What determines misallocation in innovation? A study of regional innovation in China

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Abstract

This paper sounds an alarm about disparate efficiencies among China's regions in the allocation of innovation inputs. A theoretical measure of misallocation is adopted to gauge the distortions that exacerbate the inefficiency of resource allocations across geographic innovation units; these units' usage of innovative inputs reveals the level of misallocations prevalent within the Chinese economy. The measure of innovation misallocation is computed by utilizing a micro dataset based on information from the China Statistical Yearbook for Science and Technology (CSYST) from 1999 to 2012. In addition, this paper probes the factors that co-move with China's innovation resource misallocations. We find that, although an advanced financial market is beneficial to innovation efficiency in China, both the government's extensive development of transportation infrastructure and the preferential treatment given to state-owned enterprises (SOEs) and foreign-invested enterprises (FIEs) negatively correlate with innovation efficiency. We conclude that emerging economies that are experiencing R&D input expansion, such as China, should be cautious in ensuring efficient resource allocations.

Keywords

Resource misallocation; Innovation efficiency; Financial market; Infrastructure investment; Preferential treatment

JEL classification

O11; O32; O47

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1. Introduction

History has documented that different nations follow very different development paths. Whereas some countries have successfully evolved through many stages of growth—from traditional economies to modernized economies—other countries have halted their transformations or even collapsed after enjoying some early development success. In an influential work, Acemoglu and Robinson (2012) conclude that an economy dominated by extraction, in which only a few privileged people can access limited production resources, will cause a nation's downfall. Specifically, failing nations often suffer from prevalent resource misallocation and stop embracing innovations that are critical to continuous development.[1]

Resource misallocation has been identified as a major hurdle to the delivery of high productivity in all aspects of production, as surveyed by Syverson (2011).[2] Because innovation is essential to sustaining long-run growth, timely awareness of disparate efficiencies in allocating resources across innovation units should be a priority for an economy (such as China) that is interested in modernization. Interestingly, whereas many aspects of growth have been extensively studied, the economic literature has almost entirely neglected the misallocation of innovation resources. An exception is a recent paper by Uras and Wang (2016), which emphasizes the importance of technique misallocation on industry-level total factor productivity (TFP). In their model, technique misallocations arise from heterogeneous technique capabilities, and these diverse capabilities could be thought of as a consequence of differing investments in process innovations. We further their study by investigating the determinants of misallocation in innovation activities.[3] In particular, we study cross-region misallocations in the use of innovative inputs within China. As conceptually noted by Hsieh and Klenow (2009), relative to an ideal environment in which competitive input markets ensure equalization (among regions) of the marginal contribution of the last unit of innovation inputs, differences in regional distortion

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[1] As noted by Acemoglu and Robinson, one main reason that extractive economies may not be interested in innovations arises out of their elites' concerns about creative destruction that may lead to their loss of power.

[2] For example, the relatively early work by Peek and Rosengren (2005) demonstrates that in Japan, such misallocation is severe. Greenwood and Krusell (2007) develop a model and argue that the level of financial development affects resource allocation across firms within an industry.

[3] While Uras and Wang (2016) emphasize the role played by *process* innovation, our analysis studies misallocation in innovation activities as a whole and does not explicitly differentiate between process and product innovations.

levels result in misallocations and lower aggregate performance.[4] Some of these distortions reflect intentional government policies, such as capital subsidies or preferential tax treatments that favor particular innovation units. Other distortions reflect an exclusive seller's power, which can lead to gigantic monopoly rents for their innovation outputs.

In this paper, building upon Hsieh and Klenow's (2009) insights into misallocation, we calculate a theory-based measure of innovation efficiency in China. This measure of innovation efficiency will assume a larger value if the dispersion of revenue productivity (TFPR), which is a function of the regional innovation input and output distortions, is smaller across regions. In other words, when the extent of distortion is similar across regions, our measure of innovation efficiency will be higher.[5] During our computation of the innovation efficiency measure, we have also derived the TFPR for each region in each year.[6] Because a region's TFPR can be viewed as an inverse measure of that region's distortions, in the second step of our analysis, we proceed by identifying the potential sources of regional distortions.

We collect a new micro dataset with information on regional innovation inputs and outputs in China. We obtained these data from the China National Statistical Bureau's China Statistical Yearbook for Science and Technology (CSYST) from 1998 to 2013. Our analysis covered thirty provincial-level regions in China between 1999 and 2012.[7] Following the existing literature, we use the number of patent applications under the invention and utility model categories as the innovation output and assume that the utilization of R&D capital inventories and personnel are the main innovation inputs.

Our measure of innovation efficiency increases substantially during the sample

[4] Hsieh and Klenow (2009) focus on resource misallocations in India and China and attribute those countries' losses in production efficiency primarily to differences in their government policies. These distortions influence the differences in TFP across industries in different countries.

[5] According to Bartelsman et al. (2013), the improvement in allocative efficiency is associated with the process whereby limited production inputs are reallocated from less-productive to more-productive units within an economy.

[6] The gauge of innovation productivity begins with a measurement of the idiosyncratic input distortions at the regional level. Thus, this first step requires intensive data support at the regional level, which we describe below.

[7] In our calculation, we allowed a one-year lag from the usage of innovation inputs to producing outputs. In addition, because the CSYST yearbook provides data for the previous year, our actual period of analysis is from 1999 to 2012. Furthermore, we do not include Tibet in our analysis because of a large amount of data are missing for that region.

period: it starts from 0.5023 in 1999 and rises to 0.8016 in 2012.[8] This increase indicates substantial convergence in the extent of the distortions across the regions in China. However, our result also suggests that, whereas innovation efficiency constantly improved between 1999 and 2009, beginning in 2010, there was a sign of deterioration in innovation efficiency: the efficiency measure modestly decreased for the three consecutive years between 2010 and 2012.

The second part of our empirical study further extends the literature by investigating the factors that affect innovation efficiency. A variety of setups have been adopted to robustly establish that an advanced financial market is beneficial to regional innovation efficiency in China. However, extensive development of a regional transportation infrastructure is negatively correlated with innovation efficiency. We argue that this pattern occurs because a sophisticated regional transportation infrastructure may not increase the efficient allocation of innovation resources; furthermore, devoting excessive government resources to the transportation infrastructure may have a distortive effect on public and private innovation investments. In addition, we find that preferential policy treatments issued by governments will be biased toward the misallocation of innovation inputs. More specifically, we find that higher shares of state-owned enterprises (hereafter, SOEs) and foreign invested enterprises (hereafter, FIEs) in regional industry output hurt innovation efficiency. Because SOEs and FIEs often have better access to credit or enjoy more tax deductions, preferential policies may have distortive effects on total innovation investment if SOEs and FIEs do not consider innovation activities their priority. SOEs and FIEs' hindering effect on innovation efficiency is first proposed by this paper. However, we are not alone in indicating that low productivities are associated with SOEs and sometimes with FIEs. SOEs' mediocre performance is well known (e.g., Brandt et al., 2012); recent studies also document the unexceptional performance of Chinese exporters, many of whom are FIEs (Dai et al., 2012; Lu, 2010; Yu, 2015).

Studies on resource misallocation have become a focal point in the growth

[8] This measure denotes the ratio of the actual and "efficient" production levels of innovation, where "efficient production" is defined as the output level that is obtained when there are no misallocations of resources across the regions within China. For example, a value of 0.5 means that innovation production would have doubled (1/0.5=2) had the misallocations been eliminated.

literature since the seminal work by Banerjee and Duflo (2005); those studies find that the large dispersion in the marginal product of capital among Indian firms results in significant loss of aggregate output.[9] The more recent research wave on misallocation was initiated by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). Restuccia and Rogerson (2008) argue that policy distortions that cause an incorrect match between production input usage and firm-level productivity will be harmful for aggregate TFP.[10] Furthermore, Hsieh and Klenow (2009) show that by reducing the extent of capital and output distortions in India and China to a degree that is comparable to US levels, those countries' TFPs grew by 40%-60% and 30%-50%, respectively. Several papers study the growth implications of various channels of misallocation: Banerjee and Moll (2010), Midrigan and Xu (2014), Buera et al. (2013) and Moll (2014) construct dynamic general equilibrium models of misallocation with capital market imperfections, whereas Jones (2013) elaborates that the negative effects of misallocations may be amplified through the economy's input-output structure, which would help explain cross-country TFP gaps. In addition, Jovanovic (2014) studies misallocation using an assignment framework with heterogeneous firms and workers and finds that more efficient assignments of human capital lead to faster long-run growth, more inequality, and less turnover in the distribution of human capital. A more recent contribution has been provided by Uras and Wang (2016), who find that within-industry technological gaps, which could result from different levels of investment in process innovation, are important for determining industry-level TFP.

Overall, our paper contributes to the existing literature in two important ways. First, we illuminate the current literature by conducting the first investigation of resource misallocation in innovation activities. Given that innovations have long been believed to be crucial to the sustainable growth of economies, quantifying the potential misallocation problems of R&D resource inputs is a critical first step for emerging economies (such as China) that hope to develop their innovation capacities for further development.[11] Second, this paper elaborates on all accessible data sources to probe

[9] An early paper by Baily et al. (1992) also emphasizes the importance of resource misallocation and suggests that the productivity growth in US manufacturing in the 1980s may be largely attributed to factor reallocations from low-productivity plants to high-productivity plants.

