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劳动力市场认知技能回报率及高等教育回报率的动态研究

摘要

长期以来，教育回报率都是经济学的研究重点，但近年的许多研究指出了教育作为人力资本代理变量的不足。因此，认知技能作为人力资本更好的衡量指标，开始成为研究的中心。本文利用中国家庭收入调查 (CHIP) 2007, 2013, 2018 年的三轮调查数据，研究了中国劳动力市场中认知技能以及高等教育回报率在2007-2018年间的动态变化,并且探索了影响其变化的机制。OLS 估计结果显示, 高等教育回报率在 2007 至 2013 年期间有大幅下滑，在 2018 年有小幅上升，而认知技能回报率在 2007 至 2018 年间无显著变化。进一步研究发现，高等教育回报率在 2013 年的下降是一个普遍现象，而 2018 年的上升集中在经济较不发达、市场化程度较低的地区。2007 至 2013 年间，认知技能回报率在服务业及高技能产业占经济比重更高的地区上升，在内陆地区下滑。其总体大小和地区差距在 2013 至 2018 年间没有显著变化。本文认为，高校扩招、经济减速、产业转型、跨省劳动力流动以及各地区的“引智”政策可能是上述趋势背后的主要机制。

关键词：认知技能回报率，高等教育回报率，高校扩招，产业转型

DYNAMICS OF LABOR MARKET RETURNS TO COGNITIVE SKILLS AND COLLEGE DEGREES

ABSTRACT

The return to education has been an important topic in economics for a long time, but recent studies point out that educational attainment may not be as good a proxy of human capital as we thought. Hence, cognitive skills, as a better measure of human capital, have caught research attention in recent years. Drawing on three waves of the Chinese Household Income Project (CHIP) survey in 2007, 2013, and 2018, I investigate the dynamics of returns to cognitive skills and returns to college degrees from 2007 to 2018, and explore some of the underlying mechanisms. I find that returns to cognitive skills do not change significantly from 2007 to 2018, whereas the college premium experiences a sharp decline in 2013, and rises slightly in 2018. A further examination shows that the decline of college premium in 2013 is a nationwide phenomenon, and its increase in 2018 is mainly driven by less developed and less market-oriented regions. Meanwhile, the return to cognitive skills increases in regions where the service sector or high-skilled industries account for a large share of regional GDP, and declines in inland provinces from 2007 to 2013. Its magnitude and regional distribution do not change significantly in the latter period. This thesis suggests that the expansion of the higher education system, the slowdown of economic growth, industrial transformation, inter-provincial migration, and policies that aim to attract skilled labor to less developed regions may be the primary underlying factors.

Key words: Returns to Cognitive Skills, Returns to Higher Education, College Expansion, Industrial Transformation

Contents

1 Introduction

Economists have long been interested in exploring changes in returns to human capital because the dynamics of returns to human capital reveals changes in the economy and the labor market, and generates implications for a variety of issues such as earnings inequality and economic growth. There is abundant literature documenting changes in returns to education during this period. However, recent studies have questioned the use of education as a proxy of human capital and shifted emphasis on cognitive skills, a more direct measure of human capital. In the past few decades, China has not only experienced unprecedented economic growth but also undergone tremendous changes in the economic environment. This thesis investigates the dynamics of labor market returns to cognitive skills (measured by Gaokao score) and returns to college degrees in China from 2007 to 2018; the goal is to provide an understanding of the development of the Chinese labor market in recent years.

Drawing on data from the Chinese Household Income Project (CHIP) in 2007, 2013, and 2018, I find that while returns to cognitive skills remain quite stable from 2007 to 2018, the college premium substantially declines in 2013, and shows a modest increase in 2018. An examination of regional heterogeneity shows that the decline of college premium in 2013 is a nationwide phenomenon, and its increase in 2018 concentrates on less developed and less market-oriented regions. Meanwhile, the return to cognitive skills rises in regions where the service sector or high-skilled industries account for a large share of regional GDP, and declines in inland provinces from 2007 to 2013. Its magnitude and regional distribution do not change significantly in the latter period. Changes in these returns are highly consistent with changes in the macroeconomic environment and government policies. I also investigate the dynamics of returns to cognitive skills and returns to college degrees by gender and by age. The patterns for subgroups are similar to that for the full sample.

This study contributes to the literature mainly in three aspects. First, while cognitive skills have become the focus of research in various studies about other countries, few studies investigate returns to cognitive skills in China. Existing studies that do take cognitive skills into account turn to measures such as English language skills and performance in high school, which may not be sufficient measures of cognitive ability. In this study, I exploit the self-reported Gaokao score provided by the CHIP surveys as a measure of cognitive skills. Since the college entrance examination covers a wide range of subjects and tests more advanced cognitive ability, the Gaokao score may be a better measure of cognitive skills than proxies used in previous studies. Second, the magnitude of returns to cognitive skills is closely related to the economic and institutional environment. By providing a new estimate of returns to cognitive skills in China and comparing it to returns in other countries, we can examine China's labor market in a global context. Third, although returns to education in the late 1990s and early 2000s are well-documented, literature examining recent returns to human capital is still scarce. With the slowdown of economic growth in recent years, the pattern of returns to human capital may be different. The three waves of the CHIP survey enable me to cover an extended period from 2007 to 2018 and investigate returns to human capital in a new economic environment.

The remainder of this thesis is organized as follows. Section 2 provides a literature review on studies regarding returns to education and returns to cognitive skills in China and abroad. Section 3 outlines several significant changes in China's economy and the labor market in the 21st century and discusses the potential impacts of these changes on returns to college education and cognitive skills. Section 4 describes the CHIP data and the construction of the measure of cognitive skills: Gaokao z-score. Section 5 presents the empirical results. Section 6 discusses the limitations of this study and concludes.

2 Literature Review

2.1 Returns to Human Capital: A Cross-sectional Perspective

Ever since the late 1950s, when economists began to take interest in the causal effect of schooling on earnings, there is an abundance of studies documenting the positive and significant effect of education on individual earnings (for a review, see Card, 1999)[1]. The estimates have profound implications for the optimal allocation of public resources, and improving educational attainment in the population has become an essential development strategy in many countries. However, the notion that education is a good proxy of human capital, and thus returns to years of schooling are useful in directing government policies has been challenged in recent years because educational attainment fails to reflect the disparity in school quality across regions and over time. For example, Behrman and Birdsall (1983) find that returns to education for young Brazilian males vary across regions and between subgroups, and it is largely due to the geographic differences in school quality, as measured by the average schooling of teachers[2]. Hanushek and Zhang (2009) show that after adjusting for intertemporal changes in the quality of schools, which is measured by schooling's contribution to cognitive skills, returns to schooling become significantly higher in most countries than what a traditional Mincer wage equation would suggest[3]. These findings call for policy attention to the quality of education instead of those more readily observed measures, including years of schooling.

In recent years, the availability of better microeconomic datasets enables researchers to examine returns to cognitive skills directly in both developed and developing countries. Major findings are the following. First, the positive impact of cognitive skills on earnings is quite substantial, and part of the returns to cognitive skills comes from the fact that students with higher cognitive ability are likely to receive more years of schooling. For example, Murnane et al. (2000) find that the return to standardized mathematic scores in high school (after controlling for educational attainment) is about 10% for male workers in the United States. Moreover, the indirect effect of cognitive skills through school continuation accounts for about one-third of the total effect[4]. Second, educational attainment does not merely reflect sheepskin effects: it raises wages partly, or primarily as some studies suggest, through the provision of cognitive skills. Boissiere et al. (1985) find that returns to secondary education, through the acquisition of cognitive skills, are about 25% in Kenya and 15% in Tanzania, while the signaling value of secondary education is 21% and 12%, respectively[5]. Third, the quality of schooling matters more than the quantity of schooling does. Behrman et al. (2008) estimate that returns to cognitive skills, measured by reading and mathematics tests, are about 25% in Pakistan, and predict that the benefit of improving the education quality in primary schools exceeds that of increasing access to middle schools[6]. A more comprehensive review can be found in Glewwe (2002) and Hanushek and Woessmann (2008)[7,8].

Meanwhile, literature estimating returns to cognitive skills in China is still quite scarce. A recent cross-sectional study by Huang and Xie (2017) uses numeracy and literacy test scores in the China Family Panel Studies (CFPS) as a measure of cognitive skills. They find that after controlling for educational attainment, cognitive skills have a small but positive effect on earnings[9]. Using alternative measures such as the Gaokao score is however both necessary and indispensable. On the one hand, cognitive tests in the CFPS are quite simple and thus may only reflect basic-level cognitive skills, while Gaokao scores are likely to reflect more sophisticated skills. On the other hand, the longitudinal feature of CFPS makes it difficult to investigate the dynamics of the returns to cognitive skills since it is virtually impossible to separate time effects from experience effects; whereas the cross-sectional CHIP data avoid such problems.

Understanding the supply and demand factors that influence the returns to cognitive skills is as crucial as obtaining the estimates of returns to cognitive skills. Hanushek et al. (2015) approach this problem by comparing returns to cognitive skills across countries. The dataset they use comes from the Programme for the International Assessment of Adult Competencies (PIAAC), a new international survey containing cognitive tests that focus on three domains: literacy, numeracy, and problem-solving skills. They find a systematically positive effect of cognitive skills on wages yet substantial heterogeneity across countries. Their results imply that union density, employment protection legislation, and share of the public sector may be important factors in determining returns to cognitive skills[10]. In a subsequent paper (Hanushek et al., 2017), they further examine the relationship between returns to skills and economic growth, and lend empirical support to the hypothesis that during economic changes, the demand for skilled workers is higher due to their higher adaptive ability, and thus returns to cognitive skills will be higher in countries experiencing faster economic growth[11]. Nevertheless, it is difficult to control for all relevant country characteristics in the specification. There is much less heterogeneity across provinces, in particular, in hard-to-measure characteristics such as culture and ideology. Thus, cross-province comparisons within one country will mitigate the problem to some extent.

2.2 Returns to Human Capital: A Dynamic Perspective

Another strand of literature investigates the returns to human capital from a dynamic perspective. For example, Katz and Murphy (1992) find that within-industry labor demand shifts, which likely reflects technological changes, is crucial in interpreting the widening education wage gap in the United States from 1963 to 1987[12]. Murnane et al. (1995) find that returns to basic mathematic skills in the United States are higher in the mid-1980s than in the late 1970s, which they think partly explain the rising within-group inequality since 1970[13]. China, as a large economy that is experiencing fast changes in industrial structure and the labor market, has also received much research attention about the dynamics of returns to human capital. Zhang et al. (2005) show that there is a dramatic increase in returns to education in China in the late 1990s, and supply-side factors fail to explain the phenomenon. Thus, they argue that a positive and strong demand shift for skilled workers has occurred, and that institutional reform is undoubtedly one of the most critical underlying mechanisms[14]. The rising return to education is accompanied by rising earnings inequality in the 1990s. However, Meng et al. (2013) argue that the increase in returns to unobservable skills, not education, is the primary source of widening inequality among urban young males in that period. They also find that from 2000 to 2009, within-group inequality widens for educated young males, and narrows for less-educated young males. They contend that changes in the distribution of unobservable skills within groups and the reduction in returns to unobservable skills in the 2000s due to college expansion may be the cause[15]. Whalley and Xing (2014) propose another source underlying changes in returns to education in the 2000s. They find that from 2000 to 2009, returns to education only show a significant increase in coastal regions, which reflects demand shifts for skilled workers caused by international trade[16].

