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ABSTRACT

The dramatic expansion of the education system and the transformation of the economy in China provide an opportunity to investigate how the labor market rewards skills. Between 2007 and 2018, the overall return to cognitive skills is virtually constant at 10%, whereas the college premium drops steeply by more than 20 percentage points. But, the regional differences in returns are significant and highlight the importance of differential demand factors. College returns are higher in more developed regions, but the declining trend is more pronounced. Returns to cognitive skills increase in more developed regions and decrease in less developed regions.

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1. Introduction

The simplest economic model suggests that rapidly expanding educational attainment would force relative wages of college workers down as they become more plentiful. But this *ceteris paribus* statement must obviously be balanced by changes in demand. Understanding this balance has been the subject of a variety of investigations in the United States, but the rather smooth transitions of both education and technology have made reconciliation of these influences difficult.[1] In contrast, the dramatic policy-driven changes in college availability and in industrial structure in 21st century China offer a clearer view of how the supply and demand factors play out in the labor market. Importantly, the full interplay can still be obscured by the regional complexity of Chinese labor markets.

China experienced fast growth in both supply of and demand for skills over the past two decades. The expansion of the higher education sector led to a sharp increase in college graduates and hence the supply of skilled labor since the early 2000s. But, the economy also experienced unprecedented growth, particularly among the high-skilled sectors. The overall effect on the labor market returns to skills has yet to be fully analyzed, in part because of various measurement issues.

In spite of the central importance of skills in such an investigation, measures of skills have not been readily available. While school attainment is widely available in survey data, skill measures are not. Using school attainment to gauge returns to skills can, however, be quite misleading in economies experiencing large-scale school expansions. Expansion may be accompanied by concurrent changes in the ability distribution of students across education groups and in the resources allocated to different educational sectors. Therefore, a more direct measure of skills is essential.

In this paper we construct a longitudinal database that allows us to estimate the time path of returns to both cognitive skills and educational attainment in contemporary China. We use two complementary datasets. The Chinese Household Income Project (CHIP) for 2007, 2013, and 2018 contain data on college entrance exam (Gaokao) scores for high-school and college graduates. With these data, we estimate trends in the returns to a college degree and to cognitive

[1] In the U.S., the early suggestion of falling relative wages of more educated workers (Freeman 1976) was reconciled with the subsequent rise in college wages by notions of skill-biased technology change (Goldin and Katz 2007).

skills over a period of more than a decade during which the Chinese economy experienced tremendous transformations, both in overall economic growth and in the structure of the economy. The China Family Panel Studies (CFPS) for 2014 provides measures of basic cognitive skills for individuals of all education levels that allow us to compare labor market returns to skills in China with those in other countries.

On a nationwide basis, estimates of the return to cognitive skills controlling for college degree remain quite stable at 10% for full-time workers with at least a high school degree from 2007 to 2018. But, over the same time period, the college premium relative to high school graduation declines sharply by over 20 percentage points. For all three waves of the CHIP data, the return to cognitive skills is weakly higher for female and younger workers, while the return to a college degree is significantly higher for older workers. For all demographic groups, the decline in the return to a college degree from 2007 to later years is salient.

Turning to regional data, however, brings the overall picture into sharper focus. Continued increases in the supply of college-educated workers combined with the growth of the high-skilled sector in the economy and hence increases in the demand for high-skilled workers can explain the trend in the returns to a college degree and cognitive skills. The college premium declines from 2007 to 2018 in both more and less developed regions, but only in the most developed region (Beijing, Shanghai, Zhejiang, Guangdong) is the decline monotonic. This is likely due to disproportionate increases in the supply of college-educated workers in this region that offset the upward pressure on wages from the increases in the demand for more educated workers following the growth of the high-skilled sector.

The trend in skill premium estimated on national data masks a strong regional disparity. The return to cognitive skills increases from 2007 to later years in the more developed region, but weakly decreases in the less developed region, consistent with the growth pattern of the high-skilled sector and the corresponding demand for skills in the two regions.

We can also directly compare these returns to what is observed more broadly in developed countries. The return to cognitive skills we estimate from the CHIP survey of 2013 and CFPS survey of 2014 are both comparable to estimates from surveys data collected between 2011 and 2012 for a large number of OECD countries. In all three cases, the return to cognitive skills is around 20 percent without controlling for schooling and drops to about 10 percent once schooling is controlled for; this holds for both the sample of individuals of all education levels

(CFPS 2014 in the Chinese case) and that of individuals with at least a high school education.[2] This comparability across different data sets for a particular time period is reassuring, and the comparability to estimates for OECD countries also sheds light on the progression of the market-oriented reforms of the Chinese labor market in general.

2. Related Research

This paper is related and contributes primarily to two strands of the literature.

2.1 Trends in returns to schooling

The dynamic pattern of returns to skills has received much research attention as it reflects important aspects of changes in the labor market. The bulk of the literature on this subject uses years of schooling or education degrees as measures of skills (Katz and Murphy 1992; Zhang, Zhao, Park, Song 2005; Goldin and Katz 2007 to name just a few). Yet years of schooling only captures a part of the determinants of cognitive skills, and other sources of skill formation have been left out including individual ability, family input, and school quality itself. Focusing only on the quantity of schooling can be particularly troublesome in a dynamic context due to the varying quality of education as well as the changing skill distribution within each educational group.

Some research recognizes and attempts to deal with this measurement issue via decomposition analyses. Decomposition analyses explain the variance in earnings with changes in the distribution of observed skills, such as education and experience, and their prices, and with the residual variance including changes in the distribution of unobserved skills and their prices. Essentially, skills formed through channels other than schooling are included in the unobserved component. The unobserved component of skills is found to be crucial in explaining earnings inequality, both within education groups (Juhn, Murphy, and Pierce 1993; Meng, Shen, Xue 2013) and between education groups (Carneiro and Lee 2011). For instance, Carneiro and Lee (2011) find that college premium in the United States over the period of 1960-2000 would be 6 percentage points higher (compared to an increase of 40 percentage points) if decreases in the quality of college graduates are taken into account.

The consensus of these studies is that we need variations in both the supply and demand sides to explain the observed trend in returns to observed skills (schooling) and unobserved

[2] Guido Schwerdt kindly provided us with estimates for the sample of individuals with at least a high school education for OECD countries using the PIAAC data.

skills. A surge in the supply may put a direct downward pressure on the return to a college degree, but the gradual rise in demand help maintain or even increase the price of unobserved skills. Therefore, the college premium and the return to cognitive skills may not move in parallel, and comparing their movements will provide a better understanding of changes in the labor market.

Nevertheless, investigating returns to unobserved skills still poses a challenge in these studies since it is difficult to disentangle the price and the distribution of unobserved skills in the residual component. Our strategy is to isolate some components from the unobserved skills with a direct measure of cognitive skills. We use repeated cross-sectional data that contain information on both education attainment and cognitive skill measures for high school and college graduates. This provides a very rare opportunity to study the trend in returns to skills.

2.2 Returns to cognitive skills

Studies on returns to cognitive skills usually use cross-sectional data for a particular point of time and focus on OECD countries due to data availability (Hanushek, Schwerdt, Wiederhold, and Woessmann 2015; Lindqvist and Ronie 2011). Hanushek and Woessmann (2008) review early studies for a few developing countries, but evidence on developing economies continues to be scarce. A few recent studies estimate returns to cognitive skills in China, but they either use coarse measures of skills or data with limited population coverage. Knight, Deng, and Li (2017) draw on the urban sample of CHIP 2002 and 2007 and use self-reported quintiles of high school performance in both waves and Gaokao score (unadjusted) in 2007 to measure quality of education, essentially, actual skills of individuals. They find positive and significant returns to both measures. Glewwe, Huang, and Park (2017) use longitudinal survey data of rural children in Gansu Province, one of China's least developed provinces, and find no significant explanatory power of childhood cognitive skills for wages at the very early stage of the labor market once years of schooling is controlled for. Using a new wave of data from the same survey, however, Glewwe, Song, and Zou (2022) find a positive return to cognitive skills for adults in their late 20s even after conditioning on years of schooling. Employer learning and frictions in job search are proposed as possible explanations for the discrepancy between these two studies, but the limited sample size does not allow for a formal test of these hypotheses.

This paper employs recent data for representative samples of the Chinese population working in the waged sector, which allows us to estimate the return to cognitive skills in China at large. The sample size is sufficiently large to allow us to explore the heterogeneity in the return from various perspectives. Additionally, our data cover the time period comparable to studies of OECD countries (Hanushek et al. 2015, 2017), which may serve as a benchmark for our results. Juxtaposing these results provides new insights regarding the development of China's labor market in comparison to that of the more developed countries.

