Lund University

School of Management and Economics

Department of Economics

Master Thesis

August 2015

LUND UNIVERSITY

Research on Technology Spillover Effects on Agricultural Productivity in China

Author: Shujun Wang (890824-T386)

Supervisor: Professor Sonja Opper

Abstract

Technology contributes to the modern economic development directly and indirectly, and it changes the operating system and working method during the economic transformation. Along with institutional reform and modern economic structural transformation of China, agriculture still plays an ineradicable role in the development of Chinese economy, and it is the cornerstone for countries with large population.

In this paper, the main purpose is to study how technology spillover effects work on agricultural productivity. In order to solve this question, I focus on two aspects, the one is from R&D perspective， and the other is the improvement of actual agricultural production techniques. This paper investigates the question by empirical analysis, and I collect panel data from three statistical yearbooks of China. The datasets consist of annul data from 1992 to 2013 and cross-sectional data of 30 regions of China, the statistical package Eviews will be employed to generate empirical results.

There are four models in my paper, the first three models are set to study the puzzle directly based on the hypotheses, and the last one is a modified model after some necessary tests. The results show that technology has different spillover effects on agricultural productivity in different aspects, even though some variables are insignificant in explaining the model.

Key Words: technology, spillover effects, agricultural productivity, China

Acknowledgement

I would like to thank my parents for their financial support and great confidence in me all through these years.

I would like to express my deepest gratitude to my supervisor Professor Sonja Opper, for her endless patience, constant encouragement and invaluable help.

Shujun Wang

August 2015

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1. Introduction

1.1 Research Background

The institutional reforming of Chinese economy experienced two turning points. Before the Chinese economic reform, China went through a long period of imbalanced economic development and the whole country struggled with poverty and starvation. The first turning point is in 1978, Deng Xiaoping advocated the reform and opening-up policy, which increased the total factor productivity, and in turn accelerated the growth of the Chinese economy. In 1992, Deng Xiaoping's southern tour became the second turning point that re-emphasized the reform section of the economic development, and clarified the relationship between socialism and a market economy. As a result for agricultural industry, the compound annual growth rate of gross product of agriculture from 1951 to 1977 is approximately 4.1%, whereas the annual growth rate from 1978 to 1991 is around 14.54%[1].

The 1978 economic reform began with releasing the constraint of agricultural growth by giving rural household the right to use land, which motivated more and more farmers to devote more time and energy to the agricultural industry and improved the production of agriculture, and this policy named as "the household contract responsibility system". This policy in turn increased the scarcity of land, but the gross product of agriculture keeps increasing, and I thus suspect that the technology might generate spillover effects on agriculture that increase agricultural productivity.

Technological development brought a bunch of effects to wide fields of industries, and the agricultural industry is not an exception. For developing countries, the

[1] From China Statistical Year Book, the gross product of agriculture for year 1952, 1977, 1978, 1991 are 46.1, 125.3, 139.7 and 815.7 billion Yuan respectively. And the compound annual growth rate (CAGR) can be calculated as: $CAGR(t_o, t_n) = \left(\frac{V(t_n)}{V(t_0)}\right)^{\frac{1}{t_n - t_0}} - 1$, where $V(t_n)$ is the end value and $V(t_0)$ is the start value, and $t_n - t_0$ expresses the number of years.

adoption of new technology is one of the major sources to improve productivity and a main factor in determining capital investment prospects in agriculture (Johnson and Evenson 2000). Thus, the impacts generated by technology on agriculture are worth investigating, and the pathway how it works is valuable to explore.

The production of agriculture has been increased for decades, whilst the acreage of cultivated land was decreasing and keeping the redline policy of 18 million acres arable land[2], and the proportion of the rural population to the whole population is also declining year after year. With the development of China's agriculture, one of the biggest countries in the world can support the most population in the world (Naughton 2007).

It brings out an interesting question that how the largest population country in the world feed its people with limited cultivated land and insufficient farmers? What drives China's agriculture transfer from a low-productivity and traditional one to a high-productivity and modern one? What contribute to improve China's agricultural productivity? Under these circumstances, I have reason to put technology into account and study the relationship between agricultural growth and technological development, then find out whether technology generate positive effects on agricultural growth and how it works through these years.

1.2 Research Question

The research question of this paper is: *How technology spillover effects functioning on agricultural productivity?*

Through over 30 years reform in China, agriculture has been benefit from technology development in all aspects, which can be seen as technology spillover effects on

[2] In 2006，the Sate Council of China regulated the 18 million acres arable land in the National Land Use Planning Outline (2006-2020).

agricultural productivity. Because of agricultural firms rarely have R&D activities on their own, agricultural sector usually plays the role of spill-ins, which means taken R&D spillovers from other sectors, such as public sector and industrial sector (Johnson and Evenson 1999). Based on this characteristic, agriculture always affects by other industries on technology issue. The research question mainly focus on whether technology has spillover effects on agricultural productivity, and to what extent technology spillover effect work on agricultural productivity.

1.3 Methodology

Quantitative research method will be used in this thesis to get empirical results from data collection and analysis. According to current studies of spillover effects on agriculture, in order to study the technology transfer, R&D, and productivity, I assume to use a production function that similar with the value-added Cobb-Douglas production function $Y_{it} = A_{it}C_{it}^{\alpha}L_{it}^{\beta}$, where α and β are the output elasticity of capital and labour, and A is the total factor productivity parameter, which is driven by R&D, technology transfer, and industry and ownership characteristics (Hu et al. 2005). Hence, the original model used in my thesis is a multiplicative equation, in which technological factors are the independent variables and the total value of agricultural productivity is the dependent variable.

The data are chosen from China Statistical Yearbook, Rural Statistical Yearbook of China and China Statistical Yearbook on Science and Technology. In order to explore how technology spillover effects on the agricultural productivity, on the one hand, the data should represent agricultural productivity, technological factors invested into agriculture and techniques relevant to agricultural production. On the other hand, time series need to be taken into consideration to guarantee the process of transformation of technologies functioning on agricultural productivity. So, I prefer to choose the data from the point when China began to undertake economic reforms to the year of latest updates data offered by National Bureau of Statistics of China.

However, because of immature of data collection measures and lagged economic development in rural area, to some extent, it exists unreliability of data in Chinese statistical yearbook. Moreover, some data are not contained in the yearbook in the early years. The reasons for this might be in the beginning of economic reforms, the statistical bureau explored the right way to do the statistical work and made statistical services more accurate. After all, even though there might have some unreliability of the data from the yearbook, the statistical yearbooks are still the most authoritative statistic data resources in China, and it covers most integrated data across the whole country.

1.4 Limitations

In this paper, the limitations are mainly located in the data collection part which just as mentioned in the previous section. Even though I collect data from the three statistical yearbooks, it is still exist deficiency of data. On the one hand, the technology spillover effects relate to a wide range of elements, such as patents, higher education institutions, the number of adoption of advanced techniques and so on. And the data of some factors are incomplete, and it is difficult to get the missing data from other channels. On the other hand, the data trustworthy problem is also need to be taken seriously, the three yearbooks I employed might exist problems of inappropriate ways of collecting data initially, so some data might end up with partial inaccuracy. Another limitation should be noticed is that technology spillover effects may contain various factors, which means that it is difficult to test all the possible variables, so that the analysis cannot be totally comprehensive to some extent.

1.5 Thesis Outline

This thesis includes five sections, besides the first introduction section, the following chapter introduces research background and theoretical framework, which contains background, theoretical foundation, previous studies about the theory, and the hypotheses of this research. The next two chapters are the most import part in the thesis. Chapter three explains the empirical studies, and the main task of this chapter is to set up empirical models, and the corresponding dataset and variables. Chapter four is the analyses and results of empirical studies, which gives detailed illustrations of model estimation results. The final part of the thesis presents the discussion and conclusion, and it sums up the pivotal findings of the empirical research; meanwhile, it proposes potential improvements to the future researches that related to the area of technology spillover effects on agricultural.

2. Research Background and Theoretical Framework

2.1 Background of Agriculture in China

Since 1978, agriculture in China has experienced a series of radical changes, and successfully transferred to modern agriculture by building comprehensive agricultural market, adopting advanced technology in agricultural productive process and introducing informative agricultural management system. The gradual reforms across the whole country started with agricultural household system reform, which totally changed the land system and brought a bunch of institutional changes in agriculture.

Institution and Policies Change

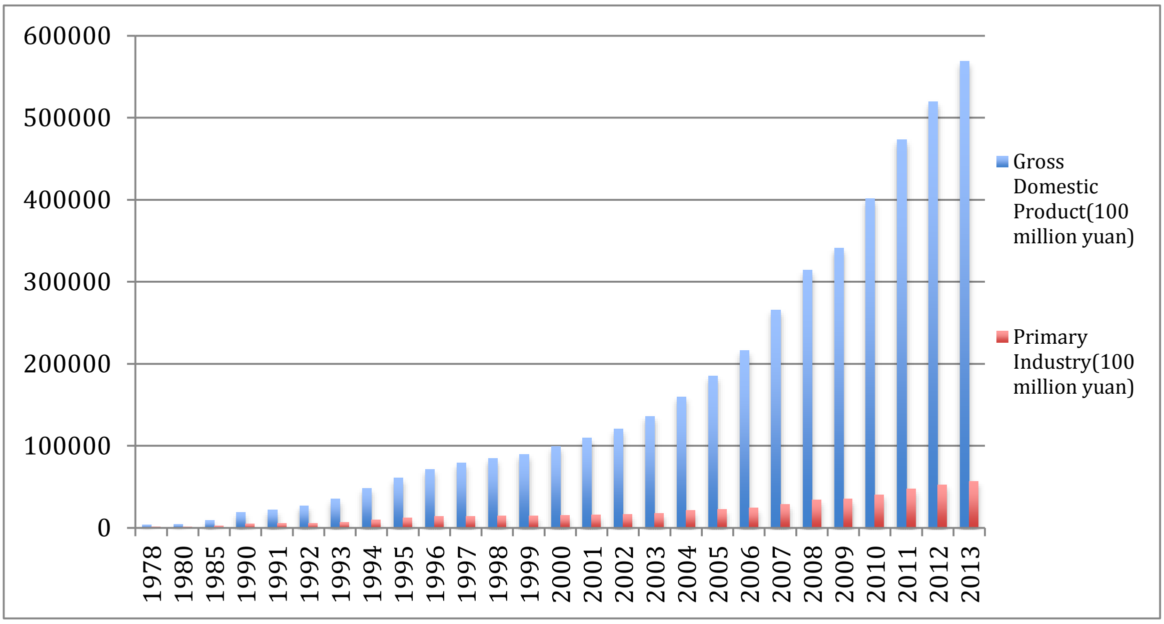
Without doubt, institution change was the foundation of the overall reform and stimulated the subsequent reforms. Introduction of household responsibility system is the first step of reforms, of which aim is to change the property rights of land in rural China. Before reforms, agricultural collectives were the dominant rural institution with the main characteristics that farmers all worked commonly and the land was pooled, and the basic accounting unit was collective and households gained their payments according to points (credits) from the collectives (Naughton 2007: 234-236). The collectives resulted in consequence that farmers in the collectives were lacking of incentives to work hard and the yields of agriculture were dissatisfactory, which totally violated the original intention of this institution—"Grain First".

Individual household responsibility system began from Anhui province and explosively spread to the whole country in a short term and finally established as a national institution in the agricultural sector. Contracts signed by households enhanced the rights of land and motivated tenants to optimize the level of investment to the land (Brandt et al. 2002). Until 1985, the transformation of household responsibility system had almost finished, and the full implementation of the rural household contract responsibility system went across the whole country. There were

569 production teams and 18387.9 households completed this household contract responsibility system reform, which account for 100 percent to the whole production teams and 97.9 percent to the whole households in rural area respectively. This property right shift affected the way that cultivated land used and grain productivity through securing the use right of land for farmers and reallocating the resources. The institution switches from the production team system to household responsibility system optimized the marginal return of efforts and increased the ratio of supply to response of each worker; moreover, it generated positive effect on agricultural production (Lin 1988).

One of the most significant impacts brought by household responsibility reform was emancipation of agricultural labor that bounded to land for a long period. Even though the existence of hukou registration system (household registration system) hampered labor freely mobile from rural area to urban area, the *litu bu lixiang* strategy made farmers depart from the farmland to devote to non-agricultural activities in rural area (Kwan 2009). The free labor expansion was a notable reaction of property rights change, and an unexpected and incredible reason contributed to China's miracle. After 1978, the gross domestic products of primary industry was increasing from 1027.5 (100 million yuan) in 1978 to 56957 (100 million yuan) in 2013, and the gross domestic products was also rising through these years in a even larger extent, from 3645.2 (100 million yuan) in 1978 to 568845.2 (100 million yuan) in 2013, just as Figure 2.1 shows. However, the ratio of gross domestic products of primary industry to gross domestic products was dropping progressively. Even though at the beginning of the economic reform, the ratio was increased a little bit from 28.2 percent in 1978 to 33.4 percent in 1982, then fell down continuously in next decades and reached 10 percent in 2013.