[10] Specifically, they study a class of distortions that lead to no changes in the aggregate prices and no changes in the aggregate factor accumulation but do have idiosyncratic distortions that create heterogeneity in the prices faced by individual producers.

[11] A strand of recent works also studies the innovation activities in China after the 1978 economic

the factors that co-move with innovation misallocations across regions within China. We conduct our analysis at the regional level—rather than at the firm level, as in Hsieh and Klenow (2009)—based on two considerations. The first is data constraints, as comprehensive panel datasets on distinct innovation inputs and outputs at the firm level are difficult to come by. Second, using a regional approach to study innovation activities is an important methodology in the innovation literature (e.g., Cooke et al., 1997).[12] This strand of literature, called the regional innovation system literature, argues that regional heterogeneity in innovation performance arises from differences not only in the involved agents performing innovation activities but also in the supporting roles played by regional institutions. As noted by Li (2009), Chinese provinces are administratively and economically independent geographical regions, so local governments have substantial autonomy in formulating economic development policies, and financial sectors also exhibit marked regional differences—these features warrant our regional framework. That said, if more detailed datasets at the firm level become available, our setup could still be used for refined policy analyses.[13]

The remainder of this article is organized as follows. In Section 2, we introduce the methodology. Section 3 demonstrates the unique dataset and details the data source and the construction process. Section 4 presents the results of our empirical analysis on the evolution of innovation efficiency and its determinants. Finally, Section 5 concludes.

2. Methodology

In this section, we describe our measure of China's innovation efficiency. Using the ideas mentioned in the previous section, we compute innovation efficiency by aggregating the extent of each individual region's resource misallocation within China.

reforms. These studies document the great efforts devoted to innovation-related activities (Chen and Guan, 2011; Li, 2009; Sun, 2003). However, the Chinese innovation system currently lacks the commercialization capacity to advance technological developments into commercial applications (Chen and Guan, 2012).

[12] This approach has also been adopted in several studies of regional innovation performance in China (e.g., Li, 2009; Bai, 2013).

[13] For example, if we had similar data at the firm level, we could analyze how changing regulations regarding foreign ownership affect innovation misallocation.

2.1. Measure of Resource Misallocation across Regions

To compute innovation efficiency in China, we develop a measurement of country-level resource misallocation in innovation production, which is governed by decreasing return-to-scale technology.[14] This version of the gauge of misallocation is conceptually adapted from Hsieh and Klenow (2009).

We begin by assuming a competitive innovation system that features a homogeneous product in terms of the generated patents. This system consists of M regions; the aggregate patented innovation output, which we denote Y, is simply the sum of the patents across all regions, that is,

$$Y = \sum_{i=1}^{M} Y_i. \quad (1)$$

[15]In equation (1), $\mathrm{Y_i}$ is the number of patents in region i, and we assume its production technology is determined by

$$Y_i = A_i(L_i^{\alpha} K_i^{1-\alpha})^{\gamma}, \gamma \in (0,1) \quad (2)$$

This setup essentially captures the decreasing return-to-scale innovative production technology, with γ governing a regional "operative returns to scale" in the innovation system. In addition, the operative returns to scale are sometimes referred to as the "span-of-control" parameter described in Lucas (1978).[16]

In our setup, the regions within the country are heterogeneous not only in terms of their innovation technology A_i but also in the distortions associated with the use of capital and labor. Here, we follow Hsieh and Klenow (2009) by assuming that regions experience two types of distortions: output distortion τ_{Y_i}, which simultaneously affects capital and labor productivities, and capital distortion τ_{K_i}, which drives up the productivity of capital relative to that of labor. A region's innovation payoff is given by

$$\pi_i = (1 - \tau_{Y_i})P_i Y_i - wL_i - (1 + \tau_{K_i})RK_i \quad (3)$$

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[14] As Jones and Williams (2000) and Weil (2013) state, innovation production function is characterized by decreasing returns to scale.

[15] In an influential work, Griliches (1979) suggests the use of the number of patents as the main measure for the innovation output. While some might question that individual patents differ greatly in "quality", Scherer (1965) and Griliches (1990) both pointed out by invoking the "law of large number," the number of patents is a reasonable indicator of innovation output. Along this reasoning, Hsu (2009) aggregate patent data and find that patent shocks have positive predictive power for China and other countries' stock market returns.

[16] Although we use a decreasing returns to scale setup, our findings do not qualitatively change if we assume a constant returns to scale innovation production technology. This is not surprising, as Hsieh and Klenow (2009) already proved the isomorphic property between a constant returns to scale model with differentiated goods and a Lucas span of control model formation.

We assume that research input markets are both competitive. With homogeneous products and assuming the standard first-order condition on demand holds, the regional output price is

$$P_i = P, \text{ for every region } i \text{ in the innovation system} \qquad (4)$$

We follow Hsieh and Klenow (2009) and solve the production input demand in perfectly competitive factor markets. The derived demand from (4) can be plugged into (3) to solve for both the input demand and the output supply, whose values are determined by the innovation technology A_i and the distortion measures τ_{Y_i} and τ_{K_i}:

$$L_i = L_i(A_i, \tau_{Y_i}, \tau_{K_i}) \qquad (5)$$

$$K_i = K_i(A_i, \tau_{Y_i}, \tau_{K_i}) \qquad (6)$$

$$Y_i = Y_i(A_i, \tau_{Y_i}, \tau_{K_i}) \qquad (7)$$

Next, profit maximization implies that regions that experience greater output distortions (higher τ_{Y_i}) will exhibit higher marginal revenue products of labor. Similarly, regions will have a higher marginal revenue product of capital when they experience more output or capital distortions (τ_{K_i}):

$$\text{MRPL}_i = \text{MRPL}_i(A_i, L_i, K_i) \triangleq w \frac{1}{1-\tau_{Y_i}} \qquad (8)$$

$$\text{MRPK}_i = \text{MRPK}_i(A_i, L_i, K_i) \triangleq R \frac{1+\tau_{K_i}}{1-\tau_{Y_i}} \qquad (9)$$

In addition, given decreasing returns, we can infer that highly distorted regions will have an equilibrium scale of production that is smaller than the optimal scale.

Following Hsieh and Klenow (2009), we differentiate between "physical productivity", which we denote TFPQ, and "revenue productivity", which we denote TFPR. Whereas TFPQ is region-specific, TFPR will be country-specific if there is no difference in the extent of the distortions across regions. We will solve the reduced forms of TFPQ and TFPR for region i as follows:

$$\text{TFPQ}_i \triangleq \frac{Y_i}{(L_i^{\alpha} K_i^{1-\alpha})^{\gamma}} \qquad (10)$$

$$\text{TFPR}_i \triangleq \frac{PY_i}{L_i^{\alpha} K_i^{1-\alpha}} \qquad (11)$$

In an ideal scenario, TFPR will be country-specific and will not vary across regions. The only reason that the regions within China have different TFPRs is that they have different levels of output and capital distortions. Without the region-specific output and capital distortions, regions with a higher TFPQ will use more production resources until the TFPRs are equalized for those regions that experience the same resource prices within the innovation system. Similar to Hsieh and Klenow (2009), we can represent TFPR_i in terms of the geometric average of the regional marginal revenue products of labor and capital. Specifically, we use equations (8), (9), and (11) to show that regional TFPR is, in effect, an indicator of the endured distortions:

$$\mathrm{TFPR}_i = \mathrm{TFPR}_i(\tau_{Y_i}, \tau_{K_i})$$
$$\propto [\left(\frac{\mathrm{MRPL}_i}{w}\right)^{\alpha}\left(\frac{\mathrm{MRPK}_i}{R}\right)^{1-\alpha}]^{\gamma} \propto \left[(1-\tau_{Y_i})^{\alpha}\left[\frac{(1-\tau_{Y_i})}{(1+\tau_{K_i})}\right]^{1-\alpha}\right]^{-\gamma} \qquad (12)$$

Because higher outputs and larger capital distortions raise the marginal products of capital and labor, region i will exhibit a smaller scale of output than the efficient scale if it experiences a large number of distortions.

Aggregate final innovation output can be derived by simply aggregating the individual region's output production, as in equation (1). Suppose we implicitly define the innovation production efficiency TFP of the country as a whole by

$$Y = \mathrm{TFP} \times L^{\alpha} \times K^{1-\alpha} \qquad (13)$$

where $L = \sum_{i=1}^{M} L_i$ and $K = \sum_{i=1}^{M} K_i$ represent the aggregate values of the labor and capital devoted to innovation activities, respectively. Next, by simplifying the linear aggregate of the production function in the innovation system, we can show that the countrywide innovation production efficiency TFP is represented by

$$\mathrm{TFP} = \frac{Y}{L^{\alpha}K^{1-\alpha}} = \frac{\left[\sum_{i=1}^{M}(\mathrm{TFPQ}_i \frac{\overline{\mathrm{TFPR}}}{\mathrm{TFPR}_i})^{\frac{1}{1-\gamma}}\right]^{1-\gamma}}{(L^{\alpha}K^{1-\alpha})^{1-\gamma}} \qquad (14)$$

where $\overline{\mathrm{TFPR}}$ is a harmonic average of the average marginal revenue product of capital and labor across the regions in China.[17]

From equation (14), one can also readily show that the countrywide innovation TFP will be that of a CES function aggregated across all of the TFPQ_i if regional revenue productivities (TFPR_i) are equalized across China's regions. In this special case,

[17] $\overline{\mathrm{TFPR}}=\left[\sum_{j=1}^{M}\left(\frac{Y_j}{Y}(1-\tau_{Y_j})\right)\right]^{-\alpha\gamma}\left[\sum_{j=1}^{M}\left(\frac{Y_j}{Y}\frac{(1-\tau_{Y_j})}{(1+\tau_{K_j})}\right)\right]^{-(1-\alpha)\gamma}$

$$\text{TFP} = \bar{A} = \frac{\left(\sum_{i=1}^{M} A_i^{\frac{1}{1-\gamma}}\right)^{1-\gamma}}{(L^{\alpha}K^{1-\alpha})^{1-\gamma}} \qquad (15)$$

With (14), we can now measure China's aggregate innovation production efficiency, which we will describe in the next subsection.

