Economic Development and Growth in 69 Major Chinese Cities[1]

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Abstract

We investigate the proximate determinants of the observed differences in levels and growth rates of output per worker across the 69 major cities in China during 1994-2010 to answer: (i) Why are some cities so much richer than others? (ii) What drives economic growth in Chinese cities? We use growth and development accounting techniques to answer these questions. We make two contributions. First, we construct a detailed dataset covering 69 major cities in China over the period 1994-2010. Our dataset contains data for (real) output, employment, (real) capital stock, and human capital per worker, and it enables us to perform accounting exercises both in levels and growth rates. Second, we present accounting exercises with a focus on the 69 major cities of China. In terms of levels, we find that variation in factor endowments has a declining role in explaining variation in output per worker levels across cities. In terms of growth rates, we argue that growth in Tier 1 cities (Beijing, Shanghai, Guangzhou, and Shenzhen) is sustainable in the long-run as growth in these cities is driven mostly by TFP growth.

Keywords: China, cities, human capital, physical capital, productivity differences.

JEL classification: O11, O47, O57.

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1. Introduction

Two of the well-known facts of the economic growth and development literature are that (i) there are significant differences in output per worker across countries and (ii) countries differ in their growth rates. Considerable progress has been made in diagnosing the proximate determinants of level and growth differences in output worker across countries.[4] Relatively less attention has been paid to the substantial differences in output per worker levels and growth rates among the states or the cities within a single country.[5] This is surprising since there are significant variations in output per worker, both in terms of levels and growth rates, within countries as well. This paper studies such issues considering the major cities in the mainland China. China is the most populous country in the world, with around 1.4 billion citizens in 2018, which is close to one-fifth of the world population (World Bank, 2019). In addition, China has been undergoing rapid urbanization since 1978. The urbanization rate in China was less than 20% between 1960 and 1980, ranging between 16.2% and 19.4%. It has risen dramatically in the post-1980 period and reached almost 60% in 2018.[6] Therefore, China presents a unique opportunity to study the economic development/growth experiences of different cities within a country.

There are enormous income differences across the major cities in China. Figure 1 plots GDP per worker (in 1994 prices) in 1994, 2001, 2008, and 2015 for the 69 major cities of China.[7] Dots indicate large outliers outside of the normal data range (Shenzhen in all four years, Guangzhou in 2008, Ningbo in 2001, and Xiamen in 1994). The richest city in 2015 is Shenzhen while the poorest is Nanchong. GDP per worker in Shenzhen is nearly 22 times of that in Nanchong. The second richest city in 2015, Guangzhou, is more than 9 times as rich as Nanchong. This motivates our first question: *Why are some cities so much richer than others?* There is also significant variation in growth rates. Hohhot has the highest growth rate in output per worker. Average annual growth rates between 1994 and 2015 range from 13.28% in Hohhot

[4] See, among many others, Klenow and Rodríguez-Clare, 1997; Hall and Jones, 1999; Parente and Prescott, 2000; Caselli, 2005; Hsieh and Klenow, 2010; Jones and Romer, 2010; Jones, 2016 and the references therein.

[5] Acemoglu and Dell (2010) document the magnitudes of cross-country, cross-municipality, and within-municipality inequality in labor incomes for the Americas. Chanda (2011) notes that income gaps among Indian states are large, persistent and increasing over time and investigates if differences in technology can account for the observed income gaps across Indian states.

[6] We use the variable "Urban population (% of total)" from the World Bank (2019). Urban population refers to people living in urban areas as defined by national statistical offices.

[7] Appendix A.1 lists these cities. The National Bureau of Statistics of China (NBS) briefly talks about its selection criteria for these major cities at http://www.stats.gov.cn/tjzs/cjwtjd/201308/t20130829_74324.html. These criteria include, among others, city size and influence. The exact criteria, however, are not published.

to 4.10% in Haikou. This motivates our second question: *What drives economic growth in Chinese cities?*

To answer these two questions and to develop a better understanding of the regional economic development and growth in the most populous country of the world, we study the proximate determinants of the observed differences in levels and growth rates of output per worker across the 69 major cities in China during 1994-2010. In doing so, we use growth and development accounting techniques. Our growth accounting looks at *growth* rates of labor productivity, and asks what has contributed to a city's growth over time. We break down each city's growth in labor productivity by accounting for what percentage of economic growth comes from capital accumulation (i.e., growth in physical and human capital) and growth in total factor productivity (TFP). On the other hand, development accounting looks at *levels*, and compares differences in factor endowments and TFP levels in determining differences in output per worker levels across the major Chinese cities.

We make two contributions. First, we construct a detailed dataset covering 69 major cities in China over the period 1994-2010. Reliable and comparable data construction has been a challenge for the Chinese economy. While national and provincial physical and human capital stock calculations abound across the related literature for the Chinese economic development,[8] the literature that considers city-specific physical and human capital stock calculations is more limited. Our dataset consists of original annual measures for physical and human capital for each city in our sample. We provide a comprehensive discussion regarding the construction of the dataset because across the China literature, the raw data used, the methods, and the assumptions vary greatly. Our dataset contains data for (real) output, employment, (real) capital stock, and human capital per worker. Together they enable us to perform accounting exercises both in levels and growth rates. Second, this paper, to the best of our knowledge, is one of the first studies (if not the first) which presents growth and development accounting exercises with a focus on the 69 major cities of China. Our quantitative analysis also allows for a three-tier breakdown as defined by NBS (see Table A.1 for cities in each tier).

[8] Holz and Yue (2017) provide provincial and national calculations for physical capital series since 1952, distinguishing between capital services and wealth capital stock. We both find exponential growth for capital stock series. Brandt et al. (2013) construct a panel data set, which includes physical and human capital estimates by province that spans the period between 1985 and 2007 and covers 27 out of 31 provinces in mainland China.

In terms of levels, we find that variation in factor endowments has a declining role in explaining variation in output per worker levels across cities. In terms of growth rates, we find that growth in Tier 1 cities (Beijing, Shanghai, Guangzhou, and Shenzhen) is sustainable in the long-run as growth in these cities is driven mostly by TFP growth. On the other hand, growth in the second- and third-tier cities may be unsustainable in the long-run since growth in these cities is driven mostly by factor accumulation. As Krugman (1994, p. 13) puts it, "productivity isn't everything, but in the long run it is almost everything." Given our findings, past rates of economic growth in many Chinese cities are unlikely to be sustained if they fail to improve their productive capacity and technological capabilities. There has been growing interest in whether China can avoid the "middle-income trap" (see Glawe and Wagner (forthcoming) and the references therein). Our findings suggest that the threat of falling into a middle-income trap is real for China. China's quarterly GDP growth rate has fallen from 11.9% in the first quarter of 2010 to 6.8% in the third quarter of 2017.[9] If growth slows down in its 69 major cities, it is doubtful that the country as a whole will do much better. Higher aggregate productivity growth can be achieved by closing the gap between the frontier and laggard cities.

This paper is organized into the following chapters. Section 2 describes the details of how we construct our dataset. Section 3 presents the development accounting framework and the related results. Section 4 provides the growth accounting framework and the related results. Section 5 concludes. Additional details on data construction, figures, and tables are in the Online Appendix.[10] This paper uses the studies and data sources written in English and Chinese. References that are written in Chinese are documented in a separate section. Unless otherwise noted, all translations are by the first author of this paper.

2. Data

2.1 Definition of a City in China

Cities with more than 10 million inhabitants are often termed megacities. According to the United Nations, there are 31 megacities in the world in 2016, of which 6 are located in China (United Nations, 2016). There are no unified or standardized international criteria for

[9] For quarterly GDP growth rates, see http://intl.ce.cn/specials/zxxx/201501/20/t20150120_4389474.shtml and http://www.stats.gov.cn/tjsj/zxfb/201710/t20171020_1544259.html

[10] The online appendix for this paper is available at the authors' research websites: (i) http://www.muratungor.com; (ii) https://benjaminshen.weebly.com.

determining the boundaries of a city and often different definitions are used. For example, the United Nations provides three definitions: (i) city proper, (ii) urban agglomeration, and (iii) metropolitan area. The *city proper* describes a city according to an administrative boundary. The *urban agglomeration* considers the extent of the contiguous urban area, or built-up area, to delineate the city's boundaries. Finally, the *metropolitan area* defines its boundaries according to the degree of economic and social interconnectedness of nearby areas. The choice of how to define a city's boundaries is consequential for assessing the size of its population. The following example from Canada illustrates this point.

> "In Toronto, Canada, for example, approximately 2.6 million people resided within the "city proper" according to the 2011 census, but the population of the surrounding "urban agglomeration" was almost twice as large, at 5.1 million, and the population of the "metropolitan area" was larger still, at 5.6 million." (United Nations, 2016).

The situation is more complex for China. A city is an administrative unit in China, with clearly-defined borders. In this regard, the entire territory of China can be broken down into numerous cities.[11] In general, cities in China consist of a contiguous, urbanized area called "districts under city", surrounded by suburbs. Altogether, "districts under city" plus the suburbs are known as "total city".[12] The *Yearbooks* report almost all data in two parallel columns, one for "total city", and the other for "districts under city". As this paper focuses on urban centers in China, all data are taken from "districts under city." This is also in line with the literature.[13]

Chan (2007) provides a very detailed analysis of the difficulties involved in properly defining a city in China. Due to data unavailability, a simplified treatment will suffice here. As described in the *City Yearbooks*, "total city" corresponds with the entire administrative area of a city. It is a political rather than an economic concept. "Districts under city", on the other hand, exclude counties and county-level cities administered by a city. Therefore, it is a reasonable choice to use data for "districts under city" when studying urban areas in China. Another issue is the administrative status of a city. Cities in China fit into the following hierarchy, from top to bottom: province-level cities > provincial capitals > vice-province level cities > prefecture-level cities > county-level cities. This paper focuses on cities at the prefecture level and above

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[11] There is the exception of autonomous regions in the far-flung regions of China, as well as different names being used such as counties and states. This holds true, however, for the rich coastal provinces of China.
[12] In practice, there is another measure in the *City Yearbooks* called "built-up area", which most closely matches the usual definition of a city. However, the only data available for built-up areas are their land areas, and therefore it is not of much use here.
[13] See, for example, Xiang (2011).

which is consistent with the literature. Since 1997, data for county-level cities are reported differently to the rest, and they are not comparable.[14]

We need data on real output, real capital stock, employment, human capital, and factor income shares to conduct our accounting exercises. Below we describe how we construct our dataset.

2.2 Main Data Sources

Data are collected mainly from three sources: (i) *China City Statistical Yearbooks*, (ii) *China Population Yearbooks*, and (iii) the website and various publications of the National Bureau of Statistics of China, (NBS).[15] The *Yearbooks* for each year report data for the previous year. For example, *China City Statistical Yearbook 2016* reports data for 2015. In mainland China, there are currently 22 provinces, four centrally administered municipalities, and five autonomous regions. Because these entities have equivalent administrative status, the term "province" is used throughout this paper. Chongqing, one of the largest cities in China, became a province-level city in 1997. Before that, it was a part of the province of Sichuan.[16] Data for Chongqing are taken directly from the *City Yearbooks*, without any adjustments. Name changes are frequent in the *Yearbooks* throughout the sample period. During 1994-2002, "total city" and "districts under city" were called *di'qu*: "regional", and *shi'qu*: "urban" respectively. They were called *quan'shi* and *shi'xia'qu* between 2003 and 2015. *Shi'qu* and *Shi'xia'qu* are taken as equivalent, and we use data under these two columns without making any adjustments.

2.3 Sample and Sample Period

As of 2015, there are 4 province-level, 15 vice-province-level, and 276 prefecture-level cities in mainland China. This makes a total of 295 cities at the prefecture level and above. Data unavailability makes it difficult to study all of them. Our accounting exercises rely on data for output, capital stock, labor, human capital and factor income shares. Many cities do not have complete datasets. A ranking of cities by population, GDP or some other measures is arbitrary. It will also be plagued by definition issues such as *hu'kou* population versus resident, also known as de facto, population.[17]

[14] See, for example, *City Yearbook 2016*.
[15] The website contains *China Statistical Yearbooks*, output and price deflators at the province level, as well as urban population for the whole country since 1949.
[16] The State Council officially announced the territorial separation of Chongqing from the control of Sichuan province to establish the fourth province-level city of China on 18 June 1997 (Martinez and Cartier, 2017).
[17] In the Online Appendix we provide more information on *hu'kou*.

NBS started publishing housing price indices for 35 large and medium-sized cities (henceforth 35 cities) in the fourth quarter of 1997. In July 2005 the sample was expanded to 70 large and medium-sized cities (henceforth 70 cities). The frequency of publication was also increased from quarterly to monthly.[18] These 70 cities thus provide a consistent sample of cities free from arbitrary choices of our own. The city of Dali is dropped from the 70-city sample, as Dali is a county-level city, data for which are reported differently from those for cities at the prefecture level and above. It is common in the literature to limit the study of Chinese cities to those 35-city or 70-city samples at the prefecture-level and above.[19] In this paper, the phrases "69 cities" and "70 cities" are used interchangeably.

It is important to note that the 70 cities are not chosen arbitrarily. They are relevant since they include all province-level cities, provincial capitals,[20] vice-province level cities, and all cities with independent budgetary status. These 70 cities are originally chosen by the NBS for tracking real estate prices. Nevertheless, a literature has developed regarding the economies of those cities. Researchers have not only been interested in housing price movements, but have also studied human capital, land policy, effectiveness of maximum housing prices, and growth. Zhang et al. (2014) find a positive relationship between real estate investment and growth. The relationship is strongest in Eastern China. This is relevant to this paper, as this part of China is where most of the 70 cities are located. Chen and Fu (2012) reach a slightly different but relevant finding. They find that in big cities the effect of real estate development on growth is relatively lower.[21] Chen and Fu also argue that big cities rely more on human capital. This is in line with the findings on human capital in this paper. The frontier city in this study, Shanghai, has one of the highest levels of human capital in the sample. Li (2004) ranks human capital in 35 cities for 2001, and finds the top four to be Shenzhen, Beijing, Shanghai, and Guangzhou. This reaffirms the first-tier status of these four cities. Haikou is second last, which corresponds to it having the lowest growth rate.

Data availability determines the sample period in this paper. The first year for which gross regional product, the city equivalent of GDP, is reported is 1994. The most recent *City*

[18] http://www.gov.cn/ztzl/2006-06/30/content_323713.htm

[19] There are, however, some exceptions. For example, Alder et al. (2016) use a panel of 276 cities between 1988 and 2010 and study the effect of place-based industrial policy on economic development, focusing on the establishment of Special Economic Zones (SEZ) in China.