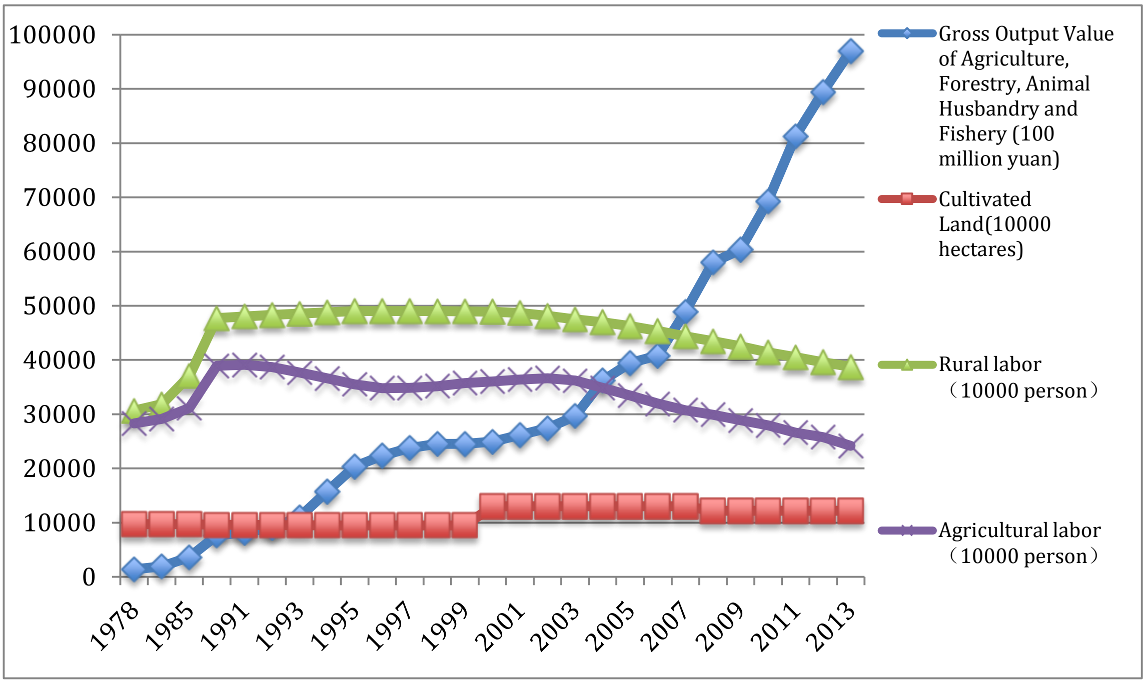
Figure 2.1 GDP and Primary Industry GDP



Data Source: China Statistical Yearbook 2014.

Besides to gross domestic products changes, another important influence brought by household responsibility system was mobility of rural labor. Rural labor can be divided as agricultural labor that people who invest in agricultural activities, and non-agricultural labor that people who live in rural area but work for non-agricultural industry. And rural labor and agricultural labor were changed correspondingly, and the ratio of agricultural labor to rural labor was reducing since 1978, from 92 percent to 62 percent in 2013. This 30-percent drop of agricultural labor to rural labor proves that there is a decreasing tendency of agricultural labor, which means there is less rural labor invested in agricultural activities. In the following figure, there are four main elements show agricultural conditions since 1978. Besides rural labor and agricultural labor, the gross output value of agriculture, forestry, animal husbandry and fishery has been climbing since 1978, from 1397 (100 million yuan) to 96995.3 (100 million yuan), whilst, the cultivated land has stayed in a relatively stable condition and keeps 12.8 percentage to total area after 2008. With less cultivated land and agricultural labor investment, the gross output of the whole agricultural industry still grow fast with large total amount, it reflects that the improvement of efficiency of agricultural productivity. It drives an interesting question, what makes this efficiency increase? The gross product of agriculture cannot keep a constant growth rate without the development of advanced technology; in contrast, technology is the primary productive force and pushes agricultural industry development in the reform times in China.

Figure 2.2 Main Features of Agriculture in China since 1978

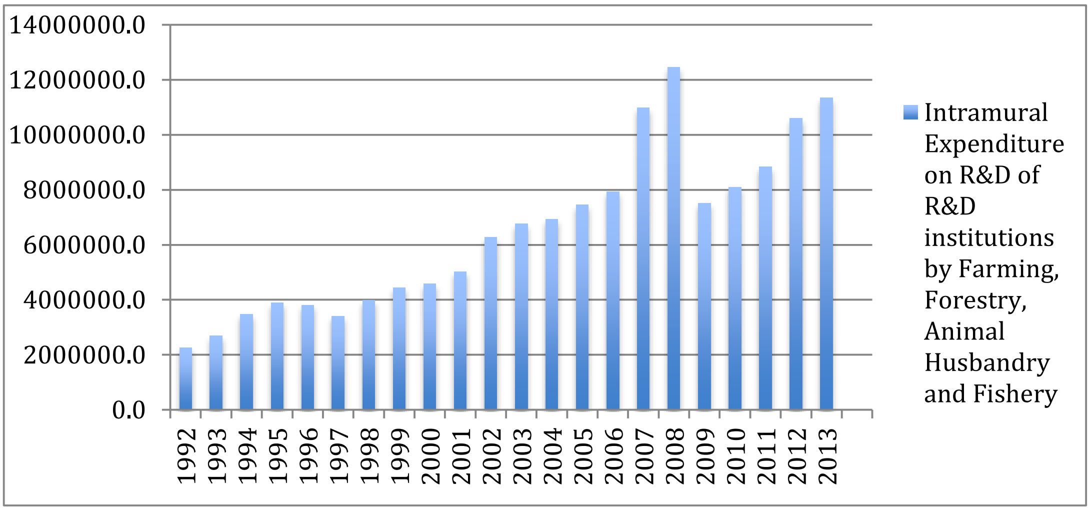


Data Source: China Statistical Yearbook 2014, Rural Statistical Yearbook of China 2014.

Technological Development

Agricultural scientific services contain various of kinds, such as agricultural scientific research and innovation on cultivation of improved varieties, research on new technology and variety, application of new varieties and technology and spread agricultural technology to households, and all these agricultural investment and increase agricultural production and farmers' income and rural prosperity (Lei 2013). To support the agricultural productivity, a comprehensive network of agricultural research stations was built to augment efficiency of land-use and modify cultivated techniques to intensify land yields (Naughton 2007). Intramural expenditure on R&D of R&D institutions by farming, forestry, animal husbandry and fishery has been increasing for decades, from 22560.79 (1000 yuan) to 11347350 (1000 yuan), peaked at 12466630 (1000 yuan) in 2008. This tendency shows that R&D institutions paid much more attention on agricultural research and development, as Figure 2.3 shows.

Figure 2.3 Intramural Expenditure on R&D of R&D institutions by Farming, Forestry, Animal Husbandry and Fishery



Data Source: China Statistical Yearbook on Science and Technology 1993 to 2013.

The number of agricultural patents was rising in the last two decades, grew up by 35 times since 1985, from almost none of patent applications increased to nearly 18,000 in 2009 that consists of both domestic part and foreign part, and the former one performing better than the latter one during the patent boom in these years. This situation represents that increase number of agricultural patents and technological development attributed to domestic agricultural research and innovation (Liu et al. 2014). The number of application and granted of new variety of agriculture plants was calculated from 1999, but the China statistical yearbook on science and technology did not exhibit statistic data each year. From 2010 China statistical yearbook on science and technology, I can illustrate that there were 6541 applications and 2807 granted of new variety rights of agriculture plants from 1999 to 2009, and this number is rising year by year. From 2009 to 2013, the statistic number of application of new variety rights of agriculture plants in total were 978, 1206, 1255, 1361, 1333, and the number of granted of new variety rights of agriculture plants were 666, 244, 163, and 138. This phenomenon shows that development of agricultural high technology and innovation stepped into a new period, and more novel inventions were brought to agricultural production to improve productive efficiency and expand variety of agricultural products.

2.2 Spillover Theory

Spillover theory is widely used in all fields, and there are different types of spillover effects in each scientific domain. There are a variety of different couples of spillovers in different fields, such as external and internal spillovers, shock and policy induced spillovers, direct and indirect spillovers, positive and negative spillovers (Weyerstrass et al. 2006). Specifically, in economics, there are three major kinds of spillovers always named as knowledge spillovers, market spillovers and network spillovers (Jaffe 1996). Spillover effect has already become one of the most significant factors in economic development and cannot be neglected in the process of production. Three main types of R&D spillovers to agriculture are direct and indirect spillovers, spatial or locational spillovers and sectorial or industrial spillovers (Johnson and Evenson 1999). The spillover effects (sometimes called externalities) are impacts of economic activities on economic actors (society, businesses, and government) who are not directly undertaking the activities. In general, technology spillover effects can be classified into two categories: one is adoption of new technological knowledge to produce more advanced goods by improving labour productivity; the other is to create new ideas and apply new inventions in research and development (R&D). In the case of innovation and the development of technology, spillovers occur when actors who are not directly involved in the activities are affected by the activities, and the effects reflected in their behaviour and economic actions (knowledge spillovers) (Medhurst et al. 2014). Due to spillover effects can be classified as different types in different circumstances, spillover effects in this paper is the one mainly applied in economic field and the spillover effect theory is also put more focuses on technology spillover effects to agriculture, then drive two hypotheses which point out two different but equally important aspects of technology spillover effects on agriculture.

Technology Spillover Effects to Agriculture

Facing the crucial fact that population doubled from three billion to six billion since 1960, how to accelerate production and improve the efficiency of productivity is a heated issue during a couple of decades. From 1960s, scholars began to study on factors relevant to agricultural productivity, and the main elements they considered were public investments like infrastructure, input qualities, educational investment on agricultural workforce, and technology contributions on agricultural R&D (Alston 2002). The study of technology generated spillover effects on agriculture had a long history that can be tracked back to mid-twenty century, when T. W. Schultz (1954) calculated total factor productivity growth as an index for American agriculture, and estimated the technological change saved resources and compared it to the total public investments in agricultural research, finally found it was a good investment (Griliches 1991). In order to convert poverty in the rural area, China seeks for efficient ways to improve agricultural productivity and increase households' income. Since entered the 21st century, an increasing number of farmers as adopters began to adopt more techniques to improve productivity, such as upland rice technologies that raise the productivity from 38% to 53% during 2002 to 2004, whilst, non-adopters did not benefit from the advanced technologies, had smaller production and lower share of land of those adopters. Furthermore, the gross income of non-adopters was much lower than the adopters, which means whether adoption of technology during the process of production is one reason contribute to poverty, and to some extent, technology generated effects on agricultural productivity (Wu 2010). From an empirical case in China, a SHASEA (Sustainable Highland Agriculture in S.E. Asia) project hold by EU (European Union) conducted in Yunnan Province, included a range of technologies such as polythene mulching, straw mulching, irrigation, contour cultivation, inter-cropping, use of grass strips, and tree planting techniques, for all of them functioned differently and really brought comprehensive effects to improve agricultural productivity, and after the project, there are markedly achievements like improvement of environment in experimental village, meanwhile, increase crop production with reducing soil erosion (Subedi et al. 2009).

Another facet of technology that cannot be totally ignored is knowledge spillovers. Technology developed with knowledge booming, and technological harvest based on a wide application of knowledge in all fields around the world. The knowledge spillovers play a significant role in supplying the sources of innovation and connecting universities with agricultural firms by offering new knowledge and skills (Laborda et al. 2011). In knowledge-economy times, economic growth is not only about increasing amount of goods production and services, but also improving the efficiency of producing a booming range of goods and services. Promoting productivity by capital and labor accumulation with an adoption of new and better technologies is an attractive and functional way to develop the agricultural economy. Knowledge stimulation function to economic growth is not fresh anymore, whilst knowledge combined with information technology, which known as ICT (Information and communication technology), is a new element push economic development (Dahlman 2002). Knowledge is an abstract object that hardly can be detected in empirical studies so that scholars tried to find some available standard or variables to discover spillover effects generated by knowledge in economic growth process. The patent, a testable variable represents knowledge development degree to large extent, has been used as the equivalent statistic measure to study R&D input and output. Taking patents' specialization and variation into account, domestic patent applications, patent grants and external patent applications are considered as part of R&D expenditure (Nadiri 1993).