2.2. Computation of Misallocation

To compute innovation efficiency, we adopt the following exogenous parameters: First, we set the rental rate of capital to be R=0.23. The rental rate is a combination of an interest rate (i) of 3% and a depreciation rate (δ) of 20%. In our accounting, we adopt full depreciation amortization within five years for any newly bought fixed capital; thus, the depreciation rate is set at 20%. The interest rate is set at 3% within the sample period that we investigate in this research.[18]

[Insert Table 1 Here.]

Next, we turn to the choice of Lucas span-of-control parameter γ, and the labor share parameter α.[19] From past work on estimating the innovation production functions, such as Hausman et al. (1984), Crépon and Duguet (1997), and Cincera (1997), we know that innovation production is governed by decreasing returns to scale. Based on Zhang et al. (2003) and Bai (2013), we choose γ=0.8 because these studies show that, in China, the mean output elasticity of innovation with respect to R&D inputs is approximately 0.8.[20] To determine the labor share parameter, Li (2009) and

[18] We understand that this rental rate of capital could be inaccurate, but in terms of production efficiency calculation, the derived efficiency measurement does not depend on the true rental rate of capital *R*. Instead, *R* affects only the capital distortion rate that we derive here. This occurs because, from equations (16) and (17), the measured capital and output distortion changes proportionally with *R*. However, the derived innovation efficiency depends on the ratio of the measured TFP of the entire innovation system relative to the efficient TFP of the entire innovation system. Therefore, the measured innovation efficiency will not depend on the chosen rental rate *R*.

[19] The span-of-control parameter (γ) records the operative returns to scale by labor (L) and fixed capital (K). This operative return-to-scale parameter is often referred to as the "span-of-control" parameter, as in Lucas (1978), Atkeson and Kehoe (2005) and many other studies. In the current context, our selection of γ can be viewed as replacing the elasticity of the substitution measure in Hsieh and Klenow (2009), and the gains from fewer distortions are increasing in γ.

[20] Depending on estimation methods, Hausman et al. (1984), Crépon and Duguet (1997), and Cincera (1997) show that the measured γ could be different. Hence, for robustness, we have also considered alternative values of γ: 0.5 and 0.9. Different choices of γ will affect only the numerical values of the measured innovation productivity, not the relative ordering or the trend in productivity. Since our primary goal is to document and explain the evolution of the innovation efficiency in China, the actual choice of γ should not be crucial. Indeed, our findings are qualitatively similar for different values of γ. These additional results are available upon request.

Bai (2013) estimate the Chinese innovation production function at the regional level, and they find that the labor share in innovation production is approximately 0.6; therefore, we set this value accordingly.[21] A summary of our parameter configuration is provided in Table 1.

We apply Hsieh and Klenow's (2009) idea of resource misallocation to compute the idiosyncratic distortions in labor and capital adoption costs. Specifically, we can compute regional distortions in the labor and capital adoption costs and TFPQs as follows:

Capital Distortion:
$$\tau_{K_i} = \frac{1-\alpha}{\alpha}\frac{wL_i}{RK_i} - 1 \qquad (16)$$

Output Distortion:
$$1 - \tau_{Y_i} = \frac{1}{\alpha\gamma}\frac{wL_i}{PY_i} \qquad (17)$$

TFPQ_i:
$$A_i = \frac{Y_i}{\left[(wL_i)^{\alpha} {K_i}^{1-\alpha}\right]^{\gamma}} \qquad (18)$$

The distortion measurement used here is easy to understand because a Cobb-Douglas innovation production technology is adopted. Equation (16) comes from the standard Cobb-Douglas result regarding the relationship between the labor share and the capital share. If the ratio of the labor share to the capital share is greater than $\alpha/(1-\alpha)$, we can infer that capital distortion exists; equation (17) illustrates that if the labor share relative to the total output is smaller than $\alpha\gamma$, we have output distortion. The TFPQ_i measurement in equation (18) is conceptually similar to the TFP in a neoclassical production function. In our database, because we have information about the innovation output (patents) Y_i and the values of the total research inputs, we can calculate the measures given in equations (16) to (18) across China's regions. Indeed, these measurements of distortion and regional productivities are the bases for us to gauge the efficiency loss of the innovation system.

To define efficiency loss, we first must define what we mean by "efficient production." Because we focus on understanding the efficiency loss associated with misallocations, "efficient production" is defined as the output level obtained when there are no idiosyncratic distortions across China's regions. Under this optimal scenario, the marginal revenue products of the innovation inputs are equalized across the regions within the innovation system in China; thus,

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[21] For a robustness check, we also considered alternative values of α: 0.5 and 0.7. Our findings are very similar to these parameter values. The additional results are available upon request.

$$TFPR_i = \overline{\text{TFPR}} \tag{19}$$

As a result, from (15) we have

$$\bar{A} = \frac{\left(\sum_{i=1}^{M} A_i^{\frac{1}{1-\gamma}}\right)^{1-\gamma}}{(L^{\alpha}K^{1-\alpha})^{1-\gamma}}$$

Accordingly, we can write the ratio of the actual and efficient production levels of innovation outputs as[22]

$$Y_R = \frac{Y}{Y_{\text{efficient}}} = \left[\sum_{i=1}^{M}\left(\frac{A_i}{\bar{A}}\frac{\overline{TFPR}}{TFPR_i}\right)^{\frac{1}{1-\gamma}}\right]^{1-\gamma} \tag{20}$$

We can see that the ratio Y_R increases as the dispersion of regional TFPRs decreases, and it will achieve its maximum value (=1) when the regional marginal payoffs of research inputs are equalized.[23] Thus, Y_R may be viewed as a measure of innovation efficiency. Later in our empirical section, we will itemize our calculation of Y_R in a figure that demonstrates how this ratio of China's actual and efficient production levels of innovation evolves across the sample period.

3. Data Description

Our empirical analysis consists of two parts. First, based on our theoretical derivation in Section 2, we will measure the extent of the misallocation in China's innovation system. Second, we will discuss the determinants of this misallocation, i.e., we will examine the factors that cause a greater distortion in innovation.

3.1. Innovation Input and Output Variables

To measure the misallocation in innovation, we will need information about both innovation inputs and outputs. We obtained this information from the China National Statistical Bureau's China Statistical Yearbook for Science and Technology (CSYST) from 1999 to 2013. In this source, there is a one-year lag in the data; thus, the actual figures correspond to data from 1998 to 2012. Our analysis covered thirty provincial-level regions in China, with the lone exception of Tibet (because of the insufficient

[22] The subscript "efficient" means the removal of all idiosyncratic barriers or frictions that cause disparities in the marginal products of labor and capital.
[23] This result has been shown in Hsieh and Klenow (2009).

data in that region).[24]

We will consider two types of innovation inputs: R&D capital and labor inputs. Both of these inputs are measured in value terms.[25] For the values of the R&D labor inputs each year, we simply consider the real R&D expenditures that were used for personnel during that year;[26] for the values of the R&D capital inputs, we follow Griliches (1980), Goto and Suzuki (1989), Wu (2006), and Bai (2013) to calculate the R&D capital inventory that could have been used as the capital input in that year. More specifically, the R&D inventory is calculated using the perpetual inventory method with the following equation (21):

$$K_{it} = (1-\delta) \times K_{i(t-1)} + E_{it} \qquad (21)$$

where K_{it} and $K_{i(t-1)}$ represent the R&D capital inventories in region i at times t and $t\text{-}1$, respectively. As in earlier work, such as Bai (2013), we set δ, which is the depreciation rate, as 0.15. In addition, E_{it} denotes the real R&D capital expenditures in region i at time t, and we construct the R&D price index to convert the capital expenditures into their equivalent 1998 values.[27]

To use equation (21), we need to estimate the initial inventory as follows:[28]

$$K_{i,1998} = E_{i,1998} \ /(\delta + g)$$

Here, $K_{i,1998}$ denotes the initial inventory in 1998, $E_{i,1998}$ denotes the initial 1998 R&D capital expenditure, and g is the average growth rate of real R&D capital expenditures between 1998 and 2012.

We use patent applications as our measure of the innovation output. There are

[24] The thirty provincial-level regions include 10 from the East Coast (Beijing, Tianjin, Shanghai, Fujian, Guangdong, Hainan, Hebei, Jiangsu, Shandong, and Zhejiang), 6 from the Central Area (Anhui, Henan, Hubei, Hunan, Jiangxi, and Shanxi), 4 from the Northeast Area (Liaoning, Heilongjiang, Jilin, and Neimenggu), and 10 from the Western Area (Chongqing, Gansu, Guangxi, Guizhou, Ningxia, Qinghai, Shaanxi, Sichuan, Xinjiang, and Yunnan).

