Additionally, different forms of capitalism or socialism might influence ESOP. According to the "varieties of capitalism" theory (Hall and Soskice, 2001), there are several different models of capitalism, which have various models of corporate governance. In the U.S., shares in firms, especially those listed in stock markets, are usually dispersed and it is mainly associated with vertical corporate governance (Roe, 2004). There are about 10 institutions about corporate governance including markets (for products, finance and managers), boards, etc., which contribute to solve principal-agent and principal-principal problems (Roe, 2004). The American model, especially those firms in Silicon Valley seem more suitable for revolutionary innovations. In Germany and Japan, most firms have close relationships with the core banks which have a large proportion of shares. Usually, there are a few employees' representatives in the board. This model seems suitable to small innovations with cumulative improvement of products with high quality. In the U.S., Germany and Japan, some middle firms and most small firms are owned by families. In contrast, in eastern Asia especially in Korea, Hong Kong and Singapore, most firms no matter how big or small are owned by founders and their families.

5.2.4 ESOP in China

Similar to other countries (Rosen, 2013), ESOPs in Chinese firms are also significantly influenced by the laws and policies of the Chinese government. Rutten (2013) analysed Chinese institutions and economic development from the angle of new institutional economics especially comparative political economy including regulation theory and argued "that the current system is one wherein state and market institutions support a distinctively industrialist orientation" (p. 3). Similarly, Fuller (2016) analysed firms' innovations and technological development in the context of the political economy of China. Before 1978, almost all firms in China were SOEs. In the early 1990s, many SOEs almost became bankrupt. The Party released the policy to "keep the big SOEs while liberate the small SOEs" in the Report of the Fifth Plenary Session of the Fourteenth Central Committee in 1995 (The 14th Central Committee of the Communist Party of China, 1995). Hence, the central, provincial and municipal governments kept and supported some big SOEs with key technologies in strategic industries. Governments provided subsidy and/or tax-cutting, and other incentives to such big SOEs to help them to survive. Those surviving SOEs became bigger and stronger with key technologies and developed better than most private firms. As the result, since the 1980s, China has two sectors in the economy (Liao, 2009). In 2016, there were about half a million big SOEs in strategic industries such as airspace, military, telecommunication, steel, fast trains and automobiles, etc. which are capital and technology intensive. The important role of SOEs in such industries were analysed by Lu (2019 and 2020). On the other hand, there are more than 20 million private firms in retailing, transportation, consumer products, and electronics, etc. Encouraged by the policy of mass entrepreneurship and innovation advocated by Chinese Prime Minister Li Keqiang in 2014, private firms have been increasing rapidly in the last 5 years. In contrast to American firms with dispersed shares, Chinese SOEs are controlled by government and private firms are usually dominated by the founders and/or their families. As a result, the principal–principal problem is common in both SOEs and private firms listed in stock markets.

In the last four decades in China, ESOP was learned from American firms and evolved in the Chinese economic and political context with the significant influence of policies and laws from the Chinese government. The real equity shared by employees appeared in China in the early 1980s. In 1984, Beijing Tian Qiao Department Store Company Limited by Shares was founded with employee shareholders. By the end of 1987, there were more than 3,200 companies limited by shares in China, 86% of which had employee shareholders (Dong, 2015). However, problems such as: employees' equity exceeding the legal quota and scope, and some obtained employees' equity by corrupt relationships (guanxi) or power. Therefore, it was soon stopped by the China State Council.

Chinese Company Law was put in practice in 1994, which provided the legal ground to transform SOEs into companies limited by shares. Shenzhen, the special economic zone, caught such an opportunity and announced its own local policy "The Regulations about Internal Employees' Equity (Trial Implementation)" in 1994. In the next 3 years, 57 firms built the system for internal employees' equity and 110 firms were working on it in Shenzhen (Dong, 2015). However, some individuals with guanxi obtained a lot of equity and sold in the capital market, which impacted the capital market. Quickly, the China Securities Regulatory Commission (CSRC) had to stop it again in 1998.

Between 1998 and 2000 after Asian financial crises in 1997, many SOEs were almost bankrupted and more than 20 million employees of SOEs were nearly laid off which resulted in big economic and social problems. In order to solve such serious problems, Chinese central and provincial governments allowed such SOEs to be privatized or shared by employees, which promoted ESOP.

In 2006, the CSRC released the Equity Incentive Management Measures for Listed Companies (EIMMLC, trial implementation), and a few firms followed EIMMLC. However, there were many problems about ESOP especially for SOEs, some of which were accused of corruption and loss of SOE assets. In 2014, the CSRC released Guidance on the Pilot Implementation of Employee Stock Ownership Plan in Listed Companies. In the explanation for why the CSRC released such a policy, the CSRC mentioned "ESOP is very popular in overseas markets" which influences Chinese firms. After practice and revisions over 10 years, the formal version of EIMMLC was released and executed by the CSRC in 2016. Since then, more and more firms adopted ESOP (SIM, 2018). In 2019, Measures for Foreign Employees' Participation in ESOP Fund Management of Domestic Listed Companies was released by the People's Bank of China and State Administration of Foreign Exchange (SAFE). This policy permits and facilitates the domestic listed companies to provide ESOP to foreign employees who can transfer their compensation to their home countries legally (SAFE, 2019).

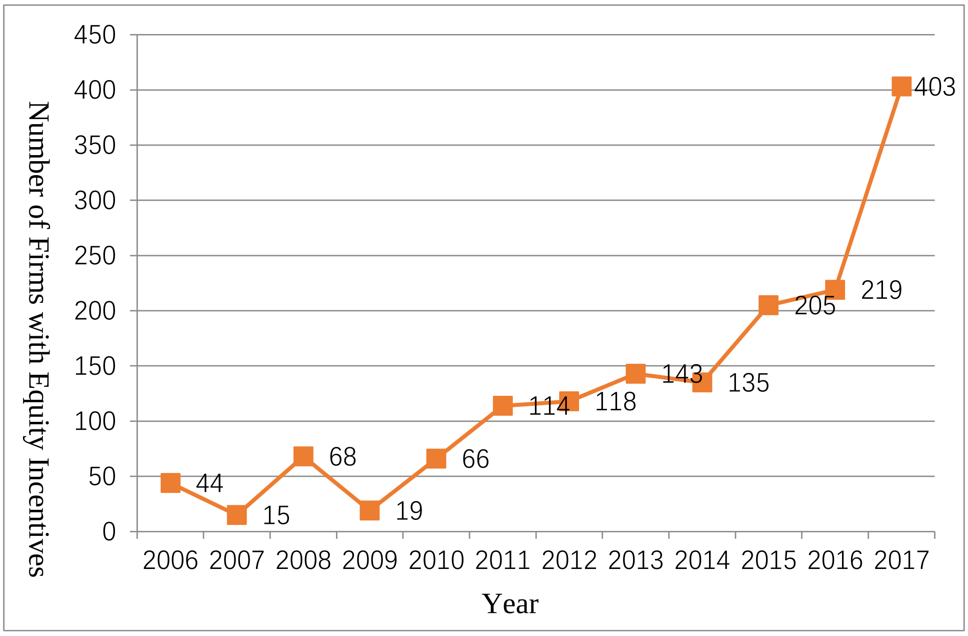

Figure 5.1 The Number of ESOPs in Chinese Listed Firms

(Data source: Zuo You Strategic Partners, 2018)

Encouraged by the policies discussed above, up to 2017, 1,549 listed firms adopted ESOP, occupying the 43.7% of the total listed firms as 3,546 in 2017. However, since 622 of them were announced in 2016 and 2017 (Zuo You Strategic Partners, 2018) and it needs time for the effect of the ESOP to become observable, such firms are not included in this research. As Chinese ESOP were modeled on American firms, there are some similarities that allows this analysis to be generalized to a degree despite legal and policy differences.

Huang and Zhang (2009) analysed the cross-section data of 1,302 Chinese listed SOEs in 2007 and found there was a positive relationship between the percentage of ESOP and firm’s earning per share (eps). The effect of ESOP to managers to influence eps was 4 to 6 times of that of employees. There was an inflection point for such effects. If the percentage of ESOP exceeded the inflection point, the positive relationship may be reversed. ESOP did not increase but reduced the firms' financial leverage. However, the authors did not explain the number of SOEs and non-SOEs with ESOP respectively before 2007. This research ignored the changes between the ESOP of the 2000s and financial data in 2007, which was a shortcoming. It used cross section data in 2007 which can be influenced by the context in 2007 and was not as robust as panel data over more years. Also, this research focused on the relationship between ESOP and eps, ignoring the influence of ESOP and other factors on innovation.

5.2.5 ESOP and principal-agent and principal-principal problems

Employee ownership, especially ESOP, "has raised numerous questions for the new institutional economics" (Estrin and Shlomowitz, 1988: 65). There are extensive publications about employee ownership especially ESOP covering various aspects.

First, ESPO helps to attract and keep talented employees. Richte and Schrader (2016) analysed a sample of more than 5,000 firms in Germany and found that firms adopted ESOP and profit sharing (PS) to attract and retain talent. Those firms with problems about recruitment and those planning to increase employment, are more likely to use ESOPs, which could help to keep talented employees and reduce employee turnover (Klein, 1987).

Second, ESOP can help to build the interest alignment among shareholders, managers and employees, and solve principal-agent and principal-principal problems, so that managers can contribute to improve the benefit of shareholders (Chang and Mayers, 1992).

Third, ESOP can help to improve management. According to extensive literature, the effect of employees participating in decision-making is positive (Estrin, Gerosk and Stewart, 1988), while the effect of profit sharing may have been overstated. But the effects of profit sharing, ownership sharing and employees participating in decision-making in French, Italian, British, Spanish and American firms (Estrin, Derek and Svejnar, 1987) were somewhat different from German and American firms (Estrin, Gerosk and Stewart, 1988).

Fourth, ESOP can help to improve productivity. Estrin, Derek and Shlomowitz (1988: 65) found that “employee involvement may be an effective way to increase company efficiency.” Estrin, Derek and Svejnar (1987) found that worker participation had an overall positive influence on productivity. Similarly, when employees begin to share ownership, the productivity increases (Estrin, Gerosk and Stewart, 1988). John Lewis is the leading firm with ownership sharing in the U.K. “In the context of John Lewis’s unique constitutional structure, employee ownership appears to offer significant advantages in the market place…. As a group, employee ownership, open information flows, high wages, and profit share are clearly associated with high productivity” (Bradley, Estrin and Taylor, 1990: 385). After analyzing a survey of 500 U.S. public companies and panel data about financial performance between 1975 and 1991, Kruse (1996) found a positive relationship between ESOP and productivity. Jones & Kato (2010: 331) found “On average, the net effect of introducing an ESOP is to increase productivity by almost 7%”.

Fifth, ESOP can help to improve the firm’s financial performance and benefit the economy. O’Boyle, et al., (2016: 425) conducted a meta-analysis of 102 samples from 56,984 firms and found “employee ownership has a small, but positive and statistically significant relation to firm performance.” Cin & Smith (2010: 263) found “an increase in an average ESOP from 2% to 3% of total shares would lead to an increase in output of 2.6%” in firms in South Korea. Hence, the South Korean government provided strong tax incentives to promote ESOP. Similarly, the British government found “profit sharing is in no individual firm’s interest but benefits the economy as a whole”, therefore, the “U.K. is the first country to subsidize profit-sharing, with tax incentives for firms which introduce profit-related pay (PRP) promised in the 1987 Finance Act" (Estrin, Gerosk and Stewart, 1988: 1).

Finally, there are by-products of ESOP. Estrin, Gerosk and Stewart (1988: 5) found "the impact becomes negative as the employee's share increases" which is similar to Far East Group in China interviewed in 2018. Other problems include "entrenchment" (Chang and Mayers, 1992; Aubert, et al., 2014) and "free riders" (Weitzman and Kruse, 1990).

However, much existing literature focused on the role of labour unions, bargaining power and unemployment, etc., which are popular in Western countries but different in China. Estrin, Gerosk and Stewart (1988) found profit sharing may influence the stock price significantly, but this is not found in the Chinese stock market.

5.2.6 Innovation, patenting and ESOP

R&D has been recognized as the main source of long-run growth of economy and productivity in many decades (Solow 1957; Grossman and Helpman 1994) and patenting is one indicator of R&D and innovation (Griliches 1989, 1990 and 1998). As one of the most important methods to protect new technologies, patent activities have been used to trace knowledge creation, spillovers and as a proxy for economic growth (Sanders, 1958; Pakes, 1984; Griliches, 1990; Lanjouw, 1996; Kortum and Lerner, 1997; Bosworth, 1997 and 1999; Klette & Kortum, 2002; Hopenhayn, 1999). Scotchmer (2006) reviewed the patent system as the institutional incentive to motivate firms and/or inventors to generate more innovation. ESOP is another institutional incentive to motivate employees to create more patent applications.

The relationship between shareholders and top management dominates the research of theory about principal-agent and principal-principal problems. But Chen, et al. (2006)

extended the application of this theory into the relationships among shareholders, management and R&D employees. Chen, et al., (2006) found there were two major agent problems influencing the R&D budget in firms. The first problem is the information asymmetry among the shareholders, the managers and key R&D employees. R&D employees have hidden information while managers feel it is difficult to supervise them which may result in distrust and uncertainty or even waste or failure in R&D. The second problem is that shareholders, managers and key R&D employees have different interests. Shareholders especially need the financial sheets to look best to raise the stock price. But R&D is uncertain or risky, hence shareholders are reluctant to invest in R&D. If such problems are not solved there may be less R&D budget permitted by shareholders and this may hurt the morale of managers and employees, resulting in the firm's decreased competitiveness and lower profits, leading to a vicious circle. In order to solve such problems, the firm should build an incentive alignment. By analysing 168 firms in information technology which were listed on the Taiwan Stock Exchange between 1996 and 2001, Chen, et al. (2006) found if firms awarded ESOP to employees, the problem could be alleviated and the firms could spend more on R&D. Chen, et al. (2006: 370) argued that ESOP "may transfer partial risk from shareholders to employees." Also, ESOP can "reduce agency conflicts between employees and shareholders, in turn decreasing R&D risks and agency costs." ESOP is recognised as one of the keys to improve the competitiveness of the IT firms in Taiwan (Chen, et al., 2006). This is consistent with what found in Chinese firms, especially Huawei. However, Chen, et al. (2006) just focused on the IT industry and have not examined how ESOP can influence the output of R&D such as patents. Similarly, Chang, at al., (2015) found non-executive employee stock options had a positive effect on corporate innovation. "The positive effect is more pronounced when employees are more important for innovation, when free-riding among employees is weaker, when options are granted broadly to most employees, when the average expiration period of options is longer" (p. 168).

Brander & Zhang (2017: 1) found both of “financial incentives [profit-sharing plans, stock option plans, and share ownership, etc.] and non-pecuniary motivations [good pension plans, good union relations, and a variety of specific benefits, e.g., flex time] had “a positive effect on innovation as measured by patenting and patent citations”. Garrett (2010) collected data about ESOPs, company savings plans, stock bonus plans, etc. in 11-k filings and analysed 77 high-tech firms which reported 11-k filings to the U.S. Securities and Exchange Commission. He found employee ownership positively moderates the effect of R&D intensity on the number of innovations measured by numbers of patent granted annually. R&D intensity is measured by the percentage of annual R&D expenses in sales. Similarly, Usman, Xiao & Li (2018: 161) found “both full-time employees’ stock options and their share ownership positively effects innovation.” But they analysed the unbalanced panel data of 284 firms among China’s innovative industries between 2009 and 2014, which has limited representativeness.

Ownership structure influences the firm’s innovation (Wang, 2011 and Kim, Lee & Lee, 2016). Choi, Lee & Williams (2011: 441) analysed the data from 548 Chinese firms between 2001 and 2004, and found the positive influence of “state and institutional ownership on innovation performance”. But Kroll and Kou (2019) analysed panel data about Chinese listed firms between 2003 and 2014 and found that state ownership weakens innovation if controlling for size. However, they ignored the influence of ESOP and little research has analysed the relationship between ESOP and patenting with sufficient representativeness.

In summary, some studies analysed the relationship between ESOP and innovation with some limitation, e.g., they may be not representative enough (Garrett, 2010). Also, none of the existing studies analyse the influence of industries, headquarters of firms by provinces, different stock boards or SOEs vs non-SOEs. The 1^{st}, 2^{nd} and 3^{rd} factors are important both in China and Western countries, while the 4^{th} factor is important in

China. According to the new institutional economics (Williamson, 1985; North, 1991), these factors provide the institutional, economic and political context (e.g., more market-oriented and flexible in Southeastern China vs more political rigid in Northwestern China) for the firms to grow, which means possibly significant impact on the firms. These important gaps will be filled by this study.

5.2.7 Hypotheses development

Chen, et al. (2006) found if firms awarded ESOP to employees, the problem could be alleviated and the firms could spend more budget on R&D. But they analysed only 168 firms in information technology listed on the Taiwan Stock Exchange between 1996 and 2001. Since Garrett (2010) focused on 77 firms only in the high-tech. industry, he noted the “limitation of whether the sample is representative and unbiased…. Future research might improve upon this limitation by collecting primary data on employee share ownership from each firm in the sample” (p. 44), which is exactly what this study does to fill the gap. Hence, it is necessary to test it in broader scenario and also there may be difference between knowledge/talent intensive industries and non-knowledge/talent intensive industries.

Similarly, according to the interviews, there is something interesting about ESOP in Huawei to promote innovation. At the end of 2020, 121,269 qualified employees or managers had the 100% share of Huawei without any external shareholders (Huawei, 2021). There is no need for Huawei to share its profit with external shareholders who may worry about the uncertain R&D as Chen, et al. (2006) found. Consequently, Huawei can spend more money on R&D and innovation, which also encourages its employees to promote innovations. This is one of the main reasons why Huawei can become leading in some technology such as 5G. In the interview, a manager of Huawei said:

“Since 2009, Huawei began to invest in the research to explore 5G. In 2013, we decided to invest US$ 600 million to 5G. Huawei is not a listed firm and does not have any external shareholders. No need for us to show a good financial report to the stock market, right? So, we can keep on investing in R&D for 8 or 10 years without any profit. This is impossible for many other firms."

Therefore, here is the first Hypotheses:

Hypothesis H5.1: There is significantly positive relationship between ESOP and annual R&D expense of firms.

As discussed in the literature review in Section 5.2, ESOP helps employees to share the financial fruits of firms and builds the interest alignment among shareholders, managers and employees. Hence, ESOP help to attract talented employees (Richte and Schrader, 2016) and encourage employees to work harder, which should have a positive relationship with innovation. Also, ESOP help to build trust among shareholders, managers and employees to solve problems of principal-agents and principal-principals (Chen, et al., 2006). But, the extant publications such as Chen, et al. (2006) and Garrett (2010) analysed the influence of ESOP on R&D expense, they ignored the influence of ESOP on the output of R&D measured by annual patent applications. Therefore, here is the second Hypothesis:

Hypothesis H5.2: There is significantly positive relationship between ESOP and the annual patent application number of firms.

As discussed in Section 5.2.4, there were several waves of reform about SOEs in China in the last 40 years and SOEs have been playing the important role in the Chinese economy (Lu, 2019 and 2020). According to the policy of the Chinese government, small and weak SOEs were privatized while only big SOEs were kept and supported by national, provincial and municipal governments. SOEs used to belong to governments, while employees have no share in SOEs. According to the interviews, ESOP helps employees to feel that their interest is bound with the SOE. For instance, a manager in China United Engineering Corporation Limited (CUEC) which is a SOE said in the interview:

"In the past, all SOEs were owned by the whole people. In fact, they were owned by the government, and everyone seems to have only 1 piece in 1.3 billion. It is impossible to have any sense about such a minimal proportion, right? Now we need to increase employees' feeling of acquiring benefit, so we have ESOP."

Similarly, in the interview, an employee in CITIC Heavy Industries Corporation Limited (CITICHIC) said:

"CITICHIC is a SOE and we have no share in it. We want CITICHIC to adopt ESOP, so that we can get some shares to be the really partial owners. After CITICHIC achieved IPO, we can harvest its partial benefits from the stock market, to compensate for our low salaries. You know, an economic incentive is important for us to work harder."

Hence, here is the third Hypothesis:

Hypothesis H5.3: The type of ownership (SOE or non-SOE) of firms influences the relationship between ESOP and the annual patent application number of firms.

With the rapid development of some industries in the context of a knowledge-based economy (OECD, 1996), the tacit knowledge held by managers and R&D employees becomes more and more specific and important. The managers and R&D employees spend a long time to accumulate such specific experience and tacit knowledge. If they change their jobs to other industries, their tacit knowledge may be devalued (Nonaka and Takeuchi, 1995a and 1995b). For instance, Wuxi Apptech is a firm to provide services of analysis and R&D for other pharmaceutical firms. Some of its employees moved to other pharmaceutical firms which will outsource their analysis and R&D to Wuxi Apptech. Hence, the former employees of Wuxi Apptech returned as the clients of Wuxi Apptech again. Similarly, an employee in Hundsun said:

"Some of my former colleagues used to work in Hundsun and gained experience about fintech. Then they jumped to the banks which used our fintech equipment. They do not want to change to another industry outside fintech. This is good for Hundsun, since all of them will naturally introduce the fintech equipment of Hundsun.”

Hence, the industry is influential and here is the fourth Hypothesis:

Hypothesis H5.4: The industry which the firms belong to influences the relationship between ESOP and the annual patent application number of firms.