[20] Excluding Lhasa, the provincial capital of Tibet. Output there is very small.

[21] The authors create their own categories for cities. Their "big cities" include Tier 1 cities and some large provincial capitals.

Yearbook, as we conducted this research, reports data for 2015 as we conducted the data collection.[22] Another issue is human capital. We estimate human capital using years of schooling found in population census reports. China has conducted a population census every decade since 1990, the most recent one being in 2010.[23] Therefore, human capital series cover the years from 1990 to 2010. As a result, the sample period with human capital is 1994-2010. When human capital is omitted from the production function, it can be extended to 1994-2015. As human capital is an important factor input, we focus on the period of 1994-2010.

2.4 Price Indices

Output is reported at current price in the *City Yearbooks*, so it has to be deflated in order to produce real series.[24] The NBS does not publish GDP deflators. Therefore, we obtain two price series with which to deflate nominal output. The first is a set of GDP deflators for all of China published by the World Bank.[25] The drawback of the World Bank series is that it neglects regional variations in price levels. The second is a set of CPI series at the province level published on the NBS website.[26] The drawback is that CPI does not completely substitute for GDP deflators. For both series the base year is set to 1994. Investment is also reported at current price in *City Yearbooks*. It has to be deflated in order to produce an estimate of the real capital stock. We use price indices for investment in fixed assets published by the NBS. This series is reported at the province level. Investment deflators suffer from missing data. The province of Guangdong is missing data for 1994-2000, the province of Hainan for 1994-1999, and Chongqing for 1994-1996.[27] We use national aggregates where provincial series are missing. Figure 2, for example, plots the provincial deflators for fixed assets for Chongqing, Guangdong, and Hainan against the deflator for fixed assets at the nation level between 1994 and 2015. The national series is a good match for the provincial ones, which justifies its use.

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[22] See *China City Statistical Yearbook 1995, 2016*.
[23] Since its founding in 1949, China conducted population censuses in 1953, 1964, 1982, 1990, 2000, and 2010.
[24] In some years, the *Yearbooks* state explicitly that a variable is reported in current prices, in other years they don't. We assume that everything in the *Yearbooks* are reported in current prices.
[25] They are available at https://data.worldbank.org/indicator/NY.GDP.DEFL.KD.ZG?locations=CN
[26] Available at http://data.stats.gov.cn/english/easyquery.htm?cn=E0103
[27] Chongqing was designated as one of the province-level cities in 1997. This change also altered its borders. Therefore, it is understandable why Chongqing is missing data prior to 1997.

2.5 Output

Output series are available under the variable "gross regional product" in the *City Yearbooks*. We use gross regional product, GDP, and output interchangeably. The Chinese government places a huge emphasis on generating high output growth. Therefore, data on output are readily available. They are also believed to be relatively reliable.[28] Furthermore, gross regional product is also the most consistent statistic over the years whose name does not change. Other variables such as employment and investment both have name changes over the period. We deflate nominal output with both the World Bank GDP deflators for all of China, and the province-level CPI series published by the NBS. The two sets of real output are added up for all cities in the sample and plotted against each other, as shown in Figure 3. Both series exhibit exponential growth. They are almost identical up to 2004, and then start to diverge, with the provincial CPI-based output series being higher than the World Bank GDP deflator-based output series. Throughout this paper, real output produced from provincial CPI series will be treated as our baseline results, as they reflect regional variation in price level which is significant in China.

Output also suffers from missing data. When data are missing, it is often the case that cities are missing data in the "districts under city" column, but have complete data in the corresponding "total city" column. Assuming that the two grow at similar rates, we fill in the missing observations by first calculating the growth rates of "total city" output, and then applying the growth rates to the most recent "districts under city" figure.[29] A special case is Ganzhou whose nominal output is missing for both "districts under city" and "total city" for 1998. The missing observation for 1998 is then interpolated using the fitted exponential curve.

2.6 Physical Capital

We employ the perpetual inventory method (PIM) to estimate capital stock for each city. The basic idea of the PIM is to interpret an economy's capital stock as an inventory. The stock of inventory increases with capital formation (i.e., investments). In discrete time the PIM can be represented in the form of $K_t = I_t + (1-\delta)K_{t-1}$, where K_t is the end-of-period capital stock, I_t the quantity of investment occurring in the period, and δ is the rate of replacement.

[28] Reliability of output data has come under scrutiny, however, in some parts of China after the GFC with several cases of inflated GDP figures. See, for example, https://qz.com/887709/chinas-liaoning-province-admitted-that-it-inflated-gdp-figures-from-2011-to-2014/ This should not affect our results, however, as the years affected were 2011 and later, and our sample period with human capital ends in 2010.

[29] As missing observations occur sporadically, and not for long periods of time, this assumption should hold.

We suppress the subscript for cities to simplify the exposition. Three data series are required in order to proceed: real investment, depreciation rates (as period averages), and initial capital stock.

The *City Statistical Yearbooks* report nominal investment series for each city, which we then deflate using price indices for investment in fixed assets published by the NBS at the province level. As per usual, all data are for districts under city. There are several problems concerning data collection and construction. One of these problems occurs because variable names are frequently changed. We use "gross fixed capital formation" for nominal investment. The specific name of the statistic has changed over the years. For 1994-2005, it is called "investment in fixed assets"; for 2006-2011, "all society investment in fixed assets"; for 2012-2014, "all society investment in fixed assets (excluding rural households)"; for 2015, "investment in fixed assets (excluding rural households). It is important to note that in recent years investment data have moved towards an urban emphasis which is in line with the focus of this paper. Missing observations are another concern. Changchun is missing data for "districts under city" for 2007-2008. The data are complete for the corresponding "total city" column. The missing data are filled in by linear interpolation. Ganzhou is missing both "districts under city" and "total city" data for 1997-1998. Again, we graph the series and fit an exponential curve, as the series clearly demonstrate exponential growth. The missing values are then interpolated.

The most detailed work on capital stock at the city level in China is Xiang (2011). She studies all cities at the prefecture-level and above. Her sample period is 1995-2009. She covers all the cities which we are studying, and her sample period overlaps with ours. Both Xiang and we use "all society investment in fixed assets" to calculate real investment. Xiang reports depreciation rates at the province level for all provinces in mainland China for the entire period. We use her provincial depreciation rates for each city in its respective province. For example, Shenzhen is in the province of Guangdong and therefore we use Guangdong's depreciation rates for Shenzhen. As our sample period is longer than the sample period of Xiang, we extend her depreciation rates at both ends. That is, for 1994 we use the numbers for 1995, and for 2010-2015 we use the numbers for 2011. One thing to note is that Xiang reports a panel of depreciation rates, δ_{it}, with *i* being the province and *t* being the year. For the sake of simplicity, we calculate the average depreciation rate for each province, δ_i after extending her panel. It is this average which we then use in our own calculations. Xiang actually reports two sets of depreciation rates, based on two different sets of assumptions about the useful life of capital stock. They serve as the upper and lower bound of the true depreciation rates. We choose the one that is closest to those reported in Bai et al. (2006), which is to say, roughly 10% per year.

The last thing to do is to calculate initial capital stock K_0 for each city. Here we use Xiang's method again, which is taken from Reinsdorf and Cover (2005) whose proof we reproduce here. Let I_0 be real investment in year zero, that is, 1994. Assuming the average growth rate of real investment during the period could be extended backward in time, and calculated as $g = (I_{2015}/I_{1994})^{1/21}$. In addition, δ is the average depreciation rate over the period. Now we can calculate initial capital stock. If I_0 is real investment in year zero, then real investment in year (-1) would be $I_{-1} = \frac{I_0}{1+g}$. The amount of that investment which survived into year zero, after taking away depreciation, would be $I_{-1}\ left\ at\ year\ 0 = \frac{I_0(1-\delta)}{1+g}$. Similarly, the amount of investment in year (-2) which remains in year zero, after taking into account investment growth and depreciation, would be $I_{-2}\ left\ at\ year\ 0 = \frac{I_0(1-\delta)^2}{(1+g)^2}$. Initial capital stock is the sum of all previous investments, taking into account investment growth and depreciation: it is the sum to infinity of a geometric sequence, that is,

$$K_0 = I_0 + I_{-1} + I_{-2} + \cdots = I_0 + \frac{I_0(1-\delta)}{1+g} + \frac{I_0(1-\delta)^2}{(1+g)^2} + \cdots = \frac{I_0}{1-\frac{1-\delta}{1+g}} = \frac{I_0(1+g)}{g+\delta}. \quad (1)$$

There is one last thing to note. We have in fact simplified Xiang's method and we explain our simplifications below. One of Xiang's innovations is to introduce a three-year period for new investments to join the productive capital stock. So, her capital stock equation is

$$K_t = K_{t-1}(1-\delta) + \frac{1}{3}(I_t + I_{t-1} + I_{t-2}). \quad (2)$$

Xiang cites Ye (2002) for being the only study that considers a three-year period before investment is turned into capital stock. She also defines $I'_t = \frac{1}{3}(I_t + I_{t-1} + I_{t-2})$. We adopt Xiang's equation for capital stock. But for the sake of simplicity, we cut our sample off at 1994 while Xiang's first year for I'_t is 1997. Xiang calculates growth rate, g, using I'_t instead of I_t, whereas we use I_t for simplicity. Our equations are as follows:

$$K_{1994} = \frac{I_{1994}(1+g)}{g+\delta}. \quad (3a)$$

$$K_{1995} = K_{1994}(1-\delta) + \frac{1}{2}(I_{1995} + I_{1994}). \tag{3b}$$

$$K_{1996} = K_{1995}(1-\delta) + \frac{1}{3}(I_{1996} + I_{1995} + I_{1994}). \tag{3c}$$

Following this procedure, one can continue to calculate the capital stock for other years. Now, We compare our series with those of Xiang (2011) graphing the real capital stock series for the four Tier 1 cities: Beijing, Shanghai, Guangzhou, and Shenzhen. As shown in each panel in Figure 4, they are reasonably close, except for Shanghai.[30] The reason we follow the methodology in Xiang (2011) is because hers is the only paper which deals extensively with capital stock at the city level in China. There are a lot of studies that calculate TFP at the national, provincial, or city level in China. They all contain estimates of capital stock. But none of them deals with city-level capital stock exclusively as their theme, and as a result their estimates of capital stock data are not as thorough as that in Xiang (2011).[31] Below we give a brief review of some studies in the literature, and point out where their treatment is not as extensive as Xiang's.

Mao and Pan's (2012) study is the closest to Xiang (2011). However, they assume a common depreciation rate of 10.96% which is taken from Shan (2008). Furthermore, they calculate city-level capital stock by multiplying province-level capital stock, for which data are more readily available, by the weight of the city's GDP in its province. This is a strong assumption. Ke and Zhao (2014) study productivity at the city level in China, and talk briefly about capital stock at the city level. However, they also rely on strong assumptions. Firstly, they set an annual depreciation rate of 5%, which is only half the size of the more realistic estimate of 10%. Secondly, they use real investment, instead of investment in fixed assets, to calculate investment series. Ye (2002) is the only study which talks about a three-year period for investment in fixed assets to be transformed into capital stock. Ye's study, however, focuses on productivity at the province level. Therefore, it is not as applicable as Xiang (2011). Other studies, such as Lin (2003), Zhang and Zhang (2003), Ren and Liu (1997), and Ye (2010b) all deal with capital stock at the national level (and Ye (2010a) talks about capital stock at the province level).

[30] As Xiang's sample period starts in 1995, our base year is also changed to 1995. Throughout this paper, this is the only instance where the base year is changed. In all other cases, the base year is 1994.
[31] We are aware of one journal paper that deals exclusively with capital stock at the city level in China. That study is Ke and Xiang, 2012, which is based on Xiang (2011).

2.7 Number of Workers

Here we use employment to mean the number of workers: that is, the *L* term that is used to deflate aggregate variables *Y* and *K* into per-worker ones, *y* and *k*. Data for employment are the most difficult to obtain, as it is not reported directly in the *Yearbooks*. The various statistics that are reported suffered frequent name changes. We explain these issues below. There are two statistics reported in the *City Yearbooks* which are related to employment, both of which have undergone extensive name changes.[32] The first is employment in work units,[33] and the second is those working in privately-owned enterprises and the self-employed. As Table 1 shows, both measures have seen frequent name changes over the period. The exact names are not translated here, but the common elements are taken out and compared. It is evident that the two measures did not converge to an ideal state until recently. For example, judging by the names, adding the two variables would have produced a reasonably accurate number for total employment in "districts under city" for 2015. For earlier years, however, this would be questionable.

The first attempt at calculating total urban employment produces dramatically underestimated figures, as we simply use the left-hand column in Table 1. Doing so completely distorts the ranking of cities in terms of output per worker levels. Relatively undeveloped cities, such as Shijiazhuang, rise to the top, while rich ones, such as Xiamen, sink to the bottom. The second attempt is to add together the left and right-hand columns. Indeed, this is what is sometimes done in the literature (See, for example, Xiang, 2011). This particular method is actually not good enough, as we go down the same path, and discover that adding the two columns does not produce satisfactory employment series, either.[34] For some cities, employment thus produced is too high, while for others it is too low. For example, in 2015, this approach yields

[32] The *City Yearbooks* are the only sources which report employment at the city level.
[33] The work unit—known as *dan'wei* in Mandarin—used to be an important aspect of life in urban China. A work unit is a workplace. Under the planned economy, all enterprises, factories, schools, public institutes, and government agencies, etc. were known as work units. Although the term *dan'wei* is used mainly in cities, communes and collective farms in rural China were also treated as work units. After 1978, however, and especially since the 1990s when private enterprises blossomed in China, the employment share of work units have declined significantly. Nowadays the term "work unit" exclusively refers to the entities outside the private economy. In casual conversations people sometimes still refer to their firm as their work unit, but in statistical publications, including the *City Yearbooks*, work units or units refer exclusively to non-private enterprises.
[34] The two employment variables also suffer from missing data. If only "districts under city" are missing, it is filled in using growth rates of the corresponding "total city" column. We interpolate the data for those cities that are missing both columns. Interpolation is done linearly except Ganzhou, where we fit an exponential curve, as linear interpolation would have produced negative values.