While there is a growing number of studies on the return to cognitive skills, research on *trends* in this returns is still rare. Murnane, Willett, and Levy (1995) study returns to cognitive skills for two cohorts of U.S. high school graduates by age 24 and find greater importance of skills in the 1980s than the 1970s, where skills are measured by test scores on elementary mathematical concepts conducted in the high school senior year. Using NLSY 1979 and 1997 data, Castex and Dechter (2014) find that returns to cognitive skills measured by the AFQT score decline by 30%-50% between 1980s and 2000s for the 18-28 year olds, which they attribute to differences in the growth rate of technology between the two periods. Both papers focus on workers in the early stage of their careers in the US. Edin, Fredriksson, Nybom, and Öckert (2022) document that the return to non-cognitive skills roughly doubles while the return to cognitive skills remains relatively stable between 1992 and 2013 for Swedish male workers aged 38-42. This paper adds to the literature by documenting trends in the skill premium in one of the largest developing economies over a ten-year period and for workers in a wide range of career stages.

3. Changing Chinese Labor market

The labor market in China has undergone substantial changes entering the new millennium. In this section, we describe major changes in the supply and demand sides that are likely to have lasting impacts on the returns to a college degree and to cognitive skills.[3]

The most important development on the supply side is the higher education expansion started in 1999. Nationwide, college admissions increased by over 40 percent in both 1999 and 2000, and continued to grow at more than 10 percent per year through 2005.[4] Because the vast majority of college students finish their study on time, the number of college graduates grows dramatically, from one million in 2000 to 8.1 million in 2018 (Figure 1). The growth rate of

[3] Major reforms that transformed the labor market from one of centrally-planned to one of market-oriented occurred in the 1990s, and the institutional changes virtually completed by the early 2000s. See, for example, Meng et al. (2013) and Ge et al. (2021).

[4] See Che and Zhang (2018) for a more detailed description of the reform of the higher education system.

college completion is the highest in 2003 (40.2 percent), when the first cohort of students admitted to college under the expansion regime graduated, and it stabilized at around 3 percent in recent years. Overall, the supply of college-educated and skilled workers has grown continuously in the past decade.

The most prominent changes on the demand side are the slowdown of the economic growth and the transition of the economic structure, in particular, post of the 2008 global economic recession. As can be seen from Figure 2, while per capita GDP has grown steadily and more than quadrupled over the past two decades,[5] the annual growth rate plunged in 2008 from an all-time high of close to 14 percent in large part due to the recession. It recovered moderately by 2010 thanks to the quick implementation of the Four-Trillion Yuan stimulus package, but the annual growth rate started a downward trend afterwards and stayed at slightly above 6 percent in recent years.

The recession and the ensuing slowdown of the economic growth prompted the central government to intensify the effort to push the transition of the economic growth from relying on heavy usage of natural resources and raw labor to being driven by innovation and adoption of frontier, more skill-biased technologies. In 2008 and subsequent years the State Council issued a series of guiding opinions regarding the upgrade of the industrial structure and measures to promote the transition such as project approval, bank loans, and tax subsidies.[6] Particularly emphasized is the upgrade of the producer service sectors including logistics, information technology, financing and leasing, research and development, business consulting, and so forth. The shift in the economic structure in the 2010s is salient. While the share of national GDP accounted for by the industrial sector was around 46 percent in the 2000s, it declined steeply after 2011. Mirroring these changes, while the size of the service sector lagged behind the industrial sector in the entire 2000s, it started to grow faster after 2008 and accelerated further in 2012. By 2019, the service sector accounted for a dominant 54% of the national GDP, compared to 39% by the industrial sector (Figure 3).

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[5] Per capita GDP measured in constant 2000 Yuan is 7,912 Yuan and 35,006 Yuan in 2000 and 2018 respectively.
[6] Examples of the State Council policy documents include Opinions of the General Office of the State Council on Implementation of Several Policies and Measures for Accelerating the Development of the Service Industry (2008), Guiding Opinions of the General Office of the State Council on Financial Support to Economic Structure Adjustment, Transformation and Upgrading (2013), Guiding Opinions of the State Council on Accelerating the Development of Producer Services and Promoting the Adjustment and Upgrading of Industrial Structure (2014), Made in China 2025 (2015). All documents can be accessed at the State Council website.

The expansion of the service sector in general tends to raise the demand for skilled labor, but clearly industries within the service sector vary substantially in the high-skilled share, ranging from 8.2 percent to 69.8 percent. The service sector includes both industries intensive in the employment of high-skilled workers such as finance and information and communication technology (ICT) and industries employing primarily low-skilled labors such as wholesale and retail and food services. To draw a more precise picture of the industrial structure and relative demand for skilled workers, we directly classify industries by the share of high-skilled employees, i.e., those with at least a 3-year college degree. Table 1 reports the share of high-skilled workers for each industry in 2017.[7]

We define high-skilled (HS) sector as industries whose nationwide share of high-skilled workers is above 30% in 2017, and low-skilled (LS) sector as industries employing less than 30% of high-skilled workers in 2017. Figure 4 depicts the per capita value-added and share in GDP of the HS and LS sectors.[8] Between 2000 and 2018, the per capita value-added of the HS sector experience a five-fold increase, from 1,808 Yuan to 9,392 Yuan measured in constant 2000 Yuan, whereas that of the LS sector grows much slower, from 6,050 Yuan to 20,670 Yuan. With the exception between 2009 and 2011, the growth rate of per capita value-added of the HS sector is quite stable at around 8 percent annually, but that of the LS sector decelerates to 5.8 percent after 2013, from 8.8 percent previously. Similar to Figure 3, HS sector's value-added share in GDP increases substantially from 23% in 2000 to 37% in 2018, with a corresponding decline of the LS sector.

As a result of both the increase in college graduates and the structural changes of the Chinese economy, the share of employed workers with at least a 3-year college education rises from 5.6 percent in 2001 to 19.1 percent in 2018 (Figure 5). Note that this share began to increase rapidly only after 2009, perhaps because although the growth rate of college graduates is high at the start of the expansion, the stock of college-educated workers in the labor force is still too small to substantially change the composition of the labor force.[9]

[7] Data come from the China Population and Employment Statistics Yearbook.

[8] Since the National Bureau of Statistics of China does not separately report the value-added of Production and Supply of Electricity, Heat, Gas, and Water industry (in the industrial sector), it is included in the low-skilled sector, even though it has 40.1% of high-skilled employees. For the same reason, Management of Water Conservancy, Environment and Public Infrastructure industry (24.9% of high-skilled employees) and Residential and Household Services industry (12.2% of high-skilled employees, both in the service sector) are included in the high-skilled sector.

[9] China's mandatory retirement age of formal sector employees varies with occupation; in general, occupations that tend to be filled by less-educated workers (for example, physically strenuous occupations) have an earlier retirement

China is a large country of tremendous regional heterogeneity, manifested also in the development of the HS sector. Figure 6 illustrates the evolution of the value-added of the HS sector by province from 2007 to 2017 (see Appendix Table A1 for the exact values).[10] Not only has the HS sector expanded over time nationwide, but the regional disparity has also grown considerably. Eastern regions have already shown advantages in the development of the HS sector in 2007, and the advantage has enlarged over time. Meanwhile, some provinces in the western and central parts of China, including Sichuan, Hunan, Hubei, Henan, and Hebei, also catch up rapidly. Nevertheless, the majority of the western and central regions experiences a much slower transition to a skill-intensive economy. For example, the value-added of the HS sector in Jiangxi Province (in the central region) increases from 85 billion Yuan in 2007 to 271 billion Yuan in 2017; meanwhile that of its neighboring Zhejiang Province (on the coast) has grown from 363 billion Yuan to 1,008 billion Yuan. Holding the relative labor supply equal, skilled workers in regions with a larger HS sector will likely enjoy a higher skill premium due to a greater relative demand for skills. At the same time, regions with a higher price for skills will likely attract more skilled workers, attenuating to some extent the skill premium. Which force dominates is intrinsically an empirical question.

4. Data and Empirical Framework

We employ two complementary data sets for the empirical analysis: The Chinese Household Income Project (CHIP) data and the China Family Panel Studies (CFPS) data. Both data are high-quality, nationally representative and have been widely used by researchers to study China's social and economic issues.[11] They both contain rich information on individual characteristics including age, gender, educational attainment, and family background, and current labor market activities such as annual salary, working hours, industry, and occupation.

One unique feature of these two data sets that is particularly valuable for our study is that they both contain cognitive skill measures for individuals. The CHIP data contain the college entrance exam (Gaokao) scores for high school and college graduates since the 2007 wave; they

age. Appendix Figure A1 shows that the share of older workers (aged 45-60) with a college degree or above have increased steadily since 2007, partially contributing to the pattern observed in Figure 5.

[10] We choose three time points (2007, 2013, and 2017) to match the years of data for the empirical analysis. Using 2018 would be preferable, but data on value-added of HS sector in 2018 is not yet available.