The headquarters of listed firms in the sample were distributed in all the 31 provinces in China, which provide the institutional and economic context for firms to do business, with possibly significant impacts on the firms (Williamson, 1985 and North, 1991). On the one hand, firms in the same province have many connections and the main cities in the same provinces compete to attract employees. But there are big differences among provinces in Eastern, Central, Western, Northern and Southern China, e.g., more market-oriented and flexible in Southeastern China vs more politically rigid in Northwestern China. Furthermore, the people in Eastern China and other areas are somewhat different which were mentioned by some interviewees. In Shenzhen in Eastern China, there are more engineers good at hardware, while there are more programmers in Chengdu in Southwestern China good at software and games with historical culture. For example, a manager of HIKVision said in the interview:

“If we inform our employees to hold meeting at 8am in the morning. All employees in Hangzhou will be on time, but some employees in Chengdu may be late.”

On the other hand, managers and R&D employees may change their jobs mostly in the same industry. It is not clear which of these two forces (same province vs same industry) is stronger. Hence, here is the fifth Hypothesis to test the influence of geographical areas:

Hypothesis H5.5: The location (by province) of firms’ headquarters influences the relationship between ESOP and the annual patent application number of firms. The

Hypothesis H5.4 and H5.5 can be compared.

There are 4 stock boards in Chinese stock markets. Initially there are different requirements to select different firms to achieve IPO in each board. However, after firms entered the stock markets, they develop with various trajectories. Some small firms developed very rapidly and surpassed the initial big firms, especially SOEs. Also, SOEs and non-SOEs are mixed in all the four boards. Hence, the initial differences among firms in different boards become vague. The effect of ESOP on the firms in different stock boards may be not significant. Therefore, here is the sixth Hypothesis:

Hypothesis H5.6: Different stock boards influence the relationship between ESOP and the annual patent application number of firms.

5.3 Research design and cases selection

5.3.1 Mixed research design

Creswell & Clark (2011) introduced some main approaches for mixed methods research, including the parallel combination of qualitative and quantitative methods, first quantitative methods followed by qualitative methods to explain, first qualitative methods to explore the unknown factors followed by quantitative methods to explain, etc. In this study, I will apply the parallel combination of qualitative and quantitative methods. In qualitative interviews, some employees in SOEs emphasized why they want ESOP in SOEs, which help me to develop the relevant Hypothesis H5.3. Also, some employees mentioned that they usually change jobs in the same industries, which help me to develop the relevant Hypothesis H5.4. Some managers in the interviews mentioned the differences of employees in various provinces, which help me to develop Hypothesis H5.5 in Section 5.2.7. Along with the quantitative analysis, the qualitative interviews help to explain the feeling and experience of employees about ESOP and its incentives in Section 5.5 Discussion.

5.3.1.1 Quantitative analysis

The quantitative analysis focuses on the panel data. There are some advantages of panel data as reviewed in Section 3.3.1.1: the panel data range from 2007 to 2015 in this study about ESOP, which can provide more information than only time series data or cross section data (Hedeker and Gibbons, 2006). For example, cross section data cannot analyse the growth trend of patent applications over 9 years in this study. Also, time series data with only one firm cannot help to find the influence of ESOP on the growth trend of patent applications. Only the panel data can help to analyse the data of 1,509 firms between 2007 and 2015 in this study to find out if and how the ESOP influence the patent application in different industries or provinces. Panel data analysis can help to "separate aging effects [i.e., changes over 9 years within firms for this study], from cohort effects [i.e., differences between firms at the baseline]. Such cohort effects are often mistaken for changes occurring within [firms]." (Hedeker, and Gibbons, 2006: 1-2). Panel data help to solve the problem of missing data. For instance, some data about annual patent applications or R&D expense in some years are not available.

As reviewed in Section 3.3.1.2, growth curve models (GCMs) are applied to analyse the panel data. GCM has some advantages and it is suitable in this study: It analyses the growth trend of the annual numbers of patent application of 1,509 listed firms between 2007 and 2015 in this study. GCM can also examine how these trends vary because of covariates at year-level, firm-level or industry-level (Rabe-Hesketh and Skrondal, 2012). GCM is easy to be extended to more levels such as industry-level or province-level in this study. GCM can reduce and divide the total residual into three parts: residuals at the levels of year, firm or industry respectively. Hence, all the residuals can be independent and nearly normally distributed.

As reviewed in Section 3.3.1.3, There are some advantages to convert data into natural logarithm (Kutner, Nachtsheim and Neter, 2004): Reduce the absolute value of the number, e.g., the annual patent application number of listed firms ranges from 0 to 6,327; Improve the reliability, stability and convenience to deal with residual, while reduce the collinearity and heteroscedasticity. The annual patent application number of listed firms cannot be fit by linear model, but can be fit by exponential model. After converting such data into natural logarithm, the linear model can be used conveniently.

5.3.1.2 Causal relationship

Causal relationships (Angrist and Pischke, 2009 and 2014) are also considered in this study. Some factors are necessary to be considered when explore the possible causal relationship: 1) the possible cause should be ahead of the result in time dimension, e.g., ESOP took place before patent applications. 2) strong correlation between possible cause and result, e.g., the coefficient of ESOP should be statistically significant. 3) exhaust other possible explanations, e.g., the main possible influential factors including SOEs vs non-SOEs, industry, location (by province) of firms' headquarters and stock boards, etc. are tested in this study. 4) analyse counterparts by random sampling. 5) find process and mechanism, e.g., how ESOP help firms to promote innovation? 6) provide the suitable theory to explain the process and mechanism: e.g., why ESOP helps to promote innovation?

Five typical methods to find causal relationship are also considered. Difference-in-differences (DD), regression discontinuity design (RDD) and synthetic control method seem reasonable to find how ESOP influences the innovation such as patent application before and after ESOP. However, these methods are all suitable for the research about the sudden influences by external rules or policies such as tax increment for the consumption of cigarettes (Angrist and Pischke, 2009 and 2014). In this study, ESOP is not the external policy. For instance, the firms choose to adopt ESOP or not. Furthermore, DD usually focus the data before and after the sudden treatment such as the quick changing of rules. But in this study, the treatment is ESOP. The employees have to keep the ESOP for at least 12 month and usually 2 to 3 years or even longer before they sell the incentive stocks. Instrument variable is also considered, but it also may be not suitable for this study.

The only method probably suitable for the study in Chapter 5 may be matching using the propensity score (MUPS) which can be applied to analyse the cases which select treatments (Angrist and Pischke, 2009). However, since the firms adopted ESOP in various years, for instance, 2007 for Firm A and 2013 for Firm B, etc. It is difficult to identify which year will be the time zero for all firms. Even if the year when the firms adopted ESOP is chosen to be the year zero, e.g., move the data of 2007 for Firm A and 2013 for Firm B to be in the same column at time zero, the context including industrial, technological, economic, political and social factors for each firm will be changed drastically. This can make the analysis based on MUPS to be unreasonable and unreliable.

5.3.1.3 Qualitative interview

Quantitative research tries to reduce a phenomenon to a simple number, but Bauer and Gaskell (2000: 8) argued for “no quantification without qualification” and “no statistical analysis without interpretation”. In this study, it is not clear about how the employees are activated by ESOP. This cannot be explained only by quantitative data. Interview is one of the most important qualitative methods to explore the truth under the quantitative data (Bauer and Gaskell, 2000). Interview tries to find what is behind the quantitative numbers by “seeking complexity and depth of thought” (Hamilton and Bowers, 2006: 821). Interview is important if want to explore what people think (Aberbach and Rockman, 2002). In this study, interviews are conducted since it can explore employees’ personal feelings and experience about the influence of ESOP. Some factors identified from interviews help to develop hypotheses and interviews help to explain the results of quantitative models.

5.3.2 Cases selection and data collection for quantitative analysis

The typical examples of Chinese innovations are selected by two criteria to have sufficient representativeness. First, the Chinese economy has both traditional and high-tech. industries, so that the sampled industries should include both industries. This is more representative than Garrett (2010) who studied only 77 firms in high-tech. industries, Chen, et al. (2006) who analysed 168 listed firms in IT industry in Taiwan and Usman, et al., (2018) who were limited to innovative industries only. Second, the industries should be competitive instead of monopoly, since it is not easy to prove firms to be innovative in a monopoly industry such as China Mobile.

Firms listed in Chinese stock markets were chosen because of the availability of relatively reliable financial and other data. The data about Chinese list firms are from the database of Wind. The R&D expense data are from the database of Shenzhen Guotaian and matched by the unique id of each listed firm. The data about industrial enterprises in industries or provinces are from *Statistical Yearbook of Scientific and Technological Activities of Industrial Enterprises* of National Bureau of Statistics of the People's Republic of China (NBSPRC, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016). Steele, French and Barltley (2013) discussed the possible bias from direct and indirect selection and suggested a method to adjust such selection bias. Initially, the financial data of 2,453 firms listed on the Chinese stock markets were obtained. It is hypothesized that lags between ESOP and innovation indicators such as R&D spending and patent application could be analysed through the panel data over 9 years, which is necessary to improve analytical reliability and validity. But those firms which initially listed on Chinese stock markets after 2012 do not have sufficient financial data, hence they are not included in this research. Second, after deleting the firms which only have data in the limited period, 1,720 firms are obtained whose financial data are available between 2007 and 2015. The firms that changed their business and owners totally, e.g., from manufacturing to delivery of e-commerce parcels, were dropped. Those firms which had major legal or business problems and were excluded from the stock markets were also dropped. Finally, those firms which filed no patent applications between 2007 and 2015 were dropped, leaving 1,509 firms. Among the 1,509 firms, the latest firm to be listed in stock market is 2012. These firms covered 60.4% of all the 2,497 firms already listed in Chinese stock markets in 2012, which is a good representative of all firms with patent applications. The main business between 2007 and 2015 is recorded to classify them into different industries.

Table 5.1 Cumulative Numbers of Firms

Listed in Chinese Stock Market and Firms in Sample

Year	2007	2008	2009	2010	2011	2012
Total firms	1,560	1,627	1,724	2,067	2,345	2,497
Firms in sample	745	808	887	1,183	1,396	1,509
Percentage	47.80%	49.70%	51.50%	57.20%	59.50%	60.40%

(Data source: Wind)

Between 2007 and 2015, 883 firms announced ESOPs, constituting 35.4% of all 2,497 listed firms in 2012. Among the firms sampled in this study, 417 firms have both data about ESOP and patent applications, which is 27.6% of 1,509 firms, or 47.2% of all 883 firms with ESOPs during the period 2007 and 2015. Many firms have ESOPs but very few patent applications, especially those firms in 49 industries that are unlikely to hold patents, including agriculture, forestry, stock farming, fishery, electricity, thermal, gas and water production and supply, housing construction, civil engineering, construction installation, architectural decoration, wholesale and retail business, transportation (railway, road, water, air and pipeline transportation), transport agents, warehousing and postal service, accommodation and catering, monetary and financial services, capital market services, insurance, real estate, leasing and business services, water conservancy, environment and public facilities management, land management, resident services, repair and other services, education, health and social work, news and publishing, broadcasting, television, film and recording, culture, sports and entertainment, etc. The details about the distributions of firms in different industries, provinces, different stock boards and categories of SOE or non-SOE, etc. will be discussed in Section 5.4.1 Summary of sample firms.

5.3.3 Dependent variables, independent variables and control variables for quantitative analysis

5.3.3.1 Dependent variables

As reviewed in Section 3.3.3.1, Schumpeter (1934) divided innovation into five categories, plus new business models in recent decades (Foss, Nicolai and Saebi, 2017). This study focuses on the technical innovations. First, the dependent variable (DV) is selected. There could be many different indicators to measure firms' innovation which have various advantages and disadvantages. Financial performances such as annual revenue, profit, net profit or earning per share (eps), etc., are relevant as inputs to innovation, but they also may be the results of firms' innovation. Patent data has been used as the best and most convenient indicators to measure innovation, despite its well-understood shortcomings (Griliches 1989, 1990 and 1998). The DV is about firms' innovation performance, which could be the annual number of patents applications, the annual number of patents granted with different time lags (Bai, 2013), the annual number of technological standards established, etc. However, it usually takes about one year for utility patents and about 3 years for invention patents to be granted by the China State Intellectual Property Office. If using only the number of patents granted, it is difficult to pinpoint when each patent was created and relate it to the effect of ESOP. Hence, in this study, the annual number of patents applications for each firm is selected to be the DV.

5.3.3.2 Independent variables and control variables

The key independent variable (IV) is the percentage point of ESOP in each firm in each year. Also, it can be interacted with other control variables (CVs). Teimpcf2 indicates the percentage points of ESOP of the firm where the employees keep ESOP for 2 years on average. Teimf is the dummy variable for teimpcf2 of the firm, 1 if the firm has teimpcf2>0 and 0 if the firm has teimpcf2=0. It is important to notice that the value of teimpcf2 for the same firm between 2007 and 2015 could be 0 or bigger than 0, but the basic unit of analysis is firm. Hence the teimf should be 1 if the firm has teimpcf2>0 in any year between 2007 and 2015. Otherwise, if the teimf is 1 when the firm has teimpcf2>0 in year A and the teimf is 0 when the same firm has teimpcf2=0 in year B, this will divide the data of the same firm into 2 groups, which is incorrect. The influence of the duration to keep ESOP from 1 year to 6 years will be discussed in Section 5.4.2

The CVs could be a long list at 2 different levels. At the level of firms, CVs could be the year of firm registered officially or achieve IPO, the registered capital, annual revenue, annual total profit, annual net profit, annual basic earnings per share (beps), annual R&D expense, annual total asset, annual net asset, annual intangible asset, and these CVs with lags of one or two years, etc.

Hypothesis H5.3 in Section 5.4.6 tests the possible influence of SOE or non-SOEs on the relationship between ESOP and the number of patent applications. There are many types of firm ownership: State-owned enterprises (SOE) belong to national, provincial, municipal, county and village government, private-owned enterprises (POE), collective-owned enterprises (COE), foreigner invested enterprises (FIE). Fu (2016) analysed the influence of FDI on Chinese innovation. Since there are few COE or FIE listed firms, all firms are demarcated as SOEs or non-SOEs. Furthermore, the possible interactions among these variables will be analysed.

Hypothesis H5.4 in Section 5.4.7 tests the possible influence of the industry on the relationship between ESOP and the number of patent applications. At the level of the industry, CVs could be the annual number of firms in the industry, annual total revenue of the industry, etc. Since the innovation performance is the focus, the relevant CVs in the industry such as the number of R&D employees, the R&D budget in the R&D departments, the project number of new products and the total sales of new products in all firms in each industry per year in official census are emphasized. There are various knowledge sharing among each industry through patent citation or infringement (Tang and Huang, 2002), reverse engineering and flow of talents, etc. (Nonaka and Takeuchi, 1995a and 1995b).

Hypothesis H5.5 in Section 5.4.8 tests the possible influence of provinces where the firms' headquarters are located on the relationship between ESOP and the number of patent applications. Similarly, at the level of province where the firm's headquarters is registered officially or located actually, CVs include the annual number of firms in each province, annual total revenue of all firms in each province, the annual number of technical employees of each province, the annual number of R&D expense of each province, the annual number of new product developments of each province, the annual budget for new product development of each province and the annual revenue of new product of each province in official census. There may be knowledge sharing via flow of talents in the same province, hence such CVs may influence the relationship between DV and IVs.

The headquarters of 73 firms, 4.8% of 1,509 firms, worked in provinces different from their registered provinces. For instance, some firms with registered headquarters in developing provinces including Tibet and Gansu in Western China settle their headquarters in the better developed neighbor, Sichuan Province. Since the actual working locations provide the real economic and social resources including human resources and technology resources, the actually working provinces (hqpid), instead of registered provinces (rprid), are used as the CV in this study.

The size of firms is also considered. Some firms grew rapidly from small into big firms between 2007 and 2015. The average size of the firms between 2007 and 2015 is not suitable. Since it is difficult to categorize some firms into any groups of small, middle or big size between 2007 and 2015, the dummy variable about the size of firms will not be analysed in this study. However, since the annual revenue of each firm is included as a CV which also considers the size of the firm, it can be regarded as a proxy.

According to Rabe-Hesketh and Skrondal (2012), it is better to set the beginning year from 0 in a growth curve model. Hence, t0 is used as 0, 1, …8 instead of year 2007, 2008 … 2015. As discussed in Section 3.3.1.3 and Section 5.3.1.1, there are some advantages to convert some data into the natural logarithm (Kutner, Nachtsheim and Neter, 2004). The list of DVs and IVs are illustrated in the following table. To be parsimonious, the CVs whose marginal contributions are not significant are dropped from the final models.

Table 5.2 Dependent Variables (DVs), Independent Variables (IVs) and Control Variables (CVs) for the Study about ESOP in Chapter 5

Groups	Order	DV or EV	Description	Unit
DV	1	tpatap	Annual patent application number per firm	
	2	lntpatap	Natural logarithm of annual number of patent application per firm	
IVs	3	teimpcf1	Percentage point of ESOP which the employees keep ESOP for 1 years.	Percentage point of the total share of the firm
	4	teimpcf2	Percentage point of ESOP which the employees keep ESOP for 2 years.	Percentage point of the total share of the firm
	5	teimpcf3	Percentage point of ESOP which the employees keep ESOP for 3 years.	Percentage point of the total share of the firm
	6	teimpcf4	Percentage point of ESOP which the employees keep ESOP for 4 years.	Percentage point of the total share of the firm

	7	teimpcf5	Percentage point of ESOP which the employees keep ESOP for 5 years.	Percentage point of the total share of the firm
	8	teimpcf6	Percentage point of ESOP which the employees keep ESOP for 6 years.	Percentage point of the total share of the firm
	9	teimpcf	Percentage point of ESOP which the employees keep ESOP to 2015.	Percentage point of the total share of the firm
	10	teimf	Dummy variable for teimpcf2, 1 if teimpcf2>0 in any year between 2007 and 2015, 0 if teimpcf2=0 in all year between 2007 and 2015.	
Unit of time	11	t0	stands for year, range from 0 to 8.	Year
interactions of t0 and IVs	12	t0teimpcf1	The interaction between t0 and teimpcf1	
	13	t0teimpcf2	The interaction between t0 and teimpcf2	
	14	t0teimpcf3	The interaction between t0 and teimpcf3	
	15	t0teimpcf4	The interaction between t0 and teimpcf4	
	16	t0teimpcf5	The interaction between t0 and teimpcf5	
	17	t0teimpcf6	The interaction between t0 and teimpcf6	
unit of analysis	18	firmid	The id of firm which is the same as the id of firm listed in the stock markets.	
CVs at firm level: financial performance of each firm in each year and their lags	19	lntreve	Natural logarithm (ln) of total revenue per firm per year	ln of amount in Chinese Yuan
	20	ltrvlg1y	Natural logarithm (ln) of total revenue per firm per year in the next year	ln of amount in Chinese Yuan
	21	ltrvlg2y	Natural logarithm (ln) of total revenue per firm per year after 2 years	ln of amount in Chinese Yuan
	22	lntprof	Natural logarithm (ln) of total profit per firm per year	ln of amount in Chinese Yuan
	23	lntpfg1Y	Natural logarithm (ln) of total profit per firm per year in the next year	ln of amount in Chinese Yuan

	24	lntpfg2Y	Natural logarithm (ln) of total profit per firm per year after 2 years	ln of amount in Chinese Yuan
	25	lnnprof	Natural logarithm (ln) of total net profit per firm per year	ln of amount in Chinese Yuan
	26	lnpflg1y	Natural logarithm (ln) of total net profit per firm per year in the next year	ln of amount in Chinese Yuan
	27	lnpflg2y	Natural logarithm (ln) of total net profit per firm per year after 2 years	ln of amount in Chinese Yuan
	28	beps	Basic earning per share per year	Chinese Yuan per share
	29	bepslg1y	Basic earning per share in the next year	Chinese Yuan per share
	30	bepslg2y	Basic earning per share after 2 years	Chinese Yuan per share
	31	lnnfixa	Natural logarithm (ln) of total net fixed asset per firm per year	ln of amount in Chinese Yuan
	32	lnfalg1y	Natural logarithm (ln) of total net fixed asset per firm per year in the next year	ln of amount in Chinese Yuan
	33	lnnitas	Natural logarithm (ln) of total net intangible asset per firm per year	ln of amount in Chinese Yuan
	34	lnitlg1y	Natural logarithm (ln) of total net intangible asset per firm per year in the next year	ln of amount in Chinese Yuan
	35	lnrdb	Natural logarithm (ln) of total R&D expense per firm per year	ln of amount in Chinese Yuan
	36	lnra1y	Natural logarithm (ln) of total R&D expense per firm in the previous year	ln of amount in Chinese Yuan
	37	lnrl1y	Natural logarithm (ln) of total R&D expense per firm in the next year	ln of amount in Chinese Yuan
CVs at ownership level	38	owid	The id of the type of ownership of firm.	
	39	ownsoedv	ownsoedv =1 if firm is SOE	
			ownsoedv=0 if firm is non-SOE	

	40	owsodvtf2	The interaction between ownsoedv and teimpcf2	
CVs at stock board level	41	stpid	The id of the stock board which the firm belong to	
	42	stpidtf2	interaction of stpid and teimpcf2	
CVs at industry level	43	induid	The id of the industry which the firm belong to	
	44	lninumfm	Natural logarithm (ln) of the number of all firms in each industry per year in official census	
	45	lnitrev	Natural logarithm (ln) of the total revenue of all firms in each industry per year in official census	ln of amount in Chinese Yuan
	46	lnifriem	Natural logarithm (ln) of the number of R&D employees in the R&D departments in all firms in each industry per year in official census	
	47	lnifriex	Natural logarithm (ln) of the R&D budget in the R&D departments in all firms in each industry per year in official census	ln of amount in Chinese Yuan
	48	lnifnpdn	Natural logarithm (ln) of the project number of new products in all firms in each industry per year in official census	
	49	lnifnprv	Natural logarithm (ln) of the total sales of new products in all firms in each industry per year in official census	ln of amount in Chinese Yuan
	50	tflninum	The interaction between teimpcf2 and lninumfm	
	51	tflnitre	The interaction between teimpcf2 and lnitrev	
	52	tflnifriem	The interaction between teimpcf2 and lnifriem	
	53	tflnifri	The interaction between teimpcf2 and lnifriex	

	54	tflnifnp	The interaction between teimpcf2 and lnifnpdn	
	55	tflnifnpr	The interaction between teimpcf2 and lnifnprv	
CVs at provincial level	56	rprid	The id of the province in which the firm's headquarter is officially registered	
	57	hqpid	The id of the province in which the firm's headquarter is actually located	
	58	lnpnumfm	Natural logarithm (ln) of the number of all firms in each province per year in official census	
	59	lnptrev	Natural logarithm (ln) of the total revenue of all firms in each province per year in official census	
	60	lnpfriem	Natural logarithm (ln) of the number of R&D employees in the R&D departments in all firms in each province per year in official census	
	61	lnpfriex	Natural logarithm (ln) of the R&D budget in the R&D departments in all firms in each province per year in official census	ln of amount in Chinese Yuan
	62	lnpfnpdn	Natural logarithm (ln) of the project number of new products in all firms in each province per year in official census	
	63	lnpfnprv	Natural logarithm (ln) of the total sales of new products in all firms in each province per year in official census	ln of amount in Chinese Yuan
	64	tflnpnumfm	The interaction between teimpcf2 and lnpnumfm	
	65	tflnpfriem	The interaction between teimpcf2 and lnpfriem	
	66	tflnpfriex	The interaction between teimpcf2 and lnpfriex	

	67	tflnpfnpdn	The interaction between teimpcf2 and lnpfnpdn	
	68	tflnpfnprv	The interaction between teimpcf2 and lnpfnprv	
	69	tflnptrev	The interaction between teimpcf2 and lnptrev	

5.3.4 Interview data collection, ethics and reflexivity and thematic analysis

Between 2017 and 2019, about 32 innovative firms in China were visited, including Huawei, Wens Group (the largest firm in stock farming) and Midea (a top firm in home appliance) in Guangdong Province, Alibaba, Hundsun (the largest firm in fintech equipment in China), Hikvision and Dahua (the 1st and 2nd largest firms in CCTV equipment), Transfar (the largest firm in e-logistics for trucks) and Huali in Zhejiang Province, Far East Group (the largest firm in electrical cables), Hodo Group and Fasten Group (the largest firm in steel cables) in Jiangsu Province, Yutong Bus (the largest bus manufacturer) and CITICHIC (the largest firm in mining equipment) in Henan Province, Haier (a top firm in home appliances) in Shandong Province, Lenovo and Xiaomi in Beijing, etc. These firms were selected with purposive sampling since they are leading innovative firms. Also, they are located in Southern China, Eastern China, Northern China and Central China, which covers key areas of the Chinese economy with representativeness. With the help of friends, about 100 interviewees in the firms were selected purposively, including the President of Hundsun, a vice president of Wens Group, managers in the office of boards, managers in the office of stocks, some general managers, engineers and employees in most firms in the sample.