18 million workers for Beijing, which has a population of 22 million. Shijiazhuang, with over 10 million residents, has less than 1 million workers in 2015, according to a simple addition of the two columns. This is obviously not true, and using these inaccurate employment figures distorts the income distribution. Shijiazhuang becomes one of the richest cities in China, while cities like Shanghai, Beijing, and Xiamen are among the poorest. The last straw is a definition change introduced by the NBS in 1997. There is a huge decline from 1997 to 1998. The NBS explains that, prior to the change, employment in rural areas is included, after 1997 it is excluded. Although the change is in line with the urban focus of this paper, such drastic definition changes and the lack of other reliable data sources on city-level employment render the employment figures in *City Yearbooks* unusable.[35] We estimate city-level employment for this paper $\left(EMP^{i}\right)$ using the following formula:

$$EMP^{i} = \frac{Urban\ population\ for\ city\ i}{Urban\ population\ for\ whole\ country} \times Urban\ employment\ for\ whole\ country. \quad (4)$$

Essentially, faced with a lack of city-level employment data, it has to be estimated using national-level data. Here the assumption is that the weight of a city's urban population in China's total urban population is equal to its percentage of employment. Admittedly, this is somewhat restrictive. The *China Statistical Yearbooks*, available on the NBS website, report consistent urban employment series for the whole country.[36] A consistent set of urban population data for the whole country can be found in the *China Population and Employment Statistics Yearbooks*.[37] Urban population figures for each city, however, are difficult to obtain. This is in large part due to the *hu'kou* system. Essentially, it is an internal passport issued at birth. *Hu'kou* information is registered with the police and is readily available. End-of-year local *hu'kou* population are reported in the *City Yearbooks*, and these are the series we use to represent urban population in each city.[38] This introduces a bias, however, as the number of local *hu'kou* holders in an area can be hugely different from the number of residents in that place, as people migrate. This differential can be especially large in coastal areas, where the prospect of finding better jobs has drawn millions of workers from inland China.

[35] Province-level cities have their own statistical bureaus and publish their own *Yearbooks*. These *Yearbooks* often report resident population going back to 1978. For the sake of consistency, however, these sources are not used.
[36] See Table 4-2 of *China Statistical Yearbook 2016*. The figures are confirmed by Table 5 of *China Compendium of Statistics 1949-2013*, under "total number of employed persons—urban area". The later, however, as its name suggests, only contains data up to 2013.
[37] See Table 1-4 of *China Population and Employment Statistics Yearbook 2016*.
[38] As per usual, we have used data under the column "districts under city".

For rich cities such as Shanghai and Shenzhen which attract workers from elsewhere in China, resident population is significantly larger than local *hu'kou* population. At the end of 2015, the local *hu'kou* population in Shanghai was 14 million, while the resident population was 24 million. In Shenzhen, the local *hu'kou* population was 3.5 million at the end of 2015, but the resident population was over 11 million. Therefore, it is important to keep in mind that differences in output levels are exaggerated, since employment in rich cities, according to this method, are underestimated. Output per worker (labor productivity) produced using our own estimates of urban employment are consistent with economic facts on the ground. Tier 1 cities are among the most productive in China, while Tier 3 cities are amongst the poorest. This lends support to our method.[39]

2.8 Human Capital

It is very important to consider human capital. Otherwise we will be treating all workers as undifferentiated raw labor with the same level of productivity. But this is obviously not true. Workers have different levels of educational attainment, for example, and therefore different levels of productivity. For the sake of simplicity and data availability, we use average years of schooling to construct human capital. The only sources that contain average years of schooling at the city level are the county-level population census reports.[40] Average years of schooling are reported directly for 2000 and 2010.[41] However, they are not reported directly for 1990 and have to be estimated.[42] In all three cases we focus on population aged six and above (H^{6+}). For 1990, the formula we use is:

$$H^{6+}_{1990} = \frac{0*H_0+5*H_1+8*H_2+10.5*(H_3+H_4)+14*(H_5+H_6)}{Pop}. \tag{5a}$$

[39] In the Online Appendix we provide another set of employment data using the *County-Level Population Census Reports*. We compare residential population series with *hu'kou* series. The two series are close for all cities except Shenzhen, which is an outlier. Nevertheless, the qualitative nature of our results does not change when Shenzhen is dropped.

[40] Not to be confused with county-level cities. In China, all cities are further divided into districts and counties which total over two thousand in number. County-level reports are collected from all the districts and counties from all cities in China. As a result, they are very rich in detail.

[41] Data for 2000 are available at http://www.stats.gov.cn/tjsj/ndsj/renkoupucha/2000fenxian/htm/table4.htm. Data for 2010 are purchased separately. For both years, we use the statistic "Average years of schooling for population aged 6 and above" of Table 4.

[42] Data for 1990 are found in Table 3-1 of *China Population Yearbook 2000*. We use the formula in Qian and Smyth (2006). We make changes to the formula, combining specialized secondary school and high school as well as college and university.

In (5a) H_0 denotes no schooling, H_1 primary school, H_2 secondary school, H_3 high school, H_4 specialized secondary school (*zhong'zhuan*), H_5 junior college (*da'zhuan*), H_6 undergraduate, and Pop denotes population aged six and above.[43] In order to keep our numbers consistent, we estimate average years of schooling for 2000 and 2010 as well. In other words, we use our own calculations for average years of schooling throughout this paper. We use the following formula to calculate average years of schooling for population aged 6 and above for 2000 (H_{2000}^{6+}):

$$H_{2000}^{6+} = \frac{0*(H_0+H_1)+5*H_2+8*H_3+10.5*(H_4+H_5)+14*(H_6+H_7)+16*H_8}{Pop}. \quad (5b)$$

In (5b) H_0 denotes no schooling, H_1 literacy class (*sao'mang'ban*), H_2 primary school, H_3 secondary school, H_4 high school, H_5 specialized secondary school (*zhong'zhuan*), H_6 junior college (*da'zhuan*), H_7 undergraduate, H_8 postgraduate, and Pop denotes population aged six and above.[44] Finally, we use the following formula to calculate average years of schooling for population aged 6 and above for the year 2010 (H_{2010}^{6+}):

$$H_{2010}^{6+} = \frac{0*H_0+5*H_1+8*H_2+10.5*H_3+14*(H_4+H_5)}{Pop}. \quad (5c)$$

In (5c) H_0 denotes no schooling, H_1 primary school, H_2 secondary school, H_3 high school, H_4 junior college (*da'zhuan*), H_5 undergraduate and above. Note that there are two changes in 2010. First, there is no separate category for literacy class.[45] Second, there are no separate categories for specialized secondary school or postgraduate, either. Rather, undergraduate and postgraduate studies are combined in H_5. We assign 14 years to both of them. Levels of educational attainment reported for 2000 are different than those reported for 1990. As a result, some further adjustments are made. No schooling and literacy class are combined. We assign 16 years to those with postgraduate degrees. As population censuses are carried out once every decade in China, data are missing for the years in between. They are filled in by interpolation.[46]

[43] $H_0 + H_1 + \ldots + H_6$ should be equal to Pop. However, this is not always the case for 1990. Several cities had minor discrepancies. These cities, however, are all Tier 3 ones, and the discrepancies, if any, are small, of the order of several tens or hundreds.

[44] For 2000, total population aged 6 and above is not reported, so we simply take the sum from H_0 to H_8. As a result, there is no discrepancy issue.

[45] This is not surprising. As the literacy rate in mainland China continues to increase, literacy classes have faded in importance.

[46] We interpolate linearly during 1990-2000 and 2000-2010.

Next, we use $h = e^{\varphi(s)}$ to construct human capital, where s is average years of schooling and $\varphi(s)$ is a function of s. Hsieh and Klenow (2010) use $\varphi(s) = 0.085s$, that is, the return to one extra year of education is constant at 8.5%. It is important to note that Hsieh and Klenow (2010) focus on productivity differences across countries, and do not pay any particular attention to China. We use the linear piecewise function following Hall and Jones (1999) and Caselli (2005) for $\varphi(s)$. The slopes are taken from Psacharopoulos (1994) and measure returns to education for the whole world. The function in Caselli (2005) is as follows:

$$\varphi(s) = \begin{cases} 0.134 * s, & s \leq 4 \\ 0.134 * 4 + 0.101 * (s - 4), & 4 < s \leq 8 \\ 0.134 * 4 + 0.101 * 4 + 0.068 * (s - 8), & s > 8. \end{cases} \tag{6a}$$

The shortcoming of this function is that the slopes represent returns to education for the whole world. The return for the first four years of schooling is 13.4%, for the next four is 10.1% and for all the years above eight the return is 6.8%.[47] Ideally, returns specific to China are needed. Peng (2011), to the best of our knowledge, is the only study which specifically focuses on the returns to education in China at the city level. Peng reports two sets of results. First, he reports average returns to schooling for province-level cities, provincial capitals, and other cities[48] Next, Peng breaks down educational attainment into three categories in order to study the returns to different levels of schooling: (i) "secondary school and below", (ii) "high school or specialized secondary school (*zhong'zhuan*)", and (iii) "junior college (*da'zhuan*) and above".

Table 2 reports Peng's returns to schooling, which are specific to China. Note that Peng finds increasing returns to education in China. This contrasts with decreasing returns discussed in Caselli (2005). Peng also finds higher returns to education in province-level cities than provincial capitals, which in turn have higher returns than other cities. Lastly, we make adjustments to Peng's method. Peng categorizes cities as province-level cities, provincial capitals, and other cities, and we relabel them as Tier 1, 2, and 3 cities. We apply the same years of schooling as found in Qian and Smyth (2006), that is, 8 years for secondary school, and 10.5 years for high school. Thus, we combine Qian and Smyth (2006) and Peng (2011) to come up with functions for human capital for cities in different tiers:

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[47] The measures are not country specific and, therefore, do not control for the quality of education in each country.

[48] Peng makes adjustments to his sample, and the cities in each group do not correspond strictly with their official designations.

Tier 1 cities:

$$\varphi(s) = \begin{cases} 0.041 * s, & s \leq 8 \\ 0.041 * 8 + 0.073 * (s - 8), & 8 < s \leq 10.5 \\ 0.041 * 8 + 0.073 * 2.5 + 0.141 * (s - 10.5), & s > 10.5. \end{cases} \tag{6b}$$

Tier 2 cities:

$$\varphi(s) = \begin{cases} 0.029 * s, & s \leq 8 \\ 0.029 * 8 + 0.086 * (s - 8), & 8 < s \leq 10.5 \\ 0.029 * 8 + 0.086 * 2.5 + 0.116 * (s - 10.5), & s > 10.5. \end{cases} \tag{6c}$$

Tier 3 cities:

$$\varphi(s) = \begin{cases} 0.043 * s, & s \leq 8 \\ 0.043 * 8 + 0.074 * (s - 8), & 8 < s \leq 10.5 \\ 0.043 * 8 + 0.074 * 2.5 + 0.115 * (s - 10.5), & s > 10.5. \end{cases} \tag{6d}$$

2.9 Factor Income Shares

Due to data unavailability it is difficult to calculate the labor share of income at the city level. The most relevant statistic reported in the *City Yearbooks*, "total wage bill of employed staff and workers", is not the same as "compensation of employees" reported on the NBS website. It is significantly lower. One possible explanation is that it includes only those employed in work units, as the word used for staff and workers, *zhi'gong*, implies employment in the public sector. Therefore, we use the provincial labor shares. Chi and Qian (2013) argue that, when indirect taxes are an important source of government revenue, the adjusted labor share should be adopted over the naïve one. Since this is indeed the case in China, adjusted labor shares are reported here. The formula for naive labor share is:

$$Naive\ labour\ share = \frac{Compensation\ of\ employees}{GDP} \times 100\%. \tag{7a}$$

There are different ways to adjust naïve labor share. Gollin (2002) discusses three different methods, while Young (1995) takes into account sex, age, and education when calculating the labor share for Hong Kong, Singapore, and South Korea. Such detailed microdata are not available for the cities and periods covered in this paper.[49] At the province level, output is broken down into compensation of employees, net taxes on production, depreciation of fixed assets, and operating surplus. Therefore, naïve labor share is adjusted by subtracting indirect taxes (taxes on production) from output. The formula for adjusted labor share is, therefore:

$$Adjusted\ labour\ share = \frac{Compensation\ of\ employees}{GDP - Indirect\ taxes} \times 100\%. \tag{7b}$$

Table 3 (4) reports the naïve (adjusted) labor shares for 31 provinces in selected years between 1994 and 2015. The reported figures are close to 0.5. The average of averages for all provinces is 0.49 for naïve labor share and 0.57 for adjusted labor share. Both naïve and adjusted labor shares have small standard deviations, so they are relatively stable over time. Labor share is also relatively stable across provinces, with the naïve labor share being around 0.5 and the adjusted labor share being 0.6. Variation over time notwithstanding, 0.5 is a good approximation for the purposes of our accounting exercises.

3. Development Accounting

3.1 Framework

In a development accounting exercise, we have a cross-section of cities, and perform the decomposition of the level of GDP per worker into the levels of factor inputs (such as physical and human capital) and TFP to answer: How much of the variation in output per worker among the major cities in China is explained by productivity differences or differences in factor inputs? Hanushek et al. (2017) conduct a development accounting exercise for different states in the US. They argue that development accounting is more appropriate for determining income differences between regions in the same country than for income differences across countries. The key reason is that regions within a country are more likely to operate under the same production function. In the same spirit, we conduct a development accounting exercise for the 69 Chinese cities in our sample.

