INTANGIBLE CAPITAL AND CHINA'S ECONOMIC GROWTH

BY

QING LI

THIS THESIS IS PRESENTED FOR THE DEGREE OF DOCTOR OF PHILOSOPHY OF

THE UNIVERSITY OF WESTERN AUSTRLIA

ECONOMICS
UWA BUSINESS SCHOOL
THE UNIVERSITY OF WESTERN AUSTRALIA
PERTH, AUSTRALIA
AUGUST 2019

To My Beloved Parents

LI Mengze & WEI Rong

ABSTRACT

Intangible capital, as a growth driver in a knowledge economy, plays a crucial role in China's economic transition. This dissertation provides novel insights into intangible capital in China and examines its contributions to China's economic growth. Intangible assets are classified into broad categories of computerisation, innovative property, and economic competency property. Detailed estimates of each item at the national level as well as the provincial level are reported. A growth accounting analysis is conducted to examine the impacts of intangible capital on China's labour productivity growth. In addition, the study examines the complementary effects between intangible capital and information and communication technology capital on growth in subsectors of the Chinese economy. Furthermore, in order to provide micro-level evidence, the relationship between intangible capital and firm performance is analysed. Particularly, intangibles' knowledge spill-over effects are taken into consideration. Finally, the possible evolution of regional intangible investment in the future is investigated. In general, China spent great efforts boosting intangible investment during the past decade, and has enjoyed fast development of intangible capital especially since the global financial crisis. However, China is still a tangible-oriented economy which emphasises traditional brick-and-mortar businesses. The involvement of intangible capital accelerates China's labour productivity growth significantly. Regions adjacent to the sea tend to benefit more from intangible economy thanks to their advancement in intangible investment. Furthermore, it is shown that intangible capital has a positive and substantial contribution to Chinese manufacturing firms' output. Especially it assists disproportionally the sectors that rely more heavily on information and communication technology to grow faster. Finally, regional inequality is more likely to deteriorate given the trend that intangible investment would be further clustered in relatively more developed Chinese regions. However, knowledge spill-over effect may help mitigate regional unbalanced development of intangible capital to some extent according to this study.

THESIS DECLARATION

I, Qing LI, certify that:

This thesis has been substantially accomplished during enrolment in the degree.

This thesis does not contain material which has been submitted for the award of any other degree or diploma in my name, in any university or other tertiary institution.

No part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of The University of Western Australia and where applicable, any partner institution responsible for the joint-award of this degree.

This thesis does not contain any material previously published or written by another person, except where due reference has been made in the text and, where relevant, in the Declaration that follows.

The work(s) are not in any way a violation or infringement of any copyright, trademark, patent, or other rights whatsoever of any person.

SIGNATURE: [redacted]

DATE: 09/08/2019

AUTHORSHIP DECLARATION: CO-AUTHORED PUBLICATIONS

This thesis contains work that has been [published and/or prepared for publication].

Details of the work: [Li, Qing & Wu, Yanrui (2018). Intangible Capital in Chinese Regional Economies: Measurement and Analysis. *China Economic Review*, 51, 323-341.]
Location in thesis: [Chapter 2 and Chapter 3]
Student contribution to work: [I am responsible for data, model construction, empirical analysis, and the completion of the draft]
Details of the work: [Li, Qing & Wu, Yanrui (2018). Intangible Capital, ICT, and Economic Growth in China. Telecommunications Policy (under review)]
Location in thesis: [Chapter 4]
Student contribution to work: [I am responsible for data, model construction, empirical analysis, and the completion of the draft]
Details of the work: [Li, Qing & Wu, Yanrui (2018). Organisation Capital and Firm Performance: Evidence from the Chinese Manufacturing Industry. *Asian Economic Journal*, (under review).]
Location in thesis: [Chapter 5]
Student contribution to work: [I am responsible for data, model construction, empirical analysis, and the completion of the draft]
Co-author signatures a[redacted] [insert signatures] [insert dates] 9/8/2019

AUTHORSHIP DECLARATION: CO-AUTHORED PUBLICATIONS

Details of the work:

[Li, Qing, Long, H. Vo, & Wu, Yanrui (2018). Intangible Capital Distribution in China. *Economic Systems*, (under review).]

Location in thesis: [Chapter 6]

Student contribution to work:

[I am responsible for data, model construction, empirical analysis, and the completion of the draft]

Co-author signatures [redacted]

[insert signatures] [redacted]

[insert dates] 9/8/2019 9/8/2019

Student signature: [redacted]

Date: 09/08/2019

I, Yanrui Wu certify that the student statements regarding her contributions to each of the works listed above are correct

Coordinating supervisor signature: [redacted]

Date: [redacted]

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

TABLE OF ABBREVIATIONS*

AISE	Annual Survey of Industrial Enterprises, China
BEA	Bureau of Economic Analysis, the United States
CHIP	Chinese Household Income Project
CHNS	China Health and Nutrition Survey
CHLR	China Centre for Human Capital and Labour Market Research
CI	Confidence Interval
CPI	Consumer Price Index
EU	European Union
FE	Fixed Effect
GDP	Gross Domestic Product
GFC	Global Financial Crisis
GFCF	Gross Fixed Capital Formation
GMM	Generalised Method of Moment
GNI	Gross National Income
GR	Great Recession
GRP	Gross Regional Product
IASB	Institute Accounting Standards Board, the United Kingdom
ICT	Information and Communication Technology
ICs	Integrated Circuits
IMF	International Monetary Fund
IOT	Internet of Things

* The list of abbreviations excludes the abbreviations of data sources that are presented in the bibliography.

TABLE OF ABBREVIATIONS

IP	Intellectual Property
IPC	International Patent Classification
IT	Information Technology
JIP	Japanese Industrial Productivity (database)
MIT	Middle-Income Trap
MPP	Mobility Probability Plot
NBS	National Bureau of Statistics, China
NIPAs	National Income and Product Accounts, the United States
OECD	Organisation for Economic Cooperation and Development
PCHC	Per Capita Human Capital
PIM	Perpetual Inventory Method
PPP	Purchasing Power Parity
R&D	Research and Development
RE	Random Effect
RICI	Relative Intangible Capital Intensity
SIPO	State Intellectual Property Office, China
SNA	System of National Accounts, the United Nations
SOEs	State-Owned Enterprises
SOG	Source-of-Growth
S&T	Science and Technology
TFP	Total Factor Productivity
WIOD	World Input-Output Database

ACKNOWLEDGEMENTS

This work was supported by UWA China SIRF Scholarship and UWA Ad Hoc Top-up Scholarship. I would like to express my gratitude to these supports.

I owe my deepest gratitude to my supervisor Professor Yanrui Wu. During my study, his constructive comments and meticulous suggestions were always an enormous help to me. His interests and expertise into economic growth and development introduced me into the amazing world of economics. Without his insightful guidance, warm encouragement and thoughtful support, this study would hardly be completed.

I appreciate the helpful feedbacks offered by Dr. Shawn Chen, Professor Ken Clement, and Professor Rod Tyers. I am particularly grateful for the working opportunities provided by Dr. Simon Chang and Dr. Ingebjorg Kristoffersen that gave me great experience of acting as a tutor and taking the role of a research assistant. I have greatly benefited from this experience and am super lucky to receive warm encouragement from my lovely students.

I would like to thank my fellow students and friends. They are Yifei Cai, Yuping Deng, Haiyan Liu, Ning Ma, Harsha Paranavithana, Sigit Perdana, Xing Shi, Achmad Tohari, Long Vo, Lily Vu, and Erchuan Zhang. I received generous support and help from them, and their encouragement always light up my daily life. My heartfelt appreciation also goes to the administrative staff members: Isabela Banea, Maryann Evetts, Mei Han, and Ha Le, for their kind assistance and efficient teamwork, which makes my work at UWA more smoothly.

I would like to offer my special thanks to my intimate friend Yuxuan Yuan for his accompanying and care. During the past three years, he was always standing by me and trying his best to help. It would be a lonely journey without his encouragement. Finally, I want to thank my parents for always understanding me, trusting me, and supporting me. Without their selfless love, I might not be the person I am today.

CHAPTER 1 - INTRODUCTION

The world is transforming into a knowledge economy and China is no exception. As a driving force in a knowledge economy, intangible capital plays a key role in China overcoming economic difficulties and sustaining long-term economic development. This chapter will provide background knowledge of China's achievements and challenges, introduce intangible capital from different perspectives, and describe the global intangible capital development. After that, it will clarify the objectives of each of the core studies in this dissertation. The structure of this dissertation will be outlined at the end of the chapter.

1.1 Background

Over the past 40 years, China has achieved extraordinary economic performance thanks to its market-oriented reforms and opening-up. By 2014, it has become the second largest economy on a nominal basis, and surpassed the United States to be the largest economy on a purchasing power parity (PPP) basis since then (IMF, 2018). In 2017, China accounted for around 12 percent of the world economy, and contributed to about 30 percent of global economic growth (**Figure 1-1**). The stunning two-digit economic growth over the past two decades in China has been praised by prestigious international organisations and economists, and nicknamed "China's economic miracle" (**Figure 1-2**).

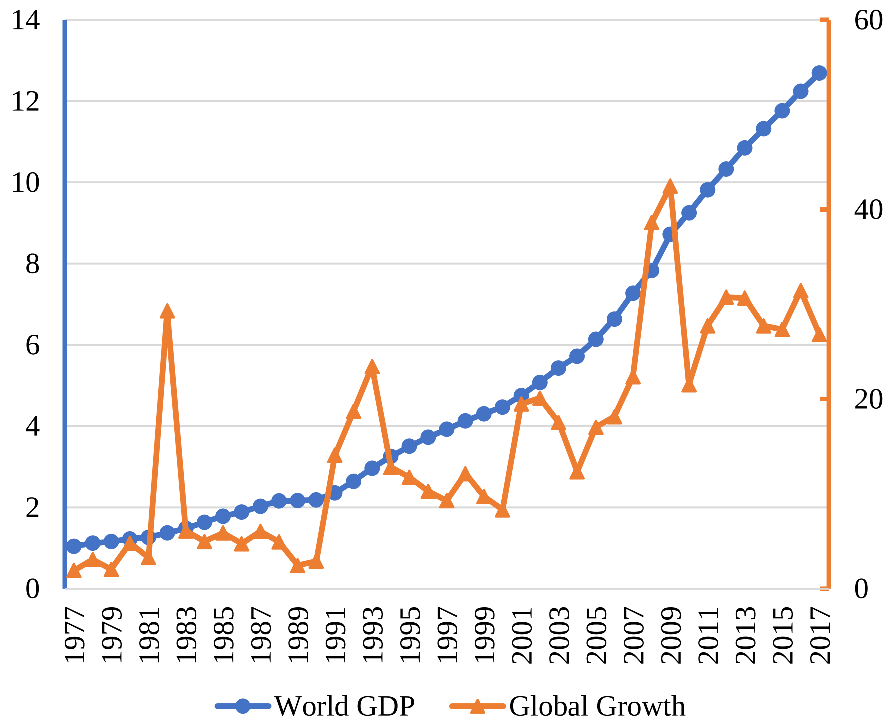


Figure 1-1: China's Contribution to the World Economy (%), 1977 – 2017

Source: World Bank (2018).
Note: The left-hand coordinate is China's share (%) in the global GDP, and the right-hand coordinate is China's contribution (%) to the global GDP growth (constant 2010 US$).

However, between 2012 and 2017, China's average economic growth decreased sharply to around 6 percent (**Figure 1-2**). China's growth miracle seems to fade away as the economic growth convergence hypothesis predicts (Barro & Sala-i-martin, 1992). It is argued that the growth of poorer economies, initially driven by multiple factors such as investment ratio and human capital accumulation, will be finally subject to the law of diminishing marginal effects and encounter economic slowdown or even stagnation. Meanwhile, China's miracle is by no means costless. Challenges such as an aging population, rising costs in labour and land, stagnant fixed investments, trade conflicts, environmental degradation, and structural imbalances may lead China to get stuck into the "middle-income trap" (MIT).[1]

[1] "Middle-income trap", first shown in the 2007 World Bank report, indicates that at some specific middle-income stages (per capita gross national income (GNI) in the range [976, 11905] US dollars), economies with high rates of growth tend to encounter economic slowdown or even stagnation (Cai, 2012; Gill & Kharas, 2007).

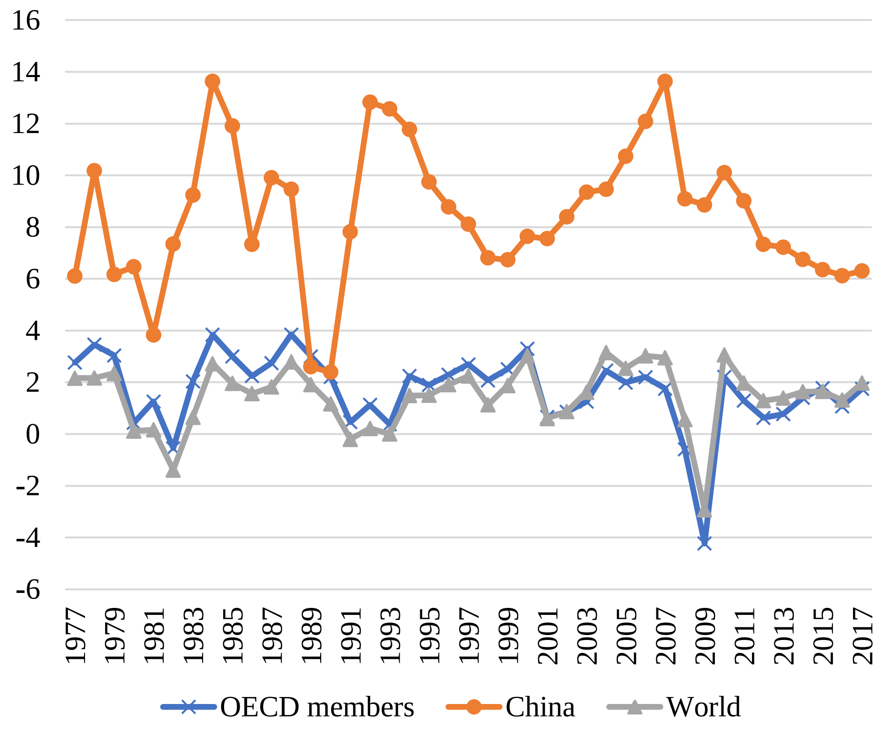


Figure 1-2: China's GDP Growth Rates (%), 1977 – 2017

Source: World Bank (2018).

In addition, China's rapid economic growth has long been associated with the pain of regional disparities and spatial imbalances, one among which is the apparent income gap between coastal regions and the inland regions (OECD, 2010). Thanks to their comparative advantages of cheap labour, geographical proximity to the world market, and policy preferences, the coastal regions became the spearhead of the open reform in the 1980s and took off in the era of globalisation. As a result, the income gap between the coastal regions and other inland regions has increased rapidly since 1978 (**Figure 1-3**). The ratio of per capita GDP in nominal terms between the wealthiest and the poorest provinces in China in 2017 was 4.54 (NBS, 2018). By comparison, in 2017, the ratio of the highest to lowest per capita GDP in nominal terms among the major states of the United States was only 2.03 (BEA, 2018).

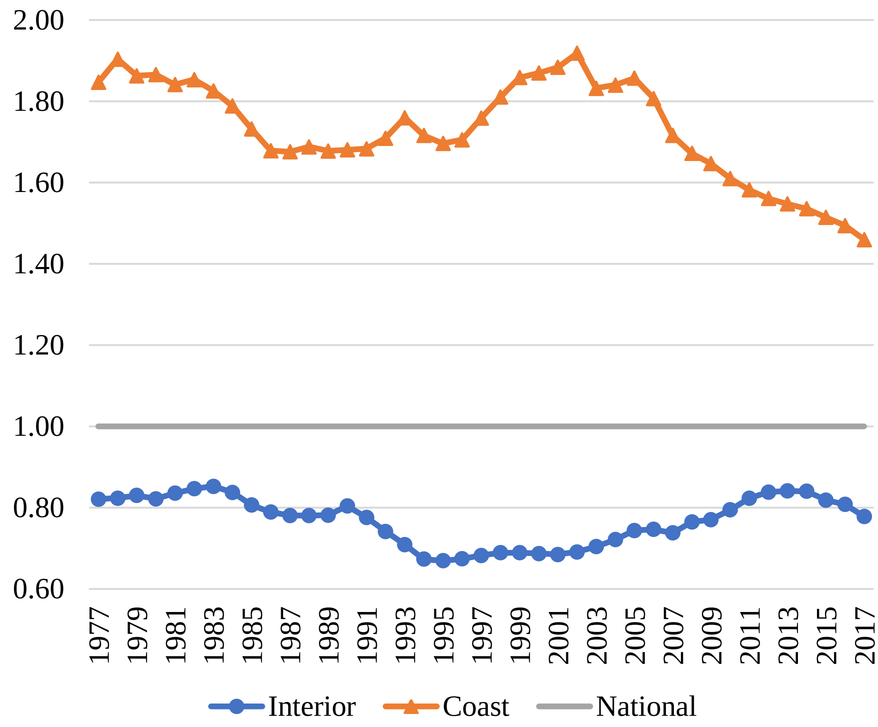


Figure 1-3: Income Gap in China: GDP per capita as Percentage of National Average

Source: China National Statistical Yearbook (Various Years). Author's own calculations.

China is now entering an era of "new normal" growth, anticipating moderate but more stable and sustainable economic growth.[2] Intangible capital, as the new source of growth, will serve as the key driver for this goal. For example, intangible capital, as a "carrier" of knowledge and innovation, is far more dynamic and does not necessarily lead to diminishing returns (Haskel & Westlake, 2018). It is potentially the route for China to overcome the economic challenges and hence to avoid the problem of MIT. Furthermore, regional imbalanced development analysis is always incomplete without being put in an intangible context. Intangible capital may have different impacts on China's regional economic growth, which may lead to totally different policy implications for regional inequality in China.

By taking a close look at the prevalence of items such as tablets, cell phones, e-mails, and the like, it is obvious that the global economy is transitioning toward a so-called "knowledge

[2] In 2014, a statement by China's president Xi Jinping indicated that China was entering a period of "new normal", being marked by a slowing-down growth and a prediction of growth at around 7 percent. It was suggested that during the "new normal period", Chinese government will anticipate a moderate but more stable economic growth in the medium-to-long term. Retrieved from https://en.wikipedia.org/wiki/New_Normal_(business).

economy". The knowledge economy, led by the revolution of information technologies, is relying increasingly more on intellectual capabilities than on traditional tangible capital inputs or natural resources (Dutta, 2012). Therefore, knowledge-based intangible resources such as trade secrets, brands, and expertise are more critical for creating value and promoting growth than ever before. At the same time, collaboration, as access to knowledge and "glue" for ideas from different innovation agents, becomes increasingly important (Dutta, 2012). Thus, innovations in intangible processes and services, such as organisation structure development and social network construction, which lubricate collaboration and improve efficiency, can also be a crucial source of growth nowadays.[3] Because of this, intangible products and processes have been put into public spotlights and have drawn increasingly great attention from entrepreneurs and politicians. In the academic field, the number of studies on intangible capital has been rising too (**Figure 1-4**).

China is the largest developing country and will soon become the largest economy in the world, so it is necessary to have a comprehensive understanding of intangible capital in China. For instance, are there any differences in the concept of intangible capital in China and developed countries? How is intangible capital investment and its capital stock in China and Chinese regions measured properly? What, how, and how much does intangible capital contribute to China's national, regional and productivity growth? What are the impacts of intangible capital on sector output and firm performance in China? Could China's regional economic disparity be explained by intangible capital, as such, would intangible investment enlarge or narrow the gap between the coast and the rest of China? The dissertation will focus on these questions.

[3] An example is Uber's organisational investment in building its vast networks of drivers (Haskel & Westlake, 2018).

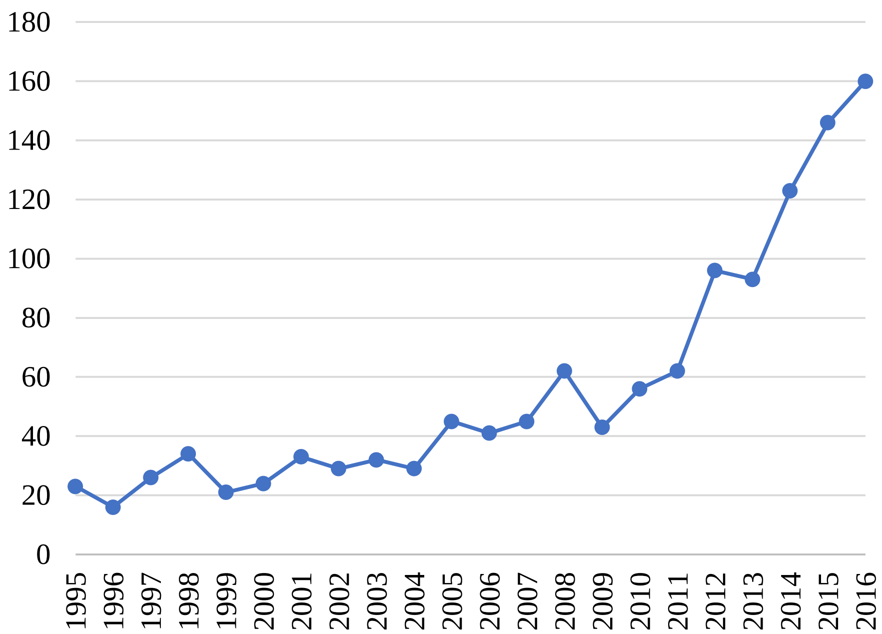


Figure 1-4: The Number of Research Articles with "Intangible" in Titles/Abstracts/Keywords in the Fields of Economics and Accounting

Source: ScienceDirect Database.

1.2 Intangible Capital from Accounting and Economic Perspectives

In contrast with tangible capital, intangible capital, literally, denotes capital that does not have physical embodiments. Previously, intangible capital has been conceptually synonymous with the terms "intellectual capital", "immaterial capital", "knowledge capital" and even "goodwill" (Zéghal & Maaloul, 2011). In fact, intangible capital is not a novel concept.[4] As far back as the late twentieth century, economists were stumped by the question of why the IT revolution had not sparked a surge in productivity improvement and a consequent supply-driven wave of economic growth. In a book review, Robert Solow, the founder of neoclassical growth theory and the Economics Nobel Laureate, remarked on the anomalous phenomenon: "You see the computer revolution everywhere except in the productivity data" (Solow, 1987). Valuable income was

[4] Examples of intangible capital range widely, from Coca-Cola's renowned coke recipe to Microsoft Inc.'s professional software.

doubtless missing from the national accounts.[5] The stylised fact was then universally referred to as the "productivity paradox" and treated as one of the leading economic puzzles in the late twentieth century. About ten years later, Alan Greenspan, then Federal Reserve Board Chairman, observed that many service sectors in the United States that had a negative productivity trend were among the top computer-using sectors (Corrado et al., 2009). Official data in United States National Income and Product Accounts (NIPAs) were thus doubted, in part because of their failure to fully capture the factors that affect growth in the backdrop of the IT revolution.

Coincidentally, there was a so-called "market-to-book" puzzle that arose at the firm level. Lev (2001) noted that the market price of corporate equities consistently exceeded the book value of the shares reported in company financial statements by the early 2000s. If stock markets are sensibly valued, and the economy is assumed not to be getting less competitive, this market-to-book ratio would reflect the proportion of off-balance sheet (essentially intangible) assets to on-balance sheet (essentially tangible) assets in the economy (Lev, 2001). For example, the tech giant Microsoft Corporation, after publishing its annual report for the fiscal year ending June 2008, traded at $25 per share or $228,775 million in total. With a book value of $36,286 million, the market value implies $192,489 million of value missing from the balance sheet. The market-to-book ratio was around 6.3 (Penman, 2009).

Evidence then demonstrated that intangible capital is the key to explain both the "market-to-book" puzzle and "productivity paradox". For instance, according to Hulten (2010a), the adjustment of intangible capital caused Microsoft's shareholder equity to jump from $40 billion to $106 billion. After the adjustment, intangible capital accounted for more than 40 percent of Microsoft's growth between 1988 and 2006, while the contributions of total factor productivity decreased to 20 percent (Hulten, 2010a). Similarly, Hulten and Hao (2008) found that the book value of equity explained only 31 percent of the market values of 617 companies drawn from the COMPUSTAT database in

[5] Nordhaus (1996) also concluded from his analysis of the history of lighting that official price and output data "miss the most important technological revolutions in history".

2006, but this ratio increased to 75 percent after the adjustment of intangible capital such as organisation capital and human resources.

An Accounting Perspective

Traditional accounting models and methods, which were mainly for tangible assets based on historical costs and accounting conservatism, were found incapable of fully evaluating intangible assets (Lev & Zarowin, 1999; Liang & Yao, 2005). The valuation of intangible assets within the accounting framework raised several problems relating to their identification, measurement and control. To identify intangible capital, Blair and Wallman (2000) tried to specify the differences between intangible capital and intellectual capital. They identified three major categories of intangibles: 1) intangibles that have clear property rights and trading markets (examples include patents, copyrights and trade names); 2) intangibles controlled by firms but lacking well-defined and legally-protected property rights, and for which trading markets are weak or non-existent (examples include R&D in process, business secrets, reputational capital, proprietary management systems, and business processes); and 3) intangibles that are tied to employees or workers, for which firms have few control rights and trading markets do not exist (examples include human assets, structural assets, and relational assets, i.e. the components of intellectual capital).[6] The categories of intangibles were consistent with the arguments of Hunter et al. (2005), who suggested that intellectual capital is a subset of intangible capital. The term “intangible”, accordingly, relates to assets without physical substance, and “capital” refers to assets retained by the organisation to contribute to future profits (Hunter et al., 2005).

The identification of intangible capital was further augmented by the International Accounting Standards Board (IASB) in the United Kingdom in 2004, further distinguishing

[6] Intellectual capital is usually classified into three categories: human assets, structural ass ets, and relational assets. Human assets refer to the knowledge, qualifications, skills and know-how of employees. Structural assets constitute the supportive infrastructure that enables human assets to function in an organisation. It comprises procedures, practices, and computer and administrative systems of the company. Relational assets concern the resources arising from the external relationships of the company with customers, suppliers and other partners (Kristandl & Bontis, 2007; Meritum Project, 2002; OECD, 2006).

intangible capital from goodwill. According to IASB, intangible capital is an "identifiable" non-monetary asset without physical substance. In the framework of IASB, an asset is defined as "a resource controlled by the enterprise as a result of past events and from which future economic benefits are expected to flow to the enterprise". Hence, these definitions go a step further to restrict intangible capital to be assets from which enterprises have power to obtain the future benefits and forbid the access of others to those benefits. A final important recognition criterion of intangible capital is "the reliability of measurement of asset cost" (Upton, 2001). In other word, the expenditures attributable to that intangible asset during its development should be measured reliably. This criterion could be easily satisfied if the intangible asset is gained externally,[7] but may have great difficulty for internally generated assets such as trademarks, patents and the like, i.e. the results of own-account research and development activities (Zéghal & Maaloul, 2011).

In summary, from an accounting point of view, expenditures can only be treated as intangible capital if they satisfy a set of restrictive conditions: 1) to have clear property rights, i.e. enterprises can "control" the assets generated; 2) to be identifiable non-monetary assets without physical substance; 3) to generate future benefits to the owner; and 4) to have reliable cost measurements. According to these rules, expenses related to the creation of intangible assets that could appear in the balance sheet are scarce. Most expenditures on intangibles have thus been treated as immediate costs with a long history. For example, internal R&D expenditures must be expensed when incurred, unless the expenditures were spent on computer software. In addition, as noted by IASB, "any expenditure that cannot be distinguished from the cost of developing the business as a whole is not recognized as an intangible asset" (IASB, 2004). Because of this, some internally generated brands and customer lists cannot be recognised as intangible assets.

[7] The cost can be reliably measured in this case as the acquisition price is usually determined during the transaction and appears mostly in monetary form.

An Economic Perspective

The above accounting problems posed great impediments on the comprehensive understanding and measuring of intangible capital that is needed for national accounting and source-of-growth analysis. Therefore, according to exogenous growth theory, any externalities due to unappropriated benefits from intangibles and from any other unobserved factors appeared all as a shift in the production function, and were picked up as a whole in the measured total factor productivity (hereafter "TFP", Hulten, 2010b). After that, subsequent developments of endogenous and so-called “Schumpeterian” models of economic growth attempted to dissect the TFP components. For example, some intangible parts were subtracted and specified, such as research and development (hereafter “R&D”, Romer, 1986) and education (Lucas, 1988). However, until recently, definitions of intangible capital in TFP components reached no consensus. For instance, Chun et al. (2015) defined intangibles as computer software, mineral exploration, cultural products like entertainment, literature and original fine art, and unproduced intangibles like patents and licensing of mobile communications. Van Ark (2004) argued that human capital, knowledge-based capital, organisational capital, marketing of new products and social capital should all be considered as intangible capital.

Meanwhile, prior to the work of Corrado, Hulten and Sichel (hereafter “CHS” framework), measurement of intangible capital in the economic literature had to resort to “indirect” approaches such as financial market valuation and external performance valuation (Jona-Lasinio et al., 2011). The financial market valuation approach assumes that the value of intangible capital corresponds to the difference between the market value of a firm and the value of the firm’s tangible assets. For instance, this approach is applied to evaluate intangible organisation capital at the firm level in the United States (Bresnahan, 2002; Brynjolfsson & Hitt, 2000, 2003; Brynjolfsson, Hitt, & Yang, 2002). The differences between the market value of firms and values of firm investment in information technologies (IT) is attributed to the existence of a large stock of intangible assets. The World Bank (2006) applied this approach to the national-level analysis. The value of intangible capital was measured as the residual of deducting natural capital and produced capital from total wealth. The latter is measured as the net present value of future sustainable consumption.

Another method of evaluating intangible capital is the external performance valuation, which is based on performance indicators like an enterprise's earnings or revenues. For instance, Cummins (2005) defined intangible capital as adjustment costs, and created a proxy for the intrinsic value of intangible capital according to the forecast index of the firm performance obtained from analysts. Based on firm-level panel data in the United States, he found sizeable intangible organisation capital created by IT. Similarly, McGrattan and Prescott (2005) estimated the value of intangible capital from corporate profits under the assumption of equal after-tax returns to tangible and intangible assets. Accordingly, they found the total value of intangible capital ranges from 31 percent to 76 percent of the national GDP of the United States.

Obviously, these two approaches are subject to considerable measurement errors (Cummins, 2005). For instance, financial market valuation which is based on values of the stock market may have mismeasurements caused by deviations between market prices and intrinsic asset values. Unobservable factors like transient shocks, for instance, will cause market prices to depart far from assets' real values. External performance valuation faces the same problem. It relies heavily on external financial markets and even analysts' predictions that involve various disturbing factors.

An expenditure-based measurement approach is finally a breakthrough in economics to evaluate intangible capital in a more direct way. The approach was first taken by Nakamura (1999, 2001) and then by CHS (2005, 2006). One virtue of this approach is its use of the same cost-based accounting criteria that are used for tangible assets. Thus, it treats intangible and tangible capital symmetrically. With this accounting-based method, Nakamura measured a gross investment in intangible capital, consisting of R&D expenditure, software, advertising and marketing expenditure, and wages and salaries of managers and creative professionals in the United States. It was found that intangible investments reached $1 trillion, with total capital stock being at least $5 trillion, in the United States in 2000. The amount was roughly close to the sum of tangible assets in nonresidential sectors. After Nakamura, CHS pointed out the most important criterion for judging business intangible investments: “Any use of resources that reduces current consumption in order to increase it in the future … qualifies as an investment” (see more details in Corrado et al., 2005). Accordingly, CHS incorporated a wider range of intangible capital like entertainment and copyright into their analysis, and identified the contributions of intangibles in the national income. In general, they found the investment in intangibles reached about $1.1 trillion between 1998 and 2000 in the United States, which is about 1.2 times the tangible capital investment, and accounted for 12 percent of the GDP during that period (Corrado et al., 2006).

Economists on both sides of the Atlantic have finally reached a consensus about intangible capitalisation. INNODRIVE and COINVEST projects, as two leading programs focusing on intangible capital in the EU, clarified the identification, definition and measurement issues of intangible capital in more detail. Specifically, expenditures attributable to intangibles should be capitalised if they satisfy the following criteria (Jona-Lasinio et al., 2011): 1) Intangible capital should be identifiable; in other words, expenditures on intangible capital should be separable (capable of being separated and sold, transferred, licensed, rented or exchanged, either individually or as part of a package); 2) Intangible capital should have clear ownership; 3) Intangible capital should gain future benefits for its owner; and 4) Intangible capital should be used in the production process over several time periods. It would be expected that the asset will provide capital services for over a year in the production of different products. Given these arguments, the relation between tangible, intangible, human capital, and TFP is drawn in **Figure 1-5**.

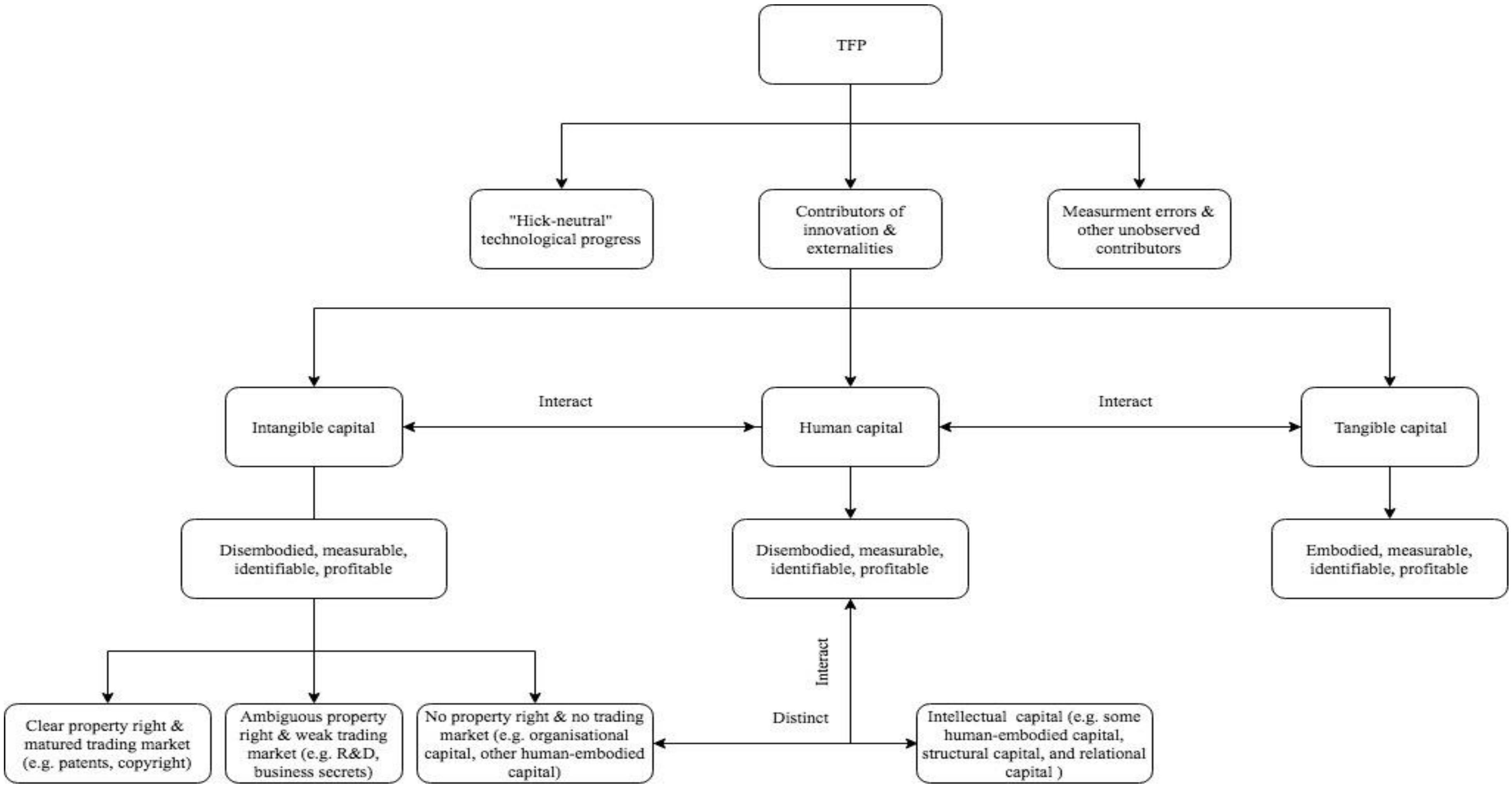


Figure 1-5: Intangible Capital, Tangible Capital, and Human Capital

The consensus on intangible capitalisation concurrently accelerates the reform of national income accounts across the world. Previously, under the guidance of the United Nations System of National Accounts in 1993 (known as SNA-1993), only computer software investments and mineral exploration expenditures were included as flows of fixed capital formation (Chun et al., 2015). In 2008, the reform of SNA (known as SNA-2008) recommended that R&D expenditures and long-lived entertainment originals be recorded as gross fixed capital formation (GFCF) if they meet the general conditions outlined above. Following the revision of SNA-2008, several national statistical institutes have developed experimental satellite accounts for R&D capitalisation in the United States (BEA, 2007), the Netherlands (Statistics Netherlands, 2008), and Norway (Statistics Norway, 2008) (Jona-Lasinio et al., 2011). Long-lived entertainment originals, such as movies, television programs, books and music, are also under serious consideration of capitalisation in the United States (Soloveichik & Wasshausen, 2013). To keep in line with SNA-2008, China's National Bureau of Statistics (NBS) incorporated R&D as capital input in national accounts in July 2016 and adjusted national GDP backward to 1952 to include R&D capital investment (Xin & Wang, 2016).

However, the scope of intangible assets considered to be capitalised is still quite narrow. Under the framework of CHS, intangible asset for capitalisation only refers to "business" intangible capital or the so-called "private" intangible capital,[8] such as scientific R&D, mineral exploration, copyrights, patents and licenses, employee-provided training, advertising, organisation capital, and so on. Intangible capitalisation still excludes types of "public" intangibles like environmental, health and social intangible capital (see more details in Corrado et al., 2014). For this reason, a much broader framework of intangible capital is still expected for a more comprehensive understanding of intangible capital in the future.

[8] The term "business" intangible investment and intangible capital stock was first adopted by CHS (Corrado et al., 2005). It refers to intangible investment in market sectors with private revenues or returns in the future. In contrast, "public" intangible investment refers to intangible investment in non-market sectors such as education, healthcare, and environment (Corrado et al., 2014).

14

1.3 Intangible Capital in the World

Intangible capitalisation spurs a remarkable number of studies around the world to examine contributions of intangible capital to economic and productivity growth. This section presents a general picture of intangible capital development in the world and reviews relevant analysis. It is found that there is a large knowledge gap between China and the advanced economies in terms of intangible capital analysis.

Intangible Capital in the United States

The United States Bureau of Economic Analysis (BEA) has pioneered in capitalising two important intangible assets, software and mineral exploration, into the national income accounts under the guidance of SNA-1993. However, the real amount of intangible investments was found to be far greater than that. It was found as much as $800 billion was still excluded from the national accounts in the United States in 2003, leading to the exclusion of more than $3 trillion of business intangible capital stock (Corrado et al., 2006, 2009). Later, the estimates were updated to 2007 and carried backward to 1948. The total investment in intangible capital reached $1.6 trillion in 2007, accounting for 11.3 percent of the national GDP. The omission of intangible capital accumulation results in an additional $4.1 trillion in capital stock beyond the conventional fixed asset measures for 2007 in the United States (Corrado & Hulten, 2010). **Figure 1-6** shows that the estimate of intangible investment was already twice as much as that of investment in tangible capital in 2010, contributing to nearly 20 percent of the national GDP in the United States. Interestingly, according to Corrado & Hulten (2010), whereas tangible investment fell massively during the Great Recession (GR) in 2008-2009, intangible investment has been relatively resilient and recovered in the United States; the growth of intangible investment during that period was found to be fast in the United States but slow in the EU countries.

Apart from macro-level estimates, intangible capital was also analysed extensively at sector and firm levels in the United States. For instance, Corrado et al. (2017) explored the economic mechanism through which intangible capital affects sector growth. By utilising sector intangible investment obtained from the INTAN-Invest database,[9] they interacted intangible capital with information and communication technology (ICT) capital, and found the output elasticity of intangible capital depends upon sectors' ICT intensity. That is, there is a complementary relationship between ICT and intangible capital. At the firm level, McGrattan and Prescott (2014) suggested the significant deviation between output and labour productivity in the United States in the GR period resulted from the omission of intangible capital. Once the firms' output was adjusted

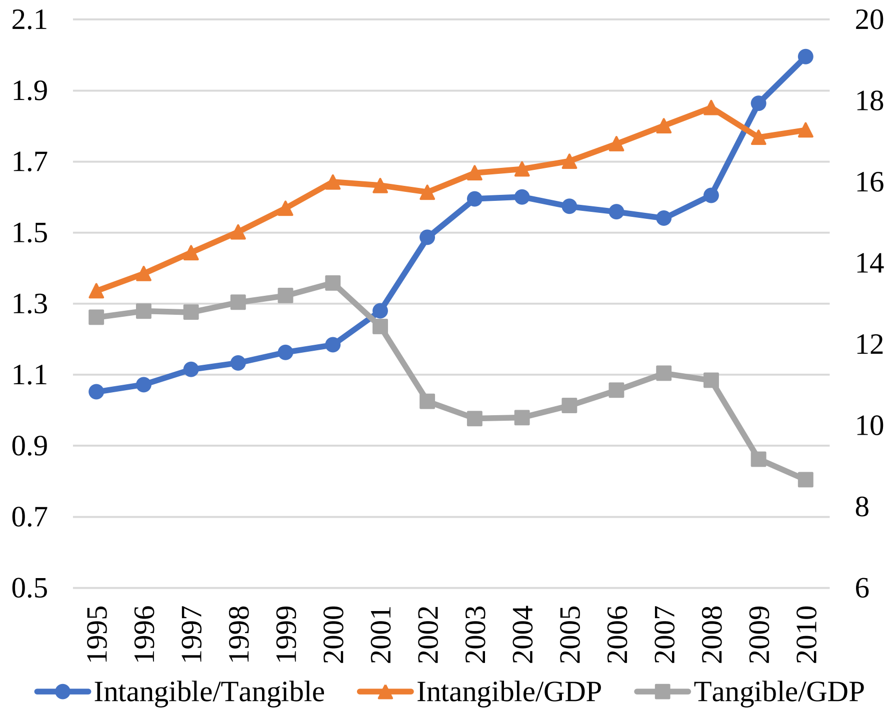


Figure 1-6: Intangible Capital Development in the United States, 1995-2010

Source: Author's own work (INTAN-Invest database).

Note: The left-hand coordinate is the ratio of intangible to tangible investment (nominal terms), and the right-hand coordinate is the share of intangible and tangible investment in the national GDP in the United States (%, nominal terms).

[9] INTAN-Invest database is joint work under three projects: COINVEST, INNODRIVE, and the ongoing effort of The Conference Board. It provides market sector data on intangible capital for 27 EU countries plus Norway and the United States. See more details via http://www.intan-invest.net/.

for intangible investment, there was no inconsistency. Similarly, McGrattan et al. (2017) combined micro- and macro-level evidence, suggesting that intangible capital can largely explain the inconsistency between the little changes in aggregate TFP and large changes in labour costs and investments within the firms.

Intangible Capital in European Countries

There are also many studies of intangible capital in European countries. Following the CHS framework, Marrano and Haskel (2006) estimated intangible capital in the United Kingdom. The estimate of intangible capital reached around £116 billion in 2004, which was about 1.04 times the fixed capital investment at that time, and accounted for about 10 percent of the national GDP. Furthermore, Goodridge et al. (2013) argued that intangible capital could explain the productivity puzzle [10] observed in the United Kingdom during the GR. Without intangibles, the real growth of market sectors was understated by 1.6 percent since the start of 2008; the omission of intangible capital can thus explain around 5 percentage points of the productivity puzzle (Goodridge et al., 2013). Analysis in other European countries also came to similar conclusions, that intangible investment accounted for remarkable portions in their national GDP and explained well the productivity growth. Examples include but not limited to Edquist (2009) for Sweden, Jalava et al. (2007) for Finland, and van Rooijen-Horsten et al. (2008) for the Netherlands.

There were also cross-country analyses under the guidance of the EU 7th framework projects of COINVEST and INNODRIVE. The gross value added in EU27 countries was found to increase by 5.5 percent after capitalising intangible capital during 1995-2005 (Jona-Lasinio et al., 2011). At sector level, a positive and significant relationship was detected between intangible investment and labour productivity growth within the business sectors in the EU area (Roth & Thum, 2013). However, since intangible investment varies considerably across the EU (**Figure 1-7**), different impacts of intangibles on labour productivity growth were found in different EU countries (van Ark

[10] The productivity puzzle in the United Kingdom denotes the phenomenon that even though the market sector value added started to grow again after 2011, the labour productivity was around 16 percent below the level of its pre-crisis trend (Goodridge et al., 2013).

et al., 2009). Compared with the leading country the United Kingdom, which has great intangible capital deepening effects, a group of laggards like Italy and Spain still shows small intangible capital deepening effects to explain their labour productivity growth. Most catching-up countries like the Czech Republic, Greece and Slovakia were also found to have much larger contributions from tangible capital than those from intangible capital (van Ark et al., 2009).

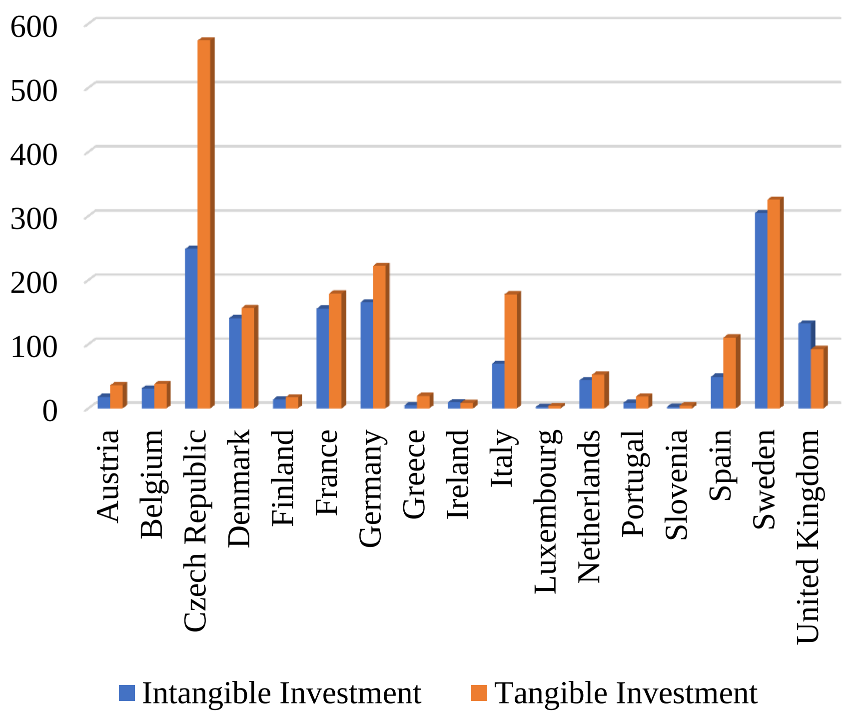


Figure 1-7: Intangible and Tangible Capital Investment in EU Countries in 2010 (€billion)
Source: Author's own work (INTAN-Invest database).

The analysis of intangible capital in the EU is not limited to the national level. Based on the INTAN-Invest database, Niebel et al. (2016) measured intangible investment in 11 sectors in 10 EU countries, and found that the contributions of intangible capital to productivity growth are much higher in manufacturing and financial sectors. The findings were supported by Crass et al. (2015), who analysed intangible investment in Germany's six sectors, and found a higher labour productivity in manufacturing after including intangibles. At firm level, it is demonstrated that intangible assets like R&D and organisation capital can promote firm-level productivity growth significantly (Bontempi & Mairesse, 2015). The propensity to invest in intangible assets will increase with the firm's size, human capital and organisational complexity, and with the past levels of the firm's investment in intangible assets (Arrighetti et al., 2014).

Additionally, under the EU 7th framework, a so-called SPINTAN program extends the analysis to "public" intangible capital in "nonmarket" sectors in the EU. The public intangible capital includes two broad categories: 1) information, scientific, and cultural assets; and 2) societal competencies. The "nonmarket" industries consist of: 1) public administration and defence; 2) education; 3) human health and social work activities; 4) scientific research and development; and 5) arts, entertainment and recreation (Corrado et al., 2014). Though this ongoing project still faces great challenges with issues like measurement, it has important implications for our work. On the one hand, according to SPINTAN's identification, we can clarify that the scope of intangible capital in this thesis can be named as "private" intangible capital. As mentioned in the study of Corrado et al. (2014), "private" intangible capital refers to "business" intangible investment in the "market" sectors. In other words, private intangible capital is the intangible capital that is owned by enterprises and firms and can gain private returns in their production process. On the other hand, we should be aware that the impacts from our analysed business intangible capital may have synergies with public intangible investments. For example, scientific R&D requires high-skilled researchers that are associated with social public investments in education. Hence, the two categories of intangible capital are more likely to be related, calling for a broader-range analysis of intangibles in the future.

Intangible Capital in Japan

In the late 1990s, Japanese government invested heavily in ICT to promote the productivity growth. The total ICT investment was equivalent to 25 percent of the total fixed capital investment during from 1990 to 2002, with an annual average growth rate of 4.2 percent (Fukao et al., 2009). However, the rapid increase in ICT investment in Japan has failed to close the productivity growth gap between Japan and the United States. Fukao et al. (2009) doubted that it is intangible investment that can explain the productivity gap between Japan and the United States in the 1990s. Utilising the CHS framework, their findings largely support their conjecture. It is shown that the share of intangible investment in GDP in Japan was only around 7.5 percent on average during 1995-2002, far less than that in the United States. The ratio of intangible to tangible investment was only 0.3, compared with the ratio of 1.2 in the United States. Finally, they attributed the low intangible investment to the unique Japanese culture: financial institutions in Japan require significant tangible assets as collateral, thus resulting in the preference for firms to accumulate tangibles over intangibles. According to their work, with a lack of investment in intangible capital, Japan was still a manufacturing-driven economy in the early 2000s. Their conclusion was further demonstrated by the work of Chun et al. (2015) who analysed the contributions of intangible capital to industrial growth in Japan. Based on the Japan Industrial Productivity Database (JIP),[11] they found the growth of intangible investment in Japan lagged behind Korea in the past 30 years. Although intangible capital accounted for larger shares in machinery industries in Japan than in Korea, it has a far lower share in the value added in services sectors. The lack of intangible investment in services sectors leads to the low efficiency of ICT, and serves as the hidden reason for the stagnant economic performance in Japan since the late 1990s. **Figure 1-8** the ratio of intangible to tangible investment and the share of intangible investment in Japan’s GDP during 1985-2012. Though intangible to tangible investment rose steadily, intangible investment only accounted for less than 10 percent of Japan’s GDP in 2012.

Intangible Capital in China

China is shifting toward an innovation-driven economy through high investment in intangibles.[12] For example, **Figure 1-9** shows China’s total spending on R&D has increased rapidly

---

[11] Japan Industrial Productivity Database (JIP) provides growth accounting information such as physical input, labour input, and TFP in 108 industries in Japan during 1970-2012. The estimates of intangible investment and capital stock are jointly collaborated with INNODRIVE and COINVEST in the EU. See more details via https://www.rieti.go.jp/en/database/JIP2011/index.html#02-6.

[12] Ambitious plans and strategies such as “China Innovation 2020”, “China Manufacturing 2025”, “Global Innovation Leader 2030” launched by the Xi-Li administration (namely, President Xi Jinping and Premier Li

since the late 1990s, and the country surpassed the United Kingdom in terms of the intangible share in GDP in 2010. According to Reuters, R&D expenditure in China was around 1.76 trillion yuan ($279 billion) in 2017, an increase of 70.9 percent from 2012 and an annual growth rate of 14 percent (Reuters, 2018).

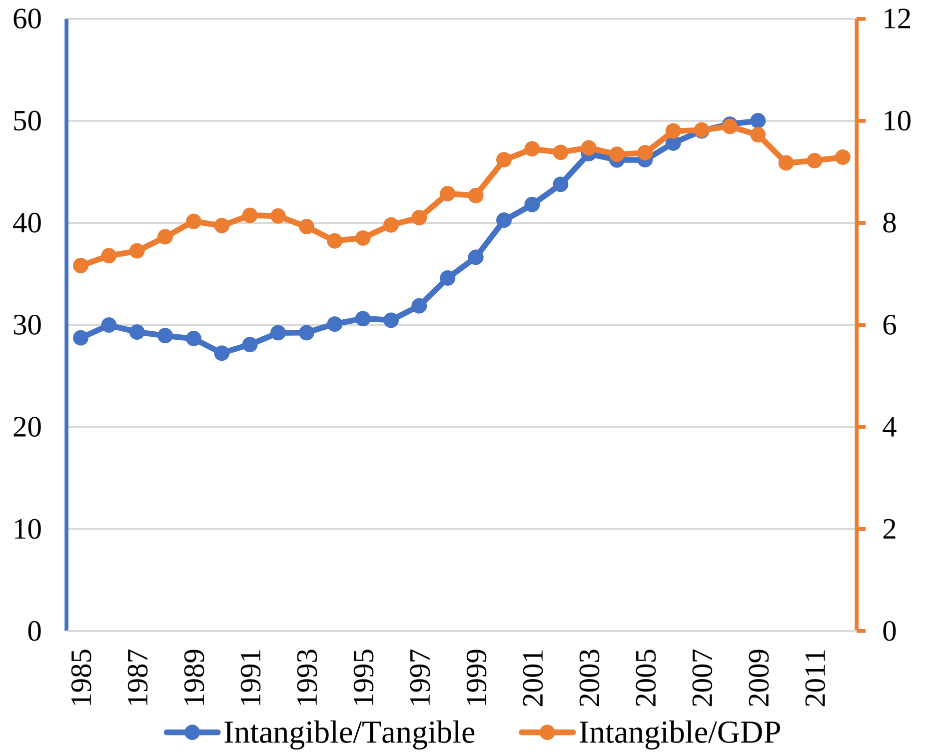


Figure 1-8: Intangible Capital Development in Japan, 1985-2012

Source: Author's own work (JIP database).
Note: Left-hand coordinate is the ratio of intangible to tangible investment (%, nominal terms, all sectors), right-hand coordinate is the share of intangible investment in Japanese GDP (%, nominal terms).

Keqiang) since their first term began in 2012 revealed the resolve of Chinese government in accelerating the reform of China's economic transformation.

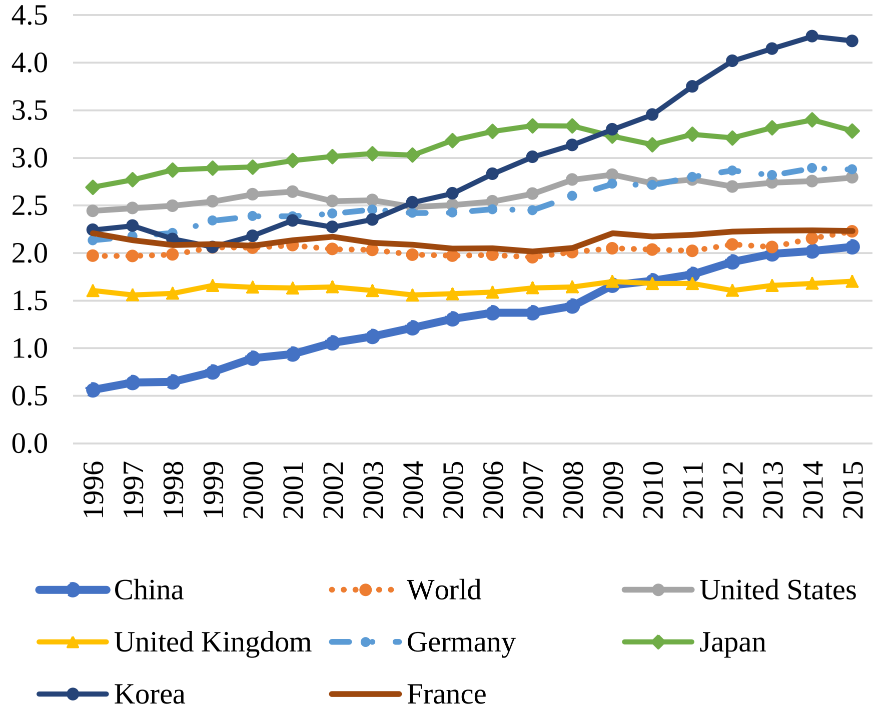


Figure 1-9: Research and Development (% GDP), 1996-2015

Source: World Bank (2018).

However, intangible capital involves more than R&D. Corrado (2017) noted that R&D capital stock was estimated to be only one-third of the total intangible capital stock in the United States. To estimate intangibles in China, other intangible assets need to be considered. As a result of measurement impediments, previous studies resort to indicators like patents and science and technology (S&T) expenses to represent total intangible investment in China (Crescenzi et al., 2012; Fleisher et al., 2013; Kuo & Yang, 2008; Scherngell et al., 2014). Until recently, few studies, to our best knowledge, examined a broad array of intangible capital in China under the CHS framework. These studies in China were only conducted at the national level. For instance, Hulten and Hao (2012) were the first to estimate the intangible investment and capital stock in China during the period 1995-2008. They noted an increasing growth rate of intangible investment starting in 1990, and emphasised that China was still a manufacturing-oriented economy during the period, with a relatively low ratio of intangible to tangible investment. In addition, the work of Tian et al. (2016, in Chinese) extended the national intangible investment measurement to 2012. The estimated intangible investment in China reached 9.03 percent of national GDP in 2012, with an increase of 21.81 percent from 2001 (**Figure 1-10**).

1.4 Objectives and Contributions

The world is shifting toward an intangible-oriented economy and China is no exception. Obviously, intangible capital plays an increasingly important role in an economy's growth and development. However, there is a large knowledge gap between China and the advanced economies. Information about intangible capital in China is still limited, and the existing studies were largely constrained to the national level. Little is known about other aspects of intangible capital in China. For example, China is well known for her geographical and demographical diversity. Does intangible capital exert different impacts on China's regional economic growth? What does intangible investment distribution and its dynamic evolvement in Chinese regions look like? Additionally, since intangible capital is invisible and disembodied, how could it affect economic growth? Does it contribute to economic growth by acting as an input factor, or by complementing tangible capital? Furthermore, due to the non-rival and non-excludable features of intangible capital,[13] knowledge spill-over becomes an unavoidable issue for intangible capital and needs to be examined. Finally, hardly any information on intangible capital is available at the micro-level in China. It is equally important to know the influence of intangible capital on China's firm performance.

[13] The non-rivalrous nature of intangibles implies that intangible capital can be employed by many users simultaneously without diminishing the quantity available to any single user, and the non-excludability of intangibles implies that intangible capital can be accessed by non-paying consumers (Corrado et al., 2009).

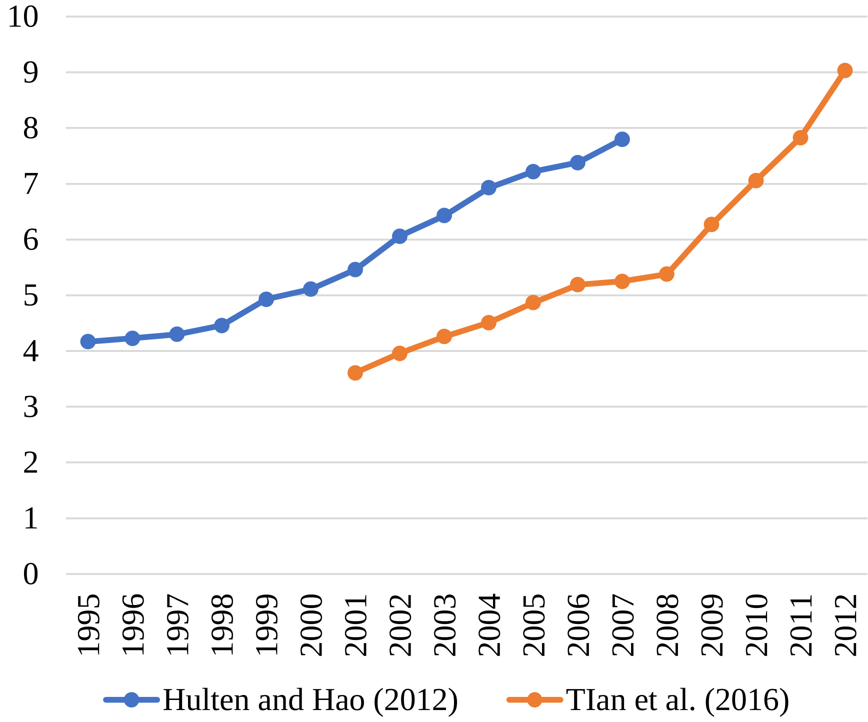


Figure 1-10: Intangible Capital Development in China (% GDP), 1995-2012

Source: Hulten and Hao (2012) and Tian et al. (2016).