The interview about ESOP is semi-structured and conducted face to face. The interview guide is in the Appendix. Before the interview, I prepared well and read much news online about the firms, so that I knew the firms well and designed critical questions with depth. Following Berry (2002), I prepared a roadmap and rules to determine where I should probe or where should I just verify the information provided by other interviewees or documents. Also, I prepared some bridges to come back to the previous questions if necessary. When the interviewee provided some interesting topics which were helpful for the research, I probed further. I balanced between the time of interview and how much I should probe. It took between 30 and 70 minutes for the interviews. Also, I tried to meet the criteria for good interviews and paid attention to external and internal reliability and validity. Since the interviews covered some topics more than ESOP, only the results about ESOP are discussed in this chapter.

Some issues about ethics and reflexivity need to be addressed. Before I visited the firms, I asked the company not to expose any confidential technical or business sensitive materials to me. Before the interviews, I obtained permissions from all interviewees. The interviewees are all adults working normally who do not have any mental disability or other vulnerability. The interviews did not bring any emotional stress to the interviewees, or involve deception. Also, I did not pay the interviewees. The main ethical concerns are to protect their privacy by keeping them anonymous. I did not provide the transcripts of interviews to the firms to avoid involving firms' internal politics. Therefore, the interviewees will not be harmed physically or mentally. I took care of myself, and there is no need to worry about my security, psychological wellbeing or any reputation harm. There are some challenges about reflections for me to finish the interviews and analyse the documents. Since the interviews are interactive, my questions' content and my style to ask such questions may influence the interviewees' attitudes and answers. Additionally, my background and understanding may distort the meanings of interviewees' answers and the documents. Therefore, I tried my best to be objective and decenter my role in the interviews and their analysis. I kept my mind open to avoid any potential pre-determined assumptions or bias. To avoid any potential mistakes, I used both interviews and documents for triangulation (Robson, 2011 and Mayan, 2009), and I found most of the interviews' transcriptions and the documents supported each other well.

Among the several methods to analyse the data, thematic analysis (TA) (Attride-stirling, 2001) is adopted in this study. Content analysis needs much more relevant documents which were not available. Also, discourse analysis or ethnographic analysis is not suitable for this study. But TA is suitable to analyse the data from the interviews' transcripts and documents, identify categories and their relationship, finally find the potential pattern and build the thematic network. I use a bottom-up approach to explore the potential pattern in the transcripts and documents. Following Attride-Stirling (2001), first, I identify some text segments, which help me to create some initial codes. Second, I use such codes to find more relevant text segments. If initial codes could not cover some important text segments, I create more codes. Third, I classify the relevant codes into categories and extract basic themes from the categories of codes by considering commonalities and coherence. The codes and themes should be very clear, concise, non-repeated, non-overlapped and mutually exclusive. Fourth, I classify basic themes into groups and integrate such groups into organizing themes. Fifth, I examine and refine the relationship between basic and organizing themes to build the theme network. Sixth, the organizing themes are integrated into one global theme. This process is nonlinear and is repeated cyclically for refinement and verification with systematic and consistent criteria. I describe, explore and analyse the codes and themes, and find the structure or pattern. Finally, I summarize and interpret thematic networks and pattern to answer the research question.

5.4 Quantitative data analysis and results

5.4.1 Summary of sample firms

5.4.1.1 Summary of different types of ownership

As illustrated in Table 5.3, among the 1,509 firms in the sample between 2007 and 2105, there are 497 SOEs which is 32.94% of the total 1,509 firms in the sample.

Among them, only 43 firms (8.65% of SOEs) had ESOPs. Due to the problems of corruption and the possible accusation of losing SOEs' assets, the Chinese government and SOEs hesitate to adopt ESOP. In contrast, there are 1,012 non-SOEs, which is 67.06% of the total 1,509 firms in the sample. There are 374 non-SOEs that had ESOPs, occupying 36.96% of the 1,012 non-SOEs, much higher than SOEs. Such 374 non-SOEs with ESOPs occupied 89.69% of the total 417 firms with ESOP in the sample. Hence, the non-SOEs are more prone to adopt ESOP. This is reasonable, since such non-SOEs have limited support of finance or human resources or monopoly from the government. They have to improve their competitiveness to attract and activate talents and enhance their innovations. The influence of SOE or non-SOE on the effect of ESOP will be analysed in Section 5.4.6.

Table 5.3 Sample Firms in Different Types of Ownership

	Number of firms (SOE)	Number of firms (non-SOE)
Number of firms with ESOP	43	374
Number of firms without ESOP	454	638
subtotal	497	1012
percent of firms with ESOP in subtotal firms	8.65%	36.96%
percent of subtotal firms in total 1,509 firms	32.94%	67.06%

5.4.1.2 Summary of sample firms in different industries

As illustrated in Table 5.4 and Figure 5.2, 1,509 firms in the sample between 2007 and 2015 distribute in 18 level-1 categories (in italics in Table 5.4) and 64 level-2 categories of industries based on the official industry categories in China. There are firms sampled in 64 industries while no firms were sampled in 26 industries, mainly because there were no patent applications. Manufacturing is the biggest level-1 category. Ranking by the number of subtotal firms in level-2 categories (induid), there are most firms in Category 39 of manufacturing of computers, communications and other electronic equipment, the second is Category 38 electrical machinery and equipment manufacturing, the third is Category 26 production of chemical materials and chemicals, and the fourth is Category 35 special equipment manufacturing. However, ranking by the number of firms with ESOP in level-2 categories (induid), there are most firms in Category 39 of manufacturing of computers, communications and other electronic equipment, the second is Category 38 electrical machinery and equipment manufacturing, the third is Category 65 software and information technology services, and the fourth is Category 26 production of chemical materials and chemicals. It is also interesting to notice that the firms with ESOP in Category 65 software and information technology services are more numerous than the firms without ESOP. This may be because Category 65 are knowledge-intensive or talent-intensive, so that the firms need ESOP to attract, keep and activate the talents. Usually knowledge-intensive industries are also talent-intensive industries. The influence of different industry categories on the effect of ESOP will be analysed in Section 5.4.7.

Table 5.4 Sample Firms in Different Industries

	Category (induid)	Number of firms with ESOP	Number of firms without ESOP	Subtotal	% of number of firms with ESOP in subtotal	% of subtotal number of firms in 1509 firms
Agriculture, forestry, stock farming, fishery		*3*	*14*	*17*	*17.6%*	*1.1%*
Agriculture	1	0	1	1	0.0%	0.1%
Forestry	2	0	2	2	0.0%	0.1%
Stock farming	3	1	3	4	25.0%	0.3%
Fishery	4	1	5	6	16.7%	0.4%
Assisting business for agriculture, forestry, stock farming, fishery	5	1	3	4	25.0%	0.3%
Mining		*2*	*33*	*35*	*5.7%*	*2.3%*
Coal mining and cleaning	6	0	13	13	0.0%	0.9%
Petroleum and gas exploit	7	0	2	2	0.0%	0.1%
Ferrous metals mining and	8	0	4	4	0.0%	0.3%

dressing						
Non-ferrous metals mining and dressing	9	0	6	6	0.0%	0.4%
Mining and assisting business	11	2	8	10	20.0%	0.7%
Manufacturing		*334*	*908*	*1242*	*26.9%*	*82.3%*
Agricultural and sideline food processing industry	13	5	15	20	25.0%	1.3%
Food production	14	6	13	19	31.6%	1.3%
Alcohol, beverage and tea production	15	2	22	24	8.3%	1.6%
Textile industry	17	5	17	22	22.7%	1.5%
Textile and apparel industry	18	5	13	18	27.8%	1.2%
Leather, fur, feather and their products and gootwear industry	19	1	3	4	25.0%	0.3%
Wood processing and wood, bamboo, rattan, brown and grass products industry	20	2	2	4	50.0%	0.3%
Furniture manufacturing	21	3	0	3	100.0%	0.2%
Paper and paper products industry	22	4	17	21	19.0%	1.4%
Printing and recording media reproduction industry	23	2	2	4	50.0%	0.3%
Production of cultural, educational, gongmei, sports and entertainment goods	24	3	7	10	30.0%	0.7%
Petroleum, coal and other fuel processing industry	25	2	6	8	25.0%	0.5%
Production of chemical materials and chemicals	26	35	96	131	26.7%	8.7%
Pharmaceutical manufacturing industry	27	32	77	109	29.4%	7.2%
Chemical fibre manufacturing Industry	28	2	16	18	11.1%	1.2%
Rubber and plastic products industry	29	11	31	42	26.2%	2.8%
Nonmetallic mineral products	30	9	34	43	20.9%	2.8%
Ferrous metal smelting and calendering industry	31	1	24	25	4.0%	1.7%
Nonferrous metals smelting and calendering industry	32	6	41	47	12.8%	3.1%

Metal products industry	33	6	27	33	18.2%	2.2%
General equipment manufacturing industry	34	17	64	81	21.0%	5.4%
Special equipment manufacturing industry	35	28	87	115	24.3%	7.6%
Automotive industry	36	8	49	57	14.0%	3.8%
Manufacturing of railway, ship, aerospace and other transportation equipment	37	2	19	21	9.5%	1.4%
Electrical machinery and equipment manufacturing industry	38	54	85	139	38.8%	9.2%
Manufacturing of computers, communications and other electronic equipment	39	70	122	192	36.5%	12.7%
Instrument manufacturing industry	40	8	13	21	38.1%	1.4%
Other manufacturing industries	41	5	5	10	50.0%	0.7%
Comprehensive utilization of waste resources	42	0	1	1	0.0%	0.1%
Electricity, thermal, gas and water production and supply industry		*4*	*11*	*15*	*26.7%*	*1.0%*
Electricity and thermal production and supply industry	44	2	9	11	18.2%	0.7%
Gas production and supply industry	45	2	0	2	100.0%	0.1%
Water production and supply industry	46	0	2	2	0.0%	0.1%
Construction business		*12*	*38*	*50*	*24.0%*	*3.3%*
Civil engineering and construction industry	48	5	31	36	13.9%	2.4%
Architectural decoration, decoration and other construction industries	50	7	7	14	50.0%	0.9%
Wholesale and retail business		*5*	*7*	*12*	*41.7%*	*0.8%*
Wholesale business	51	1	4	5	20.0%	0.3%
Retail business	52	4	3	7	57.1%	0.5%
Transportation, warehousing and postal service		*1*	*10*	*11*	*9.1%*	*0.7%*
Road transport industry	54	0	3	3	0.0%	0.2%
Water transport industry	55	0	4	4	0.0%	0.3%

Air transport industry	56	0	3	3	0.0%	0.2%
Multimodal transport and transport agent industry	58	1	0	1	100.0%	0.1%
Information transmission, software and information technology services		*42*	*40*	*82*	*51.2%*	*5.4%*
Telecommunications, radio and television and satellite transmission services	63	0	6	6	0.0%	0.4%
Internet and related services	64	3	2	5	60.0%	0.3%
Software and information technology services	65	39	32	71	54.9%	4.7%
Finance		*0*	*12*	*12*	*0.0%*	*0.8%*
Monetary and financial services	66	0	10	10	0.0%	0.7%
Capital market services	67	0	1	1	0.0%	0.1%
Insurance industry	68	0	1	1	0.0%	0.1%
Real estate		*1*	*6*	*7*	*14.3%*	*0.5%*
Real estate	70	1	6	7	14.3%	0.5%
Leasing and business services		*0*	*2*	*2*	*0.0%*	*0.1%*
Leasing industry	71	0	0	0		0.0%
Business services	72	0	2	2	0.0%	0.1%
Scientific research and technology services		*5*	*2*	*7*	*71.4%*	*0.5%*
Professional and technical services	74	5	2	7	71.4%	0.5%
Water conservancy, environment and public facilities management industry		*6*	*3*	*9*	*66.7%*	*0.6%*
Eco-protection and environmental governance industry	77	6	2	8	75.0%	0.5%
Public facility management industry	78	0	1	1	0.0%	0.1%
Health and social work		*1*	*2*	*3*	*33.3%*	*0.2%*
Social work	85	1	2	3	33.3%	0.2%
Culture, sports and entertainment		*1*	*4*	*5*	*20.0%*	*0.3%*
News and publishing industry	86	1	2	3	33.3%	0.2%
Entertainment	90	0	2	2	0.0%	0.1%

(Data source: Wind)

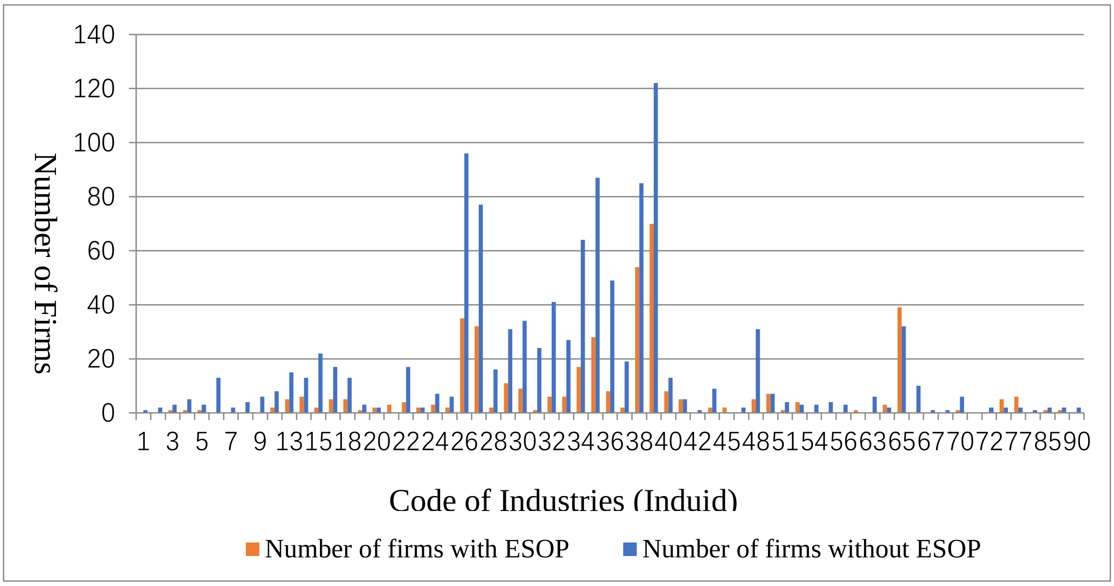

Figure 5.2 Distribution of Sample Firms in Different Industries (Data source: Wind)

5.4.1.3 Summary of sample firms' headquarters in different provinces

As illustrated in Table 5.5 and Figure 5.3, the headquarters of 1,509 sample firms are located in 31 mainland provinces, none in Hong Kong, Macau, Taiwan or overseas areas. Ranking by subtotal firms, the top five provinces are Guangdong, Zhejiang, Jiangshu, Beijing and Shanghai. Guangdong Province has the highest GDP, Zhejiang Province and Jiangshu Province have many private firms. Beijing and Shanghai are big cities where many firms, especially SOEs, settle their headquarters. Ranking by number of firms with ESOPs, the top five provinces are Guangdong, Zhejiang, Beijing, Jiangshu and Shanghai, and note that Beijing has more than Jiangshu Province. The influence of province on the effect of ESOP will be analysed in Section 5.4.8.

Table 5.5 Sample Firms Whose Headquarters in Different Provinces

	Category (hqpid)	Number of firms with ESOP	Number of firms without ESOP	Subtotal	% of number of firms with ESOP in subtotal firms	% of number of firms in 1509 firms
Beijing	1	46	107	153	30.10%	10.10%
Tianjin	2	4	17	21	19.00%	1.40%
Hebei	3	3	26	29	10.30%	1.90%
Shanxi	4	1	17	18	5.60%	1.20%
Inner Mongolia	5	1	8	9	11.10%	0.60%
Liaoning	6	6	22	28	21.40%	1.90%
Jilin	7	1	13	14	7.10%	0.90%
Heilongjiang	8	2	10	12	16.70%	0.80%
Shanghai	9	28	91	119	23.50%	7.90%
Jiangsu	10	39	120	159	24.50%	10.50%
Zhejiang	11	55	113	168	32.70%	11.10%
Anhui	12	12	47	59	20.30%	3.90%
Fujian	13	11	37	48	22.90%	3.20%
Jiangxi	14	7	12	19	36.80%	1.30%
Shandong	15	27	79	106	25.50%	7.00%
Henan	16	15	36	51	29.40%	3.40%
Hubei	17	10	33	43	23.30%	2.80%
Hunan	18	13	27	40	32.50%	2.70%
Guangdong	19	112	134	246	45.50%	16.30%
Guangxi	20	2	12	14	14.30%	0.90%
Hainan	21	1	2	3	33.30%	0.20%
Chongqing	22	2	12	14	14.30%	0.90%
Sichuan	23	8	39	47	17.00%	3.10%
Guizhou	24	2	13	15	13.30%	1.00%
Yunnan	25	3	13	16	18.80%	1.10%
Xizang	26	0	1	1	0.00%	0.10%
Shanxi	27	4	20	24	16.70%	1.60%
Gansu	28	0	8	8	0.00%	0.50%
Qinghai	29	0	4	4	0.00%	0.30%
Ningxia	30	0	6	6	0.00%	0.40%
Xinjiang	31	2	13	15	13.30%	1.00%
Hong Kong	32	0	0	0		0.00%
Macao	33	0	0	0		0.00%
Taiwan	34	0	0	0		0.00%
Overseas	35	0	0	0		0.00%
Sum		417	1092	1509	27.60%	100.00%

(Data source: Wind)

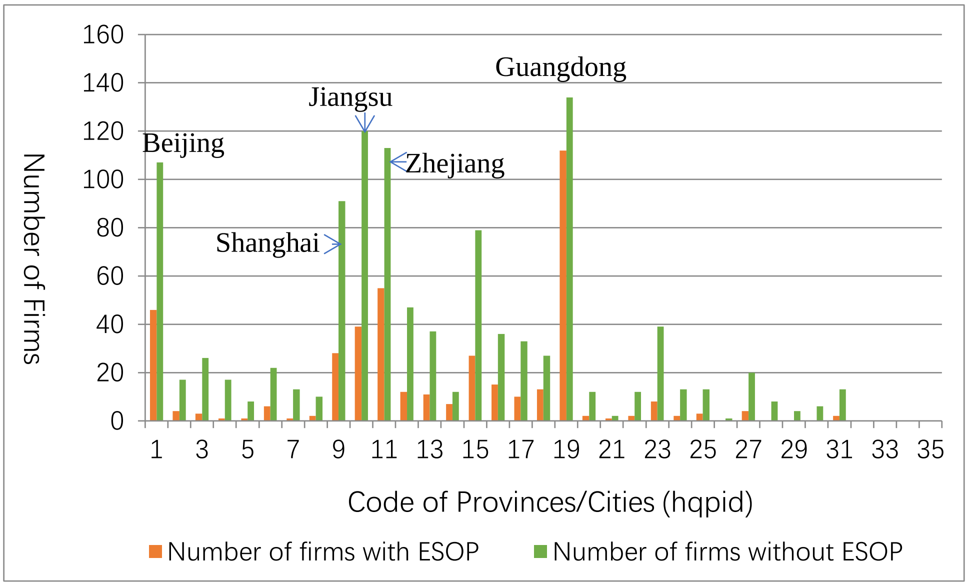

Figure 5.3 Distribution of Sample Firms whose Headquarters in Different Provinces or Provincial Cities (Data source: Wind)

5.4.1.4 Summary of sample firms in different stock boards

As illustrated in Table 5.6 and Figure 5.4, the firms are categorized into 4 stock boards. In the Shenzhen stock market, there are 3 different boards: the Shenzhen main board, the Shenzhen SME board and the Shenzhen ChiNext. The Shenzhen SME board has the most firms with ESOP, 194, 32.8% of the subtotal of 591. However, the Shenzhen ChiNext has the highest proportion of firms with ESOP, 45.8%. The influence of different stock boards on the effect of ESOP will be analysed in Section 5.4.9.