We adopt a Cobb-Douglas production function, according to which a city's GDP is:

$$\mathrm{Y} = AK^{\alpha}(hL)^{1-\alpha}, \tag{8a}$$

[49] The most detailed breakdown of output at the province level is found on the NBS website under "Regional—Annual by province—Gross Regional Product by income approach."

where Y denotes real output, K denotes capital stock, h denotes (average) human capital per worker, L denotes number of workers, α denotes capital's income share, and A denotes TFP. In per worker terms, Equation (8a) becomes

$$y = \mathrm{A}k^{\alpha}h^{1-\alpha}, \tag{8b}$$

where y represents output per worker (Y/L), with k representing the capital-labor ratio (K/L). Caselli (2005) rewrites Equation (8b) as $y = \mathrm{A}y_{KH}$, where $y_{KH} = k^{\alpha}h^{1-\alpha}$, and names y_{KH} the factor-only model. The key question Caselli addresses is: what will the world income distribution be if all countries had the same level of efficiency? (see also Arezki and Cherif, 2010). The only difference is that here we are focusing on cities in China. Next, Caselli expresses the variance of $ln(y)$ using $y = \mathrm{A}y_{KH}$:

$$\mathrm{Var}[\ln(\mathrm{y})] = \mathrm{Var}[\ln(\mathrm{A})] + \mathrm{Var}[\ln(y_{KH})] + 2Cov[\ln(A), \ln(y_{KH})]. \tag{9}$$

The key issue is how much of the variation in income levels can be explained by factor endowments, that is, the factor-only model. The more successful the factor-only model is at explaining variation in income levels, the smaller the role of TFP in determining differences in output per worker across cities, and vice versa. Caselli proposes two measures of success for the factor-only model. The first measure is this:

$$success_1 = \frac{\mathrm{Var}[\ln(y_{KH})]}{\mathrm{Var}[\ln(\mathrm{y})]}. \tag{10a}$$

If all cities had the same level of efficiency, then the variance of $ln(A)$ and the covariance between $ln(A)$ and $ln(y_{KH})$ are both zero, and $success_1$ would be equal to 1. Intuitively, (10a) shows how much of the variation in income levels, as measured by the variance of $ln(y)$, can be explained by variation in factor endowments, as measured by the variance of $ln(y_{KH})$. In a counterfactual world where all cities had the same level of efficiency, all income differences must be due to rich cities having more physical and/or human capital and poor cities having less. We also implement the second measure of success of Caselli (2005), which is $success_2$:

$$success_2 = \frac{y_{KH}^{90}/y_{KH}^{10}}{y^{90}/y^{10}}. \tag{10b}$$

In (10b), y_{KH}^{90} indicates the 90$^{\text{th}}$ percentile of y_{KH}, and y_{KH}^{10} the 10$^{\text{th}}$ percentile, and so on, etc. The most straightforward way to calculate "variation" in a variable is simply to take the ratio between the highest value and the lowest. Furthermore, in using the 90th and 10th percentiles, Equation (10b) avoids the potential distortion caused by outliers. The highest and lowest values are omitted. Therefore, it asks how much of the variation in income levels, as measured by a simple ratio between the 90th and 10th percentile, can be explained by variation in factor endowments.

There is a third measure of success proposed by Klenow and Rodríguez-Clare (1997), which is called $success_3$:

$$success_3 = \frac{Var(\ln(y_{KH})) + Cov(\ln(A), \ln(y_{KH}))}{Var(\ln(y))}. \tag{10c}$$

Now there is a covariance term in the numerator. Note that the co-efficient of the covariance term is one instead of two as found in Equation (9). This implies that, in the words of Caselli, "the contribution from the covariance term is split evenly between A and y_{KH}." In essence, $success_3$ attributes that part of the variation in A that covaries with y_{KH} also to the factor only model.

3.2 Results for Development Accounting

3.2.1 Three Success Measures: A First Look

Panel (a) in Figure 5 shows the evolution of all three success measures for the 1994-2010 period when nominal output is deflated using provincial CPI series and labor's income share is 0.5. As shown, all three measures of success have been declining over time. In 1994, according to our success indicator $success_1$, combining human and physical capital allows us to explain close to 60% of the total variance of the output per worker. In 2015, the factor-only model explains less than 27% of the total variance of the output per worker according to our success indicator $success_1$. The results are even more pronounced when we use $success_2$ as our measure of the contribution of the factor-only model. In 1994, according to our success indicator $success_2$, combining human and physical capital allows us to explain more than 90% of the total variance of the output per worker. In 2015, the factor-only model explains 60% of the total variance of the output per worker according to our success indicator $success_2$.

Panel (b) in Figure 5 shows that switching to the World Bank's GDP deflators does not change the quantitative or the qualitative nature of the results. All three success measures reported in panel (b) are very close to their counterparts in panel (a) for each year between 1994 and 2015. It is interesting to note that, depending on the series chosen, the explanatory power of the factor-only model reaches its lowest level around 2004/2005, and then increases. This is confirmed in each panel. This shows that the percentage explained by the factor-only model increased between 2004 and 2010. Having said that, the main finding of Figure 5 is that the role of TFP differences in explaining output per worker differences across cities in China has increased since 1994.

3.2.2 Level Variables Relative to Shanghai

We can express output per worker in city *i* relative to city *j* as follows:

$$\frac{y_i}{y_j} = \frac{A_i}{A_j}\left(\frac{k_i}{k_j}\right)^{\alpha}\left(\frac{h_i}{h_j}\right)^{1-\alpha}. \tag{11a}$$

Equation (11a) breaks down the variation in output per worker among cities into variations in TFP, capital per worker, and human capital. Such a decomposition is useful. For example, one can re-arrange (11a) to calculate the productivity gap between two cities:[50]

$$\frac{A_i}{A_j} = \frac{y_i/y_j}{\left(k_i/k_j\right)^{\alpha}\left(h_i/h_j\right)^{1-\alpha}}. \tag{11b}$$

Equation (11b) shows how much more productive a worker in city *i* is compared to one in city *j*. Here we compare all cities against Shanghai. Shanghai is chosen as the frontier city due to its economic prominence. It is the biggest city in China in terms of population. It ranks among the top in terms of development indicators such as average years of schooling and life expectancy. In 2009, Shanghai also became the first city in mainland China to pass the $10,000 threshold in per capita GDP.[51] Shanghai is the financial center of mainland China. It also leads China in industries and commerce.

[50] We use the same value of α for each city since the Cobb–Douglas framework suffers from the unit-invariance problem when the factor shares are indexed by city. In the Online Appendix we provide an exercise with a more flexible formulation that does not assume a common labor share across cities.

[51] Shanghai is the first province-level administrative unit to achieve that goal. There have been smaller cities, such as Ordos, a prefecture-level city in Inner Mongolia that witnessed a housing boom in the early 2000s, that have

Output per worker is written in terms of the capital-labor ratio and deflated using provincial CPI series with labor's income share being 0.5. We first investigate the relation in 1994, the start of the sample period. Then we look at the same relation in 2010, the end of the sample period. Panel (a) in Figure 6 shows that a higher level of output per worker relative to Shanghai is associated with a higher level of human capital. Panel (b) in Figure 6 shows that the relationship is stronger in 2010. In time cities with higher human capital have been able to take advantage of better technology, higher quality institutions, etc. As a result, the correlation between the two have become stronger. Most cities are clustered around the bottom-left corner in panel (a) in Figure 6. In this region, two sub-groups are visible on the graph, separated by the regression line. Cities are concentrated either below or above it. Cities above the regression line have higher levels of human capital, but they have not transformed into higher levels of income. In panel (b) in Figure 6 the separation disappears and most cities seem to cluster in the bottom-left region. This shows that cities have "caught up" to some extent in terms of human capital, but their income levels still lag behind Shanghai and gaps in output per worker levels have not been closed.

Panel (a) in Figure 7 shows that output per worker is strongly and positively correlated with capital per worker in 1994. Panel (b) in Figure 7 displays that the relationship is stronger in 2010. This finding is important in two aspects. First, it offers empirical evidence for a large body of research which links capital deepening with economic growth. Cities with higher levels of capital per worker enjoy higher levels of output per worker. Tier 1 cities, which have also been accumulating capital, seem to have not run into diminishing returns. One possible explanation may be that TFP levels are correlated with capital deepening. Regressing the logarithm of relative output per worker to the logarithm of relative capital per worker in 2010 gives a coefficient of 0.87, with a standard error of 0.0573, and R^2 is 0.77. R^2 goes up to 0.81 if we include relative human capital differences as a second explanatory variable. These may suggest that TFP levels are correlated with endowments of physical capital. Cities with higher levels of capital per worker, especially Tier 1 cities, tend to have higher levels of TFP. This provides evidence for the hypothesis that TFP is embedded in capital goods. Economies with more capital tend to be more productive (see Baier et al., 2006; Mutreja et al., 2018). The coefficient also reaffirms the high return to capital found in Bai et al. (2006). Another

already reached higher levels of output per capita. Also note that some sources claim Shanghai passed USD 10,000 in per capita GDP in 2008 instead of 2009.

interpretation may be that there is still room for capital deepening in many Chinese cities as they are far away from their balanced growth paths.

Panel (a) in Figure 8 plots relative TFP levels against relative output per worker for 1994. Here we find evidence that TFP is positively correlated with output per worker. This finding parallels a large body of research which finds that differences in measured TFP explain more than half of the cross-country differences in output per worker (Hsieh and Klenow, 2010; Jones and Romer, 2010). TFP and output per worker levels are correlated as far back as 1994, when the Chinese economy was far less efficient than it is today. In the years since, TFP's role has only become stronger. Panel (b) in Figure 8 shows that TFP differences are almost perfectly correlated with output per worker differences. Jones (2016) graphs TFP and output per worker levels for countries and find the two are highly correlated at 0.96. Here we plot TFP and output per worker levels for Chinese cities and find a correlation of 0.95. The well-documented fact that variation in TFP levels is associated with most of the variation in income levels across countries applies to the major Chinese cities as well.

3.2.3 Results for Three-Tiers

Lastly in this section, we investigate the 'level' performances of Tier 1, 2 and 3 cities as separate groups instead of looking at individual cities. Each tier is compared with all 69 cities which we have called "aggregate". Panel (a) in Figure 9 shows labor productivity levels for Tier 1, 2 and 3 cities relative to the aggregate between 1994 and 2010. Labor productivity in Tier 1 cities have been consistently higher than the Tier 2 and 3 cities and the 69-city aggregate. Tier 1 cities' labor productivity was more than 150% of the 69-city aggregate in 1994 and this increased to around 180% in 2010. Tier 2 cities' labor productivity was around 92% of the 69-city aggregate in 1994 and it declined to less than 86% in 2010. Similarly, Tier 3 cities' labor productivity was around 76% of the 69-city aggregate in 1994 and it declined to 74% in 2010. Panel (b) in Figure 9 shows relative human capital levels (based on average years of schooling) for each tier. Tier 1 cities' human capital was more than 108% of the aggregate level in 1994 and it increased to 112% of the 69-city aggregate level in 2010. There were slight decreases, in their relative human capital levels, for Tier 2 and 3 cities. Panel (c) in Figure 9 displays physical capital deepening in comparative perspective among three tiers relative to the 69-city aggregate level between 1994 and 2010. The capital-labor ratio shows the extent to which the labor force is engaged in production activities using capital. There was intensive capital deepening in Tier 2 and 3 cities, while Tier 1 cities' capital per worker decreased from 240% of the aggregate level in 1994 to 144% in 2010. Panel (d) in Figure 9 shows that TFP levels in Tier 2 and 3 cities actually fell relative to the 69-city aggregate during the 1994-2010 period, whereas Tier 1 cities' TFP levels increased significantly.

4. Growth Accounting

4.1 Framework

Taking logarithms of the terms in Equation (10b) and decomposing the average annual growth rate of output per worker over "*z*" years (from time *t* to time *t*+*z*) yields:

$$\frac{ln(y_{t+z})-ln\,(y_t)}{z} = \frac{\ln(A_{t+z})-ln(A_t)}{z} + \alpha\frac{\ln(k_{t+z})-\ln(k_t)}{z} + (1\text{-}\ \alpha)\frac{\ln(h_{t+z})-ln(h_t)}{z}. \quad (12)$$

This equation breaks down changes in output per worker into three components: changes in TFP, changes in physical capital per worker, and changes in human capital per worker. In terms of growth rates, Equation (12) can be restated as $g_y = g_A + \alpha g_k + (1-\alpha)g_h$, where g_x denotes the growth rate of variable *x*. More specifically, over a period of *z* years, the annual growth rate of a variable *x* is approximated by $g_x \approx \frac{ln(x_{t+z})-ln\,(x_t)}{z}$. The contribution of growth in TFP to growth in output per worker is $\frac{g_A}{g_Y}$, the contribution of growth in capital per worker is $\alpha\frac{g_k}{g_Y}$, and the contribution of growth in human capital per worker is $(1-\alpha)\frac{g_h}{g_Y}$.

4.2 Main Results

Table 5 presents the growth accounting results for each city. When looking at Tiers 1, 2, and 3 cities, it is obvious that Tier 1 cities make a group of their own. TFP growth accounts for more than 50% of output per worker growth between 1994 and 2010 in each first-tier city.[52] TFP contributions in Tier 2 and 3 cities overlap, with Tier 3 cities being more spread-out. These findings indicate that while the 70 cities altogether represent the economic frontier of all cities in China, the first-tier cities (Beijing, Shanghai, Guangzhou, and Shenzhen) represent the very top of the 70. Their high TFP contributions reaffirm the Tier 1 classification given to them by the NBS. Another finding is that the contribution of human capital is relatively small. This is expected, as human capital is calculated from average years of schooling, which grows at

[52] The finding that TFP contribution is the highest in Tier 1 cities holds true when α is 0.33 or 0.65.

roughly 1 extra year every decade regardless of its initial level. Therefore, growth rates in human capital are almost uniform across cities.

We now turn to specific cities, as well as sub-periods. The first city is the frontier city, Shanghai. During 1994-2010, output per worker grew at an average rate of 10.19% per year in Shanghai. In terms of sub-periods, during 1994-2001, it grew at 9.20% per year. This increased to 12.80% during 2001-2007. Remarkably, even during the global financial crisis (GFC) of the 2007-2009 period, output per worker grew at 6.41%. The corresponding growth rate was very close to 9% in the post-crisis recovery period of 2009-2010. Two events took place in the first two sub-periods. The first is Deng Xiaoping's southern tour in 1992, after which reforms picked up pace. This tour was the most dramatic political incident to occur between the Tiananmen protests in June 1989 and the Fourteenth Party Congress in October 1992 (Zhao, 1993). This paved the way for rapid economic growth in the 1990s in which TFP understandably played a significant role. The second is China joining the World Trade Organisation (WTO) in December 2001. The spectacular growth during 2001-2007 was caused by rapid export growth and reforms after entry into WTO. In the post-crisis recovery period, TFP's contribution went up to 56.6%. This could be explained partially by the World Expo which took place in Shanghai in 2010. After the financial crisis, the Chinese government put a heavy emphasis on services which tended to absorb more employment. Shanghai is also designated as the financial center on mainland China.[53] All of these reform efforts may explain the revival in TFP contribution after 2009. The experiences of the other Tier 1 cities are similar. Growth hit historical highs during 2001-2007, followed by a slow-down during the GFC. TFP contributions were high throughout the period, falling during 2007-2009, and rebounding during 2009-2010. The only exception is Shenzhen, whose output per worker fell by 0.13% each year during 2007-2009. TFP in Shenzhen fell during the period, with a growth rate of -1.29% per year. A probable reason for Shenzhen is that it is an export-oriented city, and the GFC started as the subprime mortgage crisis in the U.S., which affected China via a collapse in export demand, among other channels. As a result, Shenzhen, and in fact the entire Pearl River Delta (PRD) was hit hard.[54]

Next, we turn to those cities that have had negative TFP contributions during the period. Growth potential in cities with negative TFP contributions is questionable, as capital inevitably

[53] See http://politics.people.com.cn/GB/1026/9218435.html for more information.
[54] See http://www.china.com.cn/news/txt/2009-05/11/content_17758919.htm for more information on the GFC's effect on the PRD.

runs into diminishing returns and human capital's role (based on educational attainment) has been found to be small. The most noteworthy city is Chongqing, China's largest city by population. During 1994-2010 TFP fell by 0.51% per year. This is alarming, especially considering that Chongqing is not a rich city. Chongqing's story is one of massive investments in capital.[55] Gross fixed capital formation was less than 40% of output in 2001, and increased to nearly 100% in 2016. Post GFC, the local government in Chongqing has resorted to huge infrastructure spending in order to pump up growth. Investment in infrastructure increased by 30% in 2009.[56] Output per worker achieved a stunning growth rate of 22.39% per annum during 2007-2009, but fell to 14.49% during 2009-2010. TFP and capital contributed roughly half each during 2007-2009, but the contribution of TFP fell to 18.8% during 2009-2010. In addition, massive infrastructure projects, while helping to mitigate the effects of the GFC, resulted in inefficiency later on.