[25] In CSYST, we have annual information about total R&D expenditures, and we decompose them into parts: one that is used for personnel expenditures and one that is used for the current period's capital expenditures. Between 2009 and 2012, we have explicit information about the share of R&D expenditures that was used for personnel, so the decomposition is straightforward. However, between 1998 and 2008, we do not have such information. Thus, we use the share of S&T (science and technology) expenditures used for personnel to conduct our decomposition of the total R&D expenditures.

[26] We use the consumer price index (CPI) to calculate the real R&D personnel expenditures.

[27] To construct the R&D price index, we use the equation $\mathrm{EPI}_{it} = \alpha \times RMPI_{it} + (1-\alpha) \times IFPI_{it}$. Here, $RMPI$ denotes the raw material purchasing price index, and IFPI denotes the fixed asset investment price index. Both price indices are available from the China Statistics Yearbook; α is set to be 0.5, as in Wu (2006).

[28] This setup is made under the assumption that the capital-inventory growth rate equals the R&D capital growth rate.

three categories of patents in the Chinese patent system: inventions, utility models, and designs. Invention refers to "*new technical solutions proposed for a product, a process or the improvement thereof*," and this category is considered to represent most of the major technological creations among the three categories. The utility model refers to "*new technical solutions proposed for the shape and structure of a product, or the combination thereof, which are fit for practical use*." Design refers to the following: "*with respect to a product, new designs of the shape, pattern, or the combination thereof, or the combination of the color with shape and pattern, which are rich in an aesthetic appeal and are fit for industrial application*."[29] Although the last two models are more incremental in nature, many firms apply their patents under the utility model category instead of the invention category because the former is considered more cost effective.[30] In this paper, we will include patents under the invention and utility model categories as the innovation output, and we will calculate the sum of the patent applications under these two categories as our main output measure.[31] Nevertheless, our results would still hold if we considered invention patent applications the only innovation output.

Finally, because innovations usually take time to be realized, we allow a one-year difference between innovation inputs and outputs.[32] For example, we assume that patent applications in 1999 were determined by R&D capital and labor inputs in 1998. However, even if we ignore the time difference, all of our empirical findings hold qualitatively.

3.2. Determinants of Misallocation

The second part of our empirical analysis involves finding the determinants of misallocation; note that misallocation results from distortions in the input and output markets. Therefore, we hope to identify the factors that will cause greater distortions,

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[29] These definitions are contained in the Patent Law of the People's Republic of China.

[30] Whereas invention patents provide 20 years of protection compared with 10 years for utility model patents, it usually takes 3-5 years for approval of an invention patent. In contrast, approvals often occur within 1 year for utility model patents. In addition, annuity payments for granted utility model patents are lower. Therefore, if a particular invention has a short life cycle (likely because of the nature of the industry), applying for a utility model patent may be more cost effective.

[31] We have also used patent grants as our innovation output measure. Our findings are qualitatively similar when using this alternative measure.

[32] In our robustness checks, we also consider different time difference in the innovation input-output relationship. Our conclusions remain intact.

or equivalently in terms of equation (12), higher TFPR. As discussed in the Introduction, different sources of misallocation in goods production have been highlighted in the literature. For example, Hsieh and Klenow (2009) consider capital and output market distortions; several recent important studies further articulate the roles played by capital market imperfections; Jovanovic (2014) analyzes misallocation of human capital; Jones (2013) and Uras and Wang (2016) both demonstrate that industry characteristics matter. [33] Informed by the literature, we consider factors that might cause distortions in these aspects during the innovation process.

In our baseline model, we first consider the maturity of a region's financial market, as it has implications for capital market imperfections; we define this variable as (the log of) the ratio of the outstanding loans to the GDP. We consider the development of local transportation infrastructure, which we measure as (the log of) the ratio of the total road lengths to the region's area because we suspect that transportation investment might affect the foci of governments' or firms' operational strategies. We further consider industry shares of SOEs and foreign firms, respectively, as we conjecture that the preferential treatments these firms receive might result in both capital and output market distortions. We additionally include a variable for the ratio of the regional exports to GDP because we believe that exporting firms may also be favored. Finally, we control for a catchall variable, the (log of) real GDP per capita, to capture a region's general institutional environment. A variable indicating the (log of) regional population size is also included in our regression.

Later in our robustness checks, we further control for regional human capital compositions and industry structures because these features might also affect misallocation, as the previously mentioned important papers suggest. Our data sources and the definitions for all variables are given in Table 2.

[Insert Table 2 Here.]

4. Empirical Results

Our empirical results will be presented in three parts. First, based on equation (20), we will calculate the annual efficiency of the innovation system in China during our sample period. Next, we will examine how different areas perform in terms of

[33] For example, Banerjee and Moll (2010), Midrigan and Xu (2014), Buera et al. (2013), and Moll (2014).

efficiency and discern whether there are any recognizable trends. Finally, we will discuss the determinants of regional differences in efficiency and attempt to identify the factors that cause distortions.

4.1. Trends in Misallocation

Our efficiency measure is based on equation (20) and measures the ratio of the actual production level of innovation to the "efficient" production level of innovation. The measure will have a larger value if the dispersion of TFPRs is smaller across regions or equivalently, if the extents of the distortions are similar across regions. This efficiency measure is calculated annually between 1999 and 2012, and the result is presented in Figure 1.

[Insert Figure 1 Here.]

As seen in Figure 1, during the sample period, our efficiency measure increases substantially; it starts from 0.5023 in 1999 and rises to 0.8016 in 2012. To gauge the qualitative significance of this improvement, notice that whereas in 1999 approximately one-half of the efficiency level of innovation was actually realized, in 2012, approximately 80 percent of the efficiency level of innovation had been attained. This improvement points to substantial convergence in the extent of the distortions across regions during the sample period.

From Figure 1, we see that most of the improvement was achieved before 2003 (the efficiency measure was 0.8034 in 2003). Although there was further improvement between 2003 and 2009 (the year the measure peaked at 0.8991), since 2010, there was a sign of deterioration in efficiency.

4.2. Differences in Innovation Performance across Areas

In Figure 1, we observe an overall large improvement in innovation efficiency between 1999 and 2012. A natural question that arises is what the regional differences in efficiency are and how these differences evolve over time.

We use Figures 2a and 2b and Table 3 to address this issue. In Figure 2a, we plot the annual "demeaned" regional TFPRs for all regions, where a demeaned value is calculated by subtracting a region's TFPR by the $\overline{\text{TFPR}}$ in that year. This demeaning procedure allows us to look at the dispersions of TFPRs across years in the same figure.[34] To graphically categorize the relative position of each region's TFPR to the $\overline{\text{TFPR}}$ of that year, we explicitly draw three horizontal lines to define four zones in Figure 2a. The middle line represents zero; therefore, if a region's demeaned TFPR lies on this line, that region's TFPR equals the $\overline{\text{TFPR}}$ of that particular year. The upper and lower lines represent one "across-years" standard deviation above and below the yearly $\overline{\text{TFPR}}$, respectively.[35] We call the zone below the lower line zone 1, and the TFPRs in this zone are farthest below $\overline{\text{TFPR}}$, so zone 1 consists of regions with the best innovation efficiency;[36] on the other hand, the zone above the upper line is zone 4, and it consists of TFPRs that are farthest above $\overline{\text{TFPR}}$, so it represents the least efficient zone. The middle two zones are divided by the zero line, and we call the zones within one standard deviation below and above the middle line zone 2 and zone 3, respectively. Finally, in Figure 2a, we use different symbols for observations from different areas to help us better understand how TFPRs across areas evolve over time.

[Insert Figure 2 Here.]

There are several notable patterns in Figure 2a. First, we see that in earlier years, i.e., before 2003, many regions' demeaned TFPRs were in zone 1 and zone 4, which suggests great divergence in the TFPRs across regions. Moreover, some regions' demeaned TFPRs were deep into zone 4 in 1999 and 2000, resulting in especially low innovation efficiencies in these two years.[37] Second, we observe that after 2003, the demeaned TFPRs across regions converged; thus, most observations are found in zones 2 and 3. This convergence pattern is clearest between 2006 and 2010, and 2007 and 2008 are the two years with the fewest (2) regional demeaned TFPRs outside of the middle zones.[38] Third, after 2010, the regional demeaned TFPRs appear to have diverged again, e.g., in 2012, 8 regions had demeaned TFPRs located in zones 1 or 4.

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[34] As our measure of innovation efficiency is defined separately for each year and this measure is inverse to the dispersion of TFPRs (but not the actual levels) in that year, we demean the TFPRs so that the average TFPR, $\overline{\text{TFPR}}$, in that year is set to 0.

[35] To calculate this "across-years" standard deviation of demeaned TFPRs, we first demeaned all of the regional TFPRs by the $\overline{\text{TFPR}}$ in the corresponding years, and then we calculated the standard deviation of these 420 (30 regions×14 years=420 observations) demeaned TFPRs. The main reason that we consider this "across-years" standard deviation instead of the yearly standard deviations is to highlight the convergence of the regional TFPRs throughout the sample period.

[36] Recall that a region's TFPR is an inverse measure of its innovation efficiency.

[37] One might suspect that these outlier observations in 1999 and 2000 cause the low efficiency in those two years. However, when we take out these outlier regions (Guangxi and Zhejiang), we still see lower innovation efficiency in the early years, so our conclusion of improving innovation efficiency does not change.