Table 5.6 Sample Firms in Different Stock Boards

Stock board	Category (stpid)	Number of firms with ESOP	Number of firms without ESOP	subtotal	% of number of firms with ESOP in subtotal
Shenzhen main board	1	19	152	171	11.10%
Shenzhen SME board	2	194	397	591	32.80%
Shenzhen ChiNext	3	140	166	306	45.80%
Shanghai main board	4	64	377	441	14.50%

(Data source: Wind)

Figure 5.4 Distribution of Sample Firms in Different Stock Boards

(Data source: Wind)

5.4.2 The influence of the duration employees kept ESOP

According to the formal version of EIMMLC rules released by the CSRC in 2016, the employees have to keep the ESOP, including restricted stock or stock options, for at least 12 months before they can sell or execute it. However, there is no data about when the employees sell or execute it, as this is not reported by listed firms. According to the interviews, if this duration is too long, the employees may feel the fruits of incentive schemes are too far away and the incentive to the employees may not be attractive enough. If this duration is too short, the firms cannot benefit from such incentives before the employees sell or execute it. In order to examine this, the different scenarios are compared, including the employees who keep the ESOP for 1year (teimpcf1), 2 years (teimpcf2), 3 years (teimpcf3), 4 years (teimpcf4), 5 years (teimpcf5) and 6 (teimpcf6) years respectively before they sell or execute it.

The basic models with 2 levels including teimpcf1 to teimpcf6 are tested one by one by the Stata commands as following:

mixed lntpatap t0 teimpcf1 t0teimpcf1 beps lnrdb || firmid: t0, covariance(unstructured) mle

The results including the coefficients of t0, teimpcf1 to 6 and the interaction term t0teimpcf1 to 6 are listed in Table 5.7 as follows. Also, the changes from the previous one in percentages are also included. An important finding is that the coefficients of teimpcf2 decreases a little (-1.78%) to teimpcf3, then keep on increasing to teimpcf6. Employees have to keep ESOP for at least one year. This means that when the employees keep the ESOP longer, the relationship between the ESOP and patent applications number becomes stronger. In other words, employees will create more patent applications, which is consist with Chang, at al., (2015).

Table 5.7 The Comparison of Different Influence of teimpcf1-6

lntpatap (ln of annual patent application number for each firm)	coefficient of t0	change from previous one in %	coefficient of teimpcf1 to teimpcf6 respectively	change from previous one in %	coefficient of interaction of t0 and teimpcf1 to teimpcf6 respectively	change from previous one in %
firms teimpcf1	0.019748		0.102441		-0.01846	
firms teimpcf2	0.02081	5.37%	0.074882	-26.90%	-0.0141	-23.63%
firms teimpcf3	0.02034	-2.26%	0.073545	-1.78%	-0.0118	-16.32%
firms teimpcf4	0.02202	8.26%	0.084782	15.28%	-0.01417	20.08%
firms teimpcf5	0.021851	-0.77%	0.099394	17.23%	-0.01526	7.71%
firms teimpcf6	0.022094	1.11%	0.117163	17.88%	-0.01735	13.73%

(teimpcf1: percentage point of ESOP which the employees keep ESOP for 1 years. The results are not rounded to only 2 digits to see the differences in this table.)

Based on the findings above, the firms want to sign the agreement to let the employees to keep the ESOP as long as possible. But the employees want to obtain the benefit from the ESOP as soon as possible which means they plan to sell or execute it as early as possible. This is a game between firms and employees, depending on their different bargaining power. Also, based on the interviews in 32 firms, the duration that employees keep their ESOP varies dramatically among employees in the same firm or different firms. For instance, employees in Huawei can only sell their internal shares when they leave the firm, but the bonus is very high and actually few employees want to sell the internal shares early. On the contrary in the Wens Group, the biggest firm in stock farming, employees can sell the internal share to other colleagues, while only those who kept the internal share over a long period can obtain the full benefit from the bonus and the rising prices of internal shares. Hence, based on interviews, this study takes 2 years as the preferred period to balance both the costs and the benefits of ESOP of the firms and employees. In the following, two years (marked as teimpcf2) is used in the models. Since the longer the duration the bigger the coefficients will be, the models using 2 years are conservative and robust, increasing their reliability and validity.

5.4.3 Annual R&D expense as the dependent variable

Chen, et al. (2006) analysed 168 listed firms in IT industry in Taiwan and found that ESOP can alleviate problems of corporate governance, so that the shareholders would like to invest more budget in R&D. It is interesting to examine this argument in more firms to test its generalization. The results of growth curve models with annual R&D expense as the DV for all firms, firms only in knowledge/talent intensive industries and non-knowledge/talent intensive industries are illustrated in Table 5.8. There is only a statistically significant relationship between the natural logarithm of annual R&D expense and the percentage point of ESOP which the employees keep ESOP for 2 years (teimpcf2), the interaction between t0 (year) and teimpcf2 (t0teimpcf2) for the firms in knowledge/talent intensive industries, while not for all firms holistically and the firms only in non-knowledge/talent intensive industries. For the firms in knowledge/talent intensive industries, if there are more ESOP (teimpcf2), there will be more R&D

expense with statistical significance. But, when the year (t0) increases, the influence of ESOP (teimpcf2) on R&D expense will wither, since the employees become familiar or inertia with it. These effects are consistent with the effects of ESOP on patenting in the following sections. The VIF to check multicollinearity in three models are all lower than the threshold of 10. Similarly, if testing the R&D expenses in two groups with or without ESOP, the R&D expenses of the group with ESOP is higher than the group without ESOP with statistical significance ($p<0.001$). Hence, Hypothesis H1 is only supported for the firms in knowledge/talent intensive industries, while not for all firms holistically and firms only in non-knowledge/talent intensive industries.

Table 5.8 Results of Models Whose DV is
Natural Logarithm of Annual R&D Expense of Each Firm (lnrdb)

	All firms	Firms in knowledge/talent intensive industries	Firms in non-knowledge/talent intensive industries
	coefficient	coefficient	coefficient
intercept	15.83***	15.96***	15.71***
t0 (Year)	0.27***	0.27***	0.26***
teimpcf2 (Percentage point of ESOP which the employees keep ESOP for 2 years)	0.03	0.06**	-0.01
t0teimpcf2 (Interaction between t0 and teimpcf2)	-0.002	-0.01*	0.003
beps (Basic earning per share)	0.18***	0.17***	0.2***
AIC	26654.96	12017.98	14124.29
BIC	26720.94	12078.19	14183.53
ICC	0.87	0.88	0.86
Sample size (N)	1,483	744	739
VIF to check multicollinearity	4.3	4.84	3.72

5.4.4 Compare annual patent application number of firms with ESOP and without ESOP

In order to compare annual patent application numbers of firms with ESOP and without ESOP, a ttest is applied and the results are illustrated in Table 5.9. The annual patent application numbers of firms with ESOP are higher than those of firms without

ESOP with statistical significance (p<0.05) in 7 years and one year is almost with statistical significance (p=0.0543). Also, the differences of annual patent application numbers between these two groups kept on increasing from 2007 to 2014, as illustrated in Figure 5.5.

Table 5.9 Comparison of Annual Patent Application Number of Firms with ESOP and without ESOP

	without ESOP		with ESOP			
year	Natural logarithm of average annual number of patent applications	Average annual number of patent applications	Natural logarithm of average annual number of patent applications	Average annual number of patent applications	p value	Difference of average annual number of patent applications in two groups
2007	1.77	5.9	2.03	7.64	0.018*	1.74
2008	1.91	6.76	2.01	7.42	0.18	0.67
2009	2.02	7.55	2.23	9.34	0.01*	1.78
2010	2.21	9.11	2.35	10.44	0.0543	1.32
2011	2.31	10.05	2.5	12.23	0.009**	2.18
2012	2.45	11.59	2.7	14.95	0.001**	3.36
2013	2.46	11.76	2.62	13.72	0.03*	1.96
2014	2.47	11.79	2.76	15.81	0.0003**	4.03
2015	2.24	9.36	2.51	12.26	0.0014**	2.9

(* $p < .05$ ** $p< .01$ *** $p< .001$)

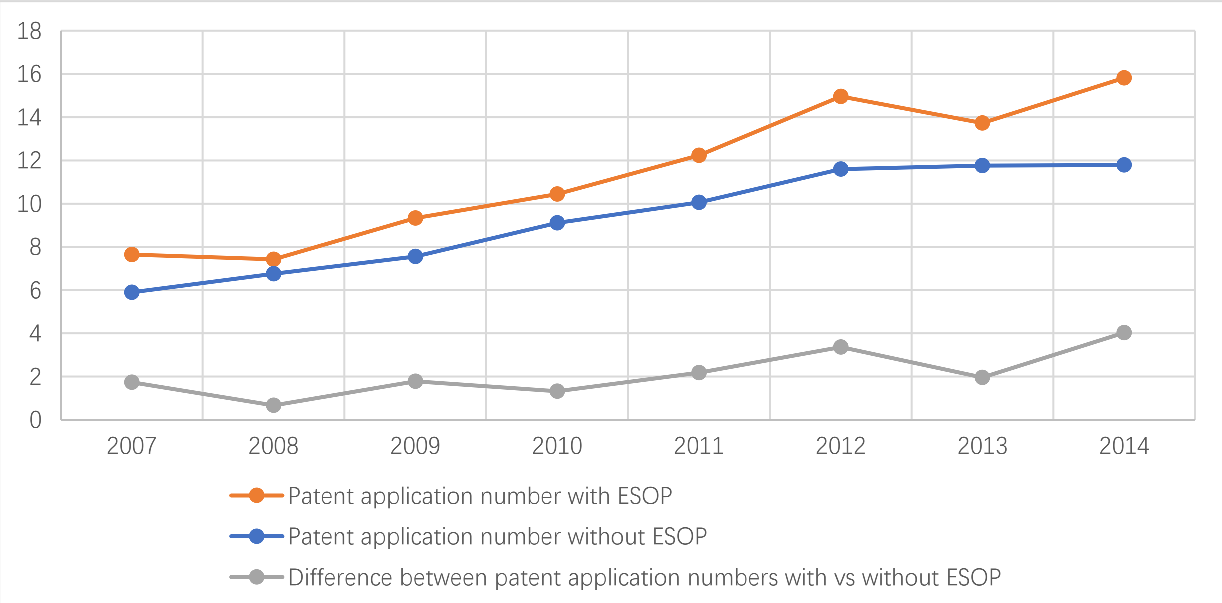

Figure 5.5 Comparison of Annual Patent Application Number of Firms with ESOP and without ESOP

5.4.5 Two-level models to test the influence of ESOP

As discussed in Section 5.3.1.1, a growth curve model (GCM) is applied to analyse the panel data between 2007 and 2015.

5.4.5.1 Two-level variance component model to calculate VPC and ICC

A variance component model is a model with 2 or more levels and only DV (only lntpatap here) without any IV or CV in the model. First, the 2-level variance component model is built and analysed, whose results are illustrated in Table 5.10.

Vvariance partition coefficients (VPCs) "measures the proportion of total variance that is due to differences between groups" (Steele, 2008: 7). The calculation of firm level VPCu is

$VPC_u = \sigma_u^2 /(\sigma_u^2 + \sigma_e^2) =1.08/(1.08+0.81)= 0.57$

The calculation of year level or within-firm level VPCe is

$VPC_e = \sigma_e^2 /(\sigma_u^2 + \sigma_e^2)= 0.81/(1.08+0.81)= 0.43$

It can be seen that 57% of the variation in the natural logarithm of the annual number of patent applications per firm lies between firms, 43% lies between years within firms.

"[I]ntraclass correlation coefficients (ICCs) measure the expected degree of similarity (or homogeneity) between responses within a given cluster" (Leckie, 2013: 20).

The firm level ICC is calculated as:

$\rho_u = corr(lntpatap_{ij}, lntpatap_{i'j}) =1.08/(1.08+0.81)= 0.57$

Here the firm level ICC (ρ_u) is equal to the firm level VPCu.

According to Cohen (1988), $0.138> \rho \geq 0.059$ is middle correlation and $\rho \geq 0.138$ is high correlation. The firm level ICC (ρ_u) is 0.57, so two years of lntpatap in the same firm is highly correlated. As the result, the VPCs and ICCs illustrate that there is a high degree of clustering in the data. This supports again the growth curve model is suitable for this study which can solve the problems of correlation.

5.4.5.2 Two-level random intercept model as the middle step to find best model

This model distinguishes from variance component model in Section 5.4.5.1 by adding more IVs and CVs such as t0 (Year), teimpcf2 (Percentage point of ESOP which the employees keep ESOP for 2 years), t0teimpcf2 (Interaction between t0 and teimpcf2), beps (Basic earnings per share), lnrdb (Natural logarithm of total R&D expense per firm per year). Following is the equation of the random intercept model. The results are illustrated in Table 5.10.

$$lntpatap = \beta_{0j} + \beta_1\, t0 + \beta_2\, teimpcf2 + \beta_3\, t0teimpcf2 + \beta_4\, beps + \beta 5\, lnrdb + e_{ij}$$

$$= -2.12 + 0.03t0 + 0.06teimpcf2 - 0.01t0teimpcf2 + 0.08beps + 0.24lnrdb + e_{ij}$$

$$\beta_{0j} = \beta_0 + u_{0j} = -2.12 + u_{0j}$$

All the coefficients are statistically significant at the level of 5%. In a random intercept model, the intercept is allowed to be random among different firms. The AIC and BIC values are 25153.57 and 25210.24 respectively, which are much smaller than those of the variance component model. The residual of this model is plotted in Figure 5.6 and it becomes closer to normal distribution.

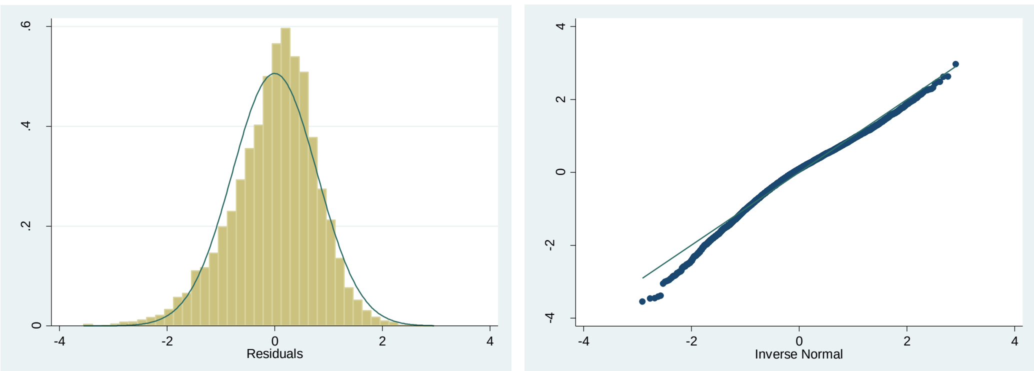

Figure 5.6 Plots of Residual of Random Intercept Model with 2 Levels whose DV is lntpatap (natural logarithm of annual number of patent application per firm)

5.4.5.3 Two-level random slope model to test the influence of ESOP

The random intercept model assumes that the slopes among different firms are the same for all firms, which is not true in reality. The random slope model including random intercept as default allows the slopes to be random among firms and can explain the real observed data better. The results are illustrated in Table 5.10. Based on the results, the equations of the model are as following. The residual is almost normally distributed in Figure 5.7, obeying the assumptions. In the following models, this step will be repeated for each model, but no need to repeat the details and the figures again to avoid redundancy.

$\text{lntpatap} = \beta_{0j} + \beta_{1j}\, t0 + \beta_2\, \text{teimpcf2} + \beta_3\, \text{t0teimpcf2} + \beta_4\, \text{beps} + \beta_5\, \text{lnrdb} + e_{ij}$

$= -2.11 + 0.02t0 + 0.07\text{teimpcf2} - 0.01\text{t0teimpcf2} + 0.1\text{beps} + 0.24\text{lnrdb} + e_{ij}$

$= -2.11 + 0.02t0 + (0.07 - 0.01t0)\text{teimpcf2} + 0.1\text{beps} + 0.24\text{lnrdb} + e_{ij}$

$\beta_{0j} = \beta_0 + u_{0j} = -2.11 + u_{0j}$

$\beta_{1j} = \beta_1 + u_{1j} = 0.02 + u_{1j}$

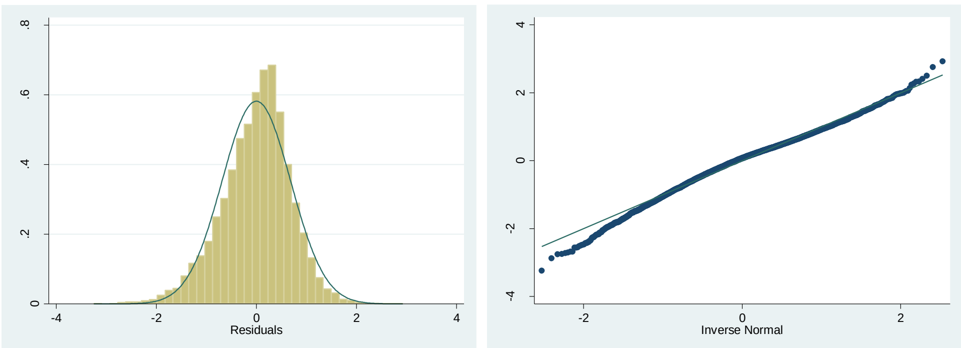

Figure 5.7 Plots of Residual of Random Slope Model with 2 Levels whose DV is lntpatap (natural logarithm of annual number of patent application per firm)

Finally, use lrtest to compare the random intercept model and the random slope model. The p-value is less than 0.0001, which means the random slope model is much better than the random intercept model.

The values of AIC and BIC of the random slope model are 24727.04 and 24797.86 respectively, which are both smaller than those in the random intercept model. This is consistent with the result of lrtest. It can also be seen that the random slope model fits the observed data better than the random intercept model in Figure 5.8 which illustrates the examples of 9 firms. The methods to compare the random slope model and the random intercept model are for the purpose of triangulation (Kutner, Nachtsheim and Neter, 2004; Agresti and Finlay, 2009).

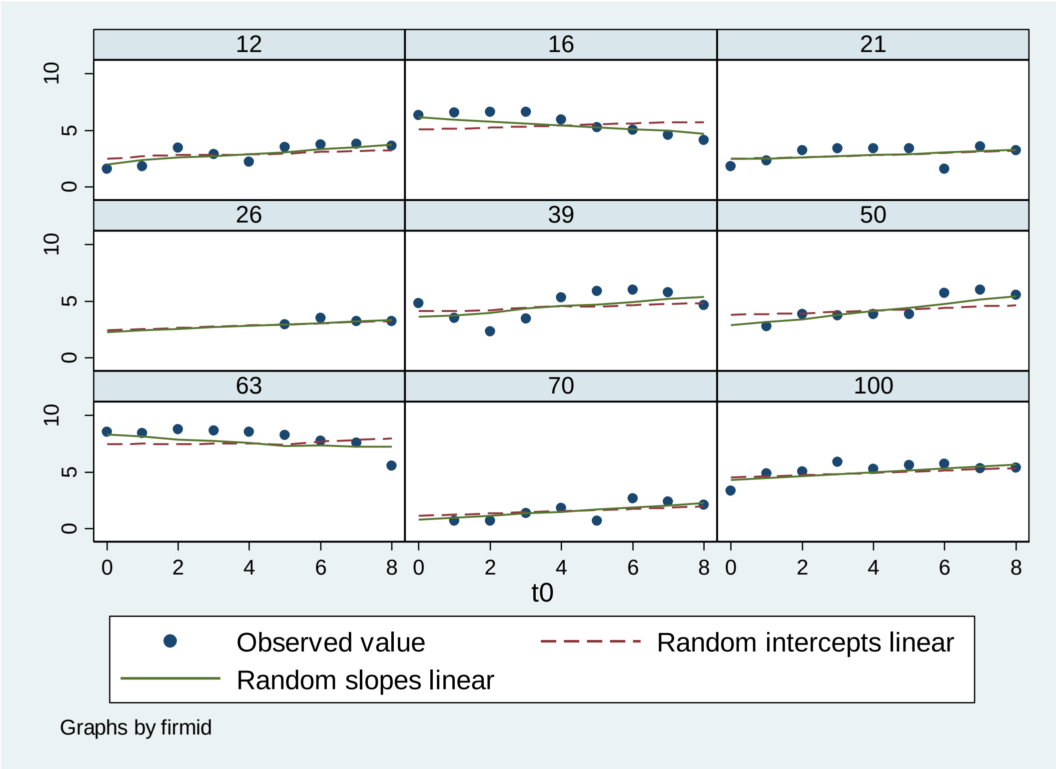

Figure 5.8 Random Slope Model Fits Observation Better Than Random Intercept Model

As discussed in Section 5.2.7, Hypothesis H5.2 is: There is a positive relationship between ESOP and the number of patent applications. From the 1-level OLS regression model, 2-level growth curve models with random intercept and random slope, all the coefficients of teimpcf2 are bigger than 0 with statistical significance illustrated in Table 5.10, so the Hypothesis H5.2 can be supported that there is positive relationship between ESOP and the number of patent applications with statistical significance. This is consistent with the finding of Chang, at al., (2015), Brander & Zhang (2017) and Usman, Xiao & Li (2018).