Therefore, the objective of this dissertation is to gain a deep insight into intangible capital in China. It attempts to define and measure intangible capital in China, and to examine the relationship between intangible capital and China's economic growth at different levels. Instead of examining individual intangible assets, the study focuses on a broader range of intangible assets, from the well-known R&D to some "novel" intangibles like advertising and entertainment originals. A direct expenditure-based approach is adopted to keep consistent with the studies of developed countries, and thus provide comparable results.

This dissertation contributes to the existing studies in multiple aspects. First, it fills the gap in the literature by extending intangible capital measurement to China's provincial level. Investment flows of nine overall types of intangible assets are constructed in China's thirty-one provinces, cities and municipalities during 2003-2016. To consider the unique features of each of the intangible assets, different price deflators and depreciation rates are used for different intangibles. Intangible capital stock is reported for each of the Chinese regions, enabling future studies of intangible capital to be based on a panel dataset. An "extended" growth accounting experiment with intangible capital is conducted afterwards at both China's national level and regional level. This study, to our best knowledge, is heretofore the first to analyse the impacts of intangible capital on regional economic growth in China.

Second, according to studies in advanced economies, intangible capital helps to utilise new technologies like ICT, and raise productivity in ICT-intensive sectors (Chen & Inklaar, 2016; Corrado et al., 2017). In contrast to developed countries, less information is found in China. Hence, our study makes the first attempt to analyse the complementary roles of intangible capital and ICT capital in China. ICT investments and capital stocks are estimated in 29 manufacturing and services sectors across 31 Chinese regions. The empirical results imply that intangible capital can act not only as an input factor but also as a complement to interact with ICT capital and jointly contribute to China's economic growth. Meanwhile, the complementary effect of intangible capital serves as a specific mechanism through which intangibles affect economic growth.

Third, this dissertation provides evidence to advocate the benefits of intangible capital to micro-level firm performance in China. Organisation capital, as one important type of intangible capital, is measured and examined at China's firm level. Organisation investment and capital stock is, for the first time, constructed for Chinese manufacturing firms based on an expenditure-based measuring approach. Furthermore, knowledge spill-over effects from organisation capital are also elucidated through two potential spill-over channels: geographical proximity and technological proximity. To construct technological proximity, we merged China's patent dataset with China's Annual Survey of Industrial Enterprises dataset. Around six-hundred specific technology fields are considered to constitute the spill-over pool based on the initial four-digit international patent classification (IPC) code.

Finally, the study attempts to examine intangible distribution dynamics and its transition path in China by using a nonparametric statistical approach. The merit of this approach is to observe transition patterns themselves without imposing any prerequisite assumptions or restrictions. In addition, in terms of methodology, the chapter augments a recently developed method, namely the mobility probability plot (MPP), by constructing bootstrap confidence intervals. The augmented MPP provides an interval estimator instead of a point estimator, thus helping draw conclusions with stronger confidence than any previous studies. The results of intangible distribution dynamics shed light on China's regional development inequality. Arguably, intangible capital will push up regional disparity, and conventional regional growth analysis in China may need a revisit in the context of an intangible-abundant economy.

1.5 Structure of the Dissertation

The dissertation is organised in seven chapters. After the Introduction, Chapter Two, "Intangible Investment and Capital Stock", introduces theories of intangible capitalisation in the CHS framework, and describes the expanded national income account with the inclusion of intangible capital. The scope of business intangible capital will be listed. Details of measurement issues of intangible data sources, price deflators, and depreciation rates are described. Intangible investment flows and capital stock are constructed at the national and regional level. The chapter will also present a general picture of intangible capital development in China and Chinese regions, and provide comparable analysis between China and developed countries.

Chapter Three, "Intangible Capital and Economic Growth", focuses on the relationship between intangible capital and China's labour productivity growth. Intangible capital is incorporated in an expanded growth accounting exercise. This analysis will be conducted at both the national and regional level. For regional-level analysis, thirty-one Chinese regions will be grouped into two broad economic regions of the coast and the interior corresponding to China's different geographical characteristics and economic growth patterns. The regional analysis will enrich the existing studies by examining the impacts of intangible capital on regional economic growth. In addition, intangible capital is treated differently from human capital. In other words, it is expected that human capital and intangible capital are conceptually different from each other and affect economic growth independently. Finally, a set of sensitivity analysis will be conducted to check the robustness of the results by adjusting parameters and using different variable definitions.

Chapter Four, “Intangible Capital, ICT and Sector Growth”, examines how intangible capital affects the growth of ICT-intensive sectors in China. The empirical strategy of the so-called fixed effect identification adopted by Rajan and Zingelas (1998) is introduced first. To examine whether ICT-intensive sectors will grow faster in regions with faster development of intangible capital, an interaction term of regional intangible development and a sector ICT intensity indicator is included in the model. By using the ICT intensity indicator, we group twenty-nine sectors in China into more ICT-intensive sectors and less ICT-intensive sectors, and compare the findings with those from studies of developed countries. Other controlling factors such as human capital, physical capital, and financial market development, are described in more detail. Finally, sensitivity analysis will be conducted to check the robustness of the results.

Chapter Five, “Intangible Capital and Firm Performance”, evaluates the role of organisation capital in firm output performance based on Chinese manufacturing enterprises. Both a static model and a dynamic model are considered. In addition, knowledge spill-over effects from organisation capital are examined through two potential spill-over channels, namely, geographical proximity and technological proximity. The geographical proximity is defined as the distance between the capital cities of Chinese regions, while the technological proximity is estimated by the granted patents of a firm. By utilising the novel merged dataset of AISE and SIPO, the study provides results that are different from those in the existing studies of advanced economies.

Chapter Six, “Intangible Dynamic Distribution in China”, analyses intangible investment distribution and its dynamic transitions across Chinese regions. This study will focus on dynamic transition paths of intangible capital development and its future evolution by using a nonparametric method. The study will provide more details of adaptive kernel estimators, the nonparametric distribution approach, the ergodic distribution evolution, and the novel MPP methods. In addition, intertemporal dynamics are analysed to examine the impacts of financial crisis on intangible distributions in China, and a conditional spatial distribution analysis is implemented to take spill-over effects into account.

Chapter Seven, “Conclusions and Policy Implications”, summarises the main findings of core studies. Based on the findings, the chapter will provide feasible policy implications and suggestions on China’s economic development in an intangible context. Finally, this chapter will also list defects and shortcomings of this study, and prospective future work.

CHAPTER 2 - INTANGIBLE INVESTMENT AND CAPITAL STOCK

2.1 Introduction

The preliminary step of analysing intangible capital in China is to define and measure it properly. This chapter reviews the theories of intangible capitalisation, describes the expanded national income accounts, and introduces the scope of business intangible capital in our analysis. Data sources of each type of individual intangible capital in this study are described in detail. To estimate intangible capital stock, a perpetual inventory method (PIM) is adopted. The chapter will discuss the perpetual inventory capital formation process and the choice of parameters of price deflators and depreciation rates for each intangible asset. Intangible investment and capital stock will be reported finally.

CHS Framework of Intangible Capitalisation

The source-of-growth (SOG) framework was first developed by Solow (1956, 1957), and then discussed and augmented by Kendrick (1961), Denison (1964, 1962), and Jorgenson and Griliches (1967), among others. The famous Solow residual, or "total factor productivity" (TFP) growth, has since been discussed and examined by using the SOG framework (see a brief review by Hulten (2001)). It measures the efficiency that is not explained by the set of input factors. Explicitly, with the assumption of a Hicksian efficiency,[14] an aggregate production function is specified as:

$$Y_t = A_t F(K_t, L_t) \tag{2-1}$$

[14] Hicksian efficiency refers to "costless" improvements in the way an economy's resources of labour and capital are transformed into real output, i.e. a shift parameter capturing "Manna from Heaven" (Hulten, 2001).

where Y_t is the real product, K_t and L_t refers to capital and labour, respectively, and A_t is the Hicksian efficiency (Solow, 1956). By taking derivatives of Equation (2-1) with respect to time, the production function is expressed in a form of growth rate:

$$\frac{\dot{Y}_t}{Y_t} = \frac{\partial Y}{\partial K}\frac{K_t}{Y_t}\frac{\dot{K}_t}{K_t} + \frac{\partial Y}{\partial L}\frac{L_t}{Y_t}\frac{\dot{L}_t}{L_t} + \frac{\dot{A}_t}{A_t} \tag{2-2}$$

The dots denote time derivatives, so the corresponding ratios are growth rates. Thus, Equation (2-2) indicates that the growth rate of output equals the growth rates of capital and labour inputs, weighted by their output elasticities, plus the growth rate of the Hicksian shift parameter. Under the assumptions of constant returns to scale and competitive equilibrium, the output elasticities are equivalent to income shares when inputs are paid the values of their marginal products, namely, wages and capital rental prices. Thus, Equation (2-2) is transformed into:

$$g_t^Y = g_t^A + s_t^K g_t^K + s_t^L g_t^L \tag{2-3}$$

where the "g-terms" denote growth rates, and the "s-terms" are income shares. Graphically, in **Figure 2-1**, the weighted growth rates of capital and labour refer to the movement along the production function (for example from point c to b), while the residual term g_t^A can be interpreted as a shift in this underlying production (for example from point a to c). Clearly, as revealed in **Figure 2-1**, an increase in TFP will in general lead to an increase in output (as the inputs are used more efficiently) and thus to additional saving and capital formation. Under the assumption of diminishing marginal returns to factor inputs, TFP is regarded as the only force for long-term growth, referring to technological progress.

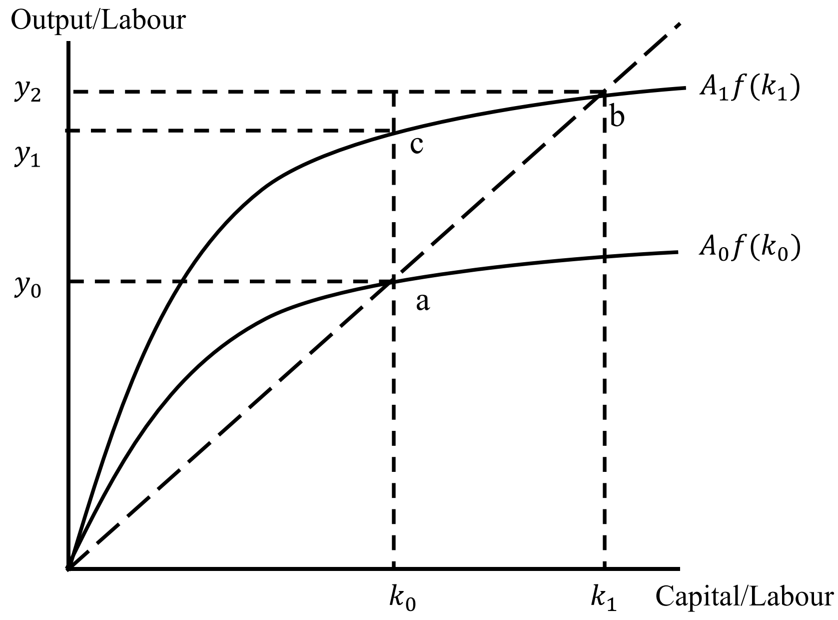


Figure 2-1: Solow's Aggregate Production Function

Source: Solow (1956).

However, the SOG framework is not free from criticism. For example, whether the residual term is an accurate index of technological progress is debatable. According to Abramovitz's famous "measure of our ignorance", the residual term is associated with measurement errors, unobserved omitted factors, and model misspecification, which cannot be attributable to technological progress (Abramovitz, 1956). Because of this, researchers attempted to endogenise technological progress by using a variety of econometric models (Aghion & Howitt, 1992; Grossman & Helpman, 1994; Lucas, 1988; Rebelo, 1991; Romer, 1986, to cite a few). In addition, the SOG model is interpreted as a contemporary analysis of the factors determining output along a growth path of an economy. That is, the model treats capital as being predetermined and cannot fully describe the growth process because saving and investment are choice variables in a complete model of growth (Corrado et al., 2005). As Corrado et al. (2005) pointed out, "Not only is this choice dimension important because it determines the quantity of capital available at each point in time, but it also determines what should be counted as capital".

Corrado et al. (2005, 2006) therefore embedded the production-function-based SOG analysis in the theory of optimal growth. By adopting an intertemporal accounting framework pointed out by Hulten (1979), they treated capital as an intermediate product that is delivered in each subsequent year within the accounting period. The final intertemporal accounting framework, therefore, is to solve the optimal intertemporal consumption utility function U $(C_{t=1}, C_{t=2}, \ldots, C_{t=T})$ under constraints. The constraints are: 1) the technological frontiers that are specified in Equation (2-1); 2) the exogenous initial and terminal quantities of capital stock K_0 and K_T; 3) the explicit capital accumulation process that is expressed in the perpetual inventory form:

$$K_t = I_t + (1 - \delta)K_{t-1} \tag{2-4}$$

where I_t is the capital investment in year t, and δ is the rate of depreciation;[15] 4) the given initial levels and paths of labour and TFP; and 5) the condition that consumption of goods cannot exceed the total output in each accounting year:

$$\mathrm{P}_t^Y Y_t = P_t^C C_t + P_t^I I_t = P_t^L L_t + P_t^K K_t \tag{2-5}$$

Equation (2-5) is the income account of an economy, where the supply side consists of intermediate goods of labour (L_t) and capital (K_t), and the demand side considers two goods of consumption (C_t) and investment (I_t). For simplicity, the economy is assumed to be "closed". If all of the above are presented in a more compact format, the optimal consumption paths can be solved through:

$$\phi\{(C_{t=1}, C_{t=2}, \ldots, C_{t=T}); (L_{t=1}, L_{t=2}, \ldots, L_{t=T}); (A_{t=1}, A_{t=2}, \ldots, A_{t=T}); K_0, K_t\} = 0 \tag{2-6}$$

Equation (2-6) solves the intertemporal production possibility frontier. This solution is illustrated in **Figure 2-2**, with all combinations of the consumption utility curves (represented by $\{\mathrm{UU}, U'U', \ldots\}$) and the feasible constraints curves (represented by $\{\mathrm{AB}, A'B', \ldots\}$). The optimal consumption plan can be solved (for example points a and b), and the optimal point is an explicit

[15] The assumption of the constant rate of depreciation δ is not necessary for holding the constraint conditions. A more general approach would replace δ with δ_t but has no apparent result differences (Hulten, 1979).

function of labour and the level of technology in that period. The most important implication of **Figure 2-2** is that capital is implicit in the optimal solution. For example, the abstinence of the AC_1 units of consumption are used up to make capital goods in period one for consuming in period two (Corrado et al., 2005; Hulten, 1979). Capital is, in fact, an intertemporal product in complete production processes.

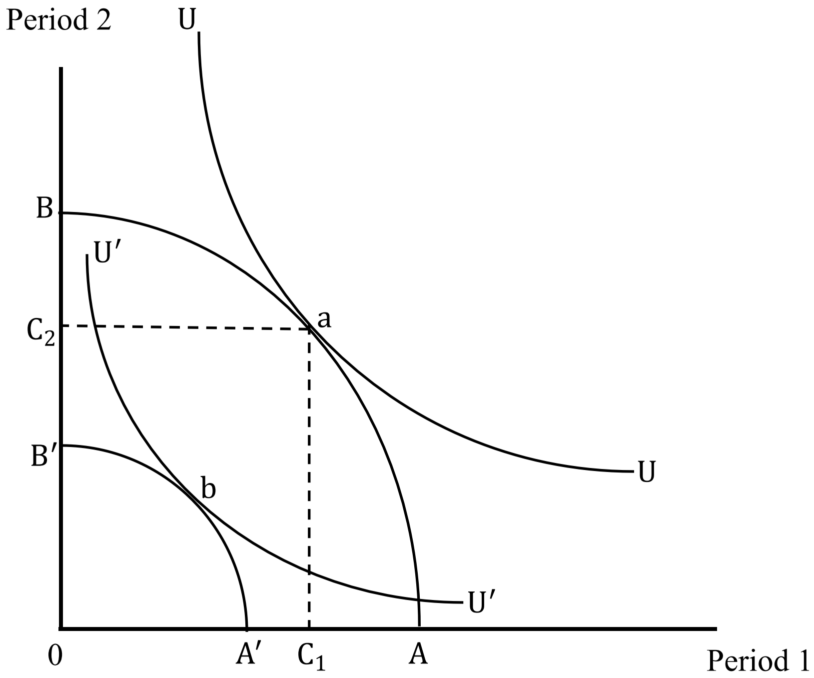


Figure 2-2: Intertemporal Framework

Source: CHS framework in Corrado, Hulten, and Sichel (2005).

Figure 2-2 demonstrates the key information of the CHS framework: all capital should be put in the context of an optimal consumption plan based on the maximisation of an intertemporal utility function subject to the usual constraints (Weitzman, 1976). As a result, any resource that reduces current consumption to increase it in the future should qualify as investment, and all types of investment should be treated symmetrically. Investment in knowledge-based intangible capital should be incorporated in the national accounts and wealth accounts even if there are practical measurement difficulties. In addition, according to this theoretical concept, whether the capital is self-owned, has a limited or no external trading market, or presents knowledge externalities, should not be treated differently. Therefore, the concept of CHS envisages an even broader scope of capital in the source-of-growth analysis, including tangible capital, tradable intangible capital, own-account intangible capital, and even as far as public intangible capital.

An Expanded National Income Account

We now turn back to Equation (2-5) that shows the conventional national income accounts. Assume an economy with three products, consumption (C_t), tangible investment goods (I_t), and intangible investment goods (denoted as "N_t"). Some tangible investment goods are not consumed currently and accumulated as capital through Equation (2-3). Traditionally, if the intangible investment goods are treated as expenditure, they will be counted as inputs to the production of the other two goods (Corrado et al., 2005). Consider the separate flow accounts for the production process in these three sectors (consumption, tangible investment goods, and intangible investment goods) in the form of:

$$P_t^C C_t = P_t^L L_t^C + P_t^K K_t^C + P_t^N N_t^C \tag{2-7a}$$

$$P_t^I I_t = P_t^L L_t^I + P_t^K K_t^I + P_t^N N_t^I \tag{2-7b}$$

$$P_t^N N_t = P_t^L L_t^N + P_t^K K_t^N \tag{2-7c}$$

The adding up conditions are: 1) $L_t = L_t^C + L_t^I + L_t^N$; 2) $K_t = K_t^C + K_t^I + K_t^N$; and 3) $N_t = N_t^C + N_t^I$. Since N_t is both an output and an immediate input, it nets out in the aggregate. The GDP identity thus is shown in Equation (2-5).

According to the symmetrical treatment of intangible and tangible investment, the intangible investment goods can be accumulated as capital through a similar "perpetual inventory" process: $R_t = N_t + (1 - \delta_R)R_{t-1}$. Because of this, the separate sector production process will become:

$$P_t^C C_t = P_t^L L_t^C + P_t^K K_t^C + P_t^R R_t^C \tag{2-8a}$$

$$P_t^I I_t = P_t^L L_t^I + P_t^K K_t^I + P_t^R R_t^I \tag{2-8b}$$

$$P_t^N N_t = P_t^L L_t^N + P_t^K K_t^N + P_t^R R_t^N \tag{2-8c}$$

The adding up conditions become: 1) $L_t = L_t^C + L_t^I + L_t^N$; 2) $K_t = K_t^C + K_t^I + K_t^N$; and 3) $R_t = R_t^C + R_t^I + R_t^N$. Therefore, the aggregate production process, which is the GDP identity, is expressed as:

$$P_t^Y Y_t = P_t^C C_t + P_t^I I_t + P_t^N N_t = P_t^L L_t + P_t^K K_t + P_t^R R_t \tag{2-9}$$

Like tangible capital input, P_t^R is the service price of the intangible capital stock and is the source of income that is omitted from the traditional GDP. With intangible capital investment, the measured GDP will be expanded.

2.2 The Scope of Business Intangible Capital

Considering the practical difficulties of intangible measurement, CHS (2005, 2006) categorised nine types of common business intangible capital into three broad groups, namely, computerised information, innovative property, and economic competency (**Figure 2-3**). [16] Computerised information indicates knowledge embedded in computer software and computer databases. Measures of computer software are sourced from the NIPAs, which have recognised both self-owned and purchased software in the United States since 1999 (Corrado et al., 2005). Computer database estimates were made up of two components: self-owned databases are jointly estimated by the NIPAs with software, and purchased databases are estimated separately and have a small value. In addition, CHS (2005, 2006) also pointed out the double-counting risk of intangible capital measurement. For example, software is an important tool in R&D and thus expenditures on R&D and software are likely to be overlapping partly. Additionally, software is often bundled with tangible assets, leading to a possibility of sometimes double counting investments in intangible capital and tangible capital.

[16] The classification of the CHS framework is close but not identical to the groupings developed by the OECD to identify knowledge-based capital (OECD Secretariat, 1998).

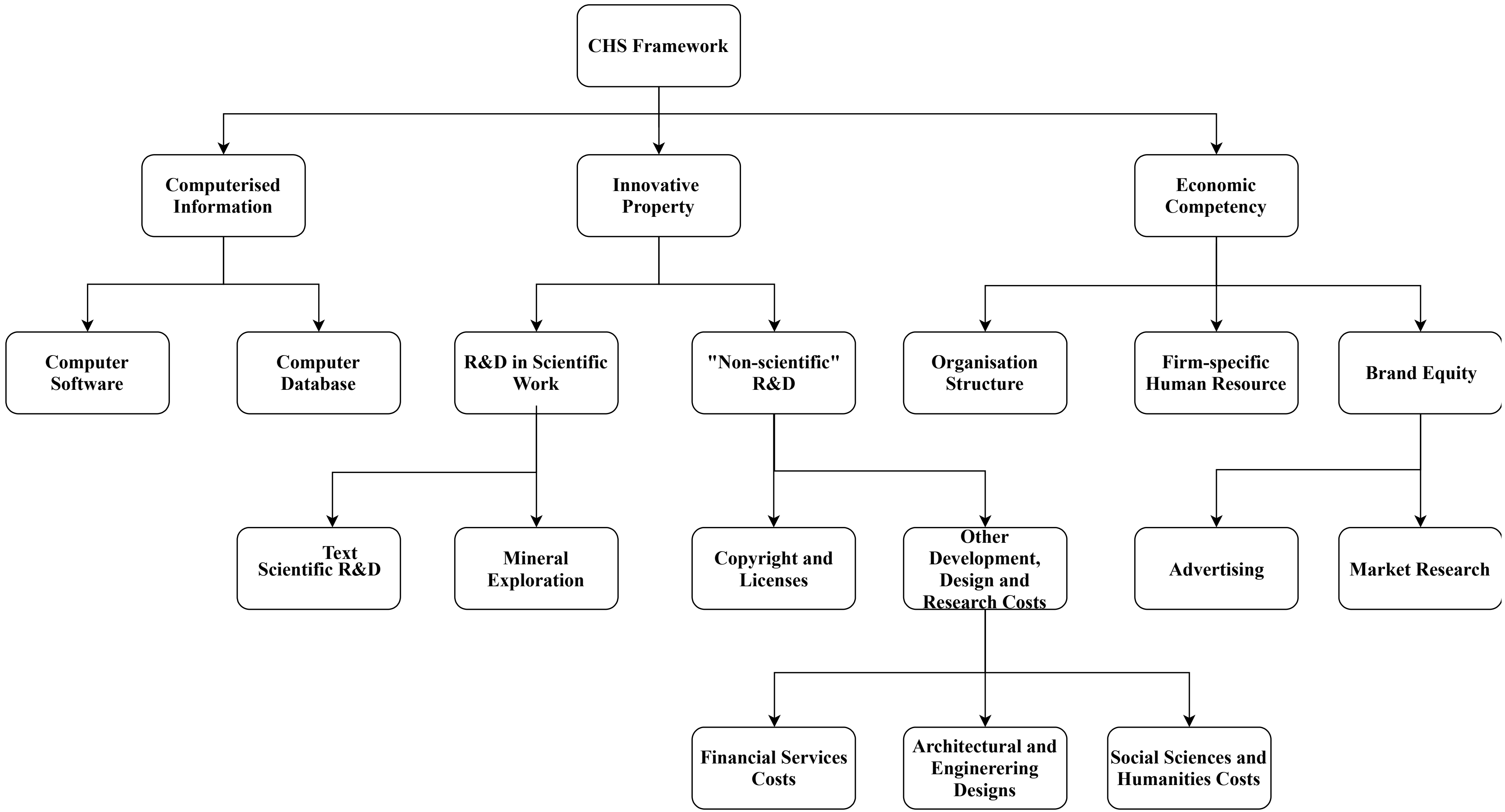


Figure 2-3: The Scope of Intangible Capital in CHS Framework.

Innovative property indicates knowledge which is acquired through innovative and creative activities. It not only reflects the best-known R&D expenses in scientific activities, which usually lead to patents or licences (known as “scientific” R&D), but also encompasses what are called “non-scientific” R&D expenses in some “non-scientific” creative activities, like entertainment, artistic originals, financial services and architecture designs, among others. Scientific R&D expenses are categorised into two groups: scientific R&D in physical sciences, biological sciences, and engineering and computer sciences; and scientific R&D in mineral exploration and geophysical and geological exploration for the acquisition of new reserves. In parallel, non-scientific R&D is divided into: 1) copyright and licence costs, which denote non-scientific R&D expenses on information services for the development of entertainment and artistic originals that usually lead to a copyright and licence. Sectors involved in this category are the motion picture, radio, television, sound recording, and book publishing industries; and 2) other product development, design, and research costs, which denote non-scientific R&D expenses in other service and humanity sectors that do not necessarily lead to a patent or copyright. Sectors involved in this category are financial sectors (banks, securities, commodity brokers, etc.), architectural designs, and social sciences and humanities.

Economic competency indicates knowledge embedded in firm-specific human resources and structures for improving firms’ productivity and profits. This concept is distinct from human capital that is also embedded in employees but sees returns accrue to workers.[17] CHS (2005, 2006) includes three basic asset types in this category: brand equity, firm-specific human capital, and organisational structure. Specifically, brand equity denotes the advertising expenditures and market research outlays for the development of firms’ brands, trademarks and reputation. Firm-specific human capital refers to both direct and indirect costs in employer-provided training for developing firm-specific workforce skills. Organisational structure is the expenses on improving the efficiency

[17] Firm-specific human resources are conceptually different from what is called human capital. Consider the most obvious example, organisational capital. The internal processes may be created and applied by managers within a firm, say Apple. Even when those managers leave the firm, Apple retains a good part if not all of that knowledge (Corrado et al., 2012).

of business organisations, of which the own-account component is the value of executive time spent on organisation change and development, and the purchased component is represented by management consultant fees.

This chapter adopts the CHS framework to categorise intangible capital in China into the same three broad groups. However, some of the asset types are excluded due to data unavailability. For example, hardly any information on computer databases can be obtained in China. Thus computer software is the sole ingredient in the category of computerised information. Market research, as well as social sciences and humanities, are excluded for the same reason. **Table 2-1** lists intangible capital in this study and describes what is currently included in China's national accounts. Accordingly, nine types of intangible assets are included in the list, among which only three have been recognised as capital in China's national accounts.

2.3 Measurement and Data Issues

Data Sources for Intangible Investment

Hulten and Hao (2012) defined computer software investment in China as total revenues minus exports in software industries. As there was a lack of information, they did not adjust the software investment for imports and thus likely obtained a downward biased measurement. To keep consistent, we also use the revenue from software industries as the proxy for software investment and adjust it for both imports and exports. The data source is the China Statistical Yearbook of Electronic Industry and the China National Statistical Yearbook (CSYEI, 2003-2016; NSY, 2017).[18] Total software revenues can be decomposed into revenues from software products, software technical services, system integration, embedded applications and IC designs. As the revenue from software products is already regarded as tangible capital investment in China's

[18] China National Statistical Yearbook released the revenues from software industries since 2013 but without reporting information of imports and exports until 2015. The statistical calibre of software revenue is the same in China National Statistical Yearbook and in China Statistical Yearbook of Electronic Industry.

national accounts, it is extracted from the total tangible investment in this study to avoid double counting (Tian et al., 2016).

Table 2-1: List of Intangible Capital

Asset Types	National Account[19]	This Chapter
Computerised Information		
1. Computer Software	Yes	Yes
2. Computer Databases	No	No
Innovative Property		
3. Mineral Exploration	Yes	Yes
4. Scientific R&D	Yes	Yes
5. Entertainment and Artistic Originals	No	Yes
6. Financial Products and Services	No	Yes
7. Architectural and Engineering Designs	No	Yes
Economic Competency		
8. Brand Equity		
a. Advertising	No	Yes
b. Market Research	No	No
9. Firm-Specific Resources		
a. Employer-provided Training	No	Yes
b. Organisational Structure	No	Yes

Source: Author's own work.
Note: "Yes" means being included and "No" means being excluded.

Mineral exploration and scientific R&D are the two intangible assets of which the investment can be obtained directly. The data sources are the China Statistical Yearbook of Mining (CSYM, 2003-2014), China Land and Resources Statistical Yearbook (CLRSY, 2015-2017),[20] and China Statistical Yearbook of Science and Technology (CSYST, 2003-2017). Since mineral exploration is included as the tangible capital investment in China's national accounts, it is

[19] Since 1993, Chinese government has compiled the System of National Accounts 2002 (CSNA-2002) on the basis of SNA-1993 to incorporate computer software and mineral exploration as components of the fixed capital investment in the national accounts. In order to reflect the operation of China's national economy more accurately, to meet the needs of the public, and to be consistent with international standards, after SNA-2008 reform, National Bureau of Statistics released a new version of System of National Accounts in 2016 (known as CSNA-2016), and capitalized R&D in July 2016 (Tang et al., 2017).

[20] The statistical calibre of mineral exploration expenses is the same as those in the China Statistical Yearbook of Mining and China Land and Resources Statistical Yearbook. Since the China Statistical Yearbook of Mining is not released/available to us, mineral exploration inputs after 2014 are obtained from the China Land and Resources Statistical Yearbook.

extracted from the total tangible investment to avoid double counting. One caution is that, in China, components of scientific R&D are basic research, applied research and experimental development, among which the last accounts for the most. However, the cost of experimental development is usually excluded in the prudent analysis of scientific R&D in developed countries since it refers more to imitation rather than original innovation activities (Hulten & Hao, 2012). As a result, the quantity as well as the quality of scientific R&D investment in China should be interpreted with caution.

For entertainment and artistic originals, CHS used the investment in motion pictures and doubled the value to crudely estimate the costs for new products in broadcasting, sound recording, and publishing industries. In the Chinese case, Hulten and Hao (2012) used one-quarter of the revenues from the publishing industry but excluded the media industry to represent intangible investment in copyright and licences. Tian et al. (2016) however omitted this item completely. In this chapter, one-quarter of the revenues of books, magazines, and newspapers is used as the value of investments in publishing industries. The same value is used to crudely represent the intangible investment in respect to the development of media industries like broadcasting, TV, sound recording and movies. The data source is the China Publishers' Yearbook (CPY, 2003-2017).

Nakamura (2001) proxies new product development costs in the financial services industries as half of the non-interest expenses of banks and non-depository institutions. CHS uses 20 percent of intermediate expenses to proxy intangible investment in a broader coverage of financial institutions including securities, commodity brokerage and others. This chapter adopts the CHS measures to use 20 percent of intermediate expenses in financial service industries as a proxy for intangible investment in the development of financial new products and services. The data sources are the China National Statistical Yearbook (NSY, 2003-2017) and the World Input-Output Tables released by the World Input-Output Database (WIOD).[21] China Statistical Yearbooks provide the

[21] The World Input-Output Database provides input-output tables for 28 EU countries and 15 other major countries in the world for the period from 2000 to 2014. The ratio of intermediate inputs to value added for

value added of the financial sector, and the Input-Output Tables provide the ratio of intermediate inputs to value added for the financial sector. The same ratio in the national Input-Output Tables is applied to regional estimates.

Based on studies of CHS and Hulten and Hao (2012), half of the revenues from the “engineering inspection and design” category are regarded as intangible investment in architecture and engineering designs. The revenues are obtained from the National Annual Reports of Firms of Engineering Inspection and Design issued by the Ministry of Housing and Urban-Rural Development, and the China National Statistical Yearbook (NARFEID, 2006-2015, NSY, 2016-2017).[22] For 2003 and 2004, we follow Hulten and Hao (2012) to extrapolate the revenues under the assumption that the growth rate of design revenues equals that of investment in construction. The assumption is reasonable since architecture design development is always highly correlated with construction development (Hulten & Hao, 2012).

Sixty percent of the advertising expenditures in the CHS framework are presumed to have long-lasting effects, and the remaining forty percent are regarded as seasonal, temporary or public service advertising with a relatively short service life. In other word, 40 percent expenditures on advertising are assumed to fail to satisfy the capitalisation criterion of living a long service life. As a result, CHS counts 60 percent of advertising expenditures as advertising investment. Without information on advertising expenditures, we follow Tian et al. (2016) to use advertising revenues instead. Sixty percent of advertising revenues in advertising industries in China are counted as intangible investment. The revenues from advertising industries in China can be obtained from the China Advertising Yearbook (CAY, 2003-2016) and extrapolation is used to fill in missing values in 2016. In addition, since own-accounted advertising spending is not reflected in revenues, it is excluded from the estimates in this study.

---

the financial sector in China in 2014 is used as a rough estimate for period 2015-2016. Retrieved via http://www.wiod.org/database/wiots16.

[22] The revenues from engineering inspection and design industries have been released in the China National Statistical Yearbook since 2016 with the same statistical calibre as that of National Annual Reports of Firms of Engineering Inspection and Design.

CHS uses 20 percent of the values of executive time devoted to management as in-house organisational capital investment, and uses management consultant fees as purchased organisational capital investment. Due to the lack of data on management consultant fees, only own-account organisational capital is considered. Following Hulten and Hao (2012), we use 5 percent of management expenses as organisational capital investment.[23] The data sources are the China Industrial Statistical Yearbook and China National Statistical Yearbook (CISY, 2003-2015; NSY, 2003-2017).[24] We calculate the ratio of management expenses to value added in the manufacturing industry and use the same ratio for agriculture and service industries. Regarding employer-provided training, we estimate the investment very crudely as a half of that in organisational development.

Deflators and Depreciations for Intangible Capital Stock

As is mentioned above, intangible capital is accumulated through a "perpetual inventory" process $R_t = N_t + (1 - \delta_R)R_{t-1}$. Thus, two further elements beyond investment flows N_t should be clarified, i.e. a depreciation rate and a price deflator for each intangible asset. While a price deflator transforms investment flows into real terms, a depreciation rate decays the productivity of an asset as it ages.

Depreciation rates in the CHS have been widely adopted in its followers' work (Baldwin et al., 2012; Dutz et al., 2012; Fukao et al., 2009; van Ark et al., 2009, to cite a few). Regarding computer software, the depreciation rate is set to be 33 percent to keep consistent with the BEA's estimation, in which software is assumed to have on average five-year service life in general. For scientific and non-scientific R&D, CHS uses the middle value of 20 percent from existing studies as the depreciation rate. In addition, a high rate of 60 percent is chosen for depreciating advertising since most advertising capital serves with a relatively short commercial life. Finally, in terms of

[23] Management expenses in Chinese firms include the initial setup costs of the firm, the costs of board of directors, the wages and welfare of non-production employees, material costs related to management, travel expense, union expense, consulting fee, legal fee, expense of hospitality, property tax, taxes (of using the land, and signing contracts, etc.), fees of licences transfer, R&D expenses, pollution expenses, etc.

[24] Management expenses are obtained directly from the China National Statistical Yearbook after 2015.

firm-specific resources, the average depreciation rate of R&D and advertising, 40 percent, is employed. On the one hand, firm-specific resources have long-lasting "learning-by-doing" characteristics, which are similar to the characteristics of R&D; on the other hand, these resources have to rapidly adapt to structural and economic changes, which are similar to features of advertising (Corrado et al., 2006). For the purpose of comparison, we adopt directly the depreciation rates from the CHS framework, shown in **Table 2-2**.

With regard to price deflators, inspired by the work of Fukao (2009), we apply different deflators to different intangible capital (**Table 2-2**). Since computer software is always embedded in computer hardware, deflators of fixed capital investment are employed for computer software. The deflators can be obtained from the China National Statistical Yearbook and the deflators have been reported at both the national and regional level since 1993. GDP deflators are used to deflate scientific and non-scientific R&D. The GDP deflator is calculated by dividing nominal GDP by real GDP. Additionally, because firm-specific human resources are associated with workforce and labour input, we use the implicit wages and salaries price deflators for brand equity, employer-provided training, and organisational structure. The deflator of wages and salaries is calculated by dividing the nominal average wage by real average wage, which can be obtained from the China National Statistical Yearbook.

Finally, initial capital stock is estimated based on the growth rate approach. The approach assumes that incremental capital stock (investment) should meet the needs of replacing deprecations of old capital and creating new capital to maintain growth (Wu, 2016), that is:

$$K_0 = \frac{\Delta K_1}{(\delta + g)} \tag{2-10}$$

where K_0 is the initial year capital stock, ΔK_1 is the annual flow in the first year, δ is the depreciation rate and g is the average growth rate of the initial five-year investment flows. The merit of this application is its simplicity and availability to small samples (Wu, 2016).

Table 2-2: Price Deflators and Depreciation Rates

Asset Types	Price Deflators	Depreciation Rates
Computer Software	Deflator of Fixed Capital Investment	0.33
Scientific R&D	GDP Deflator	0.2
Mineral Exploration	GDP Deflator	0.2
Entertainment and Artistic Originals	GDP Deflator	0.2
Financial Products and Services	GDP Deflator	0.2
Architectural and Engineering Designs	GDP Deflator	0.2
Advertising	Implicit Wages and Salaries Deflator	0.6
Employer-provided Training	Implicit Wages and Salaries Deflator	0.4
Organisational Structure	Implicit Wages and Salaries Deflator	0.4

Source: Author's own work.

2.4 Intangible Investment and Capital Stock in China

National Level

Figure 2-4 shows intangible investment and tangible investment as a percentage of China's GDP during 2003-2016. There is a substantial effort in China to invest in intangibles, especially after the financial crisis in 2007-2009. The share of intangible investment increased from 5.39 percent in 2003 to 13.27 percent in 2016 in China's national GDP. The ratio of intangible to tangible investment, plotted against the secondary axis, steadily increased from 0.14 in 2003 to 0.36 in 2016. However, tangible investment is still dominant in China's economic development, taking up on average 40 percent of China's GDP. China is still an economy driven by tangible investment. Additionally, it is observed that the share of tangible investment rocketed in China after the financial crisis shock (43 percent to 40 percent during 2009-2014 compared with 37 percent to 38 percent during 2003-2008). Probably, this can be largely explained by the Chinese economic stimulus program launched by the authorities after the crisis.[25]

[25] The 2008-09 Chinese economic stimulus plan was a 4 trillion Renminbi stimulus package announced by the State Council of People's Republic of China on 9 November 2008 as an attempt to minimise the impacts

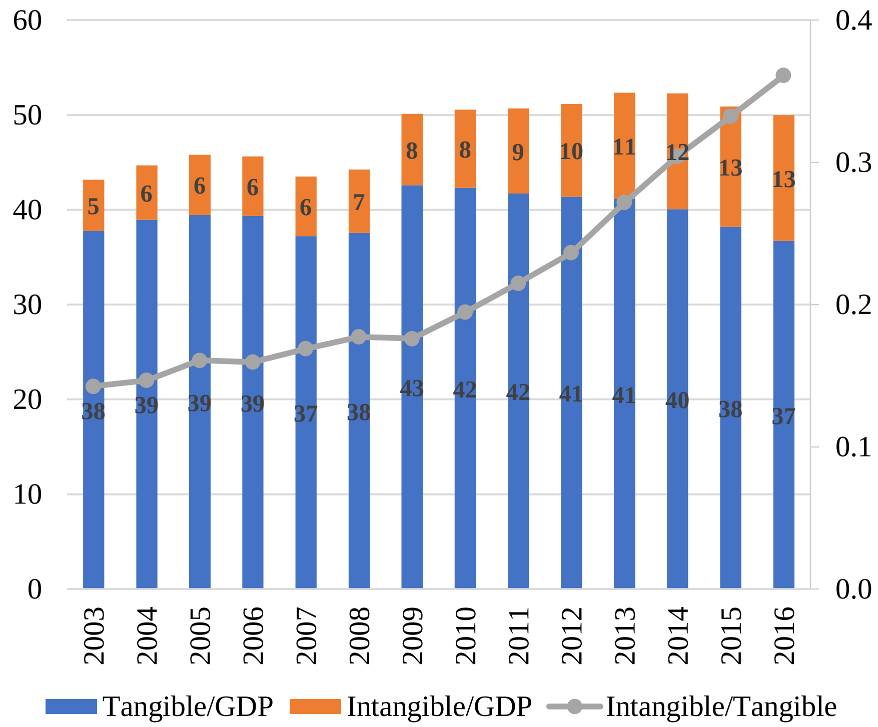


Figure 2-4: Intangible and Tangible Investments in China in 2003-2016

Source: Author's own work.

Note: The left-hand coordinate is the share of intangible and tangible investment in China's GDP (%), and the right-hand coordinate is the ratio of intangible to tangible investment (nominal terms).

The estimates of the overall intangible investment in China are consistent with the previous two studies of Hulten and Hao (2012) and Tian et al. (2016). According to Hulten and Hao (2012), the ratio of intangible investment over China's total GDP was between 6 to 8 percent during 2003-2008 (the whole period in their study is from 1995 to 2008). Meanwhile, Tian et al. (2016) estimated that the ratio varied between 4 and 9 percent during 2003-2012 (the whole period in their study is from 2001-2012). In addition, different from studies of developed countries in which non-market sectors like education, health, and government sectors are excluded, our estimates cover all sectors in China. The idea is supported by Hulten and Hao, who noted many firms that are either state-owned or collectively-owned cover both private and public sectors in China. Because of this,

of the global financial crisis and to stimulate China's economic growth. The stimulus package mainly aimed for fixed capital investments in areas such as housing, rural infrastructure, transportation, and so on. See more details via https://en.wikipedia.org/wiki/Chinese_economic_stimulus_program.

it is hard to divide the Chinese economy into the market and non-market sectors (Hulten & Hao, 2012).

Meanwhile, intangible investment in China is not distributed evenly across the three intangible categories (**Figure 2-5)**. In 2016, for example, nearly half of the investment in intangibles is due to the category of computerised information, namely, computer software. It is followed by innovative properties with a contribution of around two-fifths of the total. Economic competencies, which represent enterprises' durable competitiveness, account for less than one-fifth of the total intangible investment. Worse still, as is shown in **Figure 2-5**, the share of economic competencies seems to be shrinking over time.

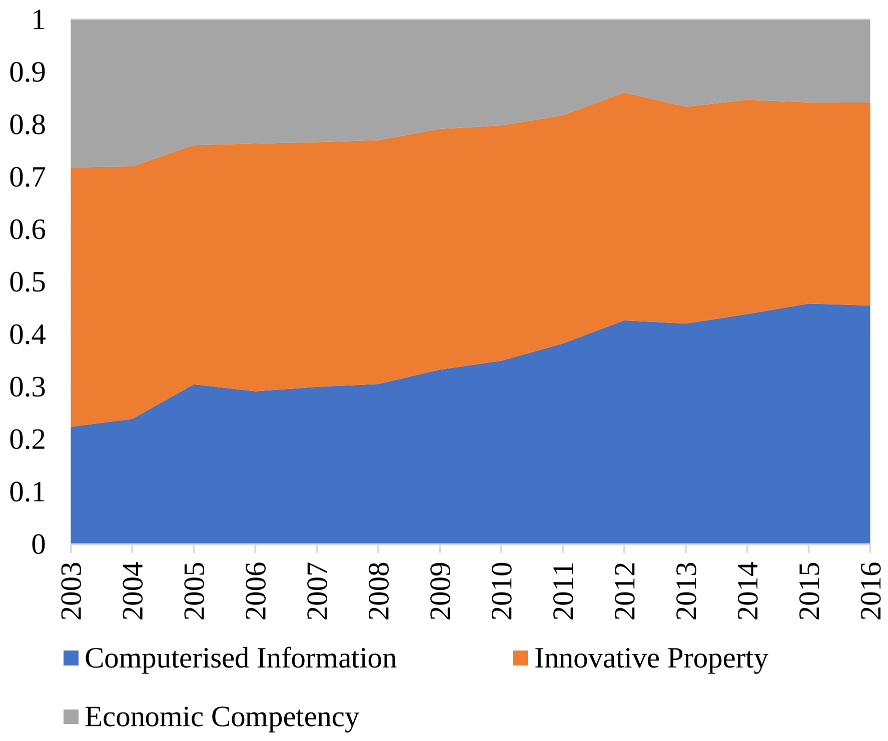


Figure 2-5: Shares of Three Intangible Categories (%)

Source: Author's own work.

By looking at intangible assets within each category, we see great structural changes of intangible investment (**Figure 2-6)**. Initially, intangible investment in China was centralised in computer software and scientific R&D, each having a roughly equivalent share of 20 percent. Investments in architecture and engineering designs, as well as organisation structures, are also sizeable, accounting for over 10 percent in total intangible investment. However, during 2003-2016, computer software squeezed out a lot of the share of economic competencies, taking up about half of the total intangible investment by the year 2016. Scientific R&D lost its share a lot but remains a big component. In addition, a great leap of investment in architecture and engineering designs is observed during the past decade. Architecture and engineering designs nowadays have surpassed scientific R&D and hit the second ranking in China's total intangible investment. In contrast, the share of organisation structure slipped down to only 7 percent during the period.

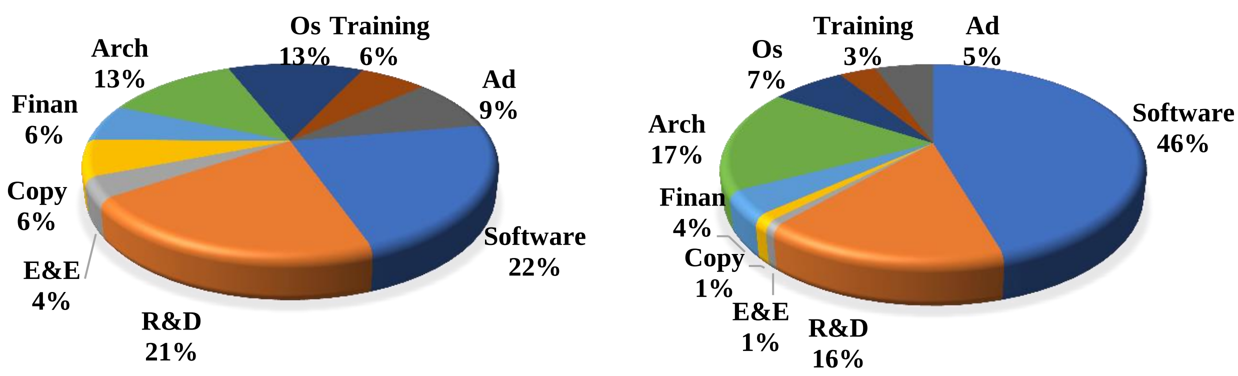


Figure 2-6: Component Shares of Intangible Investment in China (2003 vs. 2016)

Source: Author's own work.

Note: "Finan" refers to "financial products and services", "Os" refers to "organisation structure", "Arch" refers to "architecture and engineering designs", "Ad" refers to "advertising", "E&E" refers to "mineral exploration", and "Copy" refers to "copyright and licences".

Currently, more than half of intangible investment in China is attributed to the investment in computer software and architecture and engineering designs (63 percent). However, both items are tied with the investment of tangible capital in the development of IT infrastructure and residential construction, which is driven by the on-going "informatisation" and "urbanisation" political strategies.[26] As a result, it is argued in Hulten and Hao's work that these two items should be excluded for a more prudent estimate of China's intangible investment. Meanwhile, China is severely underinvesting in economic competencies compared with developed countries. As is displayed in **Table 2-3**, in the United States and the United Kingdom, the investment in economic competencies accounted for 5.50 percent and 5.84 percent in total GDP by 2006, respectively. The investment in economic competencies in countries such as Australia, Canada, and Japan also reached a range of 3 percent to 5 percent of their national GDP ten years ago. By contrast, in 2006, only 1.5 percent of China's GDP was allocated to economic competencies. What is worse, this ratio remains roughly stagnant during the decade, reaching only 2.1 percent in 2016.

Regional Level

Intangible capital is far too underinvested across Chinese regions. **Figure 2-7** displays the average ratio of intangible investment and tangible investment to regional gross output in four divisions in China,[27] during the period of 2003-2016. It is observed that the shares of tangible investment far outweigh the shares of intangible investment in gross output in all four divisions, especially in relatively less developed Chinese areas. Specifically, tangible investment is on average four times the intangible investment in the relatively more developed eastern regions, and over thirteen times the intangible investment in the relatively laggard western regions. Regional economic growth largely relies on heavy investment in tangible assets in support of the

[26] Designated by the Central Committee of the Communist Party of China (CPC) and the General Office of the State Council in 2000, "Informatisation" is set to be a national strategy for China's modernisation in the next fifteen years. After that, the Chinese government developed a number of policies to boost the IT-based industries (Kraemer & Dedrick, 2002). The "Urbanisation" strategy was launched by authorities in the 10th National Five-year Plan (2001-2005). It stimulates the rural-urban migration accompanied by the booming housing market in mega cities and provinces. https://en.wikipedia.org/wiki/Urbanization_in_China.

[27] For purposes of comparison, we categorised 31 Chinese regions into four divisions: Eastern regions (Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan); Inland regions (Inner-Mongolia, Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan, Guangxi, Sichuan, Chongqing, Guizhou, Yunnan, and Shaanxi); Northeastern regions (Heilongjiang, Jilin, and Liaoning); and Western regions (Gansu, Qinghai, Ningxia, Tibet, and Xinjiang). The division is largely based on judgement regarding economic and geographical characteristics of these "clubs" with their distinct economic growth and development in China (Fleisher et al., 2010).

Table 2-3: Intangible Investment across the Globe (% GDP)

	China 2016	China 2006	U.S. 2006	U.K. 2006	Japan 2000-05	Germany 2006	Australia 2005-06	Canada 2005	France 2006	Italy 2006	Spain 2006
Computerised Information	**6.04**	**1.83**	**1.35**	**1.55**	**2.20**	**0.73**	**1.30**	**1.03**	**1.42**	**0.64**	**0.79**
Computer software	6.04	1.83	1.35	1.55	2.00	0.71	1.30	0.83	1.42	0.64	0.79
Computer database					0.20	0.02		0.20			
Innovative Property	**5.13**	**2.97**	**4.44**	**3.16**	**6.00**	**3.59**	**3.60**	**4.97**	**3.18**	**2.21**	**2.78**
Mineral exploration and evaluation	0.10	0.23	0.85	0.04	0.00	0.01	0.40	1.11	0.04	0.09	0.04
Scientific R&D	2.11	1.38	1.84	1.07	2.80	1.72	1.30	1.90	1.30	0.58	0.63
Entertainment and artistic originals	0.15	0.25	0.60	0.22	1.10	0.21	0.10	0.11	0.31	0.10	0.18
Engineering and architecture designs	2.24	0.85	0.55	1.74	2.00	0.75	1.70	1.82	0.93	0.86	1.41
Financial new product and services	0.53	0.26	0.60	0.07		0.90		0.03	0.60	0.58	0.52
Economic Competencies	**2.10**	**1.48**	**5.50**	**5.84**	**2.90**	**2.84**	**4.70**	**3.79**	**3.30**	**2.19**	**1.90**
a) Brand Equity	0.72	0.43	1.47	1.15	1.20	0.56	1.40	0.50	0.99	0.71	0.42
Advertising	0.72	0.43	1.35	0.91		0.41	1.40	0.41	0.73	0.47	0.19
Market research			0.12	0.24		0.15		0.09	0.26	0.24	0.23
b) Firm-specific resources	1.38	1.05	4.03	4.68	1.70	2.29	3.30	3.29	2.32	1.46	2.17
Employer-provided training	0.46	0.70	1.15	2.54	0.50	1.29	0.70	2.16	1.51	1.02	1.49
Organisational structure	0.92	0.35	2.88	2.14	1.20	1.00	2.60	1.13	0.81	0.45	0.68
Total	**13.27**	**6.28**	**11.29**	**10.54**	**11.10**	**7.16**	**9.60**	**9.78**	**7.90**	**5.04**	**5.47**
Intangible to tangible investment ratio (decimal**)**	**0.36**	**0.16**	**1.20**	**1.10**	**0.60**	**0.90**	**0.44**	**0.90**	**0.80**	**0.30**	**0.40**

Source: Author's own work for China estimates. Corrado and Hulten (2010) for the United States, Van Ark et. al (2009) for the UK, Germany, France, Italy and Spain, Fukao et al. (2009) for Japan, Barnes and McClure (2009) for Australia, and Belhocine (2009) for Canada.

Note: The result in China, Japan and Canada covers all sectors while the others cover only the market sector.

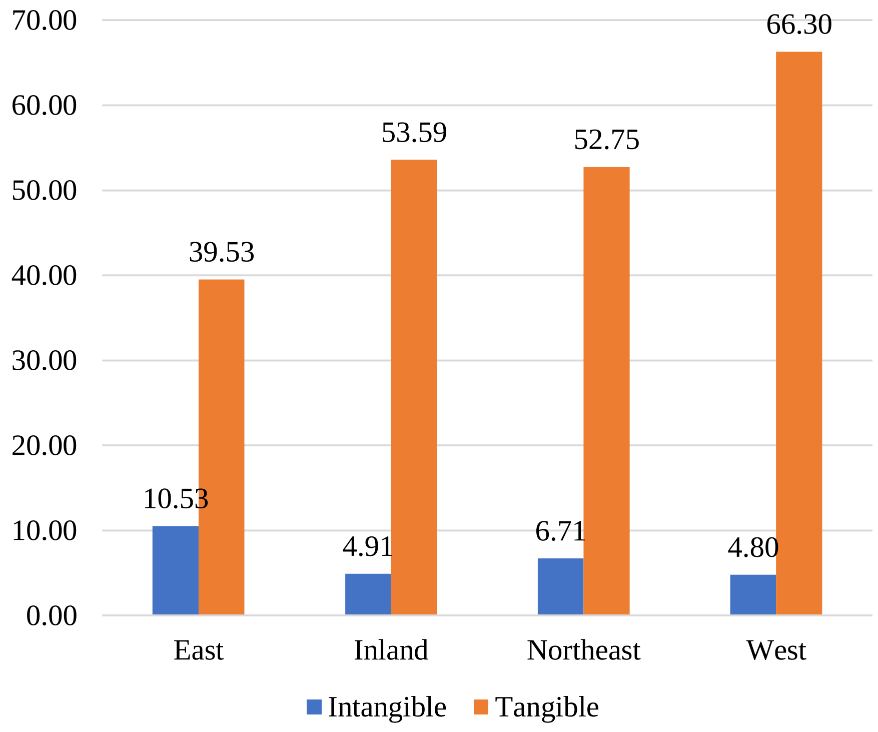


Figure 2-7: Shares of Intangible and Tangible Investment in Gross Output in Four Divisions in China (2003-2016)

Source: Author's own estimates.

development of conventional "brick-and-mortar" industries like infrastructure and transportation. What is found in Chinese regions also delivers the same message: China is still a typically a manufacturing-oriented economy. It is too early to call China a "knowledge-based" economy.

Meanwhile, **Figure 2-8** displays the ratios of intangible to tangible investment in these four regions over time. It is shown that eastern regions outperform the rest of China in terms of intangible investment. By 2016, intangible investment in the eastern regions accounted for nearly half of tangible capital investment. In contrast, this ratio stayed below 20 percent in the other three regions. In addition, it is interesting that global financial crisis (GFC) is likely to serve as a watershed to further enlarging imbalanced intangible development among Chinese regions. The intangible-tangible investment ratio soared in the eastern regions after 2010 whilst it kept quite stagnant in the other three regions. Western provinces even saw a ratio lower than before the crisis. It seems that after the GFC, eastern regions have started to implement the economic transformation, orienting toward a more knowledge-based economy, while other areas still lack of incentives for economic transition. Given this trend, imbalanced regional development in China is likely to continue in the context of intangible economy.

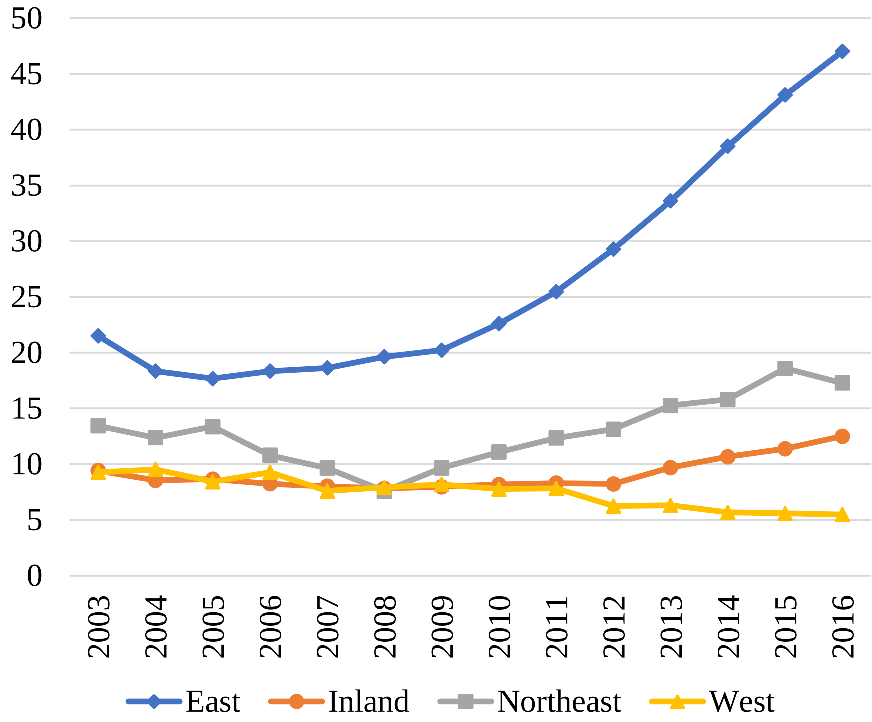


Figure 2-8: Ratios of Intangible to Tangible Investment in Four Divisions in China (%)

Source: Author’s own work.

Finally, in more detail, **Figure 2-9** displays the intangible investment in percentage of provincial GDP across Chinese regions in 2016. According to **Figure 2-8**, intangible investment is relatively highly concentrated in eastern provinces and cities, especially in a few of the most developed places. Beijing and Shanghai, ranking as the first and second, far outperform the rest of the provinces in respect to intangible investment. However, there are also variations of intangible development within four divisions. For example, eastern provinces Hebei and Hainan, are less endowed with intangibles, while inland regions Shaanxi and Sichuan, are in the top-ten regions for intangible development. In addition, according to **Figure 2-9**, intangible concentration in specific places is mainly driven by the centralisation of computer software development. The investment in top ten regions in **Figure 2-9** amounted to 86 percent of total investment in computer software, and Beijing alone accounts for 14 percent of the total.