[38] For 2009, however, the demeaned TFPRs located in zones 2 and 3 also converge. Thus, the measured innovation efficiency is actually the highest in that year.

We must assess whether there are specific patterns of TFPRs across different areas in China. A first hint is found in Figure 2b, in which we explicitly examine the distribution of demeaned TFPRs among regions in 1999 and 2012. From Figure 2b, we see improvement in innovation efficiency for the East Coast, Central Area, and Northeast Area, as in these areas, a higher percentage of regional TFPRs are in zones 1 and 2 in 2012 than in 1999. However, the same cannot be said for the Western Area, where, compared with the situation in 1999, more regional TFPRs are in the inefficient zones 3 and 4 in 2012. For a more complete picture of the evolution of TFPRs, in Table 3, we distinguish among three time spans (1999-2003, 2004-2008, 2009-2012) and observe how each area's TFPRs evolve across time. From the top panel of Table 3, which summarizes the distribution of the demeaned TFPRs for the four main economic areas (the East Coast, Central Area, Northeast Area, and Western Area) for the entire sample period, we observe that there are great differences in the TFPR distributions across these areas.[39] Although the regions in Central and Northeast China have demeaned TFPRs that are located mostly in the middle zones, the demeaned TFPRs of the regions on the East Coast and in Western China are more dispersed. For the regions on the East Coast, 3% of their yearly TFPRs are one standard deviation below the yearly $\overline{\text{TFPR}}$ (zone 1, which is the most efficient), and 18% of their TFPRs are one standard deviation above the yearly $\overline{\text{TFPR}}$ (zone 4, which is the least efficient); for the regions in Western China, 9% of their demeaned TFPRs are located in zone 1, but 20% are located in zone 4.

[Insert Table 3 Here.]

When we compare the TFPRs in different time periods, we find interesting evolution patterns across areas. For the regions on the East Coast, we find that their innovation efficiency improves over time. Whereas in the early years (1999-2003) 28% of these regions' demeaned TFPRs were in zone 4, in the most recent period (2009-2012), only 9% of the demeaned TFPRs were in this least-efficient zone. However, whereas in 1999-2003 40% of their demeaned TFPRs were in zone 1 or 2, in 2009-2012, this figure jumped to 51%. For the regions in the Northeast Area, the improvement in their innovation efficiency is even more evident: in 1999-2003, all of their demeaned TFPRs were in zones 3 or 4; in 2004-2008, the demeaned TFPRs were

[39] The definitions of the economic areas are given in footnote 20.

all found in the middle zones; and by 2009-2012, 81% of the TFPRs were in the most efficient zones 1 or 2, and 19% were in zone 1.

Unfortunately, the regions in the Central and Western Areas do not exhibit this improving trend in their innovation efficiencies. For the regions in the Central Area, although comparing the distributions in 1999-2003 and those in 2004-2008 suggests some improvement in efficiency because more demeaned TFPRs were in zone 2 in 2004-2008, in later years (2009-2012), a greater portion of the demeaned TFPRs fell into zone 4.[40] For the regions in the Western Areas, we find many dispersed demeaned TFPRs in 1999-2003, with 14% in zone 1 and 26% in zone 4; in 2003-2008, there seems to have been some convergence in the innovation efficiency because 80% of the demeaned TFPRs were in the middle zones. However, in 2009-2012, signs of divergence returned, and 19% of the demeaned TFPRs were in zone 4, which is an increase from 14% in 2003-2008.

As described earlier, the differences in the levels of the TFPRs across regions arise out of various levels of regional distortions, and these distortions may be from the input and output markets. In the next subsection, we will use regression analysis to detect the factors that induce the pattern observed above.

4.3. Determinants of Innovation Efficiency

Under our framework, regional differences in innovation efficiency are the result of regional discrepancies in the input and output markets' distortions. To empirically explore the critical factors, we conduct the following regression analysis:

$$\ln\left(\frac{\mathrm{TFPR}_{jt}}{\overline{\mathrm{TFPR}_t}}\right) = \alpha + \beta INFRA_{j,t-1} + \gamma PT_{j,t-1} + \theta_t + \theta_j + \varepsilon_{jt} \qquad (22)$$

Here, the dependent variable is ln (TFPR$_{jt}$ / $\overline{\mathrm{TFPR}}_t$); it measures the deviation of region *j*'s TFPR in year *t* from the mean TFPR in that year. A lower value in the dependent variable suggests that region *j* faces less distortion. Our explanatory variables include $INFRA_{j,t-1}$, which denotes a vector of variables related with the infrastructure in year *t-1*, including the maturity of the financial market (lnFEF), the

[40] However, for the Central Area, innovation efficiency in 2009-2012 is still better than that in 1999-2003, as fewer regional demeaned TFPRs were in the least efficient zone 4.

development of the transportation infrastructure (lnLTRANS), the real GDP per capita (lnRGDPpc), and the regional population size (lnPOP). Here, we use one-year lag values of the explanatory variables because when we calculate the yearly TFPRs, the innovation inputs (R&D capital and labor) are also one-year lag values. In addition, $PT_{j,t-1}$ denotes a vector of variables related to preferential policy treatments, namely, the share of the regional industry output produced by SOEs (SOE_share), the share of the regional industry output produced by foreign-owned firms (FIE_share), and the ratio of the regional exports to the GDP (exp_ratio).[41] We also include time-fixed effects θ_t to capture the unobservable macro environment, which may affect the distribution of the TFPRs in each year. Furthermore, because our data have a panel structure, θ_j captures the unobserved regional effects, and we use fixed effects models to allow for unrestricted correlations between the unobserved effects and the explanatory variables. Finally, ε_{jt} denotes the error term. Summary statistics for the variables used in our regression analyses are given in Table 4.

[Insert Table 4 Here.]

Our results are given in Table 5. Observe from the first column of Table 5 that among the infrastructure variables, when the regional financial market is more matured, the region's TFPR is lower. This pattern suggests that a more developed financial market may help reduce distortions and enhance innovation efficiency. With respect to the two variables, i.e., the log of the real GDP per capita (lnRGDPpc) and the log of the regional population size (lnPOP), we do not find any significant effects.

One might expect a denser transportation system to help allocate innovation resources more efficiently, but interestingly, we actually find that development of the transportation infrastructure is associated with higher TFPRs, though marginally insignificantly.[42] A potential reason for our finding may simply be that, for innovation activities, unlike for production activities – whose coordination may involve many physical movements – allocations of R&D inputs may not need many physical interactions. For example, we seldom hear of the need to move R&D equipment or "intermediate goods". Even for R&D personnel, although a better transportation system may help people interact, R&D personnel may not travel often (if they do travel, instead of traveling within provinces, they often travel across provinces or even

41 The definitions of the variables are given in Table 2.

42 With a p-value of 0.11.

countries). Note that the need for physical transportation is currently even less, as many communications can be conducted over the Internet. All of these circumstances suggest that the development of the regional transportation infrastructure may not augment the efficient allocation of innovation resources. Moreover, when the government devotes excessive resources to the transportation infrastructure, there may be a distortive effect on the innovation investment. There may be two reasons for this effect: first, given that government budgets are not infinite, investing more in transportation implies investing less in innovation; second, transportation infrastructure may be crucial for production activities. Thus, if a region devotes more resources to transportation, it will also encourage firms to expand their production activities and may crowd out their innovation endeavors.[43] We are interested in seeing if the effects of transportation infrastructure differ across areas, and from column 2 of Table 5, we find that, while the effect is basically null for the more developed East Coast and Northeastern Area (EN_areas), the development of transportation significantly negatively affects innovation efficiency in the Central and Western Areas (CW_areas). Though far from conclusive, this finding hints at the potential crowd-out effect of massive expansion of transportation investments on innovation in these less developed areas during our study's time frame.

[Insert Table 5 Here.]

With regard to the variables that are related to preferential policy treatments, we find that SOEs and FIEs' shares of regional industry output are detrimental to regional innovation efficiency. At first, these results may seem surprising because in China, relative to firms of other ownership types, SOEs and FIEs usually have better access to credit or enjoy tax deductions. Consequently, these entities' borrowing costs are relatively low, and regions with higher shares of SOEs and FIEs should have lower TFPRs (or equivalently, higher innovation efficiencies). However, there are also reasons to believe that this scenario may not be accurate. For example, whereas SOEs have better access to credits, these credits do not necessarily need to be used for innovation activities. Because the fruits of innovation investment will be realized only

[43] Although we argue that infrastructure investment negatively affects innovation activities, in the long run it is still possible that these investments will promote innovation efficiency if infrastructure induces more production, which with a larger scale or lengthier experience will be conducive to innovation. However, to test this conjecture, one would need data for a longer period of time for this potential effect to be realized.

after several years, it may not be in an SOE's best interest to channel these easy credits to risky innovation activities (relative to more predictable production activities).[44] Similarly, although FIEs are often considered more innovation-oriented than SOEs, with easy credits, they may not consider R&D a priority. In addition, FIEs are not necessarily more productive than domestic private firms. For example, Dai et al. (2012) and Yu (2015) have found that firms that conduct processing trade, which are mostly FIEs, are less productive, less capital-intensive, and more unskilled than non-exporting firms.[45] Their focus on low-quality goods suggests that some FIEs may place less emphasis on innovation activities; moreover, the preferential treatments that they receive may crowd out domestic private firms' access to innovation funding. Furthermore, sometimes FIEs are reluctant to file patents in China because of concerns about disclosures and potential leakages of their technology. This reluctance would result in an underestimation of the innovation productivities of regions with many FIEs. Finally, we do not find the ratio of regional exports to GDP to be significantly correlated with TFPRs.