Table 5.10 Results of the 1-level Model and 2-level Models Whose DV is Natural Logarithm of Annual Number of Patent Application Per Firm (lntpatap)

	1-level model	2-level model		
		Variance component model	Random intercept model	Random slope model
	estimate	estimate	estimate	estimate
intercept	-4.78***	2.19***	-2.12***	-2.11***
t0 (Year)	-0.02**		0.03***	0.02**
teimpcf2 (Percentage point of ESOP which the employees keep ESOP for 2 years)	0.13***		0.06*	0.07**
t0teimpcf2 (Interaction between t0 and teimpcf2)	-0.02**		-0.01*	-0.01**
beps (Basic earnings per share)	0.04		0.08**	0.1***
lnrdb (Natural logarithm of total R&D expense per firm per year）	0.42***		0.24***	0.24***
var(t0) 2nd level				0.02
var(_cons) 2nd level		1.08	0.86	1.16
var(Residual)		0.81	0.73	0.6
cov(t0,_cons)				-0.09
AIC		29934.91	25153.57	24727.04
BIC		29956.58	25210.24	24797.86
ICC at level of firmid		0.57	0.54	0.66
VIF to check multicollinearity	4.07	3.49	4.07	4.07

(* *p* < .05 ** *p*< .01 *** *p*< .001)

According to the equation in the random slope GCM, it can be seen that when the amount of the ESOP (teimpcf2) increases, the main effect of ESOP on the annual patent application numbers (lntpatap) also increases. If ESOP increases by 1 percentage point, lntpatap will increase by (0.07 -0.01t0) and total patent application number will increase by exp(0.07 -0.01t0). But there is a negative coefficient -0.01 for t0, which means the influence of teimpcf2 on lntpatap will wither by 0.01 if t0 increases by 1 year. This is reasonable and consistent with the qualitative interviews. Usually, the effect of the ESOP is strongest at the very beginning. But after some years, employees may be familiar or tired with it and the incentive effect withers. This was seen in the Far East Group in Jiangsu Province where interviews were conducted. There may be problems including “entrenchment” (Chang and Mayers, 1992) and “free riders” (Weitzman and Kruse, 1990). The values of ICC at level of firmid in 3 models are 0.57, 0.54 and 0.66 respectively, larger than 0.138 (Cohen, 1988), which means the group effect at the level of firmid among years of the same firm. This is reasonable, since the patent application numbers in different years of the same firm are highly correlated, which support that GCM is suitable for this study. It is the same for other ICCs at the level of firmid, which will not be repeated to be parsimonious.

5.4.6 Two-level models for different types of ownership (SOE or non-SOE)

In China, there are many SOEs dominant in some key industries (Liao, 2009; Rutten, 2013; Fuller, 2016; Lu, 2019 and 2020). It is possible the different types of ownership will influence the effect of ESOP on the number of patent applications for firms. Hence, Hypothesis H5.3 is tested here that The types of ownership (SOE or non-SOE) of firms influences the relationship between ESOP and the number of patent applications. The coefficients of 2-level model with different types of ownership are illustrated in the Table 5.11.

The firms are divided into 2 groups with dummy variable ownsoedv:

ownsoedv =1 if firm is SOE

ownsoedv =0 if firm is non-SOE.

First, ttest is used as following:

ttest lntpatap, by(ownsoedv)

SOEs have more patent application whose lntpatap=2.55 than non-SOEs whose lntpatap=2.19, which is statistically significant at the level of 0.001.

Also, generate the interaction of ownership dummy variable and ESOP (teimpcf2) as following:

gen owsodvtf2 = ownsoedv*teimpcf2

Next, the 2-level random slope model is built and its equation is as following:

lntpatap = -2.1 + 0.02t0 + 0.07teimpcf2 -0.01t0teimpcf2 + 0.1beps + 0.24lnrdb + 0.19ownsoedv + 0.11owsodvtf2

If ownsoedv=1 for SOEs

lntpatap = (-2.1+ 0.19) + 0.02t0 + (0.07teimpcf2+ 0.11teimpcf2) -0.01t0teimpcf2 + 0.1beps + 0.24lnrdb

If ownsoedv=0 for non-SOEs

lntpatap = -2.1 + 0.02t0 + 0.07teimpcf2 -0.01t0teimpcf2 + 0.1beps + 0.24lnrdb

The residual left in the model is tested and plotted, which is almost normally distributed, obeying the assumptions. It can be seen that the intercept and the effect of ESOP (measured by teimpcf2) on lntpatap of SOEs are bigger than those of non-SOEs by 0.19 and 0.11*teimpcf2 respectively, which are both statistically significant ($p<0.01$ and $p<0.05$). Teimpcf2 is the percentage point of ESOP which are kept by employees in 2 years, so it is positive. Therefore, it can be concluded that the average patent application number of SOEs is bigger than non-SOEs ($p<0.001$) and the influence of ESOP on patent application number is bigger in SOEs than non-SOEs with statistical significance ($p<0.05$), which is consistent with the finding of Choi, Lee & Williams (2011). Hence, Hypothesis H5.3 is supported that the types of ownership (SOE or non-SOE) of firms does influence the relationship between ESOP and the annual number of patent applications of firms. This supports the policy of Chinese governments to reform SOEs into mixed ownership in China in recent years, since mixed ownership usually means to share stocks with some employees in SOEs.

Table 5.11 Results of the 2-level Random slope Model for SOEs and non-SOEs Whose DV is Natural Logarithm of Annual Number of Patent Application Per Firm (lntpatap)

	coefficient
intercept	-2.1***
t0 (Year)	0.02**
teimpcf2 (Percentage point of ESOP which the employees keep ESOP for 2 years)	0.07*
t0teimpcf2 (Interaction between t0 and teimpcf2)	-0.01**
beps (Basic earning per share)	0.1***
lnrdb (Natural logarithm of total R&D expense per firm per year)	0.24***
1.ownsoedv (Dummy variable of SOE or non-SOE)	0.19**
owsodvtf2 (Interaction between ownsoedv and teimpcf2)	0.11*
AIC	24713.19
BIC	24798.18
ICC at level of firmid	0.66
VIF to check multicollinearity	3.25

(* $p < .05$ ** $p < .01$ *** $p < .001$)

The 3-levels random slope models with ownership type at the 3rd level are tried, however the value of ICC for ownsoedv is 2.15e-18. According to Cohen (1988), since ICC<0.059, the correlation is relatively low. Therefore, there is no group effect of ownership type.

5.4.7 Three-level models for different industries

5.4.7.1 Variance component model of 3-level models for different industries

With the development of modern industries, more and more tacit knowledge and knowhow are created, stored and applied by technical and management talents. Although some skilled workers change their careers across industries, most of them stay in the same industry to exploit their experience and expertise in the same industry. In each industry, there are special industry structures, competitors, and knowhow. It takes years for employees to learn and obtain experience in the specific industry and the transfer costs are very high. Hence, Hypothesis H5.4 is tested here that the industry which the firms belong to influences the relationship between ESOP and the number of patent applications. In order to test such hypothesis, one variance component model and two random slope models with IVs at the level of industry are tested, whose results are illustrated in Table 5.12.

First, the variance component model with 3 levels and different industries is obtained as following. The residual left in the model is tested and plotted, which is almost normally distributed, obeying the assumptions. Similar to the model with 2 levels, the VPC at the different levels are calculated. First, the calculation of the industry level VPCv is

$VPC_v = \sigma_v^2 /(\sigma_v^2 + \sigma_u^2 + \sigma_e^2) = 0.21/(0.21+0.92+0.81) = 0.107$

the calculation of the firm level VPC_u is

$VPC_u = \sigma_u^2 /(\sigma_v^2 + \sigma_u^2 + \sigma_e^2) = 0.92/(0.21+0.92+0.81) = 0.474$

the calculation of the year level or within-firm level VPC_e is

$VPC_e = \sigma_e^2 /(\sigma_v^2 + \sigma_u^2 + \sigma_e^2) = 0.81/(0.21+0.92+0.81) = 0.418$

It can be seen that 10.7% of the variation in the natural logarithm of annual number of patent application per firm lies between industries, 47.4% lies between firms within industries, 41.8% lies between years within firms and industries.

The industry level ICC is 0.107 and the firm level ICC is 0.582. According to Cohen (1988), $0.138 > \rho \geq 0.059$ is middle correlation and $\rho \geq 0.138$ is high correlation. Since the industry level ICC (ρ_v) is 0.107, two years of lntpatap in the different firms in the same industry is middle correlated. The firm level ICC (ρ_{vu}) is 0.582, so two years of lntpatap in the same firm in the same industry is highly correlated. As the result, the VPCs and ICCs illustrate that there is a high degree of clustering in the data (Leckie, 2013). This supports again the growth curve model are suitable for this study.

5.4.7.2 Random slope model of 3-level growth curve models (GCM) for different industries

The random intercept model and random slope model for 2-level and 3-level growth curve models considering different industries are tested. The residual left in the model is tested and plotted, which is almost normally distributed, obeying the assumptions. Next, as discussed in Section 5.3.3, some IVs and CVs including lninumfm, lnifriem, lnifriex, lnifnpdn, lnifnpDV and their various combinations at the industry level are tried and tested in the models respectively and with various combinations. Only the marginal contribution of lnifnpdn is statistically significant. Lnifnpdn is the natural logarithm of the project number of new products in all firms in each industry per year in official census. The coefficient of lnifnpdn is 0.27. This means that if lnifnpdn at each industry level increase by 1 unit, lntpatap at the firm level will increase by 0. 27 unit. This is reasonable since the projects about R&D and new products result in new products or new technologies, which are the sources of new patent applications. This reflects somewhat how the contextual IVs influence the firm, which may be the clue of the knowledge spillover across firms in the industry. The values of AIC and BIC in this random slope model with IV lnifnpdn at the industry level are 21651.61 and 21742.11, lower than 24597.54 and 24682.54 in the random slope model without IV at the industry level, illustrated in Table 5.12. Also, the values of AIC and BIC of the random slope model with 3 levels including industry are less than 21771.97 and 21848.55 of the random slope model with 2 levels. The similar conclusion can be obtained from the lrtest between these models, since LR chi2(3) = 124.36 and p-value<0.0001. Based both on the theory and statistical evidences, the random slope model with 3 levels including industrial variable lnifnpdn is preferred. Additionally, sensitivity analysis is conducted. This model is tried with more limitations such as tpatap (annual patent application number per firm) less than 4000, 3000, 2000, 1000, 500, 300, 200 and 100, the coefficients of all IVs except the intercept are still statistically significant. Hence, the model is proved to be robust enough. The VIF values are 3.48 and 4.07 respectively in Table 5.12, lower than the threshold value 10, which means there is no multicollinearity.

Table 5.12 Results of the Models for Industries Whose DV is Natural Logarithm of Annual Number of Patent Application Per Firm (lntpatap)

	3-level variance component model	3-level random slope model with industry IVs	3-level random slope model without industry IVs	2-level random slope with industry IVs
	coefficient	coefficient	coefficient	coefficient
intercept	2.09***	-3.96***	-2.03***	-3.17***
t0 (Year)		-0.03*	0.02	-0.005
teimpcf2 (Percentage point of ESOP which the employees keep ESOP for 2 years)		0.06*	0.08**	0.07*
t0teimpcf2 (Interaction between t0 and teimpcf2)		-0.01*	-0.01**	-0.0126*
beps (Basic earning per share)		0.11***	0.11***	0.09***
lnrdb (Natural logarithm of total R&D expense per firm per year）		0.24***	0.24***	0.25***
lnifnpdn (natural logarithm (ln) of the project number of new products in all firms in each industry per year in official census)		0.27***		0.11***
var(t0) 2nd level		0.02	0.02	0.02
var(t0) 3rd level		0.004	0.002	
var(_cons) 2nd level	0.92	1.14	1.1	1.2
var(_cons) 3rd level	0.21	0.23	0.07	
var(Residual)	0.81	0.59	0.6	0.59
cov(t0,_cons)		-0.09	-0.09	-0.09
AIC	29800	21651.61	24597.54	21771.97
BIC	29828.89	21742.11	24682.54	21848.55
ICC at level of induid	0.107	0.12	0.04	
ICC at level of firmid|induid	0.582	0.7	0.66	0.67
VIF to check multicollinearity		3.48	4.07	3.48

(* p < .05 ** p< .01 *** p< .001)

Similarly, ICC is calculated. ICC at the level of industry in the variance component model with 3-level is 0.107 in Table 5.12, in the middle range of $0.138>\rho\geq0.059$ (Cohen, 1988). Hence, the correlation due to industry is in the middle and cannot be ignored. The 1,509 firms in the sample do not act as 1,509 independent atoms. In contrast, they are clustered with statistically significant correlation in the industries and there is group effect at the industry level. The firms in the same industries are more alike than those in other industries, since the firms in the same industry share similar technologies and learn from similar patents from each other. Hence, the growth curve model with industrial CV at the third level analyses and reflect the internal structures of the sample, which is better than the models with only 1 level or 2 levels.

Additionally, the relationship between ESOP and the annual number of patent applications in each industry is tested, but the sample (number of firms) in each industry is reduced to very small numbers in most industries to build growth curve models (GCM). There are 64 industries with Chinese standard codes for industries and it is not reasonable to generate the interaction of induid (industry code) and teimpcf2 (percentage point of ESOP which the employees keep ESOP for 2 years). Hence, the firms are divided into two groups: knowledge/talent-intensive industries and non-knowledge/talent-intensive industries. There are 746 firms in 10 knowledge/talent-intensive industries including pharmaceutical manufacturing industry, general equipment manufacturing industry, special equipment manufacturing industry, electrical machinery and equipment manufacturing industry, manufacturing of computers, communications and other electronic equipment, instrument manufacturing industry, telecommunications, radio and television and satellite transmission services, internet and related services, software and information technology services, professional and technical services. There are 763 firms in 54 non-knowledge/talent-intensive industries. These two groups of firms are tested in growth curve models (GCM) and the results are illustrated in Table 5.13. It can be seen that the coefficients of ESOP (teimpcf2) and the interaction (t0teimpcf2) of t0 and ESOP (teimpcf2) are statistically significant for the group of knowledge/talent-intensive industries. In the model in this group, if ESOP increases by 1 percentage point, lntpatap will increase by (0.1 -0.02t0) and total patent application number will increase by exp(0.1 -0.02t0). But there is negative coefficient -0.02 for t0, which means the influence of teimpcf2 on lntpatap will wither by 0.02 if t0 increases by 1 year, since the employees feel familiar or tired with ESOP, as found in interviews. The results are consistent with the findings in the models for 1,509 firms and with the findings of Garrett (2010). It is interesting to note that the coefficients of 0.1 and -0.02 for the group in 10 knowledge/talent-intensive industries are larger than 0.06 and -0.01 in all the samples of 1,509 firms in Table 5.12. However, on the right of Table 5.13, the coefficients of ESOP (teimpcf2) and the interaction (t0teimpcf2) of t0 and ESOP (teimpcf2) are not statistically significant for 763 firms in 54 non-knowledge/talent-intensive industries. This means the effect of ESOP is not significant for this group of non-knowledge/talent-intensive industries between 2007 and 2015. This was ignored by Garrett (2010) and Chen, et al., (2006). There may be two reasons: first, these firms in those industries are not knowledge/talent-intensive, hence few firms adopted ESOP or adopted ESOP later than the knowledge/talent-intensive firms and the effect of ESOP are not obvious. Second, these firms in non-knowledge/talent-intensive industries did not focus on technical innovations or file few patent applications to protect their technical innovations.

All of these aforementioned prove Hypothesis H5.4 is supported, that the industries which the firms belong to influence the relationship between ESOP and the number of patent applications. The effect in knowledge/talent-intensive industries are statistically significant, while not in non-knowledge/talent-intensive industries.

Table 5.13 Results of the Models for Industries in Two Groups Whose DV is Natural Logarithm of Annual Number of Patent Application Per Firm (lntpatap)

	3 level random slope model for knowledge /talent-intensive industries	3 level random slope model for non-knowledge /talent-intensive industries
	coefficient	coefficient
intercept	-3.36***	-1.12***
t0 (Year)	0.02	0.01
teimpcf2 (Percentage point of ESOP which the employees keep ESOP for 2 years)	0.1*	0.05
t0teimpcf2 (Interaction between t0 and teimpcf2)	-0.02**	-0.01
beps (Basic earning per share)	0.15***	0.09**
lnrdb (Natural logarithm of total R&D expense per firm per year)	0.31***	0.19***
AIC	13322.58	11262.79
BIC	13400.2	11338.44
VIF to check multicollinearity	4.84	3.35
Number of firms	746	763

(* p < .05 ** p< .01 *** p< .001)

5.4.7.3 Ranks of industries by slope and intercept

Based on the best model with the IV at the industry level discussed above, the study "can predict empirical Bayes estimates (i.e., posterior, shrunken, or best linear unbiased predictions [BLUPs] of the [industry and firm] effects together with their associated standard errors. [The study] can examine these predictions to check whether the random effects at each level are normally distributed. [It] can also examine them in order to make inferences about specific [industries or firms]" (Leckie, 2013: 23). The industry effects and their standard errors are named as v0 and v0se. The firm effects follow the similar procedure, so there is no need to repeat the same procedure for firms again.

The following calculations are based on the 3-level random slope model with industry IV which is the best model with the smallest values for AIC and BIC and whose results are illustrated in the 2nd column in Table 5.12.

The bottom and ceiling of the rank is compared as following.

```
. | induid            v01        v0se1     v0rank1 |
  |-----------------------------------------|
  |       22    -.0852691    .0384474          1 |
  |       31     .1006868    .0353874         36 |
0.1006868-(-0.0852691)= 0.185956
Exp(0.185956)= 1.204369
```

This means the difference is 0.19 between the slopes (coefficients of t0) of the bottom line (induid=22 paper and paper products industry) and the ceiling line (induid=31 Ferrous metal smelting and calendaring industry). The industry with induid=31 is the highest with statistical significance, because in the last 20 years, the Chinese automobile market became the largest one in the world and sold 25.22 million automobiles in 2020. Steel of high quality to make automobiles used to be imported from Japan and South Korea. But now it is mass-produced in China and exported to other countries. For instance, in 2020, for the first time, Toyota imported and used Chinese automobile steel plate in passenger cars made in Japanese automobile factories (Nihon Keizai Shimbun, 2020). This means Chinese steel firms made rapid progress in innovation to produce such high-end steel. One of the results is the increasing patent applications in this industry to protect the technologies and market in China and other countries. Figure 5.9 illustrates the slopes which is the annually growth rate of natural logarithm of patent application number for each industry. It can be seen that the slopes of paper and paper products industry (induid 22), nonferrous metal smelting and calendering industry (induid 32) and pharmaceutical production industry (induid 27) are lower than the average slope with statistical significance. The slopes of production of ICT and other electronic equipment (induid 39), production of special equipment (induid 35), coal mining and washing industry (induid 6) and ferrous metal smelting and calendaring industry (induid 31) are higher than the average slope with statistical significance.