[11] Examples that use CHIP data include Wei and Zhang (2011), Nakamura, Steinsson, and Liu (2016), and Sun and Zhang (2020); examples that use CFPS data are Bai and Wu (2020), Ong, Yang, and Zhang (2020), and Fan, Yi, and Zhang (2021). Zhou (2014) uses both data sets.

are repeated cross-sections, enabling us to use the 2007, 2013, and 2018 waves to estimate the trends of returns to a college degree and cognitive skills. The CFPS data are longitudinal, collected initially in 2010 and biennially thereafter; it contains scores on basic literacy tests (math and word) administered to all individuals aged 10 and above regardless of their education level. We use the adult sample of the 2014 wave, which allows us to compare estimates with both those from the 2013 CHIP data and those of recent international studies (Hanushek et al. 2015).

4.1 Cognitive skill measures in CHIP 2007, 2013, 2018 and CFPS 2014

The 2007, 2013 and 2018 waves of the CHIP survey elicit self-reported information on individuals' college entrance exam (Gaokao) scores. Gaokao is one of the most important educational institutions in China. It is administered nationwide in the early summer each year to high school graduates in the academic track, whose eligibility for college admissions is virtually entirely determined by their Gaokao score. Students with Gaokao scores above a threshold are eligible for 4-year universities, and those with scores above a lower threshold may be admitted to a 3-year college. The raw Gaokao scores differ by year-province-subject track (sciences v. humanities) and are not directly comparable.[12] Following Démurger, Hanushek, and Zhang (2019), we normalize them in two steps. First, because the maximum possible score varies with the specific test, we divide individual scores by the maximum possible score of each specific test.[13] Assuming that the population distributions of Gaokao scores are comparable over time and across provinces and subjects, we then convert this percentage score into a z-score with a mean of zero and a standard deviation of one. The normalization is performed for the entire sample of individuals reporting the Gaokao score regardless of their current work status. While the assumption of a common distribution across provinces is strong and untested, it is unlikely to affect our empirical results. All of our estimates below include province fixed effects so that the comparisons are restricted to within-province comparisons.[14] In the regression analyses we use

[12] The college entrance exams are based on a national education curriculum. With the approval of the Ministry of Education, a province may choose to write its own tests, which may have different maximum possible scores from the national tests and from tests of other provinces.

[13] For example, the maximum possible score was 640 for the humanity-oriented test and 710 for the science-oriented test in 1989 for all provinces. It changed to 750 in 1994 for both tests nationwide. Starting in 1999, several provinces, such as Fujian, Guangdong, Shaanxi, and Hainan adopted different tests with a maximum possible score of 900 for both tests. There are larger cross-province variations in more recent years as more provinces started to experiment different test regimes. The maximum possible score is obtained from various Gaokao-related websites such as http://edu.sina.com.cn/Gaokao/. It is missing for a small number of years and provinces, and individual observations are therefore dropped for these years and provinces.

[14] For a small number of individuals, the current province of residence may not be the same province where they

the Gaokao z-score as a measure of individual cognitive skills; we however do not presume that they fully capture productivity differences among individuals.

One important advantage of using Gaokao score as the skill measure is that it is assessed before individuals enter the labor market. Thus it does not suffer from the reverse causality issue that may confound estimates using skill measures concurrent with wages. Meanwhile, Gaokao score has special features that may limit the comparability of our analyses to existing studies. First, Gaokao score is only available for college graduates and high school graduates in the academic track, limiting the population under study. Second, Gaokao is a high-stake test, on which students may exert more efforts to perform well; hence it may better reflect student capability and be more closely related to future labor market outcomes. Third, Gaokao is highly academic and abstract, and the extent to which this type of skill is valued in the labor market may be different from basic and more practical skills. We therefore employ the CFPS data for complementary analyses.

The 2014 CFPS survey administered math and word tests to all individuals aged 10 or above to assess their cognitive ability. Test questions are based on the national curriculum of the basic education (Grades 1-12). Math problems include addition, subtraction, multiplication, division, logarithms, trigonometric functions, sequence, permutation and combination, etc. In the word test, individuals are asked to read aloud Chinese characteristics presented to them. For both tests, questions are ordered from the easiest to the hardest, and the test score is assigned as the question number of the most difficult problem an individual has correctly answered. Since curriculums have changed over time, and what individuals learned in school tend to diminish with age, we normalize test scores by age to obtain z-scores with a mean of zero and a standard deviation of one within each year of age. We use the math score for the main analyses.[15]

We regard results from the 2014 CFPS data as a bridge between our analyses using the CHIP data and recent international studies for two reasons. First, estimates from the entire CFPS sample and the subsample of high school and college graduates can be compared with those from the CHIP 2013 data. This comparison allows us to infer whether returns to cognitive skills in China are robust to the use of different skill measures and estimation samples. Second, the math

went to high school and took the Gaokao test. In regressions controlling additionally for Gaokao province fixed effects and Gaokao province by Gaokao year fixed effects, estimation results are virtually unchanged.

[15] Estimation results using the word score and the average of math and word scores are available upon request.

test in CFPS evaluates basic skills, plausibly comparable to the assessment in the Programme for the International Assessment of Adult Competencies (PIAAC) data developed by OECD and collected between August 2011 and March 2012. Thus, we are able to compare returns to skills in China with those in OECD countries for the same time period estimated in Hanushek et al. (2015), allowing us to gain an understanding of the progression of China's labor market against a broader backdrop.

4.2 Sample creation and summary statistics

For the empirical analysis, we focus on the subsample of full-time employees, with full-time defined as working at least 30 hours a week.[16] We construct hourly wage by dividing the annual salary (inclusive of monetary bonuses and subsidies) by hours worked in a year.[17] All monetary values are adjusted by national CPI to constant 2007 Yuan. To mitigate the influence of outliers, we exclude individuals with hourly earnings less than 1 Yuan or greater than 100 Yuan in real terms. We also exclude observations missing information on cognitive test scores, gender, age, and province of residence. We do not impose restrictions on age, but the vast majority of the sample is between 16 and 60, and restricting the sample to this age group does not change the results.

Panel A of Table 2 reports the summary statistics of individual characteristics for the analysis sample. The average age of the three waves of the CHIP sample is between 33 and 35, slightly younger but comparable to the CFPS sample of individuals with a high school education or above. In all four samples, individuals are younger than the full CFPS sample including those with less than a high school education (column 5) due to continued improvement in the educational attainment of the population such that younger people are on average more educated. The gender composition of samples from the two data sets are also comparable, with males accounting for about 60%, likely due to the more flexible labor market participation of females.

For both the Gaokao z-score in CHIP and the math z-score in CFPS, college graduates have significantly higher scores than high school graduates. The high average math z-score in CFPS (column 4) relative to the CHIP samples is because we normalize it by age regardless of the

[16] Studies of returns to education in China generally use a sample of urban residents with local urban Hukou, excluding a large number of migrants and residents without an urban Hukou in waged jobs. Our sample includes all full-time employees regardless of their Hukou or migration status, consistent with the recent development of the Chinese labor market.

[17] Very few individuals report receiving in-kind subsidies, and the reported values are small. Results are virtually the same when we also include the monetary value of in-kind subsidies

education attainment of each age group, and those with less than a high school education account for 57% of the analysis sample in 2014 and have on average much lower math z-score (-0.13, see column 5),[18] whereas Gaokao scores are normalized for high school and college graduates. From 2007 to 2013, the Gaokao z-score declines drastically for both high school and college graduates, from -0.46 to -0.63 and from 0.3 to 0.2 respectively, reflecting the fact that with the rapid expansion of college admissions, the ability distributions of both groups have shifted leftward. Between 2013 and 2018, the decline continues but to a much lesser extent. The average real hourly wage overall almost doubled between 2007 and 2018, and it grew substantially for both high school and college graduates.

In the CHIP data, as expected, college graduates account for an increasingly larger share of the sample, but at 70%, 79%, and 83% in 2007, 2013, and 2018, these are much larger than that in the CFPS high school and above sample (52%), which helps explain the higher average hourly wage in CHIP 2013 (16.33 Yuan) relative to that in CFPS 2014 (12.83 Yuan). This discrepancy in the distribution of education attainment between the two data sets is because a large number of individuals, in particular high school graduates, are missing the Gaokao z-score in CHIP while most have math test score in CFPS.[19] Indeed, college graduates account for 50% of the high school and above sample in CHIP 2013 (Panel B of Table 2) if we do not restrict the sample to those not missing Gaokao scores, comparable to the CFPS 2014 sample.

To inspect whether the sample size reduction due to missing Gaokao z-scores pose a severe problem of sample selection, we provide in Panel B of Table 2 summary statistics of individual characteristics for the otherwise identical sample as our analysis sample but without requiring non-missing Gaokao z-scores. Individuals are slightly older due to the now larger proportion of high school graduates, and the gender distribution is similar. Most importantly, while the average hourly wage of the unrestricted sample is lower in each year due to the inclusion of more high

[18] 57% of the full-time employed adults in the CFPS 2014 data have less than a high school education. It is 77% for the entire adult population.