There are also studies investigating the dynamics of returns to cognitive skills in China. Sun (2019) uses the type of an individual's high school, individual's performance in high school, and an indicator of non-missing data on college entrance examination as proxies of cognitive ability, and finds that returns to these proxies decline from 2002 to 2013. The paper suggests that it may be due to technological change biased towards abstract skills instead of routine skills measured by exams[17]. More recently, Asadullah and Xiao (2020) find modest decreases in returns to education and returns to English language skills from 2010 to 2015, which they mainly ascribe to college expansion and the slowdown of economic growth[18]. Notwithstanding, the measures of cognitive skills in these studies may not be able to capture the full scope of cognitive skills.

2.3 Summary of the Section

First, despite the abundant literature on returns to education, recent studies begin to place more emphasis on cognitive skills as a measure of human capital because the quality of schooling varies both across regions and over time. Existing studies have confirmed the importance of cognitive skills, but literature documenting returns to cognitive skills in China is still scarce, and better proxies are needed to measure cognitive skills. Second, economists have investigated the demand and supply factors underlying the determination of returns to human capital using cross-country comparisons and dynamic analyses. However, international comparisons are beset by omitted variable bias, and most within-country dynamic analyses of returns to human capital focus on returns to schooling rather than returns to cognitive skills. Since cognitive skills may be a better measure of human capital, examining the dynamics of its returns may be more informative.

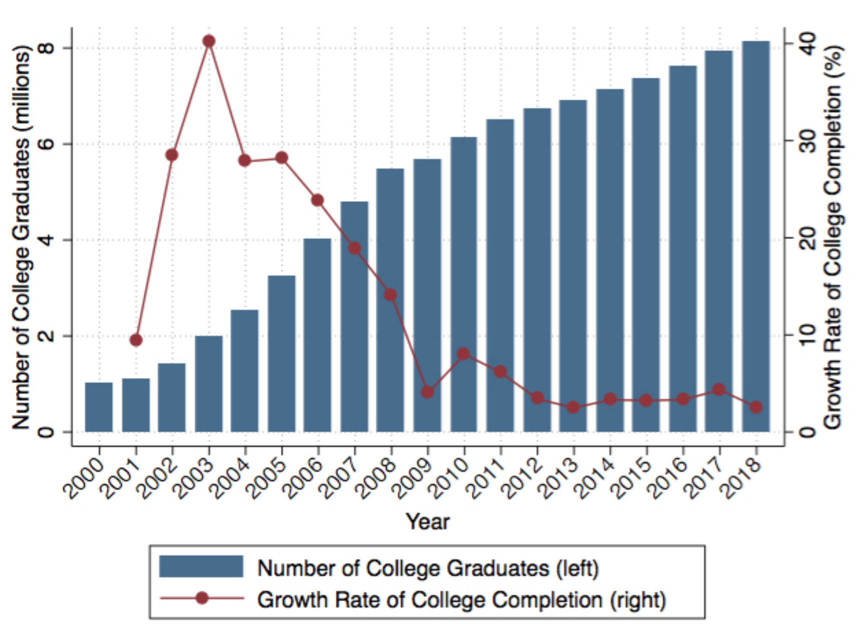
3 Background of the Chinese Labor Market

The labor market in China has undergone significant changes in the 21st century. In this section, I discuss major changes that are likely to have profound impacts on the returns to college degrees and cognitive skills.

3.1 Supply Shifts

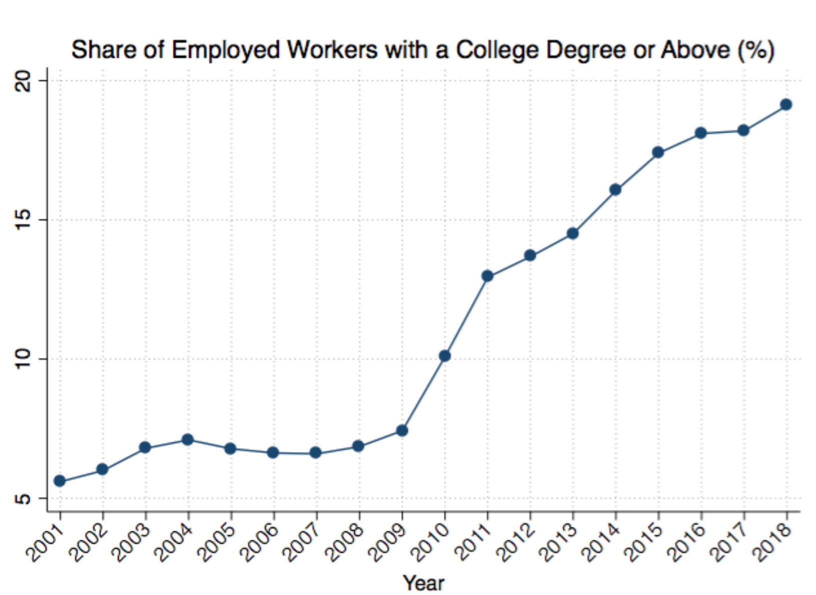
The most important development on the supply side is the higher education expansion started in 1999, which increases dramatically the supply of college-educated and skilled workers in the labor market (for a detailed discussion of the expansion of the higher education system, see Che and Zhang, 2018)[19]. Figure 3.1 shows that the number of college graduates grows from 1 million in 2000 to 8.1 million in 2018. The growth rate of college completion is highest in 2003 (40.2%), when the first wave of students admitted to college under the expansion regime graduated. The higher education expansion gradually slows down over the years, with the growth rate of college graduates fluctuating around 3 percent in recent years. Meanwhile, the share of employed workers with a 3- or 4-year college degree or above rises from 5.6 percent in 2001 to 19.1 percent in 2018 (Figure 3.2). Note that it begins to increase rapidly only after 2009, perhaps because although the growth rate of college graduates is high shortly after the expansion, the stock of college-educated workers in the labor force is still too small to make an impact.[1] If the demand for college-educated workers does not increase significantly after 2009, with such a massive supply shock, the college premium is bound to decline.

[1] Another possible explanation is that relatively more of less-educated older workers, compared to college-educated older workers, retired around 2009, when the public pension system experienced a large improvement. Appendix Figure A1 shows that the share of older workers with a college degree or above did increase in that period, but the magnitude is not enough to explain the trend in Figure 3.2.



Note: The figure depicts the number of graduates from 3- or 4-year colleges or above (the left vertical axis) and the annual growth rate of college graduates (the right vertical axis) each year from 2000 to 2018. Data comes from the China Statistics Yearbook.

Figure 3.1: Number and Growth rate of College Graduates

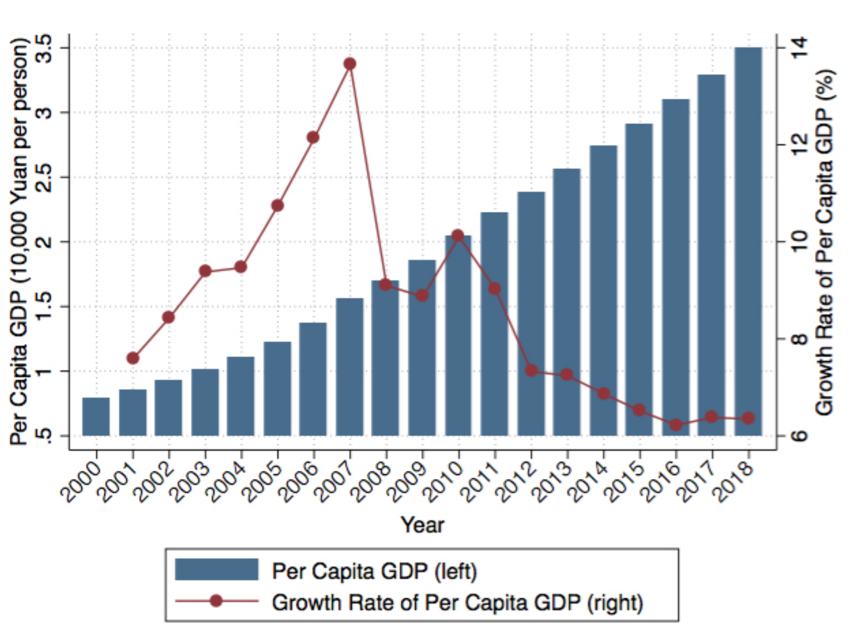


Note: The figure depicts the share of employed workers with a 3- or 4-year college degree or above each year from 2001 to 2018. Data comes from the China Labor Statistics Yearbook and China Population and Employment Statistics Yearbook. The definition of employed workers in the yearbook includes restrictions on age and working hours after 2012, but it seems to be just an elaboration of the previous definition.

Figure 3.2: Share of Workers with a College Degree or Above

3.2 Demand Shifts

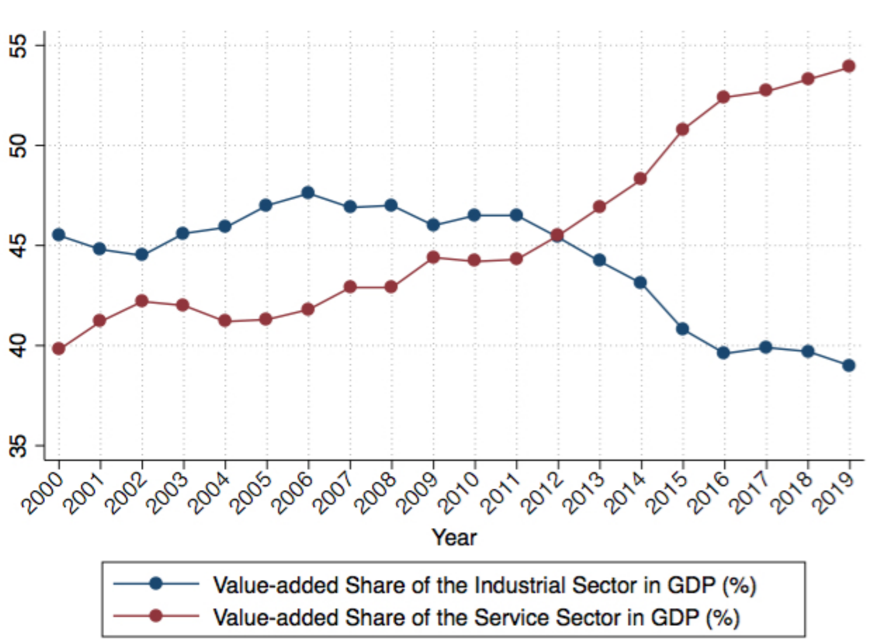
On the demand side, the most prominent changes are the slowdown of economic growth and the shift of economic structure. As is shown in Figure 3.3, although the per capita GDP in 2018 (35,006 Yuan per person, in constant 2000 Yuan) is more than four times the per capita GDP in 2000 (7,912 Yuan per person, in constant 2000 Yuan), the growth rate of per capita GDP has steadily declined since 2007, staying at around 6 percent in the past five years. This may cause significant changes in the returns to human capital. Previous studies such as Zhang et al. (2005) find that despite the high growth rate of high-educated workers, returns to education still rise during the 1990s, in part because the growth in the demand for skilled labor outpaces the growth in the supply of skilled labor[14]. However, the declining economic growth rate in recent years may not be able to sustain the high returns to education in the face of a large-scale college expansion.