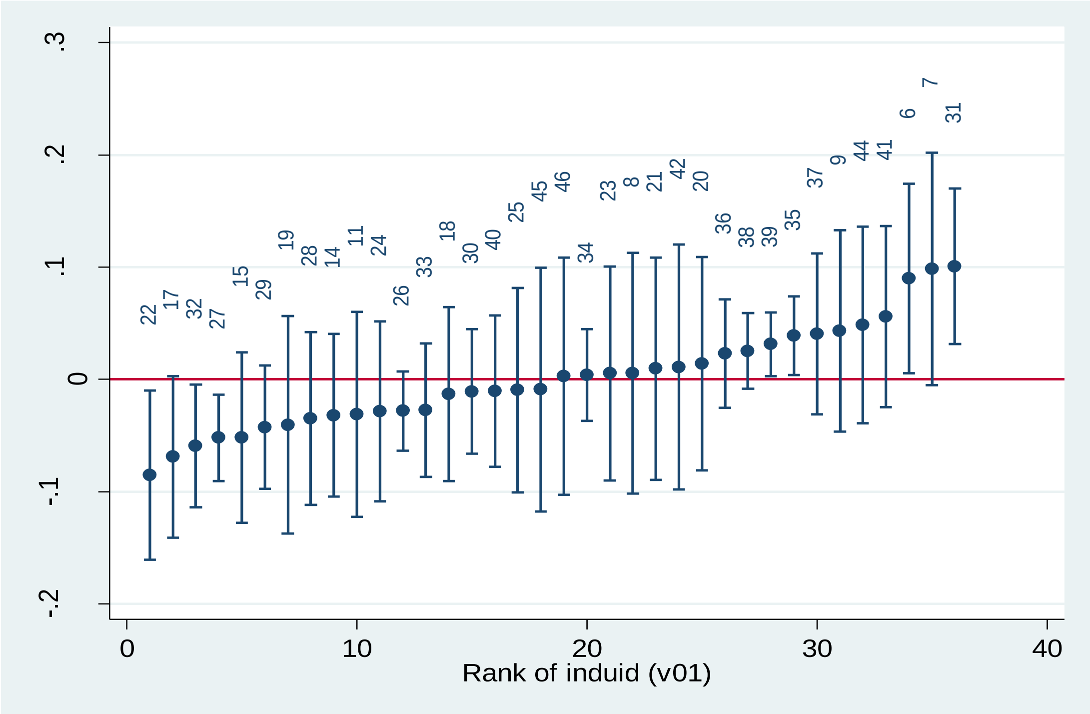

Figure 5.9 Rank of Industries by Slope

(Annual Growth Rate of Patent Application Number)

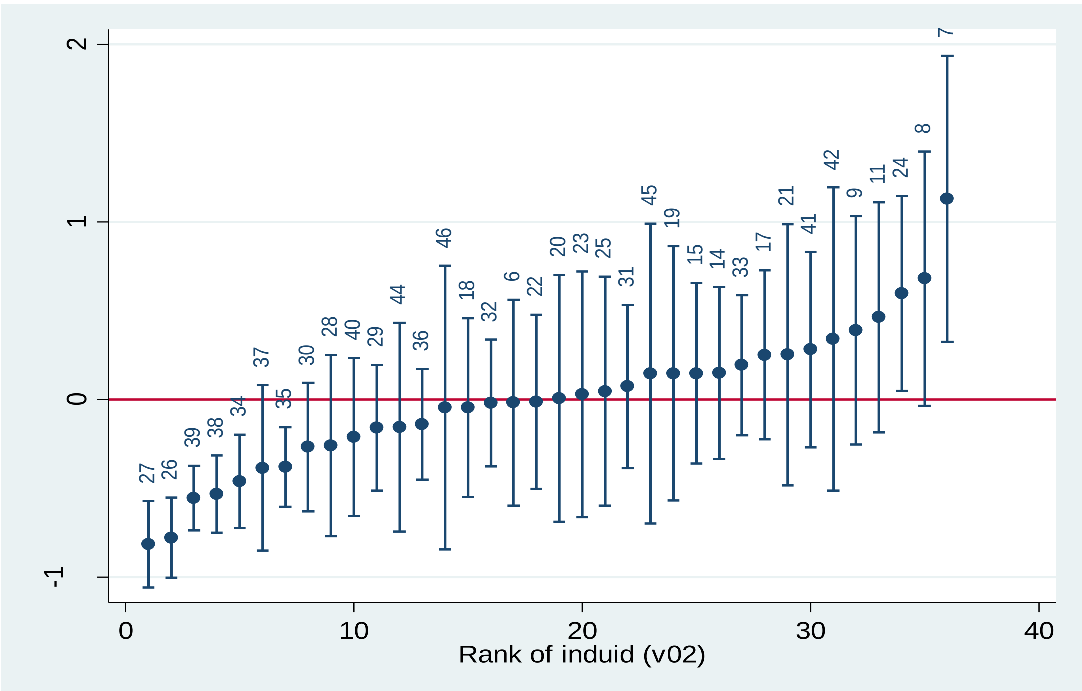

Figure 5.10 Rank of Industries by Intercept (Patent Application Number in 2007)

From Figure 5.10, it can be seen that the intercepts of pharmaceutical production industry (induid 27), production of chemical materials and chemicals (induid 26), production of ICT and other electronic equipment (induid 39), production of electric machines and equipment (induid 38), general equipment manufacturing industry (induid 34) and production of special equipment (induid 35) are lower than the average intercepts with statistical significance in 2007.

Usually in the developed countries, pharmaceutical production (induid 27) generated many patents since they need patents to protect the market. In contrast, most Chinese pharmaceutical firms have fewer patents than average. The main problem of the Chinese pharmaceutical industry is that the budget for marketing, advertisement and sales has been much higher than R&D budget in the long period. For instance, between January and June, 2018, 251 Chinese listed pharmaceutical firms spent 7.87% of their revenue on advertisements, while only 2.5% on R&D (Xiang, 2018). On the contrary, between 2010 and 2017, the percentage of R&D in revenue of global pharmaceutical industry ranged from 18.6% to 20.9%, more than 7 times of the Chinese pharmaceutical industry (Zhiyan Consulting, 2019). This is similar in production for chemical materials and chemicals (induid 26) which is relevant to pharmaceutical production industry (induid 27). The starting point of both of induid 26 and 27 were lower than average in 2007, and the growth rate between 2007 and 2015 were lower than average too.

However, manufacturing of computers, communications and other electronic equipment (induid 39) is a different story. Around 2007, most Chinese ICT firms including Lenovo and the smartphone firms focused on assembling chips and using operating systems from Intel and Microsoft or Google, as they do not have key technologies in such areas which generate many patents. Other leading Chinese ICT firms such as Alibaba and Tencent focus on digital services, which do not generate as many patents as manufacturing. Huawei has many patents, but it is not listed on any stock market. The counterpart of Huawei is ZTE, a big firm in the global telecommunication market. The patent application number of ZTE ranged from 1,932 and 6,327 between 2007 and 2014, which is the highest firm among 1,509 firms in the sample. This is reflected in the higher slope of induid 39 in Figure 5.9. The starting point of Chinese ICT was lower than average in 2007, but the growth rate between 2007 and 2015 was higher than average. In Section 5.4.7.2, the best models are repeated with more limitations such as annual patent application number per firm (tpatap) less than 4000, 3000, 2000, 1000, 500, 300, 200 and 100 respectively, the remaining models are robust with such different limits, so that the outliers do not influence the analysis.

5.4.8 Two-level models for different provinces

China has 31 provinces or provincial cities with different populations, languages and dialects, local cultures, universities, natural resources, various industries and economic development stages. All of these factors may also influence the listed firms whose headquarters are located in such various provinces or provincial cities. Therefore, Hypothesis H5.5 is tested that the locations (by province) of firms' headquarters influence the relationship between ESOP and the number of patent applications. Similar to the model with 3 levels including IVs at the industry level, the models with 3 levels including IVs at the provincial level are built and tested. The VIF values are 3.05 respectively in Table 5.14, lower than the threshold value 10, which means there is no multicollinearity.

First, the variance component model with 3 levels including IV at the province level is built. The results of models with variables at the provincial level are illustrated in Table 5.14. Similarly, the VPCs are calculated as following.

$VPC_v = \sigma_v^2 /(\sigma_v^2 + \sigma_u^2 + \sigma_e^2) = 0.02/(0.02+1.06+0.81) = 0.01$

The calculation of the firm level VPC_u is

$VPC_u = \sigma_u^2 /(\sigma_v^2 + \sigma_u^2 + \sigma_e^2) = 1.06 /(0.02+1.06+0.81) = 0.56$

The calculation of the year level or within-firm level VPC_e is

$VPC_e = \sigma_e^2 /(\sigma_v^2 + \sigma_u^2 + \sigma_e^2) = 0.81 /(0.02+1.06+0.81) = 0.43$

It can be seen that 0.01% of the variation in the natural logarithm of annual number of patent application per firm lies between provinces, 56% lies between firms within provinces, 43% lies between years within firms and provinces. Similarly, the value of ICC at province level which is 0.01. This means there is no group effect at the province level and growth curve model with 2 levels is sufficient. Next, the 1,509 firms are distributed very unevenly in 31 provinces or provincial cities, e.g., there are fewer listed firms in the 5 provinces in Northwestern China. Hence, it is not reasonable to generate the interaction of hqpid (province code) and teimpcf2 (percentage point of ESOP which the employees keep ESOP for 2 years). If adopting the fixed effect least square dummy variable (LSDV) method (Chen, 2014) and using the dummy variable for all the 31 provinces, most of the coefficients of provinces are not statistically significant. Therefore, Hypothesis H5.5 is not supported: There is no statistically significant influence of provinces where the firms' headquarters are located on the relationship between ESOP and number of patent applications.

Table 5.14 Results of the Models for Provinces Whose DV is Natural Logarithm of Annual Number of Patent Application Per Firm (lntpatap)

	3-levels variance component model	2-levels random slope model with province CV
	coefficient	coefficient
intercept	2.15***	-7.62***
t0 (Year)		-0.02*
teimpcf2 (Percentage point of ESOP which the employees keep ESOP for 2 years)		0.06*
t0teimpcf2 (Interaction between t0 and teimpcf2)		-0.01*
beps (Basic earning per share)		0.09***
lnrdb (Natural logarithm of total R&D expense per firm per year)		0.2***
lnptrev (Natural logarithm of the total revenue of all firms in each province per year in official census)		0.2***
var(t0) 2nd level		0.02
var(t0) 3rd level		
var(_cons) 2nd level	1.06	1.18
var(_cons) 3rd level	0.02	
var(Residual)	0.81	0.59
cov(t0,_cons)		-0.09
AIC	29927.63	24669.61
BIC	29956.51	24747.52
ICC at level of hqpid	0.009637	
ICC at level of firmid|hqpid	0.57	0.66
VIF to check multicollinearity		3.65

(* p < .05 ** p< .01 *** p< .001)

Table 5.15 Results of the Models for firms' Headquarter in Provinces in Two Groups Whose DV is Natural Logarithm of Annual Number of Patent Application Per Firm (lntpatap)

	2 level random slope model for firms in provinces in Eastern China	2 level random slope model for firms in other provinces
	coefficient	coefficient
intercept	-2.09**	-2.12***
t0 (Year)	0.03**	0.01
teimpcf2 (Percentage point of ESOP which the employees keep ESOP for 2 years)	0.07*	0.09
t0teimpcf2 (Interaction between t0 and teimpcf2)	-0.01*	-0.018
beps (Basic earning per share)	0.14***	0.03
lnrdb (Natural logarithm of total R&D expense per firm per year)	0.24***	0.25***
AIC	16995.7	7743.14
BIC	17062.79	7802.31
VIF to check multicollinearity	3.88	5.02
Number of firms	988	473

(* $p < .05$ ** $p < .01$ *** $p < .001$)

Table 5.16 Number of firms' Headquarter in Provinces in Two Groups

	number of firms	number of firms in 10 knowledge/talent-intensive industries	percentage of firms in 10 knowledge/talent-intensive industries in subtotal
1 (Number of firms in group of China Eastern Coast)	1,020	542	53.1%
0 (Number of firms in group of other areas)	489	204	41.7%
Sum	1,509	746	49.4%

As analysed in Section 5.4.7 to divide industries in 2 groups, it is also reasonable to divide 31 provinces into groups. In China, the Eastern coast has been leading the Chinese economy since the 1980s. Hence, it is reasonable to include the 8 provinces and provincial cities: Beijing, Tianjin, Shandon, Jiangsu, Shanghai, Zhejiang, Fujian and Guangdong as one group, while other provinces and provincial cities are the other group. Two level random slope models for firms in 8 provinces or provincial cities in Eastern China and the group of other provinces are built respectively, whose results are illustrated in Table 5.15. It can be seen that there is a significant relationship between ESOP and annual patent applications numbers in the group of provinces in Eastern China, but not significant for the other group. In order to explain this, the numbers of firms in knowledge/talent-intensive industries in the two groups of provinces are compared in Table 5.16. There are 542 firms in knowledge/talent-intensive industries, 53.1% of 1,020 firms in the group of provinces in Eastern China. There are only 204 firms in knowledge/talent-intensive industries, 41.7% of 489 firms in the group of provinces in other areas of China. Firms in knowledge/talent-intensive industries adopt more ESOPs to attract, keep and activate talents to file more patent applications. Hence, the difference of numbers and the percentage of firms in knowledge/talent-intensive industries may result in the difference of significant or not significant relationship between the two geographical groups, which is consistent with the findings in Section 5.4.7 about the influence of industries.

5.4.9 Two-level models for different stock boards

There are 4 different stock boards in the Chinese stock market. Here is Hypothesis H5.6: Different stock boards influence the relationship between ESOP and the annual patent application number of firms. The models with 2 levels and 3 levels are tested respectively as following and the coefficients are listed in the following table.

The residuals of the models are tested and plotted to prove they are almost normally distributed. If use lrtest to compare the model with 2 levels and the model with 3 levels including stpid as categorical IV, LR chi2(2)= 2.83 and Prob > chi2 =0.24, which is not statistically significant at the level of 5%. This can be verified by the values of AIC and BIC. The values of AIC and BIC of 2-level model are 24706.49 and 24798.56, lower than those of 3-level model. Also, this is consistent with the test of ICC in the 3-level model whose value is 5.78e-13 less than 0.059, and the variation across stock boards can be ignored. Hence, with such triangulation, the model with 2 levels is better than the model with 3 levels.

Table 5.17 Results of 2-level and 3-level Random Slope Model with Different Stock Boards Whose DV is
Natural Logarithm of Annual Number of Patent Application Per Firm (lntpatap)

	2-level model	3-level model
	coefficient	coefficient
intercept	-1.79***	-1.75***
t0 (Year)	0.02**	0.02
teimpcf2 (Percentage point of ESOP which the employees keep ESOP for 2 years)	0.07**	0.07**
t0teimpcf2 (Interaction between t0 and teimpcf2)	-0.01**	-0.01**
beps (Basic earning per share)	0.11***	0.11***
lnrdb (Natural logarithm of total R&D expense per firm per year)	0.24***	0.24***
stpid=2 (Stock board 2)	-0.22*	-0.24*
stpid=3 (Stock board 3)	-0.41***	-0.56***
stpid=4 (Stock board 4)	-0.07	-0.06
var(t0) 2nd level	0.02	0.02
var(t0) 3rd level		0.0003
var(_cons) 2nd level	1.11	1.104
var(_cons) 3rd level		9.85E-13
var(Residual)	0. 6	0.6
cov(t0,_cons)	-0.08	-0.08
AIC	24706.49	24707.66
BIC	24798.56	24813.9
ICC at level of stpid		5.78E-13
ICC at level of stpid|firmid	0.65	0.65
VIF to check multicollinearity	3.67	3.67

(* p < .05 ** p< .01 *** p< .001)

The baseline is the firms in stpid1 (Stock board 1). According to the results in Table 5.17, the intercept of lntpatap for firms in stpid2 (Stock board 2) is lower than the baseline by 0.22 with statistical significance. The intercept of lntpatap for firms in stpid3 (Stock board 3) is lower than the baseline lower by 0.41 with statistical significance. The intercept of lntpatap for firms in stpid4 (Stock board 4) is lower than the baseline lower by 0.07 without statistical significance. The interaction of stpid and teimpcf2 is also tested in different possible models, which are all not statistically significant. This means that different stock boards do not influence the relationship between ESOP and the annual patent application number of firms with statistical significance. Hence, Hypothesis H5.6 is not supported.

Table 5.18 Results of the Models for Firms in Four Stock Boards Whose DV is Natural Logarithm of Annual Number of Patent Application Per Firm (lntpatap)

	Firms in stock board 1 (stipd1)	Firms in stock board 2 (stipd2)	Firms in stock board 3 (stipd3)	Firms in stock board 4 (stipd4)
	coefficient	coefficient	coefficient	coefficient
intercept	-2.37***	-1.76***	-3.89***	0.79*
t0 (Year)	-0.02	0.02	0.05**	0.1
teimpcf2 (Percentage point of ESOP which the employees keep ESOP for 2 years)	-0.03	0.06	0.18*	0.02
t0teimpcf2 (Interaction between t0 and teimpcf2)	0.03	-0.01	-0.03*	0.001
beps (Basic earning per share)	0.08	0.07	0.29***	0.03
lnrdb (natural logarithm of total R&D expense per firm per year)	0.28***	0.22***	0.32***	0.18***
AIC	2351.52	10047.27	5990.39	6182.65
BIC	2398.71	10109.31	6046.91	6239.67
Number of firms	165	587	306	403

(* p < .05 ** p< .01 *** p< .001)

Similar to the analysis of firms divided into two groups of knowledge/talent-intensive industries and not, the firms are divided into four groups of the four stock boards. The 2 level random slope models for firms in four stock boards are built and the results are illustrated in Table 5.18. It can be seen that the coefficients of teimpcf2 (percentage point of ESOP which the employees keep ESOP for 2 years) and t0teimpcf2 (Interaction between t0 and teimpcf2) in stock board 1, 2 and 4 are not statistically significant, while the coefficients of stock board 3 ChiNext are statistically significant. Similarly, the number of firms in 10 knowledge/talent-intensive industries in these four stock boards are examined in Table 5.19. It is interesting to note that the percentage of firms in 10 knowledge/talent-intensive industries in stock board 3 ChiNext is 71.6%, much higher than other 3 stock boards. Hence, the difference of numbers and percentage of firms in knowledge/talent-intensive industries may result in the difference of significant or not significant relationships among the four stock boards, which is consistent with the findings in Section 5.4.7 about the influence of industries and in Section 5.4.8 about the influence of geographical areas. This is a triangulation to prove that the numbers and percentage of firms in knowledge/talent-intensive industries in different geographical areas or stock boards may determine the influence of ESOP on patenting in the geographical areas or stock boards.

Table 5.19 Number of firms in Different Stock Boards

Stock board id	number of firms in each board	number of firms in 10 knowledge/talent-intensive industries	percentage of firms in 11 knowledge/talent-intensive industries in subtotal
1	171	68	39.8%
2	591	293	49.6%
3	306	219	71.6%
4	441	166	37.6%
sum	1509	746	49.4%

5.5 Discussion with results from interviews

5.5.1 Incentive effects of ESOP evidenced by interviews

Addition to the findings from quantitative analysis aforementioned, almost all the interviewees said that they enjoyed the ESOP and that it has incentive effects. For example, Hundsun is the largest firm in fintech equipment in China. An employee (anonymized) said in the interview:

> "Having stock options is equivalent to a long-term investment in the company. If you have confidence in the company, you will have it, and you have an expectation. This is the company's vision reflected in the mind of employees. If I have some stock options, I feel my personal interests is bound with the firm. I will work harder and try my best to invent something new."

Question: Which type of employees or work should be awarded more stock options? R&D? Marketing? Management?

Answer: "I do not know other firms, but in our firm, as I know, most of the cadres in R&D, marketing and management including human resources managers have ESOP.

You see, the development of our firm depends not only in R&D, but also others, all of them are important, right? So, it is necessary to award stock options to the cadres in all departments. But there are some minor differences. The salesforce in marketing department have high bonus from their performance, so maybe their stock option is not as high as others."

Wens Group is a typical firm with internal shares before IPO and ESOP after IPO, which is the largest company in stockbreeding in China currently. From the interviews in Wens Group, it can be found that ESOP really activates the employees to work harder for innovations. Usually, most of employees in Wens Group were eager to use all the savings to buy firm's internal shares. An interviewee in Wens Group said:

> "It is the key that the people around me all buy internal shares, so I buy it with them. At that time, almost all my financial resources were exhausted to buy the internal shares. If the firm let me buy more, I didn't have any more money."

Question: Did you feel good about it?

Answered: "Right, when we went out to chat, they said they made money in internal shares, but this was none of my business, I just got my salary. But right now when the internal share's price rises, I am happy, I have money to earn too."

Employees' expectation of benefits activates them to work harder. The interviewee said:

> "The internal shares became more and more impressive after a few years especially in 2010, because every year the firm gave me more shares, and the price rose again.…At least I can expect something. … Basically, there is an expectation in our mind."

Also, employees feel to have different status to become one of the owners after they buy internal shares.

Question: Before and after you buy the internal shares, do you feel the relationship with the company has changed?

Answer: "Yes, at least I felt that my status was quite different."

Question: What status?

Answer: “Before I bought the internal shares, I always felt I like an outsider. Now, I think I have some internal shares, too. I am also part of it.”

Question: Do you have a sense of ownership as the partial boss?

Answer: “Yes, it's a natural feeling. Of course, we work harder, but not extremely hard. Anyway, I feel very simple, because maybe I just came in at the time, at that time I was not a leader, a lot of internal shares suddenly let me have the strong sense of ownership, and I think at least I am in the same circle of people.”

Question: So how do you think about the ESOP in your firm?

Answer: “I think it works well, except some problems now.”

Additionally, ESOP can help to improve corporate governance and alleviate the mistrust among shareholders, managers and employees in R&D, so that the firms can increase more R&D budget, which will encourage the employees in R&D and innovations again. Furthermore, ESOP can help to solve principal-agent and principal-principal problems. For example, in Wens Group, if an employee sees someone who tries to hurt the benefit of the firm, he/she is the shareholder and must stop such behavior and report to the management. This is proved in the interviews and supported by Wens Employee Brochure (Wens, 2016b). Therefore, no employees will permit or take part in faked accounting data as happened in the Enron Corporation, or the faked quality report of Kobe Steel, since they know such illegal actions must result in the firm’s failure and a loss of their share value as well as their unemployment. The successful financial performance and fast development proved Wens’ ESOP and corporate governance works well.