Our use of a fixed effects model controls for any time-invariant unobserved characteristics that might bias our estimation, but there may also be time-varying regional characteristics that have been omitted and may cause endogeneity problems. For example, given the data constraints, we have not distinguished between the patents' industry categories. Therefore, if a region is more concentrated in industries that are more likely to issue patents (e.g., IT industries or some highly skilled service industries), then its measured innovation efficiency may be higher. Thus, we construct variables that indicate the regional industry structures and calculate the regional output shares of the following sectors: the primary sector, the labor-intensive manufacturing sector, the capital-intensive manufacturing sector, the high-tech manufacturing sector, the skill-intensive service sector, and the other service sector. In addition, the regional differences in the quality of the labor force may also result in different regional innovation efficiencies. For instance, if it is difficult for workers to migrate in China and if a region lacks an abundant supply of high-skilled workers, then this dearth may become a source of regional distortions. To account for this problem, we calculate the

[44] It is well documented that SOEs often must comply with the local government's economic growth priorities, which often involve achieving performance targets based on short-run GDP-related figures.

[45] In fact, Lu (2010) and Dai et al. (2012) both find that in China, exporters (among whom FIEs play a crucial role) have lower average productivity than non-exporters. Dai et al. (2012) suggest that this statistic results from the unexceptional performance of processing trade exporters.

regional population shares of the following educational levels: elementary school and below, middle school, high school, and tertiary schools. Our regression results with these industry structure and human capital composition controls are shown in column 3 of Table 5. We do not find a substantial difference from our findings in column 1.

We are slightly surprised that a region's overall institutional environment, which is measured by its real GDP per capita, is not significantly correlated with the values of the TFPRs. One possibility is that inasmuch as R&D represents a very specific and small portion of economic activities, a catchall variable such as real GDP per capita does not determine the unobserved institutional factors that may affect distortions in innovation activities. To resolve this conundrum, in column 4 of Table 5, we consider regional R&D intensity an additional variable and use it to perform a supplementary measure of the innovation-related regional institutional environment. We are interested in knowing whether a region's involvement or experience in innovation improves its efficiency. We find a marginally significantly negative coefficient, implying that, when a region is more experienced in innovation activities, it also experiences less distortion. Nevertheless, after comparing the coefficients of the other main explanatory variables with those in column 1, we do not find many changes in either the signs or the magnitudes.

Finally, in column 5, we add interactions of the maturity of the regional financial market (lnFEF) with industry shares of the SOE's (SOE_share) and the FIE's (FIE_share) outputs, respectively, in our regression model. We find that the interaction of financial market maturity and the SOE's share is significantly positively associated with a region's TFPR, suggesting that deeper SOE involvement will dampen the positive effect of a matured financial market. However, we do not find a greater FIE share to exert a negative effect on the effectiveness of financial markets in enhancing efficiency.

Robustness Checks

We conduct a battery of robustness checks, and the results are presented in Table 6. For ease of comparison, we put our baseline result (column 1 of Table 5) in the first column of Table 6. When calculating TFPRs, we use the sum of the invention and utility model patents as our measure of the innovation output. Some may argue that only invention patents should be considered innovation output because they represent the most substantial improvement in technology. However, although invention patents are by definition the most prestigious type of patents and are given the longest protection time (20 years), it usually takes 3-5 years for approval, and they are more expensive to maintain. As a result, many businesses apply for the more cost-effective utility model patents. [46] Furthermore, at least in earlier years, when China's capabilities were still catching up, many technological improvements were relatively minor and were captured only by utility model patents. Thus, we believe that the sum of these two types of patents should be the more appropriate measure of innovation output. Nevertheless, in column 2, we first recalculate the TFPRs using invention patents only and redo our regression analysis. It is clear that our results in columns 1 and 2 of Table 6 are very similar, which suggests that using an alternative measure of innovation output does not alter our conclusions.

Another issue is the gestation lag (time to maturity) in regard to the timing of R&D investment and the realization of innovation output. In our setup, we assume this to be one year, but one might expect it to be longer. In columns 3 and 4 of Table 6, we assume the time difference to be 2 and 3 years, respectively, and we conduct our analyses. Again, our findings are qualitatively similar to what we see in column 1.

We use the number of patent applications as our preferred measure of innovation output because, while the timing of an application can be controlled by its inventors, the time of its approval cannot. However, an application for a patent does not necessarily imply that a patent will be granted, so our choice of output could be a source of bias if regions' patent approval rates are systematically different. Therefore, in columns 5 and 6, we show the results when using patent grants as the measure of innovation output. In column 5, we still assume the time difference between innovation inputs and output to be one year, and we see that the results are very similar in columns 1 and 5, though the coefficient on the maturity of the financial market becomes insignificant. We suspect that this might be due to the approval time issue we described earlier, so in column 6, we lengthen the time difference between inputs and output to three years. We find the effect to be statistically significant, suggesting that

[46] For example, China's IPR SME Helpdesk, which is an EU-funded organization, suggests that European SMEs use utility model patents as part of their IP strategies. http://www.china-iprhelpdesk.eu/sites/all/docs/publications/China_IPR_Guide-Guide_to_Patent_Protection_in_China_EN-2013.pdf. Furthermore, experience suggests that utility model patents are also enforced. For instance, a Chinese company, the Chint Group, was awarded approximately US $45 million (though it later settled for $23 million) in damages for the alleged infringement of its utility model patent protecting a miniature circuit breaker (Stembridge, 2010).

the uncertain time to approval could indeed be a reason for our finding.

5. Concluding Remarks

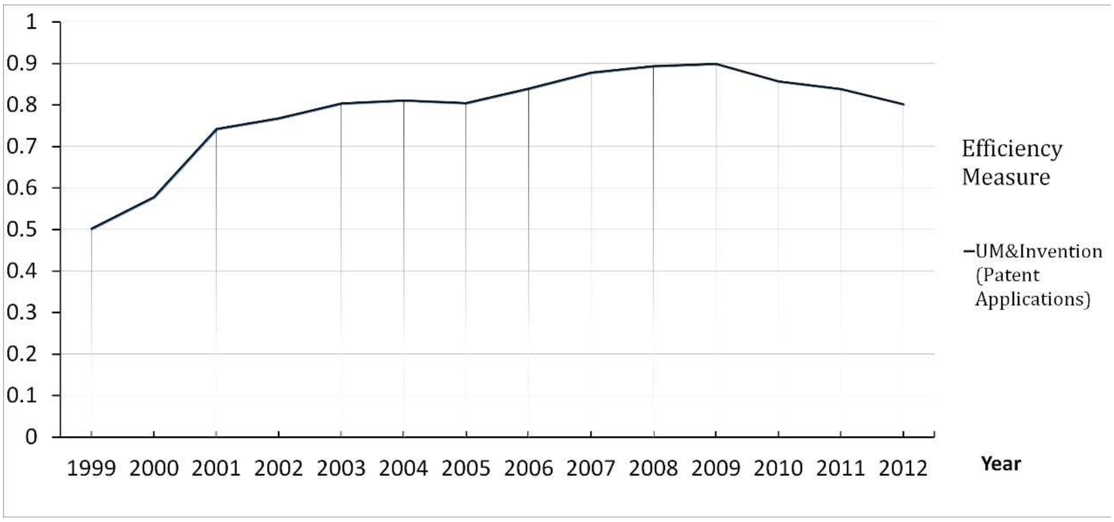
In this paper, using Hsieh and Klenow's (2009) insights into misallocation, we calculate a theory-based measure of innovation efficiency in China for 1999-2012. Overall, our measure of innovation efficiency considerably improved during the sampling period, suggesting substantial convergence in the extent of the distortions across regions. However, a more detailed analysis suggests that whereas innovation efficiency improved between 1999 and 2009, beginning in 2010, our efficiency measure modestly decreased for three consecutive years. We probe the potential factors that correlate with innovation efficiency and we find that a matured financial market has a beneficial effect. However, extensive, government-related development of the transportation infrastructure negatively correlates with innovation efficiency. SOEs and FIEs' output shares of local production are also detrimental to innovation efficiency. The hindering effect of SOEs and FIEs on innovation is first proposed by this paper.

We have conducted the first empirical analysis of misallocation in innovation activities within China, and following the insightful exercise by Hsieh and Klenow (2009), a natural extension of this paper is to conduct a cross-country comparison and quantify the potential improvement in innovation productivity that can be achieved should the distortions be removed. However, although performing such comparisons is conceptually possible, some major data hurdles must be overcome before one can successfully implement this analysis. In particular, while we use patent counts as our measure of innovation output, it is generally difficult to compare patent statistics across countries. This difficulty arises because the technology sophistication requirements for new patents and the patenting behaviors of innovators could vary considerably across nations, resulting in substantial heterogeneity in patent values and quality across patent offices. Finding a method to align this diverse patent information will be a critical first step for conducting cross-country comparisons.