Note: The figure depicts the evolution of per capita GDP (the left vertical axis) and growth rate of per capita GDP (the right vertical axis) from 2000 to 2018. Per capita GDP is calculated by dividing GDP by the total population. All monetary values are adjusted to the 2000 price level. Data comes from the National Bureau of Statistics.

Figure 3.3: Per Capita GDP and Growth Rate of Per Capita GDP

In the meantime, China is transitioning from an industrial-based economy to a service-based economy. Figure 3.4 shows that the share of national GDP accounted for by the value-added of the service sector has grown from 39.8 percent in 2000 to 53.9 percent in 2019, while the share accounted for by the industrial sector has decreased from 45.5 percent to 39 percent. This shift in economic structure may indicate an increase in the demand for skilled workers relative to unskilled workers. Nevertheless, since the service sector entails both high-skilled service jobs *and* low-skilled service jobs, the value-added share of the service sector is only a crude measure of relative demand for skilled workers. Therefore, I directly classify industries by the share of high-skilled employment, where high-skilled workers are those with at least a 3- or 4-year college degree. Table 3.1 reports the share of high-skilled workers for each industry in 2017. Data comes from China Population and Employment Statistics Yearbook. It is clear that there is large variation in the high-skilled share within the service sector.



Note: The figure depicts the evolution of shares of value-added of the industrial sector and the service sector in national GDP from 2000 to 2019. Data comes from the National Bureau of Statistics.

Figure 3.4: Value-added Shares of the Industrial and Service Sector

Table 3.1 Share of Employees with a College Degree or Above in 2017

Sector	Industry	Share of Employees with a College Degree or Above (%)
The Agricultural Sector	Farming, Forestry, Animal Husbandry and Fishery	0.7
The Industrial Sector	Mining and Quarrying	21.6
	Manufacturing	15.2
	Production and Supply of Electricity, Heat, Gas and Water	40.1
	Construction	8.6
The Service Sector	Wholesale and Retail Trade	18.3
	Transportation, Storage and Post	15.7
	Accommodation and Food Services	8.2
	Information and Communication Technology, Software	67.1
	Finance and Insurance	67
	Real Estate	36.4
	Leasing and Business Services	42.9
	Scientific Research and Technical Services	68.1
	Management of Water Conservancy, Environment and Public Infrastructure	24.9
	Personal and Household Services	12.2
	Education	69.8
	Health and Social Services	59.9
	Culture, Sports and Entertainment	41.2
	Public Administration, Social Security and Social Organizations	62.3

Note: The table reports the share of employed workers with a 3- or 4-year college degree or above by industry in 2017. The classification follows the 2017 industrial classification for national economic activities. The international organization industry is excluded since it is not relevant to this study. Data comes from the China Labor Statistics Yearbook.

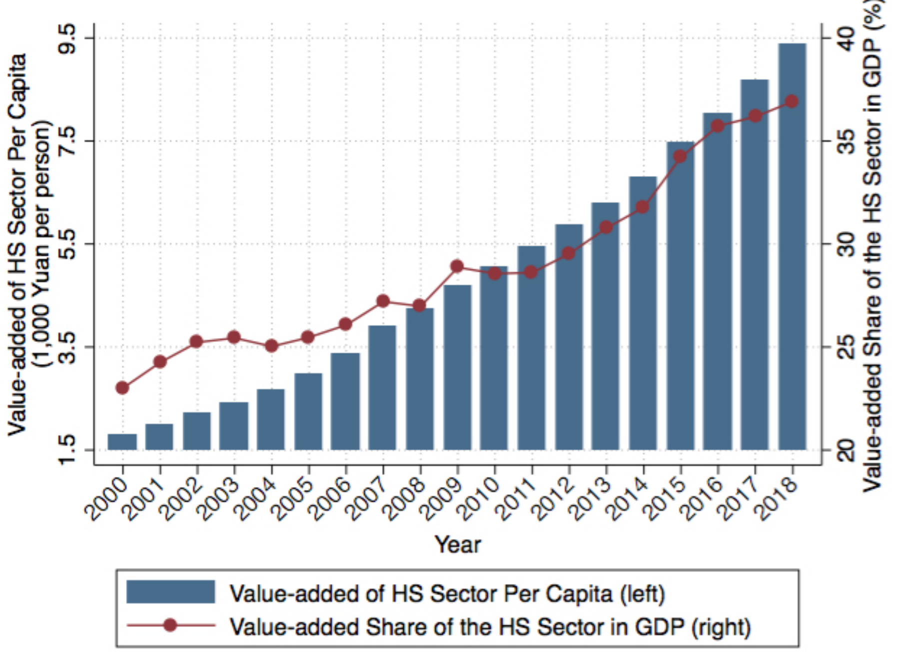
I define high-skilled sector (HS sector) as industries whose share of high-skilled workers is above 30% in 2017. Specifically, the HS sector includes information and communication technology, software, finance and insurance, real estate, leasing and business services, scientific research and technical services, management of water conservancy, environment and public infrastructure, personal and household services, education, health and social services, culture, sports and entertainment, and public administration, social security and social organizations. The LS sector, defined as industries whose share of high-skilled workers is below 30% in 2017, includes the agricultural sector, the industrial sector, and some service industries, including wholesale and retail trade, transport, storage and post, and accommodation and food services. Data from the National Bureau of Statistics lumps all HS industries together, except for real estate, and finance and insurance, in terms of value-added measures. Value-added of industries in the industrial sector, except for construction, are lumped together as well. Hence, management of water conservancy, environment and public infrastructure industry, personal and household services are included in the HS sector, and production and supply of electricity, heat, gas and water is included in the LS sector.[1]

Figure 3.5 shows that the value-added per capita of the HS sector has grown from 1,808 Yuan per person in 2000 to 9,392 Yuan per person in 2018 (in constant 2000 Yuan), a five-fold increase. Its value-added share in GDP has also experienced a continued increase from 23% in 2000 to 37% in 2018, though the increase is slower around 2009 relative to the previous trend. Meanwhile, the value-added per capita of the LS sector increases more slowly from 6,050 to 20,670 Yuan per person, and its value-added share declines from 77% to 63% (Figure 3.6). While the annual growth rate of the value-added per capita of HS sector averaged between 2008 to 2013 (8.3%) is slightly smaller than that of LS sector (8.8%), the average growth rate of the value-added per capita of HS sector from 2014 to 2018 (8.3%) is much higher than that of LS sector (5.8%). Hence, taking the economic performance of the HS sector relative to the LS sector as a measure of relative demand for skilled labor to unskilled labor, we may conjecture a deceleration of growth in the relative demand for skilled labor shortly after 2008 and an acceleration in recent years.

Accompanying the nationwide expansion of the HS sector is the widening regional difference in the development of the HS sector. Figure 3.7 illustrates the evolution of the value-added of the HS sector by province from 2007 to 2017.[2] As we can see, there is not only a nationwide expansion of the HS sector over time, but also a growing disparity in the

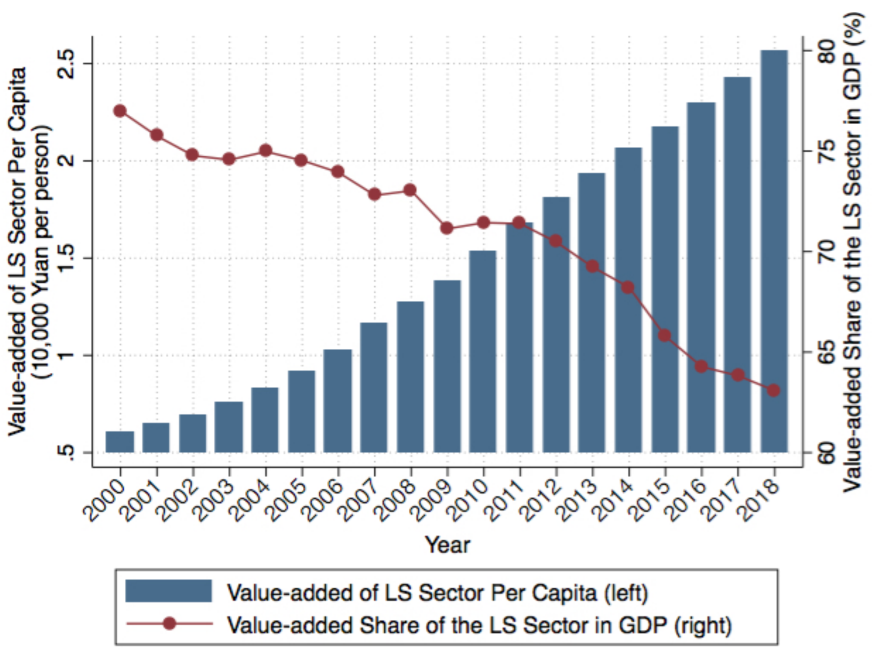
[1] Available data does not allow me to calculate the average share of college-educated workers in the industrial sector. However, I construct a crude measure by weighting the share of college-educated workers for each industry in the industrial sector in 2017 by the share of employment in the urban formal industrial sector accounted by that industry in 2017 and summing. The obtained average share of college-educated workers in the industrial sector is 24.5%. Since the urban share of employees with a college degree or above is likely to be higher than the national share, lumping production and supply of electricity, heat, gas and water with other industries in the industrial sector may be appropriate.

[2] I choose three time-points (2007, 2013, and 2017), which corresponds to the three-year dataset that I will use in the empirical analysis. Choosing 2018 instead of 2017 will be better, but data about the value-added of HS sector in that year is not yet available.