5.5.2 ESOP in SOEs vs non-SOEs

As analysed in Section 5.4.6, it is interesting that there is no group effect among SOEs. The reason may be that the SOEs do not influence each other strongly, but they are controlled by the same shareholder which is the government. However, the patent application and its annual growth rate of SOEs are higher than private firms and the effect of ESOP on the managers and employees is stronger in SOEs than non-SOEs. This is partly consistent with the finding of Boeing (2015) that Chinese SOEs generated more innovation than non-SOEs after the financial crisis in 2008. Similarly, Lu (2019 and 2020) emphasized the key role of SOEs in the development of some strategic industries such as LCD, high-speed trains, airplanes and nuclear power stations, etc. There may be a few reasons for this:

First, this may be due to their history. As discussed in Section 5.2.4, according to the policy to "keep the big SOEs while liberate the small SOEs" in the 1990s, the central, provincial and municipal governments kept and supported some big SOEs with key technologies in strategic industries. Hence, SOEs can grow much bigger and live longer than the private firms. Also, Chinese governments have been requiring SOEs to improve their technologies and increase their patent applications. In contrast, most private firms have been struggling to survive. According to Dr Gang Yi who is the President of China Central Bank, the average life expectancy of small and medium-sized enterprises (SMEs) in China is only about 3 years (Yi, 2018). Currently in China, most SMEs are private firms. Since most private firms will die after 3 years, they do not care about patents. This is consistent with the difference between the annual revenue of SOE and non-SOE firms in the sample. As illustrated in Table 5.20, in 2007, the average revenue of non-SOEs was 1,071 million Chinese Yuan, in contrast to 2,303 million Chinese Yuan for SOEs. In 2015, the average revenue was 1,457 million Chinese Yuan for non-SOE compared to 4,485 million Chinese Yuan for SOEs in the sample. The difference between non-SOEs and SOEs is statistically significant and it also enlarged between 2007 and 2015. SOEs have much higher revenue and key technologies, plus the requirement of patent by the government, hence SOEs have more patent application number than non-SOEs.

Table 5.20 Different Average Revenue of non-SOEs and SOEs in the Sample

	2007	2007	2015	2015
	coefficient	exp(coefficient) in Chinese Yuan	coefficient	exp(coefficient) in Chinese Yuan
non-SOEs	20.7917	1,070,872,957	21.1	1,456,831,924
SOEs	21.5576	2,303,233,864	22.224	4,485,204,824

Second, according to the interviews, it can be found that there are some significant differences about ESOP between SOEs and non-SOEs. Their original reasons to adopt ESOP and the problems to be solved are quite different. SOEs can obtain loans with low interest rates from banks which are also SOEs. In SOEs, the main reasons to adopt ESOP are to 1) solve the problems of principal-agent and principal-principals, 2) attract, keep and activate talents and employees by economic compensations.

In the past, SOEs were said to "belong to all the people". In practice they belonged to the different levels of governments, while some managers as insiders controlled the SOEs, which generated many principal-agent problems. For instance, corruption in SOEs used to be very common in the 1990s and 2000s, including embezzlement and bribery of managers, who often hired their relatives or vassals and assigned them in key positions to help consolidate control internally. Employees used to have no share in SOEs and seemed to just work for the SOEs. They lacked motive or power to supervise the management. However, in recent years ESOPs provide employees in SOEs some shares and they felt they become real partial owners of the SOEs since their interests were bound with the SOEs. On the one hand, they watch the behavior of management and stop or report any illegal activities to the government. On the other hand, they are activated to work harder to create more inventions. This is one of the reasons why the influence of ESOP in SOEs is higher than non-SOEs.

Another reason for ESOP in SOEs is to attract, keep and activate employees by economic benefit from ESOP since salaries in SOEs are relatively lower than private firms. Because SOEs cannot issue internal shares to their employees, the common way for SOEs to adopt ESOP is to reform SOEs to be companies limited by shares, which can then try to reach IPO in stock market. After SOEs achieved the IPO, their employees with ESOP will be benefitted significantly. This point of view was found in SOEs such as CUEC and CITICHIC, etc. discussed in Section 5.2.7.

On the contrary, the original main reason for private firms to adopt ESOP in the early period was to raise money from employees. This is common in some leading Chinese private firms including Wens Group, Hodo and Huawei in their early period. In 1983, Mr. Yaoting Zhou became the manager of a factory owned by the local community which was the predecessor of Hodo Group in Jiangsu Province. But the factory had little money, so he asked the employees to provide money to the factory which were converted to internal shares later. Similarly, Wens Group was founded in 1983 in a poor county called Xinxin County in mountains in Northwestern Guangdong Province. When Mr. Beiying Wen founded the first farm for chickens as the origin of Wens Group, his money was only sufficient to buy chickens and fodder. But he still needed more money to enlarge his farm. Hence, he issued internal shares to employees to raise more money from them (Wens, 2018b). When Wens Group grew to be a big firm, it could obtain loans from banks. But the internal shares in Wens worked well until it was listed in Shenzhen stock market in 2015 and it adopted ESOP after IPO. Consequently, many senior employees in private firms have many stocks and the problems of “entrenchment” (Chang and Mayers, 1992) and “free riders” (Weitzman and Kruse, 1990) are much more serious in private firms than in SOE, which are discussed in details in Section 5.5.4 about the limits of ESOP. This may be one of the reasons why the incentive effect of ESOP in non-SOEs is lower than SOEs.

5.5.3 Incentive effects of ESOP in industries

In Section 5.4 about the results of quantitative analysis, four main different factors are analysed, such as the types of ownership (SOEs vs non-SOEs), the different industries, provinces where the firms' headquarters are located and stock boards. Only the industry can be put into the third level to build a 3-level growth curve model since there is a group effect among firms in the industry. The reason may be that the knowledge sharing (Nonaka and Takeuchi, 1995a and 1995b) and the flow of talents mainly happens within each industry. Every industry has its own special knowledge and knowhow, which the manager and employees spend years to obtain tacit knowledge and internal experience. The ESOP usually focuses on the talents in technical, management and marketing, etc., to attract, keep and activate them to maximize their effort and enhance their performance especially in innovation. They have the tacit knowledge and change jobs primarily in the same industry. If they change to jobs in other industries, maybe their special knowledge and experience in the previous industries will be less useful or devalued. Hence, the mutual influence among firms in the same industry is stronger than the mutual influence in the same province but outside the industry. This is proved in the interviews in Hundsun which is the largest firm in Chinese Fintech and Wuxi Apptech which is a large firm in Chinese pharmaceutical industry discussed in Section 5.2.7. Another example is in Wens Group and an employee in Wens Group said:

> "You know, I major in animal science in South China Agricultural University. After I graduated, I went to work in the Zhengbang Group. It is also a big firm in stock farming. After a few years, when Wens Group contacted me and told me about the job and the compensation portfolio, I came here. I cannot go to another industry."

5.5.4 Limits of ESOP

However, some shortcomings of ESOP including "entrenchment" (Chang and Mayers, 1992) and "free riders" (Weitzman and Kruse, 1990) were found in interviews in Chinese private firms. Aubert, et al., (2014: 423) found that "good managers use employee ownership as a reward management tool, whereas bad managers implement it for entrenchment." This kind of problem is found in Wens Group. An interviewee in Wens Group said:

> "Because the firm used internal shares since its initial period, up to date, there are some problems. Our old employees have many internal shares. …The motivation sometimes may not be positive now. So, when the internal shares reach a certain threshold, it has some problems."

Even worse, the children of old employees with many internal shares do not work hard. An interviewee in Wens Group said:

> "There are shortcomings, which probably begin to emerge and are not very obvious. I think the second generation will have obvious problems. She inherited the internal shares but without the experience of her parents who worked hard. She just inherited the wealth from the previous generation, and now you let her to work in the firm, so she feels quite different from her parents."

Another problem is relevant to the growing size of the firm. A manager in Wens Group said:

> "Of course! There are some changes! At the beginning, its effect is obvious. …Now, when the organization is getting bigger and bigger, the direct relationship with every employee seems be smaller and smaller. …You cannot feel a drop of water in the sea, but you can feel a spoon inside a basin, right?"

This kind of problem is more serious in the Far East Group (FEG) than in SOEs or other private firms such as Wens Group or Huawei, according to the interviews. The Far East Group (FEG) was founded in 1990 by Mr. Xipei Jiang as a private firm to produce electric cables and it changed its ownership dramatically 4 times in its history. In 1992, FEG could not obtain loans from local banks which were all SOEs. Hence, FEG was forced to change from a private firm with net asset of 5 million Chinese Yuan to a SOE whose controlling shareholder became the local government. In 1995, Mr.

Xipei Jiang paid 50 million Chinese Yuan to buy FEG and change FEG from a SOE to a joint-stock enterprise (JSE). The policy of government required that employees must have shares in JSE, so Mr. Xipei Jiang allowed the employees to buy internal shares. The employees volunteered to spend 10 million Chinese Yuan in 1995, 50 million Chinese Yuan in 1996 and 100 million Chinese Yuan in 1997 to buy internal shares. The payment helped FEG to get large amounts of operating capital. In 1997, Mr. Xipei Jiang convinced its biggest clients which were four SOEs including the State Grid Corporation of China to become controlling shareholders. Hence, FEG has mixed ownership with 68% held by SOEs, 7% by the local collective community, 25% for Mr. Xipei Jiang and the employees. This helped FEG to sell its electric cable to big clients and FEG grew to be the biggest firm in the electric cable industry. In 2002, the Chinese central government required all SOEs to clear their peripheral businesses. Mr. Xipei Jiang bought the shares back from the SOEs and the local collective community. Hence, FEG became a fully private firm with employees as shareholders again. During these 4 transformations of ownership, Mr. Xipei Jiang was generous in allowing many employees to buy internal shares.

FEG has the ESOP system but without a sufficient complementary system, so it faced many management problems in recent years. Senior employees became inured to the incentives of internal shares and the activation effect withered. Even worse, some employees become lazy and just sat on the benefits of their internal shares. Many managers and employees are shareholders, so that everyone is friendly to others without strict management. This is consistent with what Chang and Mayers (1992) called “entrenchment”. Many employees’ capability waned and become even barriers to improvements. Some employees became the “free riders” (Weitzman and Kruse, 1990). A manager said in an interview: “The current employees cannot support the Far East Group to achieve annual revenue as high as 50 billion Chinese Yuan.” Mr. Xipei Jiang and top management noticed the internal problems and adopted strict key performance indicators to eliminate the bottom 10% of total employees annually. But this resulted into attrition, unfair compensation and reverse elimination of some competent employees. There were many complaints among the employees.

ESOP is not omnipotent. Richte and Schrader (2016) found ESOP cannot solve all problems about recruitment and retention. These problems aforementioned are mainly found in Chinese private firms, which adopted ESOP much earlier and broader than SOEs. SOEs have shorter history and fewer cases about ESOP, but the similar problems maybe emerge in SOEs in the future. Hence, SOEs have to be carefully designed to avoid similar problems.

According to the interviews in FEG, Wens Group, Huawei and other firms, some leading Chinese innovative firms have been developing the partnership system (PS) including ESOP. In PS, firms not only provide economic and non-economic incentives to employees but also share power for decision-making with good institutional norms. PS has some similarities with the Scanlon Plan in the U.S. (Markham, Scott and Cox, 1992; Scott, Davis & Cockburn, 2007; Wren, 2009), but it has some significant differences. PS will be analysed with details in future research. After analysing the transcripts of interviews by thematic analysis, four main aspects of PS are found as following and are also illustrated in Figure 5.11 tentatively.

Economic incentive: ESOP, salary increments, bonuses, subsidy for employees to eat free lunches at firms or to rent accommodation, etc. Also, some firms including Wens Group, Vanke, Dahua and HIKVision allow their employees to invest in personally relevant projects with other employees. An interviewee in Vanke said:

> "We now use the method of joint investment. You will have internal shares in the direct branch firm or that project you work on. You invest in the project. Since every project is relatively much smaller than the total firm, you will have more feeling about your internal shares or investment."

Noneconomic incentive: The employee union of the firm helps to contact local convenient kindergartens and send the employees' children to the kindergartens. Also, the firm supports activities about sports, culture or entertainments in teams in festivals, etc. This is consistent with Brander & Zhang (2017). An employee in Hundsun said in the interview:

> "Currently, the youngsters have been cherished by their parents, so they care about being loved. The benefits such as the free shift bus may be small, but it reflects that the firm is taking care of the employees warmly like a family. A cake or a small gift for an employee's birthday is better than just 100 Chinese Yuan. So this kind of small benefit cannot be cancelled or reduced, it can only be raised to take care of employees."

Similarly, an employee in an electronic firm said:

> "The free gifts from the firm to employee in holidays is a very smart incentive to make the employees to feel warm but the costs are minimal."

Sharing of decision-making power with employees: The firm should have collective decision-making harmoniously including: variety of board members (half board members are external or not from the founder's family), management panel (not just the CEO but the management panel make decisions together), technical authority (the technical authority has the power to permit or reject, whose technical decisions are mostly obeyed by even the managers which is important to encourage employees in R&D and innovations), subcompanies sharing decision-making (a subcompany can make decision with investment under some thresholds without centering to mother firm), and colleagues opinion evaluation (the decision-making about any employee must consult the colleagues around that employee).

For example, the next Presidents are usually assigned by the founder of private firms. But the founder who is the biggest shareholder of Hodo Group did not assign his son to be the next President. He asked his son to work from the lowest level in Hodo

Group during 16 years. In 2004, Hodo Group held the first democratic and equal election to choose the next President from 22 candidates. Fifty board members and big shareholders votes in 3 rounds and selected the founder's third son to be the President. Similarly, in Hodo Group, the President does not vote to promote any employees, but it is the system to select and decide the most suitable employee to be promoted. Consequently, employees need to work harder and better, instead of flattering the President.

Particularly in Huawei, three board members rotate to be the acting president for 6 months. The rotating president system can avoid problems such as strategic mistakes in the long term, dictatorship and nepotism. If a rotating president has made mistakes in his term in 6 months, the next rotating president can correct the mistakes to keep Huawei in the right track. The rotating president is always watched and supervised by other rotating presidents, the board members and about 200,000 employees in Huawei to avoid any big problems of principal-agent and principal-principal. Similarly, as an interviewee in Wens Group said:

> "It is all democratic decision-making. Sometimes, even what the chairman has something he wants to do, but it cannot be accepted if other members do not approve it. He can't do it, too. This is very democratic, very harmony."

Good institutional norms: particularly common richness, responsibility and equality. The founder of Wens Group announced his aim to reach common richness with more and more employees. This is very similar to Huawei, since its founder Mr. Ren Zhengfei keeps on diluting his own shares in Huawei and now his share is close to only 1%. Everyone in Wens or Huawei has the responsibility to defend its institutional norms and property. Hundsun and Hodo Group emphasized "fair, justice and open" in their institutional norms. In these private firms such as Hundsun, Hodo Group, Wens and Huawei, there is no political struggle and no need for employees to flatter any leaders to be promoted, which is enjoyed by their employees but is quite different from some bureaucratic SOEs.

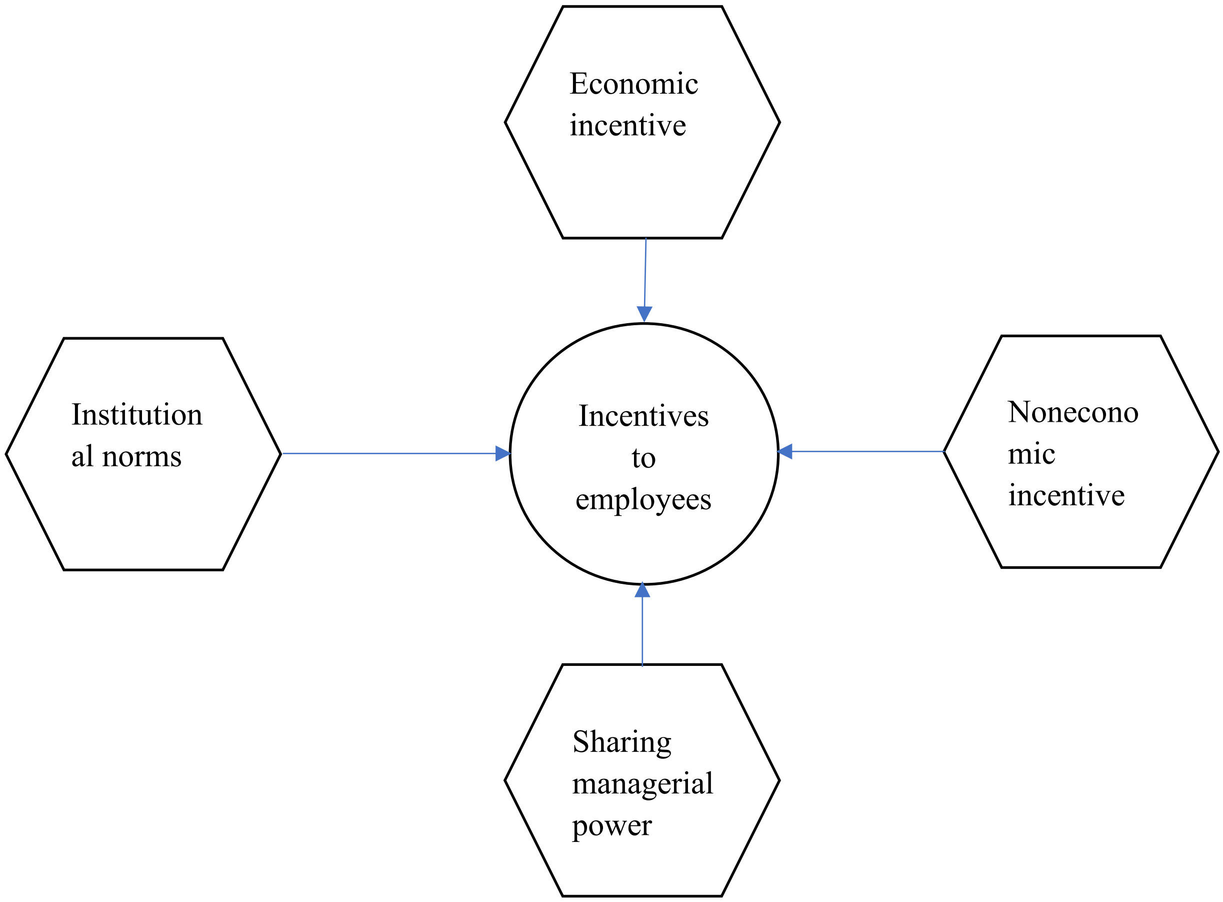

Figure 5.11 Structure of Global Theme and Organization Themes about The Partnership System (PS) including

5.6 Conclusion, limitation and suggestions

This study examines the impact of ESOP on innovation by combining both quantitative analysis and qualitative interviews. First, it proves the finding of Chen, et al. (2006) with a bigger sample that ESOP can alleviate the problems of corporate governance and promote firms to increase R&D expense. Next, it can be concluded that ESOP influences the firms' annual patent application number with statistical significance. Furthermore, in the relationship between ESOP and the firms' annual patent application number, there are group effects at the level of industry, which can be put on the third level of the growth curve models. The effect of ESOP on patent applications is very strong for the group of 10 knowledge/talent-intensive industries which is consistent with Garrett (2010), while not for the group of 54 non-knowledge/talent-intensive industries which was ignored by Garrett (2010).

There are no group effects in various types of ownership, provinces where the firms' headquarters are located and stock boards respectively. Furthermore, province and stock board do not influence the effect of ESOP on the firms' annual patent application number. But most firms in knowledge/talent-intensive industries concentrated in the 8 provinces or provincial cities in China's Eastern coast, so the effect of ESOP in the group of these 8 provinces is statistically significant, while not for the group of other provinces. Similarly, some firms in knowledge/talent-intensive industries concentrated in ChiNext. Consequently, the effect of ESOP in ChiNext is statistically significant while not for the other 3 stock boards. Therefore, the effect of ESOP in different provinces or stock boards depends on the firms of knowledge/talent-intensive industries.

The SOEs have more patent applications than non-SOEs on average and the average annual growth rate of patent applications of SOEs are higher than non-SOEs. Similarly, the influence of ESOP of SOEs on patent application number is bigger than non-SOEs with statistical significance. The reasons may be that SOEs adopt ESOP to solve problems of principal-agent and principal-principal and to attract or activate employees. But the private firms adopted ESOP to raise money from employees as their priority in early period found by the interviews. Many employees in private firms bought ESOP which result into serious problem of "entrenchment" (Chang and Mayers, 1992) and "free riders" (Weitzman and Kruse, 1990) as seen in the interviews.

Additionally, the shortcomings of ESOP are discussed. It is found especially in the interviews that ESOP by itself is not sufficient to activate employees. Chinese innovative firms developed a partnership system to solve principal-agent and principal-

principal problems. It includes four main parts: economic incentives such as ESOP and bonuses, non-economic incentives, sharing power with employees and supporting from institutional norms. The partnership system should be built in order to support the sustainable development of firms' innovation performance.

Finally, suggestions to management and government policy are provided: the Chinese government and firms should continue reforming SOEs toward mixed ownership. However, the managerial implication of this research is that the firms should include not only economic incentives, but also the non-economic incentives and sharing power with qualified employees, plus quality management and fostering suitable institutional norms. The local governments maybe can encourage local firms to adopt ESOP to attract talents and develop knowledge/talent-intensive industries.

Every method has some limitations. There are many possible indictors to measure innovation performance and this research uses patent application number, which may be not perfectly accurate. For example, patents are common in some industries including ICT but not in others such as agriculture. The data about 49 industries are not included in the analysis since they have few patent applications. Patent data has noise and patents can be divided into different categories with uneven quality. There are key patents to protect core technologies such as those patents relevant to technological standards. But there are many patents which are used to build patent walls, patent thickets or landmines to scare and stop possible aggressive competitors. "Many innovations, however ingenious, have no market potential", which is "reflected in the huge numbers of 'dark patents' which lead to no useable outcomes" (Yusuf, 2009: 2).

Also, many listed firms have business across industries and provinces, so that their categories of industries and provinces probably are not extremely accurate. Between 2007 and 2015, some listed firms among 1,509 firms changed their main business. It is tried to examine all of them but cannot found and delete all the firms with such changes from this study.