2.5 Conclusion

This chapter briefly reviewed the theories of intangible capitalisation and the impacts of intangible capitalisation on national income accounts. Intangible capitalisation conceptually originates from the optimal growth theory, and can expand national income by adding intangible capital input on the supply side and intangible investment flows on the demand side. Following the CHS framework, nine types of business intangible capital in China are grouped into three broad categories: computerised information, innovative property, and economic competency. Data sources, price deflators and depreciation rates were discussed in detail. In addition, intangible investment and its capital stock are measured both at China’s national and regional level, and capital stock estimates are reported in **Table 2A-1** in the appendix.

In general, although substantial efforts in intangible investment have been made during the last decade, China is still a manufacturing-based economy that relies heavily on tangible investment. Intangible capital accounts for a small proportion of China’s GDP compared with tangible capital investment. Second, intangible investment is unevenly distributed among different intangible assets. Computerised software, architecture designs, and scientific R&D enjoyed faster development than the other assets. However, since computer software and architecture designs are tied tightly with the development of IT and residential infrastructure, both items would be excluded to give what is argued to be a more prudent estimation. In addition, economic competencies are far less endowed in China compared with developed economies, and its share in the total intangible investment still seems to be declining. Since economic competencies are regarded as enterprise’s strong growth force in the long run, the lack of investment in this item may hamper the competitiveness of Chinese enterprises in the future.

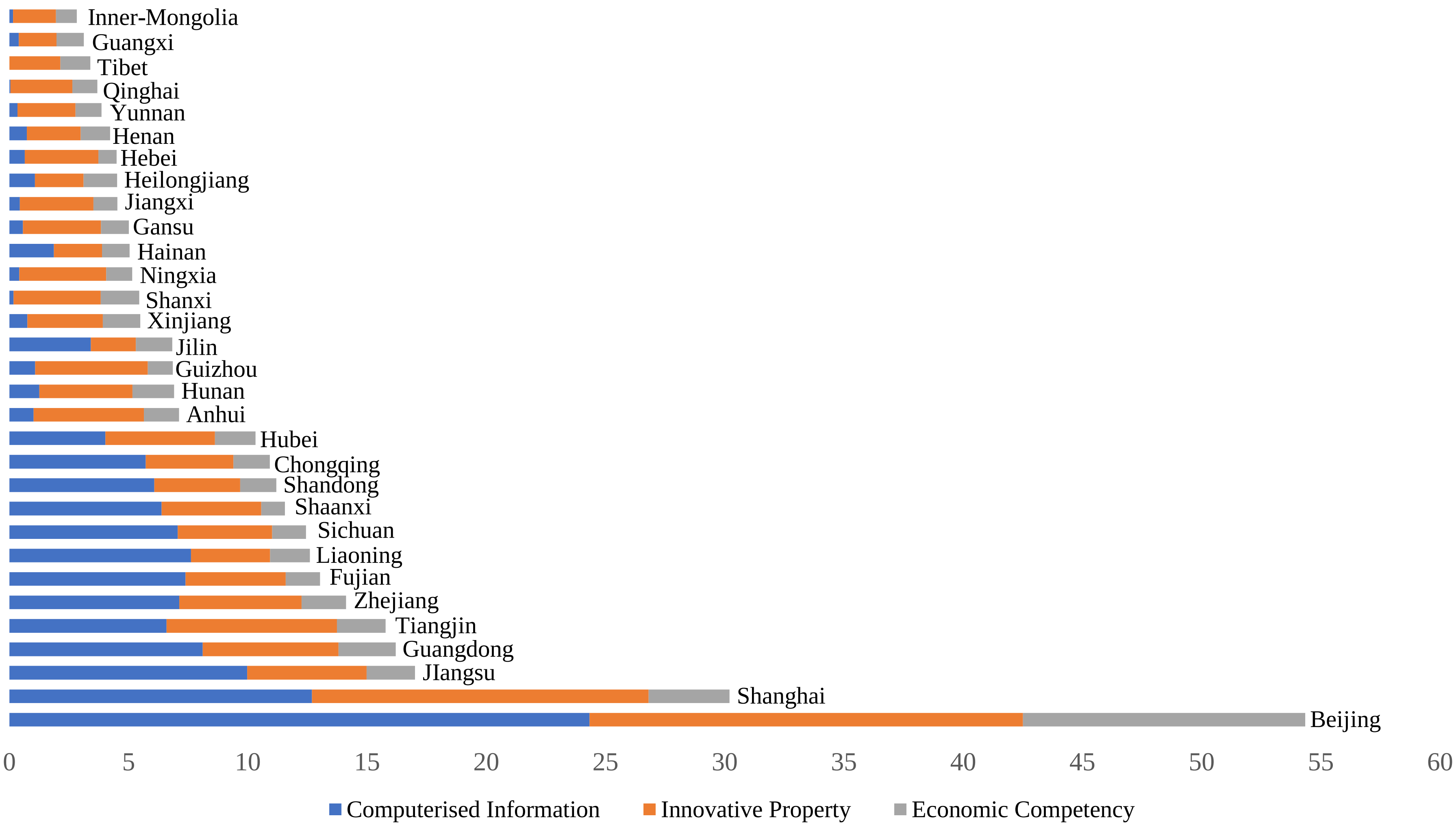


Figure 2-9: Intangible Investment in China's Provincial GDP in 2016 (%)

Source: Author's own work.

In terms of regional development, eastern regions are found to dominate intangible investment. This unbalanced intangible development was further enlarged after the GFC: eastern regions’ intangible investment accelerated whilst that in the rest of the country remained quite stagnant. Currently, intangible investment is highly centralised in a few of the most developed eastern regions such as Beijing and Shanghai. The driving force of this concentration is likely to be the extremely unbalanced development of computer software investment. It can be expected that if this trend remains, unequal regional development in China will be severe in an intangible-abundant economy.

APPENDIX A2

Table A2-1 Intangible Capital Stock in Chinese Regions (2003-2016)

Region	Year	K0	K1	K2	K3	K4	K5	K6	K7	K8	K9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
BJ	2003	3377	1009	1202	9	58	179	503	242	58	117
	2004	4018	1296	1346	12	59	200	638	261	68	137
	2005	5069	1867	1527	12	60	249	828	272	84	169
	2006	6085	2330	1718	12	59	277	1071	299	106	212
	2007	7244	2905	1920	20	59	294	1347	337	120	241
	2008	8407	3449	2111	23	60	325	1667	365	136	271
	2009	9917	4217	2393	21	60	367	2000	383	159	317
	2010	12220	5156	2736	25	61	422	2837	450	177	355
	2011	14803	6184	3068	27	65	481	3747	651	194	387
	2012	18462	7437	3432	30	72	546	5029	1278	212	425
	2013	22070	8768	3805	33	76	611	6569	1497	237	474
	2014	25565	10243	4174	36	83	695	7924	1632	259	519
	2015	29887	11923	4560	31	94	795	8902	2606	325	650
	2016	34153	13991	4902	28	104	885	9531	3620	364	728
TJ	2003	714	70	146	62	52	37	230	40	25	51
	2004	835	97	183	73	51	42	258	46	28	56
	2005	1004	175	227	73	49	50	286	53	30	61
	2006	1190	219	289	83	47	54	327	61	37	73
	2007	1337	209	357	97	45	60	383	70	38	76
	2008	1535	240	442	117	43	69	419	80	41	83
	2009	1849	324	540	133	45	86	477	90	52	103
	2010	2223	436	662	153	46	108	539	98	60	121
	2011	2645	594	812	129	46	136	616	111	67	134
	2012	3246	907	991	121	46	174	679	124	68	135
	2013	4098	1250	1201	104	47	218	882	153	81	161
	2014	5011	1666	1408	91	48	269	1079	179	90	180
	2015	6198	2066	1636	108	51	326	1381	269	120	241
	2016	7332	2509	1851	122	53	386	1679	319	138	276
HE	2003	562	16	141	18	41	99	110	10	42	84
	2004	642	23	167	28	43	101	126	11	48	96
	2005	751	35	202	48	47	103	146	10	53	106
	2006	904	41	251	93	51	105	160	10	64	129
	2007	1066	56	300	150	53	105	187	12	68	136
	2008	1221	72	353	178	55	109	215	13	76	151
	2009	1378	87	424	190	57	122	230	14	85	169
	2010	1645	180	495	184	57	140	276	12	101	201
	2011	1921	229	582	198	56	160	332	12	117	235
	2012	2133	271	696	204	59	187	397	9	104	207
	2013	2473	305	824	206	66	217	463	11	127	254
	2014	2807	342	964	203	74	264	515	7	146	291
	2015	3442	404	1132	194	81	316	689	8	206	412

Region	Year	K0	K1	K2	K3	K4	K5	K6	K7	K8	K9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	2016	4096	472	1296	185	90	375	992	7	226	452
SX	2003	297	3	71	4	67	33	40	4	25	50
	2004	345	4	88	7	67	35	47	6	31	61
	2005	416	5	104	15	70	42	56	12	37	74
	2006	507	8	128	26	69	45	69	16	48	97
	2007	579	11	161	32	71	46	81	18	53	107
	2008	667	15	194	38	69	48	96	23	61	122
	2009	796	20	244	48	69	64	114	24	71	141
	2010	929	31	285	56	70	82	134	25	82	164
	2011	1087	42	333	63	73	99	162	28	96	191
	2012	1213	56	391	71	77	121	222	31	81	162
	2013	1440	63	466	78	82	147	274	32	99	198
	2014	1818	64	529	86	88	181	514	32	108	217
	2015	2251	66	563	87	93	228	645	56	171	343
	2016	2550	67	594	89	95	272	758	63	204	408
IM	2003	178	20	21	3	47	6	38	3	13	27
	2004	225	46	28	8	43	8	41	3	16	32
	2005	254	43	38	13	40	15	46	4	18	37
	2006	307	38	51	33	38	19	51	5	24	48
	2007	392	43	68	78	36	24	56	6	27	54
	2008	520	47	89	162	32	29	59	8	31	62
	2009	672	46	126	228	31	42	70	10	40	80
	2010	800	51	164	258	29	58	82	11	49	99
	2011	937	53	211	292	27	75	93	12	58	116
	2012	1039	59	263	296	26	92	107	22	58	115
	2013	1195	65	323	304	26	111	120	26	73	147
	2014	1321	71	379	297	26	138	131	22	86	171
	2015	1522	76	446	295	27	171	139	33	112	223
	2016	1710	78	521	290	28	213	176	39	122	244
LN	2003	1053	180	400	21	58	57	119	36	61	121
	2004	1244	239	457	28	61	62	154	38	69	138
	2005	1538	391	514	32	61	72	193	46	76	153
	2006	1763	432	571	47	63	78	239	52	93	187
	2007	2053	514	644	58	64	80	333	46	105	209
	2008	2351	604	714	71	68	85	419	45	115	230
	2009	2913	887	818	81	74	106	495	45	135	271
	2010	3737	1369	942	97	77	129	587	49	163	325
	2011	4811	2075	1092	105	80	151	682	50	192	383
	2012	6046	3094	1231	112	81	182	779	74	164	328
	2013	7651	4305	1389	111	82	217	866	83	199	399
	2014	8993	5391	1508	107	85	267	922	87	209	418
	2015	10136	6235	1547	101	85	334	959	132	248	496
	2016	10012	5805	1676	104	89	416	1002	153	256	511
JL	2003	450	83	150	52	30	2	34	13	29	58
	2004	512	102	164	59	34	4	39	14	32	65

Region	Year	K0	K1	K2	K3	K4	K5	K6	K7	K8	K9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	2005	599	137	178	66	39	12	46	15	35	71
	2006	704	174	190	80	42	18	55	16	43	86
	2007	801	218	208	85	47	22	64	17	47	94
	2008	892	242	221	96	55	26	74	18	53	107
	2009	1050	299	262	101	63	33	91	21	60	120
	2010	1221	371	286	107	71	39	106	24	72	145
	2011	1408	457	312	117	79	45	130	26	81	161
	2012	1609	552	351	124	93	52	153	30	85	169
	2013	1841	670	390	124	102	60	169	31	98	196
	2014	2082	800	433	124	109	78	183	34	107	214
	2015	2507	954	483	119	118	100	194	58	160	321
	2016	2854	1134	523	113	123	124	202	65	190	380
	2003	455	82	103	144	34	8	8	18	20	39
	2004	501	93	121	147	33	10	11	18	22	45
	2005	580	115	149	152	33	11	18	19	28	56
	2006	664	131	180	158	33	14	26	19	34	69
	2007	732	143	213	154	33	18	34	20	39	78
	2008	811	153	256	150	33	24	43	20	44	88
HL	2009	951	169	322	154	34	34	57	21	53	106
	2010	1154	189	381	159	36	47	136	27	60	119
	2011	1318	210	424	161	37	60	199	31	66	131
	2012	1407	237	476	174	38	80	198	36	56	112
	2013	1597	266	538	171	39	100	220	39	75	149
	2014	1710	299	587	164	41	127	185	42	88	177
	2015	2057	338	631	170	43	162	208	68	145	290
	2016	2281	381	667	166	46	196	231	80	171	342
	2003	1892	252	493	6	150	241	296	196	86	172
	2004	2244	345	586	8	152	259	378	223	97	195
	2005	2834	645	697	9	154	273	469	259	109	219
	2006	3362	822	836	10	157	280	603	270	128	256
	2007	4005	1078	991	18	157	290	762	288	140	280
	2008	4697	1247	1156	16	160	317	1011	315	158	316
SH	2009	5588	1491	1363	22	165	372	1275	323	192	385
	2010	6433	1815	1572	33	170	432	1401	356	218	436
	2011	7749	2431	1836	35	177	498	1661	398	238	476
	2012	9604	3438	2141	38	187	566	2156	408	223	447
	2013	11623	4498	2478	41	198	644	2545	412	269	538
	2014	13597	5559	2824	45	205	744	2855	416	316	632
	2015	15731	6785	3175	54	211	877	3103	431	365	730
	2016	19311	8020	3519	83	222	1008	4818	435	402	805
	2003	1962	195	608	8	137	219	408	91	99	198
	2004	2363	295	760	15	139	239	452	104	120	239
JS	2005	2977	625	927	20	142	251	498	103	137	274
	2006	3812	1071	1144	26	144	259	528	126	171	342
	2007	4647	1510	1395	23	148	277	574	135	195	391

Region	Year	K0	K1	K2	K3	K4	K5	K6	K7	K8	K9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	2008	5796	2066	1729	32	152	312	645	148	237	475
	2009	7241	2817	2132	39	159	358	746	171	273	547
	2010	9071	3838	2564	84	166	431	849	160	326	653
	2011	11302	5090	3048	88	175	513	1030	210	382	765
	2012	14084	6851	3645	91	184	613	1257	333	370	740
	2013	17913	8976	4298	92	194	728	1813	411	467	934
	2014	22006	11333	4970	92	205	884	2458	395	556	1112
	2015	26975	13992	5658	89	216	1049	3127	578	755	1511
	2016	31932	16971	6374	82	227	1217	3748	734	860	1719
ZJ	2003	1462	537	271	2	80	124	142	78	76	152
	2004	1779	648	356	3	83	145	184	88	91	182
	2005	2150	740	477	3	86	187	235	100	107	215
	2006	2607	833	638	3	90	217	301	112	137	275
	2007	2961	872	821	4	93	238	346	124	154	309
	2008	3497	965	1022	6	97	277	468	138	175	350
	2009	4157	1139	1247	7	105	351	557	150	200	400
	2010	4994	1402	1492	10	112	441	662	175	233	466
	2011	6034	1733	1753	11	121	529	916	200	257	515
	2012	7281	2364	2082	18	132	603	1182	215	228	457
	2013	9404	3265	2430	19	141	674	1774	260	281	561
	2014	12641	4317	2803	19	153	719	3375	277	326	651
	2015	15324	5634	3210	18	163	768	3823	385	441	882
	2016	17587	7015	3624	17	171	811	4029	424	499	997
AH	2003	471	20	119	9	48	83	88	22	27	55
	2004	539	27	143	12	51	80	106	24	33	65
	2005	630	36	171	16	53	76	128	25	42	83
	2006	757	53	209	19	55	72	159	27	55	110
	2007	868	70	250	23	55	67	192	30	60	120
	2008	1012	86	306	27	59	65	233	33	68	135
	2009	1225	104	390	31	64	76	272	42	82	164
	2010	1451	121	476	38	67	88	316	52	98	195
	2011	1693	135	578	44	72	103	378	62	107	215
	2012	1968	157	719	50	76	121	472	72	100	201
	2013	2392	192	893	55	81	143	593	80	118	237
	2014	2861	255	1073	56	87	180	711	93	136	271
	2015	3523	357	1262	55	91	224	804	147	194	388
	2016	4281	476	1446	49	95	271	1125	165	218	437
FJ	2003	569	86	143	2	51	112	55	28	30	61
	2004	668	120	169	2	50	118	68	32	36	72
	2005	841	236	198	4	48	113	84	37	40	81
	2006	1017	323	237	6	46	109	103	42	50	100
	2007	1230	434	281	7	45	108	134	48	58	115
	2008	1426	503	333	11	44	115	164	54	68	135
	2009	1804	709	410	13	44	133	185	72	80	159
	2010	2360	1047	499	14	44	160	219	86	97	195

Region	Year	K0	K1	K2	K3	K4	K5	K6	K7	K8	K9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	2011	3059	1456	608	15	45	184	302	99	117	233
	2012	3802	1916	740	18	47	213	423	108	113	225
	2013	4603	2228	886	20	49	246	639	122	138	276
	2014	5589	2901	1041	20	51	290	694	135	153	305
	2015	7029	3661	1203	19	52	342	967	187	199	399
	2016	8541	4479	1382	18	54	392	1336	207	224	448
JX	2003	332	26	66	1	51	78	43	13	18	35
	2004	361	34	81	2	51	71	47	15	20	40
	2005	406	49	101	3	51	65	54	17	22	43
	2006	458	62	125	4	50	58	59	20	27	53
	2007	508	76	155	6	50	52	63	21	29	57
	2008	570	86	190	9	50	47	65	24	33	66
	2009	661	95	234	13	51	49	77	25	39	77
	2010	778	103	275	21	52	56	112	27	44	89
	2011	897	114	308	28	53	67	151	30	49	98
	2012	1009	124	350	33	54	80	193	32	48	96
	2013	1192	139	402	36	58	95	248	34	60	121
	2014	1402	158	460	38	63	122	301	34	75	151
	2015	1741	180	529	38	68	155	424	42	102	203
	2016	2083	196	613	37	73	191	581	43	116	233
SD	2003	2078	473	750	41	128	250	118	60	86	173
	2004	2316	573	774	64	130	254	144	63	105	210
	2005	2561	656	844	82	128	251	176	67	119	237
	2006	2813	672	935	99	125	246	221	74	147	294
	2007	3119	749	1085	88	123	244	261	74	165	330
	2008	3668	865	1304	112	123	254	322	75	204	409
	2009	4463	1162	1577	135	124	272	415	77	234	468
	2010	5688	1643	1934	156	126	311	516	83	306	612
	2011	7105	2317	2356	182	132	357	649	102	336	673
	2012	8613	3089	2857	210	139	413	808	142	318	636
	2013	10665	4100	3398	227	148	479	985	179	383	766
	2014	13084	5528	3965	230	161	520	1167	227	429	857
	2015	16427	7135	4562	231	172	617	1607	397	569	1138
	2016	19216	8721	5169	224	181	719	1835	512	618	1236
HA	2003	569	5	132	38	96	52	90	23	44	88
	2004	654	10	160	51	94	56	109	25	50	100
	2005	754	26	194	56	92	64	129	26	55	111
	2006	899	54	248	57	93	69	150	26	67	134
	2007	1042	99	310	52	91	73	179	26	71	142
	2008	1229	143	374	62	90	79	224	27	77	154
	2009	1491	188	483	85	90	96	255	33	87	174
	2010	1785	233	598	105	90	125	306	33	98	197
	2011	2096	276	732	128	91	158	332	34	115	231
	2012	2444	329	884	162	95	193	369	60	117	234
	2013	2953	399	1050	180	100	233	498	82	137	273

Region	Year	K0	K1	K2	K3	K4	K5	K6	K7	K8	K9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	2014	3475	483	1227	180	104	287	609	104	160	321
	2015	4149	587	1411	168	109	366	693	181	212	424
	2016	4740	675	1612	152	113	444	771	251	240	480
HB	2003	873	62	205	4	103	159	211	20	36	73
	2004	1008	101	238	8	104	160	250	21	42	84
	2005	1140	125	285	11	104	142	299	26	49	98
	2006	1299	136	345	15	105	129	357	26	62	123
	2007	1482	163	405	14	107	124	429	29	71	141
	2008	1730	218	485	21	110	123	502	31	80	159
	2009	2126	287	617	27	116	131	616	34	99	198
	2010	2579	357	758	35	124	144	744	29	129	259
	2011	3024	415	905	45	129	158	886	44	148	295
	2012	3559	607	1074	48	138	181	1042	53	139	278
	2013	4687	1042	1259	57	144	211	1389	70	171	342
	2014	5608	1461	1463	62	151	254	1526	96	198	397
	2015	6676	1893	1676	59	158	318	1663	166	248	496
	2016	7946	2463	1869	57	158	395	1940	242	274	548
HN	2003	613	60	112	5	131	103	75	10	39	78
	2004	679	74	139	6	127	100	89	12	44	88
	2005	777	120	167	7	124	94	106	19	46	93
	2006	877	152	199	10	119	91	116	28	54	108
	2007	969	176	244	12	114	86	131	32	59	117
	2008	1134	213	315	14	110	84	158	39	67	134
	2009	1393	285	416	16	109	94	200	20	84	168
	2010	1746	353	520	18	111	107	248	48	114	228
	2011	2153	433	630	22	114	118	300	80	152	304
	2012	2396	505	766	27	117	130	343	98	136	273
	2013	2839	565	907	35	124	148	397	120	181	362
	2014	3206	645	1056	36	134	177	453	145	187	373
	2015	4093	739	1220	35	147	211	715	251	258	516
	2016	5053	845	1399	33	159	248	1138	314	306	611
GD	2003	2724	784	658	37	221	96	349	215	122	243
	2004	3187	926	777	46	221	120	430	232	145	289
	2005	3710	1079	899	55	217	164	528	252	172	344
	2006	4514	1357	1065	67	218	204	675	263	221	443
	2007	5369	1664	1282	76	217	262	849	270	250	499
	2008	6337	1984	1536	97	217	334	1027	282	287	574
	2009	7785	2625	1906	144	221	417	1207	279	328	657
	2010	9438	3316	2333	171	222	517	1496	263	373	746
	2011	11901	4481	2861	142	225	605	2011	323	417	835
	2012	14682	5919	3475	119	228	694	2610	394	415	829
	2013	17757	7333	4152	102	230	806	3290	379	488	977
	2014	21866	9120	4837	87	223	934	4439	525	567	1134
	2015	26706	11260	5577	165	225	1124	5260	844	751	1502
	2016	31293	13542	6332	162	222	1288	6105	1068	858	1716

Region	Year	K0	K1	K2	K3	K4	K5	K6	K7	K8	K9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
GX	2003	236	7	40	7	56	20	24	12	23	46
	2004	261	10	48	8	56	23	29	12	25	50
	2005	295	18	56	9	57	29	34	13	27	53
	2006	341	26	67	10	56	32	38	14	32	64
	2007	383	40	78	12	58	34	45	12	35	70
	2008	436	52	97	14	60	39	53	11	37	74
	2009	535	74	128	16	64	54	65	8	42	84
	2010	678	76	166	19	66	70	79	7	65	131
	2011	804	91	207	22	67	84	92	6	78	157
	2012	884	116	255	26	70	103	105	9	66	132
	2013	1070	148	302	30	77	127	121	17	83	166
	2014	1225	169	344	31	86	157	137	19	94	188
	2015	1523	183	372	30	88	190	158	45	152	304
	2016	1698	191	404	27	91	223	187	63	171	341
HI	2003	99	3	6	0	21	37	6	3	8	15
	2004	102	3	8	0	22	33	8	3	8	17
	2005	105	4	8	0	22	28	10	3	10	20
	2006	109	4	9	0	22	24	13	4	11	22
	2007	112	5	10	2	23	20	17	4	10	21
	2008	121	7	12	4	24	18	21	4	11	21
	2009	137	7	16	6	25	19	25	5	12	24
	2010	163	8	19	13	25	20	31	5	14	27
	2011	190	11	25	16	25	23	38	8	14	29
	2012	229	22	32	21	26	26	45	11	15	31
	2013	258	29	39	22	26	30	52	11	17	33
	2014	301	35	46	35	26	37	59	8	19	38
	2015	383	62	51	32	26	44	70	10	29	59
	2016	476	112	60	28	25	52	83	10	35	70
CQ	2003	431	66	77	2	32	35	133	25	20	40
	2004	502	82	92	10	34	38	149	27	23	47
	2005	597	118	110	21	35	40	164	29	27	53
	2006	693	147	130	25	37	40	186	30	32	65
	2007	785	172	156	24	39	39	215	31	37	73
	2008	869	186	186	23	41	43	235	31	41	82
	2009	1007	207	231	23	44	60	270	33	46	93
	2010	1211	271	285	19	46	82	316	29	54	108
	2011	1527	414	346	24	49	111	368	32	61	122
	2012	1933	663	424	23	52	147	424	34	56	111
	2013	2440	937	501	28	54	185	480	43	70	141
	2014	3057	1274	586	31	57	225	559	52	91	182
	2015	3847	1641	696	40	59	270	636	85	140	279
	2016	4607	2061	830	44	59	318	699	103	164	328
SC	2003	1000	55	329	12	125	114	191	19	52	103
	2004	1130	80	361	28	122	117	220	22	60	120
	2005	1307	128	407	50	121	122	258	29	64	129

Region	Year	K0	K1	K2	K3	K4	K5	K6	K7	K8	K9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	2006	1536	198	453	74	119	123	303	35	77	155
	2007	2056	385	517	266	116	119	353	43	85	171
	2008	2472	612	580	301	114	123	398	49	98	196
	2009	2953	839	690	315	110	133	471	55	113	227
	2010	3624	1157	816	342	108	152	574	61	138	277
	2011	4512	1710	929	365	107	178	691	68	155	310
	2012	5408	2324	1070	389	107	226	782	86	141	283
	2013	6452	2988	1227	397	108	282	864	95	163	326
	2014	8057	3694	1400	389	109	343	1485	101	179	358
	2015	9343	4417	1599	359	112	419	1495	156	262	524
	2016	10708	5179	1806	337	115	512	1641	180	313	626
GZ	2003	150	1	36	4	20	17	18	0	18	35
	2004	169	3	40	6	21	19	22	1	19	38
	2005	208	15	46	8	20	23	28	5	21	42
	2006	240	17	55	11	21	25	34	7	23	46
	2007	264	24	59	14	20	27	39	8	24	48
	2008	301	28	67	16	21	29	45	15	26	53
	2009	360	42	81	20	22	36	54	11	31	62
	2010	454	64	95	26	22	45	84	9	36	72
	2011	560	91	110	34	22	55	115	9	41	82
	2012	649	118	124	41	22	66	147	12	39	79
	2013	776	145	139	50	22	78	184	7	50	101
	2014	908	178	156	54	23	90	225	4	59	119
	2015	1340	222	174	54	24	105	454	4	101	202
	2016	1729	269	196	48	24	121	692	4	125	250
YN	2003	282	38	40	18	32	31	44	12	22	44
	2004	328	47	48	26	33	34	52	13	25	50
	2005	399	61	64	37	34	41	63	15	28	56
	2006	478	64	75	66	36	45	75	17	34	67
	2007	503	64	88	58	37	45	87	17	36	71
	2008	553	68	102	57	38	49	99	18	41	81
	2009	632	72	120	59	39	62	120	20	46	92
	2010	760	90	140	67	42	76	164	21	53	107
	2011	881	105	164	73	45	90	196	25	61	122
	2012	964	122	193	79	48	105	225	30	54	108
	2013	1107	133	225	85	51	126	258	32	66	132
	2014	1228	132	255	86	53	153	294	33	74	147
	2015	1459	130	302	81	58	183	332	53	107	213
	2016	1644	134	361	74	59	214	380	59	121	241
XZ	2003	39	0	1	1	1	3	32	1	0	0
	2004	41	0	1	2	1	4	27	1	1	3
	2005	40	0	1	3	2	4	23	2	2	4
	2006	39	0	2	4	2	3	19	2	3	5
	2007	37	0	2	4	2	3	16	2	3	5
	2008	42	0	3	8	2	3	13	4	3	6

Region	Year	K0	K1	K2	K3	K4	K5	K6	K7	K8	K9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	2009	44	0	4	10	2	4	11	3	3	6
	2010	52	0	4	16	3	5	10	2	4	8
	2011	59	0	5	22	3	6	8	2	4	9
	2012	61	0	5	26	3	7	7	2	4	7
	2013	71	0	6	30	3	8	5	2	5	10
	2014	79	0	7	33	4	10	4	2	6	12
	2015	120	0	8	33	4	12	7	8	16	32
	2016	136	0	9	34	4	15	10	8	19	37
	2003	893	17	417	100	73	9	165	20	31	61
	2004	983	38	450	100	73	12	193	14	34	68
	2005	1225	215	479	102	71	21	224	8	35	70
	2006	1372	281	507	106	69	26	253	6	41	83
	2007	1490	293	547	107	68	32	301	5	46	92
	2008	1650	334	590	113	69	38	355	4	49	98
SN	2009	1980	411	677	157	72	54	417	10	61	121
	2010	2388	525	759	222	74	69	496	15	76	152
	2011	2758	674	837	244	75	83	559	18	89	179
	2012	3148	881	928	301	79	101	621	17	74	148
	2013	3735	1184	1048	319	82	122	691	16	91	182
	2014	4383	1548	1167	336	85	156	765	13	104	208
	2015	5295	2026	1307	336	89	196	868	16	153	305
	2016	6027	2478	1443	315	91	234	922	15	176	352
	2003	317	4	54	28	22	55	90	5	19	38
	2004	344	5	62	39	23	51	92	5	22	45
	2005	372	11	74	48	24	45	94	4	24	47
	2006	417	17	88	56	25	41	101	4	29	57
	2007	440	24	99	62	26	36	99	4	30	60
	2008	473	30	113	74	26	33	98	4	32	63
GS	2009	527	36	131	89	27	33	104	5	34	69
	2010	563	43	147	91	28	33	107	6	36	73
	2011	619	48	162	112	29	36	115	7	37	74
	2012	663	51	186	126	31	40	125	8	32	64
	2013	757	57	210	150	32	47	142	5	38	76
	2014	848	63	238	168	34	61	151	3	43	86
	2015	994	76	274	170	37	79	168	3	62	124
	2016	1126	91	307	167	40	99	209	3	70	140
	2003	82	0	18	33	2	10	4	1	4	9
	2004	87	0	19	36	2	10	5	1	5	9
	2005	92	0	19	38	2	11	7	1	5	9
	2006	101	0	19	43	2	10	8	2	6	11
QH	2007	111	0	20	49	2	10	9	2	6	12
	2008	121	0	20	55	2	10	12	2	6	12
	2009	138	0	24	59	3	11	15	3	8	16
	2010	160	0	29	69	3	13	16	3	9	18
	2011	196	0	35	90	3	14	19	3	11	21

Region	Year	K0	K1	K2	K3	K4	K5	K6	K7	K8	K9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	2012	230	0	40	118	4	16	21	4	9	18
	2013	257	0	44	132	4	19	25	4	10	20
	2014	282	0	48	137	4	26	28	6	11	22
	2015	311	0	50	131	5	35	34	11	16	31
	2016	335	0	53	126	5	44	39	14	18	36
	2003	51	5	13	0	5	6	7	1	5	10
	2004	60	5	15	1	5	7	8	2	6	12
	2005	72	5	17	3	5	10	10	2	6	13
	2006	87	5	21	7	6	11	13	3	8	15
	2007	98	5	26	9	5	12	15	3	8	15
	2008	113	4	29	13	6	13	17	3	9	18
NX	2009	131	5	35	17	6	16	19	2	10	20
	2010	156	8	39	22	7	20	23	3	12	23
	2011	187	10	45	28	8	24	27	3	14	28
	2012	204	13	53	26	10	30	33	3	12	25
	2013	243	16	61	29	12	36	39	3	16	31
	2014	274	19	70	32	13	43	38	3	18	36
	2015	404	23	80	35	16	51	103	5	30	60
	2016	477	28	92	72	18	59	94	5	36	73
	2003	533	14	17	340	29	28	33	13	19	39
	2004	583	19	22	368	29	30	38	14	21	43
	2005	613	22	25	378	28	33	44	13	23	46
	2006	673	22	30	424	27	35	49	14	24	48
	2007	700	23	36	430	27	37	56	14	26	51
	2008	764	31	46	464	26	40	65	15	26	52
XJ	2009	879	38	62	518	28	46	78	12	32	65
	2010	1011	45	76	598	27	53	94	11	36	72
	2011	1133	57	91	654	27	60	113	12	39	78
	2012	1242	71	109	708	29	71	144	9	34	67
	2013	1410	93	128	750	32	83	177	17	43	87
	2014	1581	108	147	784	36	99	229	19	53	105
	2015	1799	115	168	793	51	117	249	40	89	177
	2016	1937	146	191	759	61	134	265	59	108	215
	2003	26911	4302	7043	1146	3028	2436	4031	1266	1219	2439
	2004	31227	5472	8273	1337	3070	2599	4801	1384	1430	2861
	2005	37214	7840	9781	1514	3123	2833	5760	1527	1612	3224
	2006	43406	9814	11557	1827	3168	2967	6916	1676	1827	3654
	2007	50567	12141	13522	2179	3198	3083	8233	1799	2138	4275
China	2008	58842	14653	15752	2530	3257	3345	9776	1924	2535	5071
	2009	70131	18761	18808	2912	3356	3897	11486	2010	2967	5934
	2010	84763	24349	22109	3353	3442	4608	13962	2183	3586	7172
	2011	102402	31898	25721	3717	3538	5339	17142	2700	4116	8231
	2012	122323	42069	29875	4144	3671	6170	21013	3755	3875	7751
	2013	148321	53805	34363	4385	3810	7105	26265	4288	4767	9533
	2014	176942	67394	38892	4495	3958	8264	32905	4762	5424	10848

Region	Year	K0	K1	K2	K3	K4	K5	K6	K7	K8	K9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	2015	211486	82443	43410	4402	4100	9680	38078	7401	7324	14647
	2016	246128	97611	48044	4180	4224	11105	44621	9898	8815	17630

Source: Author's own work.

*Notes:*1. Numbers in Columns (2) - (11) are in 10thousand renminbin (RMB). K0 denotes "total intangible investment", K1 "computer software", K2 "scientific R&D", K3 "mineral exploration", K4 "copyright and licenses", K5 "financial products and services", K6 "architecture and designs", K7 "advertising", K8 "training", K9 "organisation structure". 2. Names of Chinese regions are abbreviated for simplicity. Sorted by initials, AH denotes "Anhui", BJ "Beijing", CQ "Chongqing", FJ "Fujian", GS "Gansu", GD "Guangdong", GX "Guangxi", GZ "Guizhou", HI "Hainan", HE "Hebei", HA "Henan", HL "Heilongjiang", HB "Hubei", HN "Hunan", JL "Jilin", JS "Jiangsu", JX "Jiangxi", LN "Liaoning", IM "Inner-Mongolia", NX "Ningxia", QH "Qinghai", SD "Shandong", SX "Shanxi", SN "Shaanxi", SH "Shanhai", SC "Sichuan", TJ "Tianjin", XZ "Tibet", XJ "Xinjiang", YN "Yunnan", ZJ "Zhejiang". 3. The estimates are based on the latest released data with slight adjustment, so the estimates are slightly different from the previous work of Li and Wu (2018).

CHAPTER 3 - INTANGIBLE CAPITAL AND ECONOMIC GROWTH

3.1 Introduction

In the SOG models, economic growth is assumed to be driven by two general factors, namely, capital formation and TFP (Jorgenson & Griliches, 1967; Solow, 1956, 1957). According to Krugman (1994), if a high rate of output growth is achieved mainly through capital formation, growth will finally slow down because of diminishing marginal returns to capital. This is nicknamed "perspiration" growth; If the fast development of an economy is driven by improvements in TFP, the high rate of growth would expect to sustain in the long run. It is nicknamed "inspiration" growth. However, this perspiration-inspiration growth dichotomy is incomplete without taking intangibles into account: the contributions of intangible capital to economic growth in traditional SOG models will be hided in the contributions of capital formation and TFP (Corrado et al., 2005). As a result, the omission of intangible capital in the SOG model will always exaggerate the impacts of TFP and underestimate the impacts of capital formation on economic growth (Corrado et al., 2006).

The miracle economic performance in China triggers the intensive discussion of the perspiration-inspiration dichotomy: whether the fast development will continue for the next few decades or whether it will eventually slow down (Fogel, 2006; Holz, 2008; Wu, 2000). Therefore, the relative importance of the role TFP and capital formation has in China's economic growth is always a debatable issue (Islam et al., 2006). Whether TFP is the main driver of China's economic growth has no consensus yet (Wu, 2014; Zhu, 2012). In addition, it is argued that aggregate measures of TFP may fail to provide adequate evidence in China due to the heterogeneities across regions and sectors. Market distortion and factor misallocation and immobility may be responsible for the poor performance of the aggregate TFP in China's economic growth (Brandt et al., 2013; Brandt et al., 2012; Ding et al., 2016; Hsieh & Klenow, 2009).

Following the trend of global economy, China is transforming into an innovation-driven economy, in which more emphasis will be put on knowledge and intelligence. Up to now, limited information can be found in China in terms of the source of growth analysis with intangibles being considered. Therefore, this study aims to fill this knowledge gap by providing growth accounting analysis in China with the involvement of intangible capital. The analysis is conducted at China's national level as well as China's regional level during 2003-2016. The national-level analysis depicts a general picture of the impacts of intangibles on China's economic growth. It provides results that are comparable with those from advanced economies. In general, the involvement of intangible capital accelerates labour productivity growth significantly, but the relative contribution of intangibles is not as large as that in developed countries. TFP still plays its role but the impacts are shrinking after the involvement of intangible capital.

In terms of regional growth accounting analysis, thirty-one provinces, municipalities, and cities are grouped into two broad regions, the coastal and the interior, corresponding to different geographical characteristics and levels of economic development.[28] By conducting regional growth accounting exercises, we can understand the imbalanced development of intangibles and its different impacts on regional economies, and thus derive practical policy implications corresponding to different regional growth patterns. In both regions, growth accounting exercises show higher labour productivity growth when intangibles are considered, together with a larger effect of capital deepening. By comparison, coastal regions tend to benefit more from intangible capital thanks to its advancement in computerisation development.

In addition, the study distinguishes intangible capital from human capital in the growth accounting analysis. Specifically, we split knowledge-based intangible input factors into the

[28] The coastal regions include Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The interior regions include Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

following components: 1) knowledge embodied in intangible products or business processes that can gain future profits to their owners i.e. enterprises or institutions, such as scientific R&D, patents, licenses, artistic originals, and so on (CHS's business intangible capital); 2) knowledge embodied in labour force (employment) that has private returns to individuals, namely, human capital; 3) knowledge disembodied, in form of technological progress, such as serendipity inspiration, and costless innovation diffusion (Władysław Welfe, 2007; Zéghal & Maaloul, 2011). Previous studies of intangibles largely ignored the impacts of human capital when growth accounting analysis is performed. Instead, they simply used working hours / head counts (workers) as proxies for labour input (Corrado et al., 2009; Roth & Thum, 2013, as two examples). By adding human capital, we can capture the impacts of quality changes in labour input on economic growth. Human capital and intangible capital are found to have orthogonal independent contributions to economic growth in China.

The rest of this chapter is organized as follows. Section 3.2 reviews the literature of intangible capital and economic growth. Section 3.3 introduces the growth accounting method with intangible capital as a new input. Section 3.4 reports the empirical results at China's national and regional level. Section 3.5 conducts a set of sensitivity analysis to check results' robustness. Section 3.6 concludes the chapter.

3.2 Literature Review

Economic theory has not completely discarded the importance of intangible capital. The impact of individual intangible capital on economic and/or productivity growth has been discussed extensively. As the most-known intangible capital, scientific R&D, for example, has been demonstrated theoretically and empirically as a growth engine for economic development (Aghion & Howitt, 1992; Griliches, 1992; Grossman & Helpman, 1993; Jones & Williams, 1997). A vast of studies claimed that scientific R&D is the fundamental driving force for economic growth because it can stimulate innovations (Baumann & Kritikos, 2016; Gkypali et al., 2017; Hsu et al., 2015;

Raymond & St-Pierre, 2010; Raymond et al., 2015), improve input efficiencies (Chen et al., 2015; Guellec & van Pottelsberghe, 2001; Khan & Luintel, 2006; Lee, 2016), and create knowledge spill-overs and transfer technologies (Coe & Helpman, 1995; Griffith et al., 2004; Griliches, 1992; Park, 1995).

Organisation capital, as another individual intangible capital, has also been investigated to have positive impacts on economic growth and firm productivity growth. It is examined that organisation development will create new knowledge that can be transformed into new skills in forms of human capital to promote output growth (Schultz, 1972). Through improvements in qualities of traditional inputs, organisation capital is posited as an explanation for some of the growth in productivity, which cannot be explained by additional amounts of capital and labour inputs (Griliches, 1963; Tomer, 1981). Evidence of the positive relationship between organisation capital and growth is also abundant at the firm level. For example, it is argued that organisation capital is the only competitive asset truly owned by the firm (Lev & Radhakrishnan, 2003, 2005; Teece, 1998; Youndt et al., 2004). Advanced organisation is shown to have strong effects on firm performance, while poor organisation structure might hamper a firm's output and productivity very significantly (Kaplan et al., 2004; Tronconi & Vittucci Marzetti, 2011; Webster & Jensen, 2006).

In addition, it is demonstrated that other individual intangible capital can affect output and/or labour productivity growth. For instance, brands are suggested to positively affect firm labour productivity growth, since an important aspect of today's products is the "image" attached to them (Roth & Thum, 2010). Popular brands generated by huge advertising investment are more attractive to customers, thus allow enterprises to obtain a higher margin for products or services than their competitors who sell similar things (Canibano et al., 2000; Joshi & Hanssens, 2010; Shah et al., 2013; Shah et al., 2009). In addition, other firm-specific intangible resources like market research and employee capabilities are also seen to have positive impacts on firm productivity growth and output performance (Abowd et al., 2005; Hart & Diamantopoulos, 1993; Tomczyk et al., 2016).

Analysis from univariate dimension is far from being enough for understanding the importance of intangible capital in economic growth. Meanwhile, univariate dimension measurement constrains studies mostly by focusing only at the micro level. For the revision of the national accounting framework, CHS generated a wider concept, largely improved the overall measurement of different dimensions of intangible capital, and hence promoted studies of intangible capital and economic/productivity growth especially at macro levels. With aggregate measures, it is clearly observed that intangible investment is positively associated with a nation's economic development level (**Figure 3-1**), that is, advanced economies with higher income levels tend to invest more in intangibles, and vice versa (Roth & Thum, 2013; van Ark et al., 2009). In addition, the contribution of intangible capital on labour productivity is examined to be remarkable across the globe (for exmple Corrado et al., 2009 for the United States; Edquist, 2009 for Sweden; Fukao et al., 2009 for Japan; Jalava et al., 2007 for Finland; van Ark et al., 2009 for multiple EU countries, to cite a few). With intangibles being considered, capital formation becomes the unambiguously dominant source of growth whilst the impacts of TFP are diminished correspondingly. Furthermore, the positive effects of intangibles on productivity growth are also found at the industry level. It is shown that intangible capital contributes to labour productivity growth disproportionally in different industries, and becomes a key driver in productivity growth in some more intangible-intensive industries (for example Borgo et al., 2013 for the United Kingdom; Chun et al., 2015 for Japan and Korea; Miyagawa & Hisa, 2013 for Japan, to cite a few).

Followed the CHS framework, Hulten and Hao (2012) found that around one-sixth of the growth in output per worker is attributed to intangible development in China in the years 2000 to 2008. However, the relative contributions of intangible capital are the smallest in China compared with that in other developed countries. China is assumed to be continually relying on tangible capital growth because of its emphasis on manufacturing production (Hulten & Hao, 2012). Their conclusion is largely supported by Tian et al. (2016, in Chinese), who analysed intangibles' impacts on China’s economic growth during 2001-2012. In their analysis, intangible capital showed a much larger contribution of one-third to China’s labour productivity growth.

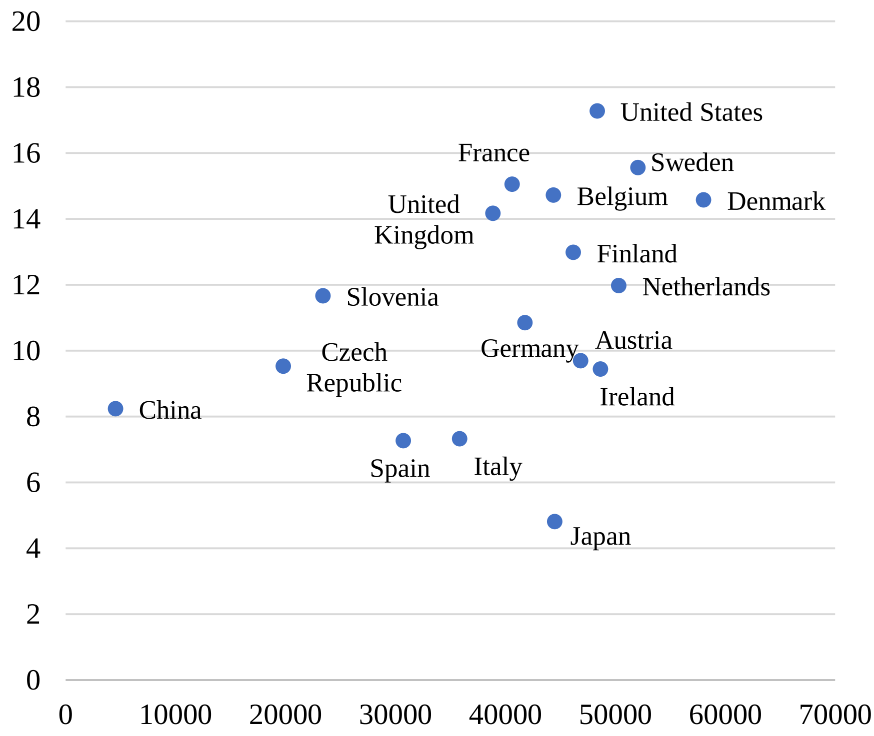


Figure 3-1: Intangible/GDP and GDP per capita in 2010 (constant 2010 US$)

Source: Author’s own work.
Note: Intangible investment in European countries and the United States is from INTAN-Invest Database; in Japan is from JIP database; in China is from our own estimates. GDP per capita is from the World Bank Database (2018).

However, due to data constraints, the above two studies of intangible capital are limited at China’s national level. **Figure 3-2** displays the ratio of intangible investment to regional GDP (hereafter GRP) against GRP per capita across Chinese 31 provinces, cities and municipalities in 2016, and demonstrates that intangible capital development varies markedly across Chinese regions. As a result, intangible capital may have different impacts on China’s regional economic development and/or regional labour productivity growth. However, because of data impediments, little information can be found about the relationship between intangible capital and economic growth at China’s regional level.

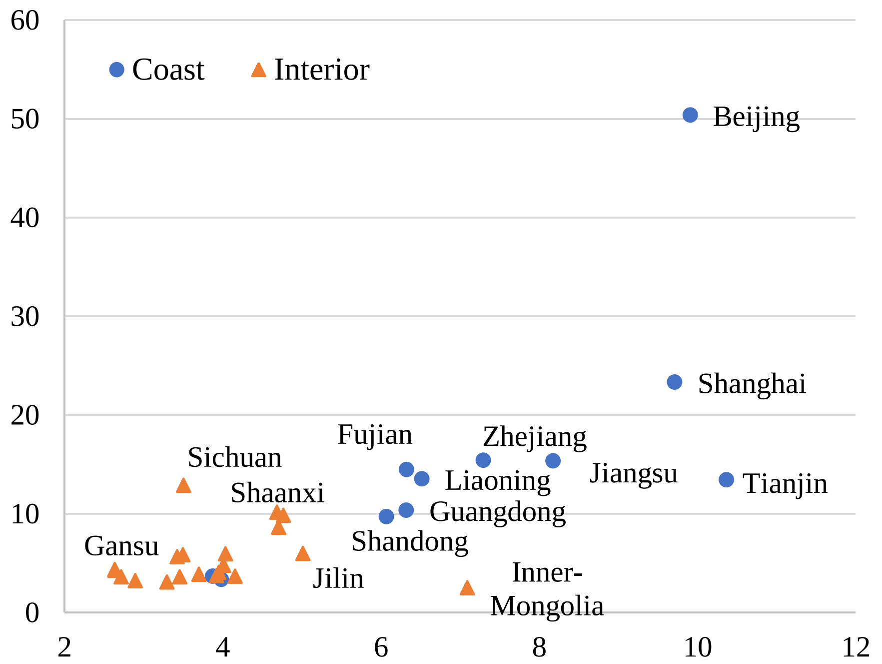


Figure 3-2: Intangible/GRP (%) and GRP per capita (1000RMB, 2010 price) in 2016

Source: Author's own work.

3.3 Growth Accounting Method

For simplicity, a Cobb-Douglas format is displayed for describing growth accounting exercise with intangible capital:

$$\mathrm{Y}_{i,t} = \mathrm{A}_{i,t}(\mathrm{K}^{T}_{i,t})^{\alpha}(\mathrm{K}^{I}_{i,t})^{\beta}(\mathrm{L}_{i,t}\mathrm{H}_{i,t})^{1-\alpha-\beta} \quad (3\text{-}1)$$

where $Y_{i,t}$ is the real GRP plus intangible investment of the i^{th} region in the year t, $K^{T}_{i,t}$ is the stock of tangible capital, $K^{I}_{i,t}$ is the stock of intangible capital, $L_{i,t}$ is the total employment, $H_{i,t}$ is human capital and $A_{i,t}$ is the TFP residual. α and β are output elasticity of tangible capital and intangible capital, respectively. Dividing (3-1) by total employment on both sides gives:

$$y_{i,t} = A_{i,t}\left(k^{T}_{i,t}\right)^{\alpha}(k^{I}_{i,t})^{\beta}(H_{i,t})^{1-\alpha-\beta} \quad (3\text{-}2)$$

where $y_{i,t}$, $k^T_{i,t}$, $k^I_{i,t}$ denotes labour and capital productivity. Equation (3-2) can be converted into the growth rate form:

$$g^y_{i,t} = g^A_{i,t} + \alpha g^{k^T}_{i,t} + \beta g^{k^I}_{i.t} + (1 - \alpha - \beta) g^H_{i,t} \tag{3-3}$$

where $g^x_{i,t} = \Delta ln x_{i,t}$ $(x = y, A, k^T, k^I, H)$. Equation (3-3) implies that labour productivity growth is decomposed into tangible capital deepening, intangible capital deepening, human capital deepening, and a residual TFP growth. The Tornqvist (1936) index is used for discrete time approximations. Under the assumption of constant returns to scale and competitive equilibrium, the output elasticity of tangible capital, intangible capital and human capital is equal to the corresponding income share (Hulten, 2010b). This income share $s^Z_{i,t}$ can be expressed in a general form of:

$$s^Z_{i,t} = (P^Z_{i,t} Z_{i,t} / P^{K^T}_{i,t} K^T_{i,t} + P^L_{i,t} L_{i,t} + P^{K^I}_{i,t} K^I_{i,t}) \tag{3-4}$$

where Z represents tangible capital, labour, and intangible capital, respectively. $s^Z_{i,t}$ indicates the share of an input factor of tangible capital ("$s^{K^T}_{i,t}$"), labour ("$s^L_{i,t}$"), and intangible capital ("$s^{K^I}_{i,t}$"). $P^L_{i,t}$ is the income accruing to per capita labour input which is estimated by wages and salaries. $P^{K^T}_{i,t}$ and $P^{K^I}_{i,t}$, known as "rental payments" of capital, are calculated by following Oulton & Srinivasan (2003), who in turn followed Jorgenson & Griliches (1967). Given these conditions, Equation (3-3) is thus converted into:

$$g^y_{i,t} = g^A_{i,t} + s^{K^T}_{i,t} g^{k^T}_{i,t} + s^{K^I}_{i,t} g^{k^I}_{i,t} + s^L_{i,t} g^H_{i,t} \tag{3-5}$$

The rental payment of capital is calculated by assuming that renting and buying one capital is the same for its owner, since the service that the capital provides for producing output is the same (Jorgensen & Griliches, 1967, Marrano & Haskel, 2006; Oulton & Srinivasan, 2003). The market-clearing rental payment for capital *j* (where *j* can be tangible or intangible capital), $P^R_{ij,t}$, can be derived as:

$$P^R_{ij,t} = T_{i,t}(R_{ij,t}(r_{i,t} + \delta_{ij,t}) - \pi_{ij,t}) \tag{3-6}$$

where $\pi_{ij,t}$ denotes the expected capital gain (or loss) ($\pi_{ij,t} = R_{ij,t} - R_{ij,t-1}$), $\delta_{ij,t}$ is the annual capital loss via wear and tear measured by the depreciation rate for asset j, and $r_{i,t}$ is the common rate of return that is assumed to be equal across all intangible and tangible capital (Corrado et al., 2009; Hall & Jorgenson, 1967).[29] $T_{i,t}$ is the after-tax adjustment term.[30] $R_{ij,t}$ is the purchasing price of capital j which is measured by investment price deflator of capital j in this study.

Finally, the overall payments ($\Pi_{i,t}$) to capital is the sum of rental payment to each capital type which can be written as:

$$\Pi_{i,t} = \sum_{j=1}^{n} P_{ij,t}^{R} K_{ij,t}^{I} + \sum_{h=1}^{m} P_{ih,t}^{R} K_{ih,t}^{T} \qquad (3\text{-}7)$$

where there are n types of intangible capital and m types of tangible capital (n=9 and m=1 in this study). As the rental payment of each capital is expressed as a function of r in Equation (3-6), the unknown $P_{ij,t}^{R}$ and $r_{i,t}$ can be obtained by combining Equations (3-6) and (3-7).

The PIM is used to estimate both the tangible ("$K_{ij,t}^{T}$") and intangible ("$K_{ij,t}^{I}$") capital stock (see more details in Chapter 2). With regard to tangible investment flows, four indicators are commonly used in the existing literature, namely, accumulation, gross capital formation (including inventories), fixed capital formation and total investment in fixed assets (Chow, 1993; Wang & Yao, 2003; Zhang et al., 2007). Here we use fixed capital formation to avoid the disturbance of inventory value change and biased land acquisition costs in China.[31] Both national and regional deflators of fixed capital investment are available in China National Statistical Yearbook after 1993 (NSY, 2003-2017). Also, different depreciation rates are used for different regions (Wu, 2016). Mineral

[29] The right-hand side of Equation (3-6) indicates that if firms buy one capital good for R, they earn a net rate of return r, but suffer a capital loss via wear and tear δ and a loss or gain in value changes in the future. There will be indifference for a profit-maximizing firm between renting the capital good for P_t^R (unobserved rental payment) and buying it.

[30] After-tax adjustment is calculated as one minus the regional tax rates, which are estimated as the share of net taxes on production (shengchanshui jinge) to GRP. Statistics are obtained from China National Statistical Yearbook (NSY, 2004-2017).

[31] Accumulation statistics discontinued after 1993. Total investment in fixed assets is unique to the China national accounts and includes the acquisition costs of land, which has deviated from intrinsic value in recent years. Gross capital formation includes fixed capital formation and inventory change. The latter often depends on market demand rather than wear and tear (Young, 2003).

investment and software product investment are subtracted from the annual fixed investment flows to avoid double counting problem.

For human capital measurement, partial measurement based on average effective schooling years is adopted here (Wang & Yao, 2003). The share (S_{it}) of workers for each of the six categories of education (primary, junior secondary, senior secondary, college, university, postgraduate) can be derived from China Labour Statistical Yearbooks (CLSY, 2003-2017). Meanwhile, the estimates of the schooling cycles are assumed to be 6, 9, 12, 15, 16 and 18.5 years, respectively (Treiman, 2013).[32] Thus, human capital ($H_{i,t}$) can be estimated as:

$$H_{i,t} = 6S_{it,primary} + 9S_{it,junior} + 12S_{it,senior} + 15S_{it,college} + 16S_{it,uni} + 18.5S_{it,post} \quad (3\text{-}8)$$

To summarize, growth accounting in this study is conducted in six steps. The first step is to measure nominal investment flows for each type of intangible and tangible assets and express them in real terms by using appropriate price deflators. The second step is to use PIM to estimate capital stock for each asset for 2003 and onwards and add them together to obtain the aggregate for each region in each year. The third step is to recalculate GRP for each region by including intangible investments. The fourth step is to estimate human capital by using the average effective education attainment data. The fifth step is to obtain the share of each input factor (human capital, tangible and intangible capital). Finally, growth accounting exercise is conducted by decomposing labour productivity growth into the share-weighted growth in factor inputs plus a residual TFP growth.

3.4 Empirical Results

<u>*National Level*</u>:

The first three columns in **Table 3-1** present growth accounting estimates without intangibles, which provide the baseline for comparison with estimates including intangibles, which

[32] It normally takes 6 years to complete primary education, 9 years to complete junior secondary school, 12 years to complete senior high school, 15 years to complete a 3-year college (“dazhuan”), 16 years to complete a 4-year bachelor degree. Further, one usually needs 19 years (or 18 years) to obtain a 3-year (or 2-year) master degree. So we use 18.5 years as the average.

are shown in Columns (4) - (6). Growth rate changes in labour productivity are allocated to share-weighted contributions of factor inputs, referring as absolute contributions. Relative contributions, shown in the bottom panel, are shares of absolute contribution of each item in total. The bottom line shows the percentage changes in labour productivity growth in the scenario when intangibles are included compared with the baseline estimates. Apparently, intangible capitalization increases growth rates of labour productivity in China in both periods of 2003-2009 and 2010-2016. While the first period saw 0.27 percentage point per annual (pppa) increase, a larger difference of 0.64 pppa is observed in the second period of 2010-2016. Faster development in intangible investment has led to a greater influence of intangible capitalization on labour productivity growth in China since the financial crisis.

Table 3-1 also displays the relative contributions of capital formation and TFP to China's labour productivity growth. The relative contributions of intangible capital accounted for about 10 percent in the first period, and further increased to over one-fifth in the second period. As a result, the introduction of intangible capital leads to a larger role of capital formation in accounting for economic growth in China, and reduces the importance of TFP correspondingly. When intangibles are omitted, TFP explained about 26 percent of labour productivity growth during 2003-2008, but about 24 percent when intangibles are included. The differences become much greater in the second period, with TFP accounting for 11 percent of growth when intangible capital is excluded and only 5 percent when intangibles are added. In other word, whilst TFP still plays its role in China's economic growth, the effects are exaggerated without considering intangible capital. Generally, this result is not surprising given that TFP is measured as a residual (Corrado et al., 2009). In addition, intangible capital is conceptually different from human capital, and their contributions to economic growth are different (Table 3-1).

Table 3-1: China Growth Accounting

	Without Intangibles (%)			With Intangibles (%)		
	03-09	10-16	03-16	03-09	10-16	03-16
	(1)	(2)	(3)	(4)	(5)	(6)
Growth Accounting Results:						
Growth Rate of Labour Productivity:	9.91	7.09	8.39	10.18	7.73	8.86
Capital Deepening:	7.30	6.03	6.76	7.76	7.33	7.52
Tangible Capital Deepening	7.03	5.85	6.39	6.52	5.29	5.85
Intangible Capital Deepening				0.98	1.61	1.32
Human Capital Deepening	0.27	0.45	0.37	0.26	0.43	0.35
TFP	2.61	0.78	1.63	2.42	0.40	1.33
Input Share:						
Labour	45	49	47	42	45	44
Tangible capital	55	51	53	51	45	48
Intangible capital				7	10	8
Relative Contributions from:						
Tangible Capital Deepening	70.94	82.51	76.16	64.05	68.43	66.03
Intangible Capital Deepening				9.63	20.83	14.90
Human Capital Deepening	2.72	6.35	4.41	2.55	5.56	3.95
TFP	26.34	11.00	19.43	23.77	5.17	15.01
Memo: Percentage Changes in Labour Productivity Growth				0.27	0.64	0.47

Source: Author’s own work.

