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Green total factor productivity in Chinese cities: Measurement and causal analysis within a new structural economics framework

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ABSTRACT

The driving force of high-quality development is to improve the total factor productivity. This paper examines this issue at the city level in China. First, input–output data are reconstructed, and then the green total factor productivity (GTFP) index of 264 Chinese cities during 2003–2018 is accounted based on the SBM-DDF-ML index under data envelopment analysis (DEA). The accounting results show distinctively temporal, regional, and city-scale heterogeneity in urban GTFP growth. Second, the analysis of the causal factors of urban GTFP growth in the framework of the new structural economics verifies the theoretical inference that structural factors not only lead to disparities in macroeconomic growth, but are also a key reason underlying heterogeneities in urban GTFP. Specifically, industrial comparative advantage based on resource endowments mainly works by optimizing the efficiency of resource allocation to enhance pure efficiency change, and its dynamics will also generate demand for technological progress to promote pure technological progress. Moreover, a mismatch between industrial structure and resource endowment structure is not conducive to improvements in urban productivity improvement, but the contemporaneous introduction of more advanced technologies can help reduce or even reverse this negative effect.

Introduction

This paper examines the trends and determinants of green total factor productivity (GTFP) in Chinese cities from 2003 to 2018 under the goal of high quality development. Key rationale for this type of research are the declining demographic and land dividends. Indeed, it is well established that these two factors are no longer the key drivers of economic growth. This study hopes to provide an adequate theoretical explanation and empirical basis for this. According to the growth theory of new structural economics (Lin & Fu, 2018), the initial impetus for economic growth comes from natural resource endowments. With the accumulation of physical capital, per capita capital stock and technological progress determine per capita output. However, given the law of diminishing returns to capital, capital accumulation cannot sustain economic growth in the long run. If an economy has a sufficiently abundant labor force, the effect of the law of diminishing returns to capital can be delayed to a large extent, and this is called the "demographic dividend" (Cai, 2004). Since all three drivers of economic growth – natural resources, physical capital accumulation, and the demographic dividend – are ultimately subject to diminishing marginal utility, sustained growth of output per capita must be shifted to technological progress or productivity gains. Total factor productivity (TFP), which measures the efficiency of production in addition to factor inputs, is considered an important indicator of the sustainability of economic growth. China has entered a stage where the marginal reward of factor inputs is decreasing and the demographic dividend is receding. The Report of the 19th National Congress of the Communist Party of China in 2017 clearly put forward that "China's economy has shifted from a stage of high speed growth to a stage of high quality development, and is in a critical period of changing its development mode, optimizing its economic structure and transforming its growth momentum, building a modern economic system is an urgent requirement for crossing the hurdle and the strategic goal of Chinese development. We must adhere to the quality first and benefit first, and take supply-side

Abbreviations: GTFP, Green total factor productivity; ML index, Malmquist–Luenberger index; DEA, Data envelopment analysis

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structural reform as the main line to promote changes in the quality, efficiency and momentum of economic development and improve total factor productivity."[1] This is the government's objective judgment vis-a-vis China's economy, which means that TFP plays a more critical role in China's economic development, and will become a sustainable source of power for China to achieve high-quality development.

In 2018, 59.58% of China's population were living in urban areas, generating 59.5% of GDP, considering only cities at the prefecture level and above.[2] As the main space for the transformation of development goals, cities need to play the role of leaders and pioneers in achieving high quality development. Therefore, it is of great practical importance to measure urban productivity and further analyze its causal factors under the goal of high-quality development.

The remainder of this paper is organized as follows: Section 2 presents a literature review on the accounting and causal analysis of urban (green) total factor productivity. Sections 3 introduces the urban GTFP accounting methodology adopted in this paper, the reconstruction of input−output data and the selection of the research sample, followed by Section 4, which analyzes the urban GTFP accounting results from multiple perspectives. Section 5 makes an empirical study on the causal factors of urban GTFP growth from the perspective of new structural economics. Section 6 concludes.

Literature review

For a long time, many scholars have conducted accounting studies on GTFP in Chinese cities, which can be divided into two cross-cutting pre- and post-periods. In the early days, the main objective of Chinese macroeconomics was economic growth rather than economic development, and the corresponding studies measuring urban productivity also ignored negative outputs in the urban production process, mainly using urban TFP rather than urban GTFP as the accounting target. The findings of these studies are highly heterogenous. First, the level of urban TFP growth varies greatly, for example, Jin (2006), and Liu and Li (2009) suggested that the average annual growth rate of TFP between 1990 and 2003 and between 1990 and 2006 was 8.3% and 2.8%, respectively. Wang, Chen, and Gao (2016), Li and Pan (2018) measured Chinese urban TFP between 2000 and 2013 and they arrived at TFP growth rates of −2% and 3.1%, respectively. Second, the source of TFP growth thus identified differs between studies, that is there is ambiguity whether technical efficiency is the main driver (Zhang & Zhao, 2010; Zhang, 2013) or technological progress (Dai, 2010; Li, 2007; Liu, Ma, & Li, 2020; Wang & Wang, 2016). In this respect, there is no consensus in the academic community. Third, there are different judgments concerning regional distribution patterns, such as decreasing TFP from east to central to west (Shao & Xu, 2010) and decreasing TFP from east to west to central (Wang & Xue, 2016).

Starting in 2012, China's fast economic growth began to turn into a moderate one. In 2014, President Xi Jinping used the term "new normal", for the first time, to describe the new state of China's economic growth. The 19th National Congress report on the status of China's economic development indicates that China's economy has entered a stage of high-quality development, no longer pursuing purely economic growth, but focusing on multiple development goals such as economic balance, innovation, ecology, and upgrading of the industrial structure. A growing number of scholars are taking resource consumption and environmental constraints into account when measuring productivity in Chinese cities, and thus conducting measurement and analysis of green TFP or using it as a basis for further research. Traditional TFP only considers good outputs, while green TFP generally refers to TFP that considers bad outputs or negative externality of environmental pollution. Because of the ease of implementing productivity indexes based on data envelopment analysis and the ability to disaggregate these indexes, most of this literature is based on the Malmquist−Luenberger index or Luenberger index. Representative examples include Xiao, Li, Tang, and Su (2013), who measured the green TFP of 286 cities at the prefecture level and above from 2003 to 2010. The average annual growth rates of GTFP, technical efficiency, and technical progress were found to be 1.1%, 0.5%, and 0.9%, respectively, and the regional distribution of GTFP showed the characteristic of "East > West > Central." By accounting and comparing the environmental economic performance of 25 cities in the Yangtze River Delta and Pearl River Delta urban agglomerations, Li (2017) clearly pointed out that the traditional economic performance evaluation method ignored the rigid constraints of resources and environment and the development demands of the times, and thus was biased. Focusing on 108 cities in the Yangtze River Economic Zone between 2003 and 2013, Lu, Song, and Huang (2017) found that the average annual growth rate of GTFP and TFP was 13.5% and 12.7%, respectively, with technological progress being the main source of growth, while the regional distribution of GTFP showed the characteristic of "East>West>Central". Compared to other literature, the use of fixed asset investment instead of capital stock and the neglect of price factors may be the main reasons for the higher productivity levels of cities measured in this paper. Li and Guo (2019) measured the GTFP of 275 cities between 2003 and 2016 and found an average annual increase of 1.33% in GTFP. However, the main purpose of the paper was to investigate the impact of industrial structure on urban GTFP, and it did not provide a specific and detailed analysis of GTFP itself. Zhao, Liu, Wang, and Sun (2020) measured GTFP of 65 cities in the Yellow River Basin from 2001 to 2017, and found that GTFP growth was higher following the 13th Five-Year Plan, with obvious spatial heterogeneity in both the GTFP growth rate and its compositions. Recently, some other scholars have optimized the data envelopment analysis (DEA) method in accounting for GTFP, such as Shi and Li (2019), who used the meta-frontier Malmquist-Luenberger (MML) productivity index to measure the GTFP of China's manufacturing; Xia and Xu (2020), who introduced bootstrap method in accounting for the DDF-ML index to correct for estimation bias and to conduct corresponding statistical significance tests for changes in GTFP index and its decomposition terms. The innovation of such research methods has further advanced the research progress in the field of GTFP accounting, but it is still in the initial stage and is mostly used in inter-provincial studies.

Based on the extant literature, this paper suggests that the main reasons for the differences in TFP or GTFP judgments among scholars are (1) different choices of indicators and the way they are handled imply different input−output index systems, which will lead to different accounting results (2) different city samples will lead to different production frontiers (3) different rates and patterns of economic growth in different periods will lead to different results. The next step of this paper is to use the input−output index system as the basis for the reconstruction and observe how differences in the configuration of city samples affect measurement results.

Further, a large number of scholars have conducted causal analysis based on urban TFP or GTFP accounting work, including innovation input (Huang & He, 2013), establishment of National High-Tech Development Zones (Tan & Zhang, 2018), government land finance centered on land concessions (Zhang & Yu, 2019), urban housing prices (Yu & Li, 2019), manufacturing industry agglomeration (Wei, Zhang, Wen, & Wang, 2020), smart city policy (Wang, Pang, Zhang, Miao, & Sun, 2022), and so on. However, few scholars have examined the causal factors that influence or determine TFP or GTFP from the perspective of new structural economics. Among the few existing studies, it is worth mentioning that Xia and Xu (2020) also examine

[1] See the website of the State Council of the People's Republic of China, i.e., http://www.gov.cn/zhuanti/2017-10/27/content_5234876.htm.

[2] Only the actual urbanized area of the city – the municipal district – is considered here.

how structural changes in the three industries affect GTFP. However, the causal analysis in their paper is fundamentally different from this paper, in a sense that on one hand they take Chinese provinces and municipality directly under the Central Government as the research objects, while the industrial structures of provinces and cities are extremely different, and on the other hand they explore how a shift in the share of the secondary industry to the primary and tertiary industries affects GTFP, that is, they focus on the effects of changes in industrial structure. However, this paper focuses on how structural changes determined by the endowment structure (i.e., industrial comparative advantage) affect urban GTFP.

Based on the theory of new structural economics, the structure of resource endowment differs from place to place, the industrial structure is embedded in the resource endowment structure, and urbanization depends, to a considerable extent, on industrial development, so it can be theoretically inferred that "structural inducements" must be considered as one of the key inducements that determine urban productivity growth. It is necessary to remind that the new structural economics has always believed that the industries with comparative advantage everywhere are essentially determined by the resource endowment of the place, but does not follow a one-size-fits-all approach and changes dynamically with the change of endowment. When a place adopts an industrial policy consistent with comparative advantage, micro enterprises in the industries with comparative advantage will gain further self-generating ability and profitability, and thus continuously engage in capital accumulation and technological innovation, and when capital accumulation and technological innovation reach a critical point, the structure of resource endowment will change profoundly, leading to the transformation and upgradation of industrial structure. On one hand, the original industrial structure is replaced by a new one, and on the other hand, the original industrial structure is upgraded to the higher end of the industrial chain. In either case, technological innovation and progress are required and accompanied, and the new structural economics considers all these situations in an integrated manner. Chinese cities have significant differences in resource endowments and industrial structures, which objectively provide a natural sample for empirically exploring the relationship between city productivity and local industrial comparative advantage. This paper is a practical application of the new structural economics in urban productivity measurement and analysis, which not only measures and compares the GTFP of different cities in different regions of China, but also infers the "structural causes" of the divergence of GTFP in different cities, thus avoiding the shortcomings of many productivity research papers with technical analysis but no theoretical framework, so that the analysis of this paper finally penetrates the relationship between industrial structure and productivity. In fact, this relationship exists and works in an endogenous mechanism. Therefore, the analysis in this paper is essentially in the perspective of the new structural economics theory.

Overall, few studies focus on urban GTFP under the perspective of the new structural economics, but research on such issues is of great significance for understanding the stage of development of China's urban economy, implementation of comprehensive comparative advantage industrial policies, improvement in urban economic quality, and implementation of a sustainable new urbanization strategy. Compared with existing studies, the marginal contributions of this paper can be delineated as follows. First, unlike the existing literature that focuses on whether GTFP is driven by efficiency change or technological progress to a greater extent, this paper places more emphasis on the role of scale effects among the drivers of GTFP growth, thus providing a new perspective of the analysis of urban GTFP growth pattern. Second, the problem of input−output indicator selection for urban total factor productivity measurement is clarified, and the inconsistency of existing literature measurement findings is critically, though partially, explained, based on which this paper reconstructs the input−output indicator data to account for urban GTFP. Third, based on the above accounting studies, this paper examines the key causal factors of urban GTFP growth based on the theory of neo-structural economics, to expand the theoretical applicability of neo-structural economics on one hand and to provide feasible industrial policy suggestions for Chinese cities to increase GTFP in the stage of high-quality development on the other.