[19] Missing Gaokao z-score is due to either missing individual Gaokao score or missing information on the maximum possible Goakao score, which is collected from the internet and is needed for the normalization and comparison of scores. In the sample of full-time employed individuals with hourly wage between 1 and 100 Yuan, 47% and 86% of college and high school graduates miss Gaokao z-score respectively, of which 12 and 5 percentage points are due to missing information on the maximum possible Gaokao score. Slightly fewer individuals miss Gaokao z-scores over time. Proportionately more high school graduates miss the Gaokao score because they may not have taken Gaokao in the first place, including the vast majority in the vocational-technical track and some in the academic track, as well as not reporting it to the interviewer. Since dropouts are included in the high school category in Chinese surveys, this group also contributes to the missing values.

school graduates, it is similar to that of the analysis sample for each education level in each year. Kernel densities of the hourly wage of the two samples are almost identical for each education level in each year (Appendix Figure A2). T-tests of equality of the mean fail to reject the null hypothesis for all but the college graduates in 2018 at 1% significance level, and Kolmogorov-Smirnov equality-of-distribution tests fail to reject the null hypothesis for all but the high school graduates in 2007 at 1% significance level. In sum, the similarities of major individual characteristics suggest that the analysis sample is a random subsample of the full-time employees.

As supplementary tests, we compare the Gaokao z-score of the analysis sample with that of the sample of all adults with non-missing Gaokao z-score regardless of their working status. Kernel densities of the Gaokao z-score of the two samples are again almost identical for each education level in each year (Appendix Figure A3); t-tests of equality of the mean fail to reject the null hypothesis for all but the high school students in 2018 (at 5% significance level), while Kolmogorov-Smirnov equality-of-distribution tests fail to reject the null hypothesis for all year-degree combinations. Thus, the analysis sample is likely a random subsample of all those reporting a Gaokao score.

While none of the above tests can definitively rule out the bias in our analysis sample due to missing Gaokao z-scores, the similarities in both the wage distribution and the Gaokao z-score distribution between the analysis sample and unrestricted samples help alleviate this concern. We provide robustness regression analyses in the next section to further address this issue.

4.3 Empirical model

Our goal is to estimate how returns to a college degree and to cognitive skills evolve over time using repeated cross-sectional data. We start with estimating a generalized Mincer equation for each cross section:

$$\ln wage_i = \beta_0 + \gamma H_i + \beta_1 PE_i + \beta_2 PE_i^2 + \beta_3 X_i + \varepsilon_i \tag{1}$$

In Equation (1), $\ln wage_i$ is the natural logarithm of hourly wage of individual i, PE_i is potential experience (=age-years of schooling-6), X_i is a vector of control variables including gender and province of residence, and ε_i is the error term. The coefficient of interest is γ, the earnings gradient associated with measures of human capital H_i, which is measured by cognitive skills (Gaokao z-score) or the attainment of a college degree or both. When both cognitive skills measure and the college degree indicator are included in the regression, the estimate on college degree reflects returns to factors that are not captured by the measure of cognitive skills such as broad subject-matter knowledge as well as noncognitive skills and the signaling value generated by a college degree.[20] Equation (1) can be further written as:

$$\ln wage_i = \beta_0 + \gamma_1 Cog_i + \gamma_2 Col_i + \beta_1 PE_i + \beta_2 PE_i^2 + \beta_3 X_i + \varepsilon_i, \tag{2}$$

where Cog_i denote cognitive skills and Col_i is an indicator for graduating from at least a 3-year college. To more conveniently compare returns over time, we estimate Equation (2) with all three waves of CHIP data and add interaction terms of the cognitive skills measure and college degree indicator with year dummies for 2013 and 2018, taking the returns in 2007 as the benchmark. In this specification, year dummies are also separately included.

Our data allow us to address several common concerns in identifying the impacts of cognitive skills on earnings. First is the reverse causality. When cognitive skills are measured concurrently with wage, estimates on cognitive skills may be upwardly biased. For example, individuals may have higher skill levels because they have better jobs on which they can constantly practice and hence sustain their skills. In the CHIP data, Gaokao score is measured at the end of high school, before individuals start their career; therefore, the estimate on Gaokao z-score is unlikely confounded by this bias. Second is the omitted variable bias. For example, family background may affect both skill formation and employment opportunities and wages. With both CHIP and CFPS data, we use mother's education to partially control for the influence of family background. Third is the measurement error in cognitive skills, which may lead to biased (generally attenuated) estimate. Since the CFPS data include measures of cognitive skills in both math and word, we use the word test score as an instrument for the math test to deal with the measurement error problem.[21]

In summary, while we are not able to use exogenous variations in measures of cognitive skills to achieve a convincing causal identification, the variety of approaches we take to deal with specific issues strengthen the interpretation of our estimates. The consistency of our estimated impacts of cognitive skills across different models and different data and comparability with that from international studies provide support for the substantial role played by cognitive

[20] A college degree as a more easily observable individual characteristic has generally a strong signaling value at the career entry when employers can only partially observe individual productivity (Altonji and Pierret 2001). It continues to have substantial impacts on wage determination later in one's career due to asymmetric learning between the current employer and the labor market in general (DeVaro and Waldman 2012; Waldman 2016).

[21] Hanushek et al. (2023) indicate that the different dimensions of cognitive skills may influence occupational choices.

skills in individual labor market outcomes in China.

5. Returns to Skills for China

In this section, we first report estimated returns to a college degree and to cognitive skills for China over the decade of 2007-2018 from the CHIP data. We then compare these estimates with those from complementary analyses using the CFPS 2014 data followed by heterogeneity estimates by gender and age. In the next section, we show the heterogeneity of returns by region, linking these returns to the differential demands for and supply of skills.

5.1 Estimates of returns to skills 2007-2018

We first estimate the wage equation for each cross section of the CHIP data. All models control for gender, potential experience and its square, and province fixed effects. Robust standard errors are reported in brackets.

We start with a traditional Mincer equation of log hourly wage using college degree as the human capital measure. Results are reported in columns 1, 4, and 7 of Table 3 for 2007, 2013, and 2018 respectively. The college wage premium decreases from 68% in 2007 to 41% in 2013, a sharp decline of 40 per cent; it recovers somewhat to 49% by 2018, but the difference between 2013 and 2018 is not statistically significant. This suggests the dominant influence of the surge in the supply of college-educated workers over the entire decade, while the restructuring of the economy may to some extent raise the demand for skilled workers and prevent a continued decline in the college premium in the second half of this period.

In columns 2, 5, and 8, we estimate the wage equation using Gaokao score as the measure of human capital for each of the three years. *Ceteris paribus*, a one standard deviation increase in Gaokao score raises hourly wage by 21% in 2007, and the return to skills drops by more than a third to 14% in 2007 and comes back slightly to 16% in 2018. This similarity in the pattern between the two sets of estimates is not surprising, as Gaokao score is closely related to college attendance, and the estimate on Gaokao score partially captures the premium to a college degree. This conjecture is born out by estimation results in columns 3, 6, and 9, where we include the indicator for a college degree and Gaokao score simultaneously. The estimated college wage premium exhibits virtually the same trend as those in columns 1, 4, and 7, whereas the estimated gradient of cognitive skills displays much muted changes over time and stays at around 10%. Estimates on both the college degree indicator and Gaokao score are smaller than when they are included individually due to the close correlation between the two measures, yet all estimates are significant at the 1% level, suggesting that they each have an independent impact on wages. Since Gaokao score, albeit imperfect, may proxy some more direct measures of cognitive skills that employers may observe,[22] when it is controlled for, the estimate on the college degree indicator is likely to reflect the impact of college education through other channels such as non-cognitive skills, networks, or its signaling values, which appear to be more affected by relative increases in the supply of college graduates.

As discussed in the previous section, our analysis sample is a relatively small subsample of all full-time employees in the CHIP data due to missing Gaokao z-scores. An alternative is to estimate the models with the full CHIP samples based on imputed Gaokao scores using either year means of all observations or means by education-year groups. These expanded models (shown in Appendix Table A2) provide very similar estimates of the human capital terms, indicating that sample selection is not important for our results.[23]

Table 4 reports estimation results using three-year pooled data, and the models include interactions of college indicator and Gaokao score with dummies for 2013 and 2018. Column 1 uses the same model as column 3 of Table 3 with added interactions and year dummies. The estimation results confirm findings in Table 3. The return to a college degree diminishes from 2007 to 2013 and ticks up slightly in 2018, but the difference between the two years is only marginally significant, whereas the return to cognitive skills is stable at around 10%. Column 2 controls for mother's education to address the concern that family background may affect both Gaokao score and employment opportunities, and returns to human capital measures may be

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[22] College graduates do not list their Gaokao score in the resume when applying for a job, but Gaokao score is highly correlated with items that are usually listed. Based on surveys of a nationally representative sample of college graduates in 2003 conducted by researchers of Peking University (the data are courtesy of Professor Changjun Yue of Peking University), we find that Gaokao score is positively associated with a variety of traits valued by employers. Students with a higher Gaokao score are significantly more likely to pass a higher level of national English test (Level 6 vs. Level 4), have taken a second major and have received merit-based college scholarships based on performance during college, and are more likely to have had any internship experience. Gaokao score alone explains about 16% of the variation in the probability of passing the higher level English test, and the combination of these correlates jointly explains 64% of the variation in the standardized Gaokao score.