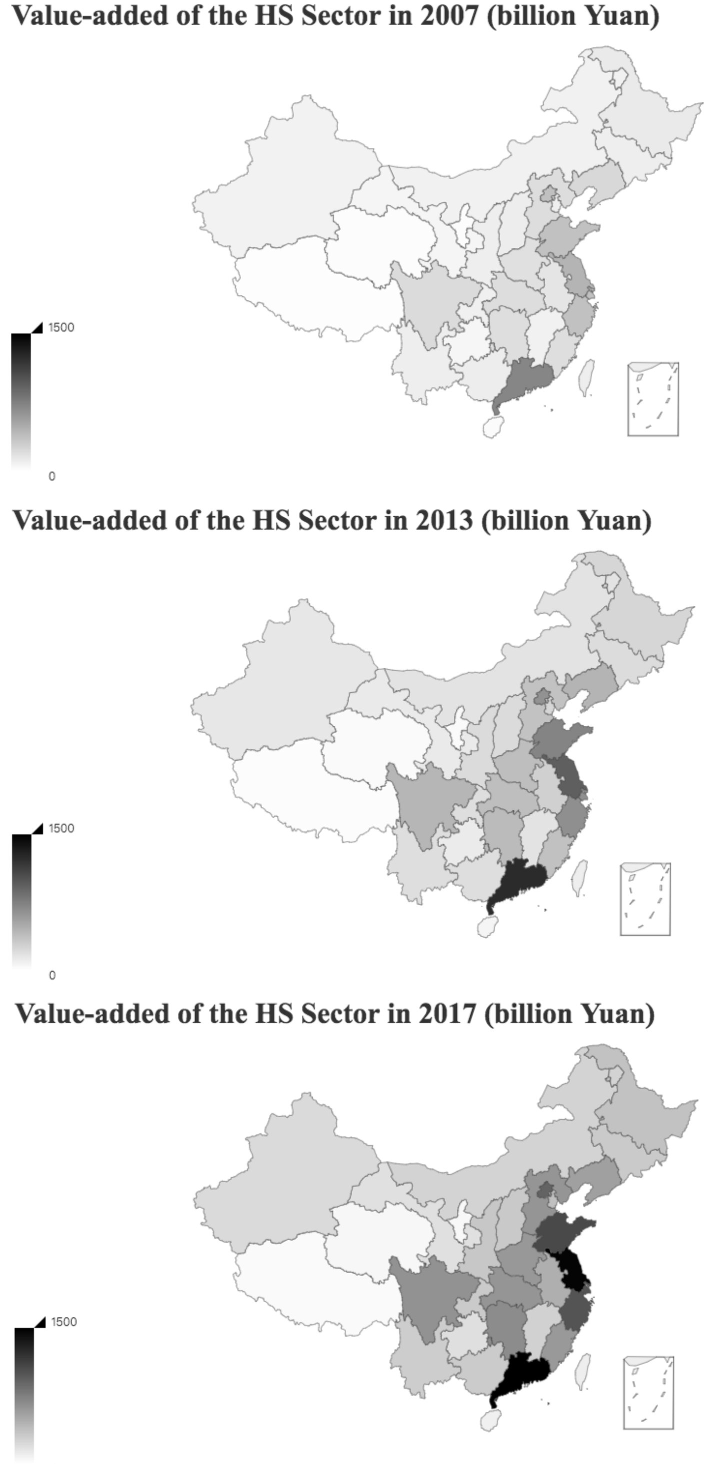
Note: The figure depicts the evolution of the value-added of HS sector per capita (the left vertical axis) and the share of HS sector value-added in national GDP (the right vertical axis) from 2000 to 2018. The value-added of HS sector per capita is calculated by dividing the value-added of HS sector by the total population. All monetary values are adjusted to the 2000 price level. Data comes from the National Bureau of Statistics.

Figure 3.5: Value-added of HS Sector Per Capita and Share of HS Sector



Note: The figure depicts the evolution of the value-added of LS sector per capita (the left vertical axis) and the share of LS sector value-added in national GDP (the right vertical axis) from 2000 to 2018. The value-added of LS sector per capita is calculated by dividing the value-added of LS sector by the total population. All monetary values are adjusted to the 2000 price level. Data comes from the National Bureau of Statistics.

Figure 3.6: Value-added of LS Sector Per Capita and Share of LS Sector



Note: The figure depicts the value-added of HS sector (in billion Yuan) by province in 2007, 2013 and 2017. Darker color indicates a higher value-added of the HS sector. The actual maximum of the value-added of the HS sector is about 1930 billion Yuan (Guangdong in 2017), but the range in the figure is censored at 1500 billion Yuan for better visual effect. No other observation exceeds 1500 billion Yuan. All monetary values are adjusted to the 2000 price level. Data comes from the National Bureau of Statistics.

Figure 3.7: Regional Distribution of the Value-added of HS Sector

size of the HS sector across regions. Eastern regions have already shown advantage in the development of the HS sector in 2007, and the advantage has strengthened over time. Meanwhile, some provinces in the western and central parts of China, including Sichuan, Hunan, Hubei, Henan, and Hebei, also catch up rapidly. However, the majority of western and central regions experience a much slower transition to a service-based economy. For example, the value-added of the HS sector in Jiangxi increases from 85 billion Yuan in 2007 to 271 billion Yuan in 2017, yet that of its neighboring province Zhejiang has grown from 363 billion Yuan to 1,008 billion Yuan. Holding the supply of labor equal, workers in regions with a larger share of the HS sector will likely enjoy a higher skill premium due to a greater relative demand for skilled workers. At the same time, regions with a higher price for skills will usually attract more skilled labor, reducing to some extent the skill premium. Despite the rapid expansion of the HS sector in some regions, if the relative supply of skilled workers to unskilled workers in these regions grows fast enough, the skill premium may not increase very quickly.

3.3 Wage-Setting Institutions

In addition to supply- and demand-side shifts, institutional factors can also affect skill premium. One well-documented institutional change in China is the economic reforms begun in the 1980s, which have significantly changed the ownership structure of the entire economy and allowed more market forces in the determination of wages. As Hanushek et al. (2015) suggest, a labor market with a higher degree of marketization will generally have a higher skill premium[10]. Several studies including Zhang et al. (2005) and Whalley and Xing (2014) show that enterprise restructuring, which greatly removes the protection on workers in the public sector and promotes the sorting of high-skilled workers into higher-paying industries, accounts for a significant part of the rise in returns to human capital in China during the 1990s[14,16]. Meanwhile, Whalley and Xing (2014) also suggest that the impact of institutional reforms has become modest in the 2002-2007 period[16]. As such, ownership restructuring may be less important for the time period I am studying.

3.4 Summary of the Section

This section outlines a few noteworthy changes in China’s economy and the labor market that may have a great impact on returns to human capital. The expansion of the higher education system since 1999 is a major supply shift. The college expansion brings about a substantial supply shock on the national labor market, but in recent years its impact may not be as significant as before. On the demand side, the slowdown of economic growth, especially in the HS sector, shortly after 2008 will have an adverse effect on the demand of skilled labor, but the rapidly rising share of HS sector in the economy during the past few years may indicate a favorable economic environment for skilled workers. Meanwhile, China's transition towards a service-based economy may widen regional differences in the education structure of labor demand.[1] In the empirical analysis section, I will link the college expansion and broad changes in the economy (the slowdown of economic growth and the expansion of HS sector) to changes in returns to human capital in the national labor market, and examine how regional demand shifts, of which the magnitude is measured by industrial structure, impact regional labor markets. Institutional changes also play a role. China's economic reforms since the 1980s increase the degree of marketization in the labor market and drive up the skill premium, but studies have shown that the effect of these policies is less prominent in the 2000s.[2] Therefore, institutional factors will not be the focus of this study, but I do compare coastal and inland regions as an examination of how the dynamics of returns to human capital differ between more market-oriented and less market-oriented regions.

[1] Another demand shifter for skilled workers to note in the last few decades is international trade. Whalley and Xing (2014) document its impact on returns to education in the early 2000s[16]. However, since 2006, the ratio of exports to GDP steadily goes down, reaching 17 percent in 2019, a number even smaller than that in 2000. Hence, the exposure to trade activity may not be as important as before, though it does give coastal regions a head-start in industrial reform.

[2] A recent study by Bai et al. (2020) suggests that the preferential lending policy after the financial crisis has an impact on the high school premium[20], but its impact on the skill premium, as defined in this study, may be much smaller.

4 Data and Summary Statistics

4.1 Data Source and Construction of Main Variables

The data mainly comes from three waves of the Chinese Household Income Project (CHIP) surveys (2007, 2013, and 2018). In each survey, the full sample including urban and rural samples is used.[1] The CHIP data is a nationally representative survey data, where the provinces are chosen to reflect variations in geography and economic development. The dataset contains a full set of demographic characteristics including age, gender, educational attainment, province of residence, as well as current employment information including annual salary, working hours, industry, and occupation. I construct hourly wage by dividing the annual salary (including monetary bonuses and subsidies) by hours worked in that year. All monetary values are adjusted to be measured in constant 2007 Yuan using national CPI.

One advantage of the CHIP survey is that it elicits information about the college entrance examination since the 2007 wave, which allows me to construct a measure of cognitive skills. I process the Gaokao score in two steps following Demurger et al. (2019): first divide the Gaokao score by the year-province-subject specific total possible score to generate a rank for every individual, then normalize the rank within each survey year to get a z-score with mean of 0 and standard deviation of 1[21]. The Gaokao z-score is thus a measure of cognitive skills comparable across individuals.

4.2 Selection of the Main Analysis Sample

For the empirical analysis, I focus on the subsample of full-time employees, where full-time is defined as working no less than 30 hours a week. To mitigate the influence of outliers, I exclude those whose hourly earnings are less than 1 Yuan or greater than 100 Yuan. Since Gaokao z-score is the primary explanatory variable, I exclude those who have never taken a college entrance examination and those who do not report their Gaokao scores. Furthermore, I include only individuals with a high school degree or above because it is generally unlikely that one would take the college entrance examination and fail to get

[1] The 2007 and 2013 waves also include a separate migrant sample, and these are included as well.

a high school degree. Finally, I exclude observations with missing information on gender, age, and province of residence. I do not impose any restriction on age, but preliminary inspection shows that restricting the sample to workers aged between 16 and 60 does not change the results by much. The baseline estimation sample includes 9710 observations.

Table 4.1 Summary Statistics

	2007	2013	2018
Age	32.93	34.56	35.00
Male (%)	60.38	56.66	57.96
Coastal (%)	49.62	36.75	33.90
College (%)	69.68	79.39	82.84
Hourly Earnings	12.61	16.33	22.89
Gaokao z-score	0.059	0.025	0.046
Observations	2259	2882	4569

Note: The estimation sample includes all full-time employees with hourly wages between 1 and 100 Yuan per hour, at least a high school degree, and non-missing information about the Gaokao score, gender, age and province of residence. High school includes ordinary high school, technical school and specialized secondary school (Zhong Zhuan). College includes ordinary college, polytechnic college (Da Zhuan) and any degree above college.