Measurement methodology and data

Measurement methodology

There are four main methods for TFP measurement: growth accounting, the production function method, the productivity index method based on data envelopment analysis, and the stochastic frontier method. The applicability of these four methods depends on the research context, data quality, and the objectives of the researcher. The Malmquist productivity index method based on DEA can handle multiple inputs and multiple outputs simultaneously and can further decompose the productivity index (Färe, Grosskopf, Lindgren, & Roos, 1992), thus giving richer results. The basic idea of the method is to construct a non-parametric production frontier, comparing the actual production of the evaluated production unit with its projection (improvement target) on the production frontier based on the Distance Function (DF), and thus calculating the productivity index and its decomposition term. Färe et al. (1992) originally calculated the Malmquist productivity index, only considering expected outputs and inputs. Chung, Färe, and Grosskopf (1997) used the directional distance function (DDF) to introduce bad outputs into the calculation of the Malmquist productivity index, and obtained the Malmquist Luenberger (ML) productivity index. Many scholars have since used this angular and radial directional distance function to calculate GTFP. However, the angle assumes that the inputs (outputs) are given, and the inefficiency is measured in terms of the degree to which each output (input) can be improved. However, the unit of production may have both over- and under-inputs, which can lead to biased results. The radial approach requires equal scaling down (up) of inputs (outputs) and ignores the possibility of individual scaling down (up) of inputs (outputs), which means that considering only equal scaling of improvement without considering slack improvement is not in line with production reality and is likely to overestimate the efficiency of the evaluated production unit. Pastor, Ruiz, and Sirvent (1999) and Tone (2001) proposed efficiency calculation methods, which consider slack improvement, namely Enhanced Russell Measure (ERM) and Slack Based Measure (SBM) respectively. These models are essentially the same, but the SBM nomenclature is more widely used. On this foundation, Cooper, Seiford, and Tone (2007), Färe and Grosskopf (2010), and others have taken combinatorial approaches and the resulting SBM-DDF-ML productivity index has been widely used in studies of total factor productivity measurements that consider resource and environmental constraints[3].

In the Variable Returns to Scale (VRS) settings[4], the ML index based on the non-radial, non-angular SBM-DDF is chosen to measure the GTFP change of Chinese cities. Furthermore, borrowing the decomposition method from Zofio (2007), the ML index is further decomposed into Pure Efficiency Change (PEC), Pure Technical

[3] The theoretical model for accounting the SBM-DDF-ML productivity index has been introduced in many literatures, which can be found in Lu, Song, and Huang (2017),Zhao, Liu, Wang, and Sun (2020), etc., and will not be repeated here.

[4] If returns to scale are constant, the results measured under the Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) settings should be the same; conversely, if there are increasing or decreasing returns to scale, the VRS setting can strip out the scale effect, while the CRS setting cannot do so.

Change (PTC), Scale Efficiency of Efficiency Change (SEEC), and Scale Efficiency of Technical Change (SETC). The following relationships exist between the ML index and the decomposition terms.

$$\text{ML index} = \text{Efficiency Change} \times \text{Technical Change}$$
$$= (\text{PEC} \times \text{SEEC}) \times (\text{PTC} \times \text{SETC})$$

where Technical Change (TC) reflects the outward shift of the production frontier, and TC greater than 1 means that the current period has achieved an outward shift of the production possibility frontier compared to the previous period, that is, the "growth effect." Efficiency Change (EC) reflects the movement of the evaluated production units to the production frontier, and EC greater than 1 means that the evaluated production unit has achieved an improvement in resource allocation efficiency in the current period, that is, the "catch-up effect." The two decompositions of the ML index may include scale effects for technical progress and efficiency change, while the four decompositions of the ML Index explicitly isolate scale effects from TC and EC, with the decompositions of scale efficiency (SEEC) and technical scale (SETC) reflecting the change in resource allocation efficiency and the movement in the production possibility frontier due to gains in scale, respectively. Thus, in Zofio's (2007) productivity decomposition framework, we can have: total scale effect = SEEC × SETC[5].

Data reconstruction of input–output indicators

(1) Desirable Output

Gross regional product is a common indicator of desirable output. Most studies use actual values, but a few studies suggest that the effect of prices will be offset if nominal values are used for both inputs and outputs, so nominal GDP is used directly (Gao, 2007; Wang, Xu, Zeng, & Guo, 2015). To offset the possible impact of prices, this paper still chooses to use real values. Due to the lack of city-level GDP deflators, most of these studies use provincial GDP indices (previous year = 100) to discount nominal GDP for each city. However, this treatment ignores the differences in price levels between cities, such that the price level in provincial capitals is usually higher than that in prefecture-level cities. We use the 2005 nominal GDP of each city and the constant price growth rate of GDP over the years to obtain real GDP (billion yuan, 2005 as the base period)[6].

(2) Undesirable Outputs

Based on the availability of pollution product data at the city level in China, this paper selects industrial wastewater emissions (10,000 tons), industrial sulfur dioxide emissions (tons), and industrial smoke (dust) emissions (tons) as proxies for undesired outputs. *China's Urban Statistical Yearbook* only gives city-wide data on pollution products, and considering that most of the industrial activities are concentrated in municipal districts which are exactly our study objects[7], rather than municipal counties or municipal cities, we believe that this error is relatively small.

(3) Input: Labor

The labor force is measured in terms of all employed people in urban areas, which is obtained by summing two indicators: urban unit employees and urban private and self-employed persons[8]. Some scholars only consider the former, which is potentially problematic. Private and self-employed workers are important components of China's urban labor force. Calculations show that the number of private and self-employed workers in urban areas as a share of total urban employment gradually increased between 2003 and 2018, and by 2018 this proportion had exceeded 50%. Private and self-employed persons have played an important role in absorbing employment and have become an important source of urban economic growth, for example, the street vendor economy that was created to boost the economy during the 2020 COVID-19 crisis.

(4) Input: Capital

In the neoclassical economic growth model, capital investment refers to the capital stock that is productive. In view of the difficulties in accounting for the capital stock of cities, a few scholars have directly used the amount of fixed asset investment in each city as a proxy for capital investment (Tao, Tan, & Chen, 2013; Yu, Zhou, & Wang, 2006). Most scholars use the perpetual inventory method to estimate the capital stock of city i in period t ($K_{it} = I_{it} + K_{i,t-1}(1-\delta)$). The capital stock depends on the base period capital stock K_0, depreciation rate δ, and investment series I. Different parameter settings result in different capital stock series.

① Determination of the base period capital stock

Drawing on Reinsdorf and Cover (2005), the base period capital stock (K_0) is estimated by means of a mathematical relational derivation.

Taking g as the average growth rate of I, then g

$$I_{-1} = I_0/(1+g)$$

The amount of investment for the previous year that still remained in the base period capital stock was $I_{-1}(1-\delta) = I_0(1-\delta)/(1+g)$.

Likewise, $I_{-2} = I_0/(1+g)^2$,

The investments for year (−2) that still remained in the base period capital stock were

$$I_{-2}(1-\delta)^2 = I_0(1-\delta)^2/(1+g)^2 = I_0[(1-\delta)/(1+g)]^2$$

Pooled Investments for all periods prior to the base period may result in

$$K_0 = I_0\left[1 + \frac{1-\delta}{1+g} + \left(\frac{1-\delta}{1+g}\right)^2 + \cdots\right] = I_0\left(\frac{1+g}{g+\delta}\right)$$

Here we take g as the average of the five-year investment growth rate from 2003 to 2007.

② The depreciation rate is based on existing studies on China, such as Zhang, Wu, and Zhang (2004) and Shan (2008), who set the depreciation rate at 9.6% and 10.96%, respectively, in their estimations of China's interprovincial capital stock. Ke (2009) and Ke and Zhao (2014) set the depreciation rate at 5% when calculating the capital stock of Chinese counties and cities. This figure has been applied in this study.

③ The increase in capital stock will only result from an increase in investment that creates real productive capacity. The existing literature, when estimating the national and interprovincial capital stock, uses three series of investment I: total societal

[5] This paper refers to it as the "total scale effect index" to indicate that it is the total productivity change arising from the scale effect.

[6] Gross domestic product, value added of tertiary and related industries, gross regional product, GDP per capita and GNI in absolute terms are calculated in current prices, and the growth rate is calculated in constant prices (National Bureau of Statistics website).

[7] "City" refers to the entire administrative area of cities at prefecture level and above, including urban areas, suburbs, and counties (cities) under their jurisdiction; "municipal districts" includes urban areas and suburbs, but excludes counties (cities) under their jurisdiction. This paper concentrates on the productivity of urbanized areas and therefore takes municipal districts as the study object.

[8] Data on urban private and self-employed workers are not as available as urban unit employees, and accordingly several cities have been further omitted from this paper.

fixed asset investment (Jin & Wang, 2016; Li, Xu, & Chen, 2005; Wang & Xiao, 2011), total fixed capital formation (Jin & Zhang, 2013; Shan, 2008; Zhang et al., 2004), and new fixed assets (Ke & Xiang, 2012). By definition, the latter two investment series are better proxies of net investment. Indicators of gross fixed capital formation are lacking in China's city-level statistics. Moreover, only half of the provinces (cities) publish data on new fixed assets, but all provinces (cities) publish indicators for total social investment in fixed assets at the city level. Therefore, in estimating the capital stock at the city level in China, the existing literature has tended to adopt the total social fixed asset investment index. A few scholars, such as Wang et al. (2016) and Wu (2019), weight the fixed capital formation of the whole province (city) by the amount of fixed asset investment in each city to obtain the city-level fixed capital formation. However, this treatment assumes that the capital formation rate is the same for all cities in the same province. In this paper, we use the total societal fixed capital investment series and convert it into actual values (million yuan, 2005 base period).

Other scholars have tried to include the land factor, and this paper finds that the TFP index remains basically unchanged after including the built-up area. Considering that land finance is an important source of revenue for local governments in China, it is speculated that the direct or indirect revenue generated by the urban land factor is eventually used as capital inputs in urban production and construction, that is, land inputs may already be reflected in capital inputs. Therefore, this paper does not include land indicators in GTFP calculations.

Selection of study period and study sample

Based on data availability, the study period is set as 2003−2018. The above data are mainly acquired from the *China City Statistical Yearbook* (2004−2019). Currently published data for Chinese cities are available for both city and municipality districts. All the above indicators, except for the non-expected output, are within the statistical range of the municipality.

Since 2017, the *China City Statistical Yearbook* no longer publishes fixed asset investment data for all cities. Therefore, the 2017 and 2018 fixed asset investment data for all cities are taken from the statistical yearbooks of all provinces (cities) separately. During data collection, it was found that five provinces did not publish municipal district data for cities under their jurisdiction in 2017, and ten provinces did not publish municipal district data for cities under their jurisdiction in 2018. However, citywide fixed asset investment data are available for all cities. For this, we assume that the growth rate of investment in the municipal districts of these cities is equal to the growth rate of investment in the city as a whole, thus filling in the missing data on fixed asset investment in these municipal jurisdictions. Since municipal districts are usually the main areas of economic activity in cities, this estimate does not introduce much bias.

The sample is selected from the 298 cities at the prefecture level and above in 2018 given in the *China City Statistical Yearbook* (2019), that is, 279 prefecture level cities, 15 sub-provincial cities, and 4 municipalities directly under the central government, excluding cities with a large number of missing data or unknown data trends and thus difficult to interpolate, resulting in a final sample of 264 cities at the prefecture level and above. Additionally, compared to 2003−2016, some cities in 2017 and 2018 have a large number of missing data on undesirable outputs which are difficult to interpolate, so this paper recorded these cities as having complete data missing in 2017 or 2018. Therefore, the final research samples from 298 cities at the prefecture level and above are 264 cities during 2003−2016, 238 cities in 2017, and 195 cities in 2018[9].

Measurement results and analysis of urban GTFP

Temporal trends in urban GTFP

Table 1, Fig.1 and Fig.2 present the green TFP and its decomposition terms for Chinese cities between 2004 and 2018. It can be found that, first, the overall GTFP in Chinese cities shows a growth trend. The average annual growth rate from 2004 to 2016 was 0.9%. The GTFP growth rate in 2017 and 2018 is higher than this average value, so the average annual growth rate from 2004 to 2018 is higher, specifically 1.3%. The corresponding cumulative growth rate is 20.6% (2003 = 1)[10]. The poor performance of TFP growth compared to the average constant price growth rate (over 10%) of China's urban area gross domestic product (GDP) over the same period reflects the fact that China's urban economic growth is still a crude form of economic growth dependent on factor inputs.