[23] To alleviate concerns that trends of returns estimated in Table 3 are due to sample selection, we perform additional regression analyses and present results in Appendix Table A2. We first estimate the traditional Mincer equation of log hourly wage on college degree. As can be seen from columns 1, 4, and 7 of Appendix Table A2, the point estimates for all three years are smaller, but their magnitude is close to those in Table 3. More importantly, the trend in the return to a college degree is identical to that reported in Table 3. In the remaining columns, we extrapolate the missing Gaokao z-scores by the mean score of either the entire sample in each year (columns 2, 5, and 8) or the mean score of the respective education level in each year (columns 3, 6, and 9) and include an indicator for individuals with missing scores. In both cases, the returns to a college degree are again smaller, of comparable magnitude, and show the same trend as those in Table 3; furthermore, the return to Gaokao score is within a narrow range around 10% for all years.

confounded if this factor is neglected. Yet, the estimated returns to a college degree and to cognitive skills are virtually unchanged. In columns 3 and 4, we control respectively for a full set of industry and occupation indicators to address the concern that estimates of returns reflect primarily selection of individuals of higher human capital levels into more lucrative jobs.[24] Returns to a college degree and cognitive skills reduce slightly once industry dummies are controlled for (column 3), and the reduction is much larger with occupation controls (column 4); however, within-industry and within-occupation returns continue to be economically significant. Thus sorting of individuals into jobs based on skills is not driving our results. Finally, in column 5 we control for mother's education along with occupation and industry dummies, and the results are qualitatively similar to that in column 1 and of comparable magnitude. For the remainder of the analysis, we adopt primarily the model in column 1 of Table 4.

In all columns, estimates on the year dummies are positive and significant both statistically and economically. On average hourly wage increases by 50% between 2007 and 2013 and by about 25% additionally from 2013 to 2018, indicating a general improvement of labor productivity. The magnitude of the increase in each period is also in line with the growth rate of per capita GDP in the respective period.

5.2 Comparability to International Estimates for Developed Countries

The Gaokao scores are a specialized skill measure developed for college admissions, leaving open the question of how this measure relates to other commonly employed measures. In this section, we report estimated returns to cognitive skills from the 2014 CFPS data and compare them with both estimates using the 2013 CHIP data and international studies using the PIAAC data collected in 2011-12. These comparisons allow us to both establish commonalities across different skill measures, data, and countries and detect and understand any differences.

Panel A of Table 5 presents estimates using the high school and above sample of the 2014 CFPS. To facilitate comparison, we also report estimates from the 2013 CHIP data. As in Table 4, we start with the baseline model controlling only for gender, a quadratic function of potential experience, and province fixed effects. We add controls of mother's education, occupation,

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[24] Occupation and industry are identified essentially at the one-digit level. Industries include: Agriculture and mining; Electricity, gas & water; Manufacturing; Construction; Transport, storage, post and telecom & IT; Wholesale and retail trade and catering services; Finance and insurance; Real estate; Social services; Health, education, culture & research; and Party and Government organs and social organizations. Occupations include: Leading cadres; Professional and technical staff; Office workers; Service workers; and Production workers.

industry, and sector in columns 2-5 separately and jointly in column 6, and an indicator for college degree in column 7.[25] The estimates on cognitive skills from the CFPS sample (0.153) is slightly higher than that from the CHIP sample (0.137) but comparable. When additional controls are included, estimates all become smaller but continue to be of similar magnitude and significant both economically and statistically. Thus, while skill measures are different in the two data sets, the similarity in the estimated returns suggests that they both capture common factors of cognitive abilities valued in the labor market. In column 8, we report IV estimation results on the CFPS sample, using word test score as instrument for math score to deal with the problem of subject-specific measurement error; the first stage estimate on the word test score is 0.78 and significant, and the second stage estimate on the math test score increases from 0.153 in the OLS model (column 1) to 0.199, suggesting that measurement error may indeed be an issue and we are likely to underestimate the returns to skills.

In panel B of Table 5, we report estimates using the CFPS sample of individuals of all education levels, along with estimates of comparable models for the pooled sample of 23 OECD countries reproduced from various tables in Hanushek et al. (2015). The baseline OLS estimate is 0.17 from the CFPS data, almost identical to the OECD average (0.178), and the IV estimates in the last column are also almost identical (0.20) and both are of larger magnitude than the OLS estimates.[26] Controlling for mother's education, occupation, industry, and individual education level reduces the estimated return to skills; the reduction is more pronounced when education level and occupation are controlled for, due perhaps to the high correlation between education level and test scores and sorting into occupations based on individual skills. Additionally, estimates presented in Panel B using the entire sample of the CFPS data are quantitatively close to those reported in Panel A for the high school and above sample.[27]

In summary, the comparability of returns to skills estimates from all three data (CHIP, CFPS, and PIAAC) lends credibility to estimates using Gaokao score as the cognitive skill measure, and the trend of returns to skills estimated from the CHIP data is plausibly not restricted to the high

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[25] Sectors include government agencies, public institutions, state-owned enterprises (SOEs), and firms and small business of all other ownerships. Sector fixed effects are not controlled for in Table 4 because this information is not available for a subset of individuals (rural residents) in the 2007 CHIP data.

[26] The first stage estimate on the word test score is 0.72 with a standard error of 0.016.

[27] Guido Schwerdt kindly provided us the estimates of returns to skills using the high school and above sample of the PIAAC data. The estimates for the pooled OECD countries are 0.175 without controlling for schooling and 0.107 controlling for schooling, which are virtually identical to those for the entire sample. Estimates for individual countries are also similar.

school and above sample, but also a good indicator of returns to skills for China's overall working population.

Returns to cognitive skills in the Chinese labor market in the mid 2010s are on average closer in magnitude to those estimated for Italy, Belgium, and the Nordic countries, and much smaller than those of the U.S., U.K, Germany, Japan, and Korea, countries that have a more dynamic economy. Meanwhile, the flatness of the returns to Gaokao score from 2007 to 2018 suggests that in spite of the growing importance of the high-skilled sector in the Chinese economy in the past decade, this growth has not translated meaningfully into higher demand for skills and hence higher returns to skills. This is in contrast to findings of Murnane, Willett, and Levy (1995) for the U.S., where the returns to cognitive skills was larger for individuals in their mid 20s in 1986 than in 1978, with a particularly substantial increase for women. They attribute this increase to higher demand for skills associated with an occupational shift. Both cross-country and over-time comparisons point to frictions existing in the Chinese economy and labor market. In the remainder of the paper, we conduct heterogeneity analyses to better understand the driving forces, first by demographics in the next subsection and then by regional development level in Section 6. We focus on results from the CHIP data that allow investigation of the time patterns of returns.

5.3 Heterogeneity by age and gender

This section reports estimated trends of returns to a college degree and cognitive skills for younger and older workers and for males and females separately. Heterogeneity analyses for important subgroups of the population facilitate understanding of the driving forces of the pattern of returns to skills estimated for the entire population in section 5.1.