Table 4.1 reports the summary statistics of the estimation sample. The average age of the sample is around 34 years, and about 60% of the sample is male. The classification of coastal and inland regions follows the National Bureau of Statistics, where coastal provinces include Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan, and other provinces are classified as inland provinces. The share of workers in coastal regions is lower in the 2013 and 2018 samples because of changes in sampling. Due to the exclusion criteria, the share of workers holding a college degree or above is quite high in all samples, and it increases steadily over the years, but the growth seems to slow down. The average real hourly earnings almost double from 2007 to 2018. The average Gaokao z-scores in the three samples are all slightly higher than the overall average (i.e., zero), indicating some degree of positive selection into full-time employment.

Since I intend to explore regional differences in the dynamics of skill premium and college premium, I present the geographic distribution of observations in each year's estimation sample in Table 4.2. Provinces common to all surveys are Jiangsu, Guangdong, Anhui, Henan, Hubei, Chongqing, and Sichuan.

Table 4.2 Geographic Distribution of the Estimation Sample By Year

Year	Coastal Provinces	Inland Provinces
2007	Jiangsu (312), Guangdong (434), Zhejiang (298), Hebei (13), Shanghai (64)	Anhui (257), Henan (269), Hubei (251), Chongqing (94), Sichuan (267)
2013	Jiangsu (223), Guangdong (265), Beijing(352), Shandong (219)	Anhui (132), Henan (299), Hubei (254), Chongqing (169), Sichuan (148), Shanxi (222), Liaoning (95), Hunan (214), Yunnan (132), Gansu (158)
2018	Jiangsu (327), Guangdong (478), Beijing (429), Shandong (315)	Anhui (310), Henan (313), Hubei (387), Chongqing (212), Sichuan (300), Shanxi (308), Liaoning (205), Hunan (321), Yunnan (133), Gansu (281), Inner Mongolia (250)

Note: The table shows the geographic distribution of observations in each year's estimation sample. Number of observations in parentheses.

4.3 Summary of the Section

This section first describes the data and relevant variables, and then briefly introduces the construction of the main explanatory variable: Gaokao z-score. Finally, I explain the selection of the main analysis sample and present some summary statistics.

5 Empirical Results

5.1 Estimates of Returns to Cognitive Skills and College Degrees

Before investigating the dynamics of returns to cognitive skills and college degrees, I first look at the cross-sectional returns. The econometric model I use is mostly based on Hanushek et al. (2015)[10]:

$$\ln y_i = \beta_0 + \gamma_1 H_i + \beta_1 E_i + \beta_2 E_i^2 + X_i' \beta_3 + \varepsilon_i \tag{5-1}$$

Here, y_i is the hourly wage of individual i. H_i is the attainment of college degree or a measure of cognitive skills (Gaokao z-score). E_i is potential experience measured by age minus six minus years of schooling. X_i is a vector of control variables including gender and province of residence. ε_i is the error term. The coefficient of interest is γ_1, which measures the college premium or the average percentage increase in one's hourly wage associated with a one-standard-deviation increase in cognitive skills, other things being equal.

Table 5.1 presents the estimation results. Column 1 shows that college education has a significant and substantial impact on individual's hourly earnings in 2007. *Ceteris paribus*, the hourly earnings of college-educated workers is on average 67.9% higher than that of workers with only a high school degree. Column 4 and column 7 show that returns to college degrees experience a sizable decline after 2007, but the magnitude is still quite large (40.6% in 2013, and 49.1% in 2018). Column 2 shows that a one-standard-deviation increase in cognitive skills will, on average, raise hourly earnings by 20.7%, other things being equal. Column 5 and column 8 show that returns to cognitive skills in 2013 and 2018 are 13.7% and 16.1%, respectively. The coefficients are all significant at the 1% level. Thus, cognitive skills have a positive and strong relationship with earnings. The remaining columns control for the attainment of college degree and cognitive skills at the same time. The decline in the coefficients on the college dummy suggests that the college premium partly comes from the fact that people with higher cognitive ability are more likely to receive higher education. Cognitive skills still exert a significant effect on earnings beyond the channel of schooling. In all three years, a one-standard-deviation increase in cognitive

Table 5.1 Returns to Cognitive Skills and Returns to College Degrees By Year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year	2007	2007	2007	2013	2013	2013	2018	2018	2018
College	0.679***		0.602***	0.406***		0.328***	0.491***		0.400***
	[0.026]		[0.028]	[0.028]		[0.030]	[0.024]		[0.025]
Gaokao z-score		0.207***	0.104***		0.137***	0.094***		0.161***	0.111***
		[0.015]	[0.014]		[0.012]	[0.013]		[0.011]	[0.011]
PE	0.054***	0.052***	0.051***	0.045***	0.042***	0.043***	0.043***	0.041***	0.040***
	[0.005]	[0.006]	[0.005]	[0.005]	[0.005]	[0.005]	[0.003]	[0.003]	[0.003]
PE Squared	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Male	0.149***	0.126***	0.145***	0.170***	0.168***	0.168***	0.146***	0.156***	0.150***
	[0.024]	[0.026]	[0.024]	[0.021]	[0.022]	[0.021]	[0.019]	[0.019]	[0.018]
Constant	0.910***	1.389***	1.001***	2.229***	2.622***	2.296***	2.424***	2.877***	2.495***
	[0.177]	[0.161]	[0.172]	[0.053]	[0.043]	[0.052]	[0.046]	[0.039]	[0.046]
Observations	2,259	2,259	2,259	2,882	2,882	2,882	4,569	4,569	4,569
Adjusted R2	0.348	0.232	0.365	0.227	0.211	0.245	0.195	0.176	0.214

Note: The sample includes all full-time employees with hourly wages between 1 and 100 Yuan per hour and at least a high school degree. The dependent variable is hourly wages (in log term). College is a dummy that takes 1 if the individual has a 3- or 4-year college degree or above, 0 if otherwise. PE is potential experience measured by age minus six minus years of schooling. All regressions control for province fixed effects. Robust standard errors in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

skills will increase one's hourly earnings by about 10%, other things being equal. It is of roughly the same magnitude as the average return to cognitive skills (after controlling for years of schooling) across countries in Hanushek et al. (2015)[10]. The results suggest that the attainment of college degree and cognitive skills are positively correlated, yet they both have an independent effect on individual earnings. It may be helpful to think of college degree as an easy-to-observe credential, which raises earnings largely through the signaling process, and cognitive skills as a better yet hard-to-observe measure of human capital as suggested by Altonji and Pierret (2001)[22]. All columns show a concave age-earnings profile and a gender wage gap (the hourly earnings of male workers is about 15% higher than that of female workers), which is consistent with previous literature.

Comparing the estimates of both returns over time, we can see that returns to college degrees decrease in 2013 and 2018 relative to 2007, but returns to cognitive skills appear to be quite stable over this ten-year period. To investigate the dynamics of both returns from 2007 to 2018 more accurately, I pool the three-year sample and estimate the following specification:

$$\begin{aligned}\ln y_i = \beta_0 + \gamma_1 C_i + \gamma_2 C_i * Year2013_t + \gamma_3 C_i * Year2018_t + \gamma_4 College_i \\ + \gamma_5 College_i * Year2013_t + \gamma_6 College_i * Year2018_t \\ + \beta_1 E_i + \beta_2 E_i^2 + X_i'\beta_3 + \theta_t + \varepsilon_i \qquad (5-2)\end{aligned}$$

Here, C_i is the measure of cognitive skills (Gaokao z-score). $College_i$ is a dummy variable that takes the value of 1 if the individual holds a 3- or 4-year college degree or above, 0 if otherwise. $Year2013_t$ and $Year2018_t$ are dummy variables indicating the year of 2013 and 2018, respectively. X_i includes gender, province of residence, and occupation and industry information. θ_t captures year fixed effects, and the omitted category is the year of 2007. The coefficients of interest are γ_2, γ_3, γ_5 and γ_6, which reflect changes in returns to cognitive skills and the college premium from 2007 to 2018. The estimation results are presented below in Table 5.2.

Table 5.2 Dynamics of Returns to Cognitive Skills and Returns to College Degrees

	(1)	(2)	(3)	(4)
College	0.608***	0.501***	0.574***	0.494***
	[0.028]	[0.028]	[0.028]	[0.028]
College*Year2013	-0.279***	-0.247***	-0.277***	-0.246***
	[0.040]	[0.039]	[0.039]	[0.039]
College*Year2018	-0.214***	-0.173***	-0.219***	-0.181***
	[0.037]	[0.036]	[0.037]	[0.036]
Gaokao z-score	0.111***	0.093***	0.100***	0.087***
	[0.014]	[0.014]	[0.014]	[0.013]
Gaokao*Year2013	-0.013	-0.017	-0.013	-0.016
	[0.019]	[0.018]	[0.018]	[0.018]
Gaokao*Year2018	-0.003	-0.001	-0.003	-0.000
	[0.018]	[0.017]	[0.017]	[0.017]
Year2013	0.510***	0.498***	0.501***	0.492***
	[0.034]	[0.034]	[0.034]	[0.034]
Year2018	0.760***	0.731***	0.759***	0.736***
	[0.033]	[0.032]	[0.032]	[0.032]
Male	0.156***	0.149***	0.147***	0.143***
	[0.012]	[0.012]	[0.012]	[0.012]
Occupation	No	Yes	No	Yes
Industry	No	No	Yes	Yes
Observations	9,710	9,650	9,697	9,641
Adjusted R2	0.344	0.367	0.361	0.378

Note: The sample includes all full-time employees with hourly wages between 1 and 100 Yuan per hour and at least a high school degree. The dependent variable is hourly wages (in log term). All regressions control for province fixed effects, as well as a quadratic polynomial in potential experience. The omitted year category is 2007. The occupation and industry code is a compressed version of the classification provided by the National Bureau of Statistics, which enables comparison of the datasets across years. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Column 1 shows that while returns to cognitive skills do not change significantly from 2007 to 2018, returns to college degrees experience a 27.9-percentage-points decline in 2013 (significant at the 1% level), and then rises slightly in 2018. Hence, the dynamics of returns to cognitive skills and returns to college degrees are driven by different forces. I control for occupation information in column 2, industry information in column 3, and include them simultaneously in the specification in column 4. The coefficients of interest do not change a lot, suggesting that the sorting of college-educated workers across occupations and industries is not a critical factor underlying the dynamics of returns to cognitive skills and the college premium, but rather the estimates reflect the overall pattern in the economy.