Another noteworthy city is Nanjing, because its TFP grew, on average, by -0.04% during 1994-2010. Nanjing has had a typical growth experience during this period, growing at a rate of 7.02% during 1994-2001, which rose to 10.36% during 2001-2007, and fell to 7.81% during 2007-2009, and finally rebounded to 12.14% during 2009-2010. However, TFP growth tells a different story. TFP grew, on average, by -1.44% during 1994-2001, and remained low throughout the period. Nanjing's growth was driven overwhelmingly by capital deepening, with growth in capital per worker contributed 85.5% to output growth during 2001-2007, and 91.6% during 2007-2009. After taking away roughly five percentage points from growth in human capital, this leaves hardly any contribution from TFP. Some insights from economic geography may help to understand Nanjing's situation. Nanjing is located far from Shanghai to benefit from agglomeration economics, but too close to draw resources to itself. Indeed, Jinhua, a city in southern Zhejiang province, located about the same distance from Shanghai as Nanjing, also has negative TFP contributions during the period, at -3.2%. On the other hand, cities closer to Shanghai experience positive, albeit lower, TFP growth rates and contributions. Cities in this category include Hangzhou, where TFP contributes 3.9% to growth, and Ningbo, a port city south of Shanghai, where TFP contributes 31.9%. Dandong stands out for having negative TFP contributions. At -19.1%, this is the lowest among the 69 major cities. In terms

[55] The mayor denies that Chongqing suffers from over-investment: http://www.china.com.cn/lianghui/news/2017-03/07/content_40420764.htm.
[56] http://www.sohu.com/a/149360319_619343.

of growth rates, TFP declines by 1.36% per annum during the period. Dandong is a border town between China and North Korea.[57]

Other cities that suffer from over-investment in capital and negative TFP contributions include Xuzhou, an old industrial town in northern Jiangsu province which is too far from Shanghai, or the Yangtze River Delta for that matter, to benefit from agglomeration economics. Another city is Kunming, the provincial capital of Yunnan, whose government has focused on investment growth in order to achieve high output growth. Unlike Chongqing, investment in Kunming comes mostly from real estate development. Lastly, there is Nanchong, a city located in far-flung regions of landlocked Sichuan. By every metric, Nanchong comes out last in the sample. Policymakers need to recognize Nanchong's geographical constraints and pursue policies that are cost-effective for that left-behind city.

4.3 Results by Groups

Here we investigate TFP performance for Tier 1, 2, and 3 cities, as well as all 69 cities in the sample. When aggregating the variables, output, labor, and capital are added up. Human capital is weighted using human capital for groupings $= \frac{h_1 L_1 + h_2 L_2 + \cdots + h_n L_n}{L_1 + L_2 + \cdots + L_n}$. Table 6 presents the growth accounting results for each tier as well as the 69-city aggregate. The sample period is divided into four sub-periods: (i) 1994-2001, (ii) 2001-2007, (iii) 2007-2009, and (iv) 2009-2010. The first period corresponds to China's take-off in the 1990s. China joined the WTO in December 2001, and subsequently experienced an economic boom during 2001-2007. The 2007-2009 period was marked by the GFC, while the period of 2009-2010 corresponds to the post-GFC era.

Taken as a whole, the 69 cities have done reasonably well over the period. For example, TFP growth contributed over 40% to output per worker growth during the 1994-2001 and the 2001-2007 periods and accounted for 27.3% of output per worker growth in the post-GFC recovery period. That being said, one has to keep in mind that the 69 cities are biased towards Tier 1 and 2 cities. TFP contribution for the 69 is pulled up by Tier 1 cities. TFP contribution in Tier 1 cities was already high during 1994-2001, at 59.2%. It increased to 61% during 2001-2007 which is a period of economic boom for China. During the GFC it went down to 34.9%. Finally,

[57] The border between the two countries stretches over 1400 kilometers. Dandong is the largest city along the border.

in the post-crisis recovery period, TFP contribution went back up to 54.9%. This pattern is found in many cities in the sample. Tier 1 is the only group with high TFP contributions. TFP contributions in both Tier 2 and 3 cities are much lower. Tier 3 cities at least had a similar TFP pattern to Tier 1 cities, peaking during 2001-2007, declining during the GFC, and rebounding afterwards. Tier 2 cities are worrisome in that their TFP contributions during the post-crisis recovery period is actually the lowest among all sub-periods. This suggests that Tier 2 cities relied heavily on capital deepening in order to recover from the GFC. TFP contribution in Tier 3 cities never exceeds 40% in any of the sub-periods. Considering that Tier 3 cities are generally poorer than Tier 1 and 2 cities, their low TFP contribution is worrisome. It indicates that poor cities are relying on capital deepening to drive growth, which might be unsustainable in the long run.

Ye (2002) utilises the Cobb-Douglas production function to study provincial TFP growth rates during 1978-1998. Ye finds that provinces with higher growth rates have higher contributions from capital deepening and less from TFP growth, whereas those with lower growth rates have lower contributions from capital deepening and more from TFP growth. The result is that TFP growth plays a bigger role in those provinces that are growing more slowly.[58] Ye calls this the growth and TFP paradox. We find highest TFP contributions in Tier 1 cities which are not necessarily the slowest in growth. This could be because of the updated study period in this paper. We do not find much correlation between TFP contributions and growth. Ye also finds little contribution from growth in human capital, which is consistent with the findings in this paper. Zhang (2014) studies 264 cities during 1990-2011 and finds that TFP growth is slowing down in recent years. He recommends policies that stimulate TFP growth, especially in eastern China, as TFP and output growth are strongly correlated in that part of the country.[59]

5. Conclusion

This paper investigates the proximate determinants of variation in output per worker levels among 69 major Chinese cities. Our biggest contribution is the construction of a detailed dataset for 69 cities in China, which contains data on real output, physical capital, human capital, and employment. We rely on the methods developed in Xiang (2011) to construct

[58] Brandt et al. (2013) list the TFP of the non-state and state sectors for each of the 27 provinces between 1985 and 2007. They show that non-agricultural TFP in the state sector is generally constant in all provinces. In the non-state sector, non-agricultural TFP is continuously increasing and the cross-province dispersion is generally declining.

[59] Note that Zhang uses output for total city instead of districts under city.

physical capital stock for cities. Xiang (2011), to the best of our knowledge, is the only detailed study on physical capital at the city level in China. We adopt her methodology and extend the period to cover the years of our sample period. We rely on returns to schooling found in Peng (2011) to construct human capital series at the city level. We make use of the log-linear wage-schooling profile. Peng (2011), to the best of our knowledge, is the only study that studies returns to schooling at the city level in China. Furthermore, Peng finds increasing returns to schooling, which contrasts with decreasing returns often found in developed economies.

We find a clear distinction between Tier 1 cities and the rest. In terms of income levels, we find that they are highly correlated with TFP levels. We also find a declining role of variation in factor endowments in explaining variation in income levels. Labor productivity (output per worker) varies significantly across cities in China. The poorest city in 2015 has a lower output per worker than that enjoyed by Shenzhen in 1994. Second, variation in labor productivity has been increasing over time. These findings clearly indicate that cities have reached very different levels of development in China.

Tier 1 cities have had modest contributions from capital deepening. But Tier 2 and 3 cities have relied heavily on it. Therefore, whereas in terms of levels, higher levels of capital have brought higher levels of income, in terms of growth rates, growth has been overwhelmingly dependent on capital deepening. This is unsustainable, which is why we argue that, apart from committing to new capital expenditures, policymakers need to pay attention to efficiency as well. Rapid accumulation of physical capital in Tier 2 cities has not closed the gap in income levels between them and Tier 1 cities. Similarly, growth in human capital has played a minor role. It is important, however, to note the increasing returns to schooling in Chinese cities. Investing in education may be an effective and affordable way for city officials to close the income gap between their cities and Shanghai. Possible channels for this can be related to the ones in Nelson and Phelps (1966) and/or Romer (1990). For example, Nelson and Phelps (1966) find human capital as a critical factor in promoting technological diffusion, providing a way of thinking about technology transfer that incorporates human capital. Romer (1990) asserts that a higher level of human capital stimulates productivity growth through new technological innovations.

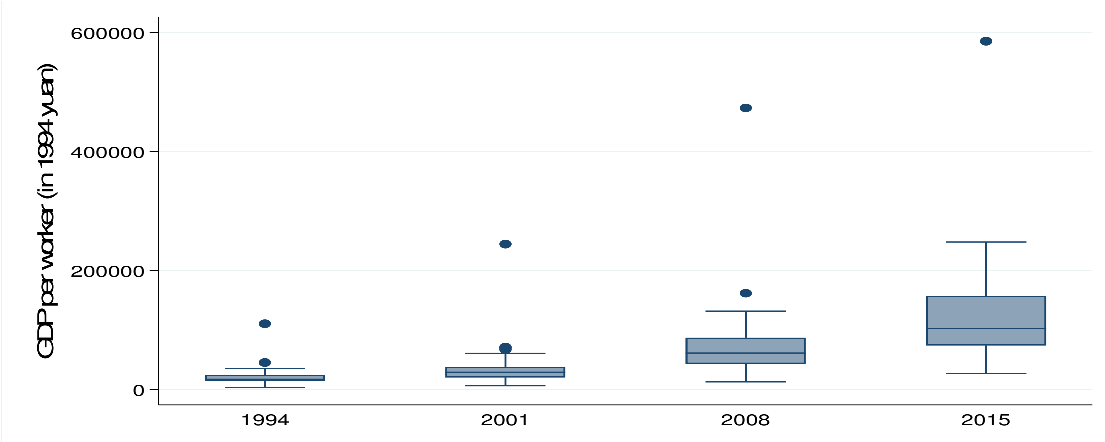
A further avenue of research is the relationship between intangible investment/capital and measured productivity since the inclusion/exclusion of intangibles (such as research and development, software, brands, etc.) changes the total output and the related calculations (see Corrado et al., 2009; McGrattan and Prescott, 2010). Li and Wu (2018) study China at the province level during 2003-2014, and find significant contribution from intangibles in coastal regions. Interior regions, on the other hand, rely more on tangible capital deepening. Having said that, Li and Wu (2018) acknowledge that TFP still plays an important role in driving growth in China. Our paper can be linked to their findings. Tier 1 cities loosely correspond with coastal regions, and Tier 2 and 3 cities with interior regions. We find that Tier 1 cities rely mostly on TFP growth whereas Tier 2 and 3 cities rely mostly on capital deepening. Li and Wu (2018) show that this result still stands when intangible capital is added to the production function.

Another avenue of research is to construct dual measures of city-specific TFP growth. We have focused on the primal (quantity) growth accounting procedure in this paper. There is also a dual (real factor prices) growth accounting specification in the literature. The construction of dual TFP growth measures relies on real user cost growth and real wage growth and can be calculated as weighted averages of the growth rates of different types of capital goods and wages of different types of workers, where the weights are the shares of payments to each factor (Hsieh, 2002). Collecting real factor prices at the city level constitutes a data challenge for China.[60] It would be interesting to see if measures of primal and dual TFP growth are close to each other for each city in China.[61]

[60] Panda (2017) exploits the dual growth accounting framework to determine the effect of schooling on TFP growth for US states over 1980-2010.

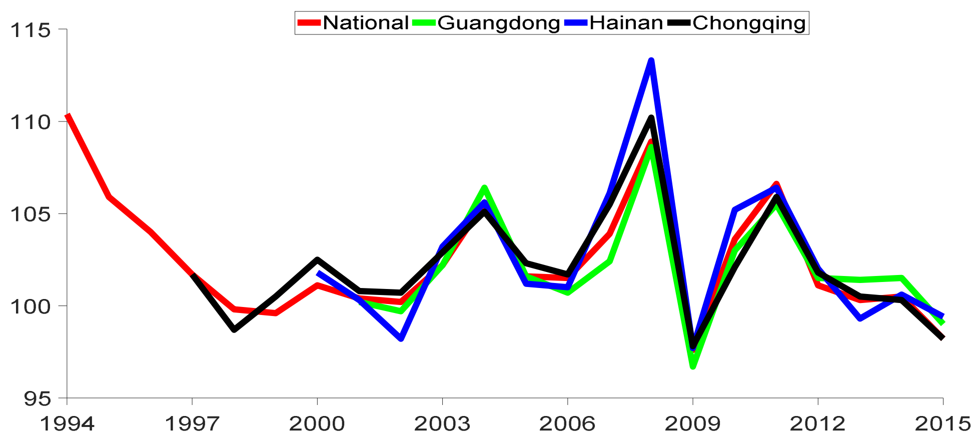
[61] Hsieh (2002) present dual estimates of TFP growth for East Asian countries. While the dual estimates of TFP growth for Korea and Hong Kong are similar to the primal estimates, they exceed the primal estimates by 1% a year for Taiwan and by more than 2% for Singapore. Fernald and Neiman (2011) show that measures of primal and dual TFP growth can diverge from each other and from true technology growth in the presence of heterogeneous capital subsidies and monopoly power.

Figure 1. Distribution of GDP per worker of the 69 major Chinese cities, 1994-2015



Source: Authors' calculations based on the City Statistical Yearbooks.

Figure 2. National and provincial deflators for fixed assets (preceding year=100)



Source: National Bureau of Statistics of China.