Columns 1-2 of Table 6 report estimates for young and older workers separately, where young workers are those aged below 35 and older workers are those aged 35 or above. Within each group, the trend is similar to that estimated for the entire population; i.e., the return to a college degree drops sharply from 2007 to 2013 and recovers somewhat in 2018, and the return to cognitive skills does not change significantly over the decade. Meanwhile, there are important differences between the two groups. First, the return to a college degree is significantly higher (at 1 percent level) for the older workers in all three years, and the gap remains the same statistically between 2007 and later years; thus the younger cohorts of college graduates bear the brunt of the changing relative supply. Second, the return to cognitive skills is somewhat higher for the younger workers in 2007 and weakly increases over time, and the return to cognitive skills for the older workers weakly decreases over time. Consequently, while the skill premium is not significantly higher for younger workers in 2007, it become significantly higher in 2013 (at 10 percent level) and 2018 (at 1 percent level).[28]

One reason for the higher returns to a college degree for older workers is that in China's fast-evolving labor market, older incumbent college-educated workers are in more stable jobs and less exposed to competition. An alternative explanation is that, if college-educated workers in different age and hence experience groups are imperfect substitutes – for example, older college-educated workers are more likely in management positions, then large increases in the supply of young college graduates will dampen the return to college education for the young cohorts but improve that for the older cohorts. Since we control for a measure of cognitive skills, the higher college premium for the older cohorts perhaps reflects a higher return to non-cognitive skills, which are likely in more use by older college-educated workers in management positions. Card and Lemieux (2001) interpret increases in college wage premium for young cohorts between 1970s and 2000 in the U.S. along the same line; i.e., it is due to a slowdown in the rate of education attainment beginning with the cohorts born in the early 1950s, a situation opposite to what China has experienced. The lower returns to cognitive skills for the older workers, in particular in more recent years, may be because their skills become quickly obsolete, given China's rapid adoption of new production technologies and expansion of new industries, along with continuous changes in curriculums that accommodate the changing economic environment. This is similar to the findings of Hanushek et al. (2015) for the transition economies but opposite to those for other OECD countries, where higher levels of cognitive skills may help older workers to adapt and stay ahead in the labor market.[29]

Columns 3-4 of Table 6 report results for males and females respectively. Here again, the estimated trends of returns to a college degree and to cognitive skills within each group are similar to that for the entire population, but between-group disparities exit. The return to a

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[28] Knight, Deng, and Li (2017), using CHIP 2002 and 2007 data, find that wage premium of self-reported high-school performance is larger for entrant cohorts than incumbents; they also find higher unemployment rate for the entry cohorts of college graduates in 2007 than in 2002.

[29] The cohort difference is more pronounced when we restrict the older group to those older than 45. The estimate of skill premium is 0.051 (significant at 10% level) in 2007 and not significantly different in 2013 and 2018. The estimate of college premium is a significant 0.77 in 2007, and drops by 34 and 20 percentage points in 2013 and 2018 respectively.

college degree, while identical in 2007 for males and females, decreases to a much smaller extent for females than for males over time, resulting in a larger return for females in 2013 (marginally significantly) and a still larger one in 2018 (significant at 1 percent level). The returns to cognitive skills is slightly larger for females in 2007 and remains stable for both gender groups over time, and the gender differences are insignificant. One explanation for the higher returns to a college degree for females in 2013 and 2018 is the continued decreases of labor force participation by women. Calculated with data from Chinese Population Censuses, full-time workers account for 83%, 81%, and 77% of all non-student female working-age population with a college degree in 2005, 2010, and 2015 respectively, whereas the ratio is almost a constant of 87% for males.[30] This leads to an increasingly stronger positive selection of female workers, and part of this positive selection is manifested in the higher returns to a college degree, which, with cognitive skills controlled for by Gaokao score, signals higher levels of other aspects of the human capital of the working women, such as non-cognitive skills (aspiration, competitiveness, perseverance, etc.) and cognitive skills unmeasured by Gaokao score.

6. Regional Heterogeneity

China is a large country, and as depicted in Figure 6, is vastly heterogeneous in regional industrial structure and hence the demand for skills; accordingly, the return to skills may also vary substantially across regions. By looking at how the returns to skills have evolved across varying subregions, we can gain further insights into the interplay of the supply and demand for skills. This analysis highlights the perhaps-obvious fact that labor markets differ sharply across China, implying that the aggregate results mask very different underlying markets.

We approach this by estimating the base model of column 1 of Table 4 for different regions defined by alternative measures of local economic development. We report the results of estimates of skill returns for alternate definitions of economic aggregates in Table 7.

We first compare returns to skills in the coastal and inland regions, where the coastal region is traditionally considered as more developed.[31] As can be seen from columns 1 and 2, the return to a college degree is significantly higher in the coastal region than the inland region in 2007,

[30] Feng, Hu, and Moffitt (2017) document the decreasing labor force participation trend for female college graduates up to 2009, and Ge, Sun, and Zhao (2021) for the overall female working-age population from 1990 to 2015.

[31] We use the classification of the National Bureau of Statistics of China. In the CHIP data, coastal regions include Beijing, Hebei, Shanghai, Jiangsu, Zhejiang, Shandong, and Guangdong. Inland regions include Shanxi, Inner Mongolia, Liaoning, Anhui, Henan, Hubei, Hunan, Chongqing, Sichuan, Yunnan, and Gansu.

and the return in the coastal region declines sharply in 2013 and remains at the same level in 2018; in the inland region the return experiences an even larger decline in 2013, but slightly recovers in 2018, which explains the trend observed for the entire CHIP sample. As a result, the gap in the return to a college degree between these two broadly-defined regions narrows over time. Controlling for college degree, the return to cognitive skills is not statistically significantly different between coastal and inland regions in each year and between years within each region, echoing the trend found for the entire sample.[32]

Grouping provinces by geographical location is intuitive but rough. We next consider subsamples based on more province-specific measures of development that are intended to capture differences in the demand for high-skilled workers across regions. Specifically, we compare provinces with above- and below-median measures of economic development based on the contribution of the high-skilled sector to regional GDP. If the value-added share of the high-skilled sector of a province is above the national median for all three waves of the survey, then the province is included in the region of above-median high-skilled sector, and vice versa.[33] In this way, we are comparing consistently well-performing provinces with consistently poorly-performing provinces in terms of the value-added share of the high-skilled sector.[34] The estimation results are reported in columns 3-4 of Table 7. The point estimate of college premium is higher in the above-median HS-sector region in all three years, but the differences are not statistically significant. In both regions, the college premium experiences significant declines between 2007 and later years, consistent with findings for the national sample. The return to cognitive skills, however, demonstrate quite different dynamics. While the point estimates are not statistically significantly different between the two regions in 2007, between 2007 and 2013, the return to cognitive skills increases substantially (significant at 5% level) in the above-median HS-sector region and decreases substantially (marginally significant) in the below-median region. As a result, the skill premium is significantly (at 1% level) higher in the former in 2013. The estimates on the interaction between Gaokao z-score and 2018 dummy for both regions are

32 All test statistics here and below are available upon request from the authors.

33 Since wages may not respond to local demand conditions immediately, we choose a time window for each survey year (2002-2006 for the 2007 survey, 2008-2012 for the 2013 survey, and 2014-2017 for the 2018 survey) and calculate the average share of GDP that comes from the service or high-skilled sector during each of the three time windows for each province. We use this average share for classification.

34 Provinces with above median high-skilled sector GDP share are Beijing, Shanghai, Zhejiang, Hunan, Guangdong, Yunnan, and Gansu, and those with below median share are Hebei, Inner Mongolia, Liaoning, Shandong, and Henan.

small and insignificant; therefore the skill premium is not significantly higher in the above-median HS-sector region.

The high-skilled sector includes the Residential and Household Services industry, whose share of college-educated workers is very small; it also includes all the public sectors, where wages are generally not set according to market conditions. This imprecise way of classification may explain why three relatively less-developed provinces – Gansu, Hunan, and Yunnan – are included in the above-median HS-sector category, which may confound the returns to a college degree and to cognitive skills determined in competitive labor markets with a high demand for high-skilled workers. To alleviate this problem, we report in column 5 estimates for the subsample of Beijing, Shanghai, Zhejiang, and Guangdong (BSZG), all of which belong to the above-median HS-sector category and are economically the most dynamic provinces in China. For these provinces, the return to a college degree declines monotonically over time, and the differences between consecutive years are statistically significant. The return to cognitive skills follows a similar trend as in column 3 but of larger magnitudes; it more than doubles from 2007 to 2013 (significant at 1% level) and is also moderately higher in 2018 than in 2007 (marginally significant).

In summary, the college premium is higher in more developed regions (coastal, regions with above-median high-skilled sector, and BSZG) than in other regions, but in all regions, the college premium declines over time. This pattern may be explained by both the demand- and supply-side forces. More developed regions have a larger HS sector, and the HS sector also grows faster in these regions, as can be seen in Figure 6 and Appendix Table A1. This leads to a continued higher demand for skilled labor and help maintain a higher college premium. Meanwhile, increasingly more college-educated working-age population resides in more developed regions, many of whom are likely attracted by better job opportunities and higher wages in these regions. Table 8 reports the education distribution of working-age population (aged 16-65) in different regions calculated from the 2005, 2010, and 2015 population censuses. Due to the higher education expansion, the share of college-educated workers continues to increase in all regions (columns 2, 4, 6), but the increase is larger in the coastal region and still larger in BSZG, the four most developed provinces on the coast than the inland region. For example, relative to the inland region, in 2005, the coastal region and BSZG have 3.5 and 5 percentage points more college-educated full-time workers respectively, and the differences rise to 5.2 and 8.5 percentage points respectively in 2015. This relative increase in the supply of college-educated workers likely slows down the wage growth in the more developed regions and reduces the gap in the college premium relative to the less developed regions. This countervailing force from the supply side appears to be stronger in BSZG than in the coastal region in general, reflected in the monotonic decline of the college premium (column 5 of Table 7).

