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The Effects of Capital and Labour Distortion on Innovation

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Declaration

I declare that this thesis presents work carried out by myself and does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any university; to the best of my knowledge it does not contain any materials previously published or written by another person except where due reference is made in the text; and all substantive contributions by others to the work presented, including jointly authored publications, is clearly acknowledged.

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Abstract

Factor misallocation has significant effects on productivity and innovation (Bento and Restuccia, 2017). Innovation is widely regarded as the most important element for economic growth (Chen et al., 2015). This thesis aims to study how capital and labour distortions influence innovation activities in China. This research applies the generalized least square method, the Generalized Method of Moments model with introduced instrumental variables, and a natural experiment with an exogenous shock. The results indicate that the measurements for factor misallocation are significantly negatively correlated to innovation. The findings have important implications for emerging countries to improve their innovation productivity.

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Chapter 1: Introduction

This chapter presents the research scope (Section 1.1), research background (Section 1.2), and objectives (Section 1.3). Section 1.4 concludes with an outline of this thesis.

1.1 Research Scope

Factor misallocation has significant effects on productivity and innovation (Bento and Restuccia, 2017). In addition, aggregate total factor productivity could be lowered by factor misallocation across heterogeneous production units (Restuccia and Rogerson, 2013). As reported by the WorldBank database, there is significant diversity in total gross domestic product (GDP) per capita (in current $US). For instance, in 2018, GDP per capita ranged from $275.4 (Burundi) to $114340.5 in Luxembourg. This disparity may be due to differences in total factor productivity that result in differences in output per worker and is also a reflection of the inequality between prosperous and poverty-stricken nations (Klenow and Rodriguez-Clare, 1997; Hall and Jones, 1999).

Prior studies on factor misallocation comprise capital misallocation (Moll, 2014; David and Venkateswaran, 2019), labour misallocation (Chaudhuri and Biswas, 2016), policy misallocation (Restuccia and Rogerson, 2008; Restuccia, 2019), energy misallocation (Peng and Yingtao, 2014; Dai and Cheng, 2016), land misallocation (Adamopoulos et al., 2017), and spatial misallocation (Hsieh and Moretti, 2019). This study follows Bai and Bian (2016) and utilizes capital distortion and labour distortion as factor misallocation elements.

Factor misallocation not only has important effects on productivity, but also plays a significant role in innovation (Bai and Bian, 2016). Innovation is widely regarded as the most important element for economic growth (Feldman and Link, 2001; Guellec and Potterie, 2004; Chen et al., 2015). By reviewing influential publications from the *Journal of Finance*, the *Journal of Financial Economics*, and the *Review of Financial Studies*, He and Tian (2018) show that only five publications between 2000 and 2008 examine corporate innovation; however, from 2009 to 2017 there are more than eleven publications that focus on the innovation stream. He and Tian (2018) also illustrate that the majority of these publications investigate the determinants of corporate innovation. The connections between innovation, firm planning, and social development pave the way for researchers to apply their knowledge to various research areas, such as accounting, finance, marketing, and management (He and Tian, 2018). Existing publications related to innovation can be classified into two main directions: innovation input and innovation output (Matzler et al., 2015; Tavassoli, 2018; Zhang et al., 2019). In terms of measurements for innovation input and innovation output, the present study follows Bai and Bian (2016), Dai and Liu (2016), and Tsamadias et al. (2019) who employ research and development (R&D) capital, R&D full time equivalent, and R&D researchers (individuals who are occupied in R&D activities at year-end) as innovation input, and the number of patents as a proxy for innovation output (Buchmann and Kaiser, 2019; Kroll and Kou, 2019). More specifically, Chang et al. (2016) highlight the significance of patent stock per capital, which is responsible for a 0.85% increase of GDP growth. Solow (1957) concludes that innovation is a core means for firms to obtain competitive advantage and in turn promote economic growth. By providing empirical results based on six developed countries, López-Pueyo, Barcenilla-Visús, and Sanaú (2008) show that innovation is positively significant correlated with total factor productivity in the national arena. Therefore, innovation is a key driver of the development of firms, industries, societies, and even countries.

The purpose of this thesis is to study how capital distortions and labour distortions influence innovation activities in China. Chinese province-level data is manually collected from the China Statistical Yearbook and the China Statistical Yearbook on Science and Technology (www.stats.gov.cn) published by the National Bureau of Statistics. Firstly, this study implements a generalized least square (GLS) regression with province and year fixed effects, finding that the measurements for factor misallocation in this research are significantly negatively correlated to innovation. A robustness analysis using a Generalized Methods of Moment (GMM) model shows that capital and labour market distortions have a negative impact on both innovation inputs and outputs. The results are further robust to the application of a natural experiment using revised China Labour Contract Law in 2008 as an exogenous shock.

1.2 Background

In China, the government is the core decision maker. Prior to 1978, the Chinese government entirely controlled prices and production (Curtis, 2016). The first economic reform was introduced by Xiaoping Deng in China, named the "Reform and Opening-up" in December 1978 (Gan and Zheng, 2009; Song et al., 2011). In the post-reform period, the government dramatically relaxed its price control, accompanied by an economic transition from a planned economy to a market economy (Lin, 2004). Although this has led to incredible economic advancement, the Chinese financial system and institutions remain underdeveloped (Allen et al., 2005). In addition, the problem of factor misallocation has surfaced during market economy reform (Bai and Bian, 2016).

Using the United States as a benchmark, Hsieh and Klenow (2009) point out that the total factor productivity in the manufacturing sector is likely to increase by thirty to fifty percent in China when capital allocation and labour allocation equalize marginal products. In addition, although the government has relaxed control of the product market, they still interfere with the allocation and prices of factor markets both directly and indirectly (Zhao et al., 2019). The Reform and Opening-up periods have led to asymmetry between development of the factor market and development of the product market, which has been a severe problem throughout the process of Chinese market reform (Zhao et al., 2019). According to the main tasks and measures of

China's economic and social development for the period of the 13th Five-Year Plan from 2016 to 2020, the Chinese government is currently concentrating on mechanisms to encourage innovation activities (Wang et al., 2017). Since R&D expenditure and innovation human capital, which are both obtained from factor markets, are involved in the input of innovation, Bai and Bian (2016) note that the misallocation of factor markets has impacts on innovation inputs and even the output of innovation. In other words, the severity of distortions in factor markets has significant effects on innovation.

As the Chinese economic reform is still being implemented, government intervention is still an issue, particularly regarding credit decisions in financial sectors, especially in the banking industry (Pill and Pradhan, 1997). The government's primary objective is GDP growth, which means that the government is more likely to invest in low-risk projects. This governmental risk aversion behaviour creates barriers for innovation (Bai and Bian, 2016). This intervention also contributes to further capital misallocation (Cooray, 2011). In the meantime, innovation projects are unable to obtain sufficient financing, thus restricting the capacity of innovation output.

In order to receive more funds or subsidies for firm innovation from the government (which has distribution power of capital), another issue becomes apparent, namely rent seeking (Krueger, 1974; Bai and Bian, 2016). Hence, investment in innovation, which is supposed to be supplied from firm capital, is essentially sourced from rent seeking activities. However, rent seeking activities enable these firms to be more competitive in the market and consolidate their monopoly position rather than pursue innovation (Pan and Wu, 2019). This rent seeking behaviour therefore leads to misallocation of innovation resources and reduced innovation productivity (Pan and Wu, 2019). Controlled capital flow by the government contributes to this capital misallocation and information asymmetry. In contrast, market-oriented capital is more efficiently allocated (Chan et al., 2012). Furthermore, in order to mitigate the economic development gap and help relatively undeveloped districts, China has introduced regional policies to address unbalanced development among provinces (Uyarra, 2010). However, the simultaneous existence of rent seeking and regional policies results in subsidy misallocation (Wang, 2011).

Local government regulations on the wage workforce decrease firms' motivations to conduct innovative production activities (Bai and Bian, 2016). Due to restraints from the Chinese style of fiscal decentralization system and the promotion of "local government officials championship" model, Bai and Bian (2016) note that some local governments prefer to restrict the wage workforce to lower firms' production costs in order to attract foreign businesses and external investment and thus achieve higher political performance. Restrictions on the wage workforce are therefore a double-edged sword. On the one hand, these restrictions lower the cost of firm labour in the short-term; on the other hand, such restrictions drive firms to focus on tangible factors and ignore independent innovation (Gao, 2008; Bai and Bian, 2016). With no incentive to conduct innovation activities, the overall market is likely to suffer (Bai and Bian, 2016).

1.3 Objectives

China plays an increasingly important role in the global economy (Zhang, 2001; Song et al., 2011; Ding and Knight, 2011; Ansar et al., 2016; Zheng and Walsh, 2019). Wang et al. (2019) and Maddison (2007) note that China's economy accounts for approximately one third of global economic growth in terms of total gross domestic product (GDP). Therefore, the issues of factor misallocation and innovation in China have begun to attract academic attention. This motivates the author to explore whether and how factor misallocation restricts innovation via productivity improvement in the form of innovation input and output. Given China's continuing economic development, this study has significant implications for other emerging markets to improve their economy.