Regarding the sharp decline of college premium in 2013, a combination of college expansion and the slowdown of economic growth can explain it quite well. As is shown in Figure 3.2, the share of employed workers with a college degree or above starts to rise rapidly after 2009. Meanwhile, the deceleration of economic growth imposes a negative demand shock on the labor market that is illustrated by the decline in the growth rate of per capita GDP (Figure 3.3). The slowdown in the expansion of HS sector, shown in Figure 3.5, suggests that the impact may be larger for industries that demand more skilled labor. The surge in the relative supply of educated workers, combined with the stagnation of product demand, may lead to a depreciation of college degrees. Moreover, changes in the skill composition of college-educated workers due to the expansion, and concerns about the quality of higher education after a surge of enrolled students will also place downward pressure on the college premium.

The fact that the college premium remains quite stable and even shows a small increase from 2013 to 2018 can also be accounted for by changes in the supply and demand forces. Figure 3.1 and Figure 3.2 show that although the college expansion continues after 2013, the growth rates of the number of college graduates and the share of college-educated workers in all employed workers are much lower in recent years. As the labor market adjusts to changes in the composition of labor force, the downward pressure on the college premium may not be as high as before. Meanwhile, the HS sector develops rapidly after 2013 (Figure 3.5), implying a higher relative demand for skilled and college-educated workers. Therefore, the college premium halts its downward trend in recent years.

The magnitude of returns to cognitive skills has been quite comparable to that in OECD (Organization for Economic Co-operation and Development) countries as reported by Hanushek et al. (2015)[10], suggesting that market force is playing a fundamental role in wage determination in China. A further examination in the next section shows that the dynamics of returns to cognitive skills differ between coastal regions and inland regions, which is probably due to differences in the strength of market forces.

5.2 Regional Heterogeneity

The impacts of changes in the economy and labor market generally differ across regions. Thus, investigating regional differences in the dynamics of returns to cognitive skills and the college premium helps us understand the underlying mechanisms. In this section, I will mainly examine how industrial structure, which is a proxy for the relative demand for skilled labor, affects returns to human capital. Specifically, I compare provinces with above- or below-median measures of economic development for the share of the agricultural sector, the industrial sector, the service sector, and the HS sector in regional GDP.[1] Since wage is sticky in the short run, I choose a time window for each survey sample (2002-2006 for the 2007 sample, 2008-2012 for the 2013 sample, and 2014-2017 for the 2018 sample), calculate the average share of GDP that comes from the above four sectors during the three time windows for each province, and then rank provinces according to the obtained figures for each time window. For example, if the value-added share of the HS sector for a province is above the national median for every time window, I classify it as a province with an above-median share of the HS sector in GDP, regardless of whether or not it enters the estimation sample in each year. Similarly, if the value-added share of the HS sector for a province is below the national median for every time window, I classify it as a province with a below-median share of the HS sector in GDP, regardless of whether or not it enters the estimation sample in each year. In this way, I am comparing consistently well-performing provinces with consistently poorly-performing provinces in terms of the value-added share of one specific sector. The hypothesis is that in regions where the service sector and the HS sector account for a larger share of regional GDP, and where the agricultural sector and the industrial sector account for a lower share of regional GDP, the relative demand for skilled workers and educated workers would be higher.

In addition, the extent to which individuals are rewarded for their human capital will likely depend on the degree of marketization in the labor market. Although Section 5.1 suggests that the labor market in China rewards skills as much as those in developed countries do, the development of market forces is likely to differ across regions. Hence, I

[1] Data comes from the National Bureau of Statistics.

also compare coastal and inland provinces, where coastal provinces are considered as more market-oriented regions relative to inland provinces.

Table 5.3 presents the estimation results of Equation 5-2 for each subsample. In columns 1-8, I examine how demand-side factors affect the dynamics of the college premium and returns to cognitive skills. In 2007, the college premium is higher in regions with a higher relative demand for educated workers. The coefficients on the interaction term between college degree and Year 2013 are all significantly negative (except for provinces with a below-median share of the industrial sector in GDP). It implies that the force behind the decline of college premium in 2013 is a nationwide phenomenon, which lends support to the mechanisms I proposed in the previous section. While Table 5.2 suggests that returns to cognitive skills are quite stable over time, a decomposition reveals that returns to cognitive skills rise in regions with a larger service sector or HS sector from 2007 to 2013. Looking at the coefficients on Gaokao z-score, we can see that the return to cognitive skills is higher in less developed regions in 2007, yet it becomes higher in regions that are more economically developed in 2013. Two factors may account for this change. First, the reduction in the signaling value of college degrees may force employers to seek hard-to-observe information about college-educated workers (Altonji and Pierret, 2001)[22], so returns to cognitive skills will be more dependent on local economic conditions. Second, the widening between-region inequality in the development of the HS sector (Figure 3.7) may enlarge the difference in relative demand for skilled workers across regions, and thus returns to cognitive skills increase in regions that are faster in the progress of industrial restructuring. We may expect migration to place some downward pressure on returns to cognitive skills in more developed regions. Nevertheless, the results suggest that the growth in the relative demand for skilled labor in these regions still outpaces the growth in the relative supply of skilled labor.

Column 9 and column 10 show that in 2007, returns to college degrees are higher in more market-oriented regions, and both coastal and inland regions experience a decline in college premium in 2013. The return to cognitive skills in inland regions is higher than that in coastal regions in 2007, yet it declines by one-third in 2013. It could be argued that employers in less market-oriented regions may find it more difficult to assess workers' productivity accurately when there is a surge in the supply of college workers, which leads

Table 5.3 Dynamics of Returns to Cognitive Skills and Returns to College Degrees By Region

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	⩾Median Agri Share	<Median Agri Share	⩾Median Indu Share	<Median Indu Share	⩾Median Serv Share	<Median Serv Share	⩾Median HS Share	<Median HS Share	Coastal	Inland
College	0.541***	0.675***	0.606***	0.505***	0.761***	0.562***	0.710***	0.618***	0.690***	0.542***
	[0.040]	[0.037]	[0.042]	[0.075]	[0.059]	[0.057]	[0.047]	[0.088]	[0.039]	[0.039]
College*Year2013	-0.278***	-0.292***	-0.289***	-0.138	-0.363***	-0.182**	-0.307***	-0.328***	-0.238***	-0.264***
	[0.056]	[0.055]	[0.061]	[0.091]	[0.078]	[0.090]	[0.066]	[0.109]	[0.061]	[0.053]
College*Year2018	-0.158***	-0.255***	-0.128*	-0.108	-0.356***	-0.213**	-0.291***	-0.310***	-0.236***	-0.172***
	[0.053]	[0.052]	[0.067]	[0.087]	[0.073]	[0.096]	[0.062]	[0.110]	[0.059]	[0.049]
Gaokao z-score	0.123***	0.090***	0.098***	0.138***	0.079***	0.123***	0.083***	0.102***	0.083***	0.127***
	[0.020]	[0.019]	[0.022]	[0.035]	[0.028]	[0.025]	[0.023]	[0.038]	[0.020]	[0.019]
Gaokao*Year2013	-0.018	0.001	-0.043	0.014	0.086**	-0.054	0.070**	-0.079	0.039	-0.048*
	[0.027]	[0.026]	[0.029]	[0.041]	[0.035]	[0.041]	[0.030]	[0.051]	[0.027]	[0.025]
Gaokao*Year2018	-0.030	0.037	-0.026	-0.032	0.043	-0.067	0.021	-0.012	0.026	-0.013
	[0.027]	[0.024]	[0.029]	[0.041]	[0.033]	[0.043]	[0.029]	[0.046]	[0.026]	[0.024]
Year2013	0.511***	0.497***	0.563***	0.451***	0.440***	0.491***	0.394***	0.592***	0.425***	0.519***
	[0.049]	[0.048]	[0.052]	[0.082]	[0.069]	[0.076]	[0.062]	[0.094]	[0.053]	[0.046]
Year2018	0.774***	0.717***	0.719***	0.741***	0.697***	0.774***	0.662***	0.813***	0.687***	0.778***
	[0.046]	[0.046]	[0.058]	[0.078]	[0.065]	[0.083]	[0.059]	[0.100]	[0.052]	[0.043]
Male	0.141***	0.165***	0.156***	0.128***	0.148***	0.149***	0.146***	0.177***	0.150***	0.158***
	[0.018]	[0.016]	[0.021]	[0.023]	[0.022]	[0.031]	[0.020]	[0.028]	[0.019]	[0.015]
Observations	4,439	5,021	3,063	2,735	2,996	1,609	3,559	1,978	3,729	5,981
Adjusted R2	0.316	0.353	0.339	0.355	0.321	0.279	0.334	0.261	0.371	0.301

Note: The sample includes all full-time employees with hourly wages between 1 and 100 Yuan per hour and at least a high school degree. The dependent variable is hourly wages (in log term). All regressions control for province fixed effects, as well as a quadratic polynomial in potential experience. The omitted year category is 2007. Columns 1 and 2 are sample of provinces whose average share of GDP that comes from the agricultural sector during a 4- or 5-year period before every survey year is above or below the national median. Similarly, samples in columns 3 and 4, columns 5 and 6, and columns 7 and 8 are classified by the national median share of regional GDP that comes from the industrial sector, the service sector and the HS sector, respectively. Coastal provinces in the estimation sample include Beijing, Shanghai, Hebei, Jiangsu, Zhejiang, Shandong and Guangdong. Inland provinces include Anhui, Henan, Hubei, Chongqing, Sichuan, Shanxi, Liaoning, Hunan, Yunnan, Gansu and Inner Mongolia. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

to a decrease in skill premium.

From 2013 to 2018, regional differences in returns to cognitive skills seem to become smaller, though a similar regression using the year of 2013 as the omitted category shows that both the magnitude and regional distribution of returns to cognitive skills do not change significantly (see Appendix Table A1). Returns to college degrees experience an increase in provinces with a larger agricultural sector or industrial sector. That is, the increase in college premium concentrates in less developed regions. Note that regional inequality in the development of HS sector continues to widen between 2013 and 2017 (Figure 3.7), yet there is no widening difference in returns to cognitive skills, and even a narrowing inequality in returns to college degrees. Thus, a natural hypothesis is that supply-side factors dominate demand-side factors during this period.