Second, the main source of GTFP growth is technological progress (TC), that is, GTFP growth is primarily due to urban best practitioners continuing to pull the production frontier outward, rather than urban laggards shifting to best practices. This growth pattern leads to a widening gap in productivity growth among cities, as confirmed by the following estimates of the nuclear density of GTFP and its components.

Third, considering the scale effect, the improvement in technical progress depends mainly on the growth of technical scale, with the average annual growth rate of pure technical progress less than 1; the improvement in technical efficiency relies mainly on the improvement of pure technical efficiency, with the average annual growth rate of scale efficiency less than 1. From Fig.2b, the relationship between technical scale and scale efficiency growth exhibits a trade-off, while the evolution of the total scale effect indicator is smoother and sharper, which allows us to capture more clearly the contribution of scale effects to urban productivity growth, with total scale effects growing at an average annual rate of 0.8% between 2004 and 2018, and contributing 65.7% to GTFP growth. The scale effect implies that in the process of factor accumulation and production scale expansion, the "learning-by-doing" effect, which is dependent on investment and human learning experience, endogenously triggers productivity growth. The total scale effect makes the largest contribution to GTFP growth, which implies a strong "learning by doing" effect in urban production in China. However, it is noteworthy that the growth of the aggregate scale effect is stable and shows a slight climb between 2004 and 2014, and the aggregate scale effect growth decreases significantly since 2015 (see Fig.1), because the "learning by doing" effect decreases rapidly with the narrowing of the technology gap and eventually shows the characteristic of diminishing returns (The Research Group of Economic Institute of CASS, 2006). This evolutionary feature of the aggregate scale effect reflects that China's urban production has entered the stage of decreasing "learning by doing" effect from the perspective of productivity growth, which is consistent with the finding of the Research Group on China's

[9] MaxDEA software allows for differences in the samples of different years when accounting for productivity changes, but in order to avoid the differences in the city samples from affecting the judgment of the mean and compositions of productivity changes in Chinese cities, we try to make the samples of each year consistent. Compared with the years 2003-2016, the data of undesirable outputs in some cities in 2017 and 2018 are more missing and difficult to interpolate, so the sample size of cities with complete data in 2017 and 2018 is relatively smaller, so too many cities will be lost if the sample is decided with the cities with available data in these two years. Therefore, in this paper, we selected a sample of 264 cities for which data were always available from 2003 to 2016, and a smaller sample of 238 and 195 cities in 2017 and 2018 respectively.

[10] The Malmquist index is a chain-change index; let 2003 = 1 and multiply the TFP index of previous years to yield the cumulative growth rate of GTFP based on 2003.

Table 1
Temporal evolution of GTFP and its compositions in Chinese cities

Year	GTFP	EC	TC	PEC	PTC	SEGTFP	SEEC	SETC	Cumulative GTFP
2004	0.995	1.027	0.969	1.039	0.951	1.007	0.988	1.019	0.995
2005	0.994	0.970	1.024	0.909	1.058	1.034	1.068	0.968	0.989
2006	1.012	1.020	0.992	1.021	0.966	1.026	0.999	1.027	1.000
2007	1.037	1.093	0.948	1.139	0.900	1.010	0.960	1.052	1.037
2008	1.034	0.883	1.171	0.918	1.123	1.003	0.962	1.043	1.073
2009	0.986	0.991	0.995	0.913	1.048	1.030	1.085	0.949	1.057
2010	1.065	0.971	1.097	1.000	1.040	1.024	0.970	1.055	1.125
2011	0.986	0.967	1.019	1.065	0.868	1.066	0.908	1.174	1.110
2012	1.005	1.029	0.977	1.133	0.871	1.019	0.908	1.122	1.115
2013	1.007	1.029	0.978	1.054	0.943	1.013	0.977	1.037	1.123
2014	0.946	0.994	0.952	0.978	0.908	1.066	1.016	1.049	1.063
2015	0.984	0.968	1.017	0.906	1.094	0.999	1.068	0.931	1.046
2016	1.073	1.003	1.070	1.009	1.136	0.927	0.995	0.939	1.122
2017	1.035	1.130	0.915	1.093	1.018	0.930	1.034	0.899	1.161
2018	1.039	1.044	0.995	1.029	1.028	0.982	1.015	0.968	1.206
Mean (2004–2018)	1.013	1.006	1.006	1.011	0.993	1.008	0.996	1.013	–
Mean (2004–2016)	1.009	0.995	1.014	1.003	0.989	1.017	0.991	1.026	–

Notes: The mean values obtained here are geometric means. Tables 2 through 4 are the same.

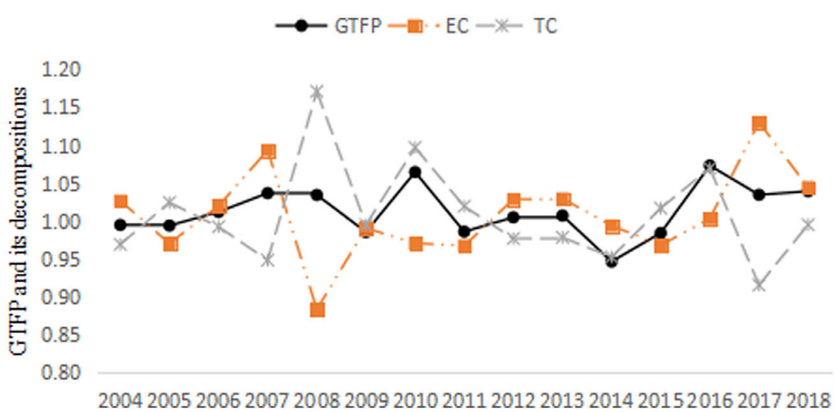
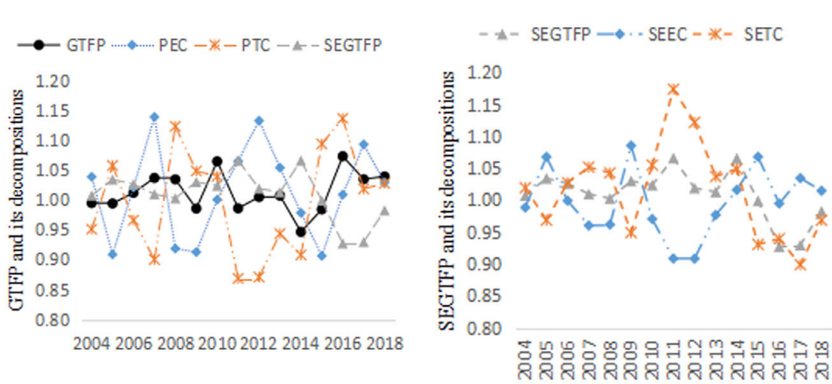


Fig. 1. Temporal trends in the GTFP two-part decompositions between 2004 and 2018.

Economic Growth (2014) that China is already in the stage of decreasing "learning by doing" effect. This also implies that the GTFP growth pattern should shift from the scale effect of production expansion to one that relies on PEC and PTC, the latter two being more dependent on organizational or institutional innovation and technological revolution.

Fourth, the entire study period can be divided into two stages, with the growth rate of GTFP oscillating between 2004 and 2014, and increasing significantly from 2015 onwards. The GTFP growth from 2004 to 2014 is mainly driven by the total scale effect, and the total effect of pure technological progress and pure technological efficiency is less than 1; after 2015, the GTFP growth is due to the growth of pure technological progress and pure technological efficiency, and the total scale effect is less than 1. In the early period, China's economy was growing at a high speed and concomitant ecological and environmental problems in the cities became increasingly serious under the heavy growth target. As such, the superposition of multiple factors leads to the fluctuating decline in GTFP growth. After 2012, the overall economy gradually entered the stage of medium-high speed growth. In 2014, President Xi Jinping for the first time



(a) (b)

Fig. 2. Temporal trends in the GTFP four-part decompositions between 2004 and 2018

Fig. 3. Comparison of urban GTFP for different city samples

described the new stage of China's economic growth in terms of the new normal, that is, the growth rate has shifted from high to medium–high speed, the economic structure has been continuously optimized and upgraded, and the growth momentum has shifted from factor-driven and investment-driven to innovation-driven. As the main carrier of economic growth, cities have transformed in terms of improving quality and efficiency, no longer blindly pursuing expansion, but focusing on the improvement of resource allocation efficiency and technological innovation. The post-2015 growth rate in GTFP and growth model changes reflect the fact that the quality of China's urban economy is gradually improving under the new governing philosophy of the "new normal" and the "new economy."

To avoid misjudging the trend due to the reduction of the city sample in 2017–2018, Fig.3 presents the temporal trends of urban GTFP for samples constituted by 264, 238, and 195 cities in China. Some years (e.g., 2004–2008) exhibit different magnitudes of GTFP rise and fall, reflecting the fact that differences in the study sample are a main reason for the different urban productivity results measured by different scholars, but they also show a consistent trend. Moreover, the evolutionary trajectories of the three series between 2009–2016 are almost identical. Therefore, based on the different number of city samples in 2017 and 2018, our judgment on the evolution of GTFP since the new normal will not be significantly biased. To avoid bias due to different city samples as far as possible, we focus on a sample of 264 cities from 2004–2016 in the next analysis. We also calculate and analyze the relevant results for the period 2004–2018, but due to space limitations, the corresponding conclusions are not given. However, where there is a large discrepancy in the conclusions, it will be noted.

Spatial characteristics of urban GTFP

(1) Green total factor productivity and its compositions in 264 cities

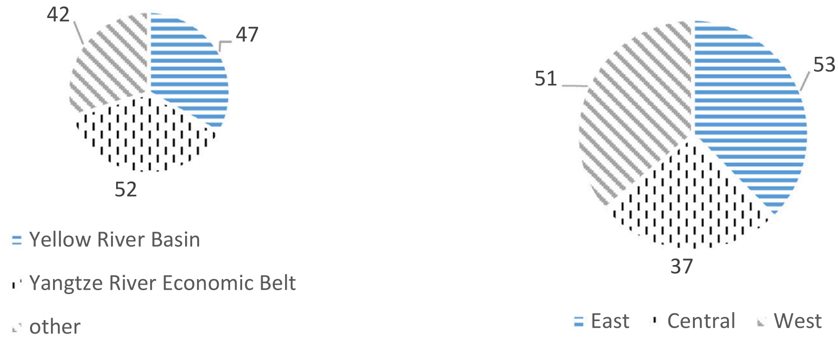
Calculating the average annual growth rate of GTFP and its components for 264 cities between 2004 and 2016, the main findings are as follows. First, 141 cities have GTFP greater than 1, accounting for 53.4% of the total sample, reflecting the poor performance of the overall growth of GTFP in Chinese cities. Among them, the top five cities in terms of average annual GTFP growth rate are Tianjin (19.4%), Changchun (16.4%), Beijing (15.8%), Ya'an (14.8%), and Chaozhou (12.2%), and the five cities with the most serious declines in GTFP are Xuancheng (−9.0%), Laibin (−9.3%), Yuxi (−10.0%), Hezhou (−10.2%), Huzhou (−10.2%), and Ningde City (−13.1%). Second, the technical efficiency of 114 cities is greater than 1; the technical efficiency of Changchun, Haikou, Shenzhen, Daqing, and Sanya is equal to 1; while that of other cities is less than 1. The top five cities in terms of technical efficiency are Ya'an (13.6%), Heihe (10.7%), Zhangjiajie (9.3%), Chaozhou (8.5%), and Jiayuguan (7.8%). Ningde City (−12.7%) has the largest decrease in technical efficiency. Third, there are 160 cities with technological progress greater than 1. The top five cities are Changchun (16.4%), Tianjin (14.7%), Hohhot (11.8%), Shanghai (10.1%), Zhongshan (10.1%). The largest decrease is in Maoming (−5.05%). Thus, the cross-sectional analysis further confirms the above-mentioned time-trend analysis results, namely, the GTFP growth performance of Chinese cities needs to be further improved; most of the cities experienced negative growth in technical efficiency; the number of cities where technical progress achieved growth and the improvement range of technical progress are both higher than for technical efficiency, making technical progress the main driver of GTFP growth.