The aim of this thesis is therefore to identify the influence of factor misallocation on innovation in China.

1.4 Thesis outline

This thesis is organized as follows. Chapter 2 provides a systematic review of literature pertaining to factor misallocation in China. Chapter 3 focuses on the effects of capital and labour distortions on innovation via thirty province-level sample firms in China between 2000 and 2017. Chapter 4 concludes the thesis and provides suggestions for future research.

Chapter 2: Literature Review

This chapter provides a systematic review of the literature pertaining to factor market misallocation. This chapter proceeds as follows. Section 2.1 presents the review methodology, followed by examination of the key research streams, namely Government Intervention (Section 2.2), Misallocation Explanation (Section 2.3), Market Distortion (Section 2.4), and Regional Factor Distortion (Section 2.5). Section 2.6 presents emerging themes and Section 2.7 concludes the chapter.

2.1 Review Methodology

This study uses "bibliographic mapping" to identify influential papers in the field of factor market misallocation and innovation. Bibliographic mapping is a technique for reviewing a field of research and its influential publications. Compared to other literature review assessment, bibliographic mapping is able to analyze the publications quantitatively. Papers in the literature review are sourced from the Web of Science within the Social Sciences Citation Index. The bibliographic map is generated using HistCite™, showing the most cited papers and the citations between them.

Three advanced searches were conducted with different keywords within the field of management, business, business finance, and economics. The first search was conducted for publications with the terms "misallocation" and "China" in the title, which led to the identification of 14 records. The second search was conducted for publications with the terms "physical", "capital", and "China" in the title, which resulted in 5 records. The third search was conducted for publications with "labo*r", "capital", and "China" in the title, which resulted in 22 records. The asterisk (*) is included as a wildcard symbol to search for variations of the term (such as labour or labor). The 41 records were downloaded from the Web of Science and imported into HistCite (version 12.03.17). A total of 4 papers were added manually, each of which is cited by at least two papers in the 41 records. A cited reference search was also used to identify a further two publications as per Garfield (2004), leading to a final data set of 45 records published from 2000 to 2019 (cut-off: 11th June 2019).

The annual output of publications on factor market misallocation in China in management, business, business finance, and economics is mapped in Figure 1. The map displays four main research streams: government intervention, misallocation explanation, market distortion, and regional factor distortion. These research streams are reviewed in detail in the following sections. Since 2008, there has been a growing body of research focusing on factor market misallocation in China. Each publication is identified as a node and linked by lines indicating the citation linkages among papers. A larger node indicates a higher number of citations measured by the local citation score (LCS). Details of citations, LCS, and global citation score (GCS) for each publication in the map are displayed in Appendix A.

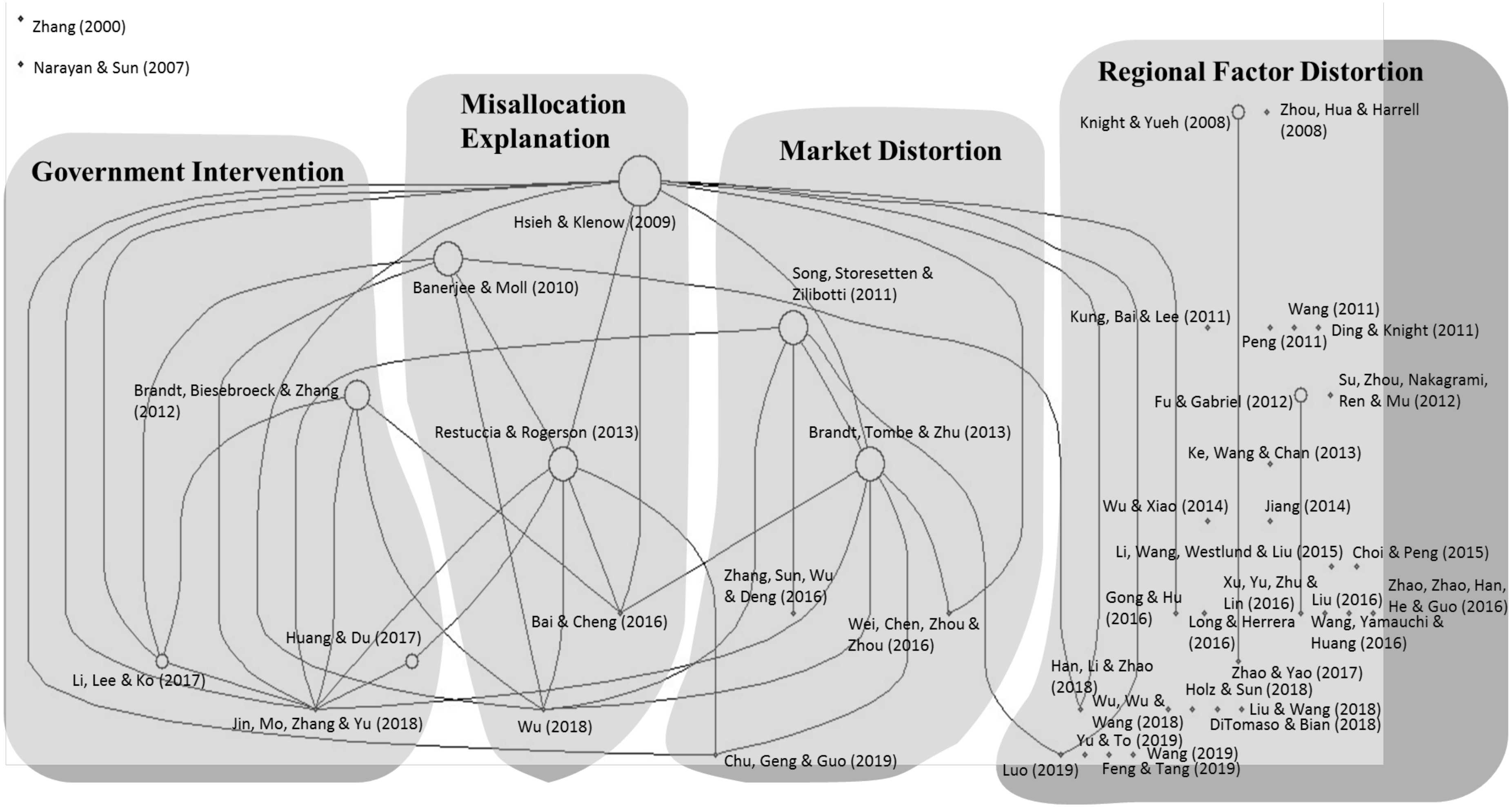


Figure 1. Citation map of the most highly cited publications pertaining to factor market misallocation in China.

This figure also plots the cross-references between these publications from 2000 to 2019. The different streams are shaded and labelled. For clarity, publications are displayed along a timeline, with older publications at the top of the citation map and newer publications at the bottom.

2.2 Government Intervention

Governments play an important role in the factor market. The allocation of factors is affected by government policies, government incentives, government reforms, and so on. A policy of liberalizing entry and facilitating exit is key for factor reallocation (Brandt et al., 2012). Moreover, Brandt et al. (2012) argue that entrants are necessary to obtain knowledge of how to identify new opportunities and improve productivity subsequent to continuous participation in the market. These two dimensions of information are facilitated by related policies for firms targeting sustained growth (Brandt et al., 2012). Additionally, Brandt et al. (2012) also point out that further reforms or transitions for enhancing efficient allocation of factors provide significant growth probability. On the basis of resource allocation, Huang and Du (2017) examine the impacts of government intervention on land misallocation in China and demonstrate that the government's well-intended land-leasing policy contributes to unintended consequences of land misallocation. They recommend that advanced reform of land leasing is required in order to mitigate issues of land misallocation (Huang and Du, 2017).

Li et al. (2017) explore another type of resource misallocation: innovation inputs. They argue that government policies give rise to distortions of innovation inputs to a certain degree, such as capital subsidies or preferential tax treatment that favours specific innovation outputs (Li et al., 2017).

In addition to resource misallocation studies, Jin et al. (2018) focus on structural transformation by comparing the degrees of factor misallocation within the manufacturing industry in China. The Chinese economy comprises three layers, namely state, group, and firm, whereas the department level comprises, industry, region, and ownership sector (Jin et al., 2018). The authors demonstrate that these three different types of structural resource misallocation are common in the capital aspect, particularly regarding labour. This scenario is probably due to the stimulation of policies on aggregate demand after the Global Financial Crisis, which occurred in 2008 (Jin et al., 2018). Therefore, Jin et al. (2018) suggest that structural reform must be continuously implemented to optimize the industrial structure, regional structure, and the discrimination of owners regarding corporate financing.

2.3 Misallocation Explanation

This stream focuses on fundamental research methods of misallocation, country-level evidence, future directions of interpretation, causal factors, and domain sources of misallocation. In their influential study, Heish and Klenow (2009) examine the reasons for misallocation. Using the United States as a benchmark, they create a standard model of monopolistic competition and qualify the potential expansion of misallocation in China and India. They find that the overall loss of total factor productivity in China ranges from 30% to 50% (Heish and Klenow, 2009).