The R&D spillovers on productivity in agriculture, especially effects brought by the technologies of the rice production, was an engine of agricultural growth. For instance, the hybrid rice adoption rise yields of rice across China, even after this technology become commercial and poured into market, the degree of adoption this technique varied from different regions, which lead to different level of productivity of rice, and this strongly proved that technology spillovers can result in improvement of agricultural productivity (Huang and Rozelle 1996). Generally speaking, R&D spillovers are a main source of endogenous growth and also treated as externalities before, while in some fresh research, conscious economic investment bring technological change that lead to social returns (Griliches 1991). Besides China, technology spillover effects also influenced other developing area, like Africa, where lagged behind the rest of the world, has benefited from the technology and enjoyed the fruitful outcomes brought by technology. Even though Africa still has a large gap with other developing countries, not to mention developed countries, it absorbs foreign technology spillovers during the process of development with mainly embodied in patent adoption and R&D investment (Johnson and Evenson 2000). Thus, technology spillover effects on agriculture and productivity can be observed in a variety of aspects, which illustrate that technology spillovers do make great function on agricultural productivity throughout decades of years.

2.3 Hypotheses

Apparently, the technology spillover effects are the main source to push productivity growth in the long-run term. And R&D is an important indicator to explain productivity through public R&D and private R&D investment in the process of production (Guellec et al. 2004). In one aspect, knowledge is one of output of R&D, and this output of R&D activity is uncertain because of its non-excludability and non-competitiveness, so government use patents to regulate and protect R&D output to stimulate the private R&D investment (Miles and Scott 2005). Thus, patents can be treated as an indicator of R&D activity. Public R&D funding has positive effects on patent outcome, and R&D is the prerequisite of technological progress (Czarnitzki and Hussinger 2004). R&D expenditure has positively direct and indirect effects on patents according to different regions based on their innovation activities (Moussa and Laurent 2015). R&D effects on some region depend on the active degree of regional innovation activities. Thus R&D spillovers need some medium to function on industry and firm. The R&D, as a component of total factor productivity (TFP), can be used as spillovers from domestic and foreign, public and private in agricultural sector, and the stock of knowledge rather than the R&D expenditures provides spillover measures of agricultural productivity, and the exact way to calculate the stocks is consisting of stocks of knowledge retrospect to 5 or more years before current time, with different ratios of each lag weights (Johnson and Evenson 1999). The R&D performance is a significant factor from technological progress in determining productivity.

Hypothesis 1: R&D (research and development) has positive spillovers on agricultural productivity.

The common measures to study agricultural productivity are land (hectares), labor (employed persons), machinery and chemical fertilizer, which are treated as the major input of agricultural productivity (Kalirajan et al. 1996). Agricultural technologies contributed to agricultural output in all kinds of improved techniques, including chemical fertilizer, high-yielding varieties, weedicides and pesticides, and utility of machinery, and etc. (Jain et al. 2009). For example, the model of spillover effects within industry can be expressed as $Y_i = BX_i^{1-\gamma}K_i^{\gamma}K_a^{\mu}$, in which Y_i represents the *i*th firm and X_i, K_i, K_a stand for the level of conventional inputs, specific knowledge capital and aggregate knowledge in the industry (Griliches 1991). China's agricultural techniques are invented by research system and then adopted by farmers to invest in agricultural production and improved the yields of agricultural grains through decades of years. The total factor productivity (TFP) is an important index showing main agricultural grains in China across regions and years, and its change including transformation in technology, institutions, infrastructure and improvements to human capital (Jin et al. 2002). The increasing input on agricultural infrastructure, such as irrigation system, water-saving technology and climate condition test system, contributed to agricultural productivity, and more effective agricultural technology extension and transformation through construction of farming practices (Shen et al. 2013). Thus, improvement of agricultural techniques needs to be considered as one of the technology spillovers on agricultural productivity.

Hypothesis 2: Improvement of techniques has positive spillover effects on agricultural productivity.

3. Empirical Studies

3.1 Data

3.1.1 Dataset

The dataset of dependent variable is gross output value of agriculture, forestry, animal husbandry and fishery (100 million yuan) from 1992 to 2013 and covers 30 provinces, municipalities and autonomous regions[3], which chosen from Rural Statistical Yearbook of China.

The data about R&D effects are chosen from China Statistical Yearbook on Science and Technology and China Statistical Yearbook. For the sake of studying technology spillovers on agriculture, I choose to use panel data to solve the puzzle, and the data are chosen from 1992 to 2013, mainly concern about R&D expenditure (1000 yuan) and personnel (person), and patents granted (piece) in 30 provinces of mainland China. The year 1992 is a turning point of China economic reform, and Deng Xiaoping had southern tour, which pushed China's economic reform to a new phase, a period with much deeper and far-reaching reform and establishment of socialist market economy institution. After year 1992, China stepped into a more open and profound and lasting economic development phase, with faster development of agriculture and technology. Hence, I choose the year 1992 as the start of collecting data.

Another aspect of my research question is the improvement effects on agricultural productive technique, and the data of this factor are chosen from Rural Statistical Yearbook of China, which introduces agricultural development conditions in detail. The data apply to explain agricultural productive conditions are chosen from 1992 to 2013 and also cover 30 provinces, municipalities and autonomous regions in mainland of China. The first data is total power of agricultural machinery (GW), the second one

[3] The motivation of selecting 30 provinces, municipalities and autonomous regions is introduced in the section 3.1.2 Limitations of Dataset.

is rural electricity consumption (million kilowatt hours), and the last one is consumption of chemical fertilizer (calculated by pure quantity) (10 kilo-tons).

3.1.2 Limitations of Dataset

The critical purpose of the study is to explore how technology effects on agricultural productivity, so from these statistical yearbooks, the chosen data have to reflect the condition of relevant variables, furthermore, to accept or reject the hypotheses mentioned before. These three statistical yearbooks all have deficiencies that hamper the data collecting process.

On the one hand, China has kept a significant developing speed since 1978, the economic reform; and statistical yearbooks also experienced continuous modifying accompanied with the whole society transitions. Some data were accumulated at the beginning of economic reform, but disappear from the statistical yearbooks when entered the 21st century.

On the other hand, Chongqing, the municipality directly under the Central Government, was established on 18th, June of 1997, so all the data of Chongqing are started from 1997. The missing data before 1997 of Chongqing led the data become unbalanced panel data, and this breach of data might result in unreasonable outcomes of regression analysis, and the data only start from 1997, even until 2013, there are just 16 years of it, and we cannot get the balanced dataset to solve the problem in the models. So, for the more logic and reasonable regression analysis, I finally put Chongqing into Sichuan province by adding all data of Chongqing to Sichuan province, and narrow 31 provinces of mainland of China to 30 provinces, since Chongqing was a part of Sichuan Province. The reason why Hong Kong, Macao, and Taiwan are not included in the data set is that these three regions implement different economic institutional systems, which are quite different with the mainland of China.

And they have different system to manage agricultural and technological section during the development process, the data of them are no comparable to other provinces in mainland of China. So the data of Hong Kong, Macao and Taiwan are not considered in my dataset. In this circumstance, all data from different provinces are stay at the same level and can be analysed together to explain research question.

3.2 Model Establishment

The spillover effects of technology on agricultural productivity can be very broadly, and in order to generate a more parsimonious and compact study, I choose to investigate the impact from two perspectives, which corresponding to two hypotheses of this paper, the R&D investment and the improvement of techniques in agricultural production process. Hence, there are two effects in my research, the R&D effects and the improvement effects.

As mentioned in previous section, my empirical model mimics the Cobb-Douglas production function, and the transformed model can be expressed as $Y_{it} = A_{it} X1_{it}^{\beta_1} X2_{it}^{\beta_2} X3_{it}^{\beta_3} X4_{it}^{\beta_4} X5_{it}^{\beta_5} X6_{it}^{\beta_6}$, where three variables ($X1, X2, X3$) are selected from the view of the R&D effects, and three variables ($X4, X5, X6$) are selected to represent the improvement effects. By splitting up the model into two parts, it is possible to test and analyse the two hypotheses or effects separately.

In order to make the variables meaningful, I decide to apply the database normalization method to get the real property of the data without losing much information. The transformed model with normalized factors thus becomes $\frac{Y_{it}}{L_{it}} = A_{it} (\frac{X1_{it}^{\beta_1}}{GRP_{it}})(\frac{X2_{it}^{\beta_2}}{P_{it}})(\frac{X3_{it}^{\beta_3}}{P_{it}})(\frac{X4_{it}^{\beta_4}}{L_{it}})(\frac{X5_{it}^{\beta_5}}{RP_{it}})(\frac{X6_{it}^{\beta_6}}{L_{it}})$, where all the denominators stand for the normalized factors[4]. And by taking the logarithm of the equation, I can transfer the

[4] All the variables (dependent and independent) and normalized factors will be introduced in the section 3.2 Variables.

multiplicative model into additive model, and I can generate a more intuitive explanation with logarithm[5].

The empirical method can be decomposed into three models. For instance, the model with both R&D effects and the improvement effects (Model 1), and its two sub-models are R&D effects model (Model 2), and the improvement effects model (Model 3). Hence, the R&D effects and the improvement effects model in this empirical study can be expressed as:

Model 1:

$$y_{it} = \beta_0 + \beta_1 x1_{it} + \beta_2 x2_{it} + \beta_3 x3_{it} + \beta_4 x4_{it} + \beta_5 x5_{it} + \beta_6 x6_{it} + \lambda_t + \mu_i + v_{it}$$

And the two corresponding effects models are shown as followings:

Model 2: $y_{it} = \beta_0 + \beta_1 x1_{it} + \beta_2 x2_{it} + \beta_3 x3_{it} + \lambda_t + \mu_i + v_{it}$

Model 3: $y_{it} = \beta_0 + \beta_4 x4_{it} + \beta_5 x5_{it} + \beta_6 x6_{it} + \lambda_t + \mu_i + v_{it}$

I employ lowercase letters to denote the log-normalized values, e.g. $y \equiv \ln\left(\frac{Y}{L}\right)$ and $y_{it} \equiv \ln(\frac{Y_{it}}{L_{it}})$. The subscript "$t$" indicates the time period for the models, where T=22 (t=1992…2013) for all three models; the index "i" expresses the 30 regions that consist of provinces，municipalities and autonomous regions[6]. It is worth to notice that the three models also include fixed effects indicators "λ_t" and"μ_i", where "μ_i" is the cross-section effect factor that captures the value of the dummy variables for each region, and "λ_t" explains the period effect for different years.

[5] We can interpret the coefficients of the log-linear equations as elasticity.

[6] For simplicity, I will use “30 regions” as a conclusive term to express 30 provinces，municipalities and autonomous regions in the following text.

3.3 Variables

3.3.1 Dependent Variable

Y: The Actual Agricultural Products (Agricultural Products): The key point in this study is to figure out how technology spillover effects influence on the agricultural productivity. The Gross Output Value of Agriculture, Forestry, Animal Husbandry and Fishery is employed to reflect the agricultural productivity, which calculates exact agricultural products in major elements and was widely used to measure the output of agricultural products (Chen et al. 2008). In order to make this dependent variable more logically and reasonably, I take area of cultivated land into consideration, since the cultivated land area is an important investment factor in agricultural production. Along with the change of cultivated land area, the gross output of agriculture will be changed simultaneously. Hence, the gross output value of agriculture, forestry, animal husbandry and fishery (100 million yuan) will be normalized by total cultivated land area (hectare) in my empirical studies, and this is the normalized dependent variable. By taking the normalization, we can intuitively know the agricultural productivity, and it can be expressed as the gross output value of agricultural production per hectare. The data of cultivated land area are obtained from the Rural Statistic Yearbook of China from 1992 to 2013 of all regions in mainland of China.

3.3.2 Independent Variables

According to two hypotheses, independent variables should represent two aspects, one is the R&D effects, and the other is the actual improvement of productive technique in agricultural production process.