One important determinant affecting the growth accounting exercise is the income share, which serves as the proxy for the corresponding output elasticity of each factor input. Since the shares sum to one, the larger the labour share is, the smaller the share associated with capital is. In addition, capital share leverages the capital deepening effects. The larger the capital share, the greater the capital deepening effects, and the smaller the share left for TFP residual (Hulten and Hao, 2012). In our baseline estimates, the income share is based on national income accruing to labour and capital. The calculation, compared with international estimates, reports a much higher share of capital and a lower share of labour. However, there is substantial disagreement about the lower labour share in China among low-income and middle-income countries based on international standards. For example, Gollin (2002) attributed the lower labour share in China to the misattribution of much of the income accruing to proprietors and the self-employed to capital.

Similarly, as pointed out by Bai et al. (2006), the misallocation of the income of state-owned enterprises (SOEs), collective farms, and individual business owners may take responsibilities for the abnormal lower labour shares in China.

For comparison purposes, our results are re-estimated by using alternative shares in the existing studies. The “EIB share”, reported by van Ark et al. (2009), is the average estimated share used for the United States, the United Kingdom, Germany, France, Italy, Spain, Austria and Denmark, and the “NBS share” is obtained by Hulten and Hao (2012) from China National Bureau of Statistics and used by Tian et al. (2016). The comparable results are displayed in **Table 3-2**. In general, our results stand in line with that of the two existing studies by using the same input shares. The results by using the “EIB share” indeed tend to show a slightly larger TFP residual and a much smaller capital deepening effect. Furthermore, slightly larger tangible capital deepening effects are found in our analysis. It is partly because our estimates covered the post-crisis period when tangible investment experienced extraordinarily high growth rates. The dependence of growth accounting estimates on the period of analysis is a well-known characteristics that can easily yield different results (Corrado et al., 2006).

Finally, **Table 3-3** provides worldwide growth accounting results for comparison. Although countries in the table are at different stages of development during different observed period, and therefore are not comparable directly to China, the information helps get a sense of China’s early stage of intangible capital development. Specifically, the relative contributions of intangible capital are still quite small in China compared with the United Kingdom, the United States, Japan, and some EU countries. For example, during 1995-2007, intangibles’ relative contributions to labour productivity growth has arrived at 24 percent in the United Kingdom, 33 percent in the United States, and 14 percent in Japan. The median value of contributions of intangible capital in EU countries was around 20 percent two decades ago. In contrast, the relative contributions of intangible capital in China attained around 20 percent after one decade from 2007. Additionally, while China’s faster economic growth is mainly driven by the fast development in tangible capital, TFP seems to be a more important factor in explaining labour productivity growth in most of the developed countries listed in **Table 3-3**.

Table 3-2: Comparison of Growth Accounting Results

	Author's Estimate			Hulten & Hao		Tian et al.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Growth Accounting Results:							
(1) Without Intangibles (%)	Est.	EIB	NBS	EIB	NBS	EIB	NBS
Growth rate of labour productivity:	8.39	8.39	8.39	9.65	9.65	9.00	9.00
Capital deepening:	6.76	4.18	7.23	3.54	6.26	2.89	5.48
Tangible capital deepening	6.39	3.62	6.88	3.54	6.26	2.89	5.48
Human capital deepening	0.37	0.56	0.34				
TFP	1.63	4.21	1.17	6.11	3.39	6.11	3.51
(2) With Intangibles (%)							
Growth rate of labour productivity:	8.86	8.86	8.86	9.72	9.72	9.42	9.42
Capital deepening:	7.52	4.74	7.24	4.70	6.70	4.93	7.26
Tangible capital deepening	5.85	3.14	5.55	3.12	5.23	2.50	4.43
Intangible capital deepening	1.32	1.11	1.36	1.58	1.47	2.43	2.83
Human capital deepening	0.35	0.49	0.33				
TFP	1.33	4.12	1.62	5.03	3.02	4.50	2.17
Input Share:							
(1) Without Intangibles (%)							
Labour	47	70	43	70	43	70	43
Tangible capital	53	30	57	30	57	30	57
(2) With Intangibles (%)							
Labour	44	61	41	61	41	61	41
Tangible capital	48	26	46	26	46	26	46
Intangible capital	8	12	14	12	14	12	14

Source: Columns (1) – (3) are author's own estimates, Columns (4) – (5) are from Hulten and Hao (2012), and Columns (6) – (7) are from Tian et al. (2016).

Notes: 1. The time span is 2000-2008 for Hulten and Hao (2012), and 2005-2007 for Tian et al. (2016). 2. Small discrepancy in summation is due to rounding errors.

Table 3-3: Growth Accounting Results for Selected Economies (1995-2007)

Countries	LPG	Source of Growth				
		Total Cap.	Tangibles	Intangibles	Human Res	TFP
	(1)	(2)	(3)	(4)	(5)	(6)
Austria	2.4	0.9	0.3	0.5	0.2	1.4
Belgium	1.8	0.7	0.2	0.5	0.1	0.9
Czech Rep.	4.2	2.4	1.9	0.5	0.3	1.5
Denmark	1.4	1.2	0.7	0.5	0.2	(0.1)
Finland	3.8	0.9	0.2	0.7	0.2	2.6
France	1.9	1.0	0.4	0.6	0.4	0.4
Germany	1.7	1.0	0.7	0.3		0.7
Ireland	3.8	1.4	0.8	0.6	0.1	2.2
Netherlands	0.6	0.7	0.5	0.2	0.2	(0.4)
Slovenia	5.3	1.7	1.2	0.5	0.7	2.8
Spain	0.8	1.0	0.7	0.3	0.5	(0.6)
Sweden	3.7	1.9	1.1	0.8	0.3	1.4
UK	2.9	1.5	0.8	0.7	0.4	1.1
US	2.7	1.7	0.8	0.9	0.2	0.8
Japan	2.1	1.1	0.8	0.3		1.0

Source: Figures of Japan are from Hulten and Hao (2012), and of the rest are from Corrado et al. (2012).
Note: Figures in Column (1) are annual percent changes, and figures in Columns (2) – (6) are percentage points.

Regional Level:

Intangible capitalization is found to increase labour productivity growth rates in both coastal and interior regions in China during the observed period. As it is shown in the bottom line in **Table 3-4**, with intangible capital, the growth rates of labour productivity raised upwards by 0.53 pppa on the coast and by 0.18 pppa in the interior during 2003-2016. Faster acceleration in labour productivity growth is found in the second period during 2010-2016. Coastal regions saw a 0.87 pppa increase in labour productivity growth when intangibles are included while interior regions had an increase of 0.28 pppa. The productivity gap with and without intangibles implies an underestimation of labour productivity growth in conventional studies when intangibles are excluded, especially in coastal areas where intangible investment grew more rapidly.

Table 3-4: Growth Accounting Analysis in Chinese Regions

	Coast			Interior		
	03-09	10-16	03-16	03-09	10-16	03-16
	(1)	(2)	(3)	(4)	(5)	(6)
Growth Accounting Results:						
(1) Without Intangibles (%)						
Growth rate of labour productivity:	10.31	6.73	8.38	11.72	8.48	9.98
Capital deepening:	8.48	5.95	7.11	9.94	7.89	8.83
Tangible capital deepening	8.20	5.66	6.83	9.74	7.39	8.47
Human capital deepening	0.28	0.29	0.28	0.20	0.50	0.36
TFP	1.82	0.79	1.27	1.79	0.59	1.14
(2) With Intangibles (%)						
Growth rate of labour productivity:	10.43	7.60	8.91	11.79	8.76	10.16
Capital deepening:	8.93	7.21	8.00	10.02	8.29	9.08
Tangible capital deepening	7.39	4.99	6.10	9.20	7.00	8.01
Intangible capital deepening	1.27	1.94	1.63	0.63	0.80	0.72
Human capital deepening	0.27	0.28	0.27	0.19	0.49	0.35
TFP	1.50	0.40	0.91	1.77	0.47	1.07
Relative Contributions from:						
(1) Without Intangibles (%)						
Tangible capital deepening	79.53	84.10	81.50	83.11	87.15	84.87
Human capital deepening	2.72	4.31	3.34	1.71	5.90	3.61
TFP	17.65	11.74	15.16	15.27	6.96	11.42
(2) With Intangibles (%)						
Tangible capital deepening	70.85	65.66	68.46	78.03	79.91	78.84
Intangible capital deepening	12.18	25.53	18.29	5.34	9.13	7.09
Human capital deepening	2.59	3.68	3.03	1.61	5.59	3.44
TFP	14.38	5.26	10.21	15.01	5.37	10.53
Memo: Percentage Changes in Labour Productivity Growth						
	0.12	0.87	0.53	0.07	0.28	0.18

Source: Author's own estimates.

Intangible capital is also found to well explain the labour productivity growth in both regions in China, and the explanatory power is much greater after GFC. The relative contributions of intangible capital to labour productivity growth increased from 12 percent to 26 percent on the coast and from 5 percent to 9 percent in the interior. Clearly, intangibles have become increasingly crucial after GFC in both regions, which is in agreement with the acceleration in China's innovation-driven economic transitions. However, according to relative contributions, economic growth in both regions is still mainly driven by tangible capital deepening effects, both with and without intangible capital.

In addition, intangible capital plays a less important role in economic growth in China's interior regions. It is found that, on the coast, intangible capital deepening effect is responsible for 18 percent of labour productivity growth during 2003-2016, whilst in the interior is only for around 7 percent. As discussed previously, intangible investment enjoyed faster growth in coastal regions in China, especially after GFC (recall **Figure 2-8**). The reasons are varied. For example, the first-mover advantages benefit coastal regions with a more developed financial market. Flexible financing support from commercial banks, equity market, and venture capital make coastal regions the natural fertile grounds for innovation-oriented enterprises that emphasise more on intangible investment. In addition, coastal regions are more labour intensive. The likely free movements of skilled labour and highly frequent face-to-face interactions accelerate knowledge spill-overs, which in turn attract more investment in knowledge-based intangible investment on the coast.

Finally, according to **Table 3-4**, the influence of TFP on productivity growth was smaller but not swayed by the introduction of intangible capital in both regions during the whole period. After considering intangibles, the relative contributions of TFP in the whole period decreased sharply from 15 percent to 10 percent on the coast and slightly from 11 percent to 10 percent in the interior. Intangible capitalization failed to shake the importance of TFP in the interior: TFP steadily contributed around 10 percent to labour productivity growth in the interior with and without intangible capital. Compared with intangible capital, TFP still has greater impacts on economic growth in Chinese interior regions. Since TFP can be largely explained by spill-overs (van Ark et al., 2009), it may indicate that interior regions in China prefer technology transfer and diffusion from frontiers (coastal areas) rather than original investment of intangible products and processes. This may be partly because technology spill-overs are less costly, and partly because interior regions cannot afford the risk of original intangible investment. For example, intangibles like scientific R&D require huge investment and are full of uncertain outcomes. Due to these factors, interior regions may have less incentive to invest more in intangible capital and prefer to absorb knowledge directly.

To explore contributions of individual intangible asset, **Table 3-5** disaggregates intangible capital deepening effect in **Table 3-4** into separate components. Accordingly, computer software is found to be the most important factor to explain intangible capital deepening effects in both regions, especially on the coast. The relative contributions of computer software are nearly a half on the coast and around 30 percent in the interior in the total intangible capital deepening effect. Scientific R&D takes the second place in explaining total intangible capital deepening effects. However, its relative importance weakened in both regions in the second period of 2010-2016. In addition, it is worth noting that non-scientific R&D became equally important with scientific R&D. Mineral exploration, entertainments, financial intangibles, and architecture designs, jointly contributed to about one-fifth of total capital deepening effects in both areas. In the second period of 2010-2016, the relative contributions of architecture and engineering designs even surpassed that of scientific R&D on the coast, and became roughly equivalent with that of scientific R&D in the interior. However, compared with computerised information and innovative property, economic competency accounted for a minor portion of total intangible capital deepening effects across Chinese regions. The results in China are in sharp contrast with those from developed countries, where economic competency accounts for an equally important portion as innovative property and computerised information in explaining total intangible capital deepening effects in the growth accounting exercises (Hulten & Hao, 2012; van Ark et al., 2009).

The rightmost two columns in **Table 3-5** show percentage point differences of intangible capital deepening effects between the two regions. Coastal regions in both sub periods tend to have larger intangible capital deepening effects than interior regions, especially in the second period of 2010-2016. The differences, according to relative contributions of intangibles, can be largely attributed to computer software. As is noticed, the unbalanced development of computer software can explain around 60 percent the differences in intangible deepening effects between two regions during 2003-2009, and about 66 percent during 2010-2016. Scientific R&D and financial products and services, taking up the second and third places, can explain less than 20 percent of this effect gap, respectively. In short, greater benefits for coastal regions from intangible capital development are mainly from the advancement of computerisation in those areas.

Table 3-5: Contributions of Individual Intangible Capital to Labour Productivity Growth

	Coast		Interior		Difference	
	03-09	10-16	03-09	10-16	03-09	10-16
	(1)	(2)	(3)	(4)	(1)-(3)	(2)-(4)
Intangible Capital Deepening Effect:	**1.27**	**1.94**	**0.63**	**0.80**	**0.64**	**1.14**
Contributions from:						
Computerised Information	0.57	1.04	0.18	0.28	0.39	0.76
Computer software	0.57	1.04	0.18	0.28	0.39	0.76
Innovative Property	0.49	0.63	0.30	0.33	0.19	0.30
Scientific R&D	0.26	0.26	0.15	0.14	0.11	0.12
Mineral Exploration	0.02	0.00	0.05	0.01	(0.03)	(0.01)
Entertainment and Artistic Originals	0.00	0.00	0.00	0.00	0.00	0.00
Financial Products and Services	0.04	0.06	0.01	0.04	0.03	0.02
Architectural and Engineering Designs	0.18	0.31	0.09	0.13	0.09	0.18
Economic Competency	0.22	0.27	0.15	0.19	0.07	0.08
Advertising	0.04	0.13	0.02	0.04	0.02	0.09
Employer-provided Training	0.06	0.05	0.05	0.05	0.01	0.00
Organisation structure	0.12	0.09	0.09	0.10	0.03	(0.01)
Relative Contributions from:						
Computerised Information	44.49	53.53	27.82	35.16	60.94	66.67
Computer software	44.49	53.53	27.82	35.16	60.94	66.67
Innovative Property	38.50	32.58	47.83	41.48	29.69	26.32
Scientific R&D	20.43	13.56	23.79	17.80	17.19	10.53
Mineral Exploration	1.62	0.11	8.14	1.84	(4.69)	(0.88)
Entertainment and Artistic Originals	(0.16)	0.11	(0.04)	0.54	4.69	1.75
Financial Products and Services	2.85	2.85	1.55	5.59	14.06	15.79
Architectural and engineering designs	13.76	15.96	14.39	15.70	10.94	7.02
Economic Competency	17.02	13.89	24.35	23.36	3.13	7.89
Advertising	3.07	6.79	2.61	5.18	1.56	0.00
Employer-provided Training	4.65	2.37	7.25	6.06	4.69	(0.88)
Organisation structure	9.29	4.74	14.49	12.12	60.94	66.67

Source: Author's own estimates.

3.5 Sensitivity Analysis

A series of sensitivity analyses are conducted in this section to check the robustness of the growth accounting results. **Table 3-6** reports the findings of six optional cases against the base case. First, software development can be classified as R&D if its aim includes the resolution of scientific or technological uncertainty on a systematic basis (Marrano & Haskel, 2006). To avoid potential double counting on R&D and routine software investment, R&D expenditures on the "computer and related activities" category is subtracted from total scientific R&D investment. Because R&D expenditures on computer and related activities are estimated to account for on average 15 percent of the total R&D spending at China's national level in recent years, 15 percent of R&D investment is deducted from total expenditures to avoid the potential double counts. The same ratio is used for regional analysis. The results are reported as Case 1 in **Table 3-6**.

Second, investment in employer-provided training and organisational capital is measured crudely based on the ratios used in the work of Hulten and Hao (2012). Here we alter the ratios by incorporating micro-level evidence. According to Tian et al. (2016), 1.46 percent of employees' wages and salaries is roughly the investment in employer-provided training. The ratio is derived from Chinese Household Income Project (CHIP) survey in 2007. In addition, they treat 5.12 percent of the total labour compensation as the share of employer's payment based on China Health and Nutrition Survey (CHNS), and use 20 percent of employer's payment as investment in organisational capital (Tian et al., 2016). In our sensitivity analysis, we adopt the same ratios for investment measurement of employer-provided training and organisational capital. The results are listed as Case 2 in **Table 3-6**.

Third, intangible capital stock depends on the annual increment (investment) as well as the annual wear and tear (depreciation). The investment shares (the portions of expenditures that can be regarded as investment) and the depreciation rates for individual intangible asset are derived directly from studies of developed countries. Since the choice of these two parameters has its

Table 3-6: Growth Accounting Sensitivity Analysis (2003-2016)

	Coast (1)	Interior (2)	China (3)		Coast (4)	Interior (5)	China (6)
Labour Productivity (%)				**Human Capital Deepening (%)**			
Base case	8.91	10.16	8.86	Base case	0.27	0.35	0.35
Case 1	8.91	10.15	8.85	Case 1	0.27	0.35	0.35
Case 2	8.89	10.14	8.84	Case 2	0.27	0.35	0.35
Case 3	8.91	10.16	8.86	Case 3	0.27	0.35	0.35
Case 4	8.91	10.16	8.86	Case 4	0.27	0.35	0.35
Case 5	8.91	10.16	8.86	Case 5	2.19	2.94	2.81
Case 6	8.95	9.97	-	Case 6	0.29	0.34	-
Tangible Capital Deepening (%)				**TFP (%)**			
Base case	6.10	8.01	5.85	Base case	0.91	1.07	1.33
Case 1	6.11	8.03	5.87	Case 1	0.92	1.07	1.34
Case 2	6.10	7.99	5.85	Case 2	0.91	1.06	1.33
Case 3	6.91	8.67	6.96	Case 3	0.86	0.66	0.67
Case 4	6.10	8.03	5.84	Case 4	0.91	1.04	1.33
Case 5	6.10	8.01	5.85	Case 5	(1.01)	(1.52)	(1.12)
Case 6	6.64	7.12	-	Case 6	0.25	1.86	-
Intangible Capital Deepening (%)							
Base case	1.63	0.72	1.32				
Case 1	1.60	0.70	1.29				
Case 2	1.61	0.74	1.30				
Case 3	0.87	0.48	0.88				
Case 4	1.62	0.74	1.34				
Case 5	1.63	0.72	1.32				
Case 6	1.78	0.65	-				

Source: Author's own estimates.

Notes: 1. Small discrepancy in summation is due to rounding errors. 2. The "coast" column and "interior" column in Case 6 refer to the "leader" and "follower" groups, respectively.

uncertainty, we explore the potential effects of different depreciation rates and different investment shares on growth accounting results in China contest. Specifically, we halve investment shares and repeat the growth accounting exercise as Case 3 (**Table 3-6**), and double the depreciation rates for all types of intangibles and repeat the growth accounting exercise as Case 4 (**Table 3-6)**, respectively. Regarding intangible investment in advertising, since the previous depreciation is set as high as 60 percent that cannot be doubled, the alternative depreciation rate is set to be 90 percent as the upper bond.

Fourth, human capital in baseline estimates is based on effective schooling years. Recently, China Centre for Human Capital and Labour Market Research (CHLR) of the Central University of Finance and Economics undertook a comprehensive study of human capital based on individuals' lifetime income (Li et al., 2014). The Jorgenson-Fraumeni lifetime income approach is expanded to estimate individual earnings as a function of not only schooling but also experience (Jorgenson & Fraumeni, 1989, 1992a, 1992b). For a robustness check, CHLR's estimates of per capita human capital (PCHC) are employed and the results of the exercise are reported as Case 5 in **Table 3-6**. Following their work, consumer price index (CPI) is used as price deflators of human capital in this case.

Finally, regions in this study are grouped based on their geographical locations in China. This distinction reflects different regional economic development levels and degrees of openness to a large extent but still needs deliberation. It is noted that some interior regions like Sichuan province perform better than some coastal areas like Hainan. In Case 6 in **Table 3-6**, regions are categorised into a leader group and a follower group based on their GRP per capita (GRPPC) rather than their geographical location. Specifically, we define provinces with GRPPC above the national mean in 2003 as the leader group and those below the national mean as the follower group. Hence, the leader group now includes nine coastal regions and one interior region, while the follower group has two coastal regions and nineteen interior regions.[33] The growth accounting analysis is then conducted and the results are reported in Case 6 in **Table 3-6**.

Compared with the base case, Cases 1, 2, and 4 in **Table 3-6** shows no significant differences. In other word, little effects are found on growth accounting results by decreasing R&D investments, re-measuring firm-specific human resources investment and applying higher depreciation rates. However, In Case 3, a substantial slump in intangible capital deepening effects is

[33] The leader group's nine coastal regions are Beijing, Tianjin, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong and Guangdong and one interior region is Heilongjiang. The follower group's two coastal regions are Hebei and Hainan and nineteen interior regions are Shanxi, Jilin, Anhui, Jiangxi, Henan, Hubei, Hunan, Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang.

found by halving intangible investment shares. Meanwhile, tangible capital deepening effects increase and TFP effects decrease significantly in Case 3 compared with that in the baseline estimates. Though the basic relationship between intangible capital and economic growth remain unchanged, growth accounting exercise is quite sensitive to the choice of intangible investment shares in China case.

In addition, while the others remain unchanged, the human capital deepening effect in Case 5 is significantly higher than that in other cases. With a bigger contribution of human capital, the residual TFP turns to be negative in the observed periods. Clearly, the estimates of human capital by CHLR increase its impact substantially. The findings of greater contributions of human capital by using CHLR estimates are supported by other studies. For example, by using CHLR datasets, Li et al. (2014) attributed 45.9 percent of China's economic growth to human capital deepening during 1986-2010, and TFP only accounted for 0.81 percent afterwards.

Finally, as shown in Case 6 in **Table 3-6**, and if we reclassify regions into the leader and follower groups, intangible capital will accelerate labour productivity growth more for relatively developed regions but less for relatively underdeveloped regions, compared with baseline estimates. Since the classification is solely based on levels of economic development in Case 6, the results can strengthen the main conclusion derived from our baseline estimates: intangible capital plays more important roles in relatively more developed regions in China. Either the coastal regions in the base case or the leader regions in Case 6, will probably benefit more from intangible capital than the less developed areas in China. In addition, in baseline estimates, TFP effect drops to 0.91 on the coast and 1.01 in the interior after introducing intangibles into growth accounting. However, with intangible capital, the TFP effects further decreased to only 0.25 in the leader group but increased to 1.86 in Case 6. The finding implies that in relatively underdeveloped regions in China, TFP, which indicates technology transfers, knowledge spill-overs, and other unexplained factors, may still play an important role in explaining economic growth.

3.6 Conclusion

Intangible capital is becoming an important growth force in the world economy. Its relationship with economic growth and labour productivity has been examined extensively in developed countries after the CHS framework. China, in stark contrast, is lack of information in this field. Therefore, this study attempts to evaluate contributions of intangible capital to China's economic growth, both at the national level and at the regional level. By categorizing knowledge capital, intangible capital is distinguished from human capital and serendipity technological progress. The main findings in this study are summarised as follows.

First, the involvement of intangible capital accelerates labour productivity growth in China significantly during the period of 2003-2016, and the influences become even greater during 2010-2016. It implies that China is accelerating her speed in transforming into a more intangible-intensive innovation-driven economy after the GFC, in which intangible capital will play an increasingly important role. In addition, the involvement of intangible capital restates the relative importance of input factors in explaining labour productivity growth in China. The introduction of intangible capital leads to a larger role of capital formation and declines the importance of TFP in China's economic growth. However, the relative contribution of intangible capital is still small in China compared with that in advanced economies. Tangible capital formation is still the main driver of China's economic growth.

Second, intangible capital is found to have different impacts on China's regional economic growth. According to different geographical characteristics and levels of economic development, 31 provinces, municipalities, and cities are grouped into the coastal regions and the interior regions. By adding intangible capital into regional growth accounting analysis, both regions see a faster growth in labour productivity, a larger capital deepening effect, and a smaller TFP residual. However, coastal regions are undoubtedly benefiting more from intangible capitalization. There is an enlarging gap between the coast and the interior in terms of intangible capital deepening effects in the growth accounting exercise, and the gap can be largely explained by the computer software advancement on the coast.

Third, the introduction of intangibles reduces the importance of TFP but does not eliminate it. TFP still plays its role in China's economic growth, especially in the interior regions. Since TFP can be explained largely by technology transfers and knowledge spill-overs, it implies that interior regions in China may still have less incentive to innovate and mainly absorb knowledge directly. The explanations can be manifold. One possible reason is that obtaining existing knowledge is more economical for less developed interior areas. The lack of financial resources, policy support and researchers may also hamper the interior regions to invest heavily in intangible capital.

CHAPTER 4 - INTANGIBLE CAPITAL, ICT, AND SECTOR GROWTH

4.1 Introduction

It is argued that information and communication technology (ICT) was responsible for explaining the resurgence of the United States economy in the late 20th century (Jorgenson & Stiroh, 2000; van Ark et al., 2002, 2003). However, European countries failed to achieve the same success of the United States (Inklaar et al., 2005; Inklaar et al., 2008; Timmer et al., 2011; van Ark et al., 2003; van Ark et al., 2008). It is thus proposed that there may be some non-measured intangible assets, which can enable better exploitation of ICT, resulting the unique success in the United States. For example, Brynjolfsson and Hitt (2000) pointed out that the IT performance depends largely on complementary investment in organisation capital. Firms with advanced organisational characteristics tend to have higher market valuations than their competitors, even when all their other measured IT assets are the same (Brynjolfsson et al., 2002). Bresnahan et al. (2002) argued that the gains from installing computer hardware can only be fully accomplished with the "instalment" of intangible capital of skilled labour force and management changes in the United States. Bloom et al. (2005) suggested that the productivity gap between US-based and non-US-based multinationals results from the superior organisation structure and management skills in these US-based firms. These intangible skills allow the US-firms to utilise new technologies like ICT more efficiently and successfully, resulting in long-term competitiveness. Recently, similar evidence in EU countries has finally shown that ICT is more productive when it is complemented with a broader range of intangible capital (Chen et al., 2016; Corrado et al., 2017).

As the cutting-edge technology, ICT also affects almost every aspect of China's economy. It is clearly stated in the 16th Communist Party Congress that one of the main tasks in China for the first twenty years of the 21th century is to promote "informatisation",[34] and to utilise ICT to boost economic and social development (Atkinson, 2014; Chen et al., 2005). However, while some studies demonstrated the economically significant contributions of ICT to China's economic growth (Cai & Zhang, 2015; Heshmati & Yang, 2006; Khuong, 2006; Meng & Li, 2002; Sun, 2012), others argued an insignificant effect of ICT since developing countries like China are less likely to invest in complementary intangible capital (Dewan & Kraemer, 2000; Niebel, 2018; Papaioannou & Dimelis, 2007; Pohjola, 2002). Therefore, this study attempts to examine the complementary relationship between intangible capital and ICT capital in China. If intangible capital is found to complement ICT capital to jointly contribute to China's economic growth, more emphasis should be put on investments in intangible capital instead of ICT capital alone.

The question we want to answer in this chapter is that, except its role of acting as an input factor, can intangible capital contribute to China's economic growth by interacting with ICT capital? The answer to this question can not only help understand economic mechanism through which intangibles impact on growth, but also shed light on the causality relationship between intangible capital and economic growth in empirical analysis. Specifically, it is a challenge to identify the causality relationship between intangible capital and economic growth by using conventional regression models based on a standard Cobb-Douglas production function. It may suffer from simultaneity and omitted variable problems especially when analysis is conducted at a more disaggregated level. For example, the simultaneity problem occurs in production models as the choice variables are determined by the same force at the disaggregated level (Griliches & Mairesse, 1995). Meanwhile, the omitted variable problem arises since there are determinants of production that are unobservable (Ackerberg et al., 2015). For these reasons, it is usually hard to identify the causal direction: whether it is intangible capital development that will trigger economic growth or vice versa. If intangible capital is found to promote economic growth through specific economic mechanism by interacting with ICT, it will solve the causality direction problems to a large extent.

[34] The word "informatisation" has a very similar form to the word "industrialization". It refers not only to the ICT industry development but also to the adoption of ICT in China's economy (Atkinson, 2014).

To explore the questions raised above, this study uses a panel fixed effect identification strategy to analyse the relationship between intangible capital and ICT capital. Introduced by Rajan and Zingales (1998), the method effectively corrects for average country (region) and sector characteristics by using indicator variables, and only considers within-country (region) between-sector differences. By interacting country (region) characteristics with sector characteristics, it captures the differential effects of specific country (region) characteristics on economic growth by interacting with specific sector characteristics. The impacts of country (region) characteristics on growth through sector characteristics are thus isolated. In this chapter, the basic cross-section model is further evolved into a panel data specification to incorporate a time dimension and control for a wider array of omitted variables (Hsu et al., 2014).

This study contributes to the existing studies in several ways. First, by analysing an economic mechanism through which intangible capital affects China's economic growth, it enriches the understanding of intangible capital in China. It demonstrates that these tacit assets can promote economic growth not only by acting as a factor input but also by interacting with ICT. Second, it fills the knowledge gap in the relationship between intangible capital and ICT in China, and provides comparable results with that in developed economies. The result provides important policy implications that China should emphasise not only ICT investment but also the development of intangible capital. Finally, the fixed effect identification strategy distinguishes this study from a few recent studies of developed countries where the traditional production function is applied.

This chapter produces new insights into the effects of intangible capital in China. Faster intangible capital development in Chinese regions is confirmed to disproportionally help more ICT-intensive sectors grow faster. The conclusion is robust in cases where alternative measures of intangible capital and different ICT intensity indicators are used, and where other potential region-level determinants of sector growth are considered, such as human capital development, non-ICT physical capital development and financial market development.

The remainder of this chapter is organised as follows. Section 4.2 presents the empirical strategy, outlines the model specification and specifies variables used in the model. The data sources and explanations are described in Section 4.3. Section 4.4 presents empirical results, robustness checks and further explanations. The final section concludes the chapter.

4.2 Empirical Strategy

This chapter examines the relationship between intangible capital and sector value-added growth in China. Specifically, we examine the *differential* impacts of intangible capital development on value-added growth of sectors. In contrast to traditional growth regression, the empirical strategy in this chapter is based on a "fixed effect identification strategy" introduced by Rajan and Zingales (1998). By correcting for both country and sector characteristics with indicator variables, they identified the specific economic mechanism through which a more developed financial market will disproportionally help sectors that are relatively more in need of external finance to grow faster. After that, the method is widely adopted in different research studies of financial development (Aghion et al., 2007; Braun et al., 2005; Fisman et al., 2007; Levchenko et al., 2009; Manova, 2008), and human capital (Ciccone & Papaioannou, 2009; Murphy & Siedschlag, 2013).

The basic framework of Rajan and Zingales's model can be expressed as follows:

$$g_{s,c} = \mu_s + \lambda_c + \beta k_s k_c + \gamma \mathbf{X}_\mathbf{s}' \mathbf{Z}_\mathbf{c} + \epsilon_{s,c} \qquad (4\text{-}1)$$

where $g_{s,c}$ is the growth rate of sector s in country c, $k_s k_c$ is the interaction term of key interests, which examines a specific economic mechanism through which a country's characteristic k_c can affect sector growth by interacting with a sector's characteristic k_s. As no one can explicitly include all country and sector characteristics that affect sector growth in Equation (4-1), Rajan and Zingales thus in turn use sector-level and country-level indicator variables μ_s and λ_c directly. With this framework, except the main variables of interest, researchers only need to consider and control for the other explanatory variables that vary at country-sector level and affect sector growth. Thus, $\mathbf{X_s'Z_c}$ represents the other country characteristics ($\mathbf{Z_c}$) that may impact on the growth of a sector by interacting with the sector characteristics ($\mathbf{X_s'}$). The advantage of this method is it focuses only on within-country between-sector variation. The country and sector fixed effects control for the *average* country and *average* sector factors affecting the sector growth. The coefficient of the interaction term in this specification is, therefore, akin to a second-order partial derivative (Jozsef Manning, 2003). As a result, all things being equal, fixed effect specification strategy will demonstrate that the *ex-ante* development of a country's characteristic will affect the *ex-post* sector growth, shedding light on the direction of the causal effect and avoiding a spurious correlation to the results to a large extent (Zingales, 2003).

In this study, the cross-section fixed effect identification strategy is further evolved into a panel data specification to incorporate a time dimension and to control for a wider array of omitted variables (Hsu et al., 2014). The benchmark model is expressed as:

$$\Delta lny_{s,r,t} = \lambda_{r,t} + u_s + \beta\left(ICT_s \times \Delta lnk^I_{r,t}\right) + \gamma \mathbf{X_s'Z_{r,t}} + size_{s,r,t-1} + \epsilon_{s,r,t} \quad (4\text{-}2)$$

In Equation (4-2), the dependent variable ($\Delta lny_{s,r,t}$) is the annual growth rate of the value added in sector s in region r over the analysed period. The explanatory interaction term of interest is the sector-level ICT intensity ICT_s interacted with the development of intangible capital in region r in year t. In the benchmark estimates, region-level intangible capital development is represented by the growth rate of intangible capital stock ($\Delta lnk^I_{r,t}$). Additionally, as suggested by Rajan and Zingales (1998) and others who have followed their model, we control for the sector share of total value added ($size_{s,r,t-1}$), due to the heterogeneous degrees of development across different sectors within one region. The interaction term $\mathbf{X_s'Z_{r,t}}$ represents other possible determinants of sector growth that vary at region-sector-year level, which will be explained later.[35]

[35] To deal with three-dimensional panel data, we group the sector and region variables to generate a panel identifier "pan_id". See more on https://www.statalist.org/forums/forum/general-stata-discussion/general/2095-three-dimensional-panel-data-regression.

Region-year and sector-level specific variations are controlled by indicators directly. The region-year fixed effect ($\lambda_{r,t}$) reflects the time-varying regional characteristics, such as the overall regional economic growth, regional political reforms, and so on (absorbs the level effects of $\Delta lnk^{I}_{r,t}$). The sector fixed effect (u_s) absorbs unobserved sector characteristics like sector techniques and performance (absorbs the level effects of ICT_s). Such regression thus is to explore whether sectors predicted to be in more need of ICT capital grow faster in regions with a faster development of intangible capital, controlling all region-year- and sector-specific factors that driving growth. Using this strategy, the sector-specific ICT intensity is the nexus to isolate the impacts of intangible capital from unobserved factors that drive both intangible development and sector growth. Finally, we cluster standard errors by region and sector to allow the error term $\epsilon_{s,r,t}$ to be heteroskedastic and correlated within each region-sector pairs. The two-dimension clustered standard error is well known to be a robust estimator and contains less bias (Petersen, 2009; Thompson, 2011).

The empirical strategy distinguishes this study from a few recent studies. One study, conducted by Corrado et al. (2017), analysed the relationship between intangible capital and ICT by using a traditional production function. As it is suggested by Griliches and Mairesse (1995), input variables are determined simultaneously by the same forces, and a production function at a more disaggregated level is more likely to be suffered from simultaneity problems. For example, growth drawn from unobservable opportunities in some sectors is always correlated with the adjustment in physical capital and labour input. Due to this, the interaction term in their study is more likely to reflect the correlation relationship rather than the causality relationship. In conventional regression model, it is safer to say that ICT capital is more productive when it is complemented with intangible capital. However, in contrast, the Rajan and Zingales model studies the intangible-ICT growth nexus, where ICT is a specific economic mechanism to capture the causality effects of intangible capital on economic growth.

Further, to control for unobserved heterogeneity from the region-sector-year level, other region-level determinants of sector growth are considered as suggested by recent literature ($\mathbf{X}_\mathbf{s}'\mathbf{Z}_{\mathbf{r},\mathbf{t}}$). First, as is suggested by Ciccone and Papaioannou (2009), the development of human capital will disproportionally help more schooling-intensive sectors grow faster. Thus, we add an interaction term to capture the impacts of human capital on sector growth by interacting with sector schooling intensity. Second, based on Rajan and Zingales (1998), we also add an interaction term to capture the effects of financial market development on sector growth by interacting with the sector's external financial dependence. Finally, region-level non-ICT physical capital development may also affect sector growth by interacting with the sector's non-ICT physical capital intensity (Murphy & Siedschlag, 2013).

Detailed information of variables used in the benchmark estimates are shown in **Table 4-1**. In addition, Equation (4-2) is estimated by both ordinary least-squares (OLS) and instrumental variables (IV) methods to account for endogeneity problems. The results with and without the consideration of other determinants are both presented. Furthermore, estimations based on Equation (4-2) will be checked against alternative measures of intangible capital and ICT intensity indicators. Intangible capital will also be interacted with other sector characteristics rather than ICT intensity, and sector ICT intensity will be interacted with other regional characteristics rather than intangible capital, to see if this specific economic mechanism is robust.

4.3 Data Issues

Details of data sources and data description are shown in the data appendix in Appendix 4A. For simplicity, we will only present the summary information in this section by grouping the variables into region-sector level, sector level, and region level.

Table 4-1: Variable Definitions in Benchmark Estimates

Variables	**Definitions**
Dependent variable:	
$\Delta \ln y_{s,r,t}$	Annual growth rate of real gross value added in sector s in region r in year t.
Independent variables (sector-level):	
ICT_s	Sector ICT intensity is calculated by averaging the ratio of ICT capital stock to labour input across region and time.
$SCHINT_s$	Sector schooling intensity is calculated by averaging employee education attainment across region and time.
$PHYINT_s$	Sector non-ICT physical capital is calculated by averaging the ratio of non-ICT physical capital stock to real gross value added in sector s across region and time.
$FINDEP_s$	Sector external financial dependence is defined as the average ratio of one minus the ratio of flows from operation over total capital expenditures in sector s across region and time.
Independent variables (region-level):	
$\Delta \ln k^{I}_{r,t}$	Annual growth rate of intangible capital stock in region r in year t.
$HC_{r,t-1}$	The average schooling years in region r at the end of previous year.
$PHY_{r,t-1}$	The ratio of non-ICT physical capital stock to real gross regional product (GRP) in region r at the end of previous year.
$FIDEV_{r,t-1}$	The ratio of total bank loans to real GRP in region r at the end of previous year.
Independent variable (region-sector level):	
$size_{s,r,t-1}$	Sector size control is calculated as the share of sector s in real GRP in region r at the end of previous year.

Region-Sector Data

The region-sector data used in this study are mainly from China Industrial Statistical Yearbook (CISY) and China National Statistical Yearbook (NSY). The dependent variable is the annual growth rate of real gross value added for 29 sectors in 30 Chinese regions. The sectors are classified according to China's one-digit sector code (GB/T 4754-2011), and the manufacturing sector is further divided into 11 subsectors to control for heterogeneity across these sectors (**Table 4-2**). The international association sector (T) is excluded. The nominal gross value added is then deflated by using region-sector gross value added price indices to obtain the real gross value added (base year: 2010). However, due to the lack of data in Tibet, only 30 Chinese regions are included in this analysis. The final time span is 2003 to 2015.

Table 4-2: Sector Classification

	Sector Classification	**GB/T2011 Code**
1	Agriculture, Forestry, Animal Husbandry and Fishery	A
2	Mining and quarrying	B
3	Food, beverages and tobacco	C13-C16
4	Textiles and leather	C17-C19
5	Wood, paper and printing	C20-C24
6	Petroleum, coal and chemicals	C25-C29
7	Non-metallic mineral products except petroleum and coal	C30
8	Metal, Fabricated metal products	C31-33
9	Machinery equipment	C34-C35
10	Transport equipment	C36-C37
11	Electrical and electronic equipment	C38
12	Computer, telecommunication and other electronic equipment	C39
13	Apparatus, instruments and other manufacturing activities	C40-C43
14	Electricity, gas and water supply	D
15	Construction	E
16	Wholesale and retail trade	F
17	Transport, storage and post	G
18	Hotel and catering services	H
19	Information transmission, software and information technology	I
20	Financial intermediation	J
21	Real estate	K
22	Leasing and business services	L
23	Science research and technical services	M
24	Management of water conservancy, environment and public facility	N
25	Service to households, repair and other services	O
26	Education	P
27	Health and social service	Q
28	Culture, sports and entertainment	R
29	Public management, social security and social organisation	S

Source: Author's own work

Note: The classification is based on GB/T 4754-2011 sector code that is consistent with China National Bureau of Statistics.

In accordance with the OECD (2002) and China National Bureau of Statistics (NBS, 2017), ICT capital is defined as ICT hardware and ICT software in this chapter (**Table 4A-1**).[36] ICT hardware refers to the investment in overall telecommunication and electronic equipment while ICT software refers to the investment in information transmission, software and information technology services. As ICT capital includes computer software, intangible capital in this study excludes computer software to avoid double counting (Corrado et al., 2017). To see the relative importance of computer software in ICT capital and intangible capital, we calculate the shares of software in ICT and intangibles (Appendix 4A **Table 4A-2**). Accordingly, software accounts for a larger share in ICT capital compared with that in intangibles. Nevertheless, different results might be generated if computer software were included as a component of intangible capital and excluded from ICT.

Sector-level Data

The effects of intangible capital on sector growth depend on sector-level ICT intensity. Sector ICT intensity is thus estimated first for ranking all 29 sectors from the least to the most ICT-intensive ones. ICT intensity is estimated by averaging a sector indicator across region and time. According to previous studies, there are mainly four ICT intensity indicators, namely the share of ICT in total physical capital investment, the share of ICT in total physical capital stock, the ratio of ICT real investment to real sector value-added, and the ratio of ICT capital stock to labour input (Corrado et al., 2017; Stiroh, 2002; van Ark et al., 2003; van Ark et al., 2002).

Sector ranking based on these four different indicators displayed in **Figure 4-1** shows no large differences in China. The most ICT-intensive sectors in China are: electrical and electronic equipment (ID 11), leasing and business services (ID 22), apparatus, instruments and other manufacturing activities (ID 13), restaurants and hotels (ID 18), and wood, paper and printing (ID 5); The least ICT-intensive sectors are agriculture (ID 1), food (ID 3), textiles (ID 4),

[36] We find the ICT definition of OECD (2002) comparable with that of the NBS (shown in Appendix 4A **Table 4A-1**). Thus, evidence of ICT capital in China is comparable with the evidence from developed countries.

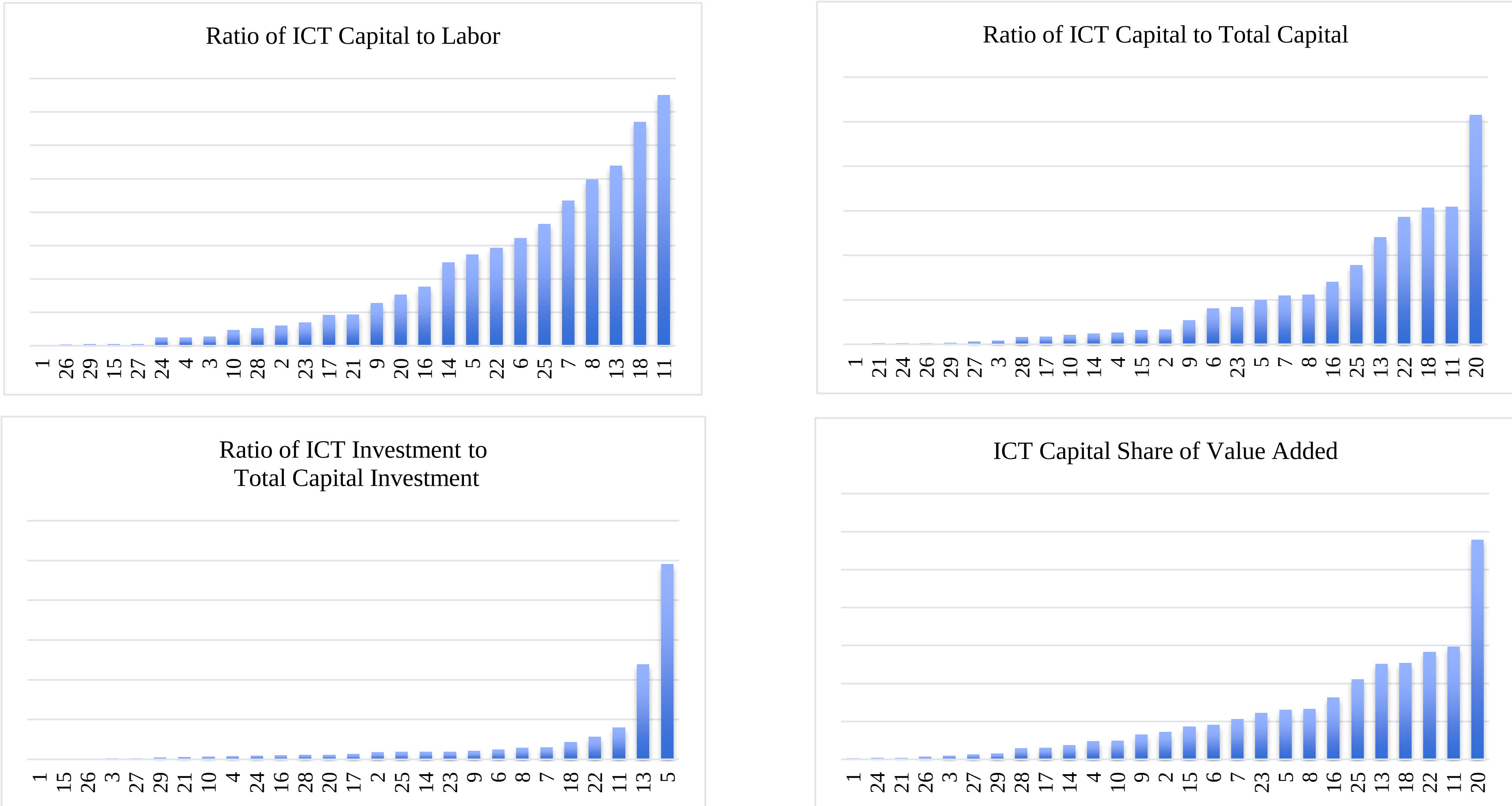


Figure 4-1*: ICT Intensity Indicators.*

Source: Author's own work.

Notes: 1. Horizontal labels are the sector codes listed in **Table 4-2**. 2. Computer equipment manufacturing sector (ID 12) and the information and communication sector (ID 19), as two ICT producing sectors, are not presented in the bar chart.

construction (ID 15), and public service sectors (ID 26-ID 29). In the benchmark analysis, we follow Corrado et al. (2017) to use the ratio of ICT capital stock to labour input, and then check the results' robustness against the other three alternative measures.

Since the United States is regarded as one of the most flexible market economies in the world, as suggested by Rajan and Zingales, the sector intensity indicator in the United States is often used as an exogenous measure for ranking sectors in countries where sector data is unavailable or suffer from endogenous problems. Corrado et al. (2017) for example used the US ICT indicator to check their results' robustness. However, institutional factors and price factors, being highly correlated with sector intensity, are significantly different between China and the United States (Murphy & Siedschlag, 2013). To identify whether the US indicators could be used in our case, we compare sector ICT dependence between China and the United States. Sectors in China are categorised into ICT-intensive and non-ICT groups by using the median value of the ICT intensity indicator, and the group components are then compared with the results from Stiroh (2002) and van Ark et al. (2002) (Appendix 4A **Table 4A-3**). Interestingly, in contrast to the United States, manufacturing sectors rather than service sectors are more ICT-intensive in China. This finding is supported by some Chinese scholars who also argued that there was a larger contribution of ICT capital in manufacturing sectors rather than in service sectors (Sun, 2013). As a result, the sector ICT intensity indicator in the United States will not be adopted to check the result robustness in this study.

Table 4-3 reports the benchmark measures of sector ICT intensity (ICT_s), alternative measures of sector ICT intensity ($ICT_s', ICT_s'', ICT_s'''$), and the variables of other sector characteristics, such as sector schooling intensity ($SCHINT_s$), sector non-ICT physical capital intensity ($PHYINT_s$) and sector external financial dependence ($FINDEP_s$). Specifically, sector schooling intensity is defined as the average years of employee education attainment. Education attainment indicates the highest level of education people complete. Overall, six categories of primary, junior secondary, senior secondary, college, university and postgraduate are included, and

Table 4-3: Summary Statistics: Sector Characteristics

ID	Sector	(1) ICT_s	(2) ICT'_s	(3) ICT''_s	(4) ICT'''_s	(5) $SCHINT_s$	(6) $PHYINT_s$	(7) $FINDEP_s$
1	Agriculture, forestry, animal husbandry and fishery	0.008	0.000	0.001	0.000	7.371	0.326	
2	Mining and quarrying	0.296	0.006	0.036	0.009	9.862	0.123	1.113
3	Food, beverages and tobacco	0.131	0.002	0.005	0.001	9.676	0.114	0.551
4	Textiles and leather	0.122	0.005	0.024	0.004	9.084	0.078	0.837
5	Wood, paper and printing	1.361	0.020	0.065	0.245	9.303	0.209	0.917
6	Petroleum, coal and chemicals	1.609	0.016	0.045	0.012	10.454	0.150	0.995
7	Non-metallic mineral products except petroleum and coal	2.169	0.022	0.053	0.015	9.270	0.205	1.133
8	Metal, fabricated metal products	2.488	0.022	0.066	0.014	9.994	0.132	1.145
9	Machinery equipment	0.635	0.011	0.033	0.010	10.434	0.091	0.882
10	Transport equipment	0.232	0.004	0.024	0.003	10.778	0.067	0.861
11	Electrical and electronic equipment	3.748	0.062	0.148	0.040	10.407	0.091	0.367
12	Computer, telecommunication and other electronic equipment	35.358	0.336	0.525	0.534	10.793	0.082	0.665
13	Apparatus, instruments and other manufacturing activities	2.692	0.048	0.126	0.119	9.345	0.095	0.644
14	Electricity, gas and water supply	1.244	0.005	0.018	0.009	11.989	0.306	1.089
15	Construction	0.021	0.006	0.043	0.001	9.129	0.015	
16	Wholesale and retail trade	0.883	0.028	0.081	0.005	10.079	0.059	
17	Transport and storage	0.453	0.003	0.015	0.006	10.140	0.268	
18	Restaurants and hotels	3.345	0.061	0.127	0.022	9.587	0.084	
19	Information and communication services	1.932	0.014	0.078	0.034	12.536	0.274	
20	Financial intermediation	0.761	0.103	0.289	0.006	13.359	0.010	
21	Real estate	0.460	0.000	0.002	0.003	11.779	1.581	
22	Leasing and business services	1.465	0.057	0.141	0.028	11.823	0.042	
23	Science research and technical services	0.342	0.017	0.061	0.009	13.584	0.026	
24	Management of water conservancy, environment and public facility	0.120	0.000	0.001	0.005	10.859	0.544	
25	Service to households, repair and other services	1.817	0.035	0.105	0.009	9.490	0.086	
26	Education	0.013	0.000	0.003	0.001	14.023	0.027	
27	Health and social service	13.072	0.023	0.001	0.006	0.001	0.022	
28	Culture, sports and entertainment	12.152	0.255	0.003	0.014	0.006	0.086	
29	Public management, social security and social organisation	13.232	0.018	0.001	0.007	0.002	0.032	
	Median	0.635	0.011	0.043	0.009	10.434	0.091	0.882
	S.D.	6.464	0.064	0.107	0.107	1.643	0.294	0.245
	25% Percentile	0.131	0.003	0.014	0.003	9.587	0.059	0.665
	75% Percentile	1.817	0.028	0.081	0.015	11.989	0.205	1.089

Source: Author's own estimates.

6 years, 9 years, 12 years, 15 years, 16 years and 18.5 years are estimated as the schooling cycle for each of the categories (Wang & Yao, 2003). Sector non-ICT physical capital intensity is calculated as the share of non-ICT physical capital in real sector value added, averaging across region and year. Sector external financial dependence is defined as one minus the ratio of operation flows over total

capital expenditure (Rajan & Zingales, 1998).[37] Information on sector financial dependence is available only in manufacturing sectors. The sample would be constrained in manufacturing sectors only if the financial interaction term is considered and added in the specification of Equation (4-2).

Region-level Data

Regional different developing levels of intangible capital is represented by the annual growth rate of regional intangible capital stock in the benchmark estimation. Except that, the ratio of regional intangible capital stock over regional total capital stock (excluding ICT capital) at the end of previous years is used as an alternative measure to check result robustness later in sensitivity analysis. As mentioned above, computer software is excluded from intangible capital. Hence, eight rather than nine individual intangible assets are included. The definitions and measurement details are in consistent with that in Chapter two.

To summarise, average annual growth rates of intangible capital (Δlnk_r^I) and average shares of intangible capital in total capital stock (exclude ICT) (k_r^I/k_r) of 30 Chinese regions are shown in **Table 4-4**. From Column (1) in the table, it is seen that most regions in China experienced two-digital rates of annual growth in intangible capital over the period of 2003-2015. Intangible capital has enjoyed faster development in China in the last decade. No matter which indices is used for intangible development, it is found that coastal regions outperform the interior regions during the last decade. Some megacities such as Beijing, Shanghai and Tianjin, take the leading positions in term of intangible development. Furthermore, intra-regional inequality development of intangible capital exists in the interior. A few interior regions like Chongqing and Anhui have shown a distinguished performance compared with other underdeveloped regions such as Gansu and Ningxia.

[37] Capital expenditure is estimated by subtracting the net amount of fixed assets in the preceding year from the net amount of fixed assets in the current year. It is adjusted by adding the depreciation change during the measurement period. The value of operation flows is defined as the increase in liquid assets minus the increase in liquid liabilities, implying internal cash flows in the sectors that can be used independently for production. A much higher ratio indicates that the sector relies more on external finance. For further information on capital expenditure estimates, see https://www.accountingtools.com/articles/how-to-calculate-capital-expenditures.html.

Table 4-4: Summary Statistics: Region Characteristics

Region ID	Region	$\Delta\ln k_r^I$	k_r^I/k_r	HC_r	PHY_r	$FIDEV_r$
		(1)	(2)	(3)	(4)	(5)
1	Beijing	0.159	0.293	10.701	1.116	2.376
2	Tianjin	0.150	0.148	9.481	1.195	1.864
3	Hebei	0.136	0.055	8.162	1.503	0.772
4	Shanxi	0.167	0.062	8.491	1.546	1.149
5	Inner-Mongolia	0.186	0.032	8.207	1.885	0.745
6	Liaoning	0.129	0.082	8.493	1.609	1.090
7	Jilin	0.120	0.074	8.281	1.782	1.685
8	Heilongjiang	0.120	0.061	8.178	1.488	0.779
9	Shanghai	0.140	0.128	10.104	1.763	1.826
10	Jiangsu	0.168	0.087	8.285	1.375	0.996
11	Zhejiang	0.200	0.089	8.170	1.266	1.549
12	Anhui	0.162	0.075	7.574	1.554	0.926
13	Fujian	0.158	0.086	8.045	1.002	1.020
14	Jiangxi	0.128	0.052	7.968	1.738	0.852
15	Shandong	0.143	0.073	8.201	1.344	0.807
16	Henan	0.155	0.061	8.081	1.386	0.728
17	Hubei	0.141	0.076	8.141	1.659	0.894
18	Hunan	0.148	0.072	8.187	1.249	0.733
19	Guangdong	0.169	0.123	8.531	0.943	1.111
20	Guangxi	0.146	0.051	7.869	1.305	0.886
21	Hainan	0.106	0.030	8.358	2.731	1.259
22	Chongqing	0.143	0.073	7.585	1.645	1.318
23	Sichuan	0.139	0.096	7.445	1.455	1.068
24	Guizhou	0.143	0.053	7.114	1.588	1.241
25	Yunnan	0.135	0.061	6.952	1.482	1.320
26	Shaanxi	0.110	0.123	8.330	1.493	1.087
27	Gansu	0.094	0.056	7.508	2.408	1.230
28	Qinghai	0.115	0.063	7.592	1.993	1.413
29	Ningxia	0.153	0.039	7.901	2.261	1.510
30	Xinjiang	0.098	0.053	8.163	3.144	1.030
Median		0.143	0.072	8.167	1.525	1.088
S.D.		0.024	0.049	0.767	0.484	0.391
25% Percentile		0.128	0.055	7.869	1.344	0.886
75% Percentile		0.158	0.087	8.330	1.763	1.320

Source: Author's own estimates.

Table 4-4 also reports the mean of other region-level characteristics variables, such as regional human capital development (HC_r), regional non-ICT physical capital development (PHY_r), and regional financial market development ($FIDEV_r$). Consistent with the related research, the level of human capital development is defined as the average education attainment of the regional population at the end of previous year. Non-ICT physical capital development is constructed by using the ratio of non-ICT physical capital stock to real GRP. Financial market development is measured by the ratio of total bank loans to real GRP. For most region-level characteristics, relatively more developed coastal regions outperform the rest. However, according to **Table 4-4**, it is noted that some underdeveloped regions like Ningxia and Qinghai show a relatively higher level of financial market development. This counterfactual statistic thus needs cautions for us to interpret regional financial market development in China. One possible explanation for underdeveloped regions with higher level financial development is the relatively small GRP in these regions; The other possible reason is that the bank loan allocation in China is subjected a lot to policy interference, and these underdeveloped regions are more likely to obtain more political financial support for their infrastructure construction and public facilities. This unusual phenomenon in regional financial market development may take responsibility for the insignificant coefficients of financial interaction terms in our empirical estimates throughout the chapter.