Drawing on the methodology of Heish and Klenow (2009), various studies have further investigated resource misallocation around the world (Camacho and Conover, 2010; Ryzhenkov, 2016; Gopinath et al., 2017). Banerjee and Moll (2010) provide explanations for the persistence of misallocation by distinguishing misallocation on the intensive margin and on the extensive margin. Their results implicate that the latter misallocation is more likely to be persistent. In addition, Rectuccia and Rogerson (2013) conduct a survey of the literature regarding misallocation and productivity, highlighting the future directions of misallocation impacts on technology adoption and innovation activities.

Building on the results from Rectuccia and Rogerson (2013), Bai and Cheng (2016) explore the causal factors or determinants of labour misallocation in China over the period of 1980 to 2010. The authors report that differences in wages or salaries across different industries or sectors are the dominant cause for labour misallocation. Nevertheless, wage deviation from marginal value of labour is also a significant contributor to labour misallocation (Bai and Cheng, 2016).

More recently, two predominant sources are applied to explain capital misallocation in China by Wu (2018), namely policy distortions and financial frictions. Their findings indicate that financial friction accounts for approximately 30% of capital misallocation observed in China.

2.4 Market Distortions

This stream refers to market distortions in the credit market and factor market. Resource distortions exist alongside the improvement, advancement, and development of China's degree of marketization.

Song et al. (2011) provide one of the earliest and most influential publications in this research area. They investigate different types of firm ownership (such as entrepreneurial firms, state-owned firms, and high-productivity firms) in China by conducting a growth model relative to the economic transition in China. This growth model includes four key elements, namely high output growth, sustained returns on capital, reallocation within the manufacturing sector, and a large trade surplus (Song et al., 2011). Moreover, their model is a neoclassical model under the specific setting of China's economic transition in which various types of firms are affected by financial and contractual imperfections (Song et al., 2011). Their results demonstrate that the ownership of firms plays an important role in China's economic transition. Another interesting finding of Song et al. (2011) is that private firms are restricted by financing options (internal financing); as a result, they are more motivated to apply productive technologies. In contrast, state-owned firms are successful because they have more opportunities to gain access to credit markets.

Building on Song et al.'s (2011) investigation of firm-level economic transition in China, Brandt et al. (2013) explore the effect of capital and labour market distortions on total factor productivity based on province- and sector-level observations from 1985 to 2007. Brandt et al. (2013) further consider three distortions, namely province-specific wedges, sector-province specific wedges, and labour wedges between state and non-state sectors. Their findings show that capital and labour market distortions have an impact on total factor productivity losses across provinces and sectors, with an average loss of twenty percent on aggregate non-agricultural total factor productivity (Brandt et al., 2013). More specifically, Zhang et al. (2016) study the effect of changes in labour and capital productivity in Shandong and Henan provinces, which are two leading provinces in grain production and also have the largest populations. They focus on rural restructuring in China and find that an increase in labour productivity results in greater wheat production than an increase in capital productivity (Zhang et al., 2016).

Wei et al. (2016) further explore the reasons for and the consequences of resource market misallocation. They add governmental decision-making procedure into their estimation model and endogenize the degree of credit distortions, finding that the performance of credit market distortion is more severe in districts where the proportion of state-owned firms is higher.

From an environmental finance perspective, Chu et al. (2019) provide empirical evidence on energy market misallocation in China. They examine the effects of energy distortion on carbon emission efficiency through spatial econometric estimation and demonstrate an inverted U-shaped correlation (Chu et al., 2019).

2.5 Regional Factor Distortion

This stream explores different types of factor markets and the impacts of factor markets on economic growth in China. The literature explores a range of factors, including labour migration (Section 2.5.1), factor relationship (Section 2.5.2), social capital (Section 2.5.3), and new data and measurement (Section 2.5.4).

2.5.1 Labour migration

This stream of literature focuses on labour migration as a result of urbanization. As one of the first studies to explore income inequality, Zhou et al. (2008) survey three villages (including 300 families) in the year 1988 and in the year 2006. The authors report dramatic increases in income inequality because of the transition from labour power to small-scale capital in the span of seventeen years. Feng and Tang (2019) explore different causes of income inequality. Using Urban Household Survey data, they find that labour market factors and declining marriage rate are two significant reasons for income inequality.

Kung et al. (2011) investigate rural labour migration in Wuxi county (which is located in the Lower Yangzi region) in the 1930s, indicating that this migration is associated with both education and income levels. Additionally, Liu (2016) studies the relationship between labour productivity and tea trade in late Qing China (1644–1911). In the context of rural labour migration, Wu and Xiao (2014) focus on the continuation of rural labour migration by examining whether it has impacts on labour and capital markets. More precisely, they show that changes in the labour market affect both labour market structure and relative factor price (Wu and Xiao, 2014).

Several influential publications examine labour agglomeration. Fu and Gabriel (2012) assess whether labour migration can be affected by regional human capital agglomeration in China. By estimating a skill-based directional migration model, Fu and Gabriel (2012) highlight the significance of human capital agglomeration, particularly its advantages for disparate regional growth trajectories. Another growing body of research is focused on the National College Entrance Examination system, which is regarded as a stimulation of potential interregional labour capital (Jiang, 2014). Furthermore, Jiang (2014) provides empirical evidence that students attending the examination from underdeveloped provinces, such as Ningxia and Qinghai, have a strong preference for universities that are located in relatively developed provinces, such as Guangdong and Shanghai. On the other hand, Choi and Peng (2015) aim to resolve labour shortage issues in terms of capital and migrant labour in southern China, indicating that this relationship has implications for the efficacy of firms in East Asia with a paternalistic management style. A summary of articles on human capital and labour market in China is introduced by Liu and Wang (2018) which classifies into several streams: educational inequality, rural children labour, internal migration, health, factor accumulation, and productivity enhancing.

Overall, publications in this stream demonstrate that labour migration is an ongoing issue and is driven by a range of factors that can be assessed from multiple perspectives.

2.5.2 Factor relationship

Su et al. (2012) study substitution among the three factor inputs of capital stock, labour, and energy from 1953 to 2006. This includes both the planned period (1953 - 1978) and market period (1979 - 2006). The authors construct a production function of two-level constant elasticity of substitution in which technological change rate is considered. Rather than considering technological change rate as a criterion, Zhao et al. (2016) identify electricity consumption as a main factor in the Cobb-Douglas production function to investigate both equilibrium and causal associations between real GDP (regarded as economic growth), electricity consumption (considered as energy), total investment in fixed assets (belonging to capital input), and employment (identified as labour force). Zhao et al. (2016) examine six provinces located in the northern part of China from 1995 to 2014, identifying mutual relationships between electricity consumption and real GDP in specific provinces.

Wang (2011) studies the impact of distortion caused by government intervention regarding housing prices. Ke et al. (2013) study risk allocation, including corruption, government intervention, government reliability, approval and permits, immature juristic system, and land acquisition. The authors find a significant and negative impact of risk allocation, which includes public-private partnership project performance.

Wang et al. (2016) estimate the substitution effect between labour and machines based on small-scale farms in China. The authors find that labour prices have increased rapidly after 2003 while machine prices fail to show volatility. This contributes to the elasticity of substitution between labour and machine presence, particularly in the areas of wheat, rapeseed, and soybean production. Han et al. (2018) further examine this substitution between labour and machines, demonstrating complementary effects between labour and farmland and substitution effects between capital and farmland, and between capital and labour.

Taking local government debt into consideration, Wu et al. (2018) show that state-dominated investment and land supply in underdeveloped or less developed regions are implemented with serious factor misallocation, leading to negative impacts on Chinese economic growth. This is consistent with Ding and Knight (2011) who state that investment in physical and human capital promotes economic growth. Peng (2011) examines the correlation of citizenship and the labour process, revealing that state-capital correlation, which is defined as a particular type of mutuality, plays a significant role in the labour process.

2.5.3 Social capital

Building on Ding and Knight (2011), Li et al. (2015) investigate the roles of physical, human, and social capital on economic growth in China. They find that social capital becomes significant after the year 2000, while physical capital and human capital exert continuous effects on the economic growth of China (Li et al., 2015). In addition, with increasing social capital, the influence of physical capital has decreased since the 1990s (Li et al., 2015). Furthermore, several publications focus on the relationships between social capital and labour income (Knight and Yueh, 2008), labour migration in rural China (Zhao and Yao, 2017), the possibility for participation in Rotating Labour Associations (ROLAs) in rural China (Wang, 2019), and the Chinese market compared with the United States market (DiTomaso and Bian, 2018).

2.5.4 New data and measurement

Extending Hsieh and Klenow (2009), Gong and Hu (2016) relax the assumption of constant returns to scale (CRS) for different products and conclude that the resource misallocation results of Hsieh and Klenow (2009) are overestimated. As no official Chinese statistics relating to capital stocks, Long and Herrera (2016) construct a new database including measurements of capital stocks, investment flows, investment shares, investment price indices, and depreciation rates. Holz and Yue (2018) develop a new measurement for physical capital, and also explore the differences between wealth capital stock and capital services.