Further from Table 2, 112 of the 141 cities that saw an increase in GTFP had a technical efficiency greater than or equal to 1, 104 had a technical progress greater than 1, and 75 had improvements in both technical progress and technical efficiency; 7 of the 123 cities that saw a decrease in GTFP had a technical efficiency improvement, 57 had a technical progress increase, and none of the 123 cities that saw a decrease in GTFP had a technical efficiency increase. No cities have achieved both technological progress and efficiency improvements at the same time. This shows that technical efficiency is a serious drag on the growth of urban GTFP in China. At the same time, implying ample scope for further improvement in technical efficiency. For example, in 2017 and 2018 the growth rate of technical efficiency is higher than that of technical progress, becoming the main driving force for the growth of GTFP. It is expected that the improvement in technical efficiency will be an important breakthrough as far as the promotion of GTFP in Chinese cities in the future goes.

Considering the East–West and North–South divisions of China's economy, Fig.4 presents the geographical distribution of the 141 cities that have achieved GTFP growth in these two dimensions, with decreasing numbers of cities in the Yangtze River Economic Zone, Yellow River Basin, and other regions, and decreasing numbers of

Table 2
China's urban GTFP and its compositions between 2004 and 2016

	Index	Number of cities
GTFP>1	EC>=1	112
	TC>1	104
	EC>=1 and TC>1	75
GTFP<1	EC>1	7
	TC>1	57
	EC>1 and TC>1	0



(a) (b)

Fig. 4. Geographic distribution of the 141 cities with GTFP positive growth between 2004 and 2016. *Notes*: Among the 264 cities in the sample, 106 and 75 are located in the Yangtze River Economic Zone and the Yellow River Basin, respectively; while the number of cities located in the East, Central, and West are 93, 97, and 74, respectively.

cities in the East, West, and Central regions. The Yangtze River Economic Zone and the Yellow River Basin account for more than 70% of the total number of cities, and the number of cities in the Yangtze River Economic Zone (52) is higher than the number of cities in the Yellow River Basin (47) which is consistent with the large gap between the economic development of northern China and southern China. The regional distribution of cities in the east and west is also in line with economic intuition, but the fact that the number of cities in the west is higher than that in the center and closer to that in the east is not consistent with the stage of economic development of the three regions. This reflects that urban GTFP is closely, but not completely, related to the level of urban economic development. Next, this paper will further analyze the regional heterogeneity of GTFP changes based on the division of China into three regions: East, Central and West.

(2) Heterogeneity Analysis of Urban GTFP in the East, West, and Central Regions of China

The study sample was divided into three major regions in the east, central, and west (Fig.5); the overall regional distribution of the sample is relatively balanced.

This paper presents a comparative analysis of GTFP and its composition in the three regions between 2004 and 2016 (Table 3). The GTFP growth performance of the three regions is "West>East>Central"; the growth performance of technical efficiency is "West>Central>East"; and the growth performance of technical progress is "East>West>Central." This paper makes the following analysis of this phenomenon. ① The eastern cities have the highest concentration of quality resources and the fastest increase in pure technological progress and thus technological progress. However, the abundant factor resources have not been effectively utilized in the eastern cities, and these cities have the lowest pure technical efficiency and technical efficiency. In the early stage of development, there are many labor-intensive technologies in the eastern region (i.e., the Pearl River Delta region), and most of them are highly polluting industries. After the 2008 financial crisis, the Pearl River Delta and Yangtze River Delta started to slowly promote industrial transformation and upgrading. However, this created pressure on the environment and because the process of transformation and upgrading is gradual, between 2004 and 2016, the performance of the efficiency component in the developed eastern region is weaker than that of the central and western regions. Considering differences in economic development, the eastern cities are the first to enter the stage where the learning-by-doing effect diminishes, thus showing the lowest total scale effects. Therefore, the GTFP of eastern cities, considering resource and environmental constraints, is not at the forefront of the three regions. ② Western cities have less high-quality factor resources, but their resource utilization efficiency is higher, and their pure technical efficiency and technical efficiency are the highest among the three regions. Although the lack of innovation resources such as human capital and R & D funds leads to the pure technological progress of western cities being less than 1, the technological progress brought by the learning-by-doing effect is larger, and the average annual growth of technology scale is 4.2%. Finally, the pure technological efficiency and technology scale are the two main reasons why the

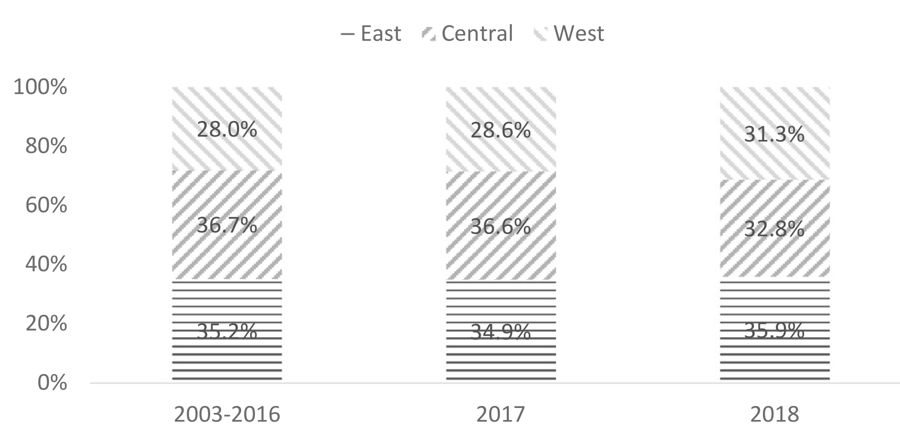


Fig. 5. Subregional Sample Composition

Table 3
GTFP and its compositions in the three regions (2004–2016)

	GTFP	EC	TC	SEGTFP	PEC	PTC	SEEC	SETC
East	1.012	0.991	1.021	1.010	0.993	1.008	0.999	1.012
Central	0.999	0.992	1.008	1.014	1.005	0.981	0.987	1.027
West	1.018	1.002	1.015	1.029	1.016	0.974	0.987	1.042

GTFP of western cities is higher than that of eastern cities. ③ The technological progress of central cities is the lowest, but the problem is that the central region is closer to the eastern region, and the technological spillover and industrial transformation of the eastern region are the first to penetrate the central region. Therefore, theoretically, it should be the case that the technological progress of the central region is better than that of the western region. However, following two facts must be emphasized. First, the industries of the eastern region undertaken by the central region are often labor-intensive, which cannot benefit pure technological progress; second, if environmental protection is considered, it is precisely because of the introduction of non-advanced production capacity that leads to a more unfavorable position in the index of technological progress. This, coupled with a lag in technical efficiency, leads to a collapse in the central GTFP.

Finally, it should be noted that there may be some sample selection bias in each region, and this bias may affect the judgment of the relative level of regional productivity to some extent. Generally, the availability and completeness of urban statistical data are positively related to the level of economic development of a city, and we see that the data availability of developed eastern provinces and cities is relatively high and the sample is more complete, while the data availability of western regions is the lowest. The western cities which are thus included in the sample are relatively developed, with some cities with low development performance in the western region being omitted. Thus, this paper may overestimate the overall productivity level of the western region by selecting a subset of cities with higher productivity levels. As of 2018, there were 297 cities at prefecture level and above in China, and this paper retains 88.9% of this population of cities. Although this is a high proportion and the resulting conclusions are generally in line with China's urban profile, there is still the possibility of misjudgment due to regional sample selection bias.

As shown in Fig.6, the cumulative growth rate of GTFP in each region is highest in the West, second highest in the East, and lowest in the Central part of the country. In terms of temporal trends, the cumulative growth rate of productivity in the west and east has gradually shifted from a widening to a narrowing gap, while the gap between the central part of the country and the eastern and western parts of the country has always been large. Although after 2015, there has been a tendency for the central region to catch up with the eastern and western parts of the country, but the reduction is small. In recent years, with the change in the prevailing conception of economic development, eastern cities are actively assuming the responsibility of being forerunner, and these cities also have sufficient resources and policy advantages to carry out the transformation of economic development mode, so that the development quality gap with the west is gradually narrowing, and further showing a trend of surpassing the west. At the same time, some eastern provinces and cities, such as Guangdong, started to transform and upgrade heavy-consuming industries during as early as 2009, and at the same time transferred some heavy-consuming and heavy-polluting industries to the central and western regions. Therefore, theoretically, the relative productivity levels of eastern, central, and western cities are also somewhat affected by such industrial transfer, and this can be reflected in the statistical indicators. Further, from the economic development stage of each region, the western region is the slowest among the three regions, but all regions must go through various stages of industrialization. If the industrialization of the western region does not learn the lessons from the early industrialization of the eastern region, it is possible that low-end industries will proliferate to take advantage of local resource endowments (such as labor and land which are relatively cheap). This may lead to a repeat of the old way of "pollution first and treatment later" in eastern China. However, in the context of high-quality development, the western region may also avoid such a situation and commit to green development, thus avoiding the old road and overtaking on curve.

In summary, from the perspective of GTFP, western cities have the highest quality economic development, eastern cities rank second, and productivity collapse exists in central China. Under the concept of high-quality development, eastern cities still play the role of pioneers, and the development gap with western cities is obviously narrowing; the development of western cities depends on their future development model; central cities are facing the most severe task of improving quality and efficiency.

(3) Dynamics of the Spatial Distribution of GTFP and its Compositions

To analyze the dynamics of the spatial distribution of urban productivity, kernel density curves of urban productivity and its composition from 2004 and 2016 are presented based on the nonparametric analysis of kernel density estimation (Fig.7).

It can be seen from Fig. 7a, compared with 2004, the peak of the distribution curve in 2016 is basically flat but the left and right tails expand further to both sides, indicating that the dispersion of the

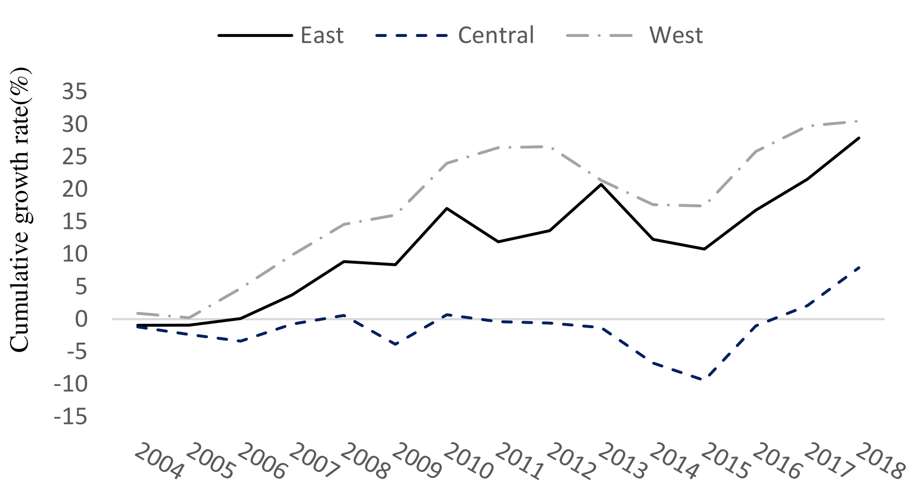
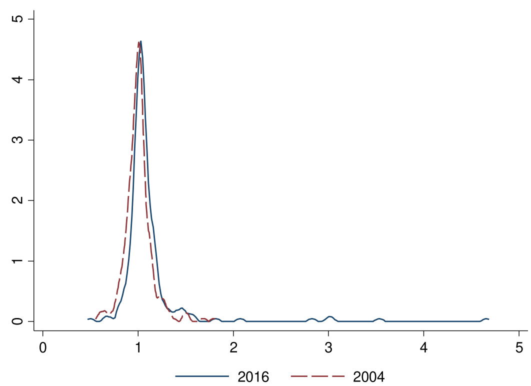
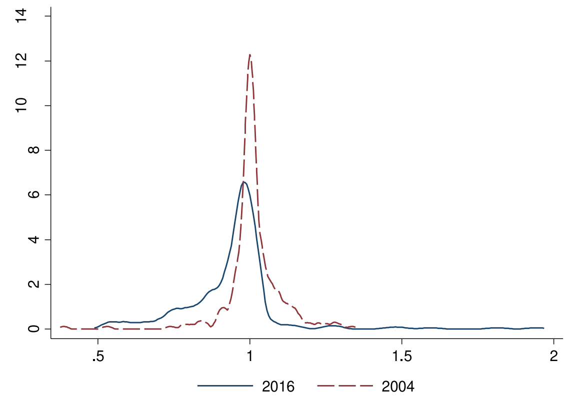