Figure 3. Comparison of two sets of real output for 69 cities

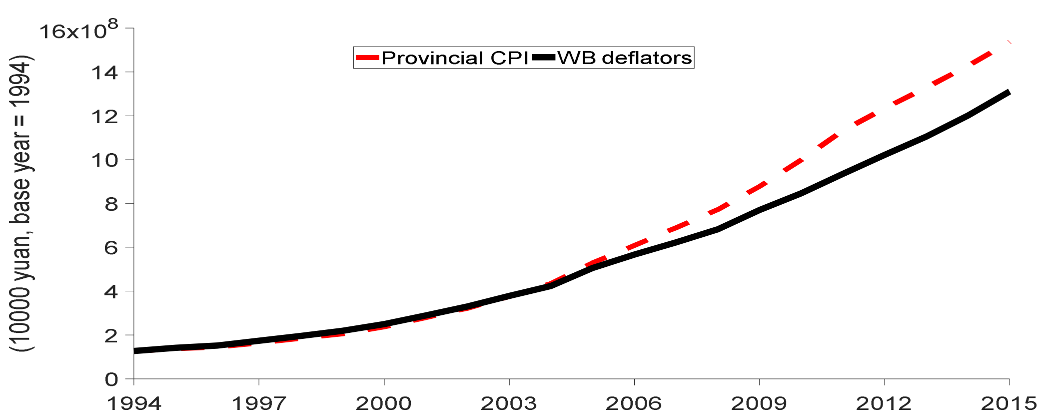


Figure 4. Capital stock series, 1994-2015 (10000 yuan, base year=1995)

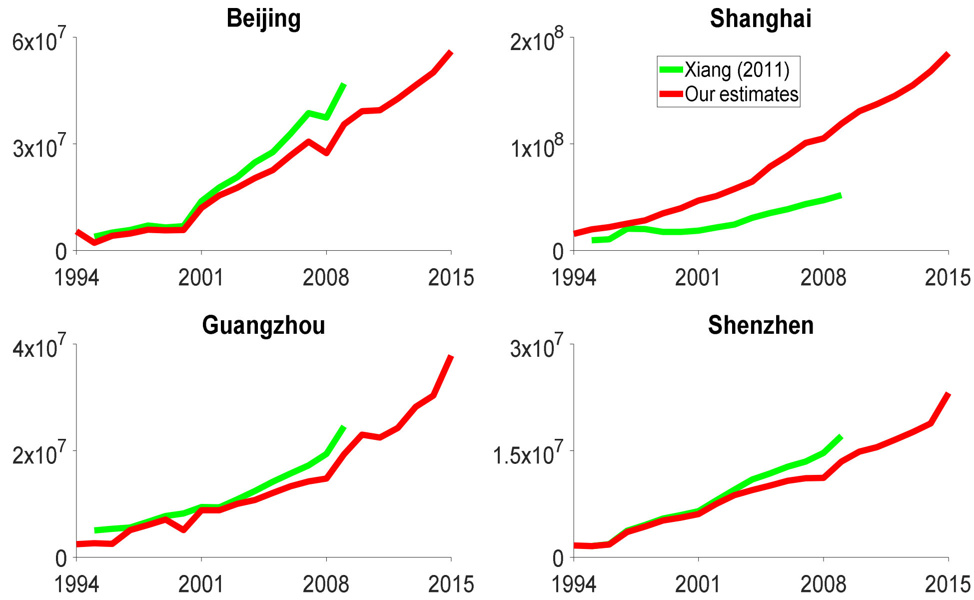
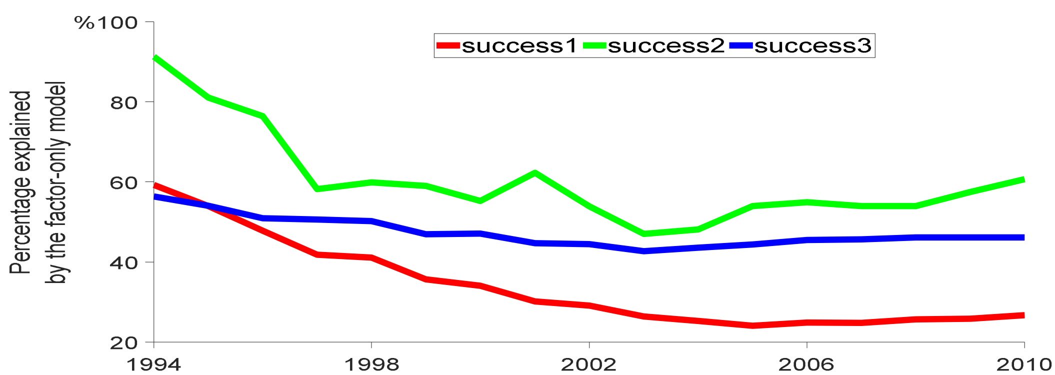


Figure 5. Success indicators over time

(a): Using province-level CPIs



(b): Using World Bank GDP deflators

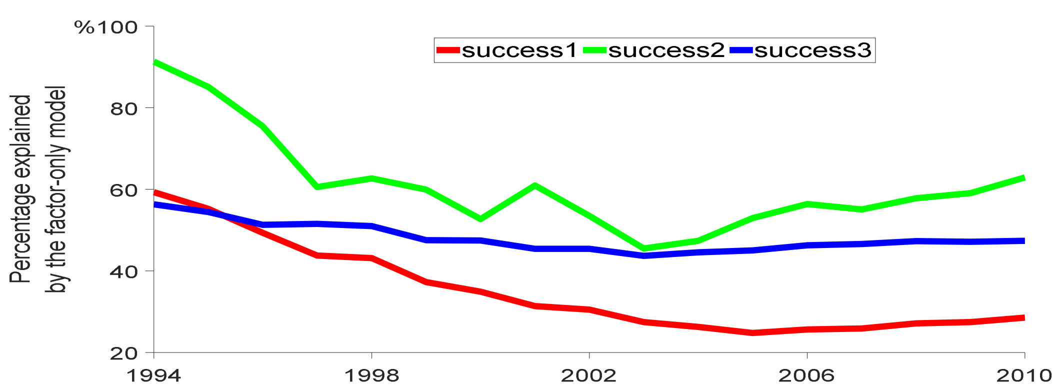
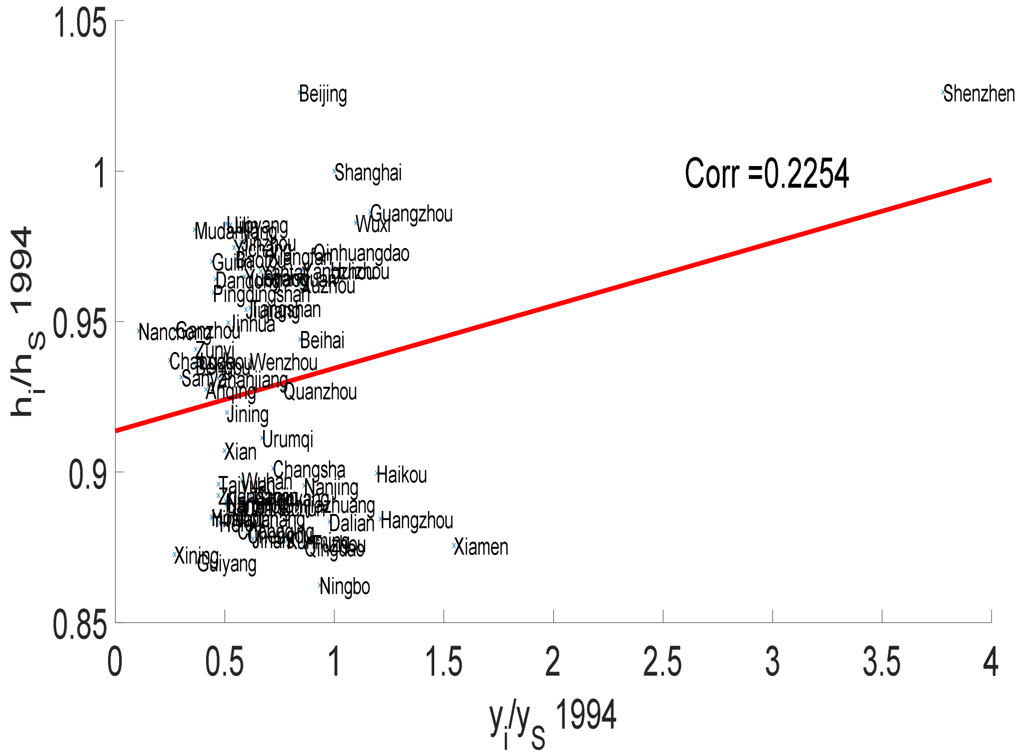


Figure 6. Human capital and output per worker

(a): 1994



(b): 2010

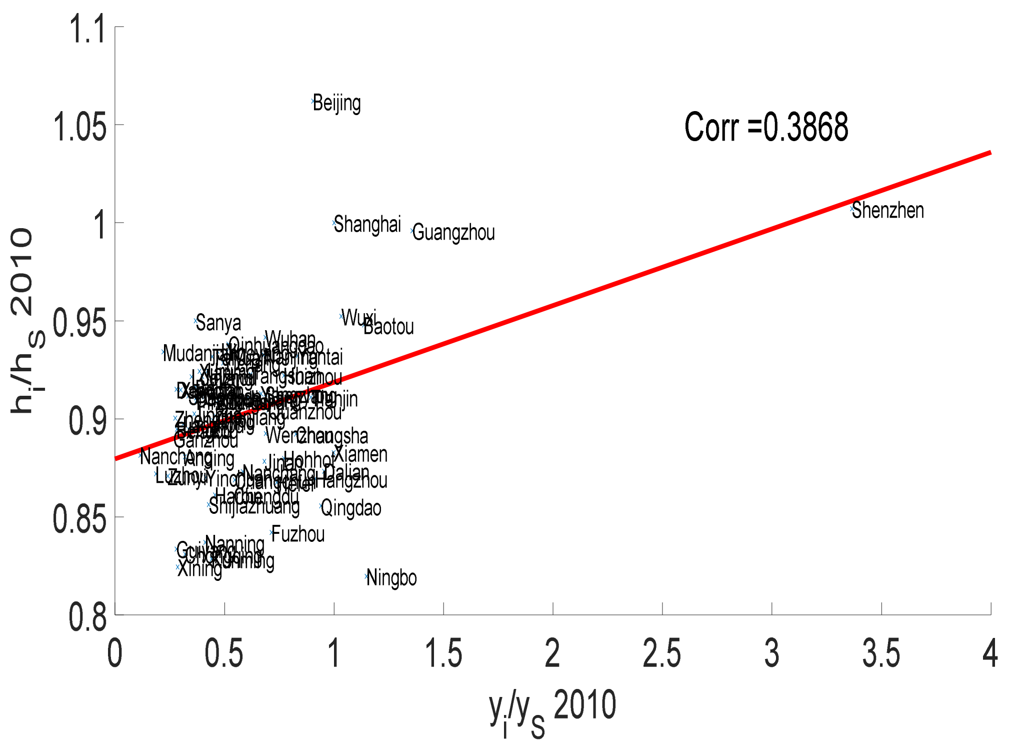
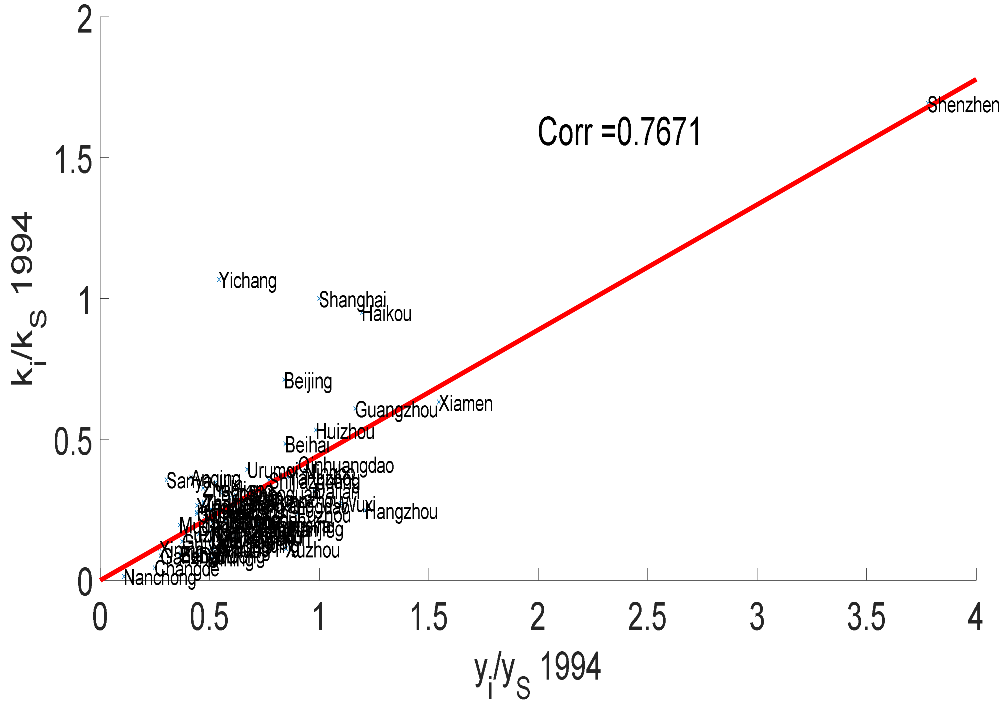