Two 'outliers' are evident in the left top corner of Figure 1. Zhang (2000) conducts an empirical study in the Shandong province of China to explore the social implications of firms funded by East Asian countries. The results show that the existence of such firms changes the government's role in the labour factor market. Narayan and Sun (2007) study the effects of labour, capital, and technology on economic growth in China from 1952 to 1999. The results indicate that capital stock and labour both have a positive effect on economic growth over the long term.

2.6 Emerging Trends

This chapter provides a comprehensive summary of factor misallocation and innovation utilized in a variety of research streams. However, the citation map developed in this chapter fails to offer a full account of emerging research trends and directions, as new publications have fewer citations. Manual assessment of recent publications facilitates discussion of important emerging research trends in three key areas, namely endogeneity (Section 2.6.1), legislation relating to factors of production (Section 2.6.2), and knowledge management (Section 2.6.3).

2.6.1. Endogeneity

Although GLS regressions provide supportive evidence, endogeneity issues are a concern in many empirical analyses (Gippel et al., 2015). There are several solutions for endogeneity problems, including two-stage least squares (2SLS), instrument variables (IV), differenced GMM (generalized method of moments), and natural experiments. Gippel et al. (2015) further suggest the application of tests such as the Hausman-Wu Test to specify endogeneity and Over-Identifying Chi-squared Test and F Test to examine the correlation between instrument variables and endogenous variables. Hille and Möbius (2019) discuss endogeneity between factors of productivity and innovation, resolving endogeneity of environmental regulation, innovation, and trade openness. In doing so, the authors demonstrate the positive relationships between increasing environmental policy stringency and factor productivity.

Atanasov and Black (2016) and Baum et al. (2017) examine endogeneity between factors of production and innovation by applying shock-based methods for examining causal inference in the field of corporate governance research. Very few studies consider convincing causal inference strategies. Due to increasing significance of endogeneity concerns, Haq et al. (2018) follow Gippel et al. (2015) to apply the F-test on the joint significance of instruments for controlling endogeneity.

2.6.2. Legislation relating to factors of production

In this study, the revision of labour law is utilized as the basis of a natural experiment (see Chapter 3 for more detail). Habib et al. (2019) empirically examine the relationship between patent law and total factor productivity in sixteen countries, revealing statistically significant effects of intellectual property rights (IPRs) on changes in total factor productivity.

Cette et al. (2018) examine the correlations of labour law and capital, focusing on the effects of Employment Protection Legislation (EPL) on capital based on fourteen Organization for Economic Cooperation and Development (OECD) countries. With a sample of eighteen industries over twenty years, they show that strengthening EPL deteriorates the negative impacts of non-Information and Communication Technology (ICT) and non-R&D capital on employment. On the contrary, Sweet and Eterovic (2019) fail to find that patent rights have a significant influence on productivity growth regarding negotiation of norms on Trade Related Intellectual Property Rights (TRIPS) within the last two decades.

2.6.3. Knowledge management

O'Dell and Grayson (1998) consider knowledge management to be an intended strategy for bringing the right or the most appropriate knowledge to the right or the most appropriate individual at the right or the most appropriate time, and in turn to help individuals to share and apply this information and knowledge. For firms, this represents a means of promoting organizational performance and outcomes.

Gold et al. (2001) demonstrate effective knowledge management from the perspective of organizational capabilities and recommend elements of a knowledge infrastructure that are constitutive of "technology, structure, and culture along with a knowledge process architecture of acquisition, conversion, application, and protection". More recently, Gunjal (2019) explores the significance of knowledge management in the context of Indian corporations regarding policy, strategy, and future practices. In order to empirically investigate knowledge management practices in China, Liu et al. (2019) conduct a survey of organizations across a number of regions (at both national and organizational levels) and find that institutional forces proportionally affect knowledge management practices. More recent publications also address knowledge management and innovation capacity (for example, Gloet and Samson, 2020).

2.7 Conclusion

This chapter employs the bibliographic mapping approach to identify influential publications on factor misallocation in China over the past 20 years. The main research streams identified are government intervention, misallocation explanation, market distortions, and regional factor distortion. Each of these areas is discussed and reviewed in detail. Following examination and review of publications published since 2000 related to factor misallocation in China, this chapter also identifies emerging research trends. These emerging trends include endogeneity concerns, legislation relating to factor productivity, and knowledge management.

Chapter 3: Empirical Study

This chapter investigates the relationship between capital and labour distortion on provincial level innovation. Following Bai and Bian (2016), capital and labour are used to examine the distortions in factors markets on innovation input and output. This research considers R&D capital stock, R&D full time equivalent, and the number of R&D researchers as innovation inputs, and the number of patents as innovation output. Relevant data are obtained from the National Bureau of Statistics. This chapter proceeds as follows. Section 3.1 describes the data and key variables, and Section 3.2 presents the research methodology and robustness tests. Section 3.3 discusses the empirical results and implications, and Section 3.4 concludes.

3.1 Data and Key Variables

3.1.1 Data Source

Data is predominantly hand-collected from the China Statistical Yearbook and the China Statistical Yearbook on Science and Technology (www.stats.gov.cn) published by the National Bureau of Statistics. The final sample includes thirty provinces in mainland China over the period 2000 – 2017. Tibet is excluded due to missing data observations (e.g. R&D researchers is not available from 2000 to 2008). Due to some data unavailability, several variables are measured using available information; for example, capital distortion is measured based on GDP, labour, capital stock, and labour wage.

The variables used in this study are displayed in Table 1. These variables are described in more detail in the following subsections, including the factor misallocation variables (Section 3.1.2), innovation variables (Section 3.1.3) and control variables (Section 3.1.4).

Table 1. Variable Definitions

Variables	Definitions
patent	R&D output
rdk	R&D capital stock
rdfull	R&D full time equivalent
rdresearcher	The number of R&D researchers
DIST_K	Capital distortion
DIST_L	Labour distortion
foreigninvest	Total foreign investment
Tech	Transaction value in technical market
cablelength	Length of long distance optical cable line

3.1.2 Measuring Factor Market Distortion

The province-level distortion variables used in this study are derived from the trans-logarithm production function of Bai and Bian (2016):

$$\mathrm{LN}(Y_{it}) = \lambda_0 + \lambda_1 LN(L_{it}) + \lambda_2 LN(K_{it}) + \frac{1}{2}\lambda_3 LN^2(L_{it}) + \frac{1}{2}\lambda_4 LN^2(K_{it}) + \lambda_5 LN(L_{it}) \times LN(K_{it}) + \varepsilon_{it} \qquad (1)$$

In the above equation, Y_{it} is the yield of province i in year t, L_{it} is the year-end number of employed persons in urban units in province i in year t, K_{it} is the capital stock of province i in year t, λ_0 is a constant term, λ_1, λ_2, λ_3, λ_4, and λ_5 are the regression coefficients, and ε_{it} is the random error term.

The nominal GDP data provided by the China National Bureau of Statistics includes changes in market prices that have occurred during the current year due to inflation or deflation. As a result, a further calculation is necessary for Y_{it} via a GDP deflator with the base year of 2000. The variable K_{it} has a similar issue; further calculation is based on Total Fix Investment data and related Fix Investment Indices data from the yearbook. This research follows Jun et al. (2004) and Bai and Bian (2016) to calculate the capital stock of each province with a perpetual inventory method with 2000 as the base year. The depreciation rate and increasing rate is assumed to be 9.6% and 13.84%, respectively (Zhang et al. 2004).

Taking the partial derivative of L and K, respectively, in Equation (1), the following equations can be obtained:

$$MP_L = \frac{(\lambda_1 + \lambda_3 LN(L_{it}) + \lambda_5 LN(K_{it})) \times Y_{it}}{L_{it}} \tag{2}$$

$$MP_L = \frac{(\lambda_2 + \lambda_4 LN(K_{it}) + \lambda_5 LN(L_{it})) \times Y_{it}}{K_{it}} \tag{3}$$

Based on the definition of the partial derivative of the production function, Equations (2) and (3) are the marginal yield of labour and capital. According to the definition of distortion of factor market misallocation, labour distortion is measured as the marginal yield of labour divided by the price of labour (which is calculated as the average of labour wages or salaries, adjusted by the GDP deflator in each province of each year).

$$DIST\_L_{it} = \frac{MP_L}{\omega_{it}} \tag{4}$$

$$DIST\_K_{it} = \frac{MP_K}{r} \tag{5}$$

Similarly, by following Hsieh and Klenow (2009), capital distortion is measured as the marginal yield of capital divided by the price of capital (which is interest rate r).

Appendix B reports the mean of capital distortion and labour distortion in each province of mainland China from 2000 to 2017 and shows that distortions are present in both the capital market and labour market in all thirty provinces of our sample.