On the one hand, college-educated workers' tendency to migrate to more developed regions may restrain the rise of college premium in these regions. Yu and Chen (2020) find that from 2010 to 2016, the migration pattern of college workers in China is quite consistent. The major hosting regions are eastern provinces and western minority provinces, and central provinces and other western provinces are the major sending regions[23]. On the other hand, less developed regions may gradually catch up in economic restructuring. While the average growth rate of the value-added share of HS sector from 2008 to 2012 is higher for provinces with an above-median share of the HS sector in GDP than provinces with a below-median share in terms of the group mean (0.9% and -0.03%, respectively), that from 2014 to 2017 is lower for provinces with an above-median share than for provinces with a below-median share (4.8% and 7.9%, respectively). Combined with a large number of policies in less developed regions that are directed at attracting high-skilled labor, regional inequality in the demand for college-educated workers may narrow in recent years. Migration-induced supply shift and economy-and-policy-induced demand shift together could result in the dynamic pattern of college premium from 2013 to 2018.

The college premium in inland regions also shows an increase in 2018. It is possible that as local governments lay more stress on the role of labor-force quality in economic development, the labor market in inland provinces becomes more market-oriented due to relevant policies.

One remaining puzzle is that returns to cognitive skills do not show the same pattern as the college premium does from 2013 to 2018. One potential explanation could be that the policies that aim to attract skilled labor usually use educational attainment as a criterion for evaluating workers. Thus, college degrees may regain its signaling value in recent years, whereas cognitive skills, which generally take some time to reveal, are less sensitive to these policies.

5.3 Heterogeneity by Gender and Age

Returns to cognitive skills and returns to college degrees may be different for certain subgroups due to different labor-market forces. Therefore, it is natural to examine heterogeneity in the dynamics of returns to human capital for some subsamples. In this section, I compare returns to cognitive skills and returns to college degrees between male workers and female workers, and between young workers and senior workers, and estimate Equation 5-2 for these subgroups separately.

Column 1 and column 2 of Table 5.4 present the estimation results for male workers and female workers, respectively. Returns to college degrees do not differ significantly by gender in 2007. Both male and female workers experience a decline of college premium in 2013, and the fall seems to be larger for male workers. It is similar to Li et al. (2014), which finds that the rise in unemployment for college-educated workers after the college expansion is larger for male workers. However, as they point out, female workers have a higher tendency to work informally when there is a negative shock in the labor market[24]. Thus, solely focusing on the change in returns to college degrees may lead to an underestimation of the impact of college expansion on female workers. The return to cognitive skills is higher for female workers, and it remains stable from 2007 to 2018 both for male workers and female workers.

Column 3 and column 4 report the results for young workers and senior workers, where young workers are defined as workers aged below 35 and senior workers as workers aged above or equal to 35. A comparison shows that returns to college degrees are higher for senior workers. One potential explanation is that college-educated workers may have more advantage on promotion. The decline of college premium in 2013 is larger for young workers. It is quite intuitive because entry-age workers are usually most vulnerable to changes in the labor market. Returns to cognitive skills are higher for young workers. It is inconsistent with returns to cognitive skills in most countries as reported by Hanushek et al. (2015)[10]. It could be argued that the Gaokao score is only a crude measure of cognitive skills. As workers age and job tasks change, skills that are tested by the college entrance examination may not be as rewarding as before, and other aspects of cognitive skills or non-cognitive skills will be of more importance. For both young workers and senior workers, returns to cognitive skills do not change significantly from 2007 to 2018.

Table 5.4: Dynamics of Returns to Human Capital By Gender and By Age

	(1) Male Workers	(2) Female Workers	(3) Young Workers	(4) Senior Workers
College	0.610***	0.610***	0.543***	0.686***
	[0.036]	[0.044]	[0.034]	[0.047]
College*Year2013	-0.318***	-0.229***	-0.330***	-0.249***
	[0.052]	[0.061]	[0.052]	[0.062]
College*Year2018	-0.275***	-0.129**	-0.249***	-0.161***
	[0.049]	[0.057]	[0.046]	[0.061]
Gaokao z-score	0.099***	0.129***	0.127***	0.090***
	[0.018]	[0.022]	[0.020]	[0.019]
Gaokao*Year2013	0.000	-0.033	0.003	-0.018
	[0.024]	[0.029]	[0.026]	[0.026]
Gaokao*Year2018	-0.004	-0.001	0.012	-0.016
	[0.023]	[0.027]	[0.024]	[0.025]
Year2013	0.552***	0.448***	0.546***	0.491***
	[0.045]	[0.054]	[0.046]	[0.052]
Year2018	0.816***	0.678***	0.786***	0.706***
	[0.043]	[0.049]	[0.041]	[0.053]
Male			0.156***	0.147***
			[0.015]	[0.020]
Observations	5,645	4,065	5,616	4,094
Adjusted R2	0.327	0.356	0.346	0.324

Note: The sample includes all full-time employees with hourly wages between 1 and 100 Yuan per hour and at least a high school degree. The dependent variable is hourly wages (in log term). Column 1 and column 2 report estimation results of Equation 5-2 for male workers and female workers, respectively. Column 3 and column 4 report estimation results of Equation 5-2 for young workers and senior workers, respectively. Young workers are those aged below 35 and senior workers are those aged above or equal to 35. The omitted year category is 2007. All regressions control for province fixed effects, as well as a quadratic polynomial in potential experience. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

5.4 Summary of the Section

In this section, I first examine returns to cognitive skills and college degrees in China by year, and compare the estimates to previous literature. Next, I investigate the dynamics of returns to cognitive skills and college degrees from 2007 to 2018, and explore their regional differences. Changes in the labor market and the economy, as well as the innate differences between the attainment of college degrees and cognitive skills, help explain the different time patterns of returns to cognitive skills and college degrees. Finally, I examine heterogeneity in the dynamics of both returns by gender and by age.

6 Conclusions

6.1 Main Results and Implications

This thesis documents the evolution of returns to cognitive skills, measured by Gaokao z-score, and returns to college degrees in China from 2007 to 2018 using three waves of CHIP survey (2007, 2013, and 2018). I find that the college premium suffers a substantial depreciation from 2007 to 2013, and rises slightly in 2018. Meanwhile, the skill premium does not change significantly from 2007 to 2018. A further examination by region shows that the decline in returns to college degrees in 2013 is a nationwide phenomenon, and the dynamics of returns to cognitive skills from 2007 to 2013 differ across regions, with the skill premium rising in more developed regions and declining in less market-oriented regions. I attribute these changes to a combination of higher education expansion, slowdown of economic growth and regional differences in the pace of industrial transformation. In the latter period, most of the rise in the college premium concentrates in less developed and less market-oriented regions, and both the magnitude and regional distribution of the skill premium remain quite stable during this period. It is rather difficult to pin down the exact mechanisms underlying changes in both returns for this period, but possible factors include the labor market's adjustment to the surge in college-educated workers, the expansion of industries that demand more skilled labor, development strategies in less developed regions, and skilled workers' migration towards more developed regions. I also conduct a crude examination of the dynamics of both returns for some subgroups. There is no significant heterogeneity in the overall patterns by gender and by age.

One thing to note is that the different time patterns of returns to cognitive skills and college degrees are essentially driven by fundamental differences between cognitive skills and the attainment of college degrees as proxies of human capital, cognitive skills being a more accurate measure than college degrees for individual skills. Furthermore, college degrees raise earnings partly through employer screening, but cognitive skills are generally harder to observe in real life. Therefore, as this study suggests, the emphasis will shift to cognitive skills if there is a shock to the signaling value of college degrees. This generates some implications for current college students, especially in this special time when there is about to be a massive expansion of master and doctoral programs. Though the effect of this policy on returns to education will only emerge a few years down the road, reflecting on the plunge of the college premium from 2007 to 2013 helps us understand its potential consequences. To adapt to the labor market that is full of uncertainty, more effort is needed to expand our skill sets and improve our competence.

6.2 Limitations of the Study

Several issues in this study are worth further discussion. First, the estimation of returns to human capital is beset by a number of difficulties. The endogeneity problem is a long-discussed issue, but this study does not focus on addressing it. As robustness checks, I additionally control for maternal education when estimating Equation 5-2 (Appendix Table A2 and Table A3), both the overall pattern and regional patterns are similar to those reported in Table 5.2 and Table 5.3. Also, the Gaokao score is clearly not a perfect measure of cognitive skills, so the measurement error could bias the results as well. Furthermore, the self-reported Gaokao score could generate selection biases. Better econometric methods are needed to produce more accurate estimates of returns to human capital. Nevertheless, since this study focuses on the dynamics of returns to human capital rather than the cross-sectional estimates, these problems may not affect my main results greatly. Second, quantifying the importance of various forces underlying the dynamics of returns to cognitive skills and college degrees is beyond the scope of this study. A rigorous analysis of the proposed mechanisms in this study would be an important topic for further research. Third, the study only focuses on workers with at least a high school degree, so the results cannot be generalized for the entire labor force, and other mechanisms may be omitted in this study. For example, as Bai et al. (2020) suggests, changes in the high school premium from 2009 to 2012 are primarily due to preferential lending policies of local governments[20]. Further studies may be done to exploit better measures of cognitive skills and broaden the research subject.

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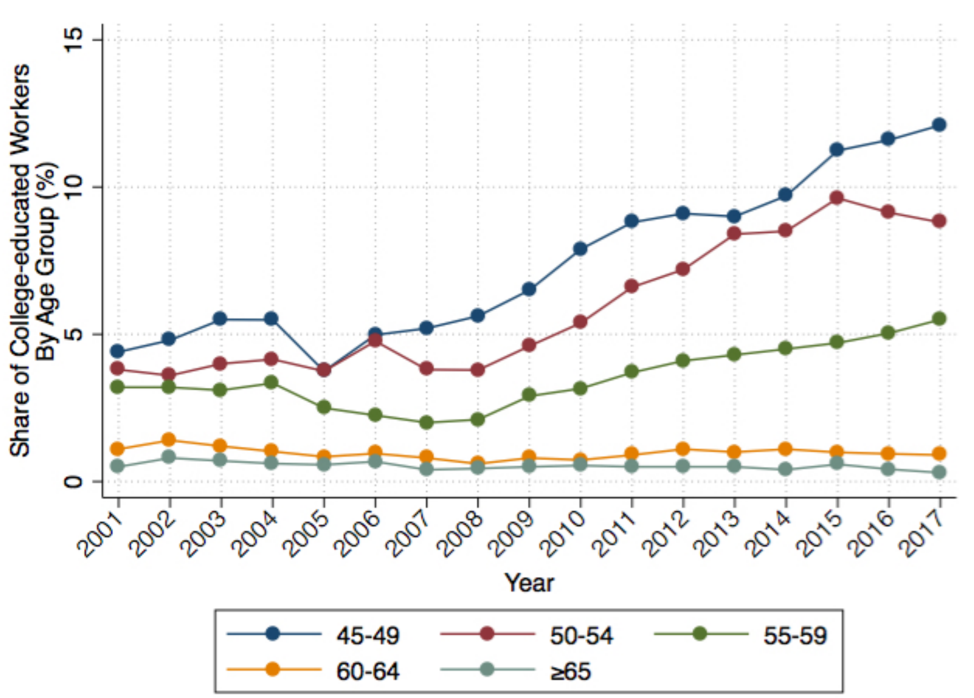
APPENDIX



Note: The figure depicts the share of employed workers with a college degree or above for age groups 45-49, 50-54, 55-59, 60-64, and 65 and above from 2001 to 2017. Data comes from the China Labor Statistics Yearbook.