Controlling for college degree, the return to cognitive skills shows the largest increases from 2007 to 2013 and 2018 in BSZG; this is likely due to the strongest growth of the high-skilled sector in these four provinces. However, the return for more developed regions does not increase monotonically over time; if anything, it is weakly lower in 2018 than in 2013. This echoes the occupational dynamics documented by Ge, Sun, and Zhao (2021). Using census data, they find that from 1990 to 2015, routine cognitive jobs increased significantly from 8% to 19%, whereas the share of non-routine cognitive jobs is flat – indeed, the share decreases from 13% to 11%. If skills are particularly more valuable in non-routine cognitive occupations, this stagnation may explain the lack of continued improvement in returns to skills. This also points to potential problems of China's high-skilled sectors: their value-added may derive more from jobs using basic skills, whereas creative jobs that demand more advanced problem-solving skills are still lacking. On balance, this reflects increases in relative demand lagging supply.

The return to skills is 0.173 in BSZG in 2013, comparable to the highest of estimates for the OECD countries, such as Germany, US, and UK. In less developed regions, the return to skills in 2013 is in a much lower range of 0.02 to 0.08. Thus, the constant average return to cognitive skills from 2007 to 2018 reported in Table 4 masks the large regional variation. This indicates the huge disparity in industrial development within China and great potential for future improvement.

7. Conclusions

The Chinese labor market has undergone tremendous shifts in the supply of and demand for skilled labor over the past decades. However, we know very little about the evolution of the returns to skills during this unprecedented period. Using data of three waves of representative samples of Chinese workers, we examine the labor market returns to a college degree and to cognitive skills from 2007 to 2018.

A decade is not a very long time to definitively define a trend, especially when we only have three data points during the decade. Some robust patterns however emerge that may provide a broad picture of the role skills play in the Chinese economy. From 2007 to 2018, the return to cognitive skills remain quite stable at 10% for full-time workers with at least a high school degree, while the college premium relative to high school graduation declines sharply by over 20 percentage points. The skill premium is larger for female and younger workers, whereas the college premium is larger for older workers. The declining trend in college premium holds for all demographic groups.

These national results, however, hide considerable heterogeneity that has accompanied the uneven geographic development of the Chinese economy. While the differential development across geographical components of China is well known, the implications of these differences for the returns to human capital have not been previously detailed.

The college premium is lower in 2013 and 2018 than in 2007 in both more and less developed regions, but only in the most developed region do we observe a monotonic decline. This is likely due to disproportionate increases in the supply of college-educated workers in this region, which to some extent reduces the upward pressure on wages of college-educated workers due to increases in demand for more educated workers following the growth of the high-skilled sector. Meanwhile, the return to cognitive skills increases from 2007 to later years in the more developed region, but weakly declines in the less developed region, consistent with the pattern of development of the high-skilled sector in these two broad regions.

We also use a supplementary dataset to link our findings with international studies. The skill premium in China in the mid 2010s is on average of comparable magnitude to those estimated for OECD countries in general and specifically to Italy, Belgium, and the Nordic countries. In the mean time, the skill premium in the most developed region in China (Beijing, Shanghai, Zhejiang, and Guangdong) is comparable to the highest estimates of OECD countries, i.e., those of U.S., U.K., and Germany, which have a more dynamic economy, whereas the estimated return for the less developed region in China is much smaller. The cross-country comparison demonstrates China's past success in transitioning towards a market-oriented and skill-based economy. The regional disparity within China raises concerns about the unbalanced regional development of the Chinese industries, while at the same time it points to the direction of future improvement.

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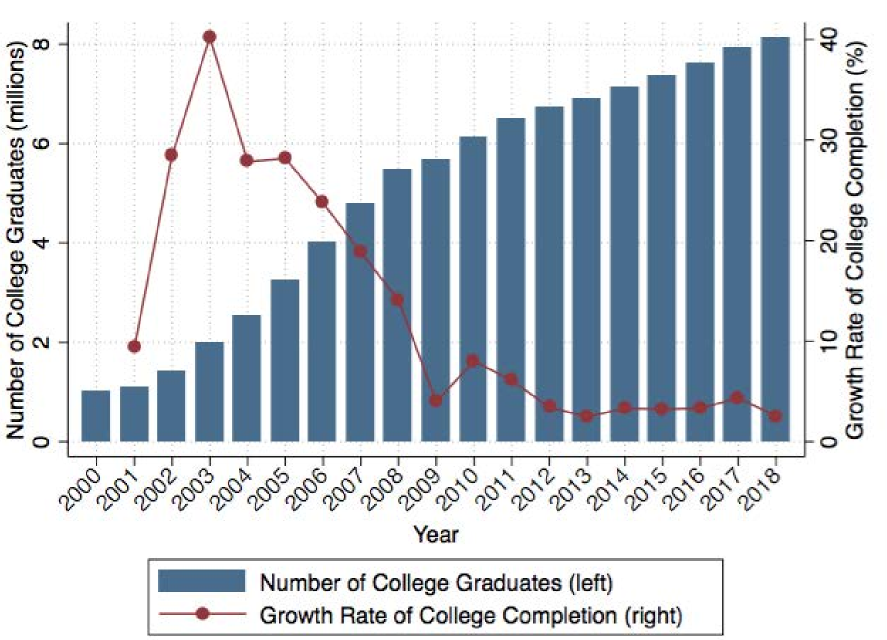
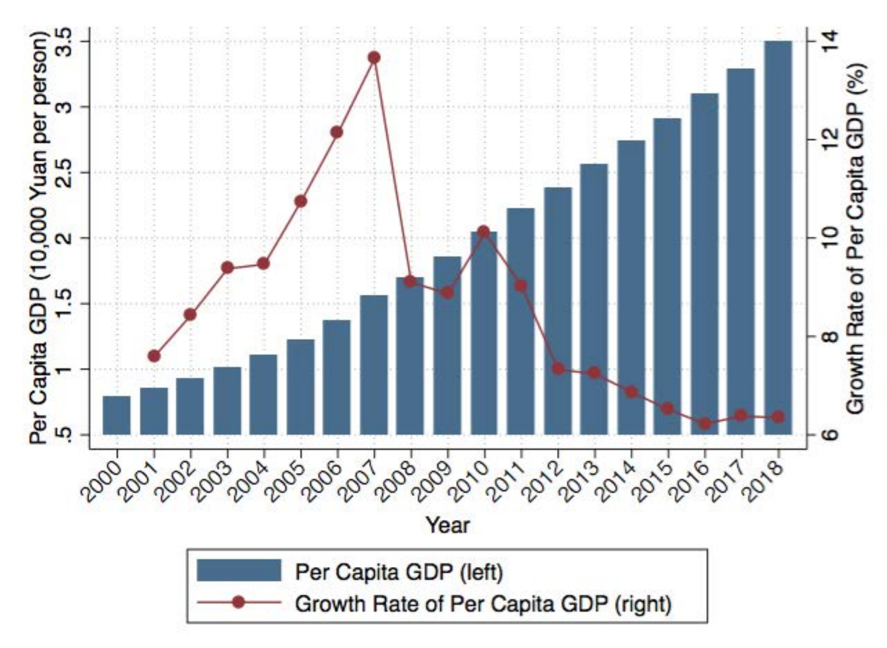
Figure 1: Number and Growth rate of College Graduates



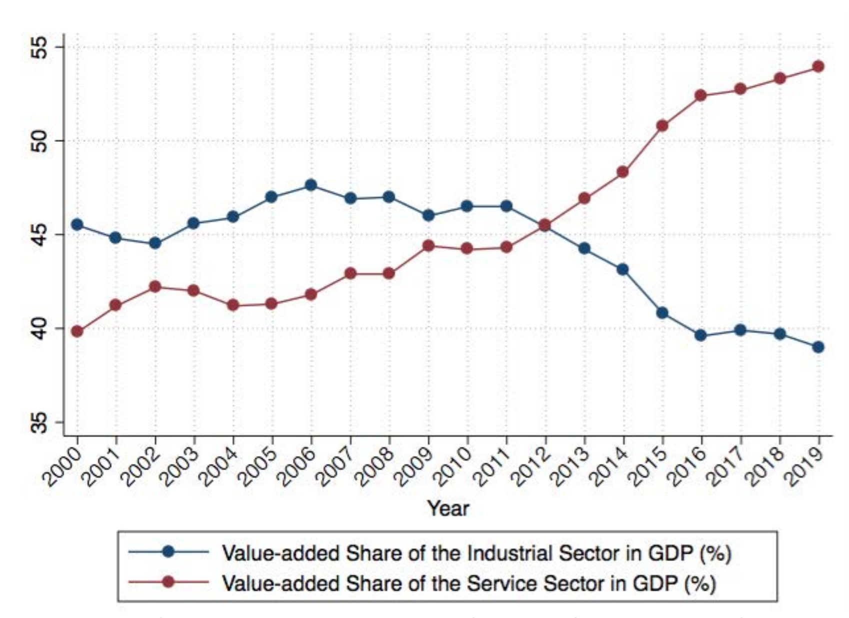
Note: The figure depicts the number of graduates from 3- or 4-year colleges or above (the left vertical axis) and the annual growth rate of college graduates (the right vertical axis) each year from 2000 to 2018. Data comes from the China Statistics Yearbook.