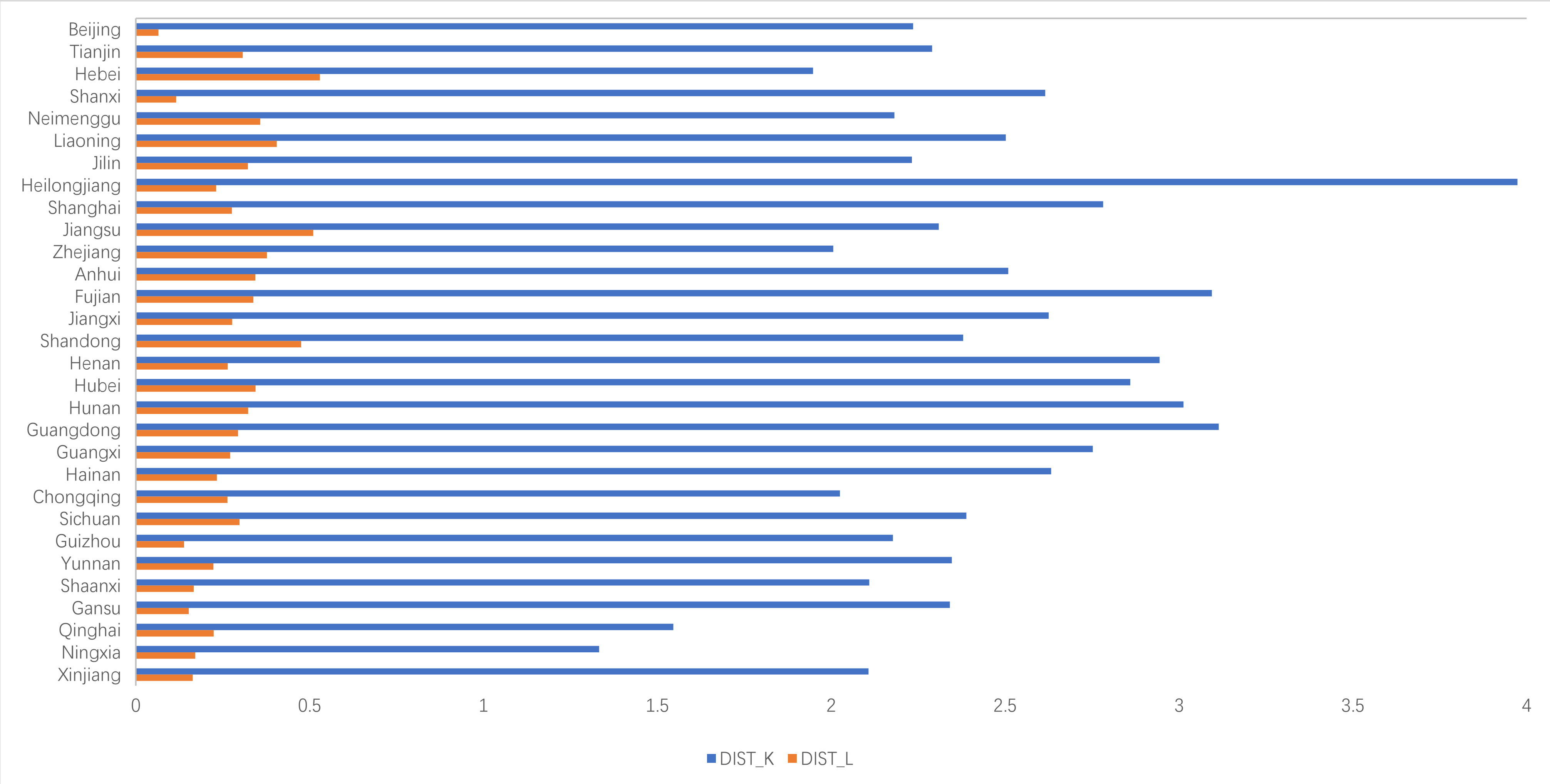
According to the report in the yearbook, if labour distortion is less than one, this means that the labour marginal production of this province is lower than average wage or salary in total. On the other hand, when capital distortion is greater than one, this indicates that capital marginal production is higher than the interest rate. Furthermore, Bai and Bian (2016) conclude that if there is a distortion in the capital market, this means that capital market distortion is influenced by some external factors (particularly, government intervention).

The mean of capital distortion and the average of labour distortion for all thirty provinces between 2000 and 2017 are 2.4458 and 0.2821, respectively. This result is very close to the calculation results of Bai and Bian (2016), who report capital distortion of 2.3027 and labour distortion of 0.2044 based on a twelve-year period from 2003 to 2014.

Figure 2 plots the average of capital distortion and labour distortion in each province from 2000 to 2017. Capital distortion is presented in blue while labour distortion is presented in orange. Capital distortion in Heilongjiang province is the most severe with an average of 3.9738, followed by Guangdong and Fujian provinces with averages of

3.114.1 and 3.0945, respectively. As mentioned earlier, a figure of labour distortion closer to one indicates alleviated labour distortion. Beijing has the most severe labour distortion with an average of 0.0654, followed by Shanxi and Guizhou provinces with averages of 0.1163 and 0.139, respectively. Details of the average capital distortion and labour distortion in other provinces are presented in Appendix B.

Figure 2. Average of capital distortion and labour distortion in each province



3.1.3 Measuring Innovation

Based on the information available in the China Statistical Yearbook and the China Statistical Yearbook on Science and Technology provided by the National Bureau of Statistics, four different measurements for innovation are constructed in this study. Patents are used to proxy for innovation output (Section 3.1.3.1), and R&D capital stock, R&D full time equivalent, and R&D researchers are used to measure innovation input (Section 3.1.3.2).

3.1.3.1 Innovation Output

Earlier studies use both patents and the number of patent citations to measure innovation output (for example, Cornaggia et al. (2015)). However, data for patent citations is not reported by the China Statistical Yearbook; therefore, this study uses patents as a proxy for innovation output. Three types of patents are provided by the yearbook: patents of inventions, patents of utility models, and patents of designs. This study follows the measurement method in Bai and Jiang (2015) and Bai and Bian (2016) to calculate the weighted mean of patents using the following weights: 50% on inventions, 30% on utility models, and 20% on designs. The weighted mean of patents is therefore used as the proxy of innovation output.

3.1.3.2 Innovation Input

Input factors during the innovation process are classified into physical capital and human capital. Human capital input refers to the number of individuals who participate in the innovation procedure. This research uses R&D full time equivalent (rdfull) and R&D researchers (rdresearcher) to index the input of human capital. Data on these two variables are provided in the China Statistical Yearbook on Science and Technology. To capture the physical capital input, R&D capital stock (rdk) is utilized. The National Bureau of Statistics also provides R&D expenditure and related indices of each province in each year. Considering the effect of inflation and the continuous process of innovation, this study follows Bai and Bian (2016) to further estimate and construct R&D capital stock based on the year 2000 using the perpetual inventory method. Specifically, R&D capital stock is calculated as follows:

$$C_t = E_{t-1} + (1 - \delta) \times C_{t-1} \quad (6)$$

where C_t and C_{t-1} are the current period and lag one phase of R&D capital stock, E_{t-1} is lag one phase of R&D real expenditure adjusted by the R&D expenditure price index, and δ is the depreciation rate which equals 15% (Bai and Bian, 2016).

R&D expenditure price indices are equal to the value of 55% of the consumer price index and 45% of the fix investment price index. For R&D capital stock in 2000, the following estimation is conducted:

$$C_0 = \frac{E_0}{(g + \delta)} \quad (7)$$

Where C_0 is the R&D capital stock in the year 2000, E_0 is the R&D expenditure in the year 2000, g is the real increasing rate of R&D expenditure, and δ is the depreciation rate which equals 15% (Bai and Bian, 2016).

3.1.4 Control Variables

The empirical model used in this research contains a number of province-level control variables, detailed in the following subsections.

3.1.4.1 Total foreign investment

During the technology adoption and innovation process, communication between countries drives innovation at the regional level. If a province displays a high level of openness, they are likely to have greater opportunities to receive advanced technology and attract foreign R&D investment. Moreover, the increasing amount of foreign investment has a positive influence on the development of local companies within the same provinces (Bai and Bian, 2016). In this study, the level of openness is represented as total foreign investment in each province in each year (*foreigninvest*).. This variable is also adjusted by GDP indices to address the inflation issue.

3.1.4.2 Transaction value in the technical market

Dai and Liu (2016) use the transaction value in the technical market as a control to estimate innovation performance. This variable includes transactions of technological development contract, technological transfer contract, and patent transfer contract, among others. Via participation in the technological transactions market, firms can benefit from the technology development or innovation of other firms. In this study, the variable of transaction value in the technical market is obtained from the China Statistical Yearbook (*tech*). This variable is also adjusted by GDP indices to address the inflation issue.

3.1.4.3 Length of long distance optical cable line

Bai and Bian (2016) apply the length of long distance optical cable line as a control variable to estimate the efficiency losses of innovative production. They position infrastructure as a fundamental guarantee of technological innovation activities that provides related services within provinces and across provinces in order to transmit information and technology instantly (Bai and Bian, 2016). Production costs and transaction costs, for example, decrease during the innovation process as infrastructure implementation increases (Bai and Bian, 2016). In other words, the necessity of high-quality telecommunications is enhanced by innovation activities that require information transmission. Other types of length, such as the length of railway or highway, are not used because the length of long distance optical cable line is more closely related to the innovation process (Bai and Bian, 2016). The length of long distance optical cable line (*cablelength*) is obtained from the China Statistical Yearbook (available from 2001 to 2017).