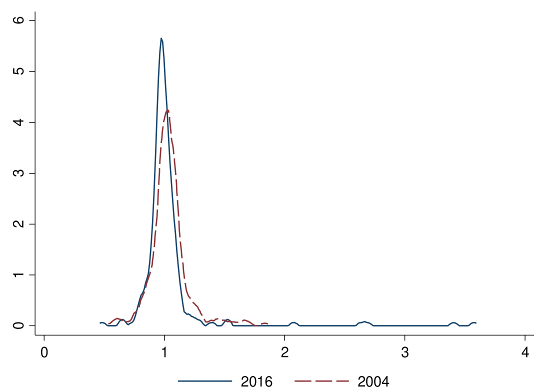
Fig. 6. Cumulative Growth Rate of GTFP by Subregion (2003=1)



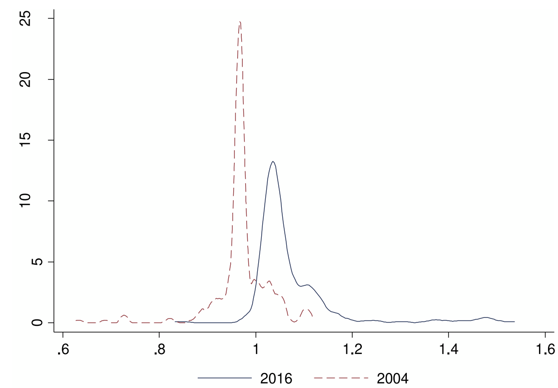
(a) Kernel density estimation of GTFP



(b) Kernel density estimation of SEGTFP



(c) Kernel density estimation of EC



(d) Kernel density estimation of TC

Fig. 7. Estimation of Kernel density of GTFP and its compositions

GTFP growth rate in China's cities increased during the study period, which is consistent with the findings of Li and Tu (2017) and Li and Pan (2018), that is, there is no σ-convergence in urban productivity in China. At the same time, the right tail extends significantly more than the left tail, implying that the number of cities with declining GTFP growth and the number of cities with sharply increasing GTFP growth are both increasing, but the latter are more numerous. The shape of the distribution curve in 2016 is reasonably similar to that in 2004, but the overall distribution curve is shifted to the right, that is, the mode value of the 2016 distribution curve is larger, the height of the left tail is lower, and the height of the right tail is higher, revealing that the overall growth performance of GTFP in China's cities has improved. This is consistent with the results of the time trend analysis above.

As can be seen from Fig. 7b and 7c, compared with 2004, the kernel density distribution curves for both scale effect and technical efficiency in 2016 are overall left-biased, that is, the value of the mode index is smaller, the left tail is higher, and the right tail is lower, reflecting the declining scale effect and the increasing probability of low technical efficiency in China's cities between 2004 and 2016. From Fig. 7d, compared with 2004, the kernel density distribution curve of technological progress in 2016 shows an overall right deviation, that is, the mode value is larger, the left-tailed extension becomes smaller, and the right-tailed extension becomes larger, indicating a greater improvement in technological progress. Further, the tail extensions of the distribution curves in Fig. 7b, 7c, and 7d are all dilated to different degrees, reflecting the widening gap between cities' GTFP components, which ultimately leads to a greater dispersion of the urban GTFP.

Urban GTFP and its compositions at different city sizes

Given the important role of scale effects in the growth of urban GTFP in China, this paper further demonstrates the heterogeneity of urban GTFP and its compositions under different city sizes. This paper first classifies the sample of 264 cities into five categories: super-metropolises, megacities, large cities, medium cities, and small cities based on the urban population indicators given in the *China Urban Construction Statistical Yearbook* (2016)[11]. In terms of the five types of city size, prefecture-level cities and above are mainly small and medium-sized cities, accounting for more than 70%, followed by large cities, accounting for more than 20%, with the number of megacities and super-metropolises being relatively small. According to the seven population classifications, nearly 90% of urban areas have a population between 0.2 and three million, which means that Type I small cities, medium cities, and Type II large cities constitute the majority of cities at the prefecture level and above in China.

[11] In 2014, the State Council issued the Notice on Adjusting City Size Classification Criteria, which classifies cities into five categories and seven levels: super-metropolises (over 10 million), megacities (5–10 million), and large cities (1–5 million, of which 3–5 million are Type I large cities and 1–3 million are Type II large cities), medium-sized cities (0.5–1 million), and small cities (200,000–500,000 are Type I small cities, and less than 200,000 are Type II small cities).

Table 4
Comparison of GTFP and its compositions at different city sizes

Type of cities	GTFP	EC	TC	PEC	PTC	SEGTFP	SEEC	SETC	Number of cities
Super-metropolises	1.169	0.996	1.174	1.000	1.204	0.971	0.996	0.975	3
Megacities	1.108	0.919	1.205	0.845	1.159	1.131	1.088	1.040	4
Large cities	1.128	1.013	1.114	1.027	1.105	0.978	0.987	1.003	62
Type I Large cities	1.307	1.069	1.223	1.069	1.231	0.993	1.000	0.994	10
Type II Large cities	1.086	0.993	1.094	1.007	1.082	0.976	0.986	1.005	50
Medium cities	1.029	0.977	1.053	1.015	1.093	0.928	0.963	0.964	96
Small cities	1.079	1.027	1.051	0.999	1.198	0.888	1.028	0.875	99
Type I Small cities	1.089	1.035	1.052	1.002	1.207	0.885	1.032	0.869	91
Type II Small cities	0.973	0.941	1.034	0.962	1.104	0.916	0.978	0.937	8

Table 4 shows the average GTFP and its composition for all types of cities, based on the results of the 2016 urban GTFP. The following conclusions can be drawn.[12]

(1) The productivity of super-metropolises, megacities, and large cities is significantly higher than that of small and medium-sized cities, reflecting the fact that large-scale cities have many advantages such as location, physical capital, and favorable policies which eventually attracts migration and drives China's urban productivity growth. This feature is also consistent with the conclusion that the scale effect plays an important role in China's urban GTFP growth. The larger the city, the more abundant the specialized division of labor, and the lower the transaction costs of industrial development. At the same time, the division of labor creates deeper and broader knowledge and technology spillovers, which are more complementary, resulting in lower costs and higher expected benefits. In addition, the quality of infrastructure and human capital also makes it easier for large cities to achieve technological progress and improve resource allocation efficiency.

(2) Technological progress indicators show the characteristics of "super-metropolises > megacities > large cities > medium cities > small cities." Similar to the GTFP, large-scale cities with an urban population of more than 1 million have the highest growth rate of technological progress, while small and medium-sized cities lag behind. From Table 4, we can see that due to the abundant innovation resources and large scale of production in large-scale cities, the technology scale brought about by the learning-by-doing effect, and the pure technological progress brought about by innovative R&D, are both considerable. It is noteworthy that the pure technological progress in small cities is outstanding, second only to mega-cities, which is inseparable from local governments' endeavors to attract talent and their efforts to create an atmosphere of "*Mass entrepreneurship and innovation*."[13] However, small cities still seldom have large-scale production enterprises, and this, coupled with the problem of losing skilled labor and talent to large cities, affects the influence of the learning-by-doing effect on technological progress.

(3) The technical efficiency indicators under the GTFP decomposition show the characteristics of "small cities > large cities > super-metropolis > medium cities > megacities." Under the combined effect of pure technical efficiency and the scale effect, the higher technical efficiency of small cities makes up for their lagging behind in technical progress, which is the key for their GTFP to surpass the average level of GTFP of Chinese cities. By contrast, medium-sized cities are similar to small cities in terms of technological progress, but also underperform in terms of technological efficiency, resulting in the lowest ranking in terms of productivity, 4.42 percentage points below the average GTFP of Chinese cities.

Further research: inference of causes in the framework of New Structural Economics

Modeling and variable selection

Based on the theory of neo-structural economics, this paper infers that industrial comparative advantage is one of the key factors of urban GTFP growth. This section empirically tests this theoretical inference based on urban panel data from the period 2004 to 2018, focusing on the static and dynamic effects played by industrial comparative advantage in urban productivity growth and the spatiotemporal heterogeneity of these effects. At the same time, control variables such as city size, human capital, and R&D will also be included in the econometric models, so as to further explore the arguments obtained from the productivity measurement analysis in the previous section, thus making the productivity analysis in this paper deeper and more complete.

The following basic panel econometric model is constructed.

$$Y_{it} = \alpha_0 + \lambda_1 RCA_{it} + \sum_j \beta_j X_{ijt} + c_i + c_t + \varepsilon_{it} \tag{1}$$

where the GTFP of city i in year t and its constituent indicators are represented by Y_{it}; RCA_{it} means the Revealed Comparative Advantage index;λ_1 reflects the effect of industrial comparative advantage on the growth of city productivity; the five control variables of X_{it} are city size, human capital, research and development, and income level; c_i,c_t reflect individual and time fixed effects, respectively; and ε_{it} is the disturbance term. See Table 5 for variable descriptions and sources.

The independent variables in model (1) are explained as follows.

First, Balassa (1965) proposed the Revealed Comparative Advantage Index (RCA), which is calculated as the ratio of the share of a country's exports of a certain commodity in its total export value to the share of global exports of that commodity in total global exports. If the RCA is greater than 1, it means that the country has a comparative advantage of the commodity in the international market, and the larger the RCA value, the stronger the country's international competitiveness in that commodity. Since then, this index has been widely used to measure the comparative advantage of a certain industry in the world or in a certain region. Here we take the whole country as the reference region and construct the following revealed comparative advantage index of the kth industry of city i.

$$RCA_i^k = \frac{Industry_i^k / GRP_i}{Industry_{China}^k / GDP_{China}} \tag{2}$$

Where,$Industry_i^k$ denotes the value added of the kth industry in city i, and under the division of the three industries (i.e., primary

[12] The findings are robust to using the 2018 city classification results and GTFP measurements. Although there may be some differences in the ranking of the average GTFP and its composition for each category of city, the main conclusions described in this paper remain consistent.

[13] "*Mass entrepreneurship and innovation*" came from the speech of Premier Li Keqiang at the Summer Davos Forum in September 2014.

Table 5
Variable Descriptions

Variable Name (Symbol)	Variable Introduction	Source
Green Total Factor Productivity (*GTFP*)	Total factor productivity change considering environmental constraints, greater than 1 means positive growth	SBM-ML index calculated by MaxDEA software based on data from *China City Statistical Yearbook* (2004−2019)
Technical Change (*TC*) Efficiency Change (*EC*) Scale Efficiency of GTFP(*SEGTFP*) Pure Technical Change (*PTC*) Pure Efficiency Change (*PEC*)	Greater than 1 means positive growth	Decomposition of SBM-ML index
Revealed Comparative Advantage index of the secondary industry (*RCA*)		Self-calculation based on data from *China City Statistical Yearbook* (2004−2019)
City scale (*Scale*)	Urban population (10000 persons)	*China Urban Construction Statistical Yearbook* (2004−2018)
Human capital (*HC*)	Teachers in regular institutions of higher education (persons)	*China City Statistical Yearbook* (2005−2019)
Research & Development (*R&D*)	Expenditure on science and technology from local general public budget (10000 yuan)	
Income level (*Income*)	Per capita gross regional product (constant prices at 2005 prices, yuan)[1]	

[1] Based on the GDP deflator at the city level (2005 as the base period), Expenditure for Science and Technology (10000 yuan), and Per Capita Gross Regional Product (current prices, yuan) from the *China City Statistical Yearbook* are converted into actual values (at 2005 price)

Table 6
Descriptive statistics of main variables

Variable Symbol	Observations	Arithmetic means	Standard deviation	Min	Max
GTFP	3,865	1.025	0.189	0.231	4.659
EC	3,865	1.019	0.185	0.252	4.539
TC	3,865	1.012	0.112	0.621	3.966
SEGTFP	3,858	1.019	0.152	0.159	2.771
PEC	3,865	1.035	0.250	0.332	4.477
PTC	3,858	1.007	0.189	0.172	6.230
RCA	3,948	1.118	0.267	0.171	1.937
Scale	3,931	4.095	0.873	0.412	7.959
HC	3,796	7.488	1.283	3.258	11.163
R&D	3,948	8.361	2.064	0.693	15.281
Income	3,912	10.409	0.717	2.264	15.314

Note: Descriptive statistics for control variables are based on the data actually used in the econometric model after taking logarithmic treatment.

industry, secondary industry, tertiary industry), k can take the values of 1, 2 and 3;GRP_i is the regional GDP of city i; $Industry^k_{China}$and GDP_{China} is the value added of the kth industry and GDP in China, respectively.