Furthermore, as discussed before, it is assumed the incentive effect to employees is only valid after the employees obtain and before they sell or execute the incentive stocks. After the employees sell restricted shares or execute stock options, the incentive effect decreases dramatically. Since the effect is not so clear-cut, this assumption may not be perfectly accurate, but it is the most convenient and practical way to analyse the incentive effect. Finally, for the qualitative interviews, the context and the relationship between interviewer and interviewees matter. Also, when the employees reply to questions in the interviews, there may be social or firm desirability bias or other kinds of bias. Nevertheless, the findings here demonstrate distinct characteristics of ESOP in China and offer new insights into how they can be measured, analysed and incorporated into managerial practice.

Chapter 6 Conclusion, Contributions and Future Research

6.1 Conclusion and contributions

Learning from the previous generations of innovations, especially iteration and mass-customization from Generations 4 and 5 (Rothwell, 1994) and open innovation (Chesbrough, 2013) in Generation 6, "Online Interactive & Integrated Innovation Model" [OIIIM] illustrated in Figure 2.11 in Section 2.4 combines both integrated product development [IPD] and online interactive innovation [OII] which generate a series of important advantages. Evidenced by the success of some leading innovative firms including Huawei and Xiaomi, it is necessary, useful and important to combine both OII and IPD together, which are complementary. OII breaks the wall at the boarder of the firm and connects millions of consumers with the firm at low costs which reflects open innovation (Chesbrough, 2013). IPD clears the barriers inside the firm and integrates all the internal departments into innovation. So that after selection and evaluation, valuable and useful suggestions, complaints or knowledge can flow easily from millions of customers to all the relevant internal departments of the firm to contribute to innovation, vice versa. This thesis first analyses OII in Chapter 3. The individual is the basic unit for innovation and OIIIM including OII addresses an employee's innovation behavior when the employee interacts with customers in OII. Hence, Chapter 4 examines the effects of education as a key personal factor which influences individual innovation. Furthermore, incentives are necessary to attract and encourage employees to improve innovation and Chapter 5 investigates how incentives such as ESOP influences firms' innovation performance.

6.1.1 What learn from the study of OII

This study explores a new innovation method 'Online Interactive Innovation' [OII] for firms to interact with millions of customers and collect valuable suggestions from them online at very low cost. In detail, this study analyses Xiaomi's panel data about suggestions and replies from Xiaomi's employees and customers, functions changed in the operating system, patent applications and annual shipments of smartphones between 2012 and 2018, and discusses 10 other firms. It finds that the number of suggestions is positively associated with the number of replies with statistical significance and then the number of functions changed in the operating system. These are associated positively with the annual numbers of patent applications and annual shipments of smartphones with statistical significance. OII also helps firms to realise mass-customisation, enact fast iteration techniques, enhance users' experience and trust, reduce costs and improve productivity, etc. OII helps Xiaomi's smartphones to keep a high performance/price ratio and OII plays the key role in Xiaomi's strategy. Additionally, OII accelerates the speed of innovation and its diffusion drastically.

OII can be generalised across different industries and countries. The various forms of OII have been applied well to not only smartphones industries, but also more industries including home appliance manufacturers such as Haier, software developers such as Microsoft and vehicles producers such as Tesla and Mercedes-Benz. OII not only works well in China, but also in other countries including India (Chhabra and Metkar, 2020) and some European countries. In the first quarter of 2021 even when the pandemic continued in Europe, Xiaomi's smartphone sales increased by 85% in European markets to be the second largest market share with 23% in Europe, higher than Apple whose market share was 19% (Calalys, 2021), this lends credence to the generality and power of OII.

Usually, most customers do not want to design products by themselves and act as lead users (von Hippel, 1986), they prefer the firms to do it. Particularly for electronic products including many new features, it is impossible for any customers to develop all the functions by themselves as lead users. This study finds that PFs and IUs in OII are different from lead users (von Hippel, 1986) or user innovators (von Hippel & Euchner, 2013). As more and more traditional products such as cars become digitalised and can be updated easily over the mobile internet, OII will be applied much more broadly than lead users (von Hippel, 1986) in this digital era. As discussed in Chapter 3, this study integrates the previous theories including open innovation (Chesbrough, 2003), interactive innovation (Lundvall, 2009), knowledge creation and sharing (Nonaka and Takeuchi, 1995a and 1995b), word of mouth (Arndt, 1967a), innovation diffusion (Rogers, 1995) and make progress to develop the new theory with much broader applications.

OII also has novel and important meanings in practice and clarifies some popular misunderstandings about 'scarcity marketing strategy' or 'hunger marketing strategy' (Shi, et al., 2020). As discussed in Section 3.4.2.7, there were 3 reasons for the shortage of Xiaomi's smartphones. First, OII increases the demand of customers dramatically but Xiaomi underestimated the significant influence of OII. Second, Xiaomi was too young to have the sufficient skilled employees and the capability to manage the supply chain on a large scale in the early period. Third, Xiaomi did not have the confidence and sufficient money to pay the manufactures in advance and order many smartphones as inventory, since cash flow was critical for Xiaomi especially in its initial stage before its IPO (Custer, 2013). Such product shortages irritated many customers and triggered illusion of "deceptiveness" (Aguirre-Rodriguez, 2013) that Xiaomi adopted scarcity or hunger marketing strategy deliberately. However, Xiaomi did not plan or adopt a 'scarcity marketing strategy', since its shortage was unintentionally demand-induced (through underestimation of the rising demand that resulted from OII) and supply-induced (mismanagement in supply chain) only during the product launch (Shi, et al, 2020), which almost destroyed Xiaomi (Lei, 2020). But this shortage is often misunderstood or mispresented as 'hunger marketing strategy', a strategy inappropriately ascribed to Xiaomi in Chinese business schools' teaching and many publications. On the contrary, Huawei has both OII and IPD without the problems of shortage in supply chain before the U.S. government sanctioned it in 2019. After Xiaomi learned IPD, Xiaomi improved its management and solved its problems of shortage successfully, evidenced by its rising market share in 2020 and 2021.

6.1.2 Conclusion and contribution of the study about individual innovation

By building a series of multilevel models, this study explores a new mechanism for how education improves individuals' innovation performance particularly via individuals' creativity. The first contribution with novelty is that it finds the chain relationship. Education, measured by the highest degree of the employee, enhances creative performances, which is in the middle of the chain relationship. The creativity then contributes to improve individual innovation performance, measured by the total number of value engineering projects (VEPs) which the employee proposed as applicants (lnveeroleta) and the total number of VEPs which the employee proposed as an applicant or took part in as a follower (lnveemt) over 6.5 years. The chain relationship is statistically significant ($p<0.01$ or 0.001) in 2 models whose dependent variables (DVs) are the first and second indicator respectively. There are direct associations between education and the total number of patent applications from the VEPs which the employee joined over 6.5 years. Next, the first and second indicators about individual innovation (lnveeroleta and lnveemt) contribute to generate economic value to the firm with statistical significance ($p<0.01$ or 0.001). Also, the employees' innovation behaviors influence each other significantly in squads since there are group effects at the level of the squad in all the models with statistical significance. This study controlled other variables including the individual differences (age, sex, majors of bachelor degree, hometown, etc.) and the external factors such as awards to employees and the investment to the different VEPs from the firm.

The second contribution with novelty of this study is that it adopts the comprehensive factors aforementioned to measure individual innovation performance and the results are consistent as seen by triangulation. If applying principal component analysis (PCA) to generate a composite index to measure the innovation performance of employees, the result is consistent with the previous findings with triangulation.

The third novelty of this study is that it measures individual creativity in a real working context with high reliability and validity. Baas, DeDreu, and Nijstad (2008) conducted a meta-analysis on mood and creativity and found "[e]xperimental studies mostly involved students" (p. 796). Similarly, Hammond, et al., (2011: 91) reviewed publications about creativity and innovation and found "the majority of the included studies were laboratory experiments with student participants." On the contrary, the indicator associated with creativity in this study has been applied to test 2,078 employees in 3,976 VEPs and has been improved in management practice by a large listed firm over 6.5 years. This is consistent with the measurement approaches of creativity proposed by Rhodes (1961) and developed by Kozbelt, Beghetto, & Runco (2010), Simonton (2012) and Tang & Werner (2017). They are much better than some previous studies which tested a few students in universities' psychology or behavior laboratories to measure creativity over relatively short periods. All of these advantages support the reliability and validity of this study.

This study is also important in management practice in more firms in more industries. It quantifies why firms should hire young and smart employees with higher degrees. The firm also should provide sufficient incentives, including ESOP, to activate employees' potential in creativity, etc., in order to improve the firms' innovation and competitiveness. Also, the firm should train employees internally or provide sources to encourage them to study for higher degrees in subjects relevant to the firm's business.

6.1.3 Conclusion and contribution of the study about ESOP

This study adopts a mixed design by combining quantitative analysis and qualitative interviews whose transcripts are analysed by thematic analysis. Some factors identified in interviews are tested in statistical models and the results from interviews help to explain the results of quantitative analyses. This study analyses panel data from 1,509 listed firms in China stock market between 2007 and 2015 by building growth curve models. It makes some contributions with novelty:

First, it proves the finding of Chen, et al. (2006) with a much larger sample and shows that ESOP can alleviate problems of corporate governance and promote firms to increase R&D expenses. Second, it finds that ESOP enhances firms' patent application practices with a big sample and sufficient representativeness. These 1,509 firms cover 18 level-1 categories and 64 level-2 categories of industries based on the official industry categories in China. Also, their headquarters cover all 31 provinces or provincial cities in China, which is sufficiently representative and much broader than previous publications. These 1,509 firms covered 60.4% of all the 2,497 firms listed in Chinese stock markets in 2012, many more than the study of Garrett (2010) which analysed only 77 firms in high-tech sectors in the U.S. and Chen, et al. (2006) which examined only 168 firms in information technology listed on the Taiwan Stock Exchange.

Third, the possible effects of various factors are analysed. The influence of ESOP on annual patent application numbers is bigger in SOEs than non-SOEs with statistical significance ($p<0.05$). The possible reasons may be that SOEs are more prone to adopt ESOP to solve principal-agent and principal-principal problems and to attract or activate employees. But private firms adopted ESOP to raise money from employees, a priority in the early period as seen in interviews. Consequently, the problems of "entrenchment" (Chang and Mayers, 1992) and "free riders" (Weitzman and Kruse, 1990) are much more serious in private firms than in SOEs as seen in interviews. There are also group effects at the level of the industry which influence the impact of ESOP on firms' annual patent application numbers. ESOP influences firms' innovation significantly in knowledge/talent-intensive industries while it is not significant in non-knowledge/talent-intensive industries which was not covered by Garrett (2010). Other factors that might be thought to have group effect do not, including stock boards and province. The impact of ESOP on firms' innovation is found only in provinces or stock boards where the knowledge/talent-intensive industries concentrate.

Fourth, these findings imply suggestions to management and government policy. Firms should provide more ESOP to cover and activate all key employees to improve the firms' innovation. But ESOP should not be awarded to non-qualified employees to avoid "entrenchment" (Chang and Mayers, 1992) and "free riders" (Weitzman and Kruse, 1990), e.g., the lessons from Far East Group and Wens Group from the interviews. Also, the findings support the policy to encourage ESOP in both private firms and SOEs by the Chinese central government. The Chinese central government and SOEs should continue the reform to mixed ownership by awarding ESOP to the key employees. Furthermore, local governments should encourage firms to award ESOP to key employees to attract and develop knowledge/talent-intensive industries to their provinces or cities.

However, based on the analysis of this study, the firms should include not only the economic incentives such as equity, but also non-economic incentives and sharing power with qualified employees, plus suitable management and fostering suitable institutional norms, whose effect has been proved by the successful practice of leading firms including Huawei, Alibaba and Wens, etc. This is the 3rd type of corporate governance solution, which will be introduced in Section 6.2.3.

6.2 Future Research

In the near future, a series of research will extend those already conducted. These studies continue the researches of the three topics in the PhD thesis, plus other relevant topics from the different angles of the new innovation model.

6.2.1 Future studies about Online Interactive Innovation

1. Integrated product development (IPD) is the essential part of the 'Online Interactive & Integrated Innovation Model' [OIIIM] discussed in Section 2.4. IPD evolved from the integrated innovation (Rothwell, 1994) and the integrated process for product and cycle-time excellence (Mcgrath, 1986). Huawei learned IPD as a big consulting project from IBM between 1999 and 2007. Huawei first implemented and then improved IPD in the Chinese context. IPD is important for Huawei to develop its business to become the leading firm in global telecommunication. More and more Chinese firms such as Xiaomi have been learning IPD now (Lin, 2019). It is necessary to explore more about how Huawei learned IPD first from IBM and what they did to improve IPD and what differences there might be between IBM's original version of IPD and Huawei's version. I would like to investigate more cases that other Chinese firms learned IPD.

2. This study will follow the analysis in Chapter 3 and investigate the network relationship among employees and customers. Networking is increasingly important, enabled by ICT, and is changing business (Castells, 1996). Networks play the most important role for knowledge sharing (Huggins, 2010). It is interesting to analyse network relationships among Xiaomi's employees and customers including participative fans [PFs] or interactive users [IUs]. This leads to questions such as: How does the network influence the knowledge sharing and intensive interaction among engineers and designers of Xiaomi and customers? How does the network influence the innovation? The network among Xiaomi's employees and the customers in this study will be compared with the network among only employees in Firm A in the planned study described below. All the data are already coded and will use the software of Stata or UCINET to analyse the networks.

3. Another planned study will analyse the new business methods associated with customer to manufacturing (C2M) relationships and its influence. OII is conducted by producers in an early stage, while C2M is developed by the e-commerce platform firm at a later stage. OII and C2M are complementary. This study will analyze the cases of C2M, e.g., Jingdong cooperated with Lenovo, Midea, etc. Also, the similarities and differences of C2M of different firms including Biyao, Jingdong and Alibaba will be compared. Additionally, the effects of C2M to mass-customization and iteration will be examined. This study will fill the gap of existing publications that have failed to analyse this phenomenon (Tu, Vonderembse & Ragu-Nathan, 2001; Rui, 2003; Kassel & Grebenstein, 2006). Some cases and materials about C2M are already collected. This paper is targeted at *Management Information Systems Quarterly.*

4. This study will explore the new business method: e-commerce via live broadcasting and its influence. During and after the pandemic of Covid-19 in China, most people had to stay home and could not go to shops or department stores. During this period, e-commerce via live broadcasting became popular in China and some popular stars became very influential to promote sales. This business method was invented by the combination of e-commerce and live broadcasting via Kuaishou or Douyin, the Chinese version of TikTok, followed by big firms including Alibaba and Gree. For example, the CEO of Gree led 6 cases of live broadcasting between April and July, 2020 and the total sales reached 22.8 billion Chinese Yuan. Also, some entrepreneurs apply this new business method to sell local specialties from poor villages in mountains to help poor people, which works very well. The key to this new business method is direct and better interaction between the firms and millions of customers to explain products, answer customers' questions and enhance the trust between them, whose logic is relevant to OII. Chinese central and local governments have released some policies including subsidies to promote this new business

method and to encourage domestic consumption to stimulate the economy. This study will analyse the evolution of this new business method and investigate its relationship with OII and C2M. Also, the effects of policies by governments will be examined. Much data and materials about this topic have been collected.

6.2.2 Future studies about individual innovation behavior

5. To follow the analysis in Chapter 4, I will examine the network relationships among employees, considering their different characteristics and different roles in innovation networks. Kratke (2011: 3) argued that creativity is "embedded in relational networks of social and economic actors". Hence, there is "collective creativity" (Halprin, et al., 1974; Bissola & Imperatori, 2011; Yu, et al., 2012). Also, innovation can take place at the level of team or more individuals, which is called "collective innovation" (Gchter, et al., 2010; Gerber, et al., 2019). It is interesting to find out the innovators, early followers, major followers and laggards among the 2,551 employees in Firm A analysed in Chapter 4, particularly the network relationships among them. The differences among them will be compared. Also, it will be useful for the management practice to find out who has the potential to be the innovators. What are the characteristics of the innovators? How will the network influence individual innovation performances?

6. This study focuses on how knowledge sharing among employees influence individual innovation, considering other factors. As discussed in Chapter 4, other external factors can influence individual innovation performance, which are not included in that study. Other contextual factors such as the level of democracy of management, knowledge sharing among employees and teams,

inhibitors or enablers about knowledge sharing, etc., are only available in questionnaires already conducted in 2018. Hence the data about value engineering projects (VEPs) and employees only in 2018 can be used in this study. Since this will reduce the large sample size between 2012 and 2018 drastically to the much smaller sample only in 2018, these contextual factors will be analyzed in this study with the results of questionnaires from 2018. There were 904 responses of similar questionnaires received from Firm A, 387 copies from the Far East Group in Jiangsu Province and about 200 copies from CITIC in Henan Province in China in 2018. This study will adopt a mixed design including qualitative interview and quantitative models. The possible methods to analyse such data are structured equation modelling since there are latent variables indicated by the answers of the questionnaires, and multilevel analysis since there are usually three levels in each firm including branch firms, department and squads. This paper is targeted at *Research Policy.*

6.2.3 Future studies about ESOP and partnership systems

7. This study will follow the analysis in Chapter 5 and investigate the five types of ESOP and find which are suitable for the firms in various types of ownership, stock board, industry or location of the firm's headquarter by province. When the study about ESOP in Chapter 5 was finished, the databased was built, including data about corporate governance and all key financial data about 2,453 Chinese listed firms between 2007 and 2015, plus 3 types of patent applications and patents granted for those firms that had any. Based on the database, more research will be conducted. For instance, there are five different types of incentive stocks: 1) listed firms awarding stock options to employees, 2) listed firms using incentive funds to buy stocks from the market then award employees, 3) shareholders of listed firms transferring stocks to employees, 4) listed firms issuing new stocks to employees, 5) listed firms

buying back stocks from employee at a high price with stock appreciation rights. These five types of ESOP will be analysed and compared. Additionally, since more and more Chinese listed firms are adopting ESOP, more data will be collected to find causal relationships by other methods including matching with continuous treatments (Angrist, et al., 2009 and Angrist, et al., 2014).

8. This study will examine the partnership system (PS) including ESOP. This study will adopt a mixed design to combine both qualitative interviews and quantitative analysis. Between 2016 and 2019, some interviews were conducted in the leading Chinese innovative firms including Alibaba, Xiaomi, Lenovo, Haier, CITICHI, HIKvision, Dahua, Hundsun, FPI, Transfar, Vanke, Midea and Wens Group. Thematic analysis is applied to analyse the transcripts of interviews qualitatively, in order to find the mechanisms, processes, employees' experiences and opinions about incentives. It is found in the interviews that only ESOP by itself has some limitations. A complete system of PS needs to be built in order to support the sustainable development of firms' innovation capability. PS consists of 4 main parts: economic incentives such as ESOP, bonus, subsidy, non-economic incentives, sharing power with employees, and institutional norms. This may be a key difference between Western ESOP and Chinese PS. Chinese firms developed PS which become more and more popular in China. Stock option to mangers is the 1st type (1T) of corporate governance solution and ESOP to employees is the 2nd type (2T) of corporate governance solution. PS is the 3rd type (3T) of corporate governance solution. 1T, 2T and 3T are not exclusive, but 3T covers 2T and 2T covers 1T. This study will explain what PS is? What are the similarities and differences among the three types of corporate governance solution? How does PS influence innovation? After analysing more about PS, theoretical contributions will be made to reform the traditional theories about innovation and corporate governance (Fama, 1980), etc. The materials about PS in some

innovative firms including Huawei, Alibaba, Tencent, Vanke and Xiaomi have been collected. Finally, Chinese listed firms in two groups (one group without PS and the other group with PS) will be compared to test if PS can contribute to improve the financial performance of firms or not. The quantitative analysis may be growth curve model similar to those in Chapter 5. This paper is targeted at the *Academy of Management Journal*.

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Appendix

Since ESOP and its relevant factors have various contents: economic incentives, noneconomic incentives, sharing management power, corporate culture (institutional norms), so that I will ask them separately in simple words and give more space for interviewees to tell me what they want.

Topic guide for Interviews only about ESOP:

Introduce myself and explain the purpose of interview.
Get the permission and tell the interviewee about privacy and anonymousness.
Explain the procedure of interview.

Ask the interviewee about the ESOP to employees in general:
Do you know any ESOP before you joined this firm?
How do you feel about ESOP in general?

Ask the interviewee his/her personal experience about ESOP in his/her firm:
When did you first know that your firm has ESOP in your firm?
How do you feel about ESOP in your firm?
Fair for you? Are you satisfied with the amount of ESOP to you?
Any changes in your attitude in your work?
Will you put more time and energy in your work after you get ESOP?
Any example?
More details?

Ask the interviewee his/her opinions about if ESOP work well in his/her firm:
Should the firm award ESOP to more employees in your firm?
Which type of employees or work should be awarded more ESOP? R&D? Marketing?

Management? And why? Any example?
Do you think ESOP works well in your firm? Any example?
Do you think there is any problem about ESOP? Any example?

Ask the interviewee his/her personal experience about other possible benefits in his/her firm:
How do you think about your salary? Bonus?
Any other benefits? Social security?

Ask the interviewee his/her feeling about the corporate culture/institutional norms:
How about the firms' corporate culture?
Do you like it?

Ask the interviewee his/her feeling about the democracy in management:
Do you feel your managers are bossy or democratic?
Do you feel free to tell your opinions to your manager?
Do your managers think about your suggestions seriously?

Ask the interviewee his/her personal opinion about principal-principal or principal-agent problems in his/her firm:
Does ESOP give you more responsibility to watch the management and prevent any problems?
Do you try to stop management to hurt the whole interests of the firm and employees?
Any example?

Ask the interviewee any suggestions to improve ESOP in his/her firm?

Thank the interviewee and keep in touch if need more information.