Figure A1: Share of Workers with a College Degree or Above By Age

Table A1: Dynamics of Returns to Cognitive Skills and Returns to College Degrees By Region

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	⩾Median Agri Share	<Median Agri Share	⩾Median Indu Share	<Median Indu Share	⩾Median Serv Share	<Median Serv Share	⩾Median HS Share	<Median HS Share	Coastal	Inland
College	0.263***	0.383***	0.317***	0.367***	0.398***	0.379***	0.402***	0.290***	0.452***	0.277***
	[0.039]	[0.041]	[0.045]	[0.052]	[0.050]	[0.070]	[0.047]	[0.065]	[0.048]	[0.036]
College*Year2007	0.278***	0.292***	0.289***	0.138	0.363***	0.182**	0.307***	0.328***	0.238***	0.264***
	[0.056]	[0.055]	[0.061]	[0.091]	[0.078]	[0.090]	[0.066]	[0.109]	[0.061]	[0.053]
College*Year2018	0.120**	0.037	0.161**	0.029	0.007	-0.031	0.016	0.018	0.002	0.092**
	[0.052]	[0.054]	[0.068]	[0.065]	[0.064]	[0.103]	[0.060]	[0.089]	[0.064]	[0.046]
Gaokao z-score	0.105***	0.092***	0.055***	0.152***	0.165***	0.070**	0.153***	0.023	0.122***	0.079***
	[0.018]	[0.017]	[0.019]	[0.020]	[0.021]	[0.032]	[0.019]	[0.033]	[0.019]	[0.017]
Gaokao*Year2007	0.018	-0.001	0.043	-0.014	-0.086**	0.054	-0.070**	0.079	-0.039	0.048*
	[0.027]	[0.026]	[0.029]	[0.041]	[0.035]	[0.041]	[0.030]	[0.051]	[0.027]	[0.025]
Gaokao*Year2018	-0.011	0.036	0.017	-0.046	-0.043	-0.014	-0.050*	0.068	-0.013	0.034
	[0.026]	[0.022]	[0.027]	[0.028]	[0.027]	[0.048]	[0.026]	[0.042]	[0.025]	[0.022]
Year2007	-0.511***	-0.497***	-0.563***	-0.451***	-0.440***	-0.491***	-0.394***	-0.592***	-0.425***	-0.519***
	[0.049]	[0.048]	[0.052]	[0.082]	[0.069]	[0.076]	[0.062]	[0.094]	[0.053]	[0.046]
Year2018	0.262***	0.221***	0.156***	0.291***	0.256***	0.283***	0.268***	0.221***	0.262***	0.259***
	[0.046]	[0.048]	[0.058]	[0.059]	[0.056]	[0.088]	[0.053]	[0.077]	[0.057]	[0.041]
Male	0.141***	0.165***	0.156***	0.128***	0.148***	0.149***	0.146***	0.177***	0.150***	0.158***
	[0.018]	[0.016]	[0.021]	[0.023]	[0.022]	[0.031]	[0.020]	[0.028]	[0.019]	[0.015]
Observations	4,439	5,021	3,063	2,735	2,996	1,609	3,559	1,978	3,729	5,981
Adjusted R2	0.316	0.353	0.339	0.355	0.321	0.279	0.334	0.261	0.371	0.301

Note: The sample includes all full-time employees with hourly wages between 1 and 100 Yuan per hour and at least a high school degree. The dependent variable is hourly wages (in log term). All regressions control for province fixed effects, as well as a quadratic polynomial in potential experience. The omitted year category is 2013. Columns 1 and 2 are sample of provinces whose average share of GDP that comes from the agricultural sector during a 4- or 5-year period before every survey year is above or below the national median. Similarly, samples in columns 3 and 4, columns 5 and 6, and columns 7 and 8 are classified by the national median share of regional GDP that comes from the industrial sector, the service sector and the HS sector, respectively. Coastal provinces in the estimation sample include Beijing, Shanghai, Hebei, Jiangsu, Zhejiang, Shandong and Guangdong. Inland provinces include Anhui, Henan, Hubei, Chongqing, Sichuan, Shanxi, Liaoning, Hunan, Yunnan, Gansu and Inner Mongolia. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Table A2: Dynamics of Returns to Cognitive Skills and Returns to College Degrees

	(1)	(2)	(3)	(4)
College	0.583***	0.487***	0.557***	0.485***
	[0.029]	[0.029]	[0.029]	[0.029]
College*Year2013	-0.285***	-0.252***	-0.279***	-0.248***
	[0.042]	[0.042]	[0.041]	[0.041]
College*Year2018	-0.280***	-0.232***	-0.286***	-0.243***
	[0.051]	[0.050]	[0.051]	[0.050]
Gaokao z-score	0.103***	0.088***	0.095***	0.084***
	[0.015]	[0.015]	[0.015]	[0.014]
Gaokao*Year2013	-0.016	-0.020	-0.016	-0.019
	[0.020]	[0.019]	[0.019]	[0.019]
Gaokao*Year2018	0.009	0.009	0.007	0.008
	[0.024]	[0.023]	[0.023]	[0.023]
Year2013	0.523***	0.510***	0.509***	0.501***
	[0.037]	[0.037]	[0.036]	[0.036]
Year2018	0.761***	0.729***	0.757***	0.733***
	[0.046]	[0.045]	[0.045]	[0.045]
Male	0.138***	0.139***	0.124***	0.127***
	[0.015]	[0.015]	[0.015]	[0.015]
Occupation	No	Yes	No	Yes
Industry	No	No	Yes	Yes
Maternal Education	Yes	Yes	Yes	Yes
Observations	6,261	6,210	6,250	6,202
Adjusted R2	0.315	0.337	0.333	0.349

Note: The sample includes all full-time employees with hourly wages between 1 and 100 Yuan per hour and at least a high school degree. The dependent variable is hourly wages (in log term). All regressions control for province fixed effects, maternal education, as well as a quadratic polynomial in potential experience. Maternal education are dummy variables that capture the educational attainment of the individual's mother, corresponding to below middle school education, middle school education, high school education and above higher education, respectively. The omitted year category is 2007. The occupation and industry code is a compressed version of the classification provided by the National Bureau of Statistics, which enables comparison of the datasets across years. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Table A3: Dynamics of Returns to Cognitive Skills and Returns to College Degrees By Region

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	⩾Median Agri Share	<Median Agri Share	⩾Median Indu Share	<Median Indu Share	⩾Median Serv Share	<Median Serv Share	⩾Median HS Share	<Median HS Share	Coastal	Inland
College	0.535***	0.639***	0.569***	0.513***	0.737***	0.550***	0.684***	0.592***	0.658***	0.528***
	[0.043]	[0.039]	[0.045]	[0.080]	[0.058]	[0.061]	[0.048]	[0.091]	[0.040]	[0.041]
College*Year2013	-0.285***	-0.304***	-0.295***	-0.154	-0.343***	-0.182*	-0.281***	-0.299***	-0.250***	-0.272***
	[0.060]	[0.059]	[0.066]	[0.098]	[0.080]	[0.099]	[0.069]	[0.112]	[0.067]	[0.055]
College*Year2018	-0.266***	-0.288***	-0.209**	-0.193*	-0.394***	-0.138	-0.323***	-0.358**	-0.274***	-0.269***
	[0.072]	[0.072]	[0.101]	[0.104]	[0.091]	[0.153]	[0.080]	[0.157]	[0.082]	[0.066]
Gaokao z-score	0.121***	0.081***	0.100***	0.145***	0.062**	0.119***	0.073***	0.094**	0.071***	0.124***
	[0.022]	[0.020]	[0.022]	[0.040]	[0.030]	[0.028]	[0.025]	[0.040]	[0.022]	[0.020]
Gaokao*Year2013	-0.017	-0.007	-0.051*	-0.006	0.084**	-0.062	0.061*	-0.107**	0.036	-0.054**
	[0.029]	[0.026]	[0.030]	[0.045]	[0.037]	[0.047]	[0.032]	[0.050]	[0.029]	[0.026]
Gaokao*Year2018	0.016	0.037	-0.013	0.004	0.079*	-0.089	0.053	-0.040	0.026	0.020
	[0.038]	[0.030]	[0.037]	[0.053]	[0.045]	[0.068]	[0.040]	[0.064]	[0.033]	[0.033]
Year2013	0.515***	0.525***	0.608***	0.417***	0.398***	0.483***	0.354***	0.612***	0.457***	0.527***
	[0.053]	[0.052]	[0.057]	[0.093]	[0.071]	[0.084]	[0.066]	[0.098]	[0.059]	[0.048]
Year2018	0.818***	0.675***	0.734***	0.714***	0.638***	0.656***	0.603***	0.813***	0.649***	0.810***
	[0.065]	[0.065]	[0.090]	[0.095]	[0.082]	[0.136]	[0.076]	[0.143]	[0.072]	[0.060]
Male	0.115***	0.153***	0.117***	0.117***	0.156***	0.124***	0.152***	0.111***	0.154***	0.126***
	[0.022]	[0.020]	[0.024]	[0.030]	[0.028]	[0.036]	[0.025]	[0.035]	[0.023]	[0.019]
Maternal Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,991	3,221	2,115	1,675	1,910	1,121	2,359	1,147	2,470	3,791
Adjusted R2	0.283	0.330	0.308	0.345	0.322	0.267	0.325	0.209	0.357	0.264

Note: The sample includes all full-time employees with hourly wages between 1 and 100 Yuan per hour and at least a high school degree. The dependent variable is hourly wages (in log term). All regressions control for province fixed effects, maternal education, as well as a quadratic polynomial in potential experience. Maternal education are dummy variables that capture the educational attainment of the individual's mother, corresponding to below middle school education, middle school education, high school education and above higher education, respectively. The omitted year category is 2007. Columns 1 and 2 are sample of provinces whose average share of GDP that comes from the agricultural sector during a 4- or 5-year period before every survey year is above or below the national median. Similarly, samples in columns 3 and 4, columns 5 and 6, and columns 7 and 8 are classified by the national median share of regional GDP that comes from the industrial sector, the service sector and the HS sector, respectively. Coastal provinces in the estimation sample include Beijing, Shanghai, Hebei, Jiangsu, Zhejiang, Shandong and Guangdong. Inland provinces include Anhui, Henan, Hubei, Chongqing, Sichuan, Shanxi, Liaoning, Hunan, Yunnan, Gansu and Inner Mongolia. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

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