X1: Intramural Expenditure for Research and Development (R&D Expenditure): This independent variable stands for R&D intramural expenditure, which indicates actual expenditure of R&D activities, including service charge, research service fee, scientific management fee, non-infrastructure investment of fixed assets, research infrastructure projects fee and other expenditure of R&D activities of research institutions, firms, universities and colleges and other organizations. However, this expenditure does not contain expenditure of productive activities, returns of loans and other expenditures transferred to other institutions. In short, this expenditure is the actual usage of R&D investment. The R&D expenditure could divided as direct and indirect R&D expenditure, the former one is conducted by industry to increase its own productivity, and the latter one is performed by other industries and affect the productivity of the industry (Meijl 1997). The reason to choose this variable is to consider the effects from capital of research and development, and to test whether practical fee of R&D activities has impact on agricultural productivity. The R&D intensity is the ratio of R&D expenditure to the GDP, is a main indicator to test the degree of investment in generating new knowledge (OECD 2011). Therefore, in my empirical studies, the ratio (or percentage) of R&D expenditure to the gross regional product of each province will be employed. After taking the normalization, we can get the percentage of R&D expenditure rather than the actual number of the expenditure, and measure the first normalized independent variable by the percentage of R&D expenditure to total output for each region. After all, it is not that meaningful to treat the actual amount of R&D expenditure of different regions on the same level of scale. The data of gross regional product are obtained from the China Statistical Yearbook from 1992 to 2013 of all regions in mainland of China.

X2: Research and Development Personnel (R&D Personnel): This variable depicts the labour investment to R&D activities, and usually used as a principle measurement of R&D spillover estimation (Lee 2005). The number of persons who devoted to R&D activities represents people directly engaged in R&D activities, and people who work for management of R&D activities and offering services to that, which embodies the power of human capital investment of research and development. The model 1 and model 2 are using this variable to test whether R&D personnel has effects on agricultural productivity and to what extent it has. Compared with the first independent variable, this variable focus on human capital, and it is one of the components of the investment in research and development. Because the number of R&D personnel will largely depend on the total number of population, I decide to use the total population of each region to normalize R&D personnel. By generating this ratio, we can obtain the percentage of R&D personnel to the total population of each region. Same as the variable of R&D expenditure, it is more useful to apply the normalized variables. The data of the total population of each region are obtained from the China Statistical Yearbook on Science and Technology from 1992 to 2013 of all regions in mainland of China.

X3: The Number of Domestic Patents Granted (Patents Granted): The reason why I choose the number of domestic patents granted is that patents granted by authorities are scientific achievements and can be transferred to practical productivity quickly. The granted patents imply that the inventions are meaningful and worthy in practical productions, and can be applied into factual productive process and making wealth. Patents are a return of R&D investment, and private activities are measured by patent and represent technology transfer (Schimmelpfennig and Thirtle 1999). Similar with the R&D personnel, the increasing number of patents will also be affected by the number of population of each region; for example, a province with large population might have more patents granted. Therefore, the number of population in each region will use to normalize the number of domestic patents granted.

X4: Total Power of Agricultural Machinery (Agricultural Machinery): This variable explains the total power of major agricultural machinery including large and medium-size tractors, small tractors and diesel engines from 30 regions. And the use of power machinery and operating machinery for non-agricultural production such as rural, town, village, group, industrial, basic construction, non-agricultural transportation, scientific experiment and teaching are not included. The change of this variable can reflect the utility of advanced machinery that related to technological development and application in agricultural productive process, and it commonly used to measure the performance of agricultural technical change and agricultural productivity (Jin et al. 2010). The total power of agricultural machinery can be normalized by cultivated land area, e.g. it is more straightforward to interpret the meaning of the increased kilowatt per hectare rather than the increased kilowatt, if we don't clarify the change of area of cultivated land.

X5: Rural Electricity Consumption (Electricity Consumption)： The consumption of electricity in rural area not only concentrates on electricity usage of agricultural production, but also includes rural residents' usage of electricity. Even though living usage of electricity is not that relevant to agricultural production, the electricity consumption in rural area can reflect utility of modern electrical equipment, which can show the level of development of whole rural area, and that can be an indirect effect on agricultural production. The electricity consumption can be used as an indicator to study the total factor productivity (Gutzler et al. 2015). However, we should notice that the rural electricity consumption highly depends on the population of rural area. I thus use the rural population of each region as the normalized factor for rural electricity consumption. The data of the number of rural population of each region are obtained from the Rural Statistic Yearbook of China from 1992 to 2013 of all regions in mainland of China.

X6: Consumption of Chemical Fertilizer (Chemical Fertilizer): This variable refers to the amount of chemical fertilizers used in agricultural production, including the use of nitrogen, phosphorus, potassium and compound fertilizer. It is a variable based on the technological development, and along with chemical technology development, the chemical fertilizer would increase the productivity of agriculture, and this variable is usually used as a measurement to study the agricultural technological improvement and to stimulate total factor productivity of agriculture (Jin et al. 2002). Meanwhile, the amounts of usage of chemical fertilizer should be measured with the one unit of land, which is the hectare. In other word, the cultivated land area will be used as the normalized factor here to normalize the original factor. And this variable can be treated as one of the representatives of technology spillover effects.

There are one explained variable and six independent variables in my model. The descriptive stats of all variables are shown as table 3.1 below. The total observations are 660, and the mean, standard deviation, minimum and maximum values are also calculated.

Table 3.1 Descriptive Statistics of Variables

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Original Variables					
Agricultural Products/Cultivated Land Area	660	40937.92	36168.70	3202.84	246193.08
R&D Expenditure/Gross Regional Products	660	0.02	0.017	0.001	0.12
R&D Personnel/ Population	660	0.003	0.004	0.0002	0.02
Patents Granted/ Population	660	0.0002030	0.0004439	0.0000004	0.0036804
Agricultural Machinery/Cultivated Land Area	660	5816.12	3620.90	1132.66	17738.35
Electricity Consumption/Rural Population	660	746.21	2475.178	7.78	34836.65
Chemical Fertilizer/Cultivated Land Area	660	0.41	0.21	0.07	0.99
Log Variables					
Agricultural Products/Cultivated Land Area	660	10.26	0.88	8.07	12.41
R&D Expenditure/Gross Regional Products	660	-4.30	0.70	-7.20	-2.09
R&D Personnel/ Population	660	-6.16	0.79	-8.39	-3.73
Patents Granted/ Population	660	-9.61	1.40	-14.64	-5.60
Agricultural Machinery/Cultivated Land Area	660	8.48	0.62	7.03	9.78
Electricity Consumption/Rural Population	660	5.58	1.28	2.05	10.46
Chemical Fertilizer/Cultivated Land Area	660	-1.06	0.60	-2.70	-0.01

Note: This table depicts the statistical properties of normalized dependent and independent variable.

4. Empirical Analysis and Results

4.1 Concepts and Terms

Goodness-of-fit (R^2): This statistical measure is used as ratio of explained variation to total variation, and its purpose is to test how close the data to the fitted regression line. The value of R^2 between 0 to 1, and the higher R^2 means greater overall fit of the estimated regression equation to the sample data. However, in general, there is no simple method to determine how high the *R2* should be in actual research.

The Adjusted R^2 ($\bar{R}^2$): $\bar{R}^2$ is a measure that taken degree of freedom into account in determining whether adding a variable will impact the equation estimation. This measure is more commonly used because its unique characteristic that compares the fits of equations with the same explained variable and different number of explanatory variables.

F-Test: The null hypothesis in this test is that all the slope coefficients in the equation equal zero simultaneously. This test measures the overall fit of the estimated equation, and if it is significant, the null hypothesis has to be rejected. The *p*-value of *F*-Test is an alternative approach associated with *F*-Test in determining the overall fit of the estimated equation.

Omitted Variable: The definition of omitted variable is that a significant independent variable that has been left out of the regression equation. The omitted variable bias (specification bias) is known as leaving a variable out of the estimation equation. If the left out variable is very important in explaining the equation, the estimation results of the equation will not be unbiased and minimum variance any longer.

Akaike's Information Criterion (AIC) and Schwarz Criterion (SC): These two methods are used to compare alternative specifications whether adding a variable is good for decreased degrees of freedom and increased complexity caused by the addition. In general, the lower AIC or SC means better specification.

Multicollinearity: The core characteristic of multicollinearity is two or more independent variables are highly correlated, and it is hard to estimate the coefficients of the equation accurately. The main consequences caused by multicollinearity are: a combination of insignificant individual regression coefficients with a high$\bar{R}^2$, which means the overall fit of the equation and the coefficients of non-multicollinearity variables have little effects; addition or deletion of an independent variable will lead to large change of the estimation coefficients; the standard error and variances of the estimation will increase. High sample correlation coefficients and high variance inflation factors can be used to detect the multicollinearity. Increase the sample size or drop redundant variables would be useful to remedy multicollinearity.

Fixed Effects Model: This model is using to estimate panel data model that allowing each cross-sectional unit to have a different intercept. The critical advantage of fixed effects model is that it can prevent biased from omitted variables that do not change over time.

4.2 Model Estimation

The estimation and testing procedure of the models are implemented by the statistical package Eviews. There are basically three cases when I am dealing with panel data, namely pooled regression model, fixed effect model and random effect model. By using the redundant fixed effect tests I reject the pooled regression model, and then Hausman tests are employed to detect whether random effects exist. The results of these two tests and model estimations are shown from Table 4.2.1 to Table 4.4.3 in Appendix. I can illustrate from redundant fixed effects tests that p-value for both cross-section and period tests are statistically significant at the 5% significance level, and I can reject the null hypothesis and eliminate the possibility of pooled regression. Meanwhile, I reject the null hypothesis of random effects of Hausman test at the 5% significance level. In light of the above two tests, I can estimate all three models by fixed effect estimators.

4.3 Empirical Results

Model 1

The estimation of model 1 is shown in Table 4.2.3 LS regression results of model 1. The LS regression results clearly exhibiting the influences generated from independent variables to dependent variables, and showing the explanatory power of each independent variable.

For model 1, from the estimation result (under 5% significance level), we can tell that except for variables $x1$ (ln(X1/GRP): R&D Expenditure/Gross Regional Products), $x3$ (ln(X3/P): Patents Granted/Population) and $x5$ (ln(X5/RP): Electricity Consumption/Rural Population), the three other variables in this model are statistically significant at the 5% significance level (the p-value of $x1$, $x3$ and $x5$ are 0.6214, 0.0868 and 0.596 respectively), which indicates independent variables that present improvement effects show significant impacts on explaining the agricultural productivity. The adjusted R-square is around 0.9822, which means this model captures approximately 98% of the variation of dependent variable around its mean, and this percentage is adjusted for degrees of freedom. In other word, the estimation regression of model 1 has strong goodness-of-fit. Meanwhile, we can see that the p-value of F-statistic is statistically significant at the 5% significant level. Overall, the joint explanatory power of all variables is significant.

From the second variable, research and development personnel, has significant effect on dependent variable (the p-value is 0.0396), and the coefficient is -0.04983, which means when 1% increases of research and development personnel, the gross output value of agriculture, forestry, animal husbandry and fishery will change negative approximately 0.05%. The estimation results of the second variable shows significant negative effect on agricultural productivity, and combined with $x1$ and $x3$, we might suspect the first hypothesis of positive spillover effects. And the above results also motivate me to divide model 1 into two sub-models, namely model 2 and model 3, and it is thus possible to test two hypotheses independently.

The rest variables of this model present the improvement of technology in agricultural production process. The fourth independent variable is the total power of agricultural machinery, and it is significant to explain the agricultural productivity, the p-value is extremely significant at the 5% significance level. The coefficient is 0.1312 that means 1% increase in total power of agricultural will lead to 0.13% increase in agricultural productivity.

The last independent variable is the consumption of chemical fertilizer, which has great significance on explaining dependent variable, and has relatively higher positive impact on dependent variable than other independent variables, the coefficient of this variable is around 0.5345, which illustrates that 1% increase of the consumption of chemical fertilizer brings 0.53% increase of gross output value of agriculture, forestry, animal husbandry and fishery.

Model 2

As mentioned above, since the estimation results of model 1 are not coinciding with the first hypothesis, it is necessary to test the two hypotheses independently. The model 2 is established to test the R&D effects (the first hypothesis). According to the estimation results on Table 4.3.3, I can tell that this model is also has strong goodness-of-fit because of high value of adjusted R-square equals 0.9713. And the p-value of F-statistic is also significance at the 5% significance level.

Two of three independent variables in this model are statistically insignificant, e.g. the p-value of $x1$ (ln(X1/GRP): R&D Expenditure/Gross Regional Products), and $x2$ (ln(X2/P): R&D Personnel/Population) are 0.0658 and 0.6890. The last variable $x3$ (ln(X3/P): Patents Granted/Population) is significant under 5% significance level, whereas this variable generates a negative effect on the agricultural productivity, for example, 1% increase of domestic patents granted leads to 0.08% decrease on the gross output value of agriculture, forestry, animal husbandry and fishery.