As in the existing innovation literature, we investigate innovation efficiencies in China at the regional level to acknowledge the crucial roles played by regional institutions, such as local governments and financial sectors. Alternatively, one may want to adopt a setup that considers innovation production at the plant level, as has been done in discussions of goods production. However, this process calls for plant- or firm-level data on both innovation inputs and outputs. Although our current analysis is carried out at the regional level due to data constraints, we provide a framework that may be used for more detailed policy analyses once more disaggregated datasets become available.

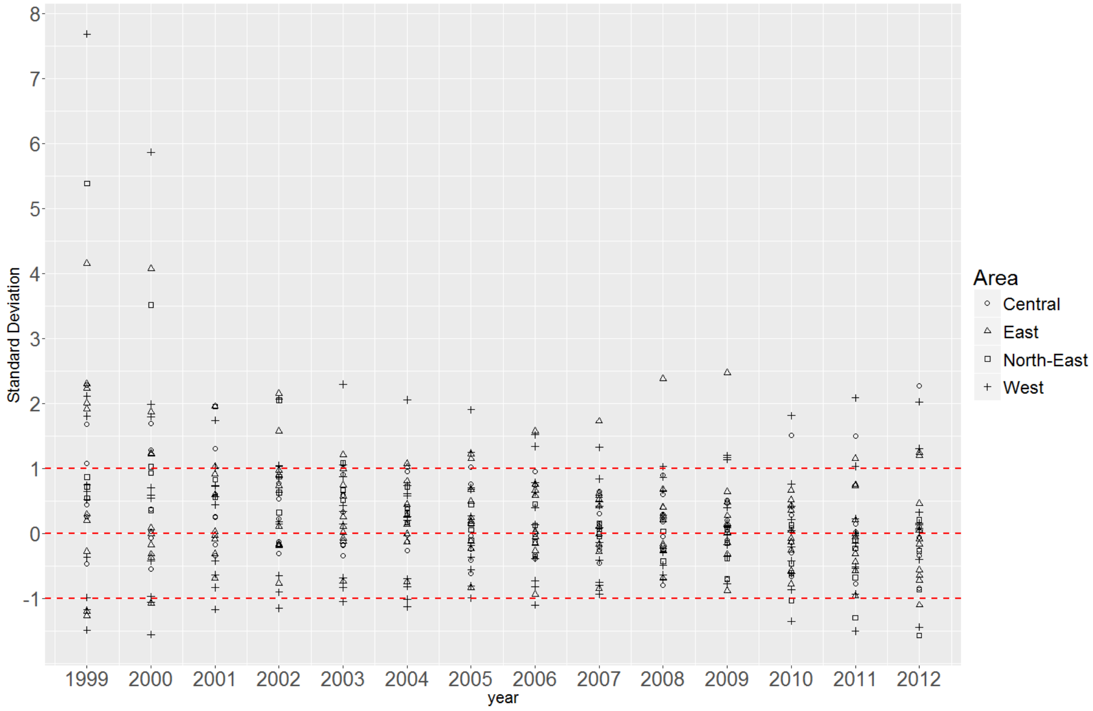
Figures and Tables

Figure 1 Trends in Chinese Innovation Efficiency (1999-2012)



Note: The efficiency measure is calculated based on equation (20), and the parameters we use are given in Table 1.

Figure 2a Distribution of Regional Demeaned TFPRs (1999-2012)



Note: Regional demeaned TFPRs are calculated by subtracting a region's TFPR by the $\overline{\text{TFPR}}$ in that year.

Figure 2b Distribution of Demeaned TFPRs across Areas (1999 and 2012)

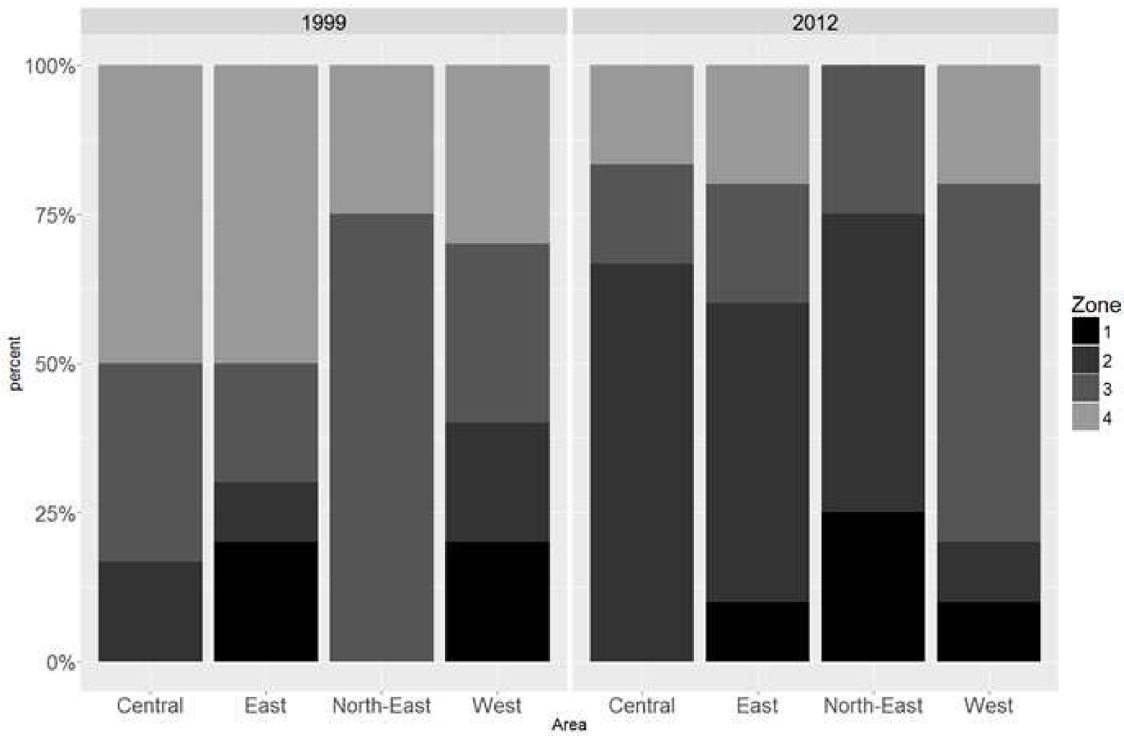


Table 1: Parameters Used in Calibrations

	α	R=δ + i: δ	R=δ + i: i	γ
Parameter values	0.60	0.20	0.03	0.8

Table 2 Variable Definitions and Data Sources

Variable Description		Definition	Data Source
Innovation inputs and output variables			
Innovation output:	Patent applications	(invention patents + utility model patents) applications in year *t*	China Statistical Yearbook for Science and Technology (CSYST) 1999-2012
	R&D labor input	Share of R&D expenditures used in personnel in year *t-1*	CSYST 1998-2011
	R&D capital input	R&D capital inventory in year *t-1* calculated using a perpetual inventory method	CSYST 1998-2011
Determinants of misallocation			
Dependent variable:	Deviation of region *j*'s TFPR from the mean of TFPR in year *t*, lnTFPR_ratio	$\ln\left(\frac{\mathrm{TFPR}_{jt}}{\overline{\mathrm{TFPR}_t}}\right)$	Calculated from equation (22)
Explanatory variable:	Maturity of the financial market, lnFEF	(Log of) Outstanding Loan/GDP in year *t-1*	Almanac of China's Finance and Banking 1998-2011 for outstanding loans; China Economic & Industry Data Database (CEIC) for GDP
	Development of transportation infrastructure, lnLTRANS	(Log of) road length/region area in year *t-1*	Year Book of China Transportation & Communications 1998-2012
	Real GDP per capita, lnRGDPpc	(Log of) Real GDP/population in year *t-1*	CEIC
	Population size, lnPOP	(Log of) population in year *t-1*	CEIC
	Industry output share by state-owned enterprises (SOEs), SOE_share	Share of industry output by SOEs in year *t-1*	CEIC
	Industry output share by foreign invested enterprises (FIEs), FIE_share	Share of industry output by FIEs in year *t-1*	CEIC

	Ratio of exports and GDP, exp_ratio	(Log of) exports/GDP in year *t-1*	CSY for exports; CEIC for GDP
	Ratio of R&D expenditure and GDP, RD_ratio	R&D expenditures/GDP in year *t-1*	CEIC
	Industry composition	Output shares of the following sectors: primary, labor-intensive manufacturing, capital-intensive manufacturing, high-tech manufacturing, skill-intensive service, and other service in year *t-1*	Statistical yearbooks for each region 1998-2011
	Human capital composition	Population shares for the following education levels: elementary school and below, middle-school, high school, and tertiary school in year *t-1*	Statistical yearbooks for each region 1998-2011