3.2 Research Methodology

In order to assess the effects of capital distortion and labour distortion on innovation output, the following model is estimated:

$$patent_{it} = \lambda_0 + \lambda_1 \times \mathrm{ABS}_{DIST_K} + \lambda_2 \times \mathrm{ABS}_{DIST_L} + \lambda_3 \times foreigninvest_{it} + \lambda_4 \times tech_{it} + \lambda_5 \times cablelength_{it} + \varepsilon_{it} \quad (8)$$

For innovation inputs, the following equation is estimated:

$$rdk_{it} = \lambda_0 + \lambda_1 \times \mathrm{ABS}_{DIST_K} + \lambda_2 \times \mathrm{ABS}_{DIST_L} + \lambda_3 \times foreigninvest_{it} + \lambda_4 \times tech_{it} + \lambda_5 \times cablelength_{it} + \varepsilon_{it} \quad (9)$$

$$rdfull_{it} = \lambda_0 + \lambda_1 \times \mathrm{ABS}_{DIST_K} + \lambda_2 \times \mathrm{ABS}_{DIST_L} + \lambda_3 \times foreigninvest_{it} + \lambda_4 \times tech_{it} + \lambda_5 \times cablelength_{it} + \varepsilon_{it} \quad (10)$$

$$rdresearcher_{it} = \lambda_0 + \lambda_1 \times \mathrm{ABS}_{DIST_K} + \lambda_2 \times \mathrm{ABS}_{DIST_L} + \lambda_3 \times foreigninvest_{it} + \lambda_4 \times tech_{it} + \lambda_5 \times cablelength_{it} + \varepsilon_{it} \qquad (11)$$

where $patent_{it}$ represents the innovation output of province i in year t;

rdk_{it} represents R&D physical capital stock of province i in year t;

$rdfull_{it}$ and $rdresearcher_{it}$ represent R&D human capital of province i in year t,

ABS_$DIST$_K represents the absolute value of one minus capital distortion;

ABS_$DIST$_L represents the absolute value of one minus labour distortion;

$foreigninvest_{it}$ represents total foreign investment;

$tech_{it}$ represents transaction value in the technical market;

$cablelength_{it}$ represents the length of long distance optical cable line;

λ_0 represents the constant term;

λ_1, λ_2, λ_3, λ_4, λ_5 are the regression coefficients:

and ε_{it} is the random error term.

Rather than compared with zero, the capital distortion and labour distortion are supposed to be compared with one. A lower degree of distortion is implied by a value close to one. Hence, the absolute value of one minus capital distortion and the absolute value of one minus labour distortion are generated for panel regression analyses.

The generalized least square (GLS) regressions are conducted with $rdk_{it}, rdfull_{it}, and\ rdresearcher_{it}$ as dependent variables and ABS_$DIST$_K and ABS_$DIST$_L as independent variables. Year and province fixed effects are added as control variables. In order to address endogeneity concerns, this study follows Gippel et al. (2015) in using instrument variables, the system generalized method of moments (GMM) model, and a natural experiment using an exogenous shock to control for the endogeneity in the independent variables ABS_$DIST$_K and ABS_$DIST$_L. The revision of China Labour Contract Law released and enacted in 2008 is defined as the exogenous shock for this study.

In order to investigate the effects of both capital and labour distortions on innovation, a new dummy variable is generated for regression estimations, namely *year*. If the year of patent, R&D capital stock, and R&D full time equivalent is between 2000 and 2007, the year dummy equals zero; the year dummy equals one when the year of patent, R&D capital stock, and R&D full time equivalent is from 2008 to 2017. The data for R&D researchers is available only from 2009, and as such it is not used in the natural experiment. The relevant equations are as follows:

$$\begin{aligned} patent_{it} = \lambda_0 + \lambda_1 \times year + \lambda_2 \times year \times \mathrm{ABS}_{DIST_K} \\ + \lambda_3 \times year \times \mathrm{ABS}_{DIST_L} + \lambda_4 \times \mathrm{ABS}_{DIST_K} + \lambda_5 \times \mathrm{ABS}_{DIST_L} \\ + \lambda_6 \times foreigninvest_{it} + \lambda_7 \times tech_{it} + \lambda_8 \times cablelength_{it} \\ + \varepsilon_{it} \qquad (8a) \end{aligned}$$

$$\begin{aligned} rdk_{it} = \lambda_0 + \lambda_1 \times year + \lambda_2 \times year \times \mathrm{ABS}_{DIST_K} + \lambda_3 \times year \times \mathrm{ABS}_{DIST_L} \\ + \lambda_4 \times \mathrm{ABS}_{DIST_K} + \lambda_5 \times \mathrm{ABS}_{DIST_L} + \lambda_6 \times foreigninvest_{it} \\ + \lambda_7 \times tech_{it} + \lambda_8 \times cablelength_{it} + \varepsilon_{it} \qquad (9a) \end{aligned}$$

$$\begin{aligned} rdfull_{it} = \lambda_0 + \lambda_1 \times year + \lambda_2 \times year \times \mathrm{ABS}_{DIST_K} \\ + \lambda_3 \times year \times \mathrm{ABS}_{DIST_L} + \lambda_4 \times \mathrm{ABS}_{DIST_K} + \lambda_5 \times \mathrm{ABS}_{DIST_L} \\ + \lambda_6 \times foreigninvest_{it} + \lambda_7 \times tech_{it} + \lambda_8 \times cablelength_{it} \\ + \varepsilon_{it} \qquad (10a) \end{aligned}$$

where i represents province, t indexes year, $year \times \text{ABS\_}DIST\_K$ represents the interactions between the time and the absolute value of the difference between one and capital distortion, $year \times \text{ABS\_}DIST\_L$ represents the interactions between time and the absolute value of the difference between one and labour distortion, and ε_{it} represents the random error term.

3.3 Empirical Results

The results demonstrate the effect of capital distortion and labour distortion on innovation inputs and outputs in 30 provinces. Section 3.3.1 provides descriptive analyses of the variables; Section 3.3.2 reports the results of panel regressions (without and with control variables) and GMM; and Section 3.3.3 presents the panel regressions under an exogenous shock.

3.3.1 Descriptive analyses

A summary of descriptive statistics is displayed in Table 2. Data is manually collected from the China Statistical Yearbook and the China Statistical Yearbook on Science and Technology for 30 provinces covering the period 2000 - 2017. The independent variables, capital distortion (DIST_K) and labour distortion (DIST_L), are detailed in Section 3.1.2. The dependent variables, innovation output (the number of patents) and innovation input (rdk: R&D physical capital stock; rdfull: R&D full time equivalent; and rdresearcher: number of R&D researchers) are detailed in Section 3.1.3. The control variables are Total Foreign Investment (foreigninvest), Transaction Value in the Technology Market (tech), and Length of Long Distance Optical Cable Line (cablelength).

Table 2. Summary of descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
patent	540	6550	12765	23.30	97154
rdk	540	567.8	910.9	1.984	5877
rdfull	540	76950	95640	848	565287
rdresearcher	270	48662	44502	1758	205616
DIST_K	540	2.4458	1.1522	0.2830	5.7931
DIST_L	540	0.2821	0.1490	-0.0060	0.7695
foreigninvest	540	9750	59906	47.80	1.010e+06
Tech	540	1.442e+06	4.077e+06	599.0	4.490e+07
cablelength	510	25032	14468	333	77865

The correlation of independent variables and control variables is displayed in Table 3. For the independent variables, the relationship between capital distortion and labour distortion is slightly negative. This is intuitive as capital and labour are both considered as factor inputs. Other independent and control variables have no significant correlations with each other.

Table 3. Correlation coefficients

	DIST_K	DIST_L	foreigninvest	tech	cablelength
DIST_K	1				
DIST_L	-0.425	1			
foreigninvest	-0.003	-0.006	1		
tech	-0.112	-0.145	0.153	1	
cablelength	-0.193	0.306	0.148	-0.152	1

3.3.2 Regression Results

This section details the results of the generalized least square regressions testing the effect of capital distortion and labour distortion on innovation outputs and inputs. Columns (1), (3), (5), and (7) of Table 4 estimate Equations (8) to (11) without control variables. The negative relationship between distortions in both the capital market and labour market and the innovation process indicate that the more severe the capital distortion and labour distortion, the more severe the loss in innovation.

The coefficients of ABS_DIST_K × patent, ABS_DIST_K × rdfull, ABS_DIST_K × rdresearcher, ABS_DIST_L × patent, ABS_DIST_L × rdk, ABS_DIST_L × rdull, and ABS_DIST_L × rdresearcher are statistically significant and negative on innovation inputs which include physical capital and human capital. These results indicate that capital distortion and labour distortion significantly decrease innovation inputs. Particularly, the results in Column (1) present negative and statistically significant impacts of capital distortion and labour distortion on patents, which implies that these two types of distortions lead to a decrease in the number of patents. These findings are consistent with Ji and Dou (2016), who demonstrate that capital and labour factor distortion significantly inhibits technology innovation in China based on panel data of 30 provinces. The negative effects of labour distortion on patents are also consistent with Li and Liu (2015) who show that labour price distortion creates barriers for technological progress.