4.4 Empirical Results

Benchmark Estimates

Table 4-5 reports the benchmark estimates of Equation (4-2). In Panel A the full sample is used, while in Panel B the sample is confined to manufacturing sectors as a result of including financial control. Columns (1) – (2) show the unconditional cases, and the following columns display the conditional cases by involving other potential determinants of sector growth, including human capital, non-ICT physical capital, and financial market development (when applicable in Panel B). While the odd columns display OLS estimators, IV estimators are shown in even columns. To test the potential endogeneity problem of the interactions in specifications, we refer to the difference of two Sargan-Hansen statistics, which are robust to violations of conditional homoscedasticity hypothesis (Hayashi, 2000). The null hypothesis is that the specified regressors

Table 4-5: Intangible Capital and Sector Value-added Growth: Benchmark Estimates

	Panel A: Total Sample							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Unconditional Estimates		Human Capital		Physical Capital		All Controls	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
$ICT_s \times \Delta lnk_{r.t}^{I}$	0.0159**	0.0381***	0.0156**	0.0375***	0.0158**	0.0378***	0.0156**	0.0373***
	(0.0063)	(0.0141)	(0.0063)	(0.0140)	(0.0063)	(0.0140)	(0.0063)	(0.0140)
$SCHINT_s \times HC_{r,t-1}$			0.0066***	0.0086***			0.0065***	0.0086***
			(0.0016)	(0.0017)			(0.0016)	(0.0017)
$PHYINT_s \times PHY_{r,t-1}$					0.0000***	0.0000**	0.0000***	0.0000**
					(0.0000)	(0.0000)	(0.0000)	(0.0000)
$size_{s,r,t-1}$	18.4107***	18.9287***	18.4474***	18.9844***	18.4036***	18.9242***	18.4403***	18.9798***
	(1.4597)	(1.5616)	(1.4605)	(1.5628)	(1.4598)	(1.5616)	(1.4606)	(1.5629)
Endogeneity Test		$\chi^2(1) = 5.03$		$\chi^2(2) = 13.59$		$\chi^2(2) = 12.31$		$\chi^2(3) = 20.29$
		$p = 0.0249$		$p = 0.0011$		$p = 0.0021$		$p = 0.0001$
Numbers of regions	30	30	30	30	30	30	30	30
Numbers of sectors	29	29	29	29	29	29	29	29
Observation	8604	7887	8604	7887	8604	7887	8604	7887
R-square	0.3358	0.3616	0.3370	0.3633	0.3360	0.3618	0.3372	0.3635

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel B: Manufacturing Sectors									
	Unconditional Estimates		Human Capital		Physical Capital		Financial Development		All Controls	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
$ICT_s \times \Delta lnk_{r,t}^I$	0.0161***	0.0175**	0.0160***	0.0172**	0.0160***	0.0163**	0.0164***	0.0164*	0.0163**	0.0147*
	(0.0053)	(0.0075)	(0.0055)	(0.0074)	(0.0057)	(0.0077)	(0.0062)	(0.0093)	(0.0066)	(0.0087)
$SCHINT_s \times HC_{r,t-1}$			0.0039	0.0049					0.0056	0.0066
			(0.0080)	(0.0078)					(0.0085)	(0.0085)
$PHYINT_s \times PHY_{r,t-1}$					0.0001	0.0001			0.0001	0.0001
					(0.0001)	(0.0001)			(0.0001)	(0.0001)
$FINDEP_s \times FIDEV_{r,t-1}$							-0.0331	-0.0477	-0.0368	-0.0469
							(0.0347)	(0.0392)	(0.0296)	(0.0321)
$size_{s,r,t-1}$	23.8899***	23.8853***	23.8893***	23.8928***	23.8716***	23.8652***	23.9645***	23.9502***	23.9467***	23.9362***
	(2.2291)	(2.2918)	(2.2285)	(2.2918)	(2.2329)	(2.2957)	(2.2536)	(2.3175)	(2.2572)	(2.3224)
		$\chi^2(1)$		$\chi^2(2)$		$\chi^2(2)$		$\chi^2(2)$		$\chi^2(4)$
Endogeneity Test		$= 1.1147$		$= 12.5282$		$= 0.9907$		$= 0.9078$		$= 13.8445$
		$p = 0.2911$		$p = 0.0019$		$p = 0.6094$		$p = 0.6352$		$p = 0.0078$
Numbers of regions	30	30	30	30	30	30	30	30	30	30
Numbers of sectors	11	11	11	11	11	11	11	11	11	11
Observation	3960	3630	3960	3630	3960	3630	3630	3300	3630	3300
R-square	0.4482	0.4532	0.4482	0.4531	0.4503	0.4549	0.4541	0.4593	0.4563	0.4609

Source: Author's own work

Notes: 1. The three-dimensional panel data is dealt by grouping sector and region for a panel identifier. 2. Dependent variable in both Panel A and Panel B is the annual growth rate of sector value added. The interaction term between intangible capital and ICT intensity is calculated as the region-level annual growth rate of intangible capital stock ($\Delta lnk_{r,t}^I$) multiplied by sector-level ICT intensity (ICT_s). Columns (1) – (2) are unconditional estimates, Columns (3) – (4) introduce the interaction term between region-level human capital development ($HC_{r,t-1}$) and sector-level schooling intensity ($SCHINT_s$), Columns (5) – (6) introduce the interaction term between region-level non-ICT physical capital development ($PHY_{r,t-1}$) and sector- level non-ICT physical capital intensity ($PHYINT_s$), Columns (7) – (8) introduce the interaction term between region-level financial market development ($FIDEV_{r,t-1}$) and sector-level external financial dependence ($FINDEP_s$) (if applicable), and the final Columns (Columns (7) - (8) in Panel A and Columns (9) – (10) in Panel B) includes all controls into specification. 3. Odd Columns show results based on OLS and even Columns show results based on IV estimation. For all columns using IV, instruments of $\Delta lnk_{r,t-1}^I$, $HC_{r,t-2}$, $PHY_{r,t-2}$, and $FIDEV_{r,t-2}$ are used where applicable. 4. All specifications include region-year and sector fixed effects. 5. Standard deviation is shown in parentheses being clustered by region and sector.

can be treated as exogenous, and the test statistic is distributed as chi-squared with degrees of freedom equal to the number of regressors tested. In addition, partial R-squared and the joint significance of the instruments in the first-step regression is used to check the instrument relevance conditions (Shea, 1997).

In general, the coefficients of the key interaction term between intangible capital and ICT are all positive and statistically significant. The exogeneity of the interactions in the model is rejected in all cases. The discussion hence is focused more on the IV estimates. To interpret the economic significance of the estimated coefficients in **Table 4-5**, we consider the growth differences between a sector at the 75th percentile of ICT intensity (service to household, ICT intensity equals 1.817) and a sector at the 25th percentile of ICT intensity (food, drink and beverage, ICT intensity equals 0.131) in different Chinese regions. The coefficient in Column (2), for example, indicates that the annual growth of service to the household sector would increase by 0.82 percent (=1.686×0.0381×0.128) more than the food, drink and beverage sector in a region with intangible capital growing at the 25th percentile (0.128). Conversely, the growth difference between these two sectors would be 1.01 percent (=1.686×0.0381×0.158) in a region with intangible capital growing at the 75th percentile (0.158).[38] The economic magnitude of differential effects of intangible capital on different ICT-dependent sectors is therefore 0.19 percentage points. Consider that the deviation in regional intangible capital growth rates of Chinese regions is not sizeable, it is worthwhile to look at growth differences by using a sector at the 90th percentile of ICT intensity (restaurants and hotels, ICT intensity equals 3.345) and a sector at the 10th percentile of ICT intensity (public management, ICT intensity equals 0.018). The growth difference between these two sectors enlarges to 0.76 percentage point in a region with intangible capital growing at 90th percentile (0.168) compared with a region with intangible capital growing at 10th percentile (0.108).

Columns (3) – (8) in Panel A extend the benchmark estimates by adding additional determinants of sector growth into Equation (4-2). The interpretation is that, after controlling for

[38] To get a sense of economic magnitude of the coefficient, average growth rates of intangible capital stock are used, shown in **Table 4-4**.

variations caused by human capital, non-ICT physical capital, or both, to how much the remaining growth variations among sectors can be explained by intangible capital. It is seen from the table that the differential effects of intangible capital on sector growth are still positive and significant in all conditional circumstances. The economic magnitudes of coefficients remain similar with those unconditional estimates.

In Panel B, the sample size shrinks to a half and is confined to China's manufacturing industry. OLS estimators perform well in some cases where the test of endogeneity fails to reject the null hypothesis. The empirical evidence based on subsample analysis still supports the main idea that intangible capital makes contributions to China's economic growth by interacting with ICT. The evidence is quite robust even in the most prudent circumstance where all three determinants of sector growth are considered. In other words, the impacts of intangible capital are still positively significant after being isolated from the impacts of region-level human capital, non-ICT physical capital and financial market development. Based on the coefficient in Column (10), the economic significance is interpreted by comparing growth differences between a manufacturing sector at 75^{th} percentile ICT intensity (metal products, ICT intensity equals 2.488) and a manufacturing sector at the 25^{th} percentile (transport equipment, ICT intensity equals 0.232). The growth difference between these two sectors is 0.10 percentage point higher in a Chinese region with intangible capital growing at the 75^{th} percentile (0.158) compared with another region with intangible capital growing at 25^{th} percentile (0.128).

In addition, region-level human capital is found to contribute to China's economic growth significantly by interacting with sector schooling intensity in Panel A. The evidence is consistent with a range of studies in developed countries. The advanced human capital can disproportionally help more schooling-intensive sectors grow faster. However, the coefficients of the human capital interaction term remain positive but turn to be insignificant when we use the manufacturing subsample for analysis. One possible explanation may be the lack of variation in sector schooling intensity among Chinese manufacturing sectors. The standard deviation of sector schooling intensity drops from 1.643 in whole sample to only 0.62 in the manufacturing subsample.

Finally, regional financial market development shows negative but insignificant effects on China's sector growth by interacting with the sector's external financial dependence. Consistent with developed countries, regional financial market development is defined as total bank loans over real GRP. As is shown in **Table 4-4**, some underdeveloped regions in China have abnormal outperformance in terms of financial market development. As discussed above, this indicator reflects a lot of the policy interference in China, and may explain the insignificant estimators that we obtained.

Alternative measure of intangible capital development

Until now, regional intangible capital development has been estimated by using the growth rate of intangible capital stock. An alternative measure of intangible capital development in Chinese regions is checked against to see if results remain unchanged. Here we use the share of intangible capital stock in total capital stock (excluding ICT) in region r at the end of previous year ($k^I_{r,t-1}/k_{r,t-1}$) as another measure, and the results are shown in **Table 4-6**. Sector ICT intensity remains to be the average ratio of ICT capital stock over labour input across region and time (ICT_s). The interaction term of the key interest is therefore $ICT_s \times \frac{k^I_{r,t-1}}{k_{r,t-1}}$. Again, odd columns show the OLS estimators and even columns show the IV estimators. In general, the positive and highly significant effects of intangible capital development on the growth of ICT-intensive sectors appear robust to the alternative measure in all cases with and without other controlled interactions. The economic magnitude also remains similar with benchmark estimates. Taking the coefficient in Column (4) as an example, the growth differentials between sectors at the 75th and 25th percentile of ICT intensity (household service vs. food, drink and beverage as above) in two regions with intangible capital development at the 75th and 25th percentile (0.087 vs. 0.055) is 0.07 percentage point

Table 4-6: Intangible Capital and Sector Value-added Growth: Alternative Measures of Intangible Capital

Panel A: Total Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Unconditional Estimates		Human Capital		Physical Capital		All Controls	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
$ICT_s \times \frac{k^{I}_{r.t-1}}{l}$	0.0165***	0.0137***	0.0161***	0.0132***	0.0142***	0.0106**	0.0136***	0.0098**
	(0.0039)	(0.0043)	(0.0039)	(0.0044)	(0.0043)	(0.0048)	(0.0044)	(0.0049)
$SCHINT_s \times HC_{r,t-1}$			0.0066**	0.0078***			0.0065**	0.0078***
			(0.0026)	(0.0025)			(0.0026)	(0.0024)
$PHYINT_s \times PHY_{r,t-1}$					0.0000*	0.0000	0.0000*	0.0000
					(0.0000)	(0.0000)	(0.0000)	(0.0000)
$size_{s,r,t-1}$	18.4139***	18.9281***	18.4509***	18.9847***	18.4063***	18.9232***	18.4433***	18.9797***
	(1.4597)	(1.5616)	(1.4605)	(1.5628)	(1.4598)	(1.5616)	(1.4606)	(1.5629)
Endogeneity Test		$\chi^2(1) = 0.7108$ $p = 0.3992$		$\chi^2(2) = 9.0829$ $p = 0.0107$		$\chi^2(2) = 10.0915$ $p = 0.0064$		$\chi^2(3) = 17.7580$ $p = 0.0005$
Numbers of regions	30	30	30	30	30	30	30	30
Numbers of sectors	29	29	29	29	29	29	29	29
Observation	8604	7887	8604	7887	8604	7887	8604	7887
R-square	0.3353	0.3623	0.3365	0.3640	0.3356	0.3624	0.3367	0.3641

Panel B: Manufacturing Sectors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Unconditional Estimates		Human Capital		Physical Capital		Financial Development		All Controls	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
$ICT_s \times \frac{k^I_{r,t-1}}{k_{r,t-1}}$	0.0158***	0.0122**	0.0155***	0.0118**	0.0119**	0.0074	0.0190***	0.0151*	0.0148**	0.0095
	(0.0049)	(0.0059)	(0.0050)	(0.0059)	(0.0050)	(0.0059)	(0.0058)	(0.0079)	(0.0060)	(0.0077)
$SCHINT_s \times HC_{r,t-1}$			0.0037	0.0049					0.0053	0.0065
			(0.0080)	(0.0078)					(0.0086)	(0.0085)
$PHYINT_s \times PHY_{r,t-1}$					0.0001	0.0001			0.0001	0.0001
					(0.0001)	(0.0001)			(0.0001)	(0.0001)
$FINDEP_s \times FIDEV_{r,t-1}$							-0.0330	-0.0475	-0.0350	-0.0459
							(0.0355)	(0.0402)	(0.0302)	(0.0329)
$size_{s,r,t-1}$	23.8998***	23.8964***	23.8998***	23.9016***	23.8776***	23.8719***	23.9736***	23.9617***	23.9520***	23.9401***
	(2.2305)	(2.2944)	(2.2301)	(2.2944)	(2.2343)	(2.2982)	(2.2550)	(2.3206)	(2.2588)	(2.3253)
Endogeneity Test		$\chi^2(1) = 2.1191$ $p = 0.1455$		$\chi^2(2) = 12.4607$ $p = 0.0020$		$\chi^2(2) = 3.6186$ $p = 0.1638$		$\chi^2(2) = 0.4223$ $p = 0.8097$		$\chi^2(4) = 13.9769$ $p = 0.0074$
Numbers of regions	30	30	30	30	30	30	30	30	30	30
Numbers of sectors	13	13	13	13	13	13	13	13	13	13
Observation	3960	3630	3960	3630	3960	3630	3630	3300	3630	3300
R-square	0.4473	0.4531	0.4473	0.4529	0.4495	0.4548	0.4533	0.4592	0.4556	0.4607

Source: Author's own work

Notes: 1. Dependent variable in both Panel A and Panel B is the annual growth rate of value added at region-sector level for the period 2003-2016. 2. The interaction term between intangible capital and ICT intensity is calculated as the region-level share of intangible capital stock in total capital stock (exclude ICT) ($k^I_{r,t-1}/k_{r,t-1}$) at the end of previous year multiplied by sector-level ICT intensity (ICT_s). Columns (1) – (2) are unconditional estimates, Columns (3) – (4) introduce the interaction term between region-level human capital development ($HC_{r,t-1}$) and sector-level schooling intensity ($SCHINT_s$), Columns (5) – (6) introduce the interaction term between region-level non-ICT physical capital development ($PHY_{r,t-1}$) and sector-level non-ICT physical capital intensity ($PHYINT_s$), Columns (7) – (8) introduce the interaction term between region-level financial market development ($FIDEV_{r,t-1}$) and sector-level external financial dependence ($FINDEP_s$) (if applicable), and the final Columns (Columns (7) – (8) in Panel A and Columns (9) – (10) in Panel B) include all controls into specification. 3. Odd Columns show results based on OLS and even Columns show results based on IV estimation. For all columns using IV, instruments of $k^I_{r,t-2}/k_{r,t-2}$, $HC_{r,t-2}$, $PHY_{r,t-2}$, and $FIDEV_{r,t-2}$ are used where applicable. 4. All specifications include region-year and sector fixed effects. 5. Standard deviation is shown in parentheses being clustered by region and sector.

((1.817-0.131)×0.0132×(0.087-0.055)), staying similar with the result of 0.19 percentage point in baseline estimates.

Alternative measure of sector ICT intensity

Furthermore, the sensitivity of benchmark estimates is checked against different measures of sector ICT intensity. According to previous studies, alternative ICT intensity indicators are: the share of ICT in total physical capital stock (ICT_s'); the share of ICT in total physical capital real investment (ICT_s''); and the ratio of ICT real investment over sector real value added (ICT_s''').

Table 4-7 reports the results. The first four rows (1) – (4) use ICT_s', rows (5) – (8) use ICT_s'' , and the final four rows (9) – (12) use ICT_s'''. All entries with odd numbers show OLS results and even ones show IV results. Intangible capital in **Table 4-7** is measured the same with benchmark estimates as the annual growth rate of intangible capital stock in Chinese regions ($\Delta\ln k_{r,t}^{I}$). As is shown in **Table 4-7**, the differential effects of intangible capital are significant in most cases by using either OLS or IV estimators. In cases where the coefficients are statistically significant, the economic magnitudes range between 0.06 percentage point and 0.27 percentage point in regions at the 75th and 25th percentile of intangible capital development between sectors at the 75th and 25th percentile of different ICT intensity indicators (calculation not shown).

Table 4-7: Intangible Capital and Sector Value-added Growth: Alternative Measures of ICT Intensity

Panel A: Total Sample

Value Added	Sector ICT	Intangible × ICT	Hum. Cap.	Phy. Cap.	Size Control	Endogeneity Test	Observation	R-square
(1) OLS	ICT_s'	1.7993***			18.4050***		8604	0.3359
		(0.6275)			(1.4598)			
(2) IV	ICT_s'	3.9055***			18.9217***	$\chi^2(1) = 5.1005$	7997	0.3618
		(1.3720)			(1.5614)	$p = 0.0239$		
(3) OLS	ICT_s'	1.7403***	0.0065***	0.0000***	18.4346***		8604	0.3373
		(0.6271)	(0.0016)	(0.0000)	(1.4607)			
(4) IV	ICT_s'	3.7259***	0.0085***	0.0000**	18.9729***	$\chi^2(3) = 19.5814$	7997	0.3637
		(1.3658)	(0.0017)	(0.0000)	(1.5628)	$p = 0.0002$		
(5) OLS	ICT_s''	1.0602***			18.4022***		8604	0.3359
		(0.3590)			(1.4600)			
(6) IV	ICT_s''	2.2868***			18.9159***	$\chi^2(1) = 5.9327$	7997	0.3618
		(0.7615)			(1.5615)	$p = 0.0149$		
(7) OLS	ICT_s''	1.0148***	0.0064***	0.0000***	18.4319***		8604	0.3373
		(0.3583)	(0.0016)	(0.0000)	(1.4609)			
(8) IV	ICT_s''	2.1410***	0.0085***	0.0000**	18.9675***	$\chi^2(3) = 19.6485$	7997	0.3637
		(0.7579)	(0.0017)	(0.0000)	(1.5628)	$p = 0.0002$		
(9) OLS	ICT_s'''	0.2576			18.4145***		8604	0.3354
		(0.3993)			(1.4598)			
(10) IV	ICT_s'''	3.0240***			18.9406***	$\chi^2(1) = 19.4408$	7997	0.3679
		(0.8524)			(1.5631)	$p = 0.0000$		
(11) OLS	ICT_s'''	0.2450	0.0065***	0.0000***	18.4441***		8604	0.3368
		(0.3999)	(0.0016)	(0.0000)	(1.4607)			
(12) IV	ICT_s'''	3.0138***	0.0086***	0.0000**	18.9916***	$\chi^2(3) = 32.0774$	7997	0.3597
		(0.8530)	(0.0017)	(0.0000)	(1.5645)	$p = 0.0000$		

Panel B: Manufacturing Sectors

Value Added	Sector ICT	Intangible × ICT	Hum. Cap.	Phy. Cap.	Finan. Dev.	Size Control	Endogeneity Test	Observation	R-square
(1) OLS	ICT_s'	1.6540***				23.8905***		3960	0.4481
		(0.3486)				(2.2291)			
(2) IV	ICT_s'	1.9607***				23.8863***	$\chi^2(1) = 1.4737$	3630	0.4530
		(0.4696)				(2.2916)	$p = 0.2248$		
(3) OLS	ICT_s'	1.6117***	0.0056	0.0001	-0.0371	23.9477***		3630	0.4562
		(0.4470)	(0.0085)	(0.0001)	(0.0306)	(2.2573)			
(4) IV	ICT_s'	1.6348***	0.0066	0.0001	-0.0472	23.9376***	$\chi^2(4) = 13.8853$	3300	0.4607
		(0.4823)	(0.0085)	(0.0001)	(0.0337)	(2.3224)	$p = 0.0077$		
(5) OLS	ICT_s''	0.9938***				23.8930***		3960	0.4480
		(0.3086)				(2.2293)			
(6) IV	ICT_s''	1.3375***				23.8891***	$\chi^2(1) = 2.1673$	3630	0.4527
		(0.3325)				(2.2918)	$p = 0.1410$		
(7) OLS	ICT_s''	0.9013**	0.0056	0.0001	-0.0370	23.9505***		3630	0.4560
		(0.4084)	(0.0085)	(0.0001)	(0.0307)	(2.2576)			
(8) IV	ICT_s''	1.0811***	0.0066	0.0001	-0.0474	23.9402***	$\chi^2(4) = 14.1012$	3300	0.4604
		(0.3450)	(0.0085)	(0.0001)	(0.0333)	(2.3225)	$p = 0.0070$		
(9) OLS	ICT_s'''	0.2239				23.9005***		3960	0.4473
		(0.9370)				(2.2302)			
(10) IV	ICT_s'''	1.4856***				23.9024***	$\chi^2(1) = 10.3167$	3630	0.4492
		(0.4591)				(2.2939)	$p = 0.0013$		
(11) OLS	ICT_s'''	-0.0164	0.0056	0.0001	-0.0353	23.9577***		3630	0.4555
		(1.1736)	(0.0083)	(0.0001)	(0.0303)	(2.2583)			
(12) IV	ICT_s'''	1.2733**	0.0067	0.0001	-0.0479	23.9541***	$\chi^2(4) = 19.7883$	3300	0.4567
		(0.5222)	(0.0084)	(0.0001)	(0.0328)	(2.3245)	$p = 0.0005$		

Source: Author's own work.

Notes: 1. Dependent variable in both Panel A and Panel B is the annual growth rate of sector value added. 2. In both panels, Rows (1) – (4) interacts region-level intangible capital growth rate with the share of ICT in total physical capital stock (ICT_s'), Rows (5) – (8) interacts region-level intangible capital growth rate with the share of ICT in total physical capital investment (ICT_s'') and Rows (9) – (12) interacts region-level intangible capital growth rate with the ratio of ICT real investment over real value added (ICT_s'''). 3. For all columns using IV, instruments of $\Delta lnk_{r,t-1}^I$, $HC_{r,t-2}$, $PHY_{r,t-2}$, and $FIDEV_{r,t-2}$ are used where applicable. 4. All specifications include region-year and sector fixed effects. 5. Standard deviation is shown in parentheses being clustered by region and sector.

Alternative Sector and Region Characteristic

Finally, we examine whether the differential effects of our key interests partly capture the effects of region-level intangible capital development from interacting with other sector characteristics, and the effects of other reginal characteristics from interacting with ICT. In Panel A of **Table 4-8** we check whether intangible capital continues to have effects on ICT-intensive sectors when it is also interacted with sector schooling intensity, non-ICT physical capital intensity and external financial dependence. In Panel B of **Table 4-8** we check the robustness of the results by allowing sector ICT intensity to interact with region-level human capital development, non-ICT physical capital development, and financial market development. Measures of sector ICT intensity and regional intangible capital development remain the same with benchmark estimates. According to Panel A in **Table 4-8**, the results of positive and significant effects of intangible capital appear to be robust. There is little evidence of the effects of intangible capital on China's economic growth by interacting with other sector characteristics. Similarly, in Panel B, the coefficient of intangible capital and ICT interaction continues to be statistically significant and of similar magnitude with benchmark estimates. The coefficients of the interaction terms between sector ICT intensity and other regional characteristics are all insignificant. More ICT-intensive sectors show no evidence of growing faster with the help of advanced human capital in China, which is different from the study of Murphy and Siedschlag (2013) who suggested a positive coefficient of the interaction term of ICT and human capital based on open economies. Possibly, the different findings in China can be partly explained by the different coverage of ICT-intensive sectors between China and the countries involved in their study. Some more ICT-dependent sectors in their study, such as education and health services, remain as less ICT-dependent sectors in China.

Table 4-8: Intangible Capital and Sector Value-added Growth: Other Region-Sector Interactions

	Panel A					
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
$ICT_s \times \Delta lnk^I_{r,t}$	0.0157**	0.0381***	0.0160**	0.0378***	0.0165**	0.0257
	(0.0063)	(0.0140)	(0.0063)	(0.0141)	(0.0070)	(0.0176)
$SCHINT_s \times \Delta lnk^I_{r,t}$	0.0384*	-0.0214				
	(0.0209)	(0.0381)				
$PHYINT_s \times \Delta lnk^I_{r,t}$			0.0000	-0.0001		
			(0.0001)	(0.0001)		
$FINDEP_s \times \Delta lnk^I_{r,t}$					0.0401	-0.6284
					(0.2517)	(0.5699)
$size_{s,r,t-1}$	18.4140***	18.9266***	18.4112***	18.9274***	17.0806***	17.9191***
	(1.4596)	(1.5622)	(1.4598)	(1.5620)	(1.9176)	(2.1099)
Endogeneity Test		$\chi^2(2) = 10.3936$ 0.0055		$\chi^2(2) = 6.7066$ 0.0350		$\chi^2(2) = 3.5286$ 0.1713
Numbers of regions	30	30	30	30	30	30
Numbers of sectors	29	29	29	29	11	11
N	8604	7887	8604	7887	4290	3900
R-square	0.3359	0.3615	0.3358	0.3616	0.3647	0.3782

	Panel B					
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
$ICT_s \times \Delta lnk^I_{r,t}$	0.0159**	0.0384***	0.0154**	0.0358***	0.0157**	0.0379***
	(0.0062)	(0.0137)	(0.0062)	(0.0137)	(0.0063)	(0.0142)
$ICT_s \times HC_{r,t-1}$	-0.0000	-0.0001				
	(0.0004)	(0.0004)				
$ICT_s \times PHY_{r,t-1}$			-0.0007	-0.0007		
			(0.0007)	(0.0009)		
$ICT_s \times FIDEV_{r,t-1}$					-0.0006	-0.0012
					(0.0005)	(0.0008)
$size_{s,r,t-1}$	18.4106***	18.9282***	18.4145***	18.9313***	18.4135***	18.9349***
	(1.4598)	(1.5617)	(1.4600)	(1.5617)	(1.4602)	(1.5620)
Endogeneity Test		$\chi^2(2) = 10.0887$ $p = 0.0064$		$\chi^2(2) = 4.9031$ $p = 0.0862$		$\chi^2(2) = 7.7970$ $p = 0.0203$
Numbers of regions	30	30	30	30	30	30
Numbers of sectors	29	29	29	29	29	29
N	8604	7887	8604	7887	8604	7887
R-square	0.3358	0.3616	0.3360	0.3621	0.3359	0.3616

Source: Author's own work.

Notes: 1. Dependent variable in both Panel A and Panel B is the annual growth rate of sector's value added. 2. In Panel A, added region-level intangible capital development is interacted with other sector characteristics such as sector-level schooling intensity ($SCHINT_s$), sector-level non-ICT physical capital intensity ($PHYINT_s$), and external financial dependence ($FINDEP_s$). In Panel B, added sector-level ICT intensity is interacted with other regional characteristics such as human capital development ($HC_{r,t-1}$), non-ICT physical capital development ($PHY_{r,t-1}$), and financial market development ($FIDEV_{r,t-1}$). 3. Odd columns show results based on OLS and even columns show results based on IV estimation. For all columns using IV, instruments of $\Delta lnk^I_{r,t-1}$, $HC_{r,t-2}$, $PHY_{r,t-2}$, and $FIDEV_{r,t-2}$ are used where applicable. 4. All specification includes region-year and sector fixed effects. 5. Standard deviation is shown in parentheses being clustered by region and sector.

4.5 Conclusion

One way to gain insights into the effects of intangible capital on economic growth is to examine the economic mechanism through which such effects could be captured. This chapter provides novel empirical evidence about how intangible capital contributes to economic growth by interacting with ICT capital in Chinese regions. Specifically, the study investigates the differential effects of intangible capital on the value-added growth of ICT-intensive sectors in China using data across 30 Chinese regions and 29 sectors between 2003 and 2015. The fixed effect identification method allows the model specification to focus on within-region between-sector differences, and include other possible determinants of sector growth at the same time.

The analysis suggests that sectors that are more dependent on ICT exhibit faster growth rates in value added in Chinese regions with faster development of intangible capital. The results are robust to alternative measures of intangible capital development and different sector ICT intensity indicators. In addition, the positive and statistically significant effects of intangible capital on growth in ICT-intensive sectors appear to be independent from other determinants of sector growth, such as region-level human capital development, non-ICT physical capital development and financial market development. The findings imply that Chinese policy makers should not only aim for more ICT infrastructure investment but should also emphasise on the development of intangible capital.

APPENDIX A4

Table A4-1: ICT Scope Comparison

ICT sectors (OECD definition)	ICT sectors (NBS classification)
Manufacturing 3000 Office, accounting and computing machinery 3130 Insulated wire and cable 3210 Electronic valves and tubes and other electronic components 3220 Television and radio transmitters and apparatus for line telephony and line telegraphy 3230 Television and radio receivers, sound or video recording or reproducing apparatus, and associated goods 3312 Instruments and appliances for measuring, checking, testing, navigating and other purposes, except industrial process equipment 3313 industrial process equipment	Manufacturing A39 Manufacture of computing, telecommunication and electronic machinery 391 Manufacture of computers and peripheral equipment 392 Manufacture of communication equipment 393 Manufacture of television and radio transmitters and apparatus for line telephony and line telegraphy 394 Manufacture of radar and radar apparatus 395 Manufacture of radio, television and communication equipment and apparatus 396-7/399 Manufacture of electronic valves and tubes and other electronic components
Services 5151 Wholesale of computers, computer peripheral equipment and software 5152 Wholesale of electronic and telecommunications parts and equipment 6420 Telecommunications 7123 Renting of office machinery and equipment (including computers) 72 Computer and related activities	Services I63 Wired, wireless, satellite and other telecommunication activities I64 Data processing, hosting and web portals and other related activities I65 Computer services and related activities

Source: OECD (2006) and China National Bureau of Statistics (2011).

Table A4-2: Shares of Computer Software in ICT and Intangible Capital

Region	ICT Investment	ICT Stock	Intangible Investment	Intangible Stock
	(1)	(2)	(3)	(4)
Beijing	78.90	65.30	25.00	18.90
Tianjin	39.30	25.60	11.30	8.60
Hebei	2.54	1.98	0.62	0.48
Shanxi	0.32	0.32	0.09	0.06
Inner-Mongolia	6.60	4.71	1.41	0.80
Liaoning	46.50	33.00	20.90	14.90
Jilin	73.10	69.30	4.59	3.75
Heilongjiang	28.90	18.80	2.72	2.12
Shanghai	34.40	17.20	9.09	6.19
Jiangsu	19.50	12.10	18.10	13.20
Zhejiang	36.80	20.60	11.60	8.96
Anhui	5.14	3.42	1.15	0.81
Fujian	34.00	17.90	20.90	15.90
Jiangxi	3.54	3.71	1.32	1.06
Shandong	30.00	18.70	13.40	9.40
Henan	3.16	2.31	1.44	1.01
Hubei	26.10	13.20	5.47	3.75
Hunan	11.20	9.29	3.02	2.07
Guangdong	25.80	13.20	12.40	9.43
Guangxi	4.90	3.42	1.25	0.87
Hainan	15.90	6.68	0.89	0.63
Chongqing	48.90	29.20	9.84	6.84
Sichuan	17.60	11.60	8.01	5.74
Guizhou	10.10	5.04	1.85	1.19
Yunnan	21.50	21.30	0.52	0.38
Shaanxi	49.40	29.80	11.10	7.25
Gansu	34.30	9.29	1.08	0.67
Qinghai	0.52	0.00	0.14	0.00
Ningxia	9.74	7.68	0.41	0.36
Xinjiang	30.70	20.70	0.82	0.57
Average	78.90	65.30	25.00	18.90

Source: Author's own work.

Note: Column (1) indicates the share of computer software in real ICT investment; Column (2) indicates the share of computer software in ICT capital stock; Column (3) indicates the share of computer software in real intangible investment; and Column (4) indicates the share of computer software in intangible capital stock.

Table A4-3: ICT-Intensive (Yes) and Non-ICT (No) Sectors in China and the US

Sectors	**This study**	**Stiroh (2002)**	**van Ark (2002)**
Agriculture, Forestry, Animal Husbandry and Fishery	No	No	No
Mining and quarrying	No	No	No
Food, beverages and tobacco	No	No/Yes	No
Textiles and leather	No	No	No
Wood, paper and printing	Yes	Yes	Yes
Petroleum, coal and chemicals	**Yes**	No	No
Non-metallic mineral products except petroleum and coal	**Yes**	No	No
Metal, Fabricated metal products	**Yes**	No	No
Machinery equipment	Yes	Yes	Yes
Transport equipment	No	No/Yes	No/Yes
Electrical and electronic equipment	Yes	Yes	Yes
Computer, telecommunication and other electronic equipment	Yes	Yes	Yes
Apparatus, instruments and other manufacturing activities	Yes	Yes	Yes
Electricity, gas and water supply	**Yes**	No	No
Construction	No	No	No
Wholesale and retail trade	Yes	Yes	Yes
Transport, storage and post	No	No/Yes	No
Hotel and catering services	**Yes**	No	No
Information transmission, software and information technology	Yes	Yes	Yes
Financial intermediation	Yes	Yes	Yes
Real estate	No	No	No
Leasing and business services	Yes	Yes	Yes
Science research and technical services	Yes	Yes	Yes
Management of water conservancy, environment and public facility	No	NA	No
Service to households, repair and other services	Yes	No/Yes	No
Education	No	Yes	No
Health and social service	No	Yes	No
Culture, sports and entertainment	No	NA	No
Public management, social security and social organisation	No	NA	No

Source: Author’s own work.

Notes: 1. “NA” means that the sector was not classified in the work due to a lack of investment data. 2. “No/Yes” means that part of the sector was classified as non-ICT and another part as ICT-intensive.

Data Sources and Description

1. Region-sector Data

$\mathbf{y_{s,r,t}}$: Real gross value added of sector s in region r in year t. Gross output is used for interpolation and extrapolation if there are missing values in gross value added. Nominal gross value added is deflated by using region-sector value added price indices. The base year is set to be 2010. Source: China Industrial Statistical Yearbook (CISY, 2004-2016), China National Statistical Yearbook (NSY, 2004-2016).

$\Delta\mathbf{ln}\boldsymbol{y}_{s,r,t}$: The annual growth rate of real gross value added in sector s in region r in year t.

$\boldsymbol{emp}_{s,r,t}$: Employment (number count) of sector s in region r in year t. Source: China Labour Statistical Yearbook (CLSY, 2004-2016).

$\boldsymbol{ict\_inv}_{s,r,t}$: Real ICT investment flows of sector s in region r in year t. Since ICT investment has not yet been recorded independently in China, as suggested by van Ark et al. (2002), commodity flow method is adopted to construct ICT investment flows. By multiplying a sector's real output with the ratio of fixed capital formation to the sector's total output in regional input-output (I-O) tables, we obtain region-level ICT investment flows first. After that, the direct consumption coefficient matrix obtained from regional I-O tables is used to allocate region-level ICT investment flows into each of 29 sectors within each region. Available regional I-O tables in China are in the years 2002, 2007, 2012. By assuming no structural changes during a short period, the fixed formation/output ratios in 2002 are used for the years 2002-2006, those in 2007 for the years 2007-2010, and those in 2012 for the years of 2011-2015. Source: China Statistical Yearbook of Electronic Industry (CSYEI, 2004-2016), China Regional Input Output Tables (2003, 2008, 2013).

$\boldsymbol{ict\_s}_{s,r,t}$: ICT capital stock of sector s in region r in year t. PIM is used for capital stock estimation. Following Cai & Zhang (2015), nominal ICT investment flows are deflated by the regional producer price index of items in the category "manufacture of computers, communication and other electronic equipment". Due to the lack of information, the national price index is used in the years 2002-2004. Moreover, according to previous studies, 15 percent and 33 percent are used for depreciating ICT hardware and software capital stock, respectively (Corrado et al., 2005, 2006; Jorgenson & Stiroh, 2000).

$\boldsymbol{phy_{s,r,t}}$: non-ICT physical capital stock of sector s in region r in year t. Newly increased fixed assets (excluding ICT investment flows) is used as non-ICT physical investment flows in sector s. PIM is applied to obtain capital stock. Nominal investment flows are deflated by regional fixed capital investment price indices. Different depreciation rates are used for different sectors and regions as suggested by Wu (2016). Source: China Statistical Yearbook of Investment in Fixed Assets (CSYIFA, 2004-2016).

$\boldsymbol{cap\_inv_{s,r,t}}$: Real total physical capital investment of sector s in region r in year t. Total physical capital investment includes investment in ICT hardware, ICT software and non-ICT physical capital.

$\boldsymbol{cap\_s_{s,r,t}}$: Total physical capital stock of sector s in region r in year t. Total physical capital stock includes ICT capital stock and non-ICT physical capital stock ($ict\_s_{s,r,t}$, $phy_{s,r,t}$).

$\boldsymbol{edu\_att_{s,r,t}}$: Average years of schooling attainment of employment in sector s in region r in year t. It is calculated by multiplying the share of employees in each educational attainment group by 6, 9, 12, 15, 16, 18.5, respectively (Wang & Yao, 2003). The educational attainment groups are primary, junior secondary, senior secondary, college, university and postgraduate. Source: China Labor Statistical Yearbook (CLSY, 2004-2016).

$\boldsymbol{fix\_net_{s,r,t}}$: Net amount of fixed assets of sector s in region r in year t. Source: China Industrial Statistical Yearbook (CISY, 2005-2016).

$\boldsymbol{liq\_ass_{s,r,t}}$: Liquid assets of sector s in region r in year t. Source: China Industrial Statistical Yearbook (CISY, 2005-2016).

$\boldsymbol{liq\_liab_{s,r,t}}$: Liquid liabilities of sector s in region r in year t. Source: China Industrial Statistical Yearbook (CISY, 2005-2016).

$\boldsymbol{size_{s,r,t}}$: The share of sector s in region r's real gross GRP in year t ($y_{s,r,t}/GRP_{r,t}$).

2. Sector-specific Data

$\boldsymbol{ICT_s}$: Sector ICT intensity in benchmark estimation. It is calculated by averaging $ict\_s_{s,r,t}/emp_{s,r,t}$ across region and time.

$\boldsymbol{ICT'_s}$: Sector ICT intensity in sensitivity analysis. It is calculated by averaging $ict\_s_{s,r,t}/cap\_s_{s,r,t}$ across region and time.

$\boldsymbol{ICT''_s}$: Sector ICT intensity in sensitivity analysis. It is calculated by averaging $ict\_inv_{s,r,t}/cap\_inv_{s,r,t}$ across region and time.

$\boldsymbol{ICT'''_s}$: Sector ICT intensity in sensitivity analysis. It is calculated by averaging $ict\_inv_{s,r,t}/y_{s,r,t}$ across region and time.

$\boldsymbol{SCHINT_s}$: Sector schooling intensity is calculated by averaging $edu\_att_{s,r,t}$ across region and time.

$\boldsymbol{PHYINT_s}$**:** Non-ICT physical capital intensity is calculated by averaging $phy_{s,r,t}/y_{s,r,t}$ across region and time.

$\boldsymbol{FINDEP_s}$: External financial dependence is defined as the one minus the ratio of flows from operation to total capital expenditure (Rajan & Zingales, 1998). Total capital expenditure is calculated by subtracting net amount of fixed assets in the preceding year from the current year (adjusted for depreciation) ($fix\_net_{r,s,t} - fix\_net_{r,s,t-1}$). The operation flow is defined as the increase in liquid assets minus the increase in liquid liabilities ($\Delta liq\_ass_{s,r,t} - \Delta liq\_liab_{s,r,t}$).

3. Region-specific Data

$\boldsymbol{k^I_{r,t}}$**:** Intangible capital stock in region r in year t. Intangible capital consists of innovative properties and economic competency properties in this study. As previously discussed, intangible capital stock excludes computer software.

$\Delta \boldsymbol{lnk}^{\boldsymbol{I}}_{\boldsymbol{r,t}}$: The annual growth rate of intangible capital stock in region r in year t.

$\boldsymbol{k}^{\boldsymbol{NICT}}_{\boldsymbol{r,t}}$**:** Non-ICT physical capital stock in region r in year t. Regional fixed capital formations is obtained as investment flows. Nominal investment flows are deflated by using fixed capital investment price indices. The depreciation rate is set to be 15 percent. Source: China National Statistical Yearbook (NSY, 2004-2016), China Statistical Yearbook of Investment in Fixed Assets (CSYIFA, 2004-2016).

$\boldsymbol{k}_{\boldsymbol{r,t}}$: Total capital stock in region r in year t. Total capital stock in region r is calculated as the sum of non-ICT physical capital stock and intangible capital stock ($k^{I}_{r,t}, k^{NICT}_{r,t}$).

$\boldsymbol{k}^{\boldsymbol{I}}_{\boldsymbol{r,t}}/\boldsymbol{k}_{\boldsymbol{r,t}}$**:** The share of intangible capital in total capital stock in region r in year t.

$\boldsymbol{GRP}_{\boldsymbol{r,t}}$: Real gross regional product in region r in year t. Source: China National Statistical Yearbook (NSY, 2004-2016).

$\boldsymbol{HC}_{\boldsymbol{r,t}}$: Average years of schooling of population in region r in year t. Like the employment education attainment in each sector, average years of schooling of population in region r is obtained by multiplying the share of population in each education group by 6, 9, 12, 15, 16 and 18.5 years. Similarly, the educational attainment groups are primary, junior secondary, senior secondary, college, university and postgraduate. Source: China Labour Statistical Yearbook (CLSY, 2004-2016).

$\boldsymbol{PHY}_{\boldsymbol{r,t}}$: Regional physical capital development is defined as non-ICT physical capital stock over real gross GRP in region r in year t ($k^{NICT}_{r,t}/GRP_{r,t}$).

$\boldsymbol{FIDEV}_{\boldsymbol{r,t}}$: Regional financial development is defined as total bank loans over real GRP in region r in year t. Source: Almanac of China Finance and Banking, edited by the People's Bank of China (PBC-ACFB, 2004-2015), China National Statistical Yearbook (NSY, 2004-2016).

CHAPTER 5 - INTANGIBLE CAPITAL AND FIRM PERFORMANCE

5.1 Introduction

While the role of aggregate intangible capital in economic growth and productivity has been examined extensively at macro level, much is yet unknown about its productive impacts on firm output performance. In addition, the non-rival and non-excludable features of the knowledge-based intangible capital lead to great probability of knowledge spill-overs. However, except scientific R&D, of which the presence of knowledge spill-overs has been demonstrated (Bloom et al., 2013; Griliches, 1992), spill-overs from other intangible assets are still hardly examined in academic studies. Meanwhile, the existing studies that examine intangible spill-over effects are largely restricted at the national level (Corrado et al., 2017) and the industry level (Goodridge et al. 2017). Corrado et al. (2017) noted that scientific R&D only accounts for around one-third of the total amount of intangible capital, and other intangible capital is equally important. Therefore, it is necessary to explore the productive impacts of other non-R&D intangible capital on firm output performance, and examine the plausible spill-over effects from other non-R&D intangible capital.

This chapter aims to examine the impacts of organisation capital on firm output performance in China. In developed economies, advanced organisational structure is shown to improve firm productivity significantly (Tronconi & Vittucci Marzetti, 2011) and create extra stock market returns (Eisfeldt & Papanikolaou, 2013); It is also examined extensively that organisation capital can play a complementary role with information technology to jointly contribute to productivity growth (Brynjolfsson & Hitt, 2000; Brynjolfsson et al., 2002; Brynjolfsson & Yang, 1999, to cite a few). In stark contrast, little is known in China due to data unavailability. Hence, this study provides insights of organisation capital in Chinese manufacturing firms. Organisation capital is measured by using firm-level data, and is found to contribute to firms' performance significantly in

China. The findings of the output elasticity of organisation capital are consistent with those obtained from developed countries.

In addition, this chapter, at the first time, analyses knowledge spill-overs from organisation capital across Chinese firms. It is found that organisation capital increases productivity of firms and that firms also benefit from the spill-overs from the others' organisation capital. Two potential spill-over channels are investigated. They are, technological proximity and geographical proximity. Following Chen and Inklaar (2016), it is expected that firms with similar technologies are more likely to gain knowledge spill-overs from each other. Technological proximity is hence used to construct the spill-over pool of organisation capital. In addition, knowledge may diffuse more easily between firms that are located closer to each other. For this reason, geographical proximity is evaluated as another possible spill-over channel in Chinese context. By analysing two potential spill-over channels, our study draw different conclusions from Chen and Inklaar (2016), who found no spill-over effects from organisation capital among manufacturing firms in the United States. In contrast, our findings strongly support the existence of organisation capital spill-overs among Chinese manufacturing firms if geographical proximity rather than technological proximity is used as the spill-over channel. It indicates that spatial distance other than technical similarity is likely to play a more important role in organisational knowledge spill-overs in China.

This chapter is organised in seven sections. After the introduction, Section 5.2 provides background knowledge of organisation capital by reviewing the existing studies. Section 5.3 discusses the empirical method, and the measurement of knowledge spill-overs. Section 5.4 describes data source and management procedures. After that, Section 5.5 presents the empirical regression results, followed by a series of sensitivity analyses in Section 5.6. Section 5.7 concludes the chapter.

5.2 Literature Review

Organisation capital has been treated as a productive form of intangible capital, and is examined widely in many fields, such as productivity growth (Black & Lynch, 2001, 2004; Eisfeldt & Papanikolaou, 2013; Ichniowski et al., 2003), labour wages (Black & Lynch, 2004; Cappelli & Neumark, 2001), information technology (Brynjolfsson & Hitt, 2003; Brynjolfsson et al., 2002), corporate finance (Lev et al., 2009; Li et al., 2018), and so on. At micro level, it is also suggested that good firm performance is always highly correlated with advanced organisation capital. There is evidence from both the developed and developing countries. For example, Brynjolfsson and Hitt (2002) found that one dollar invested in ICT by US firms will gain more than ten dollars if it is co-invested with organisation capital. Atkeson and Kehoe (2005) found that nearly a half of the output in manufacturing sectors in the United States, which is not accounted for by payments to labour and capital, could be attributed to organisation capital; Meanwhile, the total value of organisation capital is roughly two-thirds of the value of physical capital. De and Dutta (2007) suggested that organisation capabilities have large impacts on the output of the Indian IT software industry, and implied that the key element of IT-driven productivity growth is organisation capital both in developing and developed countries. Chen and Inklaar (2016) examined both internal and external organisation capital based on US firm data. Their results support the positive impacts of internal organisation capital on firms' output but fail to support the existence of organisation spill-overs.

Though a growing body of literature suggests the important role of organisation capital in firm performance, there is hardly any consensus on the definition of organisation capital at firm level. Evenson and Westphal (1995) defined organisation capital as "the knowledge that is used to combine human skills and physical capital into systems for producing and delivering want-satisfying products". Lev et al. (2009) treated organisation capital as a stealth asset of firms which is the agglomeration of business processes and systems, as well as a unique corporate culture, and which enables them to convert factors of production into output more efficiently than their competitors. Corrado et al. (2005, 2006) did not define organisation capital directly, but estimated it based on the value of executive time spent on improving the effectiveness of business organisations (own-account organisation capital), and the management consulting expenses (purchased organisation capital).

Given China's political and cultural environment, organisation capital in Chinese firms may have different definitions from that in developed countries. However, organisation capital shares some features globally. Specifically, organisation capital should be: 1) disembodied. It should be different from physical and financial assets that have visible embodiment. Because of disembodiment, contributions of organisation capital to firm performance cannot be reflected in the firm financial statements, resulting in organisation capital being treated as intermediate expenses; 2) efficient and competitive. Advanced organisation capital should be treated as firms' competitive resources which enable the owner to outperform its competitors in the long run; and 3) tacit knowledge. Organisation capital is usually hard to be imitated by other counterparts. In other word, organisation capital is a firm's capability, and others cannot obtain easily without costing extra expenses. However, because of the same reason of tacit knowledge, it is suggested that organisation capital cannot be wholly controlled by its owner. Knowledge diffusions among firms happen at the same time.

These features of organisation capital pose great impediments for its measurement. Some studies thus use business surveys to roughly measure it. For example, Lev et al. (2005) considered three broad components of organisation capital (workforce training, employee voice and work design), and used industrial survey data for rough measurement. Nonetheless, this measurement approach relies largely on the quality of the survey (participants and the response rates). Other studies resort to related indices in firm financial statements. For example, sales, general and administrative capital (SG&A), as an immediate expense in the financial statements, is widely accepted as the most related proxy for organisation capital investment (Eisfeldt & Papanikolaou, 2013; Tronconi & Vittucci Marzetti, 2011). It includes most of the expenditures for generating organisation capital, and is found to be highly correlated with firm managerial quality scores (Bloom & van Reenen, 2007). However, since SG&A covers various types of expenditures that are not broken down in more detail, there is no consensus on how much of the amount is to reflect the investment in organisation capital. Portions that are used in current studies are subjective to a large extent. For example, Chen & Inklaar (2016) used total SG&A expenses as organisation investment, but subtracted 9 percent from it to represent advertising expenditures. De & Dutta (2007) measured organisation investment in Indian firms by using 10 percent of SG&A expenditures, while Tronconi & Marzetti (2011) used 20 percent for European firms.

5.3 Empirical Method

An intuitive view to evaluate the effects of organisation capital and its potential knowledge spill-overs is to estimate a static model of firms' production function. However, some theoretical biases might be generated from traditional static models. First, as mentioned by Grillches and Mairesse (1995), input variables are determined simultaneously by the same forces; organisation capital and firm performance thus are usually simultaneously determined. Specifically, firms may choose their organisational structure in a period with a view towards achieving a certain level of output performance, and a reverse direction could also be possible when organisational structure is affected by firm performance. The bilateral causality relationship generates a simultaneity problem, leading the traditional OLS estimator to be plausibly biased.

Second, endogeneity may arise in this simple model. The production function at the individual firm level is likely to suffer from omitted variable problems. For example, other intangible assets are included in macro-level analysis (Corrado et al., 2005; 2006). It is expected that not all but at least some of these intangible assets should also be considered in a firm's production function. One example is R&D capital. It is widely supported that R&D investment has a positive relationship with firms' productivity growth and output performance. However, R&D cannot be included in our baseline model due to data constraints. If R&D has a positive effect on

Chinese manufacturing firms and is positively correlated with organisation investment, an upwardly biased estimator would be obtained in this specification due to the unobservable heterogeneity of R&D investment. Additionally, unobservable heterogeneity exists if there are unknown factors that affect both performance and other explanatory variables.

A general solution to time-invariant unobservable heterogeneity is the time-demeaning fixed effects model. However, fixed-effects estimator would be consistent only if current values of explanatory variables were completely independent of the past dependent variables. This condition is hardly met especially at the firm level. If the explanatory variable is positively (negatively) related to past values of the dependent variable, the fixed effects model will be negatively (positively) biased (Wintoki et al., 2012).

Given these problems, this study employs a dynamic model of firms' production function. The generalised method of moment (GMM) is used to reflect the dynamic process after controlling for the unobserved heterogeneity and simultaneity. This estimator was introduced by Holtz-Eakin et al. (1988) and Arellano and Bond (1991), and further developed in a series of papers including Arellano and Bover (1995) and Blundell and Bond (1998). The approach is widely believed to have merits for dealing with dynamic panel analysis. For instance, it tackles the bias problem of the dynamic fixed-effect model in the dynamic panel analysis. In addition, the lagged values of explanatory variables are used to provide an exogenous source of variation for the current dependent variable under orthogonality conditions. It avoids the problem of identifying and justifying a strictly exogenous outside instrument, which is often quite difficult to find.

However, the GMM estimator cannot solve all endogeneity problems and is quite sensitive to the choice of instruments. For a trade-off, our specifications include both the static and dynamic models. Specifically, the static model can be expressed as follows

$$\ln Y_{it} = \alpha lnH_{it} + \beta lnK_{it} + \gamma_1 lnO_{it} + \gamma_2 lnO_{it}^{s} + \eta_i + \epsilon_{it} \tag{5-1}$$

where Y_{it} denotes firms' output performance (firms' gross output), K_{it} is physical capital stock, H_{it} is human capital (person count), O_{it} is firms' own organisation capital and O_{it}^{s} indicates the potential organisation spill-over effects.[39] η_i is the unobserved firm-specific effect, and ϵ_{it} is the composite error term. The main parameters of interest in this analysis are γ_1 and γ_2. Positive values of γ_1 and γ_2 imply that firm $i's$ advanced organisation capital will contribute to its own output, and firm i will also benefit from the spill-overs of organisation capital from other firms.

If a dynamic relationship between firms' current performance and one-period lagged past performance is considered, Equation (5-1) is evolved into:

$$\ln Y_{it} = \theta lnY_{i,t-1} + \alpha lnH_{it} + \beta lnK_{it} + \gamma_1 lnO_{it} + \gamma_2 lnO_{it}^s + \eta_i + \epsilon_{it} \qquad (5\text{-}2)$$

Based on Arellano and Bond (1991), the basic estimation procedure for the dynamic process is expressed in a first-differenced form:

$$\Delta\ln Y_{it} = \theta\Delta lnY_{i,t-1} + \alpha\Delta lnH_{it} + \beta\Delta lnK_{it} + \gamma_1\Delta lnO_{it} + \gamma_2\Delta lnO_{it}^s + \Delta\epsilon_{it} \qquad (5\text{-}3)$$

First differencing eliminates the potential bias that may arise from time-invariant unobserved heterogeneity. After this, Equation (5-3) can be estimated through a difference GMM by using lagged level values of the explanatory variables as instruments for the current differenced variables, if they satisfy the following orthogonality conditions:

$$\mathrm{E}\left(\mathbf{X}_{i,t-s}\Delta\epsilon_{it}\right) = 0, \mathrm{s} > 1 \qquad (5\text{-}4)$$

where $\mathbf{X}_{i,t-s}$ indicates the lagged level values of dependent variable in Equation (5-3). Furthermore, to solve the weak instruments problems, Equation (5-3) can also be estimated by using the system GMM. In the system GMM, lagged differenced values of the explanatory variables are used as instruments for the current levels of these variables under an additional set of orthogonality conditions:

$$\mathrm{E}\left(\Delta\mathbf{X}_{i,t-s}(\epsilon_{it} + \eta_i)\right) = 0, \mathrm{s} > 1 \qquad (5\text{-}5)$$

[39] Gross output instead of value added is used as the indicator for firms' output performance, as value added contains many missing values in the sample data. GDP deflators are used to deflate firms' gross output due to the lack of firm-level price deflators in China. Similarly, the price deflator of investment in fixed assets is used to deflate firms' physical capital stock.

Although the system GMM solves the potential weak instrument problems when applying the difference GMM, it needs the additional assumption that any correlation between endogeneity problems and the unobserved fixed effect is constant over time. The additional orthogonality needs to be tested by using a difference-in-Sargan /Hansen J test as suggested by Eichenbaum et al. (1988). In our case, the difference-in-Hansen J test of exogeneity is rejected at the one percent significant level, which indicates the invalidity of the instruments in the level equation. Due to this, only the difference GMM estimator is applied in our dynamic specifications.

Organisation Capital

In this analysis, organisation capital investment is measured by using five percent of management expenses in firms' financial statements following the previous studies of organisation capital in China (Hulten & Hao, 2012; Li & Wu, 2018). To keep consistent with previous analysis of organisation capital at aggregate levels, investment flows are deflated by using the price deflator of wages and salaries, and the depreciation rate is set to be 40 percent. PIM is applied to get the firm-level organisation capital stock.

Technological proximity

With Uber's car-hailing business mode being copied by Didi successfully in China as a good example, firms are assumed to benefit more from knowledge spill-overs from the firms that are closer in technology. Because of this, we adopt the idea of Chen and Inklaar (2016) to locate each firm in a "technology space" and then use the technology space distance between firms to indicate firms' technological proximity. The technology space is defined by the patent portfolio of each firm.

Specifically, the granted patents of each firm can be obtained from China's State Intellectual Property Office (SIPO). It provides details of invention and utility granted patents for each firm based on the international patent classification (IPC) code. Firms in our sample data obtain various patents spanning 601 technology fields based on the initial four-digit IPC code (each technology field has at least one granted patent to avoid a zero vector). After that, each firm's technology space is defined by using the vector $T_i = (T_{i1,} T_{i2}, \dots, T_{i601})$, where T indicates the total number of granted patents of firm i in each technology class during the observed years. Each firm thus obtains a unique technological position. The technological proximity between firms i and j is then defined as the uncentred correlation of patent portfolios (Chen & Inklaar, 2016; Jaffe A, 1986):

$$P_{ij} = \frac{T_i T_j'}{\left(T_i T_i'\right)^{\frac{1}{2}} \left(T_j T_j'\right)^{\frac{1}{2}}} \tag{5-6}$$

The larger the technological proximity is, the greater the probability that firm i's organisation capital will diffuse to firm j. The spill-over pool of organisation capital to firm i can be calculated as:

$$O_{it}^{s} = \sum P_{ij} \times O_{j,t} \ \ (i \neq j) \tag{5-7}$$

<u>*Geographical proximity*</u>

Krugman (1998) suggested that there may be geographical boundaries to R&D spill-overs because of tacit knowledge. Unlike information transmission that may be increasingly invariant to distance due to the internet revolution, the marginal costs of tacit knowledge may rise with distance because non-codified knowledge is vague and requires face-to-face interaction. For example, an increasing geographical distance always assumes the decreasing degree of interaction among people (Funke & Niebuhr, 2005). This in turn will lead to an increase in marginal costs of interaction and thus building up boundaries for knowledge spill-overs. For this reason, we would expect knowledge spill-over from organisation capital to diminish alongside increased spatial distance. As a result, geographical proximity is used to construct the organisation spill-over pool based on a spatial distance function. The spatial distance function is defined by a negative exponential function, shown in Equation (5-8) (Kuo & Yang, 2008):

$$W_{ij} = e^{-\beta_E d_{ij}} \tag{5-8}$$

where d_{ij} is the distance between the capital cities of regions where firms i and j are located. With increasing β_E, the frictional effects of distance rise and the interaction declines more quickly with increasing distance between regions. Following Funke and Niebuhr (2005), β_E is defined in Equation (5-9):

$$\beta_E = \frac{-\ln(1-\gamma_E)}{\overline{D_{min}}} \quad 0 \leq \gamma_E \leq 1 \tag{5-9}$$

The interpretation of Equation (5-9) is based on the half-life distance measurement $d_E = (ln2)/\beta_E$, i.e. the distance that reduces the spatial interaction by 50 percent (Stetzer, 1982). In Equation (5-9), $\overline{D_{min}}$ is the average distance between the capital cities of all adjacent regions in China, and is used as a basic unit of distance. γ_E, known as the decay parameter, measures the average percentage decrease of the spatial interaction between adjacent regions. With increasing γ_E, geographical impediments increase. In existing studies, γ_E ranges from $\gamma_E = 0.1$ (low geographical impediments/large spatial extent of spillovers) to $\gamma_E = 0.99$ (high geographical impediments/small spatial extent of spill-overs) (Funke & Niebuhr, 2005). In the paper of Funke and Niebuhr, they used the least trimmed squares (LTS) and spatial diagnostic tools for identifying the distance parameter γ_E. For simplicity, we first followed them by choosing $\gamma_E = 0.7$ in the baseline regression but also consider alternative values in the robustness check later. Hence, the spill-over pool of organisation capital to firm i can be calculated as follows:

$$O_{it}^{s} = \sum W_{ij} \times O_{j,t} \;\; (i \neq j) \tag{5-10}$$

5.4 Data Issues

This chapter focuses on Chinese manufacturing firms only, given the available datasets we obtained. The data source is from China's Annual Survey of Industrial Enterprises (ASIE). ASIE (1996-2010) provides what is now the most comprehensive and rich information on Chinese industrial firms, which accounts for around 95 percent of the total Chinese industrial output and 98 percent of the total Chinese industrial exports (Eberhardt et al., 2012; Tan & Peng, 2003). It is collected and maintained by China National Bureau of Statistics (NBS), and covers a wide range of manufacturing firms across Chinese regions.[40] As a result, it is widely believed that the ASIE database is largely representative and internally consistent for empirical work (He et al., 2018).

We obtained firms' financial data from ASIE and matched each firm with its patent portfolio obtained from the database maintained by China State Intellectual Property Office (hereafter "SIPO" database) based on the previous work done by He et al. (2018). The SIPO patent datasets provide the most comparable information on all granted patents in China since 1985. Granted patents in our study include invention and utility. Design patents are out of consideration as they are less comparable and use the different code from IPC. In order to identify intangible capital spill-overs, we restrict our sample to manufacturing firms with at least one patent (Chen & Inklaar, 2016). Furthermore, based on the study of Nie et al (2012), the merged dataset is further cleaned with following considerations to avoid outlier statistics and measurement errors. First, drop companies if key financial variables like gross output, employee numbers, total fixed assets or administrative fees are missing.[41] Second, drop companies with less than eight employees. Third, drop companies if the amount of total assets is less than that of liquid assets, the amount of total assets is less than that of the net value of fixed assets, or the accumulated depreciation is less than yearly depreciation. Fourth, drop companies if the rate of profit is less than 0.1 percent or higher than 99 percent. Fifth, drop companies if the paid-in capital is less than zero.