Model 3

The model 3 is illustrated on Table 4.4.3, and it demonstrates the improvement effects that is the second hypothesis. The goodness-of-fit of this model is also strong because of high value of adjusted R-square equals 0.9818. When it comes to specific variables in the model, there is also one independent variable $x5$(ln(X5/RP): Electricity Consumption/Rural Population) is insignificant (with p-value=0.608) under the 5% significance level, which means it has insignificant explanatory power of the model.

The rest two variables are significant and have different effect level to dependent variable. For example, the p-value of both $x4$ (ln(X4/L): Agricultural Machinery/Cultivated Land Area) and $x6$ (ln(X6/L): Chemical Fertilizer/Cultivated Land Area) are extremely significance at the 5% significance level. The estimated coefficient for $x4$ (ln(X4/L): Agricultural Machinery/Cultivated Land Area) is 0.1192, which indicates 0.12 increase of gross output value of agriculture, forestry, animal husbandry and fishery is caused by 1% increase of total power of agricultural machinery. The estimated coefficient of the consumption of chemical fertilizer in agricultural production process is 0.5529, which means 1% increase of consumption of chemical fertilizer will generate 0.55% increase of gross output value of agriculture, forestry, animal husbandry and fishery, and the impact is positive and relatively large.

By comparing the SC (Schwarz criterion) value, we can see the model 3 generates the smallest SC value; meanwhile, model 3 has the highest value of F-statistic. So far, the model 3 is considered as the most preferred model among all models. I might not reject the second hypothesis of improvement of techniques has positive spillover effects on agricultural productivity. However, the model 3 is not strong enough to make the second hypothesis hold unless I test the model specification.

Model 4

To deal with high level of insignificant in model 3, it is common to suspect the potential possibilities of existence of the multicollinearity. Firstly, I apply the very common method, namely the variance inflation factors (VIF). Based on common rule of thumb, when VIF is larger than 5, we consider the multicollinearity is serve. The basic of this indicator is higher VIF implies higher variance of the estimated coefficient, which equivalent to smaller t-statistic and higher p-value. In one word, higher VIF indicates higher severity of multicollinearity. From Table 4.5.1, the VIFs for model 3 are all much higher than 5, which indicate the sever multicollinearity. Meanwhile, the $x5$ (ln(X5/RP): Electricity Consumption/Rural Population) has insignificant positive impacts on the productivity of agriculture, I thus suspect the $x5$ is the redundant variable and take the redundant variable test. The results of redundant variable test can be shown in Table 4.5.2, and the p-value of the test is statistically insignificant, I can then drop the redundant variable $x5$.

In light of my second hypothesis, the rural electricity consumption is one of the components of the improvement of the techniques has positive spillover effects on agricultural productivity. In order to test this hypothesis completely, I modify the model 3 (without $x5$) by adding the quadratic term of $x5$ and to test whether this non-linear model performs better. I thus employ the omitted variables test, and the testing result is exhibited in Table 4.5.3. From the results we can see the p-value is a 0.0165, which is significant at the 5% significance level, and I can conclude that the quadratic term of $x5$ should be included in model 3 (without $x5$).

We can eventually derive a non-linear model from the model 3, and I denote this non-linear the improvement effects model as model 4, and it can be expressed as

Model 4: $y_{it} = \beta_0 + \beta_2 x4_{it} + \beta_4 x6_{it} + \beta_3 x5_{it}^2 + \lambda_t + \mu_i + \upsilon_{it}$

Similar with the previous three models, the model 4 should be estimated by fixed effect model. The redundant fixed effects tests and Hausman tests are applied, and from the testing results in Table 4.6.1 and Table 4.6.2. I can conclude that fixed effect model is selected at the 5% significance level just as previous cases.

The model 4 is improved from the basic model 3, and it is aimed to remedy for the model misspecification. Based on the estimation results in Table 4.6.3, we can see that the non-linear improvement effect model still captures the variations in a higher level, e.g. the non-linear model yield similar level of goodness-of-fit. More specifically, all the variables are statistically significant at the 5% significance level; the $x6$ (ln(X6/L): Chemical Fertilizer/Cultivated Land Area) generates the highest coefficients, which shows the consumption of chemical fertilizer effects the agricultural productivity more than another two variables. The impact of $x4$ (ln(X4/L): Agricultural Machinery/Cultivated Land Area) to agricultural productivity increased slightly compared with model 3. It is worth to mention that the quadratic term of $x5$ (ln(X5/RP): Electricity Consumption/Rural Population), $x5^2$ has some small impacts on the agricultural productivity, for instance, 1% increase in the quadratic term of rural electricity consumption will lead to 0.0024% increase of agricultural productivity.

Additionally, model 4 also generates the highest F-value that indicates highest level of overall performance of the model. Meanwhile, the Schwarz Criterion (SC) or Akaike information criterion (AIC) is smaller than other three models[7], which indicates the nonlinear improvement effect model is the optimal model among all models. And we

[7] In my empirical studies, the Schwarz Criterion (SC) is more preferable than the Akaike information criterion (AIC). Since we have relatively large sample, and SC gives more punishment for large sample.

cannot reject the second hypothesis of improvement of techniques has positive spillover effects on agricultural productivity. The estimation results of four models are shown as following table. It is worth to notice that Table 4.7 to Table 4.10 are the fixed effects matrices for model 1 to model 4, which consist of both cross-sectional effects and period (annual data) effects. From Table 4.7 to Table 4.10, I can tell that the effects to a specific region and a specific year, e.g. the fixed effect for Beijing in year 1992 from model 1 (Table 4.7) are -0.188.

Table 4.1 Regression Models of Technology Spillover Effects on Agricultural Productivity

Independent Variables	Model 1	Model 2	Model 3	Model 4
Intercept	8.94***	9.19***	9.79***	9.64***
	(0.34)	(0.18)	(0.26)	(0.26)
Log (*R&D Expenditure/Gross Regional Products)*	-0.01	-0.04*		
	(0.02)	(0.02)		
Log (*R&D Personnel/Population)*	-0.05**	-0.01		
	(0.02)	(0.03)		
Log (*Patents Granted/Population)*	-0.03*	-0.08***		
	(0.02)	(0.02)		
Log (*Agricultural Machinery/Cultivated Land Area)*	0.13***		0.12***	0.13***
	(0.03)		(0.03)	(0.03)
Log (*Electricity Consumption/Rural Population)*	0.03*		0.01	
	(0.02)		(0.02)	
Log (*Chemical Fertilizer/Cultivated Land Area)*	0.53***		0.55***	0.56***
	(0.03)		(0.03)	(0.03)
Quadratic of Log *(Electricity Consumption/Rural Population)*				0.002**
				(0.001)
Fixed Effects (cross-sectional & period effect)	Table 4.7	Table 4.8	Table 4.9	Table 4.10
R^2	0.98	0.97	0.98	0.98
$\overline{R}^2$	0.98	0.97	0.98	0.98
AIC	-1.37	-0.89	-1.35	-1.36
SC	-0.98	-0.53	-0.98	-0.99
F	650.18	421.89	672.31	678.53
p-value	0	0	0	0

NOTE: Coefficients of beta are in the first row, standard errors are in parenthesis. Asterisks *, **, and *** represent the 10%, 5% and 1% significant level respectively. Table 4.7, Table 4.8, Table 4.9, and Table 4.10 are showing in the Appendix.

5. Conclusion and Discussion

5.1 Conclusion

From the empirical studies above, I find that R&D has insignificant negative relationship with agricultural productivity, so I have to reject the first hypothesis. While, the improvement of techniques has significant positive spillover effects on agricultural productivity, so the second hypothesis is accepted. The analysis of the first hypothesis illustrates that only R&D personnel has significant effect on agricultural productivity but a negative one, and the other two variables: R&D intramural expenditure and number of granted patents, have little significance power even negative with agricultural productivity in model 1, and the first two variables have insignificant negative effects on the dependent variable and the left one variable has significant negative effects on the dependent variable in model 2. The second hypothesis is supported by the results of empirical analysis, with two variables significant and one insignificant in model 3 and three significant variables (including a quadratic term of $x5$) in model 4, and all variables have positive coefficients. All three elements: agricultural machinery, rural electricity consumption and use of chemical fertilizer, are positive with agricultural productivity, which means that improvement of techniques, such as machinery, electricity equipment and chemical fertilizer have positive effects on agricultural productivity, especially the first and the last factors, who have relatively high significant positive spillovers on agricultural productivity.

Because of the difficulty on getting access to exact classification of R&D intramural expenditure and clarifying the details of R&D intramural expenditure, I hardly can draw a clear picture of how R&D intramural expenditure use and how much of it spend on agricultural industry. So the R&D intramural expenditure and personnel used in this paper are the general ones contain all industries. Moreover, the number of patents is a variable related to R&D and also cannot separate patents on agriculture from other industries. Thus, from the empirical results, I can conclude that R&D has little and negative spillovers on agricultural productivity. The reasons might draw on public R&D spending is mainly concern about industry sector and business sector, and financed R&D is used to affect the behavior of firms (Czarnitzki and Hussinger 2004). In this circumstance, R&D contribution to the growth of China's agriculture sector is small, but technological contribution to agricultural productivity can be coordinated with labor, capital and energy by changing the agricultural development model (Lin and Fei 2015). The R&D spillover effects on agricultural productivity could be an indirect one because the outcomes of R&D need to be transferred to real productivity, and it takes a long period and complicated procedure. And the negative and insignificant effects from R&D to agricultural productivity also shows that R&D is not the most effective way to increase agricultural productivity, so investment of R&D might not result in great improvement of agricultural productivity.

Compared with R&D, improvement of techniques does have significant positive spillovers on agricultural productivity, from where I can conclude that spillover effects from the direct techniques improvements on agricultural productivity are significant and positive. The improvements of productive techniques directly affect agricultural productivity through productive process and can be lead to straight increase of agricultural productivity, e.g. the improvement of agricultural machinery and widely use of agricultural machines can increase the output of agriculture and improve agricultural productivity. Thus, focusing on improving advanced techniques of agricultural production is better than putting much on R&D in stimulating agricultural productivity.

5.2 Discussion

The previous research paid more attention on technology spillovers in firm-level (Eden et al. 1997, Skully and Rakotoarisoa 2013, etc.) and from FDI (Cheung and Lin

2003, Fan 2002, etc.), and most technology spillover effects are studies within industry sector (Xia and Liu 2011, Hu et al. 2005, etc.), there are few research is totally focusing on technology spillover effects on agricultural productivity. In addition, technology spillover effects to agriculture are mainly about technology (knowledge) transformation (Laborda et al. 2011, Nadiri 1993, Huang and Rozelle 1996, etc.) and agricultural R&D investment (Alston 2002, Griliches 1991, Wu 2010, etc.), few studies are exploring the R&D spillovers and improvement of techniques spillovers. So, this paper supplement a scope of technology spillover effects by studying R&D effects and improvement techniques effects on agricultural productivity in China. And the empirical findings give an interesting and fresh result that R&D has insignificant negative effects on agricultural productivity.

Based on empirical results, the implications for policy are that government could put more investment on agricultural productive techniques rather than R&D, since the former one is more efficient and can generate much more positive spillover effects on agricultural productivity to promote agricultural growth. And in China, both central government and local government are intend to strengthen agriculture as foundation of all industries and guarantee its sustainable growth. Technology is an irreplaceable factor in promoting agriculture sustainable development and keep it growing in an effective way. R&D investment is a pathway to encourage the second industry than the primary industry, and there are not enough R&D achievements transferred into real productivity in agricultural sector. Contrarily, if more advanced techniques invest in agricultural productive process, it would be easier to improve agricultural productivity and ensure agricultural continuous growth. Thus, it might be better to put more investment in improving productive techniques than enhancing R&D to promote agriculture productivity.