The industrial structure of Chinese cities is principally composed of secondary and tertiary industries. In the period of our study, the sample mean value of the ratio of these two industries to the city's GDP is always over 90%, and there is a trade-off between the comparative advantages of cities in secondary and tertiary industries. Therefore, we mainly calculate the comparative advantage index of urban secondary industry which may be abbreviated as *RCA*. If the *RCA* index of the secondary industry in city i is greater than 1, it means that city i can rely more on industrialization to achieve productivity growth than the whole country, and it has a comparative advantage in the secondary industry; if the *RCA* index is less than 1, it means that city i is below the national average in industrialization process, and it is more likely that city i has a comparative advantage in the tertiary industry.

Second, the control variables are selected based on the theoretical and empirical studies obtained from the above urban productivity measurement analysis, namely, city size, human capital, R&D, and income level. Additionally, all control variables were logarithmically treated.

The specific descriptions of the variables are given in Table 5. Descriptive statistics for the main variables are given in Table 6.

The impact of industrial comparative advantage on GTFP and its compositions

The paper first examines the effect of industry comparative advantage on GTFP, and the obtained estimation results are presented in Table 7. It is evident that the F-test and Wald test show that all models except model (1) obtained from the panel mixed regression are statistically significant overall, and the difference in the chosen estimation method affects the judgment of the conclusions. In this paper, Lagrange multiplier test, test of overidentifying restrictions and likelihood-ratio test are used for model selection[14], and the test results support the establishment of two-way fixed effects panel data models, that is, models (3) and (6). In the following, if the estimation method is not explicitly stated, we all use the two-way fixed effects panel data modeling. In addition to the statistical test method, there are also practical considerations for the choice of this estimation method in this paper. Among the factors affecting urban GTFP

[14] Among them, the Lagrange multiplier test is for the choice of mixed regression or random effects regression, and the original hypothesis is that there is no individual random effect and supports mixed regression; because the traditional Hausman test is not applicable to the case of robust standard error, this paper uses the test of overidentifying restrictions for the choice of fixed effects or random effects model, and the original hypothesis is to support the establishment of a random effects model; the original hypothesis of likelihood ratio test is to support the establishment of a one-way fixed effects panel data model.

Table 7
Impact of industrial comparative advantage on GTFP

VARIABLES	(1) POLS	(2) RE	(3) FE	(4) POLS	(5) RE	(6) FE
RCA	0.0085	0.0153	0.0892***	-0.0162	-0.0121	0.0627**
	(0.0163)	(0.0166)	(0.0257)	(0.0175)	(0.0177)	(0.0257)
Scale				0.0097	0.0020	0.0257$^{\text{O}}$
				(0.0079)	(0.0087)	(0.0173)
HC				0.0022	0.0015	0.0079
				(0.0043)	(0.0044)	(0.0114)
R&D				0.0036	0.0096**	0.0249***
				(0.0030)	(0.0042)	(0.0091)
Income				-0.0162	-0.0121	0.0627**
				(0.0175)	(0.0177)	(0.0257)
Constant	1.0151***	0.9875***	0.9044***	0.7891***	0.7720***	0.4072**
	(0.0189)	(0.0210)	(0.0315)	(0.0563)	(0.0564)	(0.1704)
Observations	3,860	3,860	3,860	3,639	3,639	3,639
R^2	0.0001	0.0400	0.0424	0.0174	0.0455	0.0524
Number of cities		264	264		264	264
Time fixed effects		controlled	controlled		controlled	controlled
Individual fixed effects			controlled			controlled
F-test/ Wald test	[0.6030]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Lagrange multiplier test		[0.0001]			[0.0266]	
Test of overidentifying restrictions		[0.0015]			[0.0012]	
Likelihood-ratio test			[0.0000]			[0.0000]

Note:
① ***, **, *, O denote significant at 1%, 5%,10%, and 15% statistical levels, respectively. ② POLS, RE, FE denote panel mixed regression, random-effects panel data regression, fixed-effects panel data regression, respectively. ③ Considering the possible autocorrelation of the disturbance terms in different years of the same city, clustering robust standard errors are used in the estimation process, and the robust standard errors are in round brackets. ④ The p-values corresponding to the corresponding test statistics are in square brackets. ⑤ The estimation results of time and individual fixed effects are not given due to space limitation. The following tables are the same.

and its compositions are variables that vary with individual cities but not over time or vary over time but not with individual cities, such as the location and the natural environment of the city in the former case, and the overall national economic development strategy and changes in foreign environment in the latter case. Compared with mixed estimation or random effects panel modeling, the use of two-way fixed effects modeling can remove the effects of these unobservable variables and thus more accurately capture the true relationships between the core variables.

From models (3) and (6) in Table 7, we can see that the effect of industrial comparative advantage on GTFP is significantly positive regardless of the inclusion of control variables, indicating that comparative advantage in secondary industry is indeed one of the key drivers of urban productivity improvement. Note that the coefficient of industrial comparative advantage decreases from 0.0892 to 0.0627 with the inclusion of the control variables, while the model goodness of fit (R^2) improves from 0.0424 to 0.0524. This implies that without the inclusion of the control variables, it is possible that the effects of other factors on urban productivity are attributed to industrial comparative advantage, and the resulting effect may be the cumulative value of the direct effect of industrial comparative advantage on productivity and the indirect effect of other factors on productivity mediated by industrial comparative advantage.

When the decomposition terms of GTFP are used as the dependent variables, the obtained estimation results are shown in Table 8. It is clear that the estimated coefficients of *RCA* on the decomposition terms are all positive, and the impact of *RCA* on *EC* is greater than *TC* under the two decompositions, while the influence of industrial comparative advantage on *PEC, PTC* and *SEGTFP* decreases under the three decompositions. The starting point of comparative advantage based on resource endowment is the efficiency of endowment allocation and the core logic is to optimize the efficiency of regional resource allocation, so the effect of industrial comparative advantage on urban productivity is mainly reflected in efficiency change and pure efficiency change.

Since the principal driving force of urban productivity in China is the scale effect (SEGTFP), and the estimation results show that the *RCA* index has the least influence on *SEGTFP*. In this regard, this paper makes the explanation that the comparative advantage of the secondary industry mainly works on the secondary industry itself, but not much in other industries. The larger scale effect of the secondary industry is likely to be accompanied by a decrease in the scale effect of other industries, resulting in a smaller and insignificant impact of the secondary industry comparative advantage on the total scale effect at the whole city level. Comparatively speaking, the promotion of pure technical progress and pure technical change by the comparative advantage of secondary industry can be directly incorporated into pure technical progress and pure technical efficiency at the city level, and it will not necessarily affect the expansion of production frontiers or the approach to production frontiers of other industries.

In terms of the control variables, (1) urban population (*Scale*) has a positive effect on *PEC* and *PTC*, but a negative effect on the total scale effect (*SEGTFP*), finally showing a significant positive effect on efficiency change (*EC*) and an insignificant negative effect on technical progress (*TC*). The learning-by-doing effect caused by scale expansion is more suitable for the low-skilled labor force. With the industrial transformation and upgrading of cities, low-skilled labor has entered a decaying phase over the years, and the cheap demographic dividend has been reversed, so the allocation efficiency of urban resources depends more on higher quality human capital, that is, urban population consisting of high quality human capital drives GTFP growth through pure technical efficiency and pure technological progress to a greater extent.

(1) Human capital (*HC*) has a significant positive effect on *PTC*. The number of higher education faculty not only reflects the amount of high-quality human capital in the city, but most critically, the faculty itself is one of the main forces driving R&D and one of the main forces in expanding the frontier of production possibilities in the city. In fact, this finding coincides with (1), the

Table 8
Impact of industrial comparative advantage on the compositions of GTFP - two-way fixed-effects model

	(1) *TC*	(2) *EC*	(3) *SEGTFP*	(4) *PTC*	(5) *PEC*
RCA	0.0111	0.0481**	0.0142	0.0227	0.0549*
	(0.0102)	(0.0243)	(0.0208)	(0.0287)	(0.0320)
Scale	-0.0032	0.0289*	-0.0169	0.0083	0.0407**
	(0.0052)	(0.0167)	(0.0137)	(0.0187)	(0.0189)
HC	-0.0017	0.0075	-0.0064	0.0242*	-0.0045
	(0.0042)	(0.0109)	(0.0131)	(0.0126)	(0.0151)
R&D	-0.0008	0.0228**	0.0036	-0.0067	0.0151**
	(0.0028)	(0.0090)	(0.0045)	(0.0054)	(0.0072)
Income	0.0078	0.0161	-0.0162*	0.0368***	0.0114
	(0.0052)	(0.0113)	(0.0094)	(0.0116)	(0.0127)
Constant	0.9115***	0.5241***	1.2443***	0.4100**	0.6587***
	(0.0598)	(0.1624)	(0.1487)	(0.1749)	(0.1736)
Observations	3,639	3,639	3,632	3,632	3,639
R^2	0.3542	0.1209	0.0759	0.2384	0.1141
Number of cities	264	264	264	264	264
F-test	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]

Notes: The first column represents the independent variable and the second row represents the dependent variable of the corresponding model. The estimation results when control variables are not included remain consistent with Table 8 and are not given here due to space limitations.

difference is that the number of full-time faculty members in colleges and universities is a more precise proxy for the high-quality human capital component of the urban population, which is the main force in expanding the production frontier; whereas the urban population includes a larger proportion of the general workforce and thus has a statistically insignificant positive effect on *PTC*. Thus, the coefficient estimates for urban population and human capital actually provide mutually complementary economic explanations.

(2) The coefficient of *R&D* on urban productivity is positive and the most significant among the control variables, reflecting the fact that government-directed R&D spending has a very significant effect on urban GTFP growth. However, this effect lies mainly in improving *PEC* and technical efficiency change (*EC*). Government R&D expenditures are allocated to innovation-minded but weak high-tech firms, while large firms that really drive the productive frontier through innovation tend to be stronger and, coupled with the problems of adverse selection and rent-seeking activities, do not receive or even need government R&D funding. Looking back historically, large productive innovations have often come from the market rather than from government-supported programs, so R&D subsidies have actually helped the relative laggards catch up with the frontier firms and have not played a role in leading technological innovation. It is worth mentioning that this result shows consistency with the findings of the interprovincial study by Xia and Xu (2020). The findings of Xia and Xu (2020) may also provide some corroboration for this paper, given the differences in the study object, GTFP accounting method, study period, and the focus of causal analysis.

(3) The effect of income level (*Income*) on urban GTFP and *PTC* is positive and statistically significant at the 5% significance level. Economically strong cities have the power to provide R&D capital, attract innovative talent, and implement better industrial policies, thus continuously stimulating the expansion of the frontier of production possibilities and increasing urban productivity, and thus are more likely to be at the forefront of national cities at every stage of urban economic growth, green development, and high-quality development. In addition, the effect of income level on *SEGTFP* is negative and statistically significant at the 10% significance level, which is consistent with the characteristic that the ''learning-by-doing'' effect decreases with the narrowing of the technology gap. Economically developed cities are closer to the frontier technology and face a smaller technology gap, so they are the first to enter the stage of diminishing "learning-by-doing" effect, which will bring about a decline in the scale effect, which is manifested in the empirical study as the income level has a negative effect on the scale effect.

The impact of the dynamics of industrial comparative advantage on GTFP and its compositions

This paper incorporates several lagged terms of industrial comparative advantage (*RCA*) in model (1) and examines the impact of *RCA* on GTFP from a dynamic perspective by comparing the differential impact of the lagged and current terms of *RCA* on GTFP. From Table 9, it can be found that the coefficients of the 1−5 period lags of *RCA* on GTFP are basically negative and mostly insignificant. The explanation being that the early endowment comparative advantage can only endogenize the early industrial structure. Due to the dynamic change of resource endowment caused by continuous capital accumulation and technological progress, which leads to the continuous transformation and upgrading of industrial structure, the previous industrial structure no longer matches the current resource endowment structure. If the previous industrial structure had continued to the present, it would inevitably achieve a lower productivity than that achieved under the current endowment structure and industrial structure. Thus, in the empirical study, it shows that the previous industrial structure that does not match the current endowment has a negative effect on the current GTFP growth.

This confirms the prediction of new structural economics concerning the relationship between urban productivity and industrial comparative advantage, that is, from a static point of view, comparative advantage lies mainly in allocative efficiency, while from a dynamic point of view, comparative advantage lies not only in allocative efficiency, but also in higher levels of allocative efficiency induced by technological progress, that is, under the guidance of technological progress, allocation efficiency will increase dynamically. However, if the resource endowment changes, and the industrial structure remains unchanged, the allocative efficiency will decline due to the dynamic change of the endowment structure or the mismatch between the endowment structure and the industrial structure.