The results in Column (3) present negative and statistically significant impacts of capital distortion and labour distortion on R&D capital stock, which implies that both types of distortions reduce innovated capital stock. In other words, more severe distortions in a province decrease R&D capital stock. This finding adds support to Guo and Xiao (2019) who state that factor market distortions restrict the efficiency of regional innovation.

Column (5) of Table 4 reveals that capital distortion and labour distortion have negative and statistically significant influences on innovative human capital including R&D full time equivalent and R&D researchers. In other words, more severe distortions in factor markets decrease both R&D full time equivalent and R&D researchers. These results are consistent with Bai and Bian (2016) and Dai and Liu (2016), which demonstrate that labour factor distortions significantly suppress the improvement of Chinese regional innovation productivity. The establishment of a dual urban and rural household registration system in China is the result of the first wave of industrialization, and this system forms a dual urban-rural economic structure (Bai and Bian, 2016). This structure impedes the unrestricted flow of labour, which in turn leads to inefficient allocation of innovative talent (Bai and Bian, 2016). Furthermore, intervention from local governments regarding the wage workforce restricts free migration and optimal configuration of competent employees (Guo and Xiao, 2019). The intervention on wage workforce also lowers the motivation for firms to conduct their own innovation activities (Bai and Bian, 2016).

Firm fixed effects and year fixed effects are included as control variables in the regression analysis. The results indicate that both capital distortion and labour distortion have a negative impact on innovation inputs and outputs. This is consistent with our main findings. Table 4 demonstrates that the control variables have a statistically significant influence on innovation inputs and outputs, suggesting that innovation is also determined by the level of development in each province. The results also show that innovation inputs and outputs are significantly positively related to the level of openness, technological transaction, and infrastructure development, reflected by the positive and significant coefficients of foreigninvest × patent, tech × patent and cablelength × patent; foreigninvest × rdk, tech × rdk and cablelength × rdk; foreigninvest ×rdfull, tech × rdfull, cablelength × rdfull, and tech × rdresearcher and cablelength × rdresearcher, as those provinces with a higher level of openness, more technological transactions, and better infrastructure can produce more patents. These findings add support to Bai and Bian (2016) and Dai and Liu (2016). The unique result recorded for total foreign investment, which has an insignificant negative association with R&D researchers, motivates further robustness analyses.

Table 4. Panel Regression Results with Control Variables

VARIABLES	patent		rdk		rdfull		rdresearcher	
ABS_DIST_K	-2,518.446***	-3,722.972***	-17.11837	-169.8325***	-14,846.2***	-20,980.85***	-5,764.079***	-6,399.474***
	(710.7)	(648.7)	(48.80)	(39.21)	(4,443)	(4,357)	(1,558)	(1,447)
ABS_DIST_L	-6,712.908***	-6,678.987***	-323.946***	-336.6086***	-39,883.87***	-41,780.71***	-12,060.54***	-11,593.49***
	(500.2)	(465.2)	(34.35)	(28.12)	(3,127)	(3,125)	(1,085)	(1,038)
foreigninvest	-	0.0425697***	-	0.0023663***	-	0.1687224***	-	-0.0053347
		(0.00474)		(0.000287)		(0.0318)		(0.00665)
tech	-	0.0008385***	-	9.93e-05***	-	0.003101***	-	0.0015356***
		(0.000105)		(6.34e-06)		(0.000705)		(0.000226)
cablelength	-	0.1534097***	-	0.0099348***	-	1.140194***	-	0.4091435***
		(0.0537)		(0.00324)		(0.360)		(0.141)
Constant	13,147.05***	14,450.62***	476.6021***	711.5517***	104,336.5***	109,581.2***	73,540.36***	60,986.49***
	(2,212)	(2,119)	(151.9)	(128.1)	(13,827)	(14,230)	(4,130)	(5,090)
Observations		510		510		510		270
R-squared	0.577	0.699	0.587	0.771	0.573	0.638	0.577	0.653
NO. of provinces		30		30		30		30

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

Although GLS regressions provide supportive evidence, there is a potential endogeneity concern. Gippel et al. (2015) suggest several solutions for endogeneity problems including two-stage least squares (2SLS), instrument variables (IV), differenced GMM (generalized method of moments) model, and natural experiments. The authors also describe several tests including the Hausman-Wu Test to specify endogeneity and the Over-Identifying Chi-squared Test and F Test to examine the correlation between instrument variables and endogenous variables. The null hypothesis of the Hausman-Wu Test is rejected in this empirical study, which means there is an endogeneity problem. One year lagged capital distortion and labour distortion are used as instrument variables in system GMM to control for endogeneity. The results of the system GMM analysis are presented in Appendix C.

The results from GMM are similar to our panel regression results. The estimated coefficients of ABS_DIST_K × patent and ABS_DIST_L × patent are negative and significant, which is consistent with prior results from GLS. These findings are also consistent with Bai and Bian (2016) and Dai and Liu (2016), who indicate that capital and labour distortions, as major measurements for factor misallocation, have negative impacts on innovation output. From Row (2) of Appendix C, the effects of labour distortion on R&D capital stock, R&D full time equivalent, and R&D researchers remain negative and significant, which implies that distortions in the labour market negatively affect innovation input.

Compared with prior results, slight differences from GMM are observed in Appendix C. An interesting finding is that the effects of capital distortion on R&D capital stock become significant and negative (at 1% level). This result implies that capital market distortion is significantly associated with innovation input. This supports the finding of Bai and Bian (2016) that capital market distortion is one of the most important dimensions affecting the development of Chinese innovation productivity. Moreover, the significant effects of capital distortion on R&D full time equivalent and R&D researchers from prior regression results are eliminated in GMM models. A possible explanation for the insignificant results on capital distortion may be because both R&D full time equivalent and R&D researchers belong to the labour factor market. For control variables, the influence of total foreign investment on R&D researchers changes from negative to positive and becomes significant as well.

3.3.3 Regression with Exogenous Shock

This section provides the results of regressions under an exogenous shock with created dummy variable *year* to estimate the differences before and after the implementation of the revised China Labour Contract Law. As R&D researchers data is only available from 2009, it is not estimated in this regression.

Table 5. Panel Regression Results with Exogenous Shock

VARIABLES	patent		rdk		rdfull	
ABS_DIST_K	-1,895.244	**	-126.6135	***	-17,460.99	***
	(736.9)		(44.09)		(5,035)	
ABS_DIST_L	-5,443.942	***	-277.317	***	-38,657.28	***
	(507.0)		(30.31)		(3,481)	
year	-1,277.231		-178.514		-27,758.75	*
	(2,158)		(129.5)		(14,455)	
yearabsdistk	-615.875		15.45938		10,806.13	*
	(886.5)		(53.21)		(5,951)	
yearabsdistl	3,798.623	***	232.0367	***	27,608.12	***
	(527.4)		(31.70)		(3,516)	
foreigninvest	0.0584285	***	0.0033549	***	0.2520671	***
	(0.00550)		(0.000330)		(0.0367)	
tech	0.0011636	***	0.0001319	***	0.0063204	***
	(0.000106)		(6.32e-06)		(0.000720)	
cablelength	0.1831611	***	0.0117677	***	1.495009	***
	(0.0420)		(0.00250)		(0.299)	
Constant	9,266.904	***	576.0059	***	104,282.2	***
	(2,266)		(135.0)		(15,963)	
Observations	510		510		510	
NO. of provinces	30		30		30	

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

The results of the exogenous shock (the revised China Labour Contract Law) are presented in Table 5. In Row (1) of Table 5, capital distortion has a negative influence on the number of patents, R&D capital stock, and R&D full time equivalent. Capital distortion negatively drives both innovation input and innovation output. These findings provide further support for the main findings detailed in Section 3.3.1. These results also add support to Dai and Liu (2016) who demonstrate that an increase in innovation performance in high-tech industries is significantly barred by factor misallocation, and this negative effect is particularly critical in regions with relatively lower innovation performance. Significant effects of labour distortion are reported in Row (2) of Table 5, which imply that the higher the degree of distortion in the labour market, the greater the number of patent losses, the greater the reduction in innovative capital stock, and the greater the lack of innovative human capital. This is consistent with Li et al. (2017) who find negative effects of labour distortion on both innovation input and innovation output. The dummy variable *year* is only significant in Column (3) at the 10% level. This weak evidence shows that there might be negative outcomes for R&D full time equivalent after the revised law.

Rows (4) to (5) of Table 5 display the interaction effects of capital distortion and labour distortion with the year dummy. The only significant and positive coefficient of yearabsdistk × rdfull is found at the 10% level, which indicates that the revised law mitigates the effect of capital distortion on R&D full time equivalent, even though the overall impact is still negative. The coefficient of yearabsdistl × patent, yearabsdistl × rdk, and yearabsdistl × rdfull are significantly positive at the 1% level. These findings demonstrate that implementation of the revised China Labour Contract Law has moderated the severe and negative influence of labour distortions on innovation inputs and outputs. More precisely, the negative effects of labour distortion on the number of patents have been mitigated; however, the effects of capital distortion have worsened. Similarly, the significant positive effects of control variables (foreigninvest, tech, and cablelength) on innovation remain unchanged from the panel regression results from GLS.