After the data management, the sample is constrained to large manufacturing firms only and thus may be criticised for self-selection bias.[42] However, the empirical evidence that is collected from large firms in China can be representative, in part because small and medium-sized firms in China are unlikely to invest heavily in organisational structure development, and in part because small firms are more likely to have mismeasurement or misreporting problems in their financial

[40] ASIE covers mining industries (6 two-digit industries from 06 to 11), manufacturing industries (30 two-digit industries from 13 to 37 and from 39 to 43), and utility industries (3 digit industries from 44 to 46). See more details in He et al. (2016).
[41] There is no record of gross output in the year 2004, thus the blank values of gross output are filled in with gross sales plus the increase of ending inventory based on accounting criteria (Nie et al., 2012).
[42] Large manufacturing firms include firms whose gross sales are over 300 million Renminbi (RMB), total assets are over 400 million RMB and the number of employees is over 2000. See details from http://www.sasac.gov.cn/n2588020/n2588072/n2591020/n2591022/c3722978/content.html.

accounts that may cause measurement bias. The final balanced sample contains 1899 manufacturing firms during 1998-2009. In addition, different ownerships are included in this panel dataset. The majority are domestic companies (72.62 percent, of which state-owned companies account for 15.96 percent), followed by foreign-capital companies, which account for 27.38 percent (Hong Kong/Macao/Taiwan capital is 12.74 percent and foreign capital is 14.64 percent).

Figure 5-1 displays the distribution of firms across sectors in this dataset. Firms in the dataset are not evenly distributed across sectors. It is seen that the firms with at least one patent are more concentrated in high-tech sectors like computers & telecommunication, machinery, transportation equipment and pharmaceutical products. Firms in the top ten sectors account for about 78 percent of the total firm numbers, and the top five sectors account for over half. We will check if sector concentration will affect our results in the sensitivity analysis.

Furthermore, firms' own organisation capital intensity is calculated across different sectors (28 sectors in this case). The intensity is measured by dividing organisation capital stock by firms' employee numbers. **Table 5-1** presents the mean value of organisation capital intensity in each sector with their own standard deviations. According to the table, the differences in organisation capital intensity within sectors are substantial, as indicated by the fact that the standard deviation is larger than the mean in most of the 28 sectors. In addition, there are substantial variations across sectors too. It is straightforward to see that the industrial mean value of the organisation capital intensity is 2793 RMB/person for the whole sample, and the distribution does not seem uniform. Organisation capital per person is the lowest for the leather & feather product sector (1114.985RMB), and is the highest for the tobacco sector (7539.803RMB). The ratio of the largest to smallest sector intensity is about seven, implying that the distribution of organisation capital is likely to be heterogeneous across the sample.

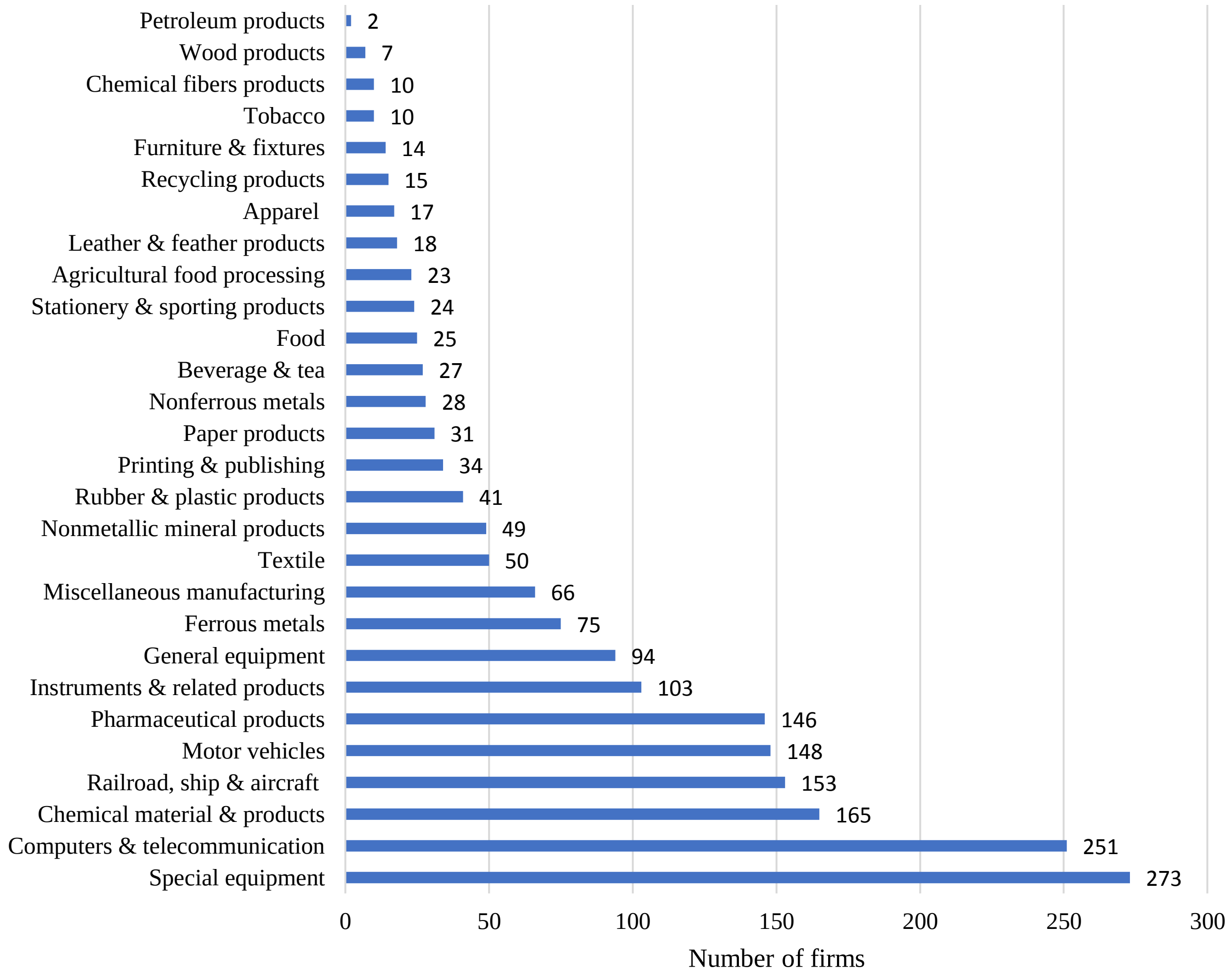


Figure 5-1: Distribution of Firms across Sectors in the Sample

Source: Author's own work.

Summary statistics of the variables included in the model are shown in **Table 5-2**. It is seen that there are big differences between two estimates of external organisation capital stock. External organisation capital stock is much larger when technological proximity is used, compared with the estimates based on geographical proximity. In addition, the mean values of all variables are much larger than the median values, implying highly right-skewed distributions of our sample data. Third, it is seen that the between standard deviations of variables, in most cases, are larger than the within ones, indicating heteroscedasticity exists more across firms rather than across years within specific firms.

Table 5-1*: Summary Statistics*

Manufacturing Sector	Number of Firms	Organisation Capital Intensity	SD
Agricultural food processing	23	2137.657	2940.912
Food	25	3334.017	5853.269
Beverage & tea	27	5092.173	7048.160
Tobacco	10	7539.803	7546.269
Textile	50	1424.656	1603.151
Apparel	17	1229.291	1828.708
Leather & feather products	18	1114.985	1053.331
Wood products	7	1306.871	1167.044
Furniture & fixtures	14	1611.705	1441.184
Paper products	31	2691.229	2271.187
Printing & publishing	34	3348.854	2167.820
Stationery & sporting products	24	1582.620	1603.880
Petroleum products	2	6157.261	3270.648
Chemical material & products	165	3213.436	3633.495
Pharmaceutical products	146	3744.479	3354.702
Chemical fibre products	10	2852.525	3906.810
Rubber & plastics products	41	1650.343	1563.437
Non-metallic mineral products	49	2342.198	1939.009
Ferrous metals	75	1865.948	1997.145
Nonferrous metals	28	2479.254	2140.799
General equipment	94	2242.524	2514.687
Special equipment	273	2694.032	3051.119
Motor vehicles	148	2633.490	2487.698
Railroad, ship & aircraft	153	3437.227	4495.635
Computers & telecommunication	251	2779.520	3411.702
Instruments & related products	103	2880.288	3341.035
Miscellaneous manufacturing	66	2908.934	3351.405
Recycling products	15	1438.394	2376.775
Total	1899	2793.023	3357.663

Source: Author’s own estimates

Note: Organisation capital intensity is the industrial mean of organisation capital stock/employee (RMB/Person)

Table 5-2: Summary Statistics

	Gross output (1)	Physical capital stock (2)	Internal OC stock (3)	External OC stock 1 (4)	External OC stock 2 (5)	Employees (6)
Mean	676.141	192.609	2.846	106.630	1.112	1010.486
Median	141.357	26.834	0.666	63.648	0.934	367
P25	56.521	8.770	0.251	25.809	0.604	170
P75	361.644	77.549	1.781	140.025	1.477	840
SD	3094.801	1438.939	17.504	127.357	0.664	3831.592
Between SD	2733.974	1333.582	15.307	101.766	0.356	3720.600
Within SD	1451.478	541.260	8.497	76.607	0.561	919.190
Panel	1899	1899	1899	1899	1899	1899
Year	12	12	12	12	12	12
Correlation with External OC Stock 1	-	0.2746	0.2318	-	-	0.1856
Correlation with External OC Stock 2	-	0.0299	0.0417	-	-	0.0113

Source: Author's own estimates

Notes: 1. External OC stock 1 is measured based on technological proximity and external OC stock 2 is measured based on geographical proximity. 2. Numbers in Columns (1) - (5) are in 100million RMB, and numbers in Column (6) are per person.

5.5 Empirical Results

5.5.1 Static Model Results

Table 5-3 displays the static model results (Equation (5-1)). We report both the fixed effect (FE) and random effect (RE) results with the statistics of Hausman test. Based on the Hausman test, the fixed effect model is preferable to the random effect model. All specifications include firm and time fixed effects with standard deviation being clustered by firms. Clearly shown in the results, the coefficients of traditional input factors are high and significant in all cases. The output is elastic, especially with respect to labour (from 0.35 to 0.52). The high labour elasticity is not surprising and confirms the evidence of other studies in different countries (Gomel et al., 2012). In addition, the sum of these two coefficients is significantly smaller than one, implying decreasing returns to scale in Chinese firms.

Table 5-3: The Effect of Organisation Capital and its Spill-over on Firms' Performance

Gross Output	FE				RE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Physical Capital	0.2089***	0.1458***	0.1459***	0.1367***	0.2501***	0.1710***	0.1706***	0.1664***
	(0.0106)	(0.0108)	(0.0108)	(0.0103)	(0.0100)	(0.0103)	(0.0103)	(0.0101)
Human Capital	0.4905***	0.3543***	0.3542***	0.3743***	0.5206***	0.3701***	0.3704***	0.3776***
	(0.0176)	(0.0176)	(0.0177)	(0.0175)	(0.0154)	(0.0158)	(0.0159)	(0.0157)
Organisation Capital		0.3116***	0.3114***	0.3026***		0.3207***	0.3193***	0.3202***
		(0.0204)	(0.0204)	(0.0199)		(0.0182)	(0.0182)	(0.0180)
Organisation Spill-over			0.0330	0.8529***			0.0264**	0.4021***
			(0.0431)	(0.0838)			(0.0129)	(0.0377)
Constant Return to Scale	0.6994***	0.8116***	0.8445***	1.6665***	0.7707***	0.8617***	0.8867***	1.2663***
Hausman Test	742.46***	361.39***	355.13***	627.80***				
Within R2	0.5724	0.6158	0.6154	0.6248				
Observations	22760	22641	22617	22641	22760	22641	22617	22641

Source: Author's own estimates.

Notes: 1. Estimations in Columns (1) – (4) are based on the two-way fixed effects model and in Columns (5) – (8) are based on the random effects model. In Columns (3) and (7) organisation spill-over is measured based on technological proximity, and in Columns (4) and (8) organisation spill-over is measured based on geographical proximity. 2. Returns to scale tests whether the sum of all inputs (physical capital, human capital, organisation capital and spill-overs where included) is significantly different from one. 3. Hausman test compares fixed effect model and random effect model. 4. All specifications control time and firm effects. 5. The standard errors shown in parentheses are clustered by firms.

* p<0.1, ** p<0.05, *** p<0.01.

The coefficients of organisation capital are all positive and significant in both FE and RE models. Compared with traditional inputs of physical and human capital, organisation capital contributes symmetrically and significantly to firms' performance in China. The output elasticity of organisation capital is close to that of human capital, falling in a similar range with the findings of Chen and Inklaar (2016) and Tronconi and Vittucci (2011). However, it is notable that the involvement of organisation capital still shows decreasing returns to scale, which differentiates our results from Chen and Inklaar (2016), whose findings suggest constant returns to scale, and from Corrado et al. (2017), whose findings suggest increasing returns to scale.

In Columns (3) and (7) organisation capital spill-over effect is evaluated based on firms' technological proximity. The coefficients are both positive but not highly significant. The result confirms the conclusions in the analysis of Chen and Inklaar, where they found positive but insignificant organisation spill-over effects based on US manufacturing firms. The magnitude of organisation spill-over effects in our analysis is much smaller than theirs. In addition, decreasing returns to scale is found in this chapter instead of constant returns to scale as found in their study. Since Chen and Inklaar attributed the failure of finding organisation spill-overs to the possibility of high correlation between R&D capital and organisation capital, we will also check the situation in the sensitivity analysis by including R&D and its spill-over effects.

Columns (4) and (8) include organisation spill-over effects based on geographical proximity among Chinese firms. Based on geographical proximity measurement, it is found that knowledge diffusions of advanced organisational structure from outside will contribute significantly to firms' output performance. The output elasticity is quite high. Furthermore, increasing returns to scale is found in Chinese manufacturing firms. It is implied that, based on evidence collected from Chinese manufacturing firms, advanced organisation capital is more likely to diffuse between firms that are spatially closer to each other, rather than firms that are technologically closer to each other. On one hand, compared with technically-similar firms, information exchange becomes more frequent between adjacent firms by channels like labour mobility. The marginal cost of knowledge diffusion will decrease with a reducing spatial distance. Because of this, it is not surprising that organisation spill-over effects can be detected based on firms' geographical proximity. On the other hand, it is possible that knowledge indeed diffuses between firms using similar technology, but technological proximity may not be fully captured by firms' patent portfolio alone. Two firms with same types of patents do not necessarily lead to the conclusion of sharing the same core technologies. A more comprehensive proxy for firms' technological proximity is needed in the future.

5.5.2 Dynamic Model Results

Table 5-4 presents the dynamic regression results with a one-period lagged dependent variable being included as an extra explanatory variable. Dynamic fixed-effect estimators are shown in Columns (1) – (4) and twostep difference GMM estimators are shown in Columns (5) – (8). In all specifications, we treat all regressors except year dummies as endogenous variables, and use variables lagged three and four periods as instruments for all of them. The failure of rejection in the Hansen J test (p values are shown at the bottom) indicates the validity of our instrumental variables.

The simple dynamic fixed-effect estimators go an intermediate step further to consider the dynamic process without controlling for unobserved heterogeneity. It is a preliminary improvement over the static FE model. One clear insight is the slight improvement in the R^2 when applying the dynamic fixed effect estimation. Firms' past performance appears to explain a significant portion of the variation in the current output performance. In addition, a sharp drop in the magnitude of the estimated coefficient on all explanatory variables when moving to the dynamic FE model suggest the correlation between the current explanatory variables and past dependent variable in our model. This is another potential indication of the possible endogeneity problems existing in the previous static model.

Nevertheless, the possible unobserved heterogeneity leads to dynamic fixed-effect estimators being biased. The difference GMM specification enables us to estimate a dynamic relationship while

Table 5-4: Dynamic Regression Results

Gross Output	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			FE				GMM	
Lag. Gross Output	0.5926***	0.5101***	0.5069***	0.5036***	0.5796***	0.5850***	0.5837***	0.6048***
	(0.0257)	(0.0292)	(0.0291)	(0.0291)	(0.1020)	(0.1024)	(0.1028)	(0.1027)
Physical Capital	0.1147***	0.0769***	0.0735***	0.0715***	0.0936***	0.0780***	0.0782***	0.0781***
	(0.0113)	(0.0095)	(0.0095)	(0.0094)	(0.0179)	(0.0171)	(0.0171)	(0.0173)
Human Capital	0.2555***	0.2134***	0.2213***	0.2263***	0.3238***	0.2895***	0.2900***	0.2916***
	(0.0226)	(0.0200)	(0.0203)	(0.0204)	(0.0421)	(0.0410)	(0.0410)	(0.0414)
Organisation Capital		0.1517***	0.1262***	0.1159***		0.1772***	0.1777***	0.1721***
		(0.0137)	(0.0153)	(0.0151)		(0.0296)	(0.0297)	(0.0298)
Organisation Spill-over			0.0458***	0.0711***			-0.0065	0.2824***
			(0.0104)	(0.0120)			(0.0360)	(0.0925)
Constant Return to Scale	0.3702***	0.4420***	0.4668***	0.4847***	0.4174***	0.5447***	0.5395***	0.8242***
R2	0.6805	0.6933	0.6938	0.6948				
Hansen J Test (p value)					0.2557	0.1478	0.1506	0.1837
Observations	20859	20750	20728	20750	18943	18844	18824	18844

Source: Author’s own estimates.

Notes: 1. Estimations in Columns (1) – (4) are based on the dynamic fixed effects model and Columns (5) – (8) are based on the twostep difference GMM. In Columns (3) and (7) organisation spill-over is measured based on technological proximity, and in Columns (4) and (8) organisation spill-over is measured based on geographical proximity. 2. Returns to scale tests whether the sum of all inputs (physical capital, human capital, organisation capital and spill-overs where included) is significantly different from one. 3. For twostep difference GMM, t-3 and t-4 lagged values are used as instruments. 4. All specifications control time and firm effects. 5. The standard errors shown in parentheses are bias-corrected Windmeijer errors (2005).

*p<0.1,**p<0.05,***p<0.01

considering fixed effects and unobserved heterogeneity at the same time. Since difference-in-Hansen test suggested by Eichenbaum et al. (1988) fails to satisfy the additional assumption of exogeneity for the system GMM estimator in our case, the twostep difference GMM estimator is used in this study. It is indicated that the endogenous variables and the unobserved fixed effect in our model is not time-invariant over the observed years. System GMM thus is not applicable.

The results show that when we include the fixed effect in a dynamic model and estimate via difference GMM, the coefficient of organisation capital is still significant but decreases sharply to 0.17 around compared with 0.32 around in the static model. The static FE estimators are supposed to be positively biased. On one hand, this bias may arise from ignoring unobservable heterogeneity. For instance, firms with a larger amount of investment in R&D are expected to be more innovation-active, thus are more likely to have advanced organisational structure. The omitted variable R&D thus will lead to a positive bias in the coefficient of organisation capital. On the other hand, the bias can be caused by the correlation between current values of independent variable and firms' past performance. If the current size of organisation capital stock is negatively related to firms' past performance, the static fixed-effect estimator will also be positively biased.

When considering the dynamic specification, the main findings of this study remain unchanged. Organisation spill-over is still estimated to positively contribute to firms' output performance based on the geographical proximity measurement. However, the magnitude of the coefficient decreases dramatically to around 0.28. A negative coefficient on organisation spill-over is found based on technological proximity and is hard to be distinguished significantly from zero. Finally, it is found that human capital remains to be a dominant input factor in Chinese manufacturing firms, based on either the static or dynamic specification.

5.6 Sensitivity Analysis

In this section, we check the robustness of our baseline results in the following steps. First, since there is no consensus on arbitrary investment portions and depreciation rates that are used to obtain organisation capital stock, different investment portions and depreciation rates that are used in existing studies are applied in this section to see if the results remain unchanged. Second, organisation spill-over is measured based either on firms' technological proximity or geographical proximity. Technological proximity is determined by patents' initial 4-digit IPC codes while geographical proximity is measured depending on the chosen decay parameter. In this section, we re-define firms' technological proximity, and try different decay parameters. Third, as the sample firms are likely to be concentrated in a few sectors, we remove each of the top five concentrated sectors from the sample to test if there is sector-selection bias. Finally, we will check the specifications with firms' value added rather than gross output as the dependent variable, with R&D and R&D spill-over effects being added, and with human capital being measured by wages and salaries instead of number counts, to see results robustness.

Table 5-5 shows the results by applying different investment portions (indicated by "ω"), and different depreciation rates (indicated by "δ") when obtaining organisation capital stock. Here, two investment portions (10 percent, 20 percent) and three deprecation rates (25 percent, 20 percent, and 10 percent) are checked (Chen & Inklaar, 2016; De & Dutta, 2007). For brevity, we present GMM estimators only. Regarding spill-over effects, Columns (1) - (5) report the results based on technological proximity, and the latter five columns report the results based on geographical proximity. Accordingly, the coefficients of organisation capital remain positive and significantly different from zero in all cases. However, the choice of depreciation rates matters for the coefficient magnitudes. It is found that applying a smaller δ will slightly decrease the coefficients of organisation capital to around 0.09 – 0.14. In contrast, no significant changes are observed when different ω are applied. In addition, organisation spill-over effects are still positive and significant where geographical proximity among firms is used for constructing the organisation spill-over pool. The coefficient magnitudes of organisation spill-over effect remain similar with the baseline estimates.

Table 5-5: Sensitivity Analysis with Different Depreciation Rates and Management Expenses Portions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Technological proximity					Geographical Proximity				
	$\omega = 10\%$	$\omega = 20\%$	$\delta = 25\%$	$\delta = 20\%$	$\delta = 10\%$	$\omega = 10\%$	$\omega = 20\%$	$\delta = 25\%$	$\delta = 20\%$	$\delta = 10\%$
Lag. Gross Output	0.5836***	0.5836***	0.6050***	0.6113***	0.5909***	0.6047***	0.6047***	0.6295***	0.6386***	0.6227***
	(0.1026)	(0.1026)	(0.1005)	(0.0987)	(0.0998)	(0.1026)	(0.1026)	(0.0998)	(0.0979)	(0.0973)
Physical Capital	0.0782***	0.0782***	0.0811***	0.0828***	0.0861***	0.0781***	0.0781***	0.0810***	0.0827***	0.0869***
	(0.0171)	(0.0171)	(0.0177)	(0.0178)	(0.0181)	(0.0173)	(0.0173)	(0.0179)	(0.0181)	(0.0183)
Human Capital	0.2899***	0.2899***	0.2994***	0.3025***	0.3126***	0.2915***	0.2915***	0.3015***	0.3050***	0.3104***
	(0.0410)	(0.0410)	(0.0420)	(0.0424)	(0.0428)	(0.0414)	(0.0414)	(0.0425)	(0.0430)	(0.0433)
Organisation Capital	0.1777***	0.1777***	0.1450***	0.1305***	0.1086***	0.1721***	0.1721***	0.1360***	0.1198***	0.0990***
	(0.0296)	(0.0296)	(0.0351)	(0.0361)	(0.0371)	(0.0298)	(0.0298)	(0.0349)	(0.0358)	(0.0359)
Organisation Spill-over	-0.0065	-0.0065	0.0002	0.0090	-0.0293	0.2826***	0.2826***	0.3408***	0.3603***	0.2779***
	(0.0360)	(0.0360)	(0.0403)	(0.0386)	(0.0265)	(0.0925)	(0.0925)	(0.0980)	(0.0876)	(0.1055)
Constant Return to Scale	0.5392***	0.5392***	0.5258***	0.5248***	0.4780***	0.8242***	0.8242***	0.8593***	0.8677***	0.7741***
Hansen J Test (p value)	0.1489	0.1489	0.1781	0.1806	0.1997	0.1818	0.1818	0.2187	0.2229	0.2270
Observations	18824	18824	18817	18808	18406	18844	18844	18837	18828	18506

Source: Author's own estimates.

Notes: 1. For brevity, only dynamic GMM specifications are shown, comparable to Columns (7) – (8) in Table 4 for the baseline specification. In Columns (1) – (5) organisation spill-over is measured based on technological proximity, and in Columns (6) – (10) organisation spill-over is measured based on geographical proximity. 2. Returns to scale tests whether the sum of all inputs (physical capital, human capital, organisation capital and spill-overs where included) is significantly different from one. 3. For twostep difference GMM, t-3 and t-4 lagged values are used as instruments. 4. All specifications control time and firm effects. 5. The standard errors shown in parentheses are bias-corrected Windmeijer errors (2005).

* p<0.1, ** p<0.05, *** p<0.01.

In our baseline regression, a firm's patent portfolio is determined based on the initial 4-digit IPC code. In other words, firms' technologies are treated as the similar technology within a specific field if the initial four-digit numbers of their granted patents are the same. In this section, we re-define firms' technological proximity by using a less restrictive classification criterion for patent portfolios. Granted patents are re-allocated into different groups based on the initial 3-digit IPC code ("Proximity 3-digit"), initial 2-digit IPC code ("Proximity 2-digit") and initial 1-digit IPC code ("Proximity 1-digit"). Firms would be expected to have greater technological proximity if being defined in a more relaxed way. Estimators of both static FE model and dynamic GMM model are displayed in **Table 5-6**. In all cases, the coefficients of organisation spill-over effects cannot be distinguished significantly from zero. We failed to detect spill-over effects from organisation capital based on firms' technological proximity measurement approach.

Table 5-6: Sensitivity Analysis with Different Technological Proximity Matrices

	(1)	(2)	(3)	(4)	(5)	(6)
Gross Output	Proximity (3-digit)		Proximity (2-digit)		Proximity (1-digit)	
	FE	GMM	FE	GMM	FE	GMM
Lag. Gross Output		0.5842***		0.5850***		0.5792***
		(0.1024)		(0.1023)		(0.1015)
Physical Capital	0.1458***	0.0780***	0.1454***	0.0780***	0.1457***	0.0780***
	(0.0107)	(0.0171)	(0.0107)	(0.0171)	(0.0107)	(0.0170)
Human Capital	0.3545***	0.2893***	0.3550***	0.2893***	0.3544***	0.2889***
	(0.0176)	(0.0410)	(0.0176)	(0.0410)	(0.0176)	(0.0409)
Organisation Capital	0.3116***	0.1775***	0.3112***	0.1771***	0.3115***	0.1785***
	(0.0204)	(0.0296)	(0.0204)	(0.0296)	(0.0204)	(0.0294)
Organisation Spill-over	0.0377	0.0184	0.1242	-0.0019	0.0273	-0.1074
	(0.0627)	(0.0500)	(0.0945)	(0.0777)	(0.1190)	(0.1068)
Constant Return to Scale	0.8497***	0.5633***	0.9358***	0.5424***	0.8389***	0.4381***
Hansen J Test (p value)		0.1431		0.1460		0.1395
Observations	22629	18834	22641	18844	22641	18844

Source: Author's own estimates.

Notes: 1. In Columns (1) - (2) technological proximity is based on 3-digit IPC code; in Columns (3) - (4) technological proximity is based on 2-digit IPC code; in Columns (5) - (6) technological proximity is based on 1-digit IPC code. 2. Static two-way fixed effect model is used in all odd columns while dynamic twostep difference GMM is used in all even columns. Returns to scale tests whether the sum of all inputs (physical capital, human capital, organisation capital and spill-overs where included) is significantly different from one. 3. For twostep difference GMM, t-3 and t-4 lagged values are used as instruments. 4. All specifications control time and firm effects. 5. The standard errors shown in parentheses are bias-corrected Windmeijer errors (2005).

* p<0.1, ** p<0.05, *** p<0.01.

Furthermore, in the baseline setting, γ_E is arbitrarily chosen to be 0.7. As mentioned by Funke and Niebuhr (2005), γ_E is related to the specified spatial structure, and the choice of γ_E is always a critical issue. As noted by Funke and Niebuhr (2005), in previous studies, the choice of γ_E ranges from 0.1 (low geographical impediments/large spatial extent of spill-overs) to 0.9 (high geographical impediments/small spatial extent of spill-overs). In our sensitivity analysis, we replace γ_E with values from 0.1 to 0.9 to see results' differences. The results are shown in **Table 5-7**. As expected, the magnitude of knowledge spill-over from organisation capital decreases with higher geographical impediments. However, the coefficients of organisation spill-over are not significant if we choose an extremely low γ_E (0.1 - 0.2).

Since the top five sectors account for more than the half of the total firm numbers, to check whether the empirical results are sensitive to the selected sample, we remove each of the top five concentrated sectors from the sample. These top five sectors include special equipment; computers & telecommunications; chemical materials & products; railroads, ships & aircraft; and motor vehicles. **Table 5-8** shows the results. Compared with the baseline regression, the coefficients of organisation capital hardly changed. Organisation spill-over effects are still shown to have positive impacts on firms' performance, given the condition that geographical proximity is used for measurement.

Finally, the following additional specifications are examined: 1) the specification with value added as the dependent variable; 2) the specification where R&D and R&D spill-overs are considered; and 3) the specification where wages and salaries instead of number counts are used for human capital stock estimation. Due to data constraints, the samples that are used for checking these specifications are shrinking a lot and become an unbalanced panel. As a result, we only use static FE models here. The results are shown in **Table 5-9**. Columns (1) – (2) and (7) – (8) have similar results compared with the baseline regression, where value added is the dependent variable and wages and salaries are used for human capital estimation. In Columns (3) – (4), R&D is added as another explanatory variable, without the consideration of R&D spill-overs. The output

Table 5-7: Sensitivity Analysis with different Distance Decay Parameters

Gross Output	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Gamma=0.1	Gamma=0.2	Gamma=0.3	Gamma=0.4	Gamma=0.5	Gamma=0.6	Gamma=0.7	Gamma=0.8	Gamma=0.9
Lag. Gross Output	0.5870***	0.5896***	0.5924***	0.5957***	0.5995***	0.6031***	0.6048***	0.6036***	0.5980***
	(0.1026)	(0.1026)	(0.1026)	(0.1027)	(0.1027)	(0.1027)	(0.1027)	(0.1027)	(0.1027)
Physical Capital	0.0781***	0.0782***	0.0782***	0.0782***	0.0782***	0.0782***	0.0781***	0.0781***	0.0780***
	(0.0171)	(0.0171)	(0.0171)	(0.0172)	(0.0172)	(0.0173)	(0.0173)	(0.0173)	(0.0172)
Human Capital	0.2899***	0.2904***	0.2907***	0.2910***	0.2913***	0.2916***	0.2916***	0.2915***	0.2910***
	(0.0409)	(0.0411)	(0.0411)	(0.0412)	(0.0413)	(0.0414)	(0.0414)	(0.0414)	(0.0413)
Organisation Capital	0.1768***	0.1761***	0.1753***	0.1745***	0.1735***	0.1725***	0.1721***	0.1723***	0.1736***
	(0.0297)	(0.0297)	(0.0297)	(0.0297)	(0.0298)	(0.0298)	(0.0298)	(0.0298)	(0.0298)
Organisation Spill-over	0.6727	0.5480	0.4569**	0.4103**	0.3735***	0.3311***	0.2824***	0.2244***	0.1604***
	(0.6334)	(0.3352)	(0.2190)	(0.1664)	(0.1340)	(0.1104)	(0.0925)	(0.0759)	(0.0597)
Constant Return to Scale	1.2176	1.0927	1.0012	0.9540	0.9165	0.8734	0.8242	0.7662	0.7031
Hansen J Test (p value)	0.1577	0.1620	0.1665	0.1715	0.1770	0.1818	0.1837	0.1818	0.1747
Observations	18844	18844	18844	18844	18844	18844	18844	18844	18844

Source: Author’s own estimates.

Notes: 1. For brevity, only dynamic twostep difference GMM specifications are shown. 2. Returns to scale tests whether the sum of all inputs (physical capital, human capital, organisation capital and spill-overs where included) is significantly different from one. 3. For twostep difference GMM, t-3 and t-4 lagged values are used as instruments. 4. All specifications control time and firm effects. 5. The standard errors shown in parentheses are bias-corrected Windmeijer errors (2005).

* p<0.1, ** p<0.05, *** p<0.01.

Table 5-8: Sensitivity Analysis by Removing Top Concentrated Sectors Respectively

Gross Output	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Technological Proximity					Geographical Proximity				
	SE	Computer	Chemicals	Railroad	Vehicles	SE	Computer	Chemicals	Railroad	Vehicles
Lag. Gross Output	0.6874***	0.5877***	0.5709***	0.6679***	0.5666***	0.7247***	0.6101***	0.5863***	0.6938***	0.5877***
	(0.1121)	(0.1204)	(0.1010)	(0.1141)	(0.1057)	(0.1110)	(0.1201)	(0.1009)	(0.1143)	(0.1063)
Physical Capital	0.0683***	0.0773***	0.0712***	0.0795***	0.0786***	0.0674***	0.0771***	0.0711***	0.0792***	0.0785***
	(0.0175)	(0.0189)	(0.0172)	(0.0190)	(0.0178)	(0.0178)	(0.0191)	(0.0174)	(0.0193)	(0.0180)
Human Capital	0.2557***	0.2855***	0.2918***	0.2867***	0.2896***	0.2549***	0.2871***	0.2934***	0.2882***	0.2913***
	(0.0347)	(0.0461)	(0.0422)	(0.0451)	(0.0432)	(0.0353)	(0.0465)	(0.0425)	(0.0456)	(0.0436)
Organisation Capital	0.1595***	0.1700***	0.1799***	0.1655***	0.1782***	0.1501***	0.1645***	0.1755***	0.1585***	0.1726***
	(0.0307)	(0.0332)	(0.0304)	(0.0318)	(0.0303)	(0.0307)	(0.0333)	(0.0305)	(0.0320)	(0.0305)
Organisation Spill-over	0.0262	0.0076	-0.0095	-0.0453	0.0007	0.2990***	0.2252**	0.2856***	0.2625***	0.3174***
	(0.0407)	(0.0377)	(0.0386)	(0.0378)	(0.0376)	(0.1091)	(0.0970)	(0.0974)	(0.0942)	(0.0934)
Constant Return to Scale	0.5097***	0.5404***	0.5334***	0.4864***	0.5470***	0.7713***	0.7539***	0.8256***	0.7885***	0.8598***
Hansen J Test										
(p value)	0.3559	0.1583	0.1127	0.2405	0.0659	0.4293	0.1902	0.1340	0.2719	0.0851
Observations	16120	16317	17188	17294	17359	16140	16337	17208	17314	17379

Source: Author's own estimates.

Notes: 1. For brevity, only dynamic twostep difference GMM specifications are shown, comparable to Columns (7) – (8) in Table 4 for the baseline specification. 2. Returns to scale tests whether the sum of all inputs (physical capital, human capital, organisation capital and spill-overs where included) is significantly different from one. 3. For twostep difference GMM, t-3 and t-4 lagged values are used as instrumental variables. 4. All specifications control time and firm effects. 5. The standard errors shown in parentheses are bias-corrected Windmeijer errors (2005).

* p<0.1, ** p<0.05, *** p<0.01.

Table 5-9: Sensitivity Analysis with Different Elements

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Physical Capital	0.1524***	0.1478***	0.0892***	0.0899***	0.0912***	0.0910***	0.1408***	0.1394***
	(0.0150)	(0.0147)	(0.0228)	(0.0227)	(0.0228)	(0.0227)	(0.0110)	(0.0108)
Human Capital	0.3840***	0.4002***	0.2760***	0.2925***	0.2911***	0.2921***	0.3070***	0.3089***
	(0.0233)	(0.0235)	(0.0327)	(0.0323)	(0.0326)	(0.0323)	(0.0148)	(0.0148)
Organisation Capital	0.3107***	0.3033***	0.4065***	0.3943***	0.3989***	0.3955***	0.2843***	0.2813***
	(0.0250)	(0.0247)	(0.0395)	(0.0391)	(0.0390)	(0.0392)	(0.0229)	(0.0226)
Organisation Spill-over	0.0244	0.6117***	0.1181	0.6333***	0.1158	0.4176*	-0.0180	0.5043***
	(0.0535)	(0.1135)	(0.0919)	(0.1296)	(0.0892)	(0.2318)	(0.0425)	(0.0837)
R&D			0.0199***	0.0195***	0.0193***	0.0193***		
			(0.0048)	(0.0048)	(0.0048)	(0.0048)		
R&D Spill-over					0.1888***	0.0746		
					(0.0403)	(0.0722)		
Constant Return to Scale	0.8715***	1.4630***	0.9097***	1.4295***	1.1050***	1.2901***	0.7141***	1.2339***
Observation	14965	14980	4852	4853	4852	4853	18826	18846

Source: Author’s own estimates.

Notes: 1. Two-way fixed effect model is used in all specifications. 2. In Columns (1) - (2) the logarithm of firms’ value added is used for dependent variables. R&D is added in Columns (3) – (4) and R&D spill-over is added in Columns (5) – (6). In Columns (7) – (8) wages and salaries instead of person count are used for human capital estimation. In odd columns organisation spill-over is estimated based on technological proximity while in even columns are based on geographical proximity. 3. All specifications include firm and year fixed effects. 4. Robust standard errors, clustered by firms, are shown in parentheses.

* p<0.1, ** p<0.05, *** p<0.01.

elasticities of organisation capital and R&D are positive and significant. In addition, as is shown in Columns (5) – (6), with the consideration of R&D and R&D spill-overs, the coefficient of organisation spill-over turns insignificant but remains positive based on the technological proximity measurement. The R&D spill-over is also insignificant in this case. Arguably, knowledge spill-overs from organisation capital and R&D are likely to be highly correlated. The conclusions are consistent with the findings of Chen and Inklaar. However, if knowledge spill-overs from organisation capital is measured by firms' geographical proximity, it still shows positive effects on firms' performance even if R&D and R&D spill-overs are added into the specification. Nevertheless, the significance level of spill-over effects is only at 10 percent.

5.7 Conclusion

This is the first study in China to analyse organisation capital and its relationship with manufacturing firm performance. The findings enrich the existing knowledge in distinct ways. First, organisation capital has a considerable positive effect on firms' output performance in Chinese manufacturing sector. The positive effect of organisation capital is robust with and without the consideration of knowledge spill-overs. The output elasticity of organisation capital in Chinese firms is comparable with that in developed economies.

By merging firms' survey dataset with the SIPO patent dataset, we locate each firm within a specific technological space vector to define an organisation spill-over pool. Spatial interaction is also considered as another potential spill-over channel. The findings suggest that knowledge spill-over exists among Chinese manufacturing firms, but relies heavily on how it is captured. Our analysis of 1899 Chinese manufacturing firms shows that positive effects of organisation capital spill-over can only be tested if geographical proximity is used for constructing the organisation spill-over pool. In other word, Chinese firms are more likely to benefit from advanced organisational knowledge of another firm if they are spatially closer to each other, rather than technologically similar to each other.

There are two possible explanations. First, technological proximity is indeed the channel for knowledge spill-over, but patent portfolio is not a proper way to capture it. It is possible that two firms that are granted with the same fields' patents may not share the same core technology. This may partly explain the failure of findings of Chen and Inklaar's study to demonstrate positive organisation spill-over effects. Another reason is that advanced organisational structure and knowledge may diffuse more easily through interactive activities like face-to-face communication or benchmarking learning processes in China. In this way, adjacent firms may encourage the mobility of workers, thus to benefit more from low costs of interaction.

CHAPTER 6 - INTANGIBLE CAPITAL DYNAMIC DISTRIBUTIONS

6.1 Introduction

Accompanied by the revolution in information technology, world economies are transforming into knowledge-based ones. The investment in intangible capital thus becomes crucial for a country's future competitiveness and sustainable development (World Bank, 2006).[43] Following this trend, intangible capital development has received increasing attention in China. In order to understand its impacts on economic and productivity growth in China, intangible investment and its capital stock is measured at different levels and examined in growth accounting exercises (Hulten & Hao, 2012; Li & Wu, 2018; Tian et al., 2016). A positive relationship between intangible capital and Chinese firm performance is also reported (Yang et al., 2018). However, these studies have not addressed the impacts of intangible capital on China's regional development. If intangible capital contributes significantly and unevenly to regional economic development, studies of Chinese would be incomplete without considering intangibles across regions.

This study aims to fill in this gap by examining regional intangible capital distribution dynamics and drawing implications for regional development in China. To achieve this goal, we analyse not only a current distribution map but also the convergence/divergence development of intangible capital investment in Chinese regions. In China, coastal regions took advantages of cheap labour, geographical proximity to the world market, and preferential policies to become the spearhead of economic reform (OECD, 2010). Spatial imbalance has therefore increased sharply since the early 1980s and rendered China among the most unequal countries in the world. However, since the mid-2000s, there has been evidence of spatial rebalancing in China because of government

[43] Intangible capital is not a novel concept in the modern world of knowledge economy. Some examples of intangible capital are the software developed by tech giants such as Microsoft Inc. and Coca-Cola's famous coke recipe which dates back to the late 19th century.

policies, structural changes, rising costs, and backwardness advantages (Andersson et al., 2013; Deng & Jefferson, 2011; Feng, 2009; OECD, 2010; Wei, 2009). Nevertheless, intangible capital was included in none of these studies. We argue that spatial rebalancing in China would be difficult if intangible investments are persistently highly concentrated in a few coastal areas.

Intangible capital is expected to further increase spatial imbalance in China. Krugman (1998) suggested that intangible capital like research and development (R&D) is tacit knowledge, which is non-codified and requires face-to-face interactions. Corrado et al. (2006) pointed that intangible investment, which is non-rival and non-excludable, is an important source of externality. Haskel & Westlake (2018) emphasised that two key characteristics of intangible capital are spill-overs and synergies: intangible investments have unusually high spill-overs and benefit from combining resources. Therefore, in an intangible economy, we would expect to see intangible-intensive firms concentrate in growing, diverse regions where they are more likely to benefit from spill-overs and synergy effects and enjoy high productivity. Meanwhile, as the “carrier” of knowledge and innovation, intangible capital could spillover knowledge to other industries and act as a catalyst for external economies of scale. Due to this, intangible capital is expected to fuel China’s diverse and growing coastal regions where large innovation hubs are located. Once the economies of scale are obtained, coastal regions in turn attract more intangible capital. By observing intangible distribution dynamics, our results imply that this type of “self-fulfilling” process worsens the existing disparity in intangible capital investment and will eventually lead to an increase in regional inequality in China.

Theories have long been developed to study regional convergence, including the neoclassical growth theory and the Kuznets’ curve (Kuznets, 1955; Solow, 1956; Williamson, 1965). Based on factor reallocation and decreasing marginal effects, these theories predict diminishing differences between leading and lagging regions when a certain development level is reached. However, intangible capital is far more mobile and does not necessarily lead to diminishing returns (Haskel & Westlake, 2018). If intangible capital is encapsulated in regional income, the trajectory of regional development in China would be more complicated than what conventional convergence theories have predicted. The existing studies on China primarily dealt with the measurement of intangible capital and examination of its contributions to output and productivity growth. Intangible investment distribution and its regional dynamics are hardly documented.

The lack of relevant research on regional development of intangibles may lead to incomplete policy design. For example, according to extant literature, intangible capitalisation will increase conventional national income measures (Corrado et al., 2005, 2006). Regional disparity studies of China mainly consider income per capita as the variable of interest (Cheong & Wu, 2013; Herrerías et al., 2011; Lemoine et al., 2015; Sakamoto & Islam, 2008). The exclusion of intangibles may result in misleading implications because income is under-estimated, especially in intangible-intensive regions. Even though the transmission of intangible investment into China's GDP growth is difficult to estimate currently, the bias due to intangible omission may have a significant impact on GDP measures in the near future. Therefore, a more thorough examination of the distribution dynamics of intangible capital is required, especially for an intangible-based transitioning economy such as China.

This study contributes to the existing literature in several ways. To the best of our knowledge, this is the first study that examines Chinese intangible capital distribution dynamics at the regional level. Utilising novel data, we provide evidence of the unbalanced development of intangible assets in Chinese regions, and predict steady-state distribution based on the current transition path. A large investment gap is detected between the coastal and interior regions, and coastal regions are expected to outperform the rest of China in terms of intangible investment in the long-run. Furthermore, intertemporal distribution dynamics are examined to analyse the impacts of global financial crisis. It is indicated that the global financial crisis exerts a significant impact on intangible investment in China, especially in intangible-intensive regions. Additionally, since geography can be a possible channel for intangible spill-over, we also study the distribution conditional on distances between regions. Knowledge spill-over is observed to be an important channel determining the convergence towards the average investment level exhibited by neighbouring regions. In terms of the research method, we apply a non-parametric approach to fully capture the complexity of the underlying distribution dynamics. The approach imposes no prerequisite assumption or restriction on the distribution function. Furthermore, we augment the mobility probability plot approach of Cheong & Wu (2013, 2014) by computing confidence intervals for the estimates of transition probabilities by using a bootstrapping method. The augmented method enables hypothesis testing and the computation of confidence levels in transition dynamic analysis.

The rest of this chapter is organised as follows. The measurement of intangible capital and an overview of the shape of capital distribution are presented in Section 6.2. Section 6.3 discusses the non-parametric approach to distribution dynamics analysis. The results based on the full sample, sub-periods, economic zones, and spatial factors are reported in Section 6.4. Section 6.5 concludes the chapter and provides policy implications.

6.2 China's Regional Intangible Capital Intensity

We first examine the distribution of total intangible capital investment across Chinese regions, which is captured in the sum of nine individual intangible asset classes listed in **Table 2-1**. These investments are deflated by the constant 2010 price, using category-specific deflators shown in **Table 2-2**. Per capita value is calculated as the ratio of total intangible investment to provincial population. This quantity is divided by its national mean to get the relative intangible capital intensity (hereafter, RICI). The descriptive statistics of regional RICI are reported in **Table 6-1**. As shown, the distribution of RICI is highly skewed to the right, indicating that a few regions are far ahead of the rest in term of intangible capital investment.

Table 6-1: Descriptive Statistics of Intangible Capital

Variable	Obs.	Mean	Median	S.D	Min	Max	Skewness	Kurtosis
RICI	434	1	0.40	1.64	0.13	10.2	3.7	18.1
log(RICI)	434	-0.6	-0.90	0.96	-2.03	2.3	0.99	3.56

Source: Author's own computations.

To reduce the data dispersion, we instead use the logarithmic transformation of RICI as our main variable of interest: let y_{it} denote intangible capital intensity of province i in year t, and $\bar{y}_t = \frac{1}{N}\sum_{i=1}^{N} y_{it}$ be the national average of y_{it}. N = 31 is the number of regions in our sample. The variable to be analysed in this study is:

$$X_{it} = \ln\left(\frac{y_{it}}{\bar{y}_t}\right) = \ln y_{it} - \ln \bar{y}_t. \tag{6-1}$$

This logarithmic transformation also has the advantage of simplifying the interpretation, while preserving the transition dynamics. Specifically, the value of X_{it} indicates the distance of province i's intangible capital investment intensity from the national mean. If the distance is sufficiently small, the percentage difference between province i's investment and the national mean can be approximated by the logarithmic difference: $100 \times X_{it} \approx 100 \times \frac{y_{it}-\bar{y}_t}{\bar{y}_t}$.[44] Additionally, when $y_{it} = \bar{y}_t$, $X_{it} = 0$. That is, the national average takes a value of zero when log-transformed. It follows that if the spatial dispersion of capital intensity from national average is small (or high), the values of X_{it} will be tightly distributed(or dispersed) around zero.

Figure 6-1 is a map that illustrates the spatial distribution of RICI in the first and last years in our sample. Provinces are colour-coded based on the ranking of RICI, from low (light) to high (dark). There are two important observations emerging from this map. First, the inland provinces (which tend to be the poorer ones) begin with lower-than-average investment, while the coastal provinces enjoy above-average investment. Second, after 13 years, a pattern of polarisation appears,

[44] However, this approximation is not precise in the case of large differences.

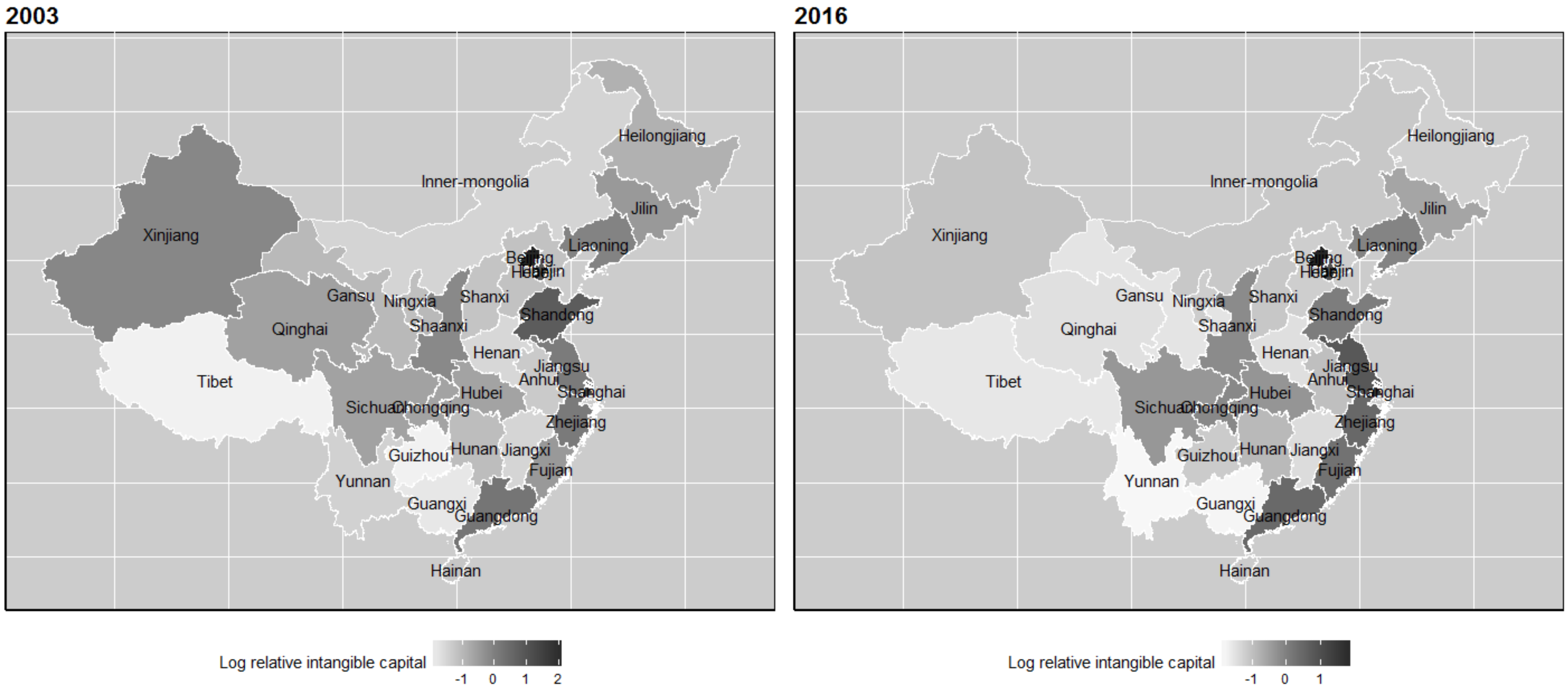


Figure 6-1: Spatial Distribution of China's Intangible Capital Intensity, 31 Provinces, in 2003 and 2016

Source: Author's own work.

Notes: 1. This figure maps the intensity of intangible capital investment in China for two selected years. 2. Darker colours signify higher degrees of capital concentration. 3. The underlying variable is $X_{it} = \ln\left(\frac{y_{it}}{\bar{y}_t}\right) = \ln y_{it} - \ln \bar{y}_t$ where y_{it} is the constant price per capita investment (in RMB) for province i in year t.

that is, inland provinces become less while coastal regions become more intangible capital-intensive. Overall, this pattern signifies impediments to the "catching up'' process of the poor regions.

Next, we study this spatial distribution formally by introducing a kernel function of the form:

$$f(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{x-X_i}{h}\right), \tag{6-2}$$

where K(.) denotes the Epanechnikov function, N is the number of regions, X_i is the logarithmic RICI of province i, and h is the selected bandwidth (also called "window width" or "smoothing parameter"). With a fixed bandwidth, an under(over)-smoothing density estimation bias may occur if there are too few (too many) observations (Silverman, 1986). To alleviate this problem, an adaptive kernel approach that allows bandwidths to vary (Abramson, 1982) is adopted. In this chapter, we use the standard estimator proposed by Silverman (1986):

$$f(x) = \frac{1}{\sum_{i=1}^{N} w_i}\sum_{i=1}^{N} \frac{w_i}{h_i} K\left(\frac{x-X_i}{h}\right), \tag{6-3}$$

where w_i is the weight associated with data point i, h_i is the flexible bandwidth that is defined as $h_i = h \times \lambda_i$. The fixed bandwidth h, called the pilot or "global" bandwidth, controls the overall degree of smoothing. λ_i is a factor that stretches or shrinks the "local" bandwidths to adapt to the density of the data (Kerm, 2003). The estimation involves two steps. In the first step, we obtain h from a "naïve" estimate. In the second, the varying local bandwidth factor λ_i is calculated as the square root of the geometric mean of the pilot density estimator over each point estimate.

Figure 6-2 presents the logarithmic RICI distributions in selected years of 2003, 2009, and 2016. The peaks of the densities in selected years lie at around -1, implying that most regions in China exhibit a lower-than-average per capita intangible capital investment during 2003-2016. The unimodal shape of the distribution is virtually unchanged from 2003 to 2009, but a weak bimodal pattern emerges in 2016. Throughout the period 2003 – 2016, the relative number of poor regions increased, which is in agreement with **Figure 6-1**. Furthermore, the GFC may have played an important role in the divergence of RICI distribution into two "clubs" in 2016. We can clearly see that the right tail becomes "fatter" after the crisis, suggesting a large developmental bias toward the richest regions.

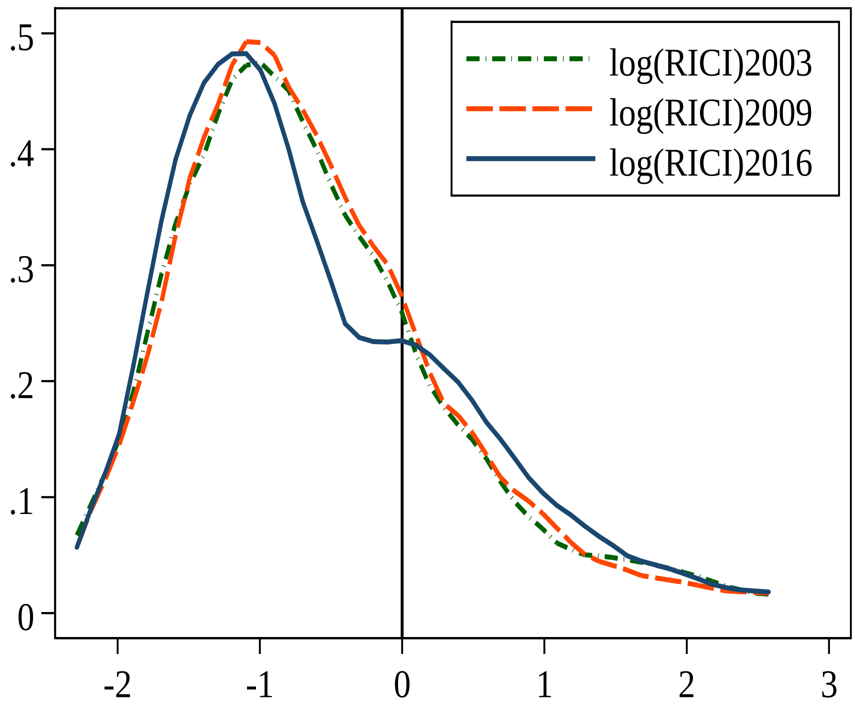


Figure 6-2: Distribution of Intangible Capital in 2003, 2009 and 2016

Source: Author's own estimates.
Notes: 1. This Figure presents the un-weighted kernel density estimates of the distribution of intangible capital in China. 2. The Silverman (1986) adaptive bandwidth estimator is used.

Being consistent with Chapter two, we group eleven regions into the "coastal" group and the rest into the "interior" group. [45] The partition into coastal and interior (inland) regions is adopted to distinguish export-oriented and more developed areas from domestic market-oriented and less developed areas in China. We found that the logarithmic RICI values in nine coastal regions are equal to or greater than the 75th percentile. Shanghai and Beijing, the two major economic hubs, lie above the 95th and 99th percentiles, respectively. The clustering of intangible investment is not surprising. In 2010, coastal regions hosted 75 percent of the biggest 500 companies (in terms of

[45] The partition into coastal and interior (inland) regions is adopted to distinguish export-oriented/more developed areas from domestic market-oriented/less developed areas in China. The division criteria are also based on economic, administrative, historical and cultural factors (Chen & Fleisher, 1996; Hao, 2008; Ying, 2003).

market capitalisation), a fifth of which are in Beijing. Headquarters of high-tech and retail giants such as Alibaba (Zhejiang), Baidu (Beijing), and Tencent, HUAWEI and ZTE (Guangdong) are all located in coastal regions, In 2015, seven out of the top ten industrial clusters were in coastal regions (Duan, 2015). But will intangible investment continue to be concentrated in these regions? What does the distribution look like in the long-run if the trend of unbalanced development continues? Will the laggards converge to the leaders in the future? These are questions which we shall address in the next two sections.

6.3 Method

6.3.1 Dynamic Distribution Approaches

Economic convergence studies have followed several approaches (Dhongde & Silber, 2016; Islam, 2003). One early mainstream approach is the so-called β- convergence method. The name of this approach stems from the traditional notation of the slope coefficient in the regression of growth rates against initial income levels. With diminishing returns, poorer economies with a lower initial income level will grow faster than richer ones with similar saving rates, leading to a process of "catching-up", i.e. convergence (Barro and Sala-i-martin, 1992; Mankiw et al., 1992). It follows that a significant negative correlation (i.e. a negative β coefficient) between the initial income level and the subsequent growth rates is expected, and is taken as evidence of convergence. Based on the concept of β- convergence, a vast body of empirical research has emerged (to name only a few, Lau, 2010; Pedroni and Yao, 2006; Westerlund et al., 2010; Chen and Fleisher, 1996; Gries and Redlin, 2009; Hao, 2008; and Weeks and Yao, 2003). However, no consensus has been reached. Different conclusions were generated by analysing different time periods and controlling for different sets of explanatory variables.

One of the main criticisms of this approach is that the nature of convergence is a complex, dynamic evolution of both income levels and growth rates, which cannot be captured by a simple catch-all measure such as a negative β (Johnson and Papageorgiou, 2018). In other words, a negative β in the regression does not necessarily imply a reduction in the dispersion; hence it is a necessary but not sufficient condition for convergence.[46] This criticism then motivates the concept of σ- convergence, which, instead of looking at the slope coefficient, studies the standard deviation (denoted as σ) of the income distribution. A large strand of empirical studies presents σ-convergence analyses in China context (Chen and Fleisher, 1996; Duan, 2008; Raiser, 1998; and Zhou and Zou, 2010, among others). However, like their predecessors, σ- convergence studies provide only one summary statistic of the distribution of interest, which cannot fully capture the complexity of the underlying distribution dynamics (for example changes from unimodality to multimodality as in the case of **Figure 6-2**).

Through a series of seminal papers, a non-parametric distribution analysis was introduced by Danny Quah to study economic convergence (Quah, 1993, 1996a, 1996b, 1997). This is in essence a data-driven approach and does not impose any prerequisite assumption or restriction on the distribution function. Distinct from analysing single summary statistics, this approach focuses on the shape of the entire distribution and its dynamics, and thus overcomes the limitations of both β and σ- convergence studies as described above (Islam, 2003). This approach can be further divided into the discrete Markov chain and stochastic kernel approaches. A major disadvantage of the discrete Markov chain method is that the demarcation of discrete states (to which each region falls into at any point in time) must be associated with an arbitrary selection of grid values (Cheong and Wu, 2018). As an alternative to circumvent the demarcation problem, a stochastic kernel approach is applied in our chapter. The following discussions primarily draw on Juessen (2009) and Cheong and Wu (2014).