Figure 7. Capital per worker and output per worker

(a): 1994



(b): 2010

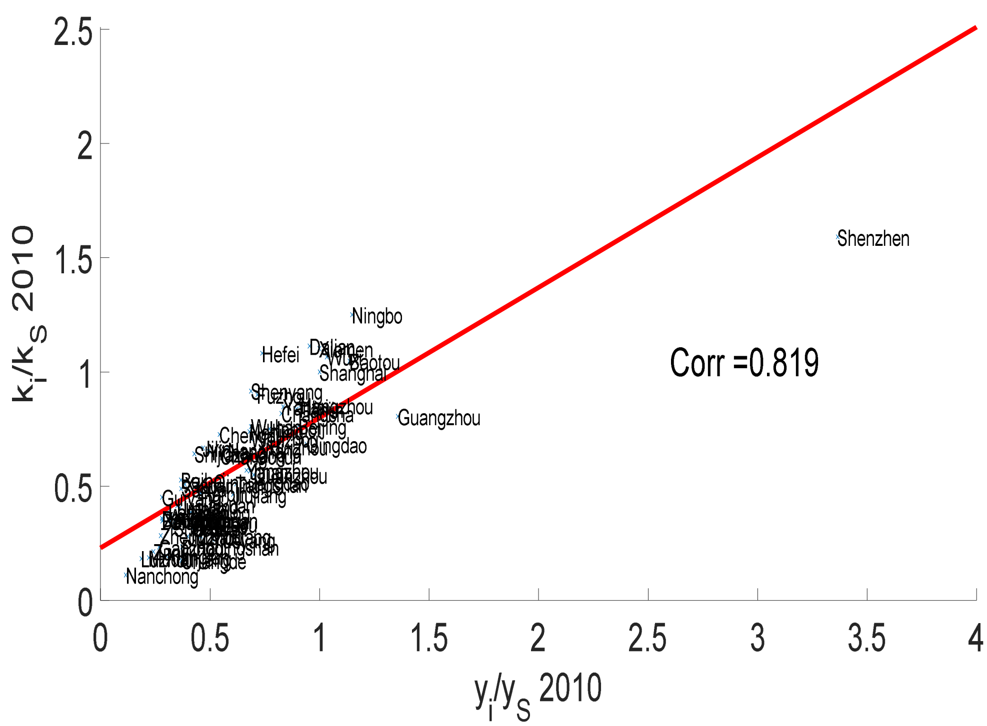
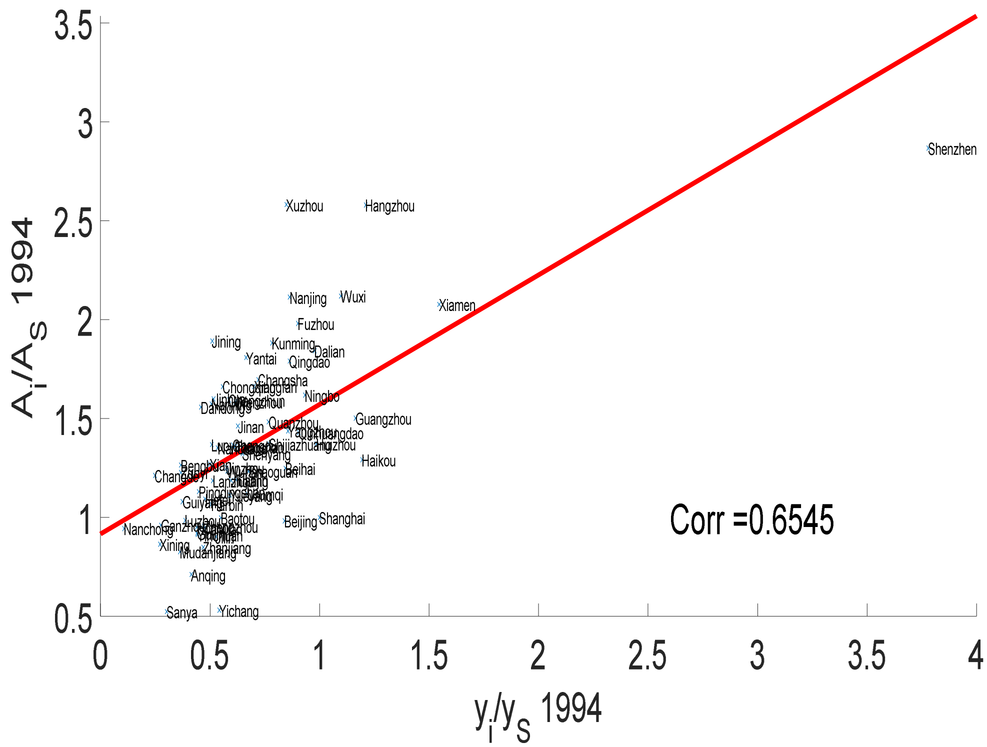


Figure 8. TFP levels and output per worker

(a): 1994



(b): 2010

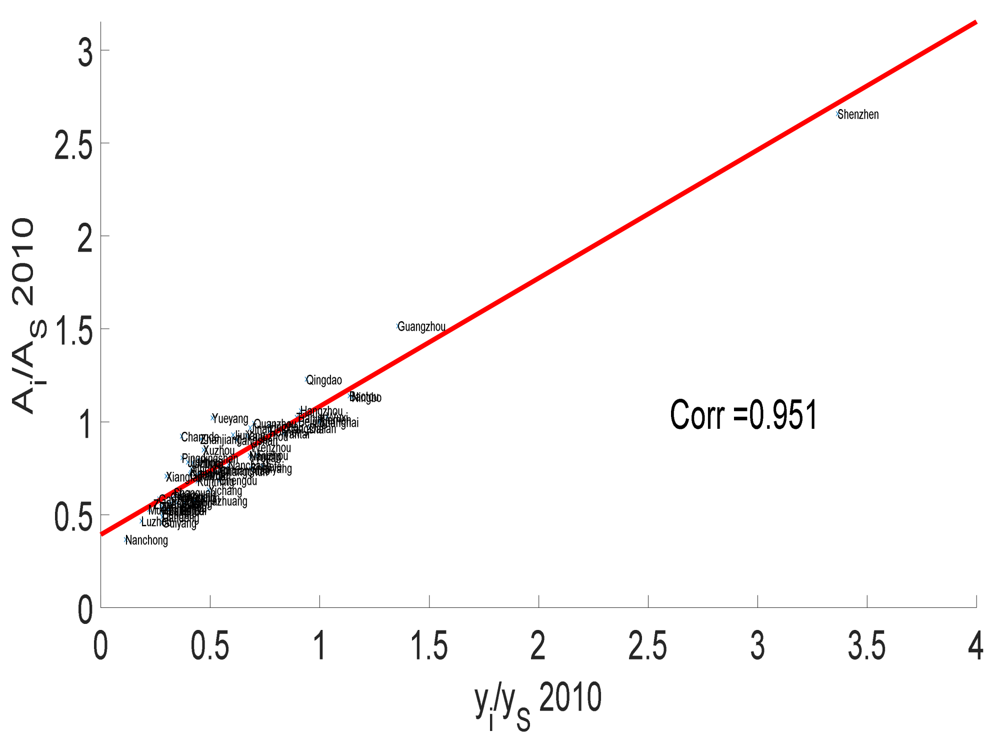


Figure 9. Relative levels of Tier 1, 2, 3 cities to the 69-city aggregate group

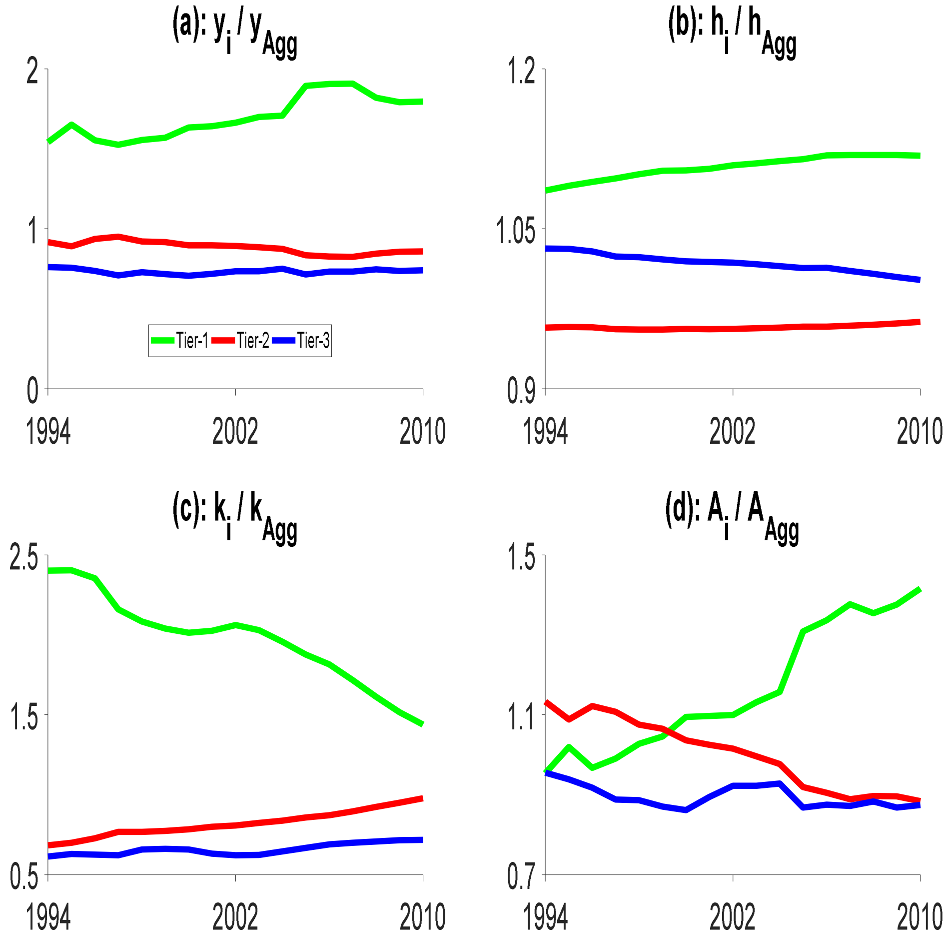


Table 1. Breakdown of changes in employment statistics

Year	Employed in work units	Employed in private firms
1994	Total, Employed	N.A.
1995	Total, Employed	Urban, Self-employed
1996	Total, Employed	Urban, Self-employed
1997	Total, Employed	Urban, Self-employed
1998	Total, Employed	Urban, Self-employed
1999	Work units, Employed	Urban, Self-employed
2000	Work units, Employed	Urban, Self-employed
2001	Work units, Employed	Urban, Self-employed
2002	Work units, Employed	Privately owned firms, Self-employed
2003	Work units, Employed	Privately owned firms, Self-employed
2004	Work units, Employed	Privately owned firms, Self-employed
2005	Work units, Employed	Privately owned firms, Self-employed
2006	End-of-year, Work units, Employed	Urban, Privately owned firms, Self-employed
2007	End-of-year, Work units, Employed	Urban, Privately owned firms, Self-employed
2008	End-of-year, Work units, Employed	Urban, Privately owned firms, Self-employed
2009	End-of-year, Work units, Employed	Urban, Privately owned firms, Self-employed
2010	End-of-year, Work units, Employed	Urban, Privately owned firms, Self-employed
2011	End-of-year, Work units, Employed	Urban, Privately owned firms, Self-employed
2012	End-of-year, Work units, Employed	Urban, Privately owned firms, Self-employed
2013	End-of-year, Employed	Urban, Privately owned firms, Self-employed
2014	End-of-year, Employed	Urban, Privately owned firms, Self-employed
2015	End-of-year, Urban, Work units, Employed	Urban, Privately owned firms, Self-employed

Source: City Yearbooks 1995-2016.

Table 2. Returns to different levels of schooling for different types of cities

	Province-level cities	Provincial capitals	Other cities
Secondary school and below	4.1%	2.9%	4.3%
High school or specialized secondary school	7.3%	8.6%	7.4%
Junior college and above	14.1%	11.6%	11.5%
Average rate of return to schooling	9.9%	8.4%	7.4%

Source: Peng (2011).

Table 3. Naïve labor shares for 31 provinces in selected years

	1994	1999	2004	2009	2015	Average	St. deviation
Beijing	0.44	0.42	0.43	0.60	0.55	0.46	0.04
Tianjin	0.44	0.50	0.34	0.38	0.41	0.40	0.06
Hebei	0.55	0.54	0.41	0.55	0.52	0.51	0.04
Shanxi	0.43	0.41	0.36	0.46	0.48	0.41	0.04
Inner Mongolia	0.60	0.53	0.43	0.46	0.49	0.48	0.07
Liaoning	0.46	0.49	0.43	0.49	0.45	0.48	0.03
Jilin	0.61	0.62	0.45	0.40	0.44	0.51	0.11
Heilongjiang	0.41	0.47	0.36	0.41	0.47	0.42	0.05
Shanghai	0.35	0.36	0.34	0.39	0.44	0.38	0.03
Jiangsu	0.45	0.46	0.40	0.44	0.44	0.44	0.03
Zhejiang	0.43	0.41	0.40	0.40	0.48	0.42	0.02
Anhui	0.57	0.52	0.45	0.50	0.47	0.50	0.05
Fujian	0.51	0.52	0.44	0.53	0.53	0.50	0.03
Jiangxi	0.65	0.62	0.56	0.41	0.42	0.52	0.09
Shandong	0.45	0.46	0.35	0.45	0.44	0.43	0.04
Henan	0.61	0.51	0.45	0.49	0.51	0.50	0.06
Hubei	0.53	0.61	0.45	0.48	0.49	0.53	0.08
Hunan	0.62	0.60	0.49	0.50	0.51	0.55	0.06
Guangdong	0.53	0.55	0.48	0.45	0.49	0.49	0.04
Guangxi	0.62	0.60	0.49	0.60	0.53	0.58	0.05
Hainan	0.47	0.49	0.49	0.52	0.56	0.50	0.03
Chongqing		0.56	0.52	0.51	0.42	0.51	0.05
Sichuan	0.57	0.58	0.49	0.48	0.48	0.52	0.06
Guizhou	0.63	0.65	0.46	0.54	0.56	0.56	0.06
Yunnan	0.44	0.48	0.44	0.50	0.50	0.47	0.02
Tibet	0.81	0.64	0.55	0.64	0.64	0.65	0.09
Shaanxi	0.58	0.50	0.40	0.45	0.43	0.47	0.07
Gansu	0.51	0.54	0.50	0.47	0.51	0.51	0.04
Qinghai	0.55	0.56	0.47	0.54	0.47	0.51	0.05
Ningxia	0.50	0.52	0.48	0.53	0.55	0.51	0.02
Xinjiang	0.52	0.56	0.54	0.54	0.59	0.53	0.04

Source: Authors' calculations based on the data from the NBS website. Note: Labor share data are not available for Chongqing for 1994.