3.4 Conclusion

This chapter presents the empirical investigation of the relationship between capital and labour distortion on provincial-level innovation in thirty provinces in China during the period 2000 - 2017. We first conduct panel regression with province and year fixed effects; number of patents, R&D capital stock, R&D full time equivalent, and R&D researchers as dependent variables; and factor market misallocation as the independent variable. The findings reveal that factor market misallocation has a strong impact on provincial-level innovation activities. Moreover, the empirical results demonstrate that capital and labour distortion have a negative influence on innovation input and outputs. Using a natural experiment with an exogenous shock, we demonstrate that the influence of labour distortion on innovation is moderated after the implementation of the revised China Labour Contract Law. Our findings imply that the measurements for factor misallocation – capital distortion and labour distortion - are significantly and negatively correlated to innovation.

Chapter 4: Conclusion

This chapter summarises the key empirical results of this thesis and directions for future research. The main purpose of this thesis is to examine whether and how capital distortion and labour distortion influence innovation activities in China. Province-level data is manually collected from the China Statistical Yearbook and the China Statistical Yearbook on Science and Technology (www.stats.gov.cn) published by the National Bureau of Statistics. Innovation output is measured as the number of patents and innovation input is measured as R&D capital stock, R&D full time equivalent, and R&D researchers.

GLS regression is used to examine the influence of both capital distortion and labour distortion. The results demonstrate that: (1) both capital and labour distortion have significantly negative impacts on innovation output; (2) R&D capital stock is significantly and negatively influenced by both capital and labour distortions; and (3) only distortion in labour markets has a significantly negative impact on R&D labour input. Our results indicate that following the implementation of the revised China Labour Contract Law, the influence of labour distortion on innovation has been significantly mitigated, though not eradicated. However, the impact of capital distortion on innovation has not been as significantly alleviated.

In line with increasing consideration of endogeneity problems in accounting and finance research (Gippel et al., 2015), this study also controls for potential endogeneity using instrument variables with system GMM. In addition, a natural experiment is conducted using the revised China Labour Contract Law (2008) to further control for endogeneity. The results are robust to these additional specifications.

This thesis addresses issues of labour distortion, capital distortion, and the effects of these two types of distortions on innovation in China using a province-level study.

There are other related issues that are beyond the scope of the current study and are therefore not addressed in this thesis. First, this thesis mainly focuses on province-level data and only thirty provinces are included. Compared with the number of cities in China, the usage of city-level data would provide more comprehensive understanding of labour and capital distortion. For example, Song (2001) uses a city-level sample in the year of 1997, indicating that larger cities are more likely to have lower unemployment rates; in turn, job creation is associated with urban size (Song and Honglin Zhang, 2002).

Second, in the area of innovation there is a significant amount of work yet to be accomplished. As one of the earliest publications to investigate the induced innovation theory, Lichtenberg (1986) examines whether large increases in the prices of energy and other intermediate materials have effects on the amount of R&D in United States manufacturing firms. Lichtenberg (1986) provides empirical evidence that the growth rate of innovation expenditure is induced by increases in energy prices. Further research considering energy factors could be undertaken in order to investigate their impact on innovation activities.

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Appendix

Appendix A. Citation details for publications used in bibliographic mapping

Rank	Author	Journal	LCS	GCS
1	Zhang YQ (2000)	Issues and Studies	0	2
2	Narayan PK (2007)	Review of Development Economics	0	4
3	Knight J (2008)	Economics of Transition	1	43
4	Zhou YY (2008)	China Quarterly	0	6
5	Hsieh CT (2009)	Quarterly Journal of Economics	11	685
6	Banerjee AV (2010)	American Economics Journal: Macroeconomics	5	43
7	Song Z (2011)	American Economics Review	5	227
8	Kung JKS (2011)	Economic History Review	0	2
9	Ding S (2011)	Oxford Bulletin of Economics and Statistics	0	18
10	Wang SY (2011)	American Economics Review	0	40
11	Peng T (2011)	Work Employment and Society	0	10
12	Brandt L (2012)	Journal of Development Economics	4	286
13	Fu YM (2012)	Regional Science and Urban Economics	1	44
14	Su XM (2012)	Energy Economics	0	18
15	Restuccia D (2013)	Review of Economics Dynamic	5	81
16	Brandt L (2013)	Review of Economics Dynamic	5	59
17	Ke YJ (2013)	International Public Management Journal	0	15
18	Wu Q (2014)	Discrete Dynamics in Nature and Society	0	1
19	Jiang YQ (2014)	Emerging Markets Finance and Trade	0	0
20	Choi SYP (2015)	Human Relations	0	13
21	Li YH (2015)	Growth and Change	0	7
22	Bai PW (2016)	Applied Economics	0	1
23	Gong G (2016)	Economics Letters	0	3
24	Wei X (2016)	Economics Letters	0	2
25	Liu AB (2016)	Past and Present	0	0
26	Wang XB (2016)	Agricultural Economics	0	10
27	Long ZM (2016)	China Economic Review	0	5
28	Xu W (2016)	China Review - An Interdisciplinary Journal on Greater China	0	2
29	Zhang Q (2016)	Journal of Rural Studies	0	5
30	Zhao HR (2016)	Energies	0	9
31	Zhao LQ (2017)	Applied Economics	0	1
32	Huang ZH (2017)	Cities	1	11
33	Li HC (2017)	Journal of Macroeconomics	1	2
34	Wu GL (2018)	Journal of Development Economics	0	1
35	DiTomaso N (2018)	Management and Organization Review	0	3
36	Han HY (2018)	China and World Economy	0	1
37	Wu JX (2018)	China and World Economy	0	0
38	Liu ZQ (2018)	China Economic Review	0	0
39	Holz CA (2018)	China Economic Review	0	0
40	Jin LQ (2018)	Sustainability	0	0

41	Yu M (2019)	Children and Youth Services Review	0	0
42	Wang S (2019)	China Economic Review	0	0
43	Feng SZ (2019)	Economic Inquiry	0	0
44	Chu XX (2019)	Sustainability	0	0
45	Luo SK (2019)	Emerging Markets Finance and Trade	0	0

Appendix B. Details of average distortions in each province

Province	DIST_K	DIST_L	Province	DIST_K	DIST_L
Beijing	2.2355	0.0654	Henan	2.9444	0.2642
Tianjin	2.2898	0.3072	Hubei	2.8599	0.3442
Hebei	1.9475	0.5297	Hunan	3.0133	0.3228
Shanxi	2.6156	0.1163	Guangdong	3.1141	0.2939
Neimenggu	2.1817	0.3581	Guangxi	2.7523	0.2714
Liaoning	2.5019	0.405	Hainan	2.6325	0.2332
Jilin	2.2316	0.3224	Chongqing	2.0249	0.2636
Heilongjiang	3.9738	0.2311	Sichuan	2.3888	0.2985
Shanghai	2.7823	0.2762	Guizhou	2.1773	0.139
Jiangsu	2.3091	0.5099	Yunnan	2.3468	0.2228
Zhejiang	2.0061	0.3770	Shaanxi	2.1094	0.1661
Anhui	2.5093	0.3439	Gansu	2.341	0.1524
Fujian	3.0945	0.3379	Qinghai	1.5458	0.2237
Jiangxi	2.6257	0.2769	Ningxia	1.3327	0.1709
Shandong	2.3793	0.4757	Xinjiang	2.1074	0.1635

Appendix C. Results of Generalized Methods of Moments (GMM) Model

VARIABLES	patent		rdk		rdfull		rdresearcher	
ABS_DIST_K	-12735.74***	-8,407.458***	-266.6855***	-230.7106***	-44,504***	-10,102.68	-21,408.92***	-1,767.661
	(1,249)	(1,198)	(65.48)	(59.41)	(8,162)	(8,052)	(4,685)	(4,252)
ABS_DIST_L	-13,869.03***	-9,652.945***	-684.7756***	-358.35***	-89,666***	-59,857.47***	-30,627.12***	-18,766.3***
	(652.3)	(621.4)	(34.39)	(31.03)	(4,261)	(4,155)	(2,315)	(2,055)
foreigninvest	-	0.0721955***	-	0.0045267***	-	0.4473591***	-	0.0278368***
		(0.00253)		(0.000128)		(0.0170)		(0.00867)
tech	-	0.0011301***	-	0.0001335***	-	0.0104497***	-	0.0066728***
		(4.51e-05)		(2.09e-06)		(0.000289)		(0.000172)
cablelength	-	0.1889279***	-	0.0046009***	-	2.553224***	-	2.2569***
		(0.0195)		(0.000936)		(0.170)		(0.124)
Constant	13,659.57***	3826.902***	1,055.678***	329.1193***	89,837.04***	-17518.17**	-41,498.66	-64111.23***
	(720.9)		(37.99)		(4,720)		(3,206)	
Observations	510	510	510	510	510	510	270	270
No. of Provinces	30	30	30	30	30	30	30	30

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