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7. Appendix

Table 4.2.1 Redundant Fixed Effects Tests of Model 1

Effects Test	Statistic	d.f.	Prob.
Cross-section F	145.3513	-29,603	0.0000
Cross-section Chi-square	1371.636	29	0.0000
Period F	55.29563	-21,603	0.0000
Period Chi-square	708.5365	21	0.0000
Cross-Section/Period F	116.4974	-50,603	0.0000
Cross-Section/Period Chi-square	1561.877	50	0.0000

Table 4.2.2 Correlated Random Effects - Hausman Test of Model 1

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	36.68443	6	0.0000
Period random	308.0919	6	0.0000

Table 4.2.3 LS Regression Results of Model 1

Dependent Variable: LNY				
Method: Panel Least Squares				
Sample: 1992 2013				
Periods included: 22				
Cross-sections included: 30				
Total panel (balanced) observations: 660				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.943805	0.337152	26.52748	0.0000
LNX1	-0.00919	0.018588	-0.49419	0.6214
LNX2	-0.04983	0.024165	-2.0621	0.0396
LNX3	-0.02631	0.015338	-1.7154	0.0868
LNX4	0.131206	0.026834	4.889581	0.0000
LNX5	0.030569	0.016195	1.887553	0.0596
LNX6	0.534477	0.034721	15.39363	0.0000
Effects Specification				
Cross-section fixed (dummy variables)				
Period fixed (dummy variables)				
R-squared	0.983709	Mean dependent var	10.25845	
Adjusted R-squared	0.982196	S.D. dependent var	0.879003	
S.E. of regression	0.117288	Akaike info criterion	-1.365958	
Sum squared resid	8.2952	Schwarz criterion	-0.977992	
Log likelihood	507.7663	Hannan-Quinn criter.	-1.215581	
F-statistic	650.182	Durbin-Watson stat	0.513253	
Prob(F-statistic)	0.0000			

Table 4.3.1 Redundant Fixed Effects Tests of Model 2

Effects Test	Statistic	d.f.	Prob.
Cross-section F	260.0623	-29,606	0.0000
Cross-section Chi-square	1715.092	29	0.0000
Period F	123.2187	-21,606	0.0000
Period Chi-square	1096.934	21	0.0000
Cross-Section/Period F	182.574	-50,606	0.0000
Cross-Section/Period Chi-square	1832.538	50	0.0000

Table 4.3.2 Correlated Random Effects - Hausman Test of Model 2

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	49.51709	3	0.0000
Period random	206.8563	3	0.0000

Table 4.3.3 LS Regression Results of Model 2

Dependent Variable: LNY				
Method: Panel Least Squares				
Sample: 1992 2013				
Periods included: 22				
Cross-sections included: 30				
Total panel (balanced) observations: 660				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.189951	0.177291	51.83539	0.0000
LNX1	-0.04323	0.023459	-1.84289	0.0658
LNX2	-0.012	0.029954	-0.40043	0.6890
LNX3	-0.0842	0.018836	-4.47035	0.0000
Effects Specification				
Cross-section fixed (dummy variables)				
Period fixed (dummy variables)				
R-squared	0.973613		Mean dependent var	10.25845
Adjusted R-squared	0.971306		S.D. dependent var	0.879003
S.E. of regression	0.148898		Akaike info criterion	-0.89283
Sum squared resid	13.43543		Schwarz criterion	-0.52528
Log likelihood	348.6343		Hannan-Quinn criter.	-0.75037
F-statistic	421.8886		Durbin-Watson stat	0.431533
Prob(F-statistic)	0.0000			

Table 4.4.1 Redundant Fixed Effects Tests of Model 3

Effects Test	Statistic	d.f.	Prob.
Cross-section F	170.0188	-29,606	0.0000
Cross-section Chi-square	1460.082	29	0.0000
Period F	65.51505	-21,606	0.0000
Period Chi-square	782.0267	21	0.0000
Cross-Section/Period F	177.7558	-50,606	0.0000
Cross-Section/Period Chi-square	1815.999	50	0.0000

Table 4.4.2 Correlated Random Effects - Hausman Test of Model 3

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	11.74609	3	0.0083
Period random	326.1795	3	0.0000

Table 4.4.3 LS Regression Results of Model 3

Dependent Variable: LNY				
Method: Panel Least Squares				
Sample: 1992 2013				
Periods included: 22				
Cross-sections included: 30				
Total panel (balanced) observations: 660				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.790489	0.263242	37.19193	0.0000
LNX4	0.119231	0.026936	4.426414	0.0000
LNX5	0.007861	0.015317	0.513221	0.6080
LNX6	0.552897	0.03434	16.10069	0.0000
Effects Specification				
Cross-section fixed (dummy variables)				
Period fixed (dummy variables)				
R-squared	0.983277		Mean dependent var	10.25845
Adjusted R-squared	0.981815		S.D. dependent var	0.879003
S.E. of regression	0.118535		Akaike info criterion	-1.34894
Sum squared resid	8.514668		Schwarz criterion	-0.98139
Log likelihood	499.1489		Hannan-Quinn criter.	-1.20647
F-statistic	672.3126		Durbin-Watson stat	0.498009
Prob(F-statistic)	0.0000			

Table 4.5.1 VIF Testing for Multicollinearity of Model 3

Variable	Coefficient Variance	VIF
LNX4	0.000726	13.01829
LNX5	0.000235	18.0138
LNX6	0.001179	20.14586

Table 4.5.2 Redundant Variables Test of Model 3

Specification: LNY C LNX4 LNX6 LNX5			
Redundant Variables: LNX5			
	Value	df	Probability
t-statistic	0.513221	606	0.608
F-statistic	0.263395	(1, 606)	0.608
Likelihood ratio	0.286804	1	0.5923

Table 4.5.3 Omitted Variables Test of Model 3

Specification: LNY C LNX4 LNX6			
Omitted Variables: (LNX5)^2			
	Value	df	Probability
t-statistic	2.403762	606	0.0165
F-statistic	5.77807	(1, 606)	0.0165
Likelihood ratio	6.263136	1	0.0123

Table 4.6.1 Redundant Fixed Effects Tests of Model 4

Effects Test	Statistic	d.f.	Prob.
Cross-section F	163.7667	-29,606	0.0000
Cross-section Chi-square	1438.107	29	0.0000
Period F	70.19587	-21,606	0.0000
Period Chi-square	813.9765	21	0.0000
Cross-Section/Period F	169.4337	-50,606	0.0000
Cross-Section/Period Chi-square	1786.418	50	0.0000

Table 4.6.2 Correlated Random Effects - Hausman Test of Model 4

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	10.056	3	0.0181
Period random	257.6797	3	0.0000

Table 4.6.3 LS Regression Results of Model 4

Dependent Variable: LNY				
Method: Panel Least Squares				
Sample: 1992 2013				
Periods included: 22				
Cross-sections included: 30				
Total panel (balanced) observations: 660				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.638378	0.256757	37.53896	0.0000
LNX4	0.134358	0.027547	4.877459	0.0000
(LNX5)^2	0.002443	0.001017	2.403762	0.0165
LNX6	0.564498	0.033812	16.69529	0.0000
Effects Specification				
Cross-section fixed (dummy variables)				
Period fixed (dummy variables)				
R-squared	0.983428	Mean dependent var		10.25845
Adjusted R-squared	0.981979	S.D. dependent var		0.879003
S.E. of regression	0.118	Akaike info criterion		-1.35799
Sum squared resid	8.437915	Schwarz criterion		-0.99044
Log likelihood	502.1371	Hannan-Quinn criter.		-1.21553
F-statistic	678.5321	Durbin-Watson stat		0.511087
Prob(F-statistic)	0.0000			

Table 4.7 Fixed Effects of Model 1

	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Beijing	-0.188	-0.023	0.279	0.477	0.553	0.575	0.559	0.452	0.482	0.508	0.546	0.624	0.753	0.815	0.860	0.997	1.148	1.152	1.279	1.425	1.511	1.589
Tianjin	-0.669	-0.505	-0.202	-0.004	0.072	0.094	0.078	-0.029	0.001	0.027	0.064	0.143	0.271	0.334	0.379	0.515	0.667	0.670	0.798	0.944	1.030	1.108
Hebei	-1.132	-0.968	-0.665	-0.468	-0.392	-0.370	-0.386	-0.493	-0.463	-0.437	-0.399	-0.321	-0.192	-0.130	-0.084	0.052	0.203	0.207	0.334	0.480	0.566	0.645
Shanxi	-1.665	-1.501	-1.198	-1.001	-0.925	-0.903	-0.919	-1.026	-0.996	-0.969	-0.932	-0.854	-0.725	-0.663	-0.617	-0.481	-0.329	-0.326	-0.199	-0.053	0.033	0.112
Inner Mongolia	-1.327	-1.163	-0.860	-0.663	-0.587	-0.565	-0.581	-0.688	-0.658	-0.632	-0.594	-0.516	-0.387	-0.325	-0.279	-0.143	0.008	0.012	0.139	0.285	0.371	0.450
Liaoning	-0.607	-0.443	-0.140	0.058	0.133	0.155	0.139	0.032	0.062	0.089	0.126	0.204	0.333	0.395	0.441	0.577	0.729	0.732	0.859	1.005	1.092	1.170
Jilin	-1.176	-1.012	-0.709	-0.512	-0.436	-0.414	-0.430	-0.537	-0.507	-0.480	-0.443	-0.365	-0.236	-0.174	-0.128	0.008	0.160	0.163	0.290	0.436	0.523	0.601
Heilongjiang	-1.313	-1.149	-0.846	-0.648	-0.572	-0.550	-0.566	-0.673	-0.643	-0.617	-0.580	-0.501	-0.373	-0.311	-0.265	-0.129	0.023	0.026	0.154	0.299	0.386	0.464
Shanghai	-0.134	0.031	0.333	0.531	0.607	0.629	0.613	0.506	0.536	0.562	0.600	0.678	0.807	0.869	0.914	1.051	1.202	1.206	1.333	1.479	1.565	1.643
Jiangsu	-0.767	-0.603	-0.300	-0.103	-0.027	-0.005	-0.021	-0.128	-0.098	-0.071	-0.034	0.044	0.173	0.235	0.281	0.417	0.569	0.572	0.699	0.845	0.931	1.010
Zhejiang	-0.371	-0.207	0.096	0.294	0.370	0.392	0.376	0.269	0.299	0.325	0.362	0.440	0.569	0.631	0.677	0.813	0.965	0.968	1.095	1.241	1.328	1.406
Anhui	-1.182	-1.018	-0.715	-0.518	-0.442	-0.420	-0.436	-0.543	-0.513	-0.487	-0.449	-0.371	-0.242	-0.180	-0.134	0.002	0.153	0.157	0.284	0.430	0.516	0.595
Fujian	-0.326	-0.161	0.141	0.339	0.415	0.437	0.421	0.314	0.344	0.370	0.408	0.486	0.615	0.677	0.722	0.859	1.010	1.013	1.141	1.287	1.373	1.451
Jiangxi	-0.857	-0.693	-0.390	-0.193	-0.117	-0.095	-0.111	-0.218	-0.188	-0.161	-0.124	-0.046	0.083	0.145	0.191	0.327	0.479	0.482	0.609	0.755	0.841	0.920
Shandong	-0.898	-0.734	-0.431	-0.234	-0.158	-0.136	-0.152	-0.259	-0.229	-0.203	-0.165	-0.087	0.042	0.104	0.150	0.286	0.437	0.441	0.568	0.714	0.800	0.879
Henan	-1.188	-1.024	-0.721	-0.524	-0.448	-0.426	-0.442	-0.549	-0.519	-0.493	-0.455	-0.377	-0.248	-0.186	-0.141	-0.004	0.147	0.151	0.278	0.424	0.510	0.588
Hubei	-0.960	-0.796	-0.493	-0.295	-0.219	-0.197	-0.213	-0.320	-0.290	-0.264	-0.227	-0.148	-0.020	0.042	0.088	0.224	0.376	0.379	0.507	0.652	0.739	0.817
Hunan	-0.717	-0.553	-0.250	-0.052	0.024	0.046	0.030	-0.077	-0.047	-0.021	0.016	0.095	0.223	0.285	0.331	0.467	0.619	0.622	0.750	0.895	0.982	1.060
Guangdong	-0.385	-0.221	0.082	0.279	0.355	0.377	0.361	0.254	0.284	0.311	0.348	0.426	0.555	0.617	0.663	0.799	0.951	0.954	1.081	1.227	1.313	1.392
Guangxi	-0.967	-0.803	-0.500	-0.302	-0.226	-0.204	-0.221	-0.327	-0.297	-0.271	-0.234	-0.156	-0.027	0.035	0.081	0.217	0.369	0.372	0.499	0.645	0.732	0.810
Hainan	-0.353	-0.189	0.114	0.312	0.387	0.409	0.393	0.286	0.316	0.343	0.380	0.458	0.587	0.649	0.695	0.831	0.983	0.986	1.113	1.259	1.346	1.424
Sichuan	-0.768	-0.604	-0.301	-0.104	-0.028	-0.006	-0.022	-0.129	-0.099	-0.072	-0.035	0.043	0.172	0.234	0.280	0.416	0.568	0.571	0.698	0.844	0.930	1.009
Guizhou	-1.224	-1.060	-0.757	-0.559	-0.483	-0.461	-0.477	-0.584	-0.554	-0.528	-0.491	-0.413	-0.284	-0.222	-0.176	-0.040	0.112	0.115	0.243	0.388	0.475	0.553