Table 3 Distribution of Demeaned TFPRs across Areas

	East Coast	Central	Northeast	West	Entire China
All years (1999-2012)					
Zone 1	4 (3%)	0 (0%)	3 (5%)	13 (9%)	20 (5%)
Zone 2	55 (39%)	38 (45%)	18 (32%)	47 (34%)	158 (38%)
Zone 3	56 (40%)	36 (43%)	29 (52%)	52 (37%)	173 (41%)
Zone 4	25 (18%)	10 (12%)	6 (11%)	28 (20%)	69 (16%)
Total	140 (100%)	84 (100%)	56 (100%)	140 (100%)	420 (100%)
Years 1999-2003					
	East Coast	Central	Northeast	West	Entire China
Zone 1	3 (6%)	0 (0%)	0 (0%)	7 (14%)	10 (7%)
Zone 2	17 (34%)	11 (37%)	0 (0%)	12 (24%)	40 (27%)
Zone 3	16 (32%)	13 (43%)	14 (70%)	18 (36%)	61 (41%)
Zone 4	14 (28%)	6 (20%)	6 (30%)	13 (26%)	39 (26%)
Total	50 (100%)	30 (100%)	20 (100%)	50 (100%)	150 (100%)
Years 2004-2008					
	East Coast	Central	Northeast	West	Entire China
Zone 1	0 (0%)	0 (0%)	0 (0%)	3 (6%)	3 (7%)
Zone 2	19 (38%)	15 (50%)	8 (40%)	20 (40%)	62 (47%)
Zone 3	24 (48%)	14 (47%)	12 (60%)	20 (40%)	70 (39%)
Zone 4	7 (14%)	1 (3%)	0 (0%)	7 (14%)	15 (7%)
Total	50 (100%)	30 (100%)	20 (100%)	50 (100%)	150 (100%)
Years 2009-2012					
	East Coast	Central	Northeast	West	Entire China
Zone 1	1 (3%)	0 (0%)	3 (19%)	3 (8%)	7 (6%)
Zone 2	19 (48%)	12 (50%)	10 (62%)	15 (38%)	56 (47%)
Zone 3	16 (40%)	9 (38%)	3 (19%)	14 (35%)	42 (35%)
Zone 4	4 (9%)	3 (12%)	0 (0%)	8 (19%)	15 (12%)
Total	40 (100%)	24 (100%)	16 (100%)	40 (100%)	120 (100%)

Note: The values within each cell are the frequency (outside the parentheses) and the share (within the parentheses) of the regional demeaned TFPRs located in a particular zone for the area during a specific time period.

Table 4 Summary Statistics

Variable Name	Obs.	Mean	Standard Deviation	Min.	Max.
lnTFPR_ratio	390	0.038	0.322	-0.884	1.159
lnFEF	390	0.050	1.585	-9.348	2.587
lnLTRANS	390	2.450	0.933	-0.030	4.463
lnRGDPpc	390	-2.018	0.681	-3.698	-0.403
lnPOP	390	8.128	0.770	6.234	9.260
SOE_share	390	0.500	0.208	0.107	0.899
FIE_share	390	0.135	0.121	0.002	0.540
exp_ratio	390	0.160	0.196	0.002	0.917
RD_ratio	390	0.011	0.010	0.001	0.058
Industry Composition					
Primary	363[a]	0.185	0.079	0.017	0.396
Labor-intensive manufacturing	363[a]	0.072	0.033	0.013	0.170
Capital-intensive manufacturing	363[a]	0.107	0.045	0.016	0.240
High-tech manufacturing	363[a]	0.127	0.065	0.018	0.265
Skill-intensive service	390	0.146	0.039	0.079	0.300
Other service	363[a]	0.360	0.050	0.256	0.589
Human capital composition					
Elementary school and below	390	0.422	0.114	0.124	0.720
Middle school	390	0.373	0.060	0.205	0.499
High school	390	0.134	0.043	0.036	0.290
Tertiary school	390	0.071	0.050	0.009	0.339

Note a. For some regions, there are missing values in the industry shares for some years.

Table 5 Determinants of Regional Distortions

Dependent Variable: ln_TFPRratio	(1) Baseline Model	(2)	(3)	(4)	(5)
lnFEF	-0.0328**	-0.0329***	-0.0261**	-0.0297**	-0.106***
	(0.0123)	(0.0114)	(0.0123)	(0.0127)	(0.0315)
lnLTRANS	0.319		0.346**	0.421**	0.341*
	(0.193)		(0.154)	(0.174)	(0.189)
lnLTRANS*EN_areas		0.00601			
		(0.334)			
lnLTRANS*CW_areas		0.422**			
		(0.163)			
SOE_share	1.316***	1.395***	1.441***	1.432***	1.342***
	(0.397)	(0.370)	(0.362)	(0.369)	(0.398)
FIE_share	1.311***	1.494***	1.493***	1.238***	1.337***
	(0.329)	(0.314)	(0.385)	(0.321)	(0.360)
exp_ratio	0.0790	0.326	-0.0526	0.406	0.0315
	(0.402)	(0.390)	(0.318)	(0.339)	(0.403)
lnRGDPpc	-0.301	-0.174	-0.379	-0.372	-0.304
	(0.565)	(0.499)	(0.539)	(0.506)	(0.572)
lnPOP	-1.221	-0.684	-2.241***	-0.914	-1.258
	(0.760)	(0.724)	(0.611)	(0.787)	(0.783)
RD_ratio				-29.07*	
				(16.35)	
lnFEF*SOE_share					0.0807*
					(0.0451)
lnFEF*FIE_share					0.561
					(0.435)
Observations	390	390	363	390	390
Ind. Composition Vlbs.	No	No	Yes	No	No
Human Capital Vlbs	No	No	Yes	No	No
Year-Fixed Effects	Yes	Yes	Yes	Yes	Yes
Patent Types	invention + UM	invention + UM	invention + UM	invention + UM	invention + UM
Model Type	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects

Note: The standard errors are in parentheses. *** <0.01, **<0.05, *<0.1.

Table 6 Robustness Checks

Dependent Variable: ln_TFPRratio	(1) Baseline Model	(2) Invention Only	(3) Lag 2 years	(4) Lag 3 years	(5) Grant-Lag 1 year	(6) Grant-Lag 3 years
lnFEF	-0.0328**	-0.0293***	-0.0289**	-0.0254*	-0.0248	-0.0280*
	(0.0123)	(0.00544)	(0.0138)	(0.0139)	(0.0161)	(0.0158)
lnLTRANS	0.319	0.298	0.359*	0.334*	0.293	0.446***
	(0.193)	(0.217)	(0.192)	(0.190)	(0.175)	(0.159)
SOE_share	1.316***	1.407***	1.110**	0.864*	0.966***	0.811**
	(0.397)	(0.463)	(0.420)	(0.453)	(0.337)	(0.350)
FIE_share	1.311***	1.427***	1.140***	0.844**	1.413***	1.363***
	(0.329)	(0.416)	(0.333)	(0.373)	(0.345)	(0.417)
exp_ratio	0.0790	0.370	-0.0846	-0.269	-0.00819	-0.429
	(0.402)	(0.452)	(0.417)	(0.447)	(0.402)	(0.380)
lnRGDPpc	-0.301	-0.141	-0.376	-0.453	-0.589	-0.632
	(0.565)	(0.587)	(0.556)	(0.568)	(0.509)	(0.475)
lnPOP	-1.221	-1.682*	-1.270*	-1.337*	-0.763	-0.901
	(0.760)	(0.884)	(0.738)	(0.728)	(0.658)	(0.615)
Year-Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Patent Types	invention + UM	invention	invention + UM	invention + UM	invention + UM	invention + UM
Model Type	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects

Note: The standard errors are in parentheses. *** <0.01, **<0.05, *<0.1.

References

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ems: Institutional and organisational dimensions. Res. Policy 26, 475–491.

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b

2006. R&D stock, knowledge function and productive efficiency. China Econ. Q. Beijing 5, 1129–1156.

d

A., Zhang, Y., Zhao, R., 2003. A study of the R&D efficiency and

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B

productivity of Chinese firms. J. Comp. Econ. 31, 444–

Appendix

Table A1 Sector Classification

Primary Sector
Agriculture, Forestry, Animal Husbandry and Fisheries
Mining and Washing of Coal
Extraction of Petroleum and Natural Gas
Mining and Processing of Ferrous Metal Ores
Mining and Processing of Non-Ferrous Metal Ores
Mining and Processing of Nonmetal Ores
Mining of Other Ores
Labor-Intensive Manufacturing Sector
Processing of Food from Agriculture Products
Manufacture of Foods
Manufacture of Beverages
Manufacture of Tobacco
Manufacture of Textile
Manufacture of Textile Wearing Apparel, Footwear and Caps
Manufacture of Leather, Furs, Feather (Down) and Related Products
Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm and Straw Products
Manufacture of Furniture
Manufacture of Paper and Paper Products
Printing, Reproduction of Recording Media
Manufacture of Articles for Culture, Education and Sports Activities
Capital-Intensive Manufacturing Sector
Processing of Petroleum, Coking, Processing of Nuclear Fuel
Manufacture of Rubber
Manufacture of Plastics
Manufacture of Non-Metallic Mineral Products
Smelting and Pressing of Ferrous Metals
Smelting and Pressing of Non-Ferrous Metals
Manufacture of Metal Products
High-Tech Manufacturing Sector

Manufacture of Raw Chemical Materials and Chemical Products
Manufacture of Medicines
Manufacture of Chemical Fibers
Manufacture of General Purpose Machinery
Manufacture of Special Purpose Machinery
Manufacture of Transport Equipment
Manufacture of Electrical Machinery and Equipment
Manufacture of Communication Equipment, Computers and Other Electronic Equipment
Manufacture of Measuring Instruments and Machinery for Culture Activity and Office Work
Skill-Intensive Service Sector
Transport, Storage, and Post
Financial Intermediation
Real Estate
Other Service Sectors
Production and Distribution of Electric Power and Heat Power
Production and Distribution of Gas
Production and Distribution of Water
Wholesale and Retail Trades
Retail Trades
Hotels and Catering Services
Real Estate
Construction