[46] Some advocates for this line of criticism attribute this error to the classical Galton fallacy (see e.g. Friedman, 1992 and Quah, 1993b). The origin of this fallacy dates back to the studies by Charles Darwin's cousin Sir Francis Galton, who studied the regression towards the mean for human heights. Specifically, he discovered a "paradox": The sons of tall fathers tend to reverse towards a pool of mediocrity along with the sons of everyone else, yet male height dispersion does not fall overtime. Quah (1993) shows that a given cross-sectional distribution that dynamically evolves is not inconsistent with arbitrary signs of the initial level regression coefficients (i.e. β). Therefore, a β-type convergence analysis is insufficient for a direct inference of convergence or divergence.

Specifically, let $f_t(x)$ be the distribution of a variable x at time t, and let $f_{t+\tau}(z)$ denote the distribution of a variable z at time $t+\tau$. For our purposes, x refers to the current RICI level, while z refers to the τ-period-ahead level. If we suppose the evolution of the distribution is time invariant, and assume that the distribution at time $t+\tau$ depends solely on the distribution at time t, the dynamic evolution process of the distribution from time t to $t+\tau$ is can be expressed in the following differential equation:

$$f_{t+\tau}(z) = \int_0^{\infty} g_\tau(z|x) f_t(x) dx\,, \tag{6-4}$$

where $g_\tau(z|x)$ is the conditional transition probability kernel that maps the distribution at time t to that at $t+\tau$.

Since it is a density function, the integration of $g_\tau(z|x)$ over z is unity, that is, $\int_0^{\infty} g_\tau(z|x)dz = 1$. To compute $g_\tau(z|x)$, we first derive the bivariate joint-density:

$$f_{t,t+\tau}(x,z) = \frac{1}{nh_zh_x}\sum_{i=1}^{n} K\left(\frac{z-Z_i}{h_z}, \frac{x-X_i}{h_x}\right), \tag{6-5}$$

where K(.) denotes the Epanechnikov function, n is the number of observations, and X_i and Z_i denote the logarithmic RICI of province i at time t and $t+\tau$, respectively. h_x and h_z are the selected bandwidths for x and z. Similar to the case of univariate density estimates, we mitigate under/over smoothing biases using the two-step adaptive kernel method of Silverman (1986). Due to restrictive sample sizes, annual transition probability estimators are used in order to obtain more reliable results, as suggested by Quah (2001).[47] Then the transition probability kernel density can be computed as:

$$g_\tau(z|x) = \frac{f_{t,t+\tau}(x,z)}{f_t(x)}, \tag{6-6}$$

[47] The primary results do not change substantially when we instead use 3-year and 5-year transitions. These results are reported in the appendix. Longer horizons allow for greater mobility of the regions, but also reduce the number of observations.

where $f_t(x)$ is the marginal kernel density of x [defined by Equation (3)]. Finally, given the time-invariant $g_\tau(z|x)$, the current distribution will evolve into a "steady-state" when τ goes to infinity. This ergodic distribution can be expressed as:[48]

$$f_\infty(z) = \int_0^\infty g_\tau(z|x) f_\infty(x) dx \,. \tag{6-7}$$

6.3.2 The Augmented Mobility Probability Plot

In addition to the above functions, we adopt another, recently developed tool in transition dynamics literature, namely, the mobility probability plot (MPP) proposed by Cheong and Wu (2014). Compared with traditional tools such as the kernel density plot, the contour plot, and the ergodic density plot, the MPP offers both a more direct interpretation and a broad overview of the results. Specifically, for each level of RICI at time t, the net probability of moving up to higher RICI levels is defined as the sum of the probabilities of moving up in the future distribution minus the sum of the probabilities of moving down. The MPP can be computed as:

$$p(x) = \int_x^\infty g_\tau (z|x) dz - \int_0^x g_\tau(z|x) dz \,. \tag{6-8}$$

The MPP in its current form is not without flaws. It is, in essence, a non-parametric point estimate and does not offer much in terms of how certain we are about whether our estimate of transition probability is statistically different from zero, that is, from immobility. It follows that hypothesis testing is infeasible in this case. To alleviate this concern, we propose our own novel augmentation of the MPP method: A simple bootstrap confidence interval (hereafter, CI) for the estimated probabilities. To construct this CI, we follow a five-step simulation procedure:

1. Randomly draw with replacements from the actual sample of region-year $n = N \times T$ RICI values ($N = 31,\ T = 13$) and denote this series as x_s. This series can be considered as the realisation of the underlying data generating process at time t.

[48] We solve for the ergodic distribution following the procedures outlined in Johnson (2005) and Juessen (2009).

2. Locate the one-period ahead values of x_s, then stack them into a new series denoted as z_s, which is the simulated series at time t+1.

3. Using x_s and x_z as inputs, re-estimate the joint density $[f_{t,t+\tau}(x_s, z_s)]$ and conditional transition density $[g_\tau(z_s|x_s)]$.

4. Re-estimate the mobility probabilities $[p(x_s)]$.

5. Repeat steps one to four 10,000 times. Then, record the 2.5 percentile and 97.5 percentile of the 10,000 simulated mobility probabilities. These thresholds are the lower and upper bounds of the 95% confidence interval for our original estimates of mobility probabilities.

With the constructed CI, we are able to draw conclusions on the likelihood of movements for regions at different RICI levels with stronger confidence than any previous studies. The wider the CI, the more uncertainty involves the RICI transition probability estimates.

6.4 Results

6.4.1 Full Sample Dynamics

Panel A of **Figure 6-3** displays a three-dimensional (hereafter 3D) distribution of the annual transition probability of log RICI across all Chinese regions during 2003-2016. It can be interpreted as a posterior probability distribution at time $t + 1$, given a specific distribution at time t. Imagine a line parallel to the $t + 1$ axis at a chosen point on the t axis. The intersection of a vertical plane with the base coincides to this line and the three-dimensional surface will give us the density plot of the logarithmic RICI at $t + 1$. A more intuitive perspective can be obtained from the corresponding density contour map, which is embedded in the t - t+1 plane in panel A, and plotted separately in panel B. It offers a “bird’s-eye view” of the 3D surface, and the interpretation is straightforward. The spread of contour lines implies that intangible investment is widely dispersed across Chinese regions in the last two decades. The probability mass concentrating along the 45-degree line indicates low regional mobility: provinces that are more intangible-intensive in the previous year tend to sustain their advantages in the following year.[49] Consistent with the 3D plot, two peaks can be seen clearly from the contour map, which indicates that regions tend to cluster into two groups. The higher peak is at -1.2 and the lower is at -0.4, implying that the intangible investment intensity in most Chinese regions remains lower than the national average.

A. Conditional Probability Kernel B. Contour of Conditional Probability Kernel

C. Mobility Probability Plot D. Ergodic Density Distribution

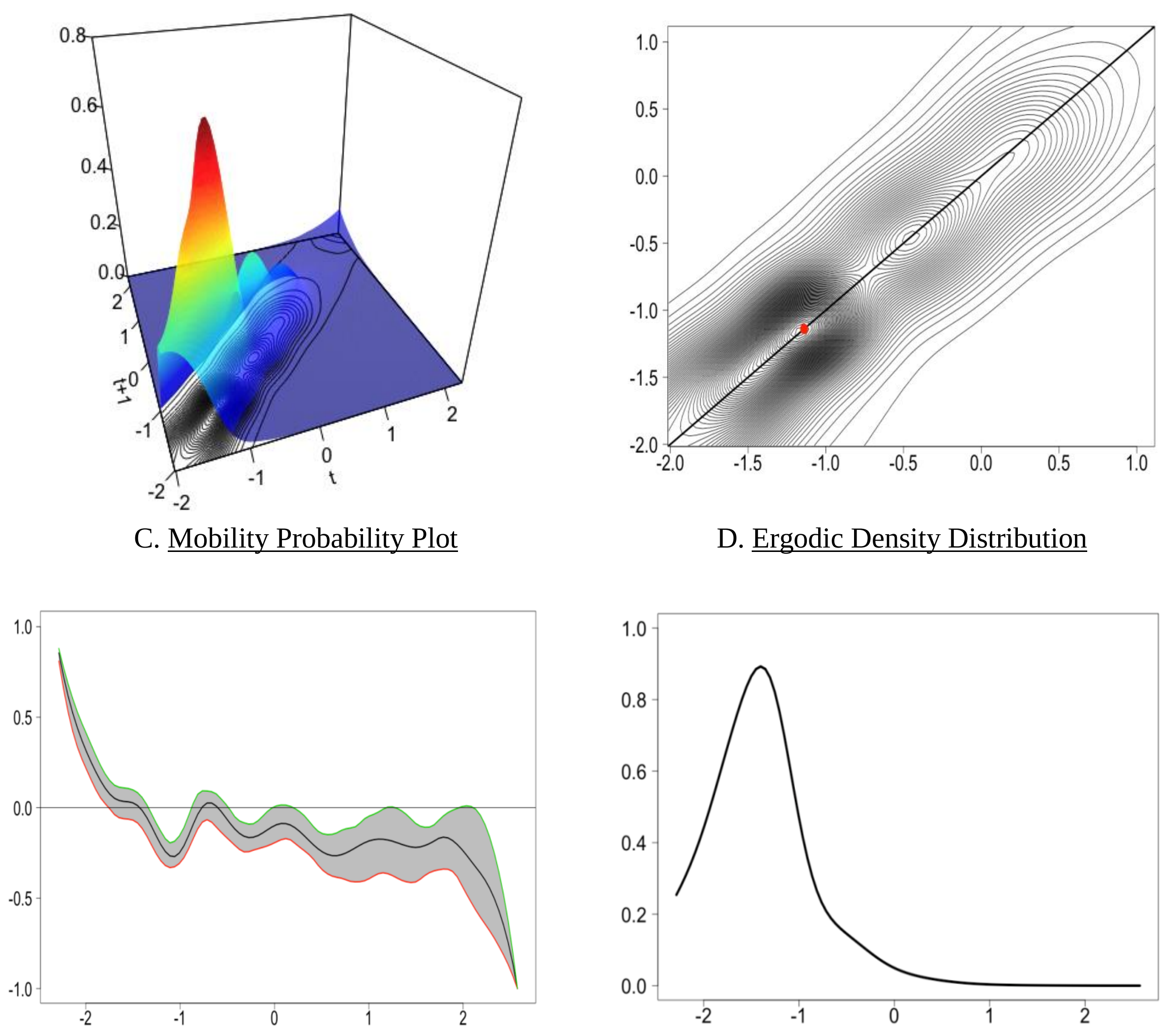


Figure 6-3. Annual Transition Dynamics of Intangible Capital, 31 Provinces, 2003-2016

Source: Author's own work.

Notes: 1. In panel B, and in corresponding panels in subsequent figures, the red dot indicates the highest peak of the conditional transition kernel. 2. In panel C, bootstrap confidence interval is constructed at 95% level of confidence. The number of bootstrap replications is 10,000.

[49] If instead we observe a probability mass lying above the diagonal line in regions with below-average RICIs, and/or below the diagonal line in regions which have above-average RICIs, then a convergence is feasible: poor/rich regions (in terms of capital intensity) will grow faster/slower in the future.

It is, however, somewhat difficult to determine where most of the probability mass lies by observing either the 3D plot or the contour (see e.g. Cheong and Wu, 2014), prompting us to use the MPP that shows the net probabilities of moving upwards (i.e. the probability of increasing capital intensity). This MPP is shown in panel C of **Figure 6-3**. In terms of point estimates, a positive net probability is observed for provinces with current intensity smaller than -1.3 and in the interval [-0.8, -0.5]. The majority of provinces, however, exhibit a net negative mobility probability, that is, their level of intangible capital tends to be reduced in the future. This finding is strengthened with the addition of the bootstrap CI. It can be seen that upward mobility probability is only significant for very poor regions (values close to -2). Note that the curves of actual estimates and both CI bounds start at 1 and end at -1 by construction (from left to right), i.e. probability of moving up (down) is 100% for the poorest (richest) region, hence there is no uncertainty at these extreme points. We can also see that uncertainty tends to increase when regions move upwards. This finding is because estimation precision is reduced due to the decreasing number of observations. In short, the MPP reveals a lack of incentives to invest in intangible capital in Chinese provinces. Because of this, Chinese regions tend to converge to a lower-than-average intangible intensity in the long run.

This result is corroborated in the ergodic distribution plot shown in panel D. This plot presents the steady-state distribution based on the current transition path. The distribution's shape is unimodal with the highest peak at -1.2, and the lower peak is now "absorbed" into the higher. It can be argued that our results are driven by a lack of mobility over the short time period of annual transitions. To alleviate this concern, we extend our examination based on a three-year and a five-year transition probability path, of which results are reported in appendix **Figure 6A-1**.[50] Increasing the length of the time span does produce more mobility, but also reduces the numbers of transitions and therefore affects estimate precision. In general the conclusions from these analyses are similar

[50] The choices of horizons are in general aligned with typical business cycle literature and/or the "five-year plan" schedule often adopted by Chinese policy makers. China's five-year plans, also known collectively as the five-year guidelines (wunian jihua or guihua, in Chinese), are a series of crucial social and economic guidelines issued since 1953 to direct its political and economic transitions.

to those based on the annual transition analyses. For this reason, the rest of the chapter will focus on annual transitions only.

6.4.2 Intertemporal Dynamics

To get better insights on the evolution of capital distribution over time, we examine the dynamics exhibited in two sub-periods, 2003-2009 and 2010-2016. These samples correspond to the pre- and post-global financial crisis. The time division enables us to have roughly equal observations in sub-periods and to examine plausible different distribution dynamics before and after the GFC. **Figure 6-4** illustrates the analogous plots to those in **Figure 6-3** using observations partitioned into these sub-periods. According to the 3D transition kernel plots (panel A), in the second period the peak clearly moves downward to a relatively lower level than that in the first. Thus it implies that intangible-intensive regions in China tended to reduce their investment after outbreak of the GFC. The shape of the distribution also changed considerably. Two obvious clusters are found during 2003-2009, but only one cluster is prominent during 2010-2016. The coordinates of the peaks in sub periods are highlighted in the contour maps (panel B). The highest peak moves from around -1.1 during 2003-2009 to about -1.3 during 2010-2016. As a result most regions in China reach a lower level of intangible capital investment intensity after the crisis.

According to both MPPs (panel C), the majority of regions tends to reach a lower future level of capital investment. For richer regions, negative net mobility is actually desirable if long-run convergence is to come. However, for poorer regions, especially those with RICI ranging from -1.5 to 0, difficulty in moving upward hinders convergence. Additionally the CI gets wider for regions with high RICI levels, leading us to predict movements with less certainty. The inclusion of the horizontal zero line within the CI at some low, middle and high RICI values indicates that we cannot reject the null hypothesis of immobility, or persistence, at these data points. This pattern is in agreement with the short-run concentration of the probability mass along the diagonal lines as shown in panels A and B.

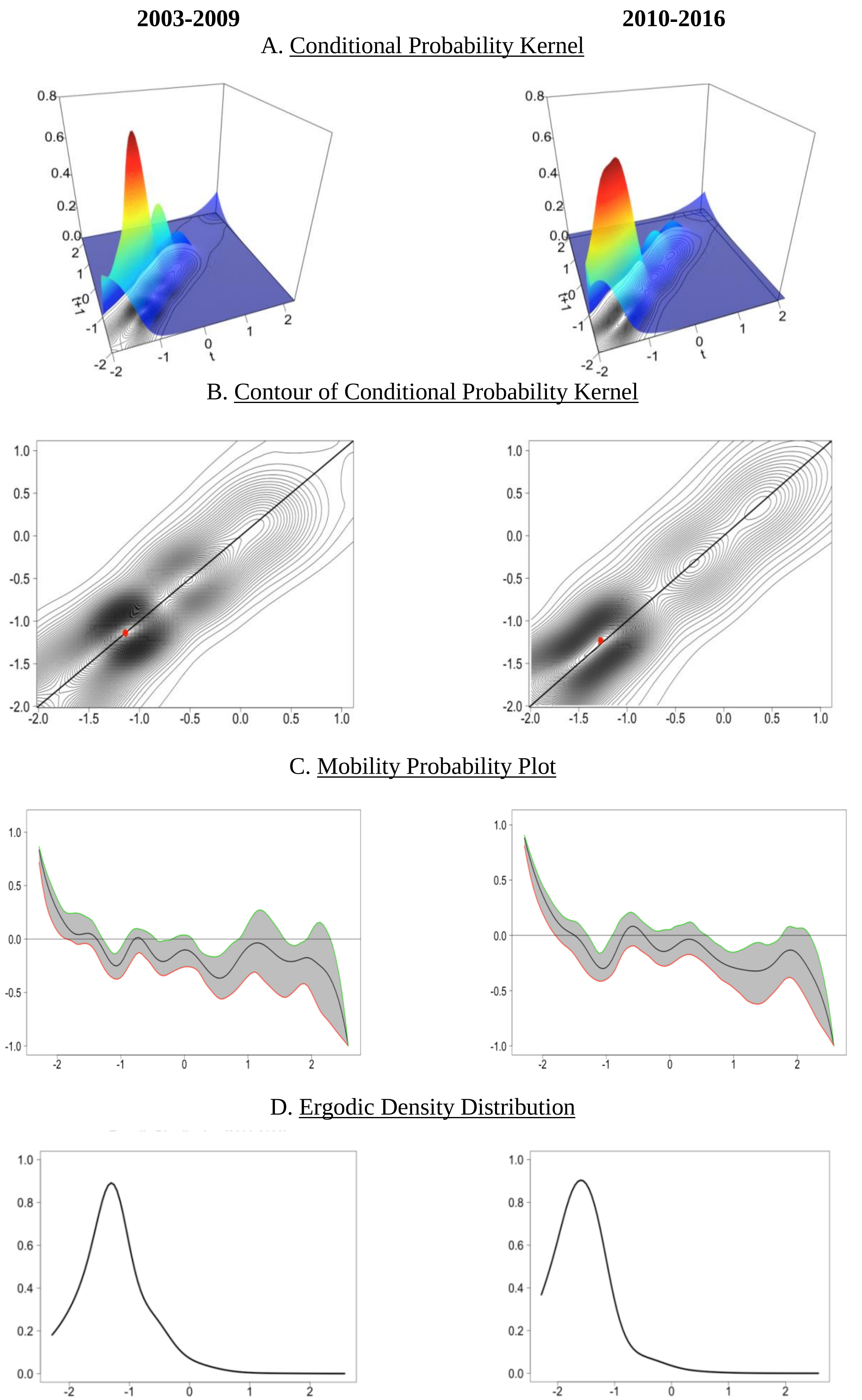


Figure 6-4: Annual Transition Dynamics of Intangible Capital, Two Sub-Periods

Source: Author’s own work. *Note*: See notes to **Figure 6-3**.

According to ergodic distributions in panel D, the RICI for most Chinese regions is far lower than the national mean (zero) in the steady-state distribution. In addition, the peak of the ergodic distribution is situated farther away from zero in the post-crisis period than in the pre-crisis period. It can be concluded that the under-development of intangible capital is exacerbated after the GFC.

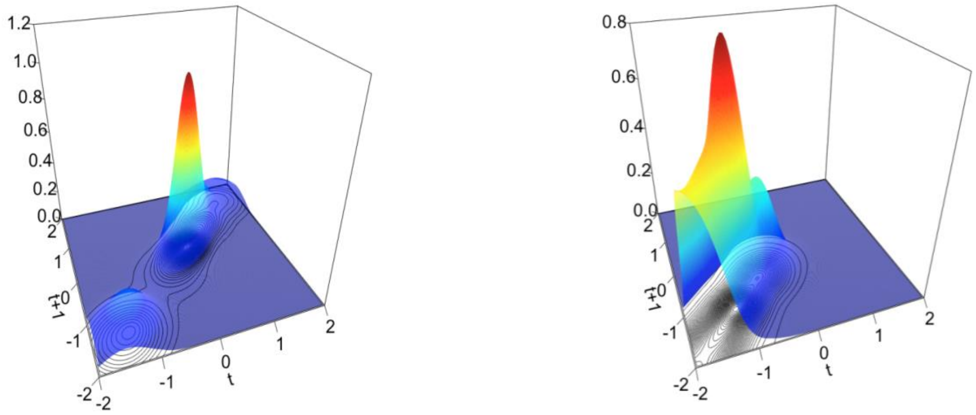
Corrado et al. (2018) investigated the trends of tangible and intangible investment across 18 European economies and the United States over the period 2000-2013. After the shock from global financial crisis, intangible investment has been relatively resilient and recovered fast in the United States, but has experienced a slower recovery in most European economies. By comparison, our results show that Chinese regions may follow a different pattern. The impact of the global financial crisis was quite strong in China where investment in intangibles declined continuously during the post-crisis period of 2010-2016.

6.4.3 Spatial Unconditional Dynamics

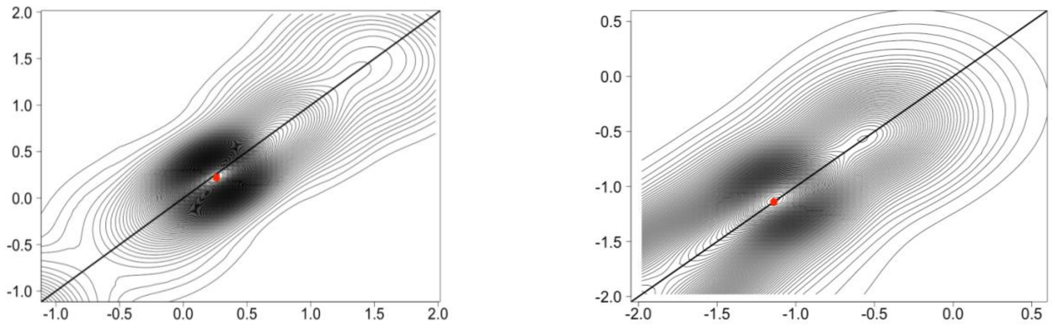
To understand regional disparity in China's intangible investment, we group the regions into two economic zones, namely, the coastal and the interior zones. This division is consistent with previous studies and is largely based on the economic and geographical clusters that characterise "clubs" of economic growth and development in China (Li & Wu, 2018). Considerable differences between these two economic zones can be found in the 3D transition probability plot and the corresponding contours. Panels A and B of **Figure 6-5** show log RICI values in most coastal regions are higher than the national mean, with the peak at around 0.3. In contrast, the peak of the interior regions' contour map is far below 0, lying around -1.2. In most interior regions, the level of RICI is lower than the average. Panel B reveals that the largest probability mass of coastal regions is roughly located between [-0.5, 1.0], while for interior regions it is between [-1.5, -0.5]. In summary, there is a large gap in intangible capital investment between coastal and interior regions in China.

Coastal **Interior**

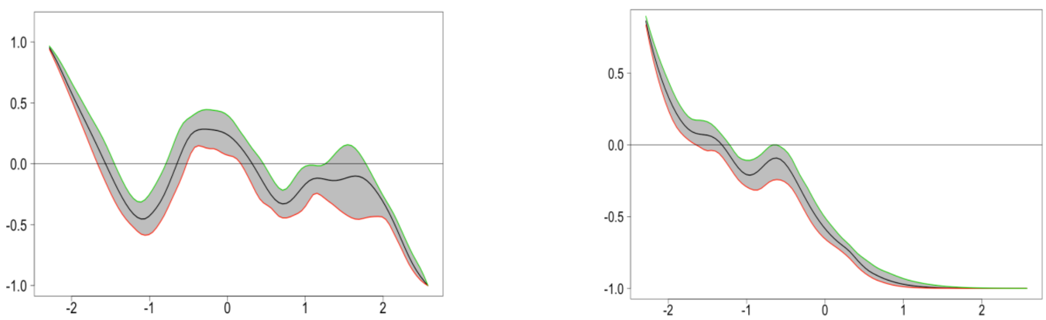
A. Conditional Probability Kernel



B. Contour of Conditional Probability Kernel



C. Mobility Probability Plot



D. Ergodic Density Distribution

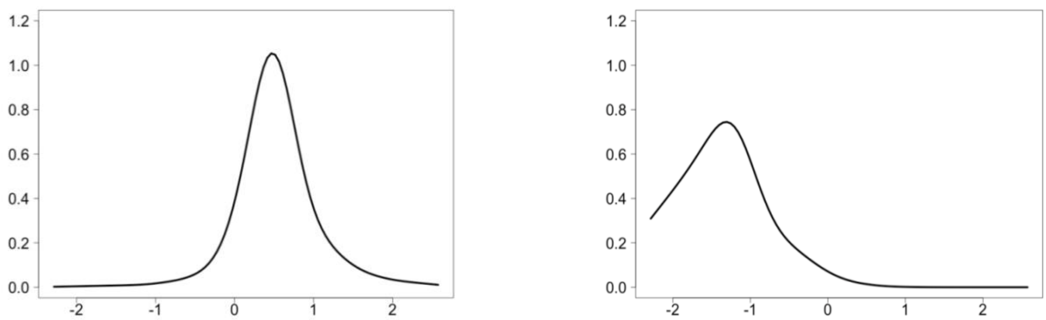


Figure 6-5: Annual Transition Dynamics of Intangible Capital, Two Economic Zones

Source: Author’s own work. *Note*: See notes to **Figure 6-3**.

More importantly, the investment gap in China is predicted to be gradually widened. According to the left-hand side plot of panel C, the coastal regions' MPP curve lies above the horizontal zero line not only for very poor regions, but also in the [-0.5, 0.5] range, which corresponds to where most of the probability mass concentrates. In other words, provinces with investment level in the range of approximately 39 percent below to 65 percent above the national mean tend to enjoy increasing investment.[51] Furthermore, due to greater uncertainty associated with regions located at the right tail of the distribution, the CI implies that more developed coastal regions can still sustain their intangible advantages. This inference can be seen by the upper bound of the CI crossing the horizontal zero line in the [1.2, 1.8] range. As a result, in the long-run the coastal regions will cluster to a higher-than-average investment peak, as illustrated by the steady-state unimodal distribution shown in the left-hand side plot of panel D. In stark contrast, the MPP for interior regions indicates strong trend of moving downward. Since there are only a few regions here belonging to the right tail, compared with the coastal sample, we observe a much narrower CI towards the high values. There seem to be impediments for the convergence of interior provinces to reach the national mean. Additionally, "rich" regions in the interior sample will almost certainly become poorer in the long-run. Consequently, the ergodic distribution for this sample exhibits a very heavy left tail with a peak around -1.2.

Therefore, the main finding demonstrates that China's coastal regions will continuously outperform interior regions in terms of intangible capital investments. In intangible context, the benefits of spill-overs and synergies in more-developed coastal regions induce business and talent to congregate to exploit and expand the already large cumulative network effects. This newly developed "intangible economy of scale" mechanism is predicted to create a winner-takes-all scenario and will increase Chinese regional inequality in the long-run. The result corroborates the view of high regional inequality in China. It enriches the extant studies of spatial imbalance which focus on the role of preferential policies, decentralization, globalization, marketization and so on

[51] Since the horizontal axis displays the log of the ratio with respect to the average, the range of investment levels goes approximately from 39 percent below to 65 percent above average.

(Bao et al., 2002; Démurger, et al., 2002; Liao & Wei, 2012; Wei, 2015). By considering intangible capital as new factor inputs, the trajectory of regional development in China would be more complicated.

6.4.4 Spatial Conditional Dynamics

As mentioned above, intangible investment is perceived to involve knowledge spill-over effects. Geography is thus considered as one of the important determinants of the intangible investment distribution. Therefore, in the following discussion we re-examine the distribution with a geographical consideration. Specifically, we define conditional RICI of region i as the log of the ratio of per capita intangible investment of i $(\mathrm{y_{it}})$ over the average of its geographical neighbours $(\tilde{\mathrm{y}}_{\mathrm{i,t}})$: $\mathrm{X}'_{\mathrm{it}} = \ln\frac{\mathrm{y_{it}}}{\tilde{\mathrm{y}}_{\mathrm{i,t}}}$. Neighbouring regions (excluding i) are those sharing borders with i. As the conditional distribution represents the impact of the conditioning factor on the distribution of the conditioned variable, the larger the distinction between unconditional and conditional distributions, the higher the explanatory power of the factor (Wu et al., 2018).

Figure 6-6 shows that the dynamic of the spatially conditional RICI is markedly different from that of the unconditional RICI (from **Figure 6-3**). Firstly, as shown by the transition kernel and contour plots (panel A and B), the probability mass of the conditional RICI lies in a range of [-1, 0.5] compared with lying in [-2, 0] in the original transition plot. Different convergence clubs also appear, and the peak is close to the neighbours' average, which is zero in this case. In panel C, there are only a few intersection points between the horizontal zero line and the conditional MPP estimate, meaning provinces move up and down with more or less equal probabilities. The results are quite robust with a narrow CI that has relatively stable width. As a result, the ergodic distribution resembles normality, with a peak located near zero. The finding that regional intangible investment levels in China are more likely to converge towards the mean of their geographical neighbours instead of the national average strengthens our proposition that investment distribution is a result of spill-over effects.

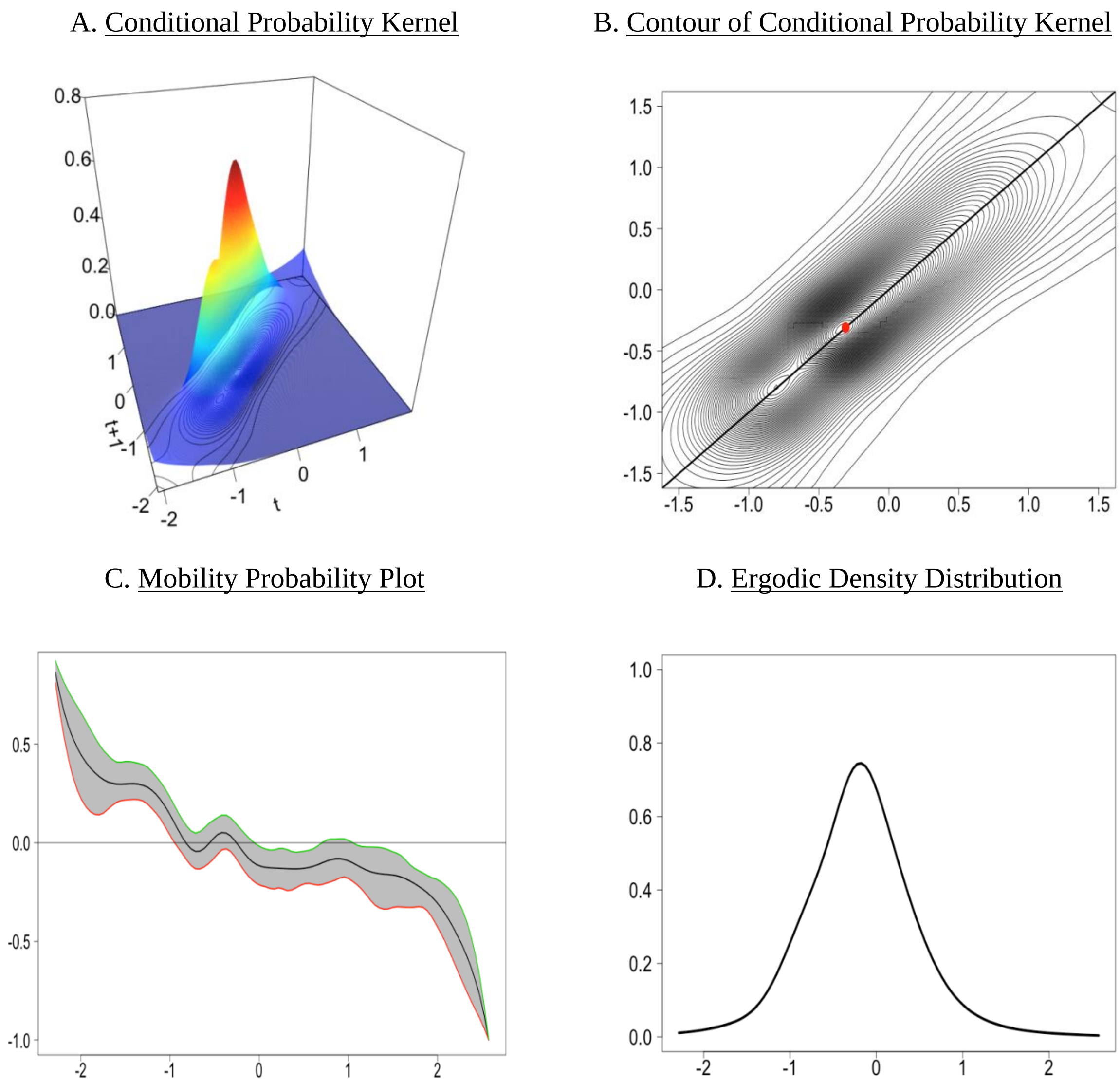


Figure 6-6: Annual Conditional Transition Dynamics, 31 Provinces, 2003-2016

Source: Author’s own work.
Note: See notes to **Figure 6-3**.

As a robustness check, we repeat the above conditioning exercises for the two economic zones examined previously. If our hypothesis regarding spill-over effects is valid, this effect should be more profound for less geographically dispersed areas, i.e. those with lower physical costs of knowledge transfer. The results are presented in **Figure 6A-2** in the appendix, and we highlight the main findings here. In general, knowledge spill-overs affect intangible dynamic distributions in both economic zones in China: multimodality is found in the short-run distributions for both. Overall, the results echo those presented in the unconditional spatial distribution analyses.

According to the conditional MPP of the coastal sample, the richest regions (with logarithmic RICI values in the [1, 1.8] range) can still move up. More importantly, it appears that knowledge spill-overs tend to have a larger impact on regions with already high intangible capital intensity, than that on less-developed regions. The accumulation of intangible capital may lead to stronger economies of scale in these regions.[52]

The findings highlight the existence of knowledge spill-overs of intangible capital, which has also been demonstrated by a body of research using parametric modelling techniques (Corrado et al., 2017; Goodridge et al., 2017). Intangible capital is therefore an important source of externalities. In addition, spatial distance is important to understanding intangible distributions in China. The regional long-run intangible investment is more likely to be determined by the levels of the nearest neighbours rather than the national average.

6.5 Conclusions

Global economy has been shifting gradually, and will continue to shift from the tangible to the intangible economy across the globe. China is no exception. Intangible investment associated with high spill-over effects becomes the growth driver for regional development. Therefore, a comprehensive interpretation of regional intangible investment is of importance to understand China's regional economic growth and disparity. Adopting a non-parametric transition dynamics approach, we examine the short-run transitional patterns as well as the long-term trends of per capita intangible capital investments in 31 Chinese provinces during the period 2003-2016. In addition, the intertemporal analysis and spatial conditional analysis was implemented to examine the impacts of global financial crisis and knowledge spill-over on intangible investment distribution dynamics, respectively.

[52] Regarding interior regions, intersection values are greater in the conditional MPP compared with that in the unconditional one. The peak of the corresponding ergodic distribution also moves closer to zero. Similar to the coastal zone, it is easier for interior regions to converge to their neighbours' mean than to the national mean.

The results indicate the underinvestment and unbalanced intangible investment in Chinese regions, which tend to manifest into convergence "clubs". While there are only a few mega cities that are well endowed with intangible capital, most Chinese regions achieve below-average intangible capital intensity. Long-term investment is projected to be low, leading to a steady-state distribution converging towards a level far lower than the national average. In addition, considerable differences are found in pre- and post-crisis transition probabilities. In general, intangible capital investment is adversely affected by the crisis. Chinese regions, especially those with higher intangible capital intensity, tend to reduce investment in the post-crisis era. Compared with the pre-crisis transition path, most Chinese regions tend to converge to a lower RICI level based on the post-crisis transition path.

Furthermore, evidence shows that coastal regions are dominant in intangible capital investment. In contrast, most interior regions lag behind, with investment levels far below the national average. According to mobility probability plots and ergodic distribution plots, interior regions struggle to increase investment in the long run. As a robustness check of the importance of spatial factors, intangible investment distributions are re-estimated conditional on the average level of neighbouring provinces. The conditional RICI distribution dynamics change considerably, which highlights the role of knowledge spill-overs. It is easier for Chinese regions to converge to their neighbours' mean rather than the national mean of intangible investment.

The results of this study clearly point out that regional intangible inequality would remain to be a major challenge for central government. . Though a converging growth trend was preferable to smooth the uneven development between Chinese coastal and interior regions, this seems to be more unlikely when we consider intangible capital distribution. According to our transition dynamics analysis, the long-run intangible investment will persistently favour coastal regions' development due to an "intangible economy of scale". Coastal mega cities continue to expand as innovation hubs, where intangible investments concentrate and generate large externality. The process thus crowds out interior regions and forces the laggards to fall into a poor cluster.

Numerous regional rebalancing strategies have been implemented by the central government but the focus is mostly on the infrastructure investment and fiscal transfers.[53] Our findings identify the need not only to understand regional development in a more comprehensive intangible context, but also to restructure regional development policies in China. It is proposed that economic policies should be adapted to an intangible economy to effectively reduce regional inequality.

First, it is important to strengthen intangible infrastructure development in the laggards, such as standards, rules and norms, which can underpin business' intangible investment and safeguard synergy effects. For instance, some intangible assets like computer software are becoming more compatible but also more susceptible to illegal intellectual property (IP) rights violations and privacy breaches. As such, well-designed regulations and social norms will be of great use to facilitate balance between personal privacy and data collection and analyses.

Second, a well-developed transaction market is required to encourage intangible capital investment. At present, some endeavours have supported the transfer and commercialisation of intangible assets, such as the establishment of national funds for technology transfer, copyright transaction centres, and pilot commercialisation centres (located in Xi'an and Zhuhai). In addition, these kinds of markets should not be limited to major intangible assets like patents and copyrights. A more developed market should also be applicable to other valuable intangibles like software and databases.

Third, spill-over effects play a crucial role in the distribution of intangible capital investment, and convergence is more likely to happen in adjacent regions first. With respect to this empirical regularity, the government may take advantage of spill-over effects by establishing intangible-intensive centres in middle-sized interior regions, reducing geographical barriers, and expanding internet coverage. From the experiences of the special economic zone program, these clusters will benefit from a combination of intangible tax breaks, flexible financial support, university-industry research collaborative joint-ventures, and intangible capital subsidies, among other policies.

[53] Programs like China Western Development and Northeast Area Revitalization Plan mostly emphasise the infrastructure development such as transportation, telecommunication, and construction in interior regions.

Finally, as our results show, intangible-driven regional inequality would be highly influenced by geographic scales, spatial heterogeneity, and network effects. Central cities and urban areas are expected to become growth poles. Intensifying inequalities will exist not only between but also within provinces. However, many preferential policies target central cities within provinces, and therefore establish conflict of interest between central and subordinate regions. For example, economic development polices in interior regions are mostly biased toward central cities and leave other rural areas far behind. More efforts should be put to inspire development initiatives of county-level governments and to stimulate county-level intangible economies of scale.

APPENDIX A6

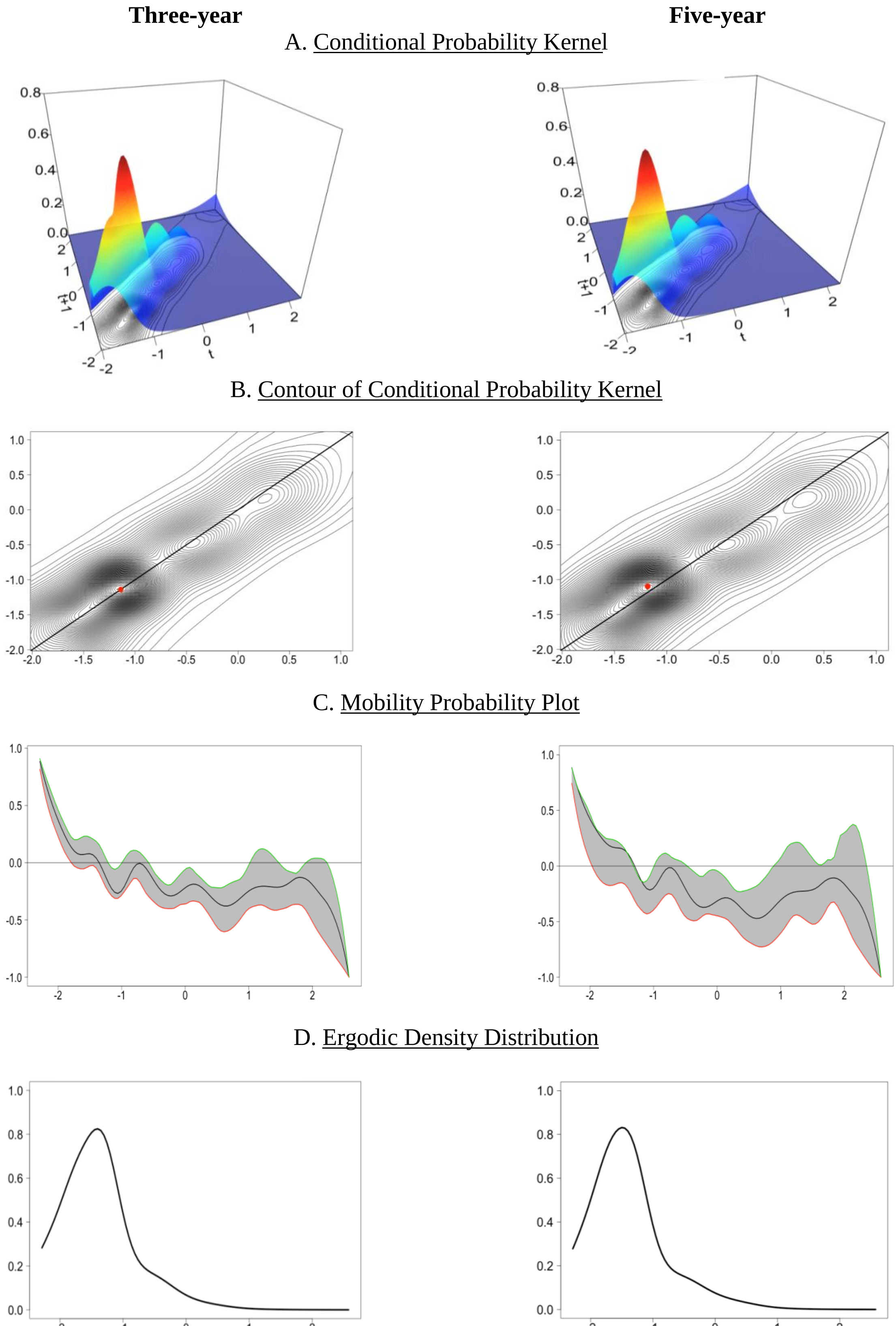
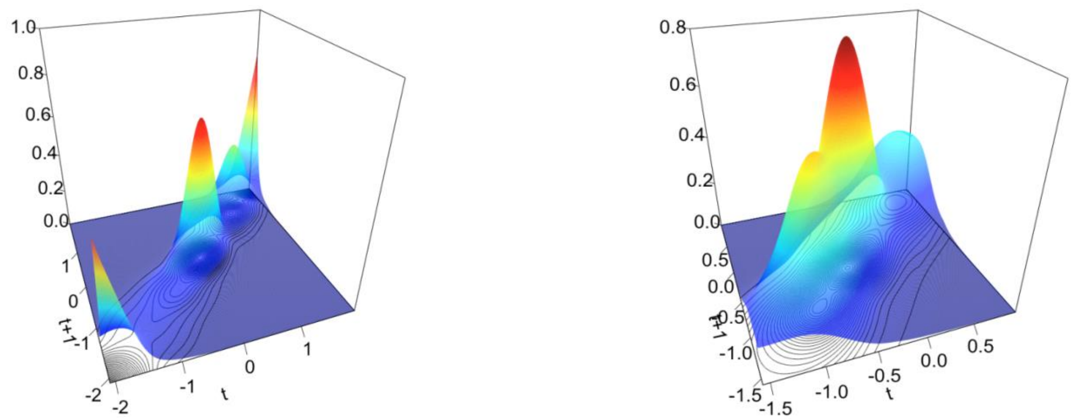


Figure 6A-1:Three-year and Five-year Transition Dynamics, 31 Provinces

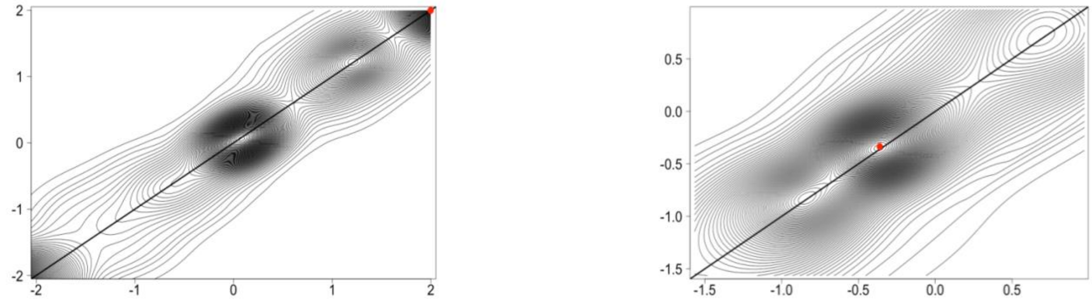
Source: Author’s own work. *Note*: See notes to **Figure 6-3** of the main text.

Coastal **Interior**

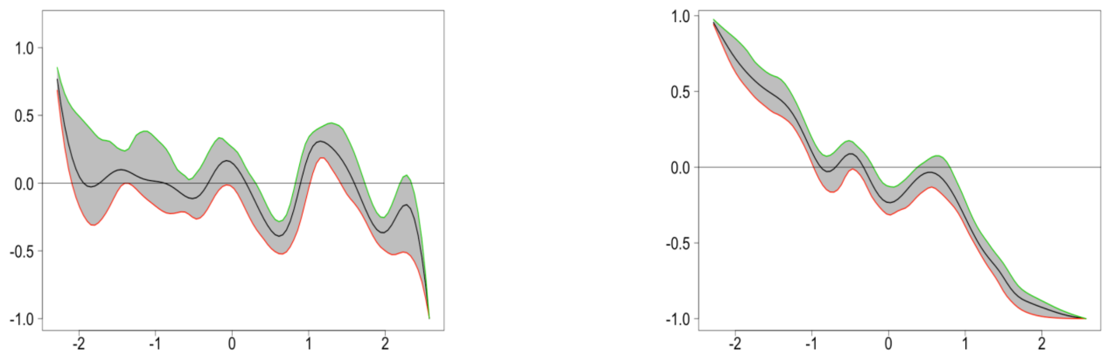
A. <u>Conditional Probability Kernel</u>



B. <u>Contour of Conditional Probability Kernel</u>



C. <u>Mobility Probability Plot</u>



D. <u>Ergodic Density Distribution</u>

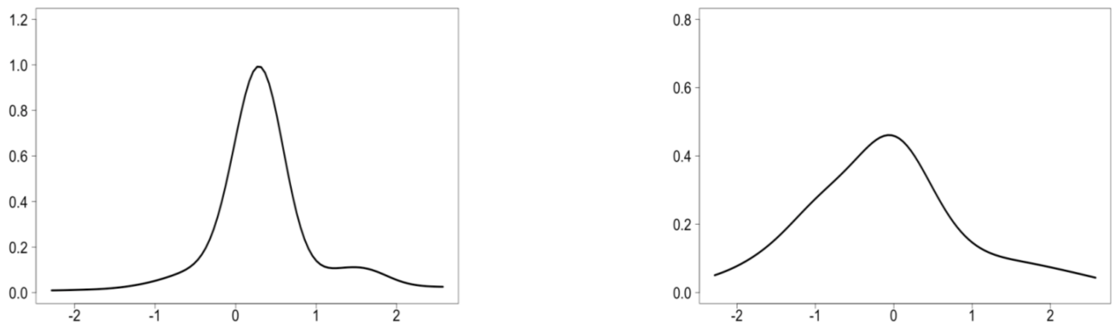


Figure 6A-2: Annual Conditional Transition Dynamics, Coastal and Interior Regions

Source: Author's own work. *Note:* See notes to **Figure 6-3** of the main text.

CHAPTER 7 - CONCLUSION

In this dissertation intangible capital is analysed at different levels in order to examine its contributions to China's labour productivity growth, its relationship with ICT capital, its impacts on Chinese firm performance, and its dynamic distributions across Chinese regions. This chapter will summarise the main findings of each core chapter in the dissertation, provide policy implications and practical suggestions for China's economic development, and present what is still unknown for future work.

7.1 Summary of the Main Findings

As intangible ideas and products are penetrating people's daily life, no one can deny that we are entering a knowledge economy. Intangible capital becomes an increasingly important factor underlying economic and productivity growth. In contrast with advanced economies, less is known about intangible capital in China. One of the major reasons for this knowledge blank is the ambiguous definitions and measurement impediments of intangible capital. Therefore, by adopting the framework used in developed countries, Chapter Two defined nine types of business intangible assets, and constructed intangible investment flows in China and in 31 Chinese regions during 2003-2016. Intangible capital stock was then estimated at both the national and regional level by using the PIM approach. The main findings in Chapter Two are as follows. First, China has made substantial efforts in intangible investment during the last decade. Intangible investment accounts for an increasing share in China's GDP during 2003-2016, especially after the GFC in 2007-2009. However, compared with tangible investment, intangible capital still accounts for a small portion in China's national GDP. Tangible investment is still the dominate factor explaining China's economic growth. There is a large gap in tangible capital investment and intangible capital investment in China. It may too early to say that China is already an economy driven by knowledge and innovation. Second, intangible capital is unevenly distributed across different components. Computer software, accounts for over a half of the total investment, followed by architecture designs and scientific R&D. Economic competencies, which represent an enterprise's durable competitiveness, only account for a minimal portion. What's worse, the share of economic competencies in total intangible investment seems to be shrinking over time. This phenomenon places China in stark contrast with advanced economies, where economic competency is equally important as innovative property and computerisation. Finally, intangible capital development is unbalanced among Chinese regions. Regions adjacent to the sea far outperform the rest in terms of intangible development. Driven by the advancement in computerisation, mega cities like Beijing and Shanghai are becoming intangible investment hubs.

Chapter Three examines the contributions of intangible capital to China's economic growth by using a growth accounting analysis. An expanded growth accounting exercise is conducted by including intangible capital as a new input factor at supply side and intangible investment as a new income at demand side in a production function. To explore different impacts of intangibles on Chinese regions, the analysis is also implemented in 31 Chinese regions that are grouped into the coast and the interior. The main findings of Chapter Three are as follows. First, labour productivity growth in China is higher if intangible capital is considered. A greater influence of intangible capital on labour productivity growth was found after the GFC. Second, capital formation becomes a dominant power to drive China's economic growth. TFP still plays its roles, but the effects are shrinking a lot when intangibles are involved. Third, intangible capital is conceptually different from human capital. The contributions of human capital to China's economic growth will not be affected by introducing intangibles into analysis. Fourth, compared with developed economies, intangible capital still plays a less important role in labour productivity growth in China. Finally, intangible capital exerts different impacts on China's regional economic growth. Coastal regions can benefit more from intangible capitalisation than the interior. After considering intangibles, there is an enlarging gap of labour productivity growth between these two regions. The gap can be explained to a large extent by coastal regions' leadership in investment in computerisation, scientific R&D, and financial products and services.

Causality relationship is a common problem in growth regression analysis, as it is not clear whether intangible capital development leads to faster economic growth or faster economic growth leads to intangible capital development. Chapter Four, therefore, aims to find specific mechanism through which intangible capital can contribute to economic growth. Sector ICT intensity is used as a nexus to detect the relationship between intangible capital and sector output growth. Intangible capital is found to disproportionally help more ICT-intensive sectors grow faster in China. The positive relationship between intangibles and ICT is robust to the use of different measures of intangible capital development and different sector ICT intensity indictors, and if other potential region-level determinants of sector growth are considered. The finding implies that intangible capital can contribute to economic growth not only by acting as an input factor but also by complementing with tangible capital investment.

Chapter Five explores the relationship between intangible capital and economic growth from a micro prospective. Organisation capital in Chinese manufacturing firms, as one productive intangible asset, is analysed. In addition, due to non-rival and non-excludable features of intangible capital, knowledge spill-over effects from organisation capital are also explored by considering two potential spill-over channels of technological proximity and geographical proximity. The main findings are as follows. First, organisation capital has a considerably positive effect on Chinese manufacturing firm output performance. The output elasticity of organisation capital is close to that of human capital, and falls into a similar range as these of developed countries. Second, knowledge spill-overs from organisation capital are detected among Chinese firms, and depend on how the spill-over pool is constructed. Specifically, advanced organisation capital diffuses among firms mainly through geographical proximity rather than technological proximity. On the one hand, technological proximity cannot be captured by patent portfolio of firms in China. On the other hand, knowledge spill-overs from organisation capital would be more likely to diffuse through face-to-face interactions. Since the marginal costs of such interaction increase alongside the spatial distance, adjacent firms would be more likely to benefit from spill-overs due to the low costs of interactions.

Finally, by adopting a nonparametric distribution approach, Chapter Six analysed intangible capital investment distribution dynamics and predicted the future development of intangible capital among Chinese regions. It shed light on whether the laggards will catch up finally with the leaders. The main findings are as follows. First, a few mega cities / provinces invest heavily in intangible capital, while most regions have below-average investment levels. Intangible investment is unequally developed among Chinese regions. Second, long-term convergence clusters are detected. While high levels of investment tend to be persistently concentrated in a few coastal regions, investment in poorer regions is projected to be much lower than the national average. In other word, the leader is predicted to perform better in the future while the laggards may do worse. Third, dynamic transition patterns are distinct in pre- and post- crisis era. GFC is supposed to pose a heavy toll on the development of intangible capital in Chinese regions. Fourth, regions are found to have less difficulty in converging towards their neighbouring regions than the national average. Knowledge spill-over is an important mechanism to help mitigate the unbalanced intangible development. The findings thus shed light on China’s regional economic development. Intangible capital development may eventually push up regional inequality in China in the long run, and the conventional growth convergence analysis is incomplete without considering regional unbalanced intangible capital development. However, knowledge spill-over is probably an important mechanism that helps mitigate the level of regional imbalance in the context of intangible economy.

7.2 Policy Implications

One of the most important policy implications in this study is to accelerate the reform of China’s accounting systems in regard to intangible capitalisation. Intangible capital has become the important source of economic growth and explains labour productivity growth significantly in China, and it is of necessity for China to accelerate the process of intangible capitalisation.

However, currently, scientific R&D, mineral exploration, and computer software, are the only three intangible assets that are capitalised into China's national account, and none of these is recorded as a separate accounting item. Other intangible capital, such as entertainment originals, designs, and brands, is still being treated as intermediate expenditures, which are not required to be reported in either firm financial statements or national income accounts. Associated with the growing importance of intangible capital in economic development, there will be an increasingly downward bias in China's national income if most intangibles are still excluded from the national account. The analysis based on China's conventional national GDP will suffer from measurement errors in the future, and thus may lead to infeasible economic policies. To reform accounting system, the Chinese government can learn lessons from the United States to establish satellite accounts for some well-known intangible capital first, and to report investment flows and capital stock of these intangibles in more detail. For other less-known intangibles, it is time to recognise their importance, and to start the process of defining and measuring these assets properly under the guidance of international standards.

Second, less investment in economic competencies is observed in China than in advanced economies. Economic competencies, consisting of brand equity, employer-provided training, and organisation capital, are the most valuable intangibles that can gain long-term competitiveness for enterprises. The lack of investment in economic competency may hamper the competitiveness of Chinese firms in the future. While it is possible that our estimates underestimated real investment in economic competencies by Chinese firms to some extent, many Chinese enterprises still underinvested in this intangible asset. At least, China should spend more efforts in economic competency investment and learn lessons from the experiences in developed countries. For example, several studies of developed countries showed that employees with higher education levels receive more training, and large firms tend to offer more trainings for their employees (Holzer & Reaser, 1999; Lynch, 1992; Lynch & Black, 1998). Similarly, underinvestment in employer-provided training in China exists more likely among small and median sized enterprises, and is more common for less-educated and less-experienced employees. Therefore, to encourage investment in economic competencies, governments should reduce the expense gap by paying special attention to training opportunities provided by small-sized and/or median-sized enterprises. Furthermore, government policies should focus on increasing access to training for junior employees and for those underrepresented groups, rather than simply require firms to spend a percentage of wages on training.

In CHS framework, management consulting service has become an important source of organisation capital investment in the advanced economies. It is reported that management consulting has become routines for around 75 percent of the US enterprises and 50 percent of the Japanese enterprises.[54] However, since the concept of management consulting was first introduced from developed economies to China in the 1980s, the management consulting industry in China is still in its growth stage. In contrast, in the United States, management consulting services have soared from the early 1960s and has gained a market value of about US$ 20 billion nowadays.[55] The top consulting firms by revenue, prestige, and growth are mostly occupied by firms in the United States. In an intangible economy, it can be predicted that management consulting will become more important for Chinese companies for their routinely business operation, brand management, and information integration. The growing demand in China will provide great opportunities for management consulting companies and management consultants. As a result, it is urgent for China to breed its local consulting firms and brands, and to be aware of the coming talent shortage in this sector.

Third, intangible capital can complement ICT capital to jointly contribute to China's economic growth. Economic benefits come from not only the ICT-producing sectors but also the

[54] More details can be found from http://www.pinlue.com/article/2018/09/2012/237314785137.html. (in Chinese).

[55] More details can be found from https://www.consultancy.asia/news/84/management-consulting-market-of-china-grows-12-to-45-billion.

ICT-using sectors. Thus, instead of focusing on the development of ICT-producing industry alone,[56] the Chinese government should put more emphasis on ICT-using industries at the same time.[57] In addition, more investments are needed for intangible development. These intangible investments will include but not limited to investments in human resources and organisation structural development, which facilitate firm-level efficient use of ICT; and investments in innovations of financial services and products, flexible and sound legislative systems, and even the "soft intangible infrastructures" of social standards, rules, and norms, which guarantee higher ICT benefits at aggregate levels. [58]

Fourth, the findings of knowledge spill-over effects of intangibles have important implications. For example, conventional tax policies, which can be easily applied to plants and equipment, seem infeasible when they are applied to idea and innovation. A more flexible taxation system is thus needed. In addition, the free-rider problems caused by knowledge spill-overs may lead social returns to exceed private returns from business intangible investment. As a result, private enterprises may be less likely to invest in some intangible capital whose private returns are far less than social returns (for example, basic scientific research). In this case, the policy makers should always feel obliged to step in. Meanwhile, to encourage private intangible investment, for the same reason, the government is required to secure the rights of invested companies to minimize the spill-overs and maximize the private benefits from their original intangible investment. A practical implementation is to establish judicial and efficient legislation system to protect intellectual property rights.

---

[56] ICT has been put as the top agenda in each of the five-year plans for China's societal and economic development from the past decade. In the latest "The Twelfth Five-Year Plan", ICT producing industries have been designated as one of China's seven strategic industries. The specific industries include area sectors such as cloud computing, the internet of things (IOT), integrated circuits (ICs), basic software, and broadband technology (Atkinson, 2014).

[57] In fact, the lion's share of economic benefits come from ICT use rather that ICT produce (Atkinson, 2014).

[58] As pointed out by Haskel and Westlake (2018), an intangible-rich economy will have a greater need for intangible infrastructures of the social standards, rules, and norms that underpin businesses' intangible investment. For example, the process of the development and launch of a new medicine will involves a complex dance between payers of health insurers, governments, regulators, clinicians, patients, researchers, and institutions. Each of these collaboration has rules about what sorts of medicine they will fund, study, do laboratory and market test. Advanced intangible infrastructure will allow agents to collaborate smoothly, share knowledge spill-overs, and exploit synergies (Haskel & Westlake, 2018).

However, it is also suggested that intangible convergence is more likely to happen in Chinese adjacent regions first thanks to the knowledge spill-over effects. In other word, knowledge spill-overs from intangible capital is of help to mitigate regional unbalanced development of intangible investment. As a result, policies that focus on regional inequality development in China should be put in the context of intangible economy. To mitigate regional unbalanced development, the government may take advantage of the knowledge spill-over effects by reducing geographical barriers and establishing intangible-intensive centres in some underdeveloped regions. These centres will serve as the spill-over pole to diffuse knowledge and innovation among adjacent regions. However, the current policy of establishing national central cities in China mainly focuses on relatively developed regions.[59] Unfortunately, we may expect an enlarging regional inequality in China in the near future.