Yunnan	-1.206	-1.042	-0.739	-0.542	-0.466	-0.444	-0.460	-0.567	-0.537	-0.510	-0.473	-0.395	-0.266	-0.204	-0.158	-0.022	0.130	0.133	0.260	0.406	0.493	0.571
Tibet	-0.809	-0.644	-0.342	-0.144	-0.068	-0.046	-0.062	-0.169	-0.139	-0.113	-0.075	0.003	0.131	0.194	0.239	0.376	0.527	0.530	0.658	0.804	0.890	0.968
Shaanxi	-1.383	-1.219	-0.916	-0.718	-0.642	-0.620	-0.636	-0.743	-0.713	-0.687	-0.650	-0.571	-0.443	-0.380	-0.335	-0.199	-0.047	-0.044	0.084	0.230	0.316	0.394
Gansu	-1.440	-1.276	-0.973	-0.775	-0.700	-0.677	-0.694	-0.801	-0.771	-0.744	-0.707	-0.629	-0.500	-0.438	-0.392	-0.256	-0.104	-0.101	0.026	0.172	0.259	0.337
Qinghai	-1.049	-0.885	-0.582	-0.385	-0.309	-0.287	-0.303	-0.410	-0.380	-0.353	-0.316	-0.238	-0.109	-0.047	-0.001	0.135	0.287	0.290	0.417	0.563	0.649	0.728
Ningxia	-1.699	-1.535	-1.232	-1.035	-0.959	-0.937	-0.953	-1.060	-1.030	-1.003	-0.966	-0.888	-0.759	-0.697	-0.651	-0.515	-0.363	-0.360	-0.233	-0.087	-0.001	0.078
Xinjiang	-1.191	-1.027	-0.724	-0.526	-0.450	-0.428	-0.445	-0.551	-0.521	-0.495	-0.458	-0.380	-0.251	-0.189	-0.143	-0.007	0.145	0.148	0.275	0.421	0.508	0.586

Table 4.8 Fixed Effects of Model 2

	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Beijing	-0.019	0.222	0.540	0.795	0.916	0.969	1.003	0.717	0.762	0.810	0.863	0.976	1.150	1.241	1.336	1.572	1.754	1.805	1.966	2.140	2.259	2.360
Tianjin	-0.649	-0.408	-0.090	0.165	0.286	0.339	0.373	0.087	0.132	0.180	0.233	0.346	0.520	0.611	0.706	0.942	1.124	1.175	1.337	1.510	1.629	1.730
Hebei	-1.198	-0.957	-0.639	-0.384	-0.262	-0.209	-0.176	-0.462	-0.417	-0.369	-0.315	-0.203	-0.029	0.062	0.157	0.393	0.575	0.627	0.788	0.961	1.080	1.182
Shanxi	-2.207	-1.966	-1.648	-1.393	-1.272	-1.219	-1.185	-1.471	-1.426	-1.378	-1.325	-1.212	-1.038	-0.947	-0.852	-0.616	-0.434	-0.383	-0.221	-0.048	0.071	0.172
Inner Mongolia	-2.238	-1.998	-1.680	-1.425	-1.303	-1.250	-1.217	-1.503	-1.458	-1.410	-1.356	-1.244	-1.069	-0.979	-0.883	-0.648	-0.466	-0.414	-0.253	-0.080	0.039	0.141
Liaoning	-0.917	-0.676	-0.359	-0.103	0.018	0.071	0.104	-0.182	-0.137	-0.089	-0.035	0.078	0.252	0.343	0.438	0.674	0.856	0.907	1.068	1.242	1.361	1.462
Jilin	-1.695	-1.454	-1.136	-0.881	-0.760	-0.707	-0.673	-0.959	-0.914	-0.866	-0.813	-0.700	-0.526	-0.435	-0.340	-0.104	0.078	0.129	0.291	0.464	0.583	0.684
Heilongjiang	-2.226	-1.986	-1.668	-1.413	-1.291	-1.238	-1.205	-1.491	-1.446	-1.398	-1.344	-1.232	-1.057	-0.967	-0.871	-0.636	-0.454	-0.402	-0.241	-0.068	0.051	0.153
Shanghai	-0.013	0.228	0.546	0.801	0.922	0.975	1.009	0.723	0.768	0.816	0.869	0.982	1.156	1.247	1.342	1.578	1.760	1.811	1.972	2.146	2.265	2.366
Jiangsu	-0.558	-0.318	0.000	0.255	0.377	0.430	0.463	0.177	0.222	0.270	0.324	0.436	0.611	0.701	0.797	1.032	1.214	1.266	1.427	1.600	1.719	1.821
Zhejiang	-0.237	0.004	0.322	0.577	0.698	0.751	0.785	0.499	0.544	0.591	0.645	0.758	0.932	1.023	1.118	1.354	1.536	1.587	1.748	1.922	2.041	2.142
Anhui	-1.270	-1.029	-0.711	-0.456	-0.335	-0.282	-0.248	-0.534	-0.489	-0.442	-0.388	-0.275	-0.101	-0.010	0.085	0.321	0.503	0.554	0.715	0.889	1.008	1.109
Fujian	-0.014	0.226	0.544	0.799	0.921	0.974	1.007	0.721	0.766	0.814	0.868	0.981	1.155	1.246	1.341	1.577	1.758	1.810	1.971	2.144	2.264	2.365
Jiangxi	-1.043	-0.802	-0.484	-0.229	-0.107	-0.054	-0.021	-0.307	-0.262	-0.214	-0.161	-0.048	0.126	0.217	0.312	0.548	0.730	0.782	0.943	1.116	1.235	1.337
Shandong	-0.762	-0.522	-0.204	0.051	0.173	0.226	0.259	-0.027	0.018	0.066	0.120	0.232	0.407	0.497	0.593	0.828	1.010	1.062	1.223	1.396	1.515	1.617
Henan	-1.133	-0.892	-0.574	-0.319	-0.198	-0.145	-0.111	-0.397	-0.352	-0.304	-0.251	-0.138	0.036	0.127	0.222	0.458	0.640	0.691	0.853	1.026	1.145	1.246
Hubei	-0.937	-0.696	-0.379	-0.123	-0.002	0.051	0.085	-0.202	-0.157	-0.109	-0.055	0.058	0.232	0.323	0.418	0.654	0.836	0.887	1.048	1.222	1.341	1.442
Hunan	-0.725	-0.484	-0.166	0.089	0.210	0.263	0.297	0.011	0.056	0.103	0.157	0.270	0.444	0.535	0.630	0.866	1.048	1.099	1.260	1.434	1.553	1.654
Guangdong	-0.118	0.123	0.441	0.696	0.818	0.871	0.904	0.618	0.663	0.711	0.764	0.877	1.051	1.142	1.237	1.473	1.655	1.706	1.868	2.041	2.160	2.262
Guangxi	-1.147	-0.907	-0.589	-0.334	-0.212	-0.159	-0.126	-0.412	-0.367	-0.319	-0.265	-0.153	0.022	0.112	0.208	0.443	0.625	0.677	0.838	1.011	1.130	1.232
Hainan	-0.569	-0.328	-0.011	0.245	0.366	0.419	0.452	0.166	0.211	0.259	0.313	0.426	0.600	0.691	0.786	1.022	1.204	1.255	1.416	1.590	1.709	1.810
Sichuan	-1.061	-0.820	-0.503	-0.247	-0.126	-0.073	-0.039	-0.326	-0.281	-0.233	-0.179	-0.066	0.108	0.199	0.294	0.530	0.712	0.763	0.924	1.098	1.217	1.318
Guizhou	-1.954	-1.713	-1.396	-1.141	-1.019	-0.966	-0.933	-1.219	-1.174	-1.126	-1.072	-0.959	-0.785	-0.694	-0.599	-0.363	-0.182	-0.130	0.031	0.204	0.324	0.425

Yunnan	-1.746	-1.506	-1.188	-0.933	-0.811	-0.758	-0.725	-1.011	-0.966	-0.918	-0.864	-0.752	-0.577	-0.486	-0.391	-0.156	0.026	0.078	0.239	0.412	0.531	0.633
Tibet	-1.896	-1.655	-1.338	-1.082	-0.961	-0.908	-0.875	-1.161	-1.116	-1.068	-1.014	-0.901	-0.727	-0.636	-0.541	-0.305	-0.123	-0.072	0.089	0.262	0.382	0.483
Shaanxi	-1.715	-1.474	-1.157	-0.901	-0.780	-0.727	-0.694	-0.980	-0.935	-0.887	-0.833	-0.720	-0.546	-0.455	-0.360	-0.124	0.058	0.109	0.270	0.444	0.563	0.664
Gansu	-2.273	-2.032	-1.715	-1.459	-1.338	-1.285	-1.252	-1.538	-1.493	-1.445	-1.391	-1.278	-1.104	-1.013	-0.918	-0.682	-0.500	-0.449	-0.288	-0.114	0.005	0.106
Qinghai	-1.992	-1.751	-1.434	-1.178	-1.057	-1.004	-0.970	-1.257	-1.212	-1.164	-1.110	-0.997	-0.823	-0.732	-0.637	-0.401	-0.219	-0.168	-0.007	0.167	0.286	0.387
Ningxia	-2.198	-1.957	-1.640	-1.384	-1.263	-1.210	-1.176	-1.463	-1.418	-1.370	-1.316	-1.203	-1.029	-0.938	-0.843	-0.607	-0.425	-0.374	-0.213	-0.039	0.080	0.181
Xinjiang	-1.696	-1.455	-1.137	-0.882	-0.760	-0.707	-0.674	-0.960	-0.915	-0.867	-0.813	-0.701	-0.527	-0.436	-0.341	-0.105	0.077	0.129	0.290	0.463	0.582	0.684