Table 9
Impact of the dynamics of industrial comparative advantage on GTFP

Variables	(1)	(2)	(3)	(4)	(5)	(6)
RCA						0.1928***
						(0.0616)
L1.*RCA*	-0.0289					-0.1937***
	(0.0268)					(0.0644)
L2.*RCA*		-0.0138				0.0306
		(0.0266)				(0.0469)
L3.*RCA*			-0.0086			-0.0381
			(0.0260)			(0.0593)
L4.*RCA*				0.0038		0.0543
				(0.0221)		(0.0495)
L5.*RCA*					-0.0091	-0.0124
					(0.0223)	(0.0302)
Constant	0.3825**	0.3864**	0.3866**	0.3937**	0.3971**	0.3809**
	(0.1754)	(0.1730)	(0.1745)	(0.1739)	(0.1788)	(0.1775)
Observations	3604	3604	3594	3579	3549	3536
R^2	0.051	0.051	0.051	0.051	0.05	0.058
Number of cities	264	264	264	264	264	264
F-test	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]

Note: Lk.*RCA* denotes the kth period lagged term of *RCA* index. The symbols and significance of the control variables are all consistent with Table 7 and are not given here.

Table 10
Impact of the dynamics of industrial comparative advantage on the compositions of GTFP[17]

	(1) *GTFP*	(2) *SEGTFP*	(3) *PTC*	(4) *PEC*	(5) *GTFP*	(6) *SEGTFP*	(7) *PTC*	(8) *PEC*
L3.*RCA*	-0.0470	-0.0178	0.0546*	-0.1088**	-0.1665***	-0.0403	0.0864*	-0.2067***
	(0.0295)	(0.0284)	(0.0307)	(0.0431)	(0.0548)	(0.0438)	(0.0461)	(0.0560)
L3.*RCA* × *R&D*					0.0152**	0.0028	-0.0040	0.0123**
					(0.0062)	(0.0034)	(0.0036)	(0.0049)
RCA	0.0856***	0.0200	0.0015	0.1025***	0.0942***	0.0213	-0.0012	0.1074***
	(0.0292)	(0.0259)	(0.0322)	(0.0389)	(0.0296)	(0.0260)	(0.0325)	(0.0382)
Scale	0.0268	-0.0166	0.0084	0.0412**	0.0306*	-0.0162	0.0072	0.0429**
	(0.0173)	(0.0138)	(0.0185)	(0.0187)	(0.0171)	(0.0139)	(0.0186)	(0.0188)
HC	0.0093	-0.0052	0.0227*	-0.0022	0.0128	-0.0047	0.0217*	0.0000
	(0.0116)	(0.0132)	(0.0128)	(0.0152)	(0.0126)	(0.0132)	(0.0124)	(0.0148)
R&D	0.0244***	0.0037	-0.0073	0.0151**				
	(0.0092)	(0.0045)	(0.0053)	(0.0069)				
Income	0.0252**	-0.0150	0.0337***	0.0170	0.0267**	-0.0148	0.0332***	0.0177
	(0.0116)	(0.0093)	(0.0109)	(0.0131)	(0.0118)	(0.0093)	(0.0108)	(0.0130)
Constant	0.3931**	1.2345***	0.4172**	0.6507***	0.5071***	1.2539***	0.3845**	0.7313***
Observations	3,626	3,619	3,619	3,626	3,626	3,619	3,619	3,626
R-squared	0.0532	0.0762	0.2395	0.1165	0.0511	0.0762	0.2392	0.1167
Number of cityid	264	264	264	264	264	264	264	264
F-test	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]

Further, we examine how the dynamics of *RCA* affects the components of GTFP with a three-period lagged term[15], see models (1)-(4) in Table 10. It is clear that the negative effect of the lagged term of industrial comparative advantage on GTFP is mainly reflected in the *PEC* and scale effect (*SEGTFP*), while there is a positive effect on the *PTC*[16]. In other words, since industrial comparative advantage promotes productivity improvement mainly by optimizing resource allocation efficiency, the early industrial structure that does not match the current endowment structure will inevitably reduce resource allocation efficiency and will also fail to realize the scale effect, thus having a negative effect on *PEC* and *SEGTFP*. The dynamic change in the early endowment and industrial comparative advantage must be accompanied by technical progress, so as to gradually cause industrial transformation and upgrading, and its ultimate effect will bring about the expansion of the current production frontier. Given that the dynamics of endowments spontaneously endogenize the need for technological progress, what happens if external forces introduce more advanced technologies? We interact the three-stage lagged term of comparative advantage with *R&D*, and the estimated results are shown in models (5)–(8) in Table 10. The coefficients of the interaction term on GTFP and *PEC* are significantly positive[18]. This implies that strengthening R&D can help reduce or even reverse the negative effect of the lagged term of industrial comparative advantage on current efficiency change and GTFP. This estimation result further supports the conclusion of new structural economics that the negative effect of lagged industrial comparative advantage on current productivity is an indication that resource endowments have changed and

[15] To fully account for the effects of lagged variables, we include the three-phase lag term. The signs of the coefficient estimates obtained by selecting other lag periods are completely consistent, but there are some significant differences, which do not affect our main conclusions. Further details are available from the authors on request.

[16] China is already at the stage of diminishing "learning by doing" effect (Research Group on China's Economic Growth, 2014), so it has more practical policy implications to examine the effect of *RCA* on *PEC* and *PTC* after stripping out the scale effect than the two decomposition scenarios of *EC* and *TC*.

[17] To fully account for the effects of lagged variables, we include the three-phase lag term. The signs of the coefficient estimates obtained by selecting other lag periods are completely consistent, but there are some significant differences, which do not affect our main conclusions. Further details are available from the authors on request.

[18] The *R&D* indicator used here is government R&D spending, which mainly plays a role in the technical efficiency of the GTFP decomposition terms. The inference that market-led R&D (e.g., the number of patents granted) is more likely to lead to significant changes in social production, expanding the production frontier and thus contributing to pure technological progress in the GTFP decomposition terms, warrants exploration in future research.

Table 11
Temporal and regional heterogeneity in the impact of industrial comparative advantage on GTFP

	(1) Whole sample	(2) East	(3) Central	(4) West
RCA	0.0821***	0.1675**	0.1049**	0.0650
	(0.0266)	(0.0762)	(0.0452)	(0.0451)
RCA × dummystage	-0.0621	-0.2567*	-0.0384	0.0457
	(0.0536)	(0.1298)	(0.0674)	(0.0669)
Scale	0.0246	0.0085	0.0153	0.1066**
	(0.0175)	(0.0299)	(0.0155)	(0.0446)
HC	0.0065	0.0185	-0.0106	0.0180
	(0.0110)	(0.0173)	(0.0182)	(0.0164)
R&D	0.0259***	0.0258**	0.0008	0.0594**
	(0.0091)	(0.0109)	(0.0058)	(0.0262)
Income	0.0225*	0.0278	-0.0224	0.0352**
	(0.0118)	(0.0281)	(0.0349)	(0.0135)
Constant	0.3977**	0.1759	1.1046***	-0.1833
	(0.1675)	(0.3374)	(0.3700)	(0.2694)
Observations	3,639	1,291	1,365	983
R^2	0.0538	0.0620	0.0846	0.1230
Number of cities	264	93	97	74
F-test	[0.0000]	[0.0000]	[0.0000]	[0.0000]

that the adoption of more advanced technologies is more consistent with the upgraded resource endowment structure and the new industry structure that is now in place.

In summary, based on the empirical study under the perspective of new structural economics theory, this paper finds that the mechanism of industrial comparative advantage on urban GTFP under the static perspective is mainly reflected in the *PEC*. Additionally, in the long run, the dynamic changes of industrial comparative advantage determined by resource endowment will also significantly affect *PTC*, as well as continuous R&D will help to improve resource allocation efficiency and GTFP. This study confirms that in China's high-quality development stage, giving full play to the comparative advantages of local industries and strengthening R&D innovation are key initiatives to improve pure efficiency change and pure technological progress and thus sustainably increase GTFP in cities.

Further heterogeneity analysis

The above analysis of GTFP measures shows that there is temporal and regional heterogeneity in urban GTFP changes, and this section focuses on whether such heterogeneity also exists in the effect of *RCA* on urban GTFP. This paper first constructs the stage dummy variable (*dummystage*) with 2014 as the node[19], and examines the temporal heterogeneity of the effect of *RCA* on GTFP by including the interaction term of *RCA* and *dummystage* in the baseline regression model. Second, this paper also conducts subsample regressions for the three major regions of East, West, and Central in China to discuss the regional heterogeneity of the effect of *RCA* on GTFP and whether this regional heterogeneity further varies over time. The estimation results are shown in Table 11. Model (1) shows that the coefficient estimate of the effect of *RCA* on urban GTFP growth is 0.0821 for 2004−2014, and this estimate is 0.02 for 2015−2018, which is the sum of the coefficient estimate of *RCA* and the coefficient estimate of *RCA* × *dummystage*. This implies that the positive effect of the comparative advantage of the secondary industry on urban GTFP is weakening over time. Since the New Normal, China's economy has gradually entered the stage when the tertiary industry has become the leading industry. In the future, cities with comparative advantages in the tertiary industry will be at the forefront of development, and from the industrial development trend, the enhancement effect of the secondary industry's comparative advantages on urban GTFP may be gradually replaced by the tertiary industry's comparative advantages that are more in line with the endowment structure. Models (2)−(4) show that the coefficient of the impact of the comparative advantage of the secondary industry on GTFP decreases with the East, Central, and West in order during 2004−2014. The coefficients of the impact of the comparative advantage of the secondary industry on the East, Central, and West during 2005−2018 are −0.0892, 0.0665, and 0.1107, respectively. This means that the impact of *RCA* on GTFP not only has obvious regional heterogeneity, but also that this regional heterogeneity changes over time. In the perspective of the new structural economics theory, such temporal and regional heterogeneity are essentially rooted in differences in resource endowments and industrial comparative advantages and their dynamics.

[19] Based on the temporal trend in urban GTFP growth in Section 4.1, we choose to take 2014 as the node. Additionally, the *dummystage* is a 0 and 1 dichotomous variable, i.e., when year t is in the period 2015-2018, let $dummystage_t$=1; otherwise, let $dummystage_t$=0.

Robustness test

(1) Granger causality analysis

The productivity difference of different industrial sectors is also an important factor in the factor flow and structural change between industries, so there may be a reverse causality from urban GTFP to industrial comparative advantage. Here, we conduct a panel Granger causality test on the relationship between the *RCA* index and urban GTFP.

Before conducting the causal analysis, the stationarity of *GTFP* and the *RCA* index is first tested. Since the sample in this paper belongs to a short panel, the Harris-Tzavalis unit root test (requiring a balanced panel and not allowing different autoregressive coefficients) and the Im-Pesaran-Shin unit root test (allowing an unbalanced panel and allowing different autoregressive coefficients) are applied. The results of both unit root tests reject the null hypothesis of all panels containing unit roots [20], thus allowing a direct panel Granger causality analysis of the two variables. The results for Granger causality test (see Table 12) show that at a significance level of 5%, the *RCA* index is the Granger cause of urban GTFP, but the reverse is not true. This implies that industrial comparative advantage (*RCA*) is indeed a key causal factor in urban GTFP changes, and the possible existence of reverse causality does not constitute a key confounding issue in the empirical study of this paper.

(2) Handling of endogenous problem

Table 12
Results for Granger causality in panel data

Null Hypothesis	Lag Order	Z-bar tilde statistic[p-value][1]
RCA does not Granger-cause GTFP	1	2.385[0.017]
GTFP does not Granger-cause *RCA*	1	1.483[0.138]

Note: Granger non-causality test by Dumitrescu and Hurlin (2010) was performed based on the xtgcause command in STATA. During the test procedure, the optimal lag order was determined based on the BIC criterion.
[1] Lopez and Weber (2017) pointed out that among the three test statistics given by Dumitrescu & Hurlin (2010), *i.e.*, average Wald statistic, Z-bar statistic, Z-bar tilde statistic, for short panels with large N and small T, the Granger non-causality test result with reference to the Z-bar tilde statistic is most reasonable, which is also the statistic given in Table 5.

[20] Considering that different cities in China face the same macroeconomic and institutional factors and may have cross-sectional correlation, cross-sectional correlation is moderated by subtracting the cross-sectional mean in the testing process. Meanwhile, there are obvious time trends in green total factor productivity and capital organic composition indices in cities, and time trend terms are included in the testing process. Due to the limitation of space, the test results are not presented.