7.3 Future Work

Because of measurement impediments, analysis of intangible capital in China is limited. For example, this research measures intangible capital at China's provincial level, and focuses on coastal-interior growth inequality with the consideration of intangibles. Intangible capital is shown to worsen regional growth inequality in the future according to its dynamic distribution evolvement. However, apart from coastal-interior unbalanced development, the rural-urban growth inequality becomes another severe impediment of China's sustainable development. Detailed information of intangible capital distribution would help understand its impacts on China's rural-urban gap and thus provide ground work for future studies.

[59] National central city is a concept proposed by the Ministry of Housing and Urban-Rural Development of the People's Republic of China in 2005 to reform urbanization. Currently, nine central cities in mainland China were designated in charge of leading, developing, and performing tasks in political, economic, and cultural aspects. They are: Beijing and Tianjin for developing the north, Chongqing and Chengdu for the southwest, Guangzhou for the south, Shanghai for the east, Zhengzhou and Wuhan for the central, and Xi'an for the northwest. See more details via https://en.wikipedia.org/wiki/National_Central_City.

In addition, there is little information about intangible capital at China's disaggregate level. Less is known about intangibles at the sector and the firm level in China. This research did not examine how intangible capital performs in different sectors, and focuses on one intangible asset, organisation capital in Chinese manufacturing firms. Nevertheless, huge heterogeneity must exist at disaggregate level in terms of intangible capital development and its impacts on growth. For example, the dominance of intangible capital verses tangible capital would depend on business modes and strategy, and the complement resources would vary considerably across sectors. How intangible capital impacts on growth and development should be discussed to provide practical implications after coping with heterogeneity.

Third, due to the lack of harmonised price deflator and depreciation rate, there are no studies examining the plausible different functions of intangible capital in China and in other developed economies. Finally, the "real" scope of intangibles is far beyond the business intangible capital that is analysed in this study. Public intangible capital such as education, health, and environment, is not independent with private business intangibles, and plays its own role. Although some of the public intangible capital has been analysed independently, it is still a long way before all intangibles are incorporated into the same framework in order to understand their interaction effects and joint contributions to China's growth and economic development.

BIBLIOGRAPHY

Abowd, J. M., Haltiwanger, J., & Jarmin, R. (2005). The Relation among Human Capital, Productivity, and Market Value: Building up from Micro Evidence. In C. A. Corrado, J. Haltiwanger, & D. E. Sichel (Eds.), *Measuring Capital in the New Economy*. Chicago: University Chicago Press.

Abramovitz, M. (1956). Resource and Output Trends in the United States since 1870. *American Economic Review*, *46*(2), 5–23.

Abramson, I. S. (1982). On Bandwidth Variation in Kernel Estimates-A Square Root Law. *The Annals of Statistics*, *10*(4), 1217–1223.

Ackerberg, D. A., Caves, K., & Frazer, G. (2015). Identification Properties of Recent Production Function Estimators. *Econometrica*, *83*(6), 2411–2451. https://doi.org/10.3982/ECTA13408

Aghion, P., Fally, T., & Scarpetta, S. (2007). Credit Constraints as a Barrier to the Entry and Post-Entry Growth of Firms. *Economic Policy*, *22*(52), 731–779. https://doi.org/10.1111/j.1468-0327.2007.00190.x

Aghion, P., & Howitt, P. (1992). A Model of Growth Through Creative Destruction. *Econometrica*, *60*(2), 323–351.

Andersson, F. N. G., Edgerton, D. L., & Opper, S. (2013). A Matter of Time: Revisiting Growth Convergence in China. *World Development*, *45*, 239–251. https://doi.org/10.1016/j.worlddev.2012.12.013

Arellano, M., & Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *The Review of Economic Studies*, *58*(2), 277. https://doi.org/10.2307/2297968

Arellano, M., & Bover, O. (1995). Another Look at the Instrumental Variable Estimation of Error-Components Models. *Journal of Econometrics*, *68*(1), 29–51. https://doi.org/10.1016/0304-4076(94)01642-D

Arrighetti, A., Landini, F., & Lasagni, A. (2014). Intangible Assets and Firm Heterogeneity: Evidence from Italy. *Research Policy*, *43*(1), 202-213. https://doi.org/10.1016/j.respol.2013.07.015

Atkeson, A., & Kehoe, P. J. (2005). Modeling and Measuring Organization Capital. *Journal of Political Economy*, *113*(5), 1026–1053. https://doi.org/10.1086/431289

Atkinson, R. D. (2014). *ICT Innovation Policy in China: A Review*. Washington, D.C: Information Technology & Innovation Foundation. Retrieved from http://www2.itif.org/2014-china-ict.pdf

Bai, C., Hsieh, C., & Qian, Y. (2006). The Return to Capital in China. *Brookings Papers on Economic Activity*, *37*(2), 61–102. https://doi.org/10.1002/mus.880181431

Baldwin, J. R., Gu, W., & MacDonald, R. (2012). Intangible Capital and Productivity Growth in Canada. *The Canadian Productivity Review*, *Jul*(29), 6–41. https://doi.org/10.2139/ssrn.2093526

Bao, S., Chang, G. H., Sachs, J. D., & Woo, W. T. (2002). Geographic Factors and China's Regional Development under Market Reforms, 1978-1998. *China Economic Review*, *13*(1), 89–111. https://doi.org/10.1016/S1043-951X(02)00055-X

Barnes, P., & McClure, A. (2009). *Investments in Intangible Assets and Australia's Productivity Growth*. *Productivity Commission*. Canberra. Retrieved from https://ssrn.com/abstract=1616921

Barro, R. J., & Sala-i-martin, X. (1992). Convergence. *Journal of Political Economy*, *100*, 223–251.

Baumann, J., & Kritikos, A. S. (2016). The Link between R&D, Innovation and Productivity: Are Micro Firms Different? *Research Policy*, *45*(6), 1263–1274. https://doi.org/10.1016/j.respol.2016.03.008

BEA. (2018). The United States Bureau of Economic Analysis. Retrieved from https://www.bea.gov/itable

Belhocine, N. (2009). *Treating Intangible Inputs as Investment Goods: The Impact on Canadian GDP* (IMF Working Papers No. 09240). Retrieved from http://www.imf.org/external/pubs/ft/wp/2009/wp09240.pdf

Black, S. E., & Lynch, L. M. (2001). How to Compete: The Impact of Workplace Practices and Information Technology on Productivity. *Review of Economics and Statistics*, *83*(3), 434–445. https://doi.org/10.1162/00346530152480081

Black, S. E., & Lynch, L. M. (2004). What’s Driving the New Economy? The Benefits of Workplace Innovation. *The Economic Journal*, *114*(493), 97–116. https://doi.org/10.1111/j.0013-0133.2004.00189.x

Blair, M. M., & Wallman, S. M. H. (2000). *Unseen Wealth: Report of the Brookings Task Force on Intangibles*. Washington, DC: The Brookings Institution Press.

Bloom, N., Sadun, R., & Reenen, J. Van. (2005). *It Ain’t What You Do It’s the Way That You Do I.T.- Testing Explanations of Productivity Growth Using U.S. Affiliates*. *Centre for Economic Performance* (Vol. September). London. Retrieved from citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.169.778

Bloom, N., Schankerman, M., & Reenen, J. Van. (2013). Identifying Technology Spillovers and Product Market Rivalry. *Econometrica*, *81*(4), 1347–1393. https://doi.org/10.3982/ECTA9466

Bloom, N., & Van Reenen, J. (2007). Measuring and Explaning Management Practices across Firms and Countries. *The Quarterly Journal of Economics*, *122*(4), 1169–1208. https://doi.org/10.1093/qje/qjs044.Advance

Blundell, R., & Bond, S. (1998). Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of Econometrics*, *87*(1), 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8

Bontempi, M. E., & Mairesse, J. (2015). Intangible Capital and Productivity at the Firm Level : A Panel Data Assessment. *Economics of Innovation and New Technology*, *24*, 22–51. https://doi.org/10.1080/10438599.2014.897859

Borgo, M. D., Goodridge, P., Haskel, J., & Pesole, A. (2013). Productivity and Growth in UK Industries: An Intangible Investment Approach. *Oxford Bulletin of Economics and Statistics*, *75*(6), 806–834. https://doi.org/10.1111/j.1468-0084.2012.00718.x

Brandt, L., Tombe, T., & Zhu, X. (2013). Factor Market Distortions across Time, Space and Sectors in China. *Review of Economic Dynamics*, *16*(1), 39–58. https://doi.org/10.1016/j.red.2012.10.002

Brandt, L., Van Biesebroeck, J., & Zhang, Y. (2012). Creative Accounting or Creative Destruction? Firm-level Productivity Growth in Chinese Manufacturing. *Journal of Development Economics*, *97*(2), 339–351. https://doi.org/10.1016/j.jdeveco.2011.02.002

Braun, M., & Larrain, B. (2005). Finance and the Business Cycle : International Inter-industry Evidence. *Journal of Finance*, *60*(3), 1097–1128.

Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-level Evidence. *The Quarterly Journal of Economics*, *117*, 339–376.

Brynjolfsson, E., & Hitt, L. M. (2000). Beyond Computation: Information Technology, Organizational Transforimation and Business Perforimance. *The Journal of Economic Perspectives*, *14*(4), 23–48.

Brynjolfsson, E., & Hitt, L. M. (2003). Computing Productivity: Firm-level Evidence. *The Review of Economics and Statistics*, *85*(4), 793–808.

Brynjolfsson, E., Hitt, L. M., & Yang, S. (2002). Intangible Assets: Computers and Organizational Capital. *Brookings Papers on Economic Activity*, *2002*(1), 137–198. https://doi.org/10.1353/eca.2002.0003

Brynjolfsson, E., & Yang, S. (1999). The Intangible Benefits and Costs of Computer Investments: Evidence from the Financial Markets. In *the International Conference on Information Systems*. Atlanta, Georgia. Retrieved from https://pdfs.semanticscholar.org/f180/2fecacf9c5a687c0509d24c038043fa64d97.pdf

Cai, F. (2012). Is There a “Middle-income Trap”? Theories, Experiences and Relevance to China. *China and World Economy*, *20*(1), 49–61. https://doi.org/10.1111/j.1749-124X.2012.01272.x

Cai, Y., & Zhang, J. (2015). The Substitution and Pervasiveness Effects of ICT on China's Economic Growth. *Economic Research Journal*, *12*, 100–114.

Canibano, L., Garcia-Ayuso, M., & Sanchez, P. (2000). Accounting for Intangibles: A Literature Review. *Journal of Accounting Literature*, *19*, 102–130.

Cappelli, P., & Neumark, D. (2001). Do "High-Performance" Work Practices Improve Establishment-Level Outcomes? *Labour Economics*, *54*(4), 411–423.

CAY. (n.d.). China Advertising Yearbook (zhongguo guanggaoye tongji nianjian).

Chen, J., & Fleisher, B. M. (1996). Regional Income Inequality and Economic Growth in China. *Journal of Comparative Economics*, *22*(2), 141–164. https://doi.org/10.1006/jcec.1996.0015

Chen, J. R., Chu, Y. P., Ou, Y. P., & Yang, C. H. (2015). R&D Specialization and Manufacturing Productivity Growth: A Cross-Country Study. *Japan and the World Economy*, *34*, 33–43. https://doi.org/10.1016/j.japwor.2015.03.002

Chen, W., & Inklaar, R. (2016). Productivity Spillovers of Organization Capital. *Journal of Productivity Analysis*, *45*(3), 229–245. https://doi.org/10.1007/s11123-015-0463-x

Chen, W., Niebel, T., & Saam, M. (2016). Are Intangibles More Productive in ICT-intensive Industries? Evidence from EU Countries. *Telecommunications Policy*, *40*, 471–484. Retrieved from http://www.sciencedirect.com/science/article/pii/S0308596115001524

Chen, X., Gao, J., & Tan, W. (2005). ICT in China: A Strong Force to Boost Economic and Social Development. In J. Berleur & C. Avgerou (Eds.), *Perspective and Policies on ICT in Society*. Boston: Springer.

Cheong, T. S., & Wu, Y. (2013). Regional Disparity, Transitional Dynamics and Convergence in China. *Journal of Asian Economics*, *29*, 1–14. https://doi.org/10.1016/j.asieco.2013.08.007

Cheong, T. S., & Wu, Y. (2014). The Impacts of Structural Transformation and Industrial Upgrading on Regional Inequality in China. *China Economic Review*, *31*, 339–350. https://doi.org/10.1016/j.chieco.2014.09.007

Cheong, T. S., & Wu, Y. (2018). Convergence and Transitional Dynamics of China's Industrial

Output: A County-Level Study using a New Framework of Distribution Dynamics Analysis. *China Economic Review*, *48*, 125–138. https://doi.org/10.1016/j.chieco.2015.11.012

Chow, G. C. (1993). Capital Formation and Economic Growth in China. *The Quartely Journal of Economics*, *108*(3), 809–842.

Chun, H., Miyagawa, T., Pyo, H. K., & Tonogi, K. (2015). *Do Intangibles Contribute to Productivity Growth in East Asian Countries? Evidence from Japan and Korea* (RIETI Discussion Paper Series No. 15- E-055). Retrieved from http://www.rieti.go.jp/jp/publications/dp/15e055.pdf

Ciccone, A., & Papaioannou, E. (2009). Human Capital, the Structure of Production, and Growth. *The Review of Economics and Statistics*, *91*(1), 66–82.

CISY. (n.d.). China Industrial Statistical Yearbook (zhongguo gongye tongji nianjian).

CLRSY. (n.d.). China Land and Resources Statistical Yearbook (zhongguo guotu ziyuan tongji nianjian).

CLSY. (n.d.). China Labour Statistical Yearbook (zhongguo laodong tongji nianjian).

Coe, D. T., & Helpman, E. (1995). International R&D Spillovers. *European Economic Review*, *39*(5), 859–887. https://doi.org/10.1016/0014-2921(94)00100-E

Corrado, C. A., Haskel, J., & Jona-Lasinio, C. (2017). Knowledge Spillovers, ICT and Productivity Growth. *Oxford Bulletin of Economics and Statistics*, *79*(4), 592–618. https://doi.org/10.1111/obes.12171

Corrado, C. A., Haskel, J., Jona-lasinio, C., & Iommi, M. (2012). *Intangible Capital and Growth in Advanced Economies : Measurement Methods and Comparative Results* (IZA Discussion Papers No. 6733). Retrieved from repec.iza.org/dp6733.pdf

Corrado, C. A., & Hulten, C. R. (2010). How Do You Measure a “Technological Revolution”? *American Economic Review*, *100*(2), 99–104.

Corrado, C. A., Hulten, C. R., & Sichel, D. E. (2005). Measuring Capital and Technology: An Expanded Framework. In C. A. Carrodo, J. Haltiwanger, & D. E. Sichel (Eds.), *Measuring*

Capital in the New Economy (pp. 11–46). Washinton, D.C.: University Chicago Press.

Corrado, C. A., Hulten, C. R., & Sichel, D. E. (2006). *Intangible Capital and Economic Growth* (NBER Working Paper No. 11948). Retrieved from http://www.nber.org/papers/w11948

Corrado, C. A., Hulten, C. R., & Sichel, D. E. (2009). Intangible Capital and U.S. Economic Growth. *Review of Income and Wealth*, *55*(3), 661–685. https://doi.org/10.1111/j.1475-4991.2009.00343.x

Corrado, C. A., Haskel, J., & Jona-lasinio, C. (2014). Private and Public Intangible Capital : Productivity Growth and New Policy. *Unpublished Work*. Retrieved from https://www.aeaweb.org/conference/2015/retrieve.php?pdfid=1129

Corrado, C. A., Haskel, J., Jona-Lasinio, C., & Iommi, M. (2018). Intangible Investment in the EU and US before and since the Great Recession and Its Contribution to Productivity Growth. *Journal of Infrastructure, Policy and Development*, *2*(1), 11–36. https://doi.org/10.13140/RG.2.2.35860.71042

CPY. (n.d.). China Publishers' Yearbook (zhongguo chuban nianjian).

Crass, D., Licht, G., & Peters, B. (2015). Intangible Assets and Investments at the Sector Level: Empirical Evidence for Germany. In A. Bounfour & T. Miyagawa (Eds.), *Intangible, Market Failure and Innovation Performance* (pp. 57–111). Springer. Retrieved from https://www.zew.de/en/publikationen/intangible-assets-and-investments-at-the-sector-level-empirical-evidence-for-germany-1/

Crescenzi, R., Rodríguez-Pose, A., & Storper, M. (2012). The Territorial Dynamics of Innovation in China and India. *Journal of Economic Geography, 12*(5), 1055–1085. https://doi.org/10.1093/jeg/lbs020

CSYEI. (n.d.). China Statistical Yearbook of Electronic Industry (zhongguo dianzi chanye tongji nianjian).

CSYIFA. (n.d.). China Statistical Yearbook of Investment in Fixed Assets (zhongguo guding zichan touzi tongji nianjian).

CSYM. (n.d.). China Statistical Yearbook of Mining (zhongguo kuangye tongji nianjian).

CSYST. (n.d.). China Statistical Yearbook of Science and Technology (zhongguo keji tongji nianjian).

Cummins, J. G. (2005). A New Approach to the Valuation of Intangible Capital. In C. A. Corrado, J. Haltiwanger, & D. E. Sichel (Eds.), *Measuring Capital in the New Economy* (pp. 47–72). Chicago: University Chicago Press.

De, S., & Dutta, D. (2007). Impact of Intangible Capital on Productivity and Growth: Lessons from the Indian information Technology Software Industry. *Economic Record*, *83*(Supplement), 73–86. https://doi.org/10.1111/j.1475-4932.2007.00406.x

Démurger, S., Sachs, J. D., Bao, S., Chang, G., & Mellinger, A. (2002). Geography, Economic Policy,and Regonal Development in China. *Asian Economic Papers*, *1*(1), 146–197.

Deng, P. D., & Jefferson, G. H. (2011). Explaining Spatial Convergence of China’s Industrial Productivity. *Oxford Bulletin of Economics and Statistics*, *73*(6), 818–832. https://doi.org/10.1111/j.1468-0084.2011.00675.x

Denison, E. F. (1962). United States Economic Growth. *The Journal of Business*, *35*(2), 109–121. https://doi.org/http://dx.doi.org/10.1177/0038038508088833

Denison, E. F. (1964). The Unimportance of the Embodied Question. *American Economic Review*, *54*(2), 90–94.

Dewan, S., & Kraemer, K. L. (2000). Information Technology and Productivity: Evidence from Country-Level Data. *Management Science*, *46*(4), 548–562. https://doi.org/10.1287/mnsc.46.4.548.12057

Dhongde, S., & Silber, J. (2016). On Distributional Change, Pro-Poor Growth and Convergence. *Journal of Economic Inequality*, *14*(3), 249–267. https://doi.org/10.1007/s10888-016-9321-y

Ding, S., Guariglia, A., & Harris, R. (2016). The Determinants of Productivity in Chinese Large and Medium-Sized Industrial Firms, 1998–2007. *Journal of Productivity Analysis*, *45*(2), 131–155. https://doi.org/10.1007/s11123-015-0460-0

Duan, P. (2008). Influence of China's Population Mobility on the Change of Regional Disparity since 1978. *China Population Resources and Environment*, *18*(5), 27–33. https://doi.org/10.1016/S1872-583X(09)60018-8

Dutta, S. (2012). *The Global Innovation Index: Stronger Innovation Linkages for Global Growth*. Geneva: World Intellectual Property Organization. Retrieved from http://www.codespring.ro/wp-content/uploads/2012/11/GII-2012_Cover.pdf

Dutz, M. A., Kannebley Jr., S., Scarpelli, M., & Sharma, S. (2012). *Measuring Intangible Assets in an Emerging Market Economy: An Application to Brazil* (Policy Research Working Paper No. WPS6142). Retrieved from http://documents.worldbank.org/curated/en/2012/07/16530073/measuring-intangible-assets-emerging-market-economy-application-brazil

Eberhardt, M., Helmers, C., & Strauss, H. (2013). Do Spillovers Matter When Estimating Private Returns to R&D? *The Review of Economics and Statistics*, *95*(2), 436–448. https://doi.org/10.1162/REST_a_00272

Edquist, H. (2009). *How Much Does Sweden Invest in Intangible Assets?* (IFN Working Paper No. No. 785). Retrieved from http://www.ifn.se/Wfiles/wp/wp809.pdf

Eichenbaum, M. S., Hansen, L. P., & Singleton, K. J. (1988). A Time Series Analysis of Representative Agent Models of Consumption and Leisure Choice under Uncertainty. *The Quarterly Journal of Economics*, *103*(1), 51–78.

Eisfeldt, A. L., & Papanikolaou, D. (2013). Organization Capital and the Cross-Section of Expected Returns. *Journal of Finance*, *68*(4), 1365–1406. https://doi.org/10.1111/jofi.12034

Evenson, R. E., & Westphal, L. E. (1995). Technology Change and Technology Strategy. In H. Chenery & T. N. Srinivasan (Eds.), *Handbook of Development Economics* (pp. 2209–2299). Elsevier.

Feng, L. (2009). New Trends in China ' s Regional Economic Development. In S.-H. Saw & J. Wong (Eds.), *Regional Economic Development in China* (pp. 9–14). Singapore: ISEAS

Publishing Institute.

Fisman, R., & Love, I. (2007). Financial Development and Growth. *Journal of the European Economic Association*, *5*, 470–479.

Fleisher, B., Li, H., & Zhao, M. Q. (2010). Human Capital, Economic Growth, and Regional Inequality in China. *Journal of Development Economics*, *92*(2), 215–231. https://doi.org/10.1016/j.jdeveco.2009.01.010

Fleisher, B. M., McGuire, W. H., Smith, A. N., & Zhou, M. (2013). *Intangible Knowledge Capital and Innovation in China* (IZA Discussion Paper No. 7798). Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2367673

Fogel, R. W. (2006). *Why China is Likely to Achieve its Growth Objectives* (NBER Working Paper No. 12122). Retrieved from https://www.nber.org/papers/w12122

Friedman, M. (1992). Do Old Fallacies Ever Die? *Journal of Economic Literature*, *30*(4), 2129–2132.

Fukao, K., Hamagata, S., Miyagawa, T., & Tonogi, K. (2009). Intangible Investment in Japan: Measurement and Contribution to Economic Growth. *Review of Income and Wealth*, *55*(3), 717–736.

Funke, M., & Niebuhr, A. (2005). Regional Geographic Research and Development Spillovers and Economic Growth: Evidence from West Germany. *Regional Studies*, *39*(1), 143–153. https://doi.org/10.1080/0034340052000321904

Gill, I., & Kharas, H. (2007). *An East Asian Renaissance: Ideas for Economic Growth*. Washington, D.C.: The World Bank Publishing.

Gkypali, A., Filiou, D., & Tsekouras, K. (2017). R&D Collaborations: Is Diversity Enhancing Innovation Performance? *Technological Forecasting and Social Change*, *118*, 143–152. https://doi.org/10.1016/j.techfore.2017.02.015

Gollin, D. (2002). Getting Income Shares Right. *Journal of Political Economy*, *110*(2), 458–474. https://doi.org/10.1086/338747

Gomel, G., Marconi, D., Musu, I., & Quintieri, B. (2012). *The Chinese Economy: Recent Trends and Policy Issues*. Springer Sicence & Business Media.

Goodridge, P., Haskel, J., & Wallis, G. (2013). Can Intangible Investment Explain the UK Productivity Puzzle? *National Institute Economic Review*, *224*(1), R48–R58. https://doi.org/10.1177/002795011322400104

Goodridge, P., Haskel, J., & Wallis, G. (2017). Spillovers from R&D and Other Intangible Investment: Evidence from UK Industries. *The Review of Income and Wealth*, *63*(1), 22–48. https://doi.org/10.1111/roiw.12251

Gries, T., & Redlin, M. (2009). China's Provincial Disparities and the Determinants of Provincial Inequality. *China's Three Decades of Economic Reforms*, *5284*(May), 113–132. https://doi.org/10.4324/9780203873885

Griffith, R., Redding, S., & Van Reenen, J. (2004). Mapping The Two Faces Of R&D: Productivity Growth in a Panel of OECD Industries. *The Review of Economics and Statistics*, *86*(4), 883–895.

Griliches, Z. (1963). The Sources of Measured Productivity Growth: United States Agriculture, 1940-1960. *Journal of Political Economy*, *71*(4), 331–346.

Griliches, Z. (1992). The Search for R&D Spillovers. *Scandinavian Journal of Economics*, *94*(1), 29–47.

Griliches, Z., & Mairesse, J. (1995). *Production Functions: The Search for Identification* (NBER Working Paper No. 5067). Retrieved from http://www.nber.org/papers/w5067

Grossman, G. M., & Helpman, E. (1993). *Innovation and Growth in the Global Economy*. MA: MIT Press.

Grossman, G. M., & Helpman, E. (1994). Endogenous Innovation in the Theory of Growth. *The Journal of Economic Perspectives*, *8*(1), 23–44.

Guellec, D., & van Pottelsberghe, B. (2001). R&D and Productivity Growth Panel Data Analysis of 16 OECD Countries. In *OECD Science, Technology and Industry Working Papers 2001/03*.

Paris: OECD Publishing.

Hall, R. E., & Jorgenson, D. W. (1967). Tax Policy and Investment Behavior: Reply and Further Results. *American Economic Review*, *57*(3), 391–414.

Hao, R. (2008). Opening up, Market Reform, and Convergence Clubs in China. *Asian Economic Journal*, *22*(2), 133–160. https://doi.org/10.1111/j.1467-8381.2008.00272.x

Hart, S., & Diamantopoulos, A. (1993). Marketing Research Activity and Company Performance: Evidence from Manufacturing Industry. *European Journal of Marketing*, *27*(5), 54–72. https://doi.org/http://dx.doi.org/10.1108/MRR-09-2015-0216

Haskel, J., & Westlake, S. (2018). *Capitalism without Capital*. Princeton: Princeton University Press.

Hayashi, F. (2000). *Econometrics*. Princeton: Princeton University Press.

He, Z., Tong, T. W., Zhang, Y., & He, W. (2018). Data Descriptor: A Database Linking Chinese Patents to China's Census Firms. *Scientific Data*, *5*, 1–16. https://doi.org/10.1038/sdata.2018.42

Herrerías, M. J., Orts, V., & Tortosa-Ausina, E. (2011). Weighted Convergence and Regional Clusters across China. *Papers in Regional Science*, *90*(4), 703–734. https://doi.org/10.1111/j.1435-5957.2010.00339.x

Heshmati, A., & Yang, W. (2006). *Contribution of ICT to the Chinese Economic Growth* (Ratio Working Papers No. 91). Retrieved from https://ideas.repec.org/p/hhs/ratioi/0091.html

Holtz-Eakin, D., Newey, W., & Rosen, H. S. (1988). Estimating Vector Autoregressions with Panel Data. *Econometrica*, *56*, 1371–1395. https://doi.org/10.2307/1913103

Holz, C. A. (2008). China's Economic Growth 1978-2025: What We Know Today About China's Economic Growth Tomorrow. *World Development*, *36*(10), 1665–1691. https://doi.org/10.1016/j.worlddev.2007.09.013

Holzer, H. J., & Reaser, J. (1999). Firm-Level Training for Newly Hired Workers: Its Determinants and Effects. *Research in Labour Economics*, *18*, 377–402.

Hsieh, C., & Klenow, P. J. (2009). Misallocation and Manufacturing TFP in China and India. *The Quarterly Journal of Economics*, *124*(4), 1403–1448.

Hsu, C. W., Lien, Y. C., & Chen, H. (2015). R&D Internationalization and Innovation Performance. *International Business Review*, *24*(2), 187–195. https://doi.org/10.1016/j.ibusrev.2014.07.007

Hsu, P. H., Tian, X., & Xu, Y. (2014). Financial Development and Innovation: Cross-Country Evidence. *Journal of Financial Economics*, *112*(1), 116–135. https://doi.org/10.1016/j.jfineco.2013.12.002

Hulten, C. R. (1979). On the "Importance" of Productivity Change. *American Economic Review*, *69*(1), 126–136.

Hulten, C. R. (2001). Total Factor Productivity: A Short Biography. In *Studies in Income and Wealth Volume 65, New Developments in Productivity Analysis*. Chicago: The University of Chicago Press.

Hulten, C. R. (2010a). *Decoding Microsoft: Intangible Capital as a Source of Company Growth* (NBER Working Paper No. 15799). Retrieved from http://www.nber.org/papers/w15799

Hulten, C. R. (2010b). *Growth Accounting*. *Handbook of the Economics of Innovation* (Vol. 2). Elsevier. https://doi.org/10.1016/S0169-7218(10)02007-1

Hulten, C. R., & Hao, J. X. (2008). *What is a Company Really Worth? Intangible Capital and the "Market to Book Value" Puzzle* (NBER Working Papers No. 14548). Retrieved from www.nber.org/papers/w14548

Hulten, C. R., & Hao, J. X. (2012). *The Role of Intangible Capital in the Transformation and Growth of the Chinese Economy* (NBER Working Paper No. 18405). Retrieved from http://www.nber.org/papers/w18405

Hunter, L., Webster, E., & Wyatt, A. (2005). Measuring Intangible Capital: A Review of Current Practice. *Australian Accounting Review*, *15*(36), 4–21. https://doi.org/10.1111/j.1835-2561.2005.tb00288.x

IASB. (2004). *International Accounting Standards Board. Intangible Assets*. London.

https://doi.org/10.17226/12745

Ichniowski, C., & Shaw, K. (2003). Beyond Incentive Pay: Insiders' Estimates of the Value of Complementary Human Resource Management Practices. *The Journal of Economic Perspectives, 17*(1), 155–180.

IMF. (2018). International Monetary Fund World Economic Outlook. Retrieved from http://statisticstimes.com/economy/projected-world-gdp-capita-ranking.php

Inklaar, R., O'Mahony, M., & Timmer, M. (2005). ICT and Europe's Productivity Performance: Industry-Level Growth Account Comparisons with The United States. *Review of Income and Wealth*, *51*(4), 505–536. https://doi.org/10.1093/jac/dkg150

Inklaar, R., Timmer, M., & van Ark, B. (2008). Market Services Productivity across Europe and the US. *Economic Policy*, *23*(53), 139–194.

Islam, N. (2003). What have We Learnt from the Convergence Debate? *Journal of Economic Surveys*, *17*(3), 309–362. https://doi.org/10.1111/1467-6419.00197

Islam, N., Dai, E., & Sakamoto, H. (2006). Role of TFP in China's growth. *Asian Economic Journal*, *20*(2), 127–159. https://doi.org/10.1016/j.jviromet.2005.10.009

Jaffe, A. (1986). Technological Opportunity and Spillover of R&D: Evidence from Firm's Patents, Profits, and Market Value. *American Economic Review*, *76*(5), 984–1001.

Jalava, L., Aulin-Ahmavaara, P., & Alanen, A. (2007). *Intangible Capital in the Finnish Business Sector, 1975-2005* (ETLA Working Paper No. 1103). Retrieved from https://www.etla.fi/en/publications/dp1103-en

Johnson, P. A. (2005). A Continuous State Space Approach to "Convergence by Parts." *Economics Letters, 86*(3), 317–321. https://doi.org/10.1016/j.econlet.2004.06.023

Johnson, P., & Papageorgiou, C. (2018). *What Remains of Cross-Country Convergence* (Munich Personal RePEc Archive No. 89355). Retrieved from https://mpra.ub.uni-muenchen.de/89355/

Jona-Lasinio, C., Lommi, M., & Roth, F. (2011). National Measures of Intangible Capital in EU27 and Norway. In *Intangible Capital-Driver of Growth in Europe* (pp. 20–62). Retrieved from http://innodrive.org/attachments/File/Intangible_Capital_Driver_of_Growth_in_Europe_Piekkola(ed).pdf

Jones, C. I., & Williams, J. C. (1997). Measuring the Social Return to R&D. *The Quarterly Journal of Economics*, *113*(4), 1119–1135.

Jorgenson, D. W., & Fraumeni, B. M. (1989). The Accumulation of Human and Nonhuman Capital, 1948-84. In R. E. Lipsey & H. S. Tice (Eds.), *The Measurement of Saving, Investment, and Wealth* (pp. 227–286). Chicago: University of Chicago Press.

Jorgenson, D. W., & Fraumeni, B. M. (1992a). Investment in Education and U.S. Economic Growth. *The Scandinavian Journal of Economics*, *94*(Supplement), 51–70.

Jorgenson, D. W., & Fraumeni, B. M. (1992b). The Output of the Education Sector. In Z. Griliches (Ed.), *Output Measurement in the Service Sectors* (pp. 303–341). Chicago: University of Chicago Press.

Jorgenson, D. W., & Griliches, Z. (1967). The Explanation of Productivity Change. *The Review of Economic Studies*, *34*(3), 249–283. https://doi.org/10.2307/2296675

Jorgenson, D. W., & Stiroh, K. J. (2000). Raising the Speed Limit: U.S. Economic Growth in the Information Age. *Brookings Papers on Economic Activity*, *1*, 125–210.

Joshi, A., & Hanssens, D. M. (2010). The Direct and Indirect Effects of Advertising Spending on Firm Value. *Journal of Marketing*, *74*(1), 20–33. https://doi.org/10.1509/jmkg.74.1.20

Jozsef Manning, M. (2003). Finance Causes Growth: Can We Be So Sure? *Contributions in Macroeconomics*, *3*(1), 1–24. https://doi.org/10.2202/1534-6005.1100

Juessen, F. (2009). A Distribution Dynamics Approach to Regional GDP Convergence in Unified Germany. *Empirical Economics*, *37*, 627–652. https://doi.org/10.1055/s-0028-1128055

Kaplan, R S. Norton, D. P. (2004). The Strategy Map: A Guide to Aligning Intangible Assets. *Strategy & Leadership*, *32*(5), 10–17.

Kendrick, J. W. (1961). *Productivity Trends in the United States*. Princeton: Princeton University Press.

Kerm, P. Van. (2003). Adaptive Kernel Density Estimation. *Stata Journal*, *3*(2), 148–156. https://doi.org/The Stata Journal

Khan, M., & Luintel, K. B. (2006). Sources of Knowledge and Productivity How Robust is the Relationship? In *OECD Science, Technology and Industry Working Papers 2006/06*. Paris: OECD Publishing.

Khuong, V. (2006). *ICT Penetration and Economic Growth in Developing Asia: Issues and Policy Implications* (Standford Centre on Global Poverty and Development Working Papers No. 307). Retrieved from https://globalpoverty.stanford.edu/publications/ict-penetration-and-economic-growth-developing-asia-issues-and-policy-implications

Kraemer, K. L., & Dedrick, J. (2002). Enter the Dragon : China's Computer Industry. *Computer*, *35*(2), 28–36.

Kristandl, G., & Bontis, N. (2007). The Impact of Voluntary Disclosure on Cost of Equity Capital Estimates in a Temporal Setting. *Journal of Intellectual Capital*, *8*(4), 577–594. https://doi.org/10.1108/14691930710830765

Krugman, P. (1994). The Myth of Asia' s Miracle. *Foreign Affairs*, *73*(6), 62–77.

Krugman, P. (1998). What's New About the New Economic Geography ? *Oxford Review of Economic Policy*, *14*(2), 7–17. https://doi.org/10.1093/oxrep/14.2.7

Kuo, C. C., & Yang, C. H. (2008). Knowledge Capital and Spillover on Regional Economic Growth: Evidence from China. *China Economic Review*, *19*(4), 594–604. https://doi.org/10.1016/j.chieco.2008.06.004

Kuznets, S. (1955). Economic Growth and Income Inequality. *American Economic Review*, *45*(1), 1–28.

Lau, C. K. M. (2010). New Evidence about Regional Income Divergence in China. *China Economic Review*, *21*(2), 293–309. https://doi.org/10.1016/j.chieco.2010.01.003

Lee, D. (2016). Role of R&D in the Productivity Growth of Korean Industries: Technology Gap and Business Cycle. *Journal of Asian Economics*, *45*, 31–45.

https://doi.org/10.1016/j.asieco.2016.06.002

Lemoine, F., Poncet, S., & Ünal, D. (2015). Spatial Rebalancing and Industrial Convergence in China. *China Economic Review*, *34*, 39–63. https://doi.org/10.1016/j.chieco.2015.03.007

Lev, B. (2001). *Intangibles: Management, Measurement, and Reporting* (Vol. 220). Washington, D.C.: Brookings Institution Press.

Lev, B., & Radhakrishnan, S. (2003). *The Measurement of Firm-Specific Organization Capital* (NBER Working Paper No. 9581). Retrieved from https://www.nber.org/papers/w9581

Lev, B., & Radhakrishnan, S. (2005). The Valuation of Organization Capital. In C. A. Corrado, J. Haltiwanger, & D. E. Sichel (Eds.), *Measuring Capital in the New Economy* (pp. 73–110). Chicago: University Chicago Press.

Lev, B., Radhakrishnan, S., & Zhang, W. (2009). Organization Capital. *Abacus*, *45*(3), 275–298. https://doi.org/10.1111/j.1467-6281.2009.00289.x

Lev, B., & Zarowin, P. (1999). The Boundaries of Financial Reporting and How to Extend Them. *Journal of Accounting Research*, *37*(2), 353. https://doi.org/10.2307/2491413

Levchenko, A. A., Rancière, R., & Thoenig, M. (2009). Growth and Risk at the Industry Level: The Real Effects of Financial Liberalization. *Journal of Development Economics*, *89*(2), 210–222. https://doi.org/10.1016/j.jdeveco.2008.06.003

Li, H., Liu, Q., Li, B., Fraumeni, B., & Zhang, X. (2014). Human Capital Estimates in China: New Panel Data 1985-2010. *China Economic Review*, *30*, 397–418. https://doi.org/10.1016/j.chieco.2014.07.006

Li, K., Qiu, B., & Shen, R. (2018). Organization Capital and Mergers and Acquisitions. *Journal of Financial and Quantitative Analysis*, *53*(4), 1871–1909. https://doi.org/10.2139/ssrn.2511675

Li, Q., & Wu, Y. (2018). Intangible Capital in Chinese Regional Economies: Measurement and Analysis. *China Economic Review*, *51*, 323–341. https://doi.org/10.1016/j.chieco.2017.07.002

Liang, C. J., & Yao, M. L. (2005). The Value-Relevance of Financial and Nonfinancial Information-Evidence from Taiwan's Information Electronics Industry. *Review of Quantitative*

Finance and Accounting, *24*(2), 135–157. https://doi.org/10.1007/s11156-005-6334-1

Liao, F. H. F., & Wei, Y. D. (2012). Dynamics, Space, and Regional Inequality in Provincial China: A Case Study of Guangdong Province. *Applied Geography*, *35*(1–2), 71–83. https://doi.org/10.1016/j.apgeog.2012.05.003

Lucas, R. E. (1988). On the Mechanics of Economic Development. *Journal of Monetary Economics*, *22*(February), 3–42.

Lynch, L. M. (1992). Private-Sector Training and the Earnings of Young Workers. *American Economic Review*, *82*(1), 299–312.

Lynch, L. M., & Black, S. E. (1998). Beyond the Incidence of Employer-Provided Training. *Industrial and Labor Relations Review*, *52*(1), 64–81.

Mankiw, N. G., Romer, D., & Weil, D. N. (1992). A Contribution to the Empirics of Economic Growth. *The Quarterly Journal of Economics*, *107*, 407–437. https://doi.org/10.1016/j.jpolmod.2014.01.001

Manova, K. (2008). Credit Constraints, Equity Market Liberalizations and International Trade. *Journal of International Economics*, *76*(1), 33–47. https://doi.org/10.1016/j.jinteco.2008.03.008

Marrano, M. G., & Haskel, J. (2006). *How Much Does the UK Invest in Intangible Assets* (Department of Economics Queen Mary University of London Working Paper No. 578). Retrieved from www.econ.qmul.ac.uk › Research › Working papers › 2006%0A

Mcgrattan, E. R. (2017). *Intangible Capital and Measured Productivity* (NBER Working Paper No. 23233). Retrieved from http://www.nber.org/papers/w23233

McGrattan, E. R., & Prescott, E. C. (2005). Taxes, Regulations, and the Value of U.S. and U.K. Corporations. *Review of Economic Studies*, *72*, 767–796.

McGrattan, E. R., & Prescott, E. C. (2014). A Reassessment of Real Business Cycle Theory. *American Economic Review*, *104*(5), 177–182. https://doi.org/10.1257/aer.104.5.177

Meng, Q., & Li, M. (2002). New Economy and ICT Eevelopment in China. *Information Economics* *and Policy*, *14*(2), 275–295. https://doi.org/10.1016/S0167-6245(01)00070-1

Meritum Project. (2002). *Guidelines for Managing and Reporting on Intangibles*. *Madrid: European Commission.*

Miyagawa, T., & Hisa, S. (2013). Estimates of Intangible Investment by Industry and Productivity Growth in Japan. *Japanese Economic Review*, *64*(1), 42–72. https://doi.org/10.1111/jere.12000

Murphy, G., & Siedschlag, I. (2013). Human Capital and Growth of Information and Communication Technology-Intensive Industries: Empirical Evidence from Open Economies. *Regional Studies*, *47*(9), 1403–1424. https://doi.org/10.1080/00343404.2010.529115

Nakamura, L. (1999). Intangibles: What Put the New in the New Economy? *Business Review - Federal Reserve Bank of Philadelphia*, (Jul/Aug), 3–16. https://doi.org/Article

Nakamura, L. (2001). *What Is the U.S. Gross Investment in Intangibles? (At Least) One Trillion Dollars a Year!* Economic Research Division, Federal Reserve Bank of Philadelphia.

NARFEID. (n.d.). National Annual Reports of Firms of Engineering Inspection and Design (jianzhu sheji kancha nianbao).

NBS. (2017). China National Bureau of Statistics.

Nie, H., Jiang, T., & Yang, R. (2012). the Use and Problems of China’s Annual Survey of Industrial Enterprises Database. *World Economy*, *5*, 1–13.

Niebel, T. (2018). ICT and Economic Growth – Comparing Developing, Emerging and Developed Countries. *World Development*, *104*, 197–211. https://doi.org/10.1016/j.worlddev.2017.11.024

Niebel, T., O’Mahony, M., & Saam, M. (2016). The Contribution of Intangible Assets to Sectoral Productivity Growth in the EU. *Review of Income and Wealth*, *63*(13), S49–S67. https://doi.org/10.1111/roiw.12248

Nordhaus, W. D. (1996). Do Real-Output and Real-Wage Measures Capture Reality? The History of Lighting Suggests Not. In T. F. Bresnahan & R. J. Gordon (Eds.), *The Economics of New Goods* (pp. 27–70). Chicago: University Chicago Press.

NSY. (n.d.). China National Statistical Yearbook (zhongguo tongji nianjian).

OECD. (2002). *Measuring the Information Economy*. Paris: OECD Publishing.

OECD. (2006). *Intellectual Assets And Value Creation: Implications for Corporate Reporting*. Paris: OECD Publishing.

OECD. (2010). *OECD Economic Surveys: China*. Paris: OECD Publishing. https://doi.org/10.1787/eco_surveys-chn-2010-en

OECD Secretariat. (1998). *Measuring Intangible Investment: Selected Bibliography*. Retrieved from http://www.oecd.org/dsti/sti/industry/indcomp/prod/paper16.pdf

Papaioannou, S. K., & Dimelis, S. P. (2007). Information Technology as a Factor of Economic Development: Evidence from Developed and Developing Countries. *Economics of Innovation and New Technology*, *16*(3), 179–194. https://doi.org/10.1080/10438590600661889

Park, W. G. (1995). International R&D Spillovers and OECD Economic Growth. *Economic Inquiry*, *33*(4), 571–591. https://doi.org/10.1111/j.1465-7295.1995.tb01882.x

Pedroni, P., & Yao, J. Y. (2006). Regional Income Divergence in China. *Journal of Asian Economics*, *17*(2), 294–315. https://doi.org/10.1016/j.asieco.2005.09.005

Penman, S. H. (2009). Accounting for Intangible Assets: There is also an Income Statement. *Abacus*, *45*(3), 358–371. https://doi.org/10.1111/j.1467-6281.2009.00293.x

Petersen, M. A. (2009). Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *Review of Financial Studies*, *22*(1), 435–480. https://doi.org/10.1093/rfs/hhn053

Pohjola, M. (2002). The New Economy in Growth and Development. *Oxford Review of Economic Policy*, *18*(3), 380–296. https://doi.org/10.1007/978-3-319-04414-9_46

Quah, D. (1993). Galton’s Fallacy and Tests of the Convergence Hypothesis. *Scandinavian Journal of Economics*, *95*(4), 427–443.

Quah, D. (1996a). Aggregate and Regional Disaggregate Fluctuations. *Empirical Economics*, *21*(1), 137–159. https://doi.org/10.1007/978-3-642-61211-4_7

Quah, D. (1996b). Twin Peaks: Growth and Convergence in Models of Distribution Dynamics. *The Economic Journal*, *106*(437), 1045–1055.

Quah, D. (1997). Empirics for Growth and Distribution: Stratification, Polarization, and Convergence Clubs. *Journal of Economic Growth*, *2*(1), 27–59. https://doi.org/10.1023/a:1009781613339

Quah, D. (2001). Searching for Prosperity A Comment. *Carnegie-Rochester Conference Series on Public Policy*, *55*(1), 305–319.

Raiser, M. (1998). Subsidising Inequality: Economic Reforms, Fiscal Transfers and Convergence across Chinese Provinces. *Journal of Development Studies*, *34*(3), 1–26. https://doi.org/10.1080/00220389808422518

Rajan, R. G., & Zingales, L. (1998). Financial Dependence and Growth. *American Economic Review*, *88*(3), 559–586.

Raymond, L., & St-Pierre, J. (2010). R&D as a Determinant of Innovation in Manufacturing SMEs: An Attempt at Empirical Clarification. *Technovation*, *30*(1), 48–56. https://doi.org/10.1016/j.technovation.2009.05.005

Raymond, W., Mairesse, J., Mohnen, P., & Palm, F. (2015). Dynamic Models of R&D, Innovation and Productivity: Panel Data Evidence for Dutch and French Manufacturing. *European Economic Review*, *78*, 285–306. https://doi.org/10.1016/j.euroecorev.2015.06.002

Rebelo, S. (1991). Long-Run Policy Analysis and Long-Run Growth. *Journal of Political Economy*, *9*(3), 500–521. https://doi.org/10.1086/261764

Reuters. (2018). China Spent an Estimated $279 Billion on R&D Last Year. Retrieved from https://www.cnbc.com/2018/02/26/china-spent-an-estimated-279-billion-on-rd-last-year.html

Romer, P. M. (1986). Increasing Returns and Long-run Growth. *Journal of Political Economy*, *94*(5), 1002–1037.

Roth, F., & Thum, A. E. (2010). *Does Intangible Capital Affect Economic Growth?* (CEPS Papers No. 3667). Retrieved from https://ideas.repec.org/p/eps/cepswp/3667.html

Roth, F., & Thum, A. E. (2013). Intangible Capital and Labor Productivity Growth: Panel Evidence for the EU from 1998-2005. *Review of Income and Wealth*, *59*(3), 486–508.

https://doi.org/10.1111/roiw.12009

Sakamoto, H., & Islam, N. (2008). Convergence across Chinese Provinces: An Analysis using Markov Transition Matrix. *China Economic Review*, *19*(1), 66–79. https://doi.org/10.1016/j.chieco.2006.07.002

Scherngell, T., Borowiecki, M., & Hu, Y. (2014). Effects of Knowledge Capital on Total Factor Productivity in China: A Spatial Econometric Perspective. *China Economic Review*, *29*, 82–94. https://doi.org/10.1016/j.chieco.2014.03.003

Schultz, T. W. (1972). Investment in Human Capital: The Role of Education. *The Journal of Business*, *45*(1), 113. https://doi.org/10.2307/1237858

Shah, S. Z. A., Mirza, H. H., & Abbas, Q. (2013). Advertising Effects on Firm Economic Performance. *Actual Problems of Economics*, *141*(3), 519–525.

Shah, S. Z. A., Stark, A. W., & Akbar, S. (2009). The Value Relevance of Major Media Advertising Expenditures: Some U.K. Evidence. *International Journal of Accounting*, *44*(2), 187–206. https://doi.org/10.1016/j.intacc.2009.03.004

Shea, J. (1997). Instrument Relevance in Multivariate Linear Models, a Simple Measure. *Review of Economics and Statistics*, *79*(2), 348–352.

Silverman, B. W. (1986). *Density Estimation for Statistics and Data Analysis*. New York: Routledge. https://doi.org/10.2307/2347507

Soloveichik, B. R., & Wasshausen, D. (2013). *Copyright - Protected Assets in the National Accounts* (Bureau of Economic Analysis No. 0102). Retrieved from https://sites.nationalacademies.org/cs/groups/pgasite/documents/.../pga_063401.pdf

Solow, R. M. (1987). We'd Better Watch Out. *New York Times Book Review*, 36.

Solow, R. M. (1956). A Contribution to the Theory of Economic Growth. *The Quarterly Journal of Economics*, *70*(1), 65–94. https://doi.org/10.2307/1884513

Solow, R. M. (1957). Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics*, *39*(3), 312–320. https://doi.org/10.2139/ssrn.918489

Stetzer, F. (1982). Specifying Weights in Spatial Forecasting Models: The Results of Some Experiments. *Environment and Planning A*, *14*(5), 571–584.

Stiroh, K. J. (2002). Information Technology and the U . S . Productivity Revival : What Do the Industry Data Say ? *American Economic Review*, *92*(5), 1559–1576.

Subramaniam, M., & Youndt, M. A. (2016). The Influence of Intellectual Capital on the Types of Innovative Capabilities. *The Academy of Management Journal*, *48*(3), 450–463. https://doi.org/10.5465/AMJ.2005.17407911

Sun, C. (2013). The Estimation of Provincial ICT Capital Stock in China. *Statistical Research*, *30*(3), 35–42.

Sun, L., Zheng, H., & Ren, R. (2012). The Contribution of ICT to China's Economic Growth: Evidence from Industrial Panel Data Analysis. *The Journal of World Economy*, *2*, 3–25.

Tan, J., & Peng, M. W. (2003). Organizational Slack and Firm Performance during Economic Transitions: Two Studies from an Emerging Economy. *Strategic Management Journal*, *24*(13), 1249–1263. https://doi.org/10.1002/smj.351

Tang, L., Song, X., & Peng, X. (2017). The Evolution of Intellectual Property Products in the System of National Accounts: A Case Study of R&D Product. *Public Policy and Administration Research*, *7*(9), 24–29.

Teece, D. J. (1998). Capturing Value from Knowledge Assets: The New Economy, Markets for Know-How, and Intangible Assets. *California Review Management*, *40*(3), 55–79.

Thompson, S. B. (2011). Simple Formulas for Standard Errors that Cluster by Both Firm and Time. *Journal of Financial Economics*, *99*(1), 1–10. https://doi.org/10.1016/j.jfineco.2010.08.016

Tian, K., Ni, H., & Li, L. (2016). National Measures of Intangible Asset and Its Role in Growth of China Economy. *China Industrial Economics*, (3), 5–19.

Timmer, M. P., Inklaar, R., O'Mahony, M., & van Ark, B. (2011). Productivity and Economic Growth in Europe: A Comparative Industry Perspective. *International Productivity Monitor*, *21*, 3–23. https://doi.org/10.1017/CBO9780511762703

Tomczyk, P., Doligalski, T., & Zaborek, P. (2016). Does Customer Analysis Affect Firm Performance? Quantitative Evidence from the Polish Insurance Market. *Journal of Business Research*, *69*(9), 3652–3658. https://doi.org/10.1016/j.jbusres.2016.03.026

Tomer, J. (1981). Organizational Change, Organization Capital and Economic Growth. *Eastern Economic Journal*, *7*(1), 1–14.

Tornqvist, L. (1936). The Bank of Finland's Consumption Price Index. *Bank of Finland Bulletin*, *16*(10), 1–8.

Treiman, D. J. (2013). Trends in Educational Attainment in China. *Chinese Sociological Review*, *45*(3), 3–25. https://doi.org/10.2753/CSA2162-0555450301

Tronconi, C., & Vittucci Marzetti, G. (2011). Organization Capital and Firm Performance. Empirical Evidence for European Firms. *Economics Letters*, *112*(2), 141–143. https://doi.org/10.1016/j.econlet.2011.04.004

Upton, W. S. (2001). *Special Report: Business and Financial Reporting, Challenges from the New Economy*. Norwalk: Financial Accounting Stardards Board. Retrieved from https://www.cs.trinity.edu/~rjensen/Calgary/CD/fasb/uptonApril01.pdf

van Ark, B. (2004). The Measurement of Productivity: What Do the Number Mean? In G. Gelauff, L. Klomp, S. Raes, & T. Roelandt (Eds.), *Fostering Productivity: Patterns, Determinants and Policy Implications*. Amsterdam: Elsevier.

van Ark, B., Hao, J. X., Corrado, C. A., & Hulten, C. R. (2009). Measuring Intangible Capital and its Contribution to Economic Growth in Europe. *EIB Papers*, *14*(1), 62–93.

van Ark, B., Inklaar, R., & Mcguckin, R. H. (2002). *"Changing Gear" Productivity , ICT and Services Industries: Europe and the United States* (Economics Program Working Paper No. #02-02). Retrieved from https://ideas.repec.org/p/gro/rugggd/200260.html

van Ark, B., Inklaar, R., & Mcguckin, R. H. (2003). ICT and Productivity in Europe and the United States Where do the Differences Come from ? *CESifo Economic Studies*, *49*(3), 295–318. https://doi.org/https://doi.org/10.1093/cesifo/49.3.295

van Ark, B., Melka, J., Mulder, N., Timmer, M., & Ypma, G. (2002). ICT Investment and Growth Accounts for the European Union, 1980-2000. *Brussels, European Commission*, *24*(January), 1–93.

van Ark, B., O'Mahony, M., & Timmer, M. P. (2008). The Productivity Gap between Europe and the United States: Trends and Causes. *Journal of Economic Perspectives*, *22*(1), 25–44. https://doi.org/10.1257/jep.22.1.25

van Rooijen-Horsten, M., van den Bergen, D., & Tanriseven, M. (2008). *Intangible Capital in the Netherlands: A Benchmark* (Statistics Netherlands Discussion Papers No. 08001). Retrieved from https://www.cbs.nl/-/media/imported/documents/2008/05/2008-01-x10-pub.pdf

Wang, Y., & Yao, Y. (2003). Sources of China's Economic Growth 1952-1999: Incorporating Human Capital Accumulation. *China Economic Review*, *14*(1), 32–52. https://doi.org/10.1016/S1043-951X(02)00084-6

Webster, E., & Jensen, P. H. (2006). Investment in Intangible Capital: An Enterprise Perspective. *Economic Record*, *82*(256), 82–96. https://doi.org/10.1111/j.1475-4932.2006.00296.x

Weeks, M., & Yao, J. Y. (2003). Provincial Conditional Income Convergence in China, 1953-1997: A Panel Data Approach. *Econometric Reviews*, *22*(1), 59–77. https://doi.org/10.1081/ETC-120017974

Wei, H. (2009). Regional Economic Development in China: Agglomeration and Relocation. In S.-H. Saw & J. Wong (Eds.), *Regional Economic Development in China* (pp. 28–52). Singapore: ISEAS Publishing Institute. Retrieved from https://books.google.nl/books?id=DhIcTvNRt-MC&dq=The+development+of+Pudong+would+have+great+impact&source=gbs_navlinks_s

Wei, Y. D. (2015). Spatiality of Regional Inequality. *Applied Geography*, *61*, 1–10. https://doi.org/10.1016/j.apgeog.2015.03.013

Weitzman, M. L. (1976). On the Welfare Significance of National Product in a Dynamic Economy. *The Quarterly Journal of Economics*, *90*(1), 156–162.

Westerlund, J., Edgerton, D. L., & Opper, S. (2010). Why is Chinese Provincial Output Diverging?

Journal of Asian Economics, *21*(4), 333–344. https://doi.org/10.1016/j.asieco.2010.03.007

Williamson, J. G. (1965). Regional Ineqaulity and the Process of National Development: A Description of the Patterns. *Economic Development and Cultural Change*, *13*(4), 1–84.

Windmeijer, F. (2005). A Finite Sample Correction for the Variance of Linear Efficient Two-step GMM Estimators. *Journal of Econometrics*, *126*(1), 25–51. https://doi.org/10.1016/j.jeconom.2004.02.005

Wintoki, M. B., Linck, J. S., & Netter, J. M. (2012). Endogeneity and the Dynamics of Internal Corporate Governance. *Journal of Financial Economics*, *105*(3), 581–606. https://doi.org/10.1016/j.jfineco.2012.03.005

Władysław Welfe. (2007). *Knowledge Capital and Total Factor Productivity* (Department of Applied Econometrics Working Papers No. 2). Madrid. Retrieved from https://ideas.repec.org/p/wse/wpaper/2.html

World Bank. (2006). *Where is the Wealth of Nations ? Measuring Capital for the 21st Century*. Washington, D.C: World Bank.

Wu, H. X. (2014). *China's Growth and Productivity Performance Debate Revisited-Accounting for China's Sources of Growth with a New Data Set* (Economics Program Working Paper Series No. #14-01). Retrieved from https://www.conference-board.org/pdf_free/workingpapers/EPWP1401.pdf

Wu, J., Wu, Y., Se Cheong, T., & Yu, Y. (2018). Distribution Dynamics of Energy Intensity in Chinese Cities. *Applied Energy*, *211*(October), 875–889. https://doi.org/10.1016/j.apenergy.2017.10.097

Wu, Y. (2000). Is China's Economic Growth Sustainable? A Productivity Analysis. *China Economic Review*, *11*(3), 278–296. https://doi.org/10.1016/S1043-951X(00)00022-5

Wu, Y. (2016). China' s Capital Stock Series by Region and Sector. *Frontiers of Ecocnomics in China*, *11*(1), 156–172.

Xin, Z. M., & Wang, Y. F. (2016). China Adjusts Method of Calculating GDP, Including R&D

Expenditure. Retrieved from http://www.chinadaily.com.cn/business/2016-07/06/content_25983079.htm

Yang, S., Zhou, Y., & Song, L. (2018). Determinants of Intangible Investment and Its Impacts on Firm's Productivity: Evidence from Chinese Private Manufacturing Firms. *China and World Economy*, *26*(6), 1–26.

Ying, L. G. (2003). Understanding China's Recent Growth Experience: A Spatial Econometric Perspective. *Annals of Regional Science*, *37*(4), 613–628. https://doi.org/10.1007/s00168-003-0129-x

Youndt, M. A., Subramaniam, M., & Snell, S. A. (2004). Intellectual Capital Profiles: An Examination of Investments and Returns. *Journal of Management Studies*, *41*(2), 335–361. https://doi.org/10.1111/j.1467-6486.2004.00435.x

Young, A. (2003). Gold into Base Metals: Productivity Growth in the People's Republic of China. *Journal of Political Economy*, *111*(6), 1220–1261.

Zéghal, D., & Maaloul, A. (2011). The Accounting Treatment of Intangibles - A Critical Review of the Literature. *Accounting Forum*, *35*(4), 262–274. https://doi.org/10.1016/j.accfor.2011.04.003

Zhang, J., Wu, G. Y., & Zhang, J. P. (2007). *Compilation of China's Provincial Capital Stock Series Using Perpetual Inventory Method* (International Workshop on Productivity in China at Tsinghua University No. 13). Beijing. Retrieved from http://www.cces.fudan.edu.cn/newstxt/China capital stock series.pdf

Zhou, H., & Zou, W. (2010). Income Distribution Dynamics of Urban Residents: The Case of China (1995-2004). *Frontiers of Economics in China*, *5*(1), 114–134. https://doi.org/10.1007/s11459-010-0006-3

Zhu, X. (2012). Understanding China's Growth: Past, Present, and Future. *Journal of Economic Perspectives*, *26*(4), 103–124. https://doi.org/10.1257/jep.26.4.103

Zingales, L. (2003). The Weak Links. *Federal Reserve Bank of St. Louis Review*, *85*(4), 47–52.