Table 4. Adjusted labor shares for 31 provinces in selected years

	1994	1999	2004	2009	2015	Average	St. deviation
Beijing	0.52	0.50	0.51	0.60	0.64	0.54	0.05
Tianjin	0.52	0.61	0.41	0.45	0.49	0.48	0.07
Hebei	0.61	0.60	0.47	0.63	0.59	0.58	0.04
Shanxi	0.50	0.47	0.42	0.54	0.57	0.49	0.05
Inner Mongolia	0.68	0.60	0.50	0.54	0.56	0.54	0.08
Liaoning	0.54	0.54	0.50	0.59	0.54	0.56	0.03
Jilin	0.68	0.70	0.53	0.47	0.51	0.58	0.11
Heilongjiang	0.50	0.57	0.42	0.47	0.54	0.50	0.06
Shanghai	0.42	0.46	0.41	0.49	0.55	0.47	0.04
Jiangsu	0.53	0.53	0.48	0.52	0.51	0.51	0.03
Zhejiang	0.50	0.47	0.47	0.47	0.56	0.49	0.03
Anhui	0.67	0.61	0.52	0.59	0.55	0.58	0.05
Fujian	0.57	0.58	0.51	0.61	0.63	0.57	0.04
Jiangxi	0.73	0.69	0.65	0.51	0.51	0.60	0.09
Shandong	0.53	0.54	0.41	0.53	0.51	0.50	0.04
Henan	0.69	0.58	0.51	0.59	0.57	0.57	0.06
Hubei	0.60	0.70	0.52	0.56	0.57	0.61	0.08
Hunan	0.73	0.68	0.57	0.59	0.60	0.64	0.05
Guangdong	0.61	0.65	0.56	0.53	0.57	0.58	0.04
Guangxi	0.70	0.67	0.55	0.68	0.65	0.66	0.04
Hainan	0.53	0.55	0.56	0.62	0.64	0.58	0.05
Chongqing		0.65	0.61	0.59	0.51	0.60	0.05
Sichuan	0.66	0.71	0.58	0.57	0.58	0.61	0.07
Guizhou	0.75	0.79	0.54	0.63	0.68	0.67	0.08
Yunnan	0.58	0.63	0.55	0.62	0.63	0.61	0.02
Tibet	0.83	0.67	0.58	0.69	0.70	0.68	0.08
Shaanxi	0.63	0.60	0.46	0.54	0.53	0.55	0.07
Gansu	0.60	0.63	0.59	0.54	0.60	0.60	0.04
Qinghai	0.61	0.63	0.54	0.63	0.53	0.58	0.04
Ningxia	0.58	0.60	0.56	0.60	0.63	0.59	0.02
Xinjiang	0.58	0.63	0.61	0.64	0.68	0.60	0.04

Source: Authors' calculations based on the data from the NBS website. Note: Labor share data are not available for Chongqing for 1994.

Table 5. Contributions to output per worker, 1994-2010 (α=0.5)

	Using Provincial CPI Deflators for Output				*Using Implicit GDP Deflator for China*			
	Y/L	TFP	K/L	h	Y/L	TFP	K/L	h
Beijing	100.0	56.5	40.0	3.5	100.0	53.7	42.6	3.7
Tianjin	100.0	39.6	57.8	2.6	100.0	33.2	63.9	2.9
Shijiazhuang	100.0	7.3	90.4	2.2	100.0	-13.2	110.5	2.7
Taiyuan	100.0	41.9	54.1	3.9	100.0	37.4	58.3	4.3
Hohhot	100.0	42.8	55.4	1.8	100.0	39.8	58.3	1.9
Shenyang	100.0	22.2	74.6	3.2	100.0	12.1	84.3	3.6
Dalian	100.0	18.5	79.2	2.3	100.0	7.3	90.1	2.6
Changchun	100.0	10.9	87.1	2.0	100.0	-1.2	98.9	2.3
Harbin	100.0	35.6	62.7	1.7	100.0	27.0	71.0	1.9
Shanghai	100.0	57.8	39.6	2.6	100.0	54.2	43.0	2.8
Nanjing	100.0	-0.5	96.0	4.5	100.0	-14.4	109.3	5.1
Hangzhou	100.0	3.9	93.6	2.5	100.0	-11.4	108.4	2.9
Ningbo	100.0	31.9	67.2	0.9	100.0	24.3	74.7	1.0
Hefei	100.0	28.1	70.3	1.6	100.0	21.5	76.7	1.8
Fuzhou	100.0	4.4	94.0	1.6	100.0	-14.1	112.2	1.9
Xiamen	100.0	18.7	77.4	3.9	100.0	-0.3	95.5	4.8
Nanchang	100.0	22.0	75.9	2.1	100.0	13.6	84.1	2.3
Jinan	100.0	30.8	66.7	2.5	100.0	24.6	72.7	2.7
Qingdao	100.0	32.9	65.2	1.8	100.0	27.0	71.1	2.0
Zhengzhou	100.0	34.7	61.0	4.3	100.0	25.3	69.8	4.9
Wuhan	100.0	28.9	67.4	3.7	100.0	24.0	72.1	3.9
Changsha	100.0	21.4	76.4	2.1	100.0	17.4	80.4	2.2
Guangzhou	100.0	53.3	44.1	2.6	100.0	44.9	52.0	3.1
Shenzhen	100.0	57.2	40.6	2.2	100.0	47.9	49.5	2.7
Nanning	100.0	11.6	87.6	0.8	100.0	-3.3	102.4	0.9
Haikou	100.0	50.2	38.9	10.9	100.0	-82.1	142.3	39.7
Chongqing	100.0	-7.5	106.3	1.2	100.0	-31.0	129.5	1.5
Chengdu	100.0	16.6	81.3	2.1	100.0	13.3	84.5	2.2
Guiyang	100.0	6.2	92.3	1.6	100.0	0.3	98.1	1.7
Kunming	100.0	-6.9	105.6	1.3	100.0	-13.6	112.2	1.4
Xian	100.0	9.2	87.0	3.8	100.0	0.7	95.2	4.1
Lanzhou	100.0	11.3	84.5	4.2	100.0	5.8	89.8	4.4
Xining	100.0	26.7	72.4	0.8	100.0	29.1	70.1	0.8
Yinchuan	100.0	47.3	50.5	2.2	100.0	43.8	53.8	2.3
Urumqi	100.0	49.7	46.1	4.3	100.0	46.6	48.9	4.5
Tangshan	100.0	32.6	65.9	1.6	100.0	23.8	74.5	1.8
Qinhuangdao	100.0	26.6	71.2	2.2	100.0	10.9	86.4	2.7
Baotou	100.0	45.6	53.1	1.3	100.0	42.9	55.7	1.4
Dandong	100.0	-19.1	117.7	1.4	100.0	-43.7	141.9	1.7
Jinzhou	100.0	37.5	61.4	1.1	100.0	26.1	72.6	1.3
Jilin	100.0	34.5	64.4	1.2	100.0	25.3	73.4	1.3
Mudanjiang	100.0	43.6	54.8	1.6	100.0	33.0	65.1	1.9
Wuxi	100.0	13.7	84.6	1.7	100.0	3.3	94.8	1.9
Xuzhou	100.0	-16.4	115.0	1.4	100.0	-39.0	137.4	1.6
Yangzhou	100.0	36.2	62.8	1.0	100.0	27.3	71.6	1.1
Wenzhou	100.0	19.3	79.7	1.0	100.0	9.7	89.1	1.2
Jinhua	100.0	-3.2	101.8	1.3	100.0	-20.6	119.0	1.5
Bengbu	100.0	1.9	96.6	1.5	100.0	-12.4	110.7	1.7
Anqing	100.0	51.5	47.2	1.2	100.0	44.5	54.1	1.4
Quanzhou	100.0	35.1	63.0	2.0	100.0	23.9	73.8	2.3
Jiujiang	100.0	42.4	56.4	1.2	100.0	35.8	62.9	1.3
Ganzhou	100.0	27.8	71.5	0.7	100.0	19.3	79.9	0.8
Yantai	100.0	15.4	83.3	1.3	100.0	8.4	90.2	1.4
Jining	100.0	4.6	93.4	2.1	100.0	-5.3	103.0	2.3
Luoyang	100.0	4.7	94.5	0.8	100.0	-7.0	106.1	0.9
Pingdingshan	100.0	41.8	57.1	1.1	100.0	35.7	63.1	1.2
Yichang	100.0	72.8	26.0	1.2	100.0	70.5	28.2	1.3
Xiangyang	100.0	11.2	87.3	1.6	100.0	-4.6	102.7	1.8
Yueyang	100.0	57.6	40.6	1.8	100.0	55.0	43.1	1.9
Changde	100.0	32.9	65.7	1.4	100.0	30.0	68.6	1.4
Shaoguan	100.0	27.5	71.0	1.5	100.0	-2.4	100.2	2.2
Zhanjiang	100.0	62.8	35.6	1.6	100.0	55.2	42.8	2.0
Huizhou	100.0	43.6	55.1	1.3	100.0	29.9	68.4	1.7
Guilin	100.0	44.7	54.6	0.7	100.0	36.3	62.9	0.8
Beihai	100.0	10.0	86.6	3.4	100.0	-21.3	116.6	4.6
Sanya	100.0	53.1	44.0	2.9	100.0	45.2	51.5	3.3
Luzhou	100.0	21.4	77.8	0.7	100.0	15.9	83.3	0.8
Nanchong	100.0	-0.4	100.0	0.4	100.0	-4.0	103.6	0.4
Zunyi	100.0	12.9	86.8	0.3	100.0	6.8	92.8	0.3

Source: Authors' calculations based on data presented in Section 2.

Table 6. Growth accounting results

	Average annual changes (%)				Contributions			
Tier 1	*Y/L*	*TFP*	*K/L*	*h*	*Y/L*	*TFP*	*K/L*	*h*
1994-2001	9.0	5.3	3.5	0.2	100	59.2	38.4	2.4
2001-2007	14.3	8.7	5.2	0.4	100	61.0	36.3	2.7
2007-2009	7.2	2.5	4.3	0.4	100	34.9	59.9	5.2
2009-2010	10.2	5.6	4.2	0.4	100	54.9	41.5	3.6
1994-2010	**10.8**	**6.3**	**4.3**	**0.3**	**100**	**57.8**	**39.3**	**2.8**
	Average annual changes (%)				Contributions			
Tier 2	*Y/L*	*TFP*	*K/L*	*h*	*Y/L*	*TFP*	*K/L*	*h*
1994-2001	7.8	1.9	5.8	0.1	100	24.5	74.6	0.9
2001-2007	10.4	2.5	7.5	0.3	100	24.6	72.4	3.0
2007-2009	12.2	2.9	8.9	0.4	100	24.0	72.6	3.5
2009-2010	10.2	1.4	8.3	0.5	100	13.8	81.4	4.8
1994-2010	**9.5**	**2.2**	**7.0**	**0.2**	**100**	**23.7**	**73.8**	**2.5**
	Average annual changes (%)				Contributions			
Tier 3	*Y/L*	*TFP*	*K/L*	*h*	*Y/L*	*TFP*	*K/L*	*h*
1994-2001	7.3	2.4	4.9	0.0	100	33.0	67.1	-0.1
2001-2007	12.1	4.5	7.4	0.2	100	37.1	61.2	1.8
2007-2009	10.5	2.3	8.0	0.2	100	22.2	75.6	2.2
2009-2010	10.7	3.4	7.0	0.3	100	31.8	65.8	2.4
1994-2010	**9.7**	**3.2**	**6.3**	**0.1**	**100**	**33.3**	**65.4**	**1.3**
	Average annual changes (%)				Contributions			
Aggregate	*Y/L*	*TFP*	*K/L*	*h*	*Y/L*	*TFP*	*K/L*	*h*
1994-2001	8.1	3.3	4.7	0.1	100	41.2	57.7	1.0
2001-2007	11.7	4.9	6.6	0.3	100	41.8	55.8	2.4
2007-2009	10.3	2.5	7.4	0.4	100	24.6	71.8	3.6
2009-2010	10.0	2.7	6.9	0.4	100	27.3	68.8	4.0
1994-2010	**9.9**	**3.8**	**5.9**	**0.2**	**100**	**38.4**	**59.4**	**2.2**

Source: Authors' calculations based on data presented in Section 2.

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Appendix

A.1 List of Cities in the Sample

70-city sample: (1) Anqing, (2) Baotou, (3) Beihai, (4) Beijing, (5) Bengbu, (6) Changchun, (7) Changde, (8) Changsha, (9) Chengdu, (10) Chongqing, (11) Dalian, (12) Dandong, (13) Fuzhou, (14) Ganzhou, (15) Guangzhou, (16) Guilin, (17) Guiyang, (18) Haikou, (19) Hangzhou, (20) Harbin, (21) Hefei, (22) Hohhot, (23) Huizhou, (24) Jilin, (25) Jinan, (26) Jinhua, (27) Jining, (28) Jinzhou, (29) Jining, (30) Kunming, (31) Lanzhou, (32) Luoyang, (33) Luzhou, (34) Mudanjiang, (35) Nanchang, (36) Nanchong, (37) Nanjing, (38) Nanning, (39) Ningbo, (40) Pingdingshan, (41) Qingdao, (42) Qinhuangdao, (43) Quanzhou, (44) Sanya, (45) Shanghai, (46) Shaoguan, (47) Shenyang, (48) Shenzhen, (49) Shijiazhuang, (50) Taiyuan, (51) Tangshan, (52) Tianjin, (53) Urumqi, (54) Wenzhou, (55) Wuhan, (56) Wuxi, (57) Xiamen, (58) Xian, (59) Xiangfan/Xiangyang, (60) Xining, (61) Xuzhou, (62) Yangzhou, (63) Yantai, (64) Yichang, (65) Yinchuan, (66) Yueyang, (67) Zhanjiang, (68) Zhengzhou, (69) Zunyi.

Dali is dropped because it is a county-level city. Statistics for county-level cities are calculated differently to those for prefecture-level cities. As a result, they are not comparable (See, for example, *China City Statistical Yearbook 2015*, p. 1.)

Table A1. Tier-1, 2, and 3 cities as defined by the NBS[62]

Tier-1 cities:	Beijing, Shanghai, Guangzhou, Shenzhen.
Tier-2 cities:	Tianjin, Shijiazhuang, Taiyuan, Hohhot, Shenyang, Dalian, Changchun, Harbin, Nanjing, Hangzhou, Ningbo, Hefei, Fuzhou, Xiamen, Nanchang, Jinan, Qingdao, Zhengzhou, Wuhan, Changsha, Nanning, Haikou, Chongqing, Chengdu, Guiyang, Kunming, Xian, Lanzhou, Xining, Yinchuan, Urumqi.
Tier-3 cities:	Tangshan, Qinhuangdao, Baotou, Dandong, Jinzhou, Jilin, Mudanjiang, Wuxi, Xuzhou, Yangzhou, Wenzhou, Jinhua, Bengbu, Anqing, Quanzhou, Jiujiang, Ganzhou, Yantai, Jining, Luoyang, Pingdingshan, Yichang, Xiangyang[63], Yueyang, Changde, Shaoguan, Zhanjiang, Huizhou, Guilin, Beihai, Sanya, Luzhou, Nanchong, Zunyi, *Dali(dropped)*

[62] All information accurate as of 2015.
[63] Changed from Xiangfan in 2011.