Table 13
CUE estimation of the impact of industrial comparative advantage on urban GTFP

	(1)		(2)	
	First-stage regression D.(*RCA*)	Second-stage regression D.(GTFP)	First-stage regression D.(*RCA*)	Second-stage regression D.GTFP
D.(*RCA*)		1.9904***		1.6963**
		(0.6140)		(0.7943)
D.(*BartikIV*)	-0.0307		-0.0383	
	(0.0616)		(0.0666)	
D.(*NunnIV*)	0.2495***		0.2057***	
	(0.0491)		(0.0518)	
Control variables	Not Controlled	Not Controlled	Controlled	Controlled
Observations	3325	3325	3091	3091
Number of cities	264	264	264	264
Kleibergen-Paap rk LM statistic		[0.0000]		[0.0004]
Kleibergen-Paap rk Wald F statistic		14.203{8.68,5.33}		8.319{8.68,5.33}
Hansen J statistic		[0.5069]		[0.2223]

Note: ① The first column represents the independent variables and the third row represents the dependent variables of the corresponding models. ② The CUE estimation proposed by Hansen, Heaton, and Yaron (1996) is performed based on the xtivreg2 command in STATA. The estimation process is set to allow heteroskedasticity and intra-group correlation clustering on cities with small sample corrections. ③ Robust standard errors are in round brackets, p-values corresponding to the corresponding test statistics are in square brackets, and Stock-Yogo weak ID test critical values at the 10% and 15% significance level are in curly brackets respectively ({}). ④ D.(X) denotes the difference term of variable X. ⑤ The estimation results of the control variables and constant terms are not given any more due to space limitation.

In order to alleviate the potential endogeneity problem, this paper attempts to introduce the instrumental variables of *RCA* index. Firstly, drawing on Bartik (2009), the "Bartik instrument" is constructed as follows.

$$Bartik\ IV_{it} = RCA_{i,t-1} \times \dot{RCA_t} \,/\, RCA_{t-1}$$

Where i denotes city (1,2...,264), and $\dot{RCA_t}$ is the arithmetic mean of the RCA index for all cities in year t. This instrumental variable simulates the expected value of the industries comparative advantage in each city under the same industrial development trend.

Also referring to the treatment of Nunn and Qian (2014), using the secondary industry comparative advantage index of each city in 2003 as an instrumental variable, and a time-varying factor is introduced to form a panel instrumental variable, which may be taken as the growth of $\dot{RCA_t}$, that is, $\dot{RCA_t} \,/\, \dot{RCA_{t-1}}$, thus obtaining another instrumental variable.

$$Nunn\ IV_{it} = RCA_{i,2003} \times \dot{RCA_t} \,/\, \dot{RCA_{t-1}}$$

In this paper, the baseline model (1) is regressed on the panel fixed effects instrumental variables method, that is, the fixed effects model is first-order differenced, and then Continuously-updated GMM estimation (CUE), which is efficient in the presence of arbitrary heteroskedasticity, is conducted using the two instrumental variables. The results are shown in Table 13. Regardless of the inclusion of control variables (i.e., models (1), (2) respectively), the corresponding Kleibergen-Paap rk LM statistic and Kleibergen-Paap rk Wald F statistic show that there is no unidentifiable problem in model (1) and (2), and it can be considered that there is no weak instrumental variable problem at 15% significance level[21] in both models. The corresponding Hansen J statistic cannot reject the null hypothesis of "all instrumental variables are exogenous" at the 5% significance level, indicating that the selection of instrumental variables in this paper is valid. After dealing with potential endogeneity, the effect of *RCA* on urban GTFP remains significantly positive, thus confirming the robustness of the conclusion that industrial comparative advantage determined by endowments is a key causal factor for urban GTFP growth under the new structural economics theory perspective.

(3) Replacement of the core explanatory variable

In this paper, we replace the key explanatory variable (*RCA*) in the benchmark model (1) with the industrial comparative advantage index of the tertiary industry (which may be denoted as RCA^3) and several structural change indicators constructed based on the output value of the three industries, including the value added of the secondary industry as a percentage of regional GDP (*Secondary*) which measures the industrialization process, the value added of the tertiary industry as a percentage of regional GDP (*Tertiary*) which measures the service process, and the index of industrial sophistication (*TS*) which measures the degree of industrial structure upgrading[22]. Moreover, different interaction terms for the core explanatory variables and *dummystage* are included in the corresponding fixed-effects panel data models, so that we can examine how the development of industries with and without comparative advantage, measured by multiple variables, affects urban GTFP over time. The estimation results are presented in Table 14. It is obvious that the effects of RCA^3, *Tertiary*, and *TS*, which reflect the comparative advantage of the service sector, the development level of service sector, and the relative process of the service sector, respectively, on GTFP show consistency, that is, there is a significant negative effect on GTFP in 2004–2014 when the service sector does not have industrial comparative advantage; the effect on GTFP becomes positive in 2015–2018 when the service sector crosses over the secondary sector to become the dominant industry in society; the secondary sector remains the dominant industry in the whole study period, so the total effect of these three indicators on GTFP still shows a negative direction. Correspondingly, the effect of *Secondary* which reflects the industrialization process on GTFP remains consistent with the effect of *RCA* on GTFP as demonstrated in Table 11. This comparative analysis, on the one hand, verifies the above assertion that there is a trade-off relationship between cities' comparative advantage in the secondary industry and the tertiary industry, and thus it is feasible to conduct an empirical study

[21] Kleibergen-Paap rk LM statistic corresponds to the under identification test, the null hypothesis is that the equation is under identified; Kleibergen-Paap rk Wald F statistic corresponds to the weak identification test, and the corresponding statistic value of 14.203 for model (1) is greater than the Stock-Yogo weak ID test critical value of 8.68 at the 10% significance level, and the corresponding statistic value of 8.319 for model (2) is greater than the Stock-Yogo weak ID test critical value of 5.33 at the 15% significance level.

[22] The index of comparative advantage of the tertiary industry (RCA^3) is constructed in a similar way as the comparative advantage of the secondary industry (*RCA*). The index of industrial sophistication (*TS*) is the ratio of the value added of the tertiary industry (%) to the value added of the secondary industry (%) in the compositions of the regional GDP of each city municipality, i.e., *TS=Tertiary/Secondary*.

Table 14
Impact of different core explanatory variables on urban GTFP – panel two-way fixed effects estimations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RCA^3	-0.0608**	-0.0693**						
	(0.0263)	(0.0283)						
RCA^3 × dummystage		0.0957^{O}						
		(0.0648)						
Secondary			0.0016***	0.0018***				
			(0.0005)	(0.0006)				
Secondary × dummystage				-0.0013				
				(0.0013)				
Tertiary					-0.0012**	-0.0016**		
					(0.0006)	(0.0007)		
Tertiary × dummystage						0.0021^{O}		
						(0.0013)		
TS							-0.0067	-0.0448***
							(0.0142)	(0.0128)
TS × dummystage								0.0758**
								(0.0297)
Scale	0.0348^{O}	0.0374*	0.0253^{O}	0.0245	0.0347^{O}	0.0374*	0.0352^{O}	0.0384*
	(0.0220)	(0.0220)	(0.0174)	(0.0175)	(0.0220)	(0.0220)	(0.0219)	(0.0219)
HC	0.0169	0.0174	0.0074	0.0063	0.0169	0.0174	0.0168	0.0156
	(0.0135)	(0.0135)	(0.0113)	(0.0110)	(0.0135)	(0.0136)	(0.0134)	(0.0132)
R&D	0.0264***	0.0276***	0.0250***	0.0258***	0.0263***	0.0276***	0.0266***	0.0290***
	(0.0099)	(0.0098)	(0.0091)	(0.0091)	(0.0099)	(0.0099)	(0.0099)	(0.0100)
Income	0.0262**	0.0294***	0.0220*	0.0223*	0.0261**	0.0292***	0.0275**	0.0277**
	(0.0117)	(0.0112)	(0.0119)	(0.0118)	(0.0116)	(0.0112)	(0.0113)	(0.0111)
Constant	0.3970*	0.3536*	0.4089**	0.3999**	0.3875*	0.3537*	0.3299*	0.3427*
	(0.2080)	(0.2036)	(0.1703)	(0.1674)	(0.2066)	(0.2033)	(0.1996)	(0.1956)
Observations	3,412	3,412	3,639	3,639	3,412	3,412	3,412	3,412
R^2	0.0550	0.0569	0.0528	0.0538	0.0547	0.0570	0.0538	0.0642
Number of cities	264	264	264	264	264	264	264	264
F-test	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]

Note: ***, **, *
O ***, **, *, O denote significant at 1%, 5%,10%, and 15% statistical levels, respectively.

with only the comparative advantage in secondary industry as the core explanatory variable; on the other hand, it not only verifies that the industrial comparative advantage consistent with endowment is the key causal factor of GTFP growth in cities, but also implies that since endowment is dynamic and thus industries with comparative advantage are not static, it is reasonable for the government to identify the changes in the endowment and develop the industries with comparative advantage in a timely manner.

Conclusion

This paper measures the GTFP of 264 cities at the prefecture level and above in China during 2004–2018, and further examines the structural factor of GTFP growth from the perspective of the new structural economics. The main findings of the paper are as follows.

We find that the average annual growth rate of China's urban GTFP from 2004 to 2018 was 1.3%. Compared with the average growth rate of China's urban GDP in the same period, the GTFP growth performance is poor, and China's urban economic growth is still a crude form of economic growth that relies on factor inputs. The space-time evolution characteristics of GTFP and its compositions are further analyzed. Two main conclusions are drawn. First, the quality of China's urban economy is gradually improving under the new governance concept of "new normal" and "high-quality development." Second, there is obvious regional and city-scale heterogeneity in urban GTFP.

The decompositions of urban GTFP show that, without considering scale effects, the main source of GTFP growth is technological progress while technological efficiency lags. Combined with the kernel density estimation results, this growth pattern leads to a gradual widening of the urban productivity gap in China. It is found that the total scale effect contributes 65.7% to the GTFP growth between 2004 and 2018. However, since 2015 the Chinese urban production has passed the stage of being substantively influenced by the learning-by-doing effect, which makes it unsustainable for promoting productivity by the scale effect brought by factor input and entering the transformation of growth momentum to pure technical efficiency and pure technological progress. Further analysis of the inducement proves that it is very important to give full play to local industrial comparative advantages in the process of transformation.

Further, it is verified in the framework of new structural economics that industrial comparative advantage is indeed one of the key factors in enhancing GTFP in Chinese cities, and this finding passes multiple robustness tests such as dealing with endogeneity issues, causality analysis, and replacement of core explanatory variables. In the short run, it works mainly by optimizing the resource allocation efficiency to improve the pure technical efficiency, and in the long run, it will endogenize the demand for technical progress to promote pure technical progress, while R&D helps to reduce the drag on resource allocation efficiency and hence on the productivity caused by the mismatched industrial structure. Therefore, this paper empirically verifies that industrial comparative advantage, technology, and knowledge innovation play an important role in improving urban productivity. In addition, the GTFP growth of Chinese cities is also constrained by the size of their population, research and development, human capital, and income level.

The findings of this paper have implications for how to improve the GTFP and quality of urban development in China's cities and promote coordinated regional development and new urbanization strategies. First, while technological progress has made a major contribution to the improvement of China's urban GTFP, technological efficiency is a serious drag on the growth of total factor productivity in China's cities. To transform China's urban economic growth mode from relying on factor inputs to being efficiency-driven and innovation-driven, it is necessary to solve the problem of lagging technical efficiency and realize the "dual-track" drive of technical progress and technical efficiency. Therefore, improving technical efficiency will be the main breakthrough for China's cities to achieve significant improvement in GTFP. Second, China's urban production has entered the stage of decaying learning by doing effect, and relying on scale expansion to enhance productivity is not sustainable. This phenomenon should be recognized now, and the comparative advantages of local industries should be given full play while strengthening R&D innovation. In this process, it is also necessary to strengthen intercity division of labor coordination to achieve optimal resource allocation, so as to enhance pure technical efficiency and pure technological progress. Finally, it should be recognized that most of China's prefecture-level cities are still relatively small in terms of population size and have not reached the optimal level of productivity, which results in lowering the quality of China's overall urban development. It is recommended that local governments actively configure mechanisms for cross-location collaboration, whereby large cities transfer mature industries and enterprises with declining scale effects to small and medium-sized cities, while small and medium-sized cities provide services for industry transfer and labor settlement, which is expected to lead to a win−win situation for both types of cities in terms of improving economic performance.

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