Table 4.9 Fixed Effects of Model 3

	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Beijing	-0.311	-0.165	0.149	0.349	0.432	0.452	0.430	0.317	0.329	0.359	0.397	0.471	0.601	0.657	0.699	0.828	0.975	1.004	1.119	1.258	1.335	1.407
Tianjin	-0.708	-0.562	-0.248	-0.047	0.035	0.055	0.034	-0.079	-0.068	-0.038	0.000	0.074	0.204	0.260	0.302	0.431	0.578	0.607	0.722	0.861	0.938	1.010
Hebei	-1.057	-0.911	-0.597	-0.397	-0.314	-0.294	-0.316	-0.429	-0.417	-0.387	-0.349	-0.275	-0.145	-0.089	-0.047	0.082	0.229	0.258	0.373	0.511	0.589	0.661
Shanxi	-1.618	-1.471	-1.158	-0.957	-0.875	-0.854	-0.876	-0.989	-0.978	-0.948	-0.909	-0.836	-0.706	-0.650	-0.607	-0.478	-0.332	-0.303	-0.188	-0.049	0.029	0.101
Inner Mongolia	-1.258	-1.112	-0.799	-0.598	-0.516	-0.495	-0.517	-0.630	-0.619	-0.589	-0.550	-0.477	-0.346	-0.290	-0.248	-0.119	0.027	0.056	0.171	0.310	0.388	0.460
Liaoning	-0.607	-0.461	-0.148	0.053	0.136	0.156	0.134	0.021	0.032	0.062	0.101	0.174	0.305	0.361	0.403	0.532	0.678	0.707	0.822	0.961	1.039	1.111
Jilin	-1.172	-1.025	-0.712	-0.511	-0.429	-0.408	-0.430	-0.543	-0.532	-0.502	-0.463	-0.390	-0.260	-0.204	-0.161	-0.032	0.114	0.143	0.258	0.397	0.475	0.547
Heilongjiang	-1.297	-1.150	-0.837	-0.636	-0.554	-0.533	-0.555	-0.668	-0.657	-0.627	-0.588	-0.515	-0.385	-0.329	-0.286	-0.157	-0.011	0.018	0.133	0.272	0.350	0.422
Shanghai	-0.197	-0.050	0.263	0.464	0.546	0.567	0.545	0.432	0.443	0.473	0.512	0.585	0.715	0.771	0.814	0.943	1.089	1.118	1.233	1.372	1.450	1.522
Jiangsu	-0.778	-0.632	-0.318	-0.118	-0.035	-0.015	-0.037	-0.150	-0.138	-0.108	-0.070	0.004	0.134	0.190	0.232	0.361	0.508	0.537	0.652	0.790	0.868	0.940
Zhejiang	-0.366	-0.220	0.094	0.294	0.377	0.397	0.375	0.262	0.274	0.304	0.342	0.416	0.546	0.602	0.644	0.773	0.919	0.949	1.063	1.202	1.280	1.352
Anhui	-1.142	-0.996	-0.682	-0.481	-0.399	-0.379	-0.401	-0.513	-0.502	-0.472	-0.434	-0.360	-0.230	-0.174	-0.132	-0.003	0.144	0.173	0.288	0.427	0.504	0.576
Fujian	-0.303	-0.157	0.157	0.358	0.440	0.461	0.439	0.326	0.337	0.367	0.406	0.479	0.609	0.665	0.708	0.836	0.983	1.012	1.127	1.266	1.344	1.415
Jiangxi	-0.805	-0.658	-0.345	-0.144	-0.062	-0.041	-0.063	-0.176	-0.165	-0.135	-0.096	-0.023	0.107	0.163	0.206	0.335	0.481	0.510	0.625	0.764	0.842	0.914
Shandong	-0.886	-0.740	-0.426	-0.226	-0.143	-0.123	-0.145	-0.258	-0.246	-0.216	-0.178	-0.104	0.026	0.082	0.124	0.253	0.400	0.429	0.544	0.682	0.760	0.832
Henan	-1.138	-0.992	-0.678	-0.478	-0.395	-0.375	-0.397	-0.510	-0.498	-0.468	-0.430	-0.356	-0.226	-0.170	-0.128	0.001	0.148	0.177	0.292	0.431	0.508	0.580
Hubei	-0.960	-0.814	-0.500	-0.299	-0.217	-0.196	-0.218	-0.331	-0.320	-0.290	-0.251	-0.178	-0.048	0.008	0.051	0.179	0.326	0.355	0.470	0.609	0.687	0.758
Hunan	-0.689	-0.542	-0.229	-0.028	0.054	0.075	0.053	-0.060	-0.049	-0.019	0.020	0.093	0.223	0.279	0.322	0.451	0.597	0.626	0.741	0.880	0.958	1.030
Guangdong	-0.389	-0.243	0.071	0.272	0.354	0.375	0.353	0.240	0.251	0.281	0.320	0.393	0.523	0.579	0.622	0.751	0.897	0.926	1.041	1.180	1.258	1.330
Guangxi	-0.908	-0.761	-0.448	-0.247	-0.165	-0.144	-0.166	-0.279	-0.268	-0.238	-0.199	-0.126	0.005	0.061	0.103	0.232	0.378	0.407	0.522	0.661	0.739	0.811
Hainan	-0.289	-0.143	0.171	0.372	0.454	0.475	0.453	0.340	0.351	0.381	0.420	0.493	0.623	0.679	0.722	0.850	0.997	1.026	1.141	1.280	1.357	1.429
Sichuan	-0.761	-0.615	-0.301	-0.101	-0.018	0.002	-0.020	-0.133	-0.121	-0.091	-0.053	0.021	0.151	0.207	0.249	0.378	0.525	0.554	0.669	0.808	0.885	0.957
Guizhou	-1.156	-1.009	-0.696	-0.495	-0.413	-0.392	-0.414	-0.527	-0.516	-0.486	-0.447	-0.374	-0.244	-0.188	-0.145	-0.016	0.130	0.159	0.274	0.413	0.491	0.563

Yunnan	-1.139	-0.992	-0.679	-0.478	-0.396	-0.375	-0.397	-0.510	-0.499	-0.469	-0.430	-0.357	-0.226	-0.171	-0.128	0.001	0.147	0.176	0.291	0.430	0.508	0.580
Tibet	-0.686	-0.540	-0.226	-0.026	0.057	0.077	0.055	-0.058	-0.046	-0.016	0.022	0.096	0.226	0.282	0.324	0.453	0.599	0.628	0.743	0.882	0.960	1.032
Shaanxi	-1.397	-1.251	-0.937	-0.736	-0.654	-0.634	-0.656	-0.768	-0.757	-0.727	-0.689	-0.615	-0.485	-0.429	-0.387	-0.258	-0.111	-0.082	0.033	0.172	0.249	0.321
Gansu	-1.390	-1.244	-0.930	-0.730	-0.647	-0.627	-0.649	-0.762	-0.750	-0.720	-0.682	-0.608	-0.478	-0.422	-0.380	-0.251	-0.105	-0.076	0.039	0.178	0.256	0.328
Qinghai	-0.999	-0.852	-0.539	-0.338	-0.256	-0.235	-0.257	-0.370	-0.359	-0.329	-0.290	-0.217	-0.087	-0.031	0.012	0.141	0.287	0.316	0.431	0.570	0.648	0.720
Ningxia	-1.657	-1.510	-1.197	-0.996	-0.914	-0.893	-0.915	-1.028	-1.017	-0.987	-0.948	-0.875	-0.745	-0.689	-0.646	-0.517	-0.371	-0.342	-0.227	-0.088	-0.010	0.062
Xinjiang	-1.125	-0.979	-0.665	-0.465	-0.382	-0.362	-0.384	-0.497	-0.485	-0.455	-0.417	-0.343	-0.213	-0.157	-0.115	0.014	0.160	0.189	0.304	0.443	0.521	0.593

Table 4.10 Fixed Effects of Model 4

	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Beijing	-0.327	-0.184	0.127	0.323	0.402	0.421	0.397	0.291	0.300	0.328	0.364	0.435	0.562	0.615	0.648	0.771	0.915	0.937	1.053	1.189	1.262	1.331
Tianjin	-0.729	-0.585	-0.275	-0.079	0.000	0.019	-0.005	-0.111	-0.102	-0.074	-0.037	0.034	0.160	0.213	0.247	0.370	0.514	0.535	0.652	0.787	0.860	0.930
Hebei	-1.056	-0.912	-0.602	-0.406	-0.327	-0.308	-0.332	-0.438	-0.429	-0.401	-0.364	-0.293	-0.167	-0.114	-0.080	0.043	0.187	0.208	0.325	0.460	0.533	0.602
Shanxi	-1.584	-1.440	-1.130	-0.934	-0.855	-0.836	-0.860	-0.966	-0.956	-0.928	-0.892	-0.821	-0.695	-0.642	-0.608	-0.485	-0.341	-0.320	-0.203	-0.068	0.005	0.075
Inner Mongolia	-1.203	-1.059	-0.749	-0.553	-0.474	-0.455	-0.478	-0.585	-0.575	-0.547	-0.511	-0.440	-0.314	-0.261	-0.227	-0.104	0.040	0.061	0.178	0.313	0.386	0.456
Liaoning	-0.597	-0.453	-0.143	0.053	0.132	0.151	0.127	0.021	0.031	0.059	0.095	0.166	0.292	0.345	0.379	0.502	0.646	0.667	0.784	0.919	0.992	1.062
Jilin	-1.123	-0.979	-0.669	-0.473	-0.394	-0.375	-0.399	-0.505	-0.495	-0.468	-0.431	-0.360	-0.234	-0.181	-0.147	-0.024	0.120	0.141	0.258	0.393	0.466	0.536
Heilongjiang	-1.235	-1.092	-0.781	-0.586	-0.506	-0.487	-0.511	-0.617	-0.608	-0.580	-0.544	-0.473	-0.347	-0.293	-0.260	-0.137	0.007	0.029	0.145	0.281	0.354	0.423
Shanghai	-0.240	-0.097	0.213	0.409	0.489	0.508	0.484	0.378	0.387	0.415	0.451	0.522	0.648	0.701	0.735	0.858	1.002	1.023	1.140	1.276	1.348	1.418
Jiangsu	-0.797	-0.654	-0.344	-0.148	-0.068	-0.049	-0.073	-0.179	-0.170	-0.142	-0.106	-0.035	0.091	0.144	0.178	0.301	0.445	0.466	0.583	0.719	0.792	0.861
Zhejiang	-0.388	-0.245	0.066	0.261	0.341	0.360	0.336	0.230	0.239	0.267	0.303	0.374	0.501	0.554	0.587	0.710	0.854	0.876	0.992	1.128	1.201	1.270
Anhui	-1.108	-0.965	-0.655	-0.459	-0.380	-0.360	-0.384	-0.490	-0.481	-0.453	-0.417	-0.346	-0.220	-0.167	-0.133	-0.010	0.134	0.155	0.272	0.407	0.480	0.550
Fujian	-0.303	-0.160	0.151	0.346	0.426	0.445	0.421	0.315	0.324	0.352	0.388	0.459	0.586	0.639	0.672	0.795	0.939	0.961	1.077	1.213	1.286	1.355
Jiangxi	-0.769	-0.625	-0.315	-0.119	-0.040	-0.021	-0.045	-0.151	-0.141	-0.113	-0.077	-0.006	0.120	0.173	0.207	0.330	0.474	0.495	0.612	0.747	0.820	0.890
Shandong	-0.882	-0.739	-0.429	-0.233	-0.154	-0.134	-0.158	-0.264	-0.255	-0.227	-0.191	-0.120	0.006	0.059	0.093	0.216	0.360	0.381	0.498	0.633	0.706	0.776
Henan	-1.119	-0.975	-0.665	-0.469	-0.390	-0.371	-0.395	-0.501	-0.491	-0.463	-0.427	-0.356	-0.230	-0.177	-0.143	-0.020	0.124	0.145	0.262	0.397	0.470	0.540
Hubei	-0.936	-0.792	-0.482	-0.286	-0.207	-0.188	-0.212	-0.318	-0.308	-0.281	-0.244	-0.173	-0.047	0.006	0.040	0.163	0.307	0.328	0.445	0.580	0.653	0.723
Hunan	-0.661	-0.517	-0.207	-0.011	0.068	0.087	0.064	-0.042	-0.033	-0.005	0.031	0.102	0.228	0.281	0.315	0.438	0.582	0.603	0.720	0.855	0.928	0.998
Guangdong	-0.404	-0.260	0.050	0.246	0.325	0.344	0.320	0.214	0.223	0.251	0.288	0.359	0.485	0.538	0.572	0.695	0.839	0.860	0.977	1.112	1.185	1.254
Guangxi	-0.863	-0.720	-0.410	-0.214	-0.135	-0.115	-0.139	-0.245	-0.236	-0.208	-0.172	-0.101	0.025	0.078	0.112	0.235	0.379	0.400	0.517	0.652	0.725	0.795
Hainan	-0.237	-0.094	0.217	0.413	0.492	0.511	0.487	0.381	0.390	0.418	0.455	0.525	0.652	0.705	0.738	0.861	1.005	1.027	1.143	1.279	1.352	1.421
Sichuan	-0.717	-0.574	-0.263	-0.068	0.012	0.031	0.007	-0.099	-0.090	-0.062	-0.026	0.045	0.172	0.225	0.258	0.381	0.525	0.547	0.663	0.799	0.872	0.941
Guizhou	-1.087	-0.944	-0.634	-0.438	-0.358	-0.339	-0.363	-0.469	-0.460	-0.432	-0.396	-0.325	-0.199	-0.146	-0.112	0.011	0.155	0.176	0.293	0.429	0.502	0.571

Yunnan	-1.084	-0.940	-0.630	-0.434	-0.355	-0.336	-0.360	-0.466	-0.457	-0.429	-0.392	-0.321	-0.195	-0.142	-0.108	0.015	0.159	0.180	0.297	0.432	0.505	0.574
Tibet	-0.611	-0.467	-0.157	0.039	0.118	0.137	0.114	0.007	0.017	0.045	0.081	0.152	0.278	0.331	0.365	0.488	0.632	0.653	0.770	0.905	0.978	1.048
Shaanxi	-1.361	-1.217	-0.907	-0.711	-0.632	-0.613	-0.637	-0.743	-0.734	-0.706	-0.669	-0.598	-0.472	-0.419	-0.385	-0.262	-0.118	-0.097	0.020	0.155	0.228	0.297
Gansu	-1.334	-1.191	-0.881	-0.685	-0.606	-0.586	-0.610	-0.716	-0.707	-0.679	-0.643	-0.572	-0.446	-0.393	-0.359	-0.236	-0.092	-0.071	0.046	0.181	0.254	0.324
Qinghai	-0.936	-0.793	-0.482	-0.287	-0.207	-0.188	-0.212	-0.318	-0.309	-0.281	-0.245	-0.174	-0.048	0.006	0.039	0.162	0.306	0.327	0.444	0.580	0.653	0.722
Ningxia	-1.618	-1.474	-1.164	-0.968	-0.889	-0.870	-0.894	-1.000	-0.991	-0.963	-0.926	-0.855	-0.729	-0.676	-0.642	-0.519	-0.375	-0.354	-0.237	-0.102	-0.029	0.040
Xinjiang	-1.087	-0.943	-0.633	-0.437	-0.358	-0.339	-0.363	-0.469	-0.460	-0.432	-0.395	-0.324	-0.198	-0.145	-0.111	0.012	0.156	0.177	0.294	0.429	0.502	0.571