Figure 2: Per Capita GDP and Growth Rate of Per Capita GDP



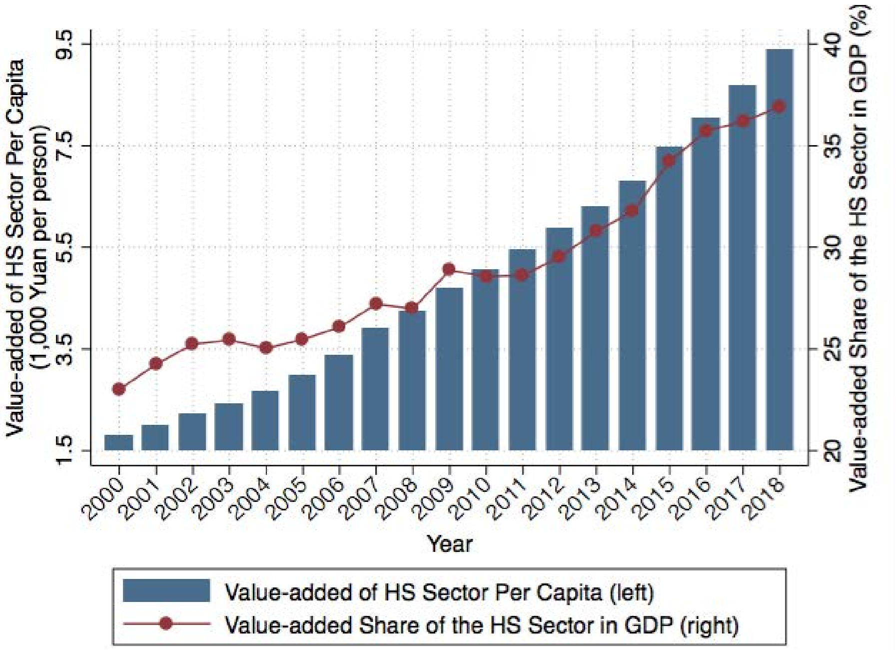
Note: The figure depicts the evolution of per capita GDP (the left vertical axis) and growth rate of per capita GDP (the right vertical axis) from 2000 to 2018. Per capita GDP is calculated by dividing GDP by the total population. All monetary values are adjusted to the 2000 price level. Data comes from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

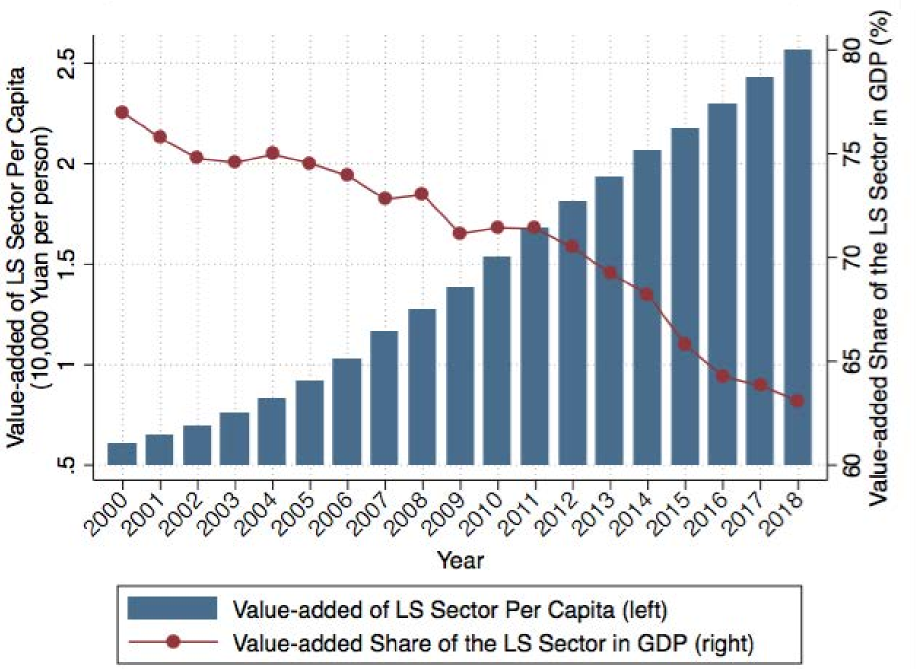
Figure 3: Value-added Shares of the Industrial and Service Sectors



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.

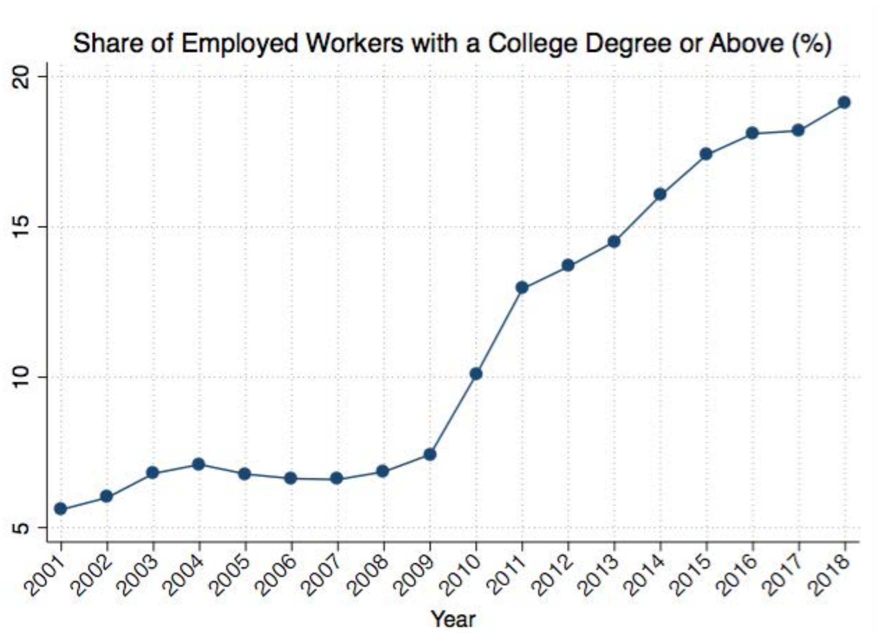
Figure 4: Value-added of HS Sector Per Capita and Share of HS Sector





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

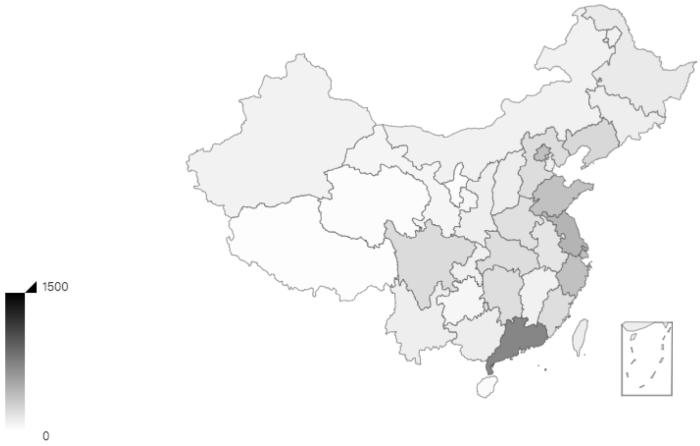
Figure 5: Share of Workers with a College Degree or Above



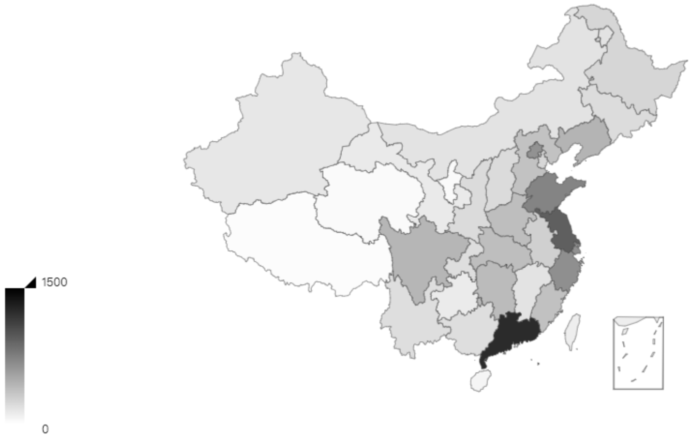
Note: The figure depicts the share of employed workers with a 3- or 4-year college degree or above each year from 2001 to 2018. Data comes from the China Labor Statistics Yearbook and China Population and Employment Statistics Yearbook. The definition of employed workers in the yearbook includes restrictions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

Figure 6: Regional Distribution of the Value-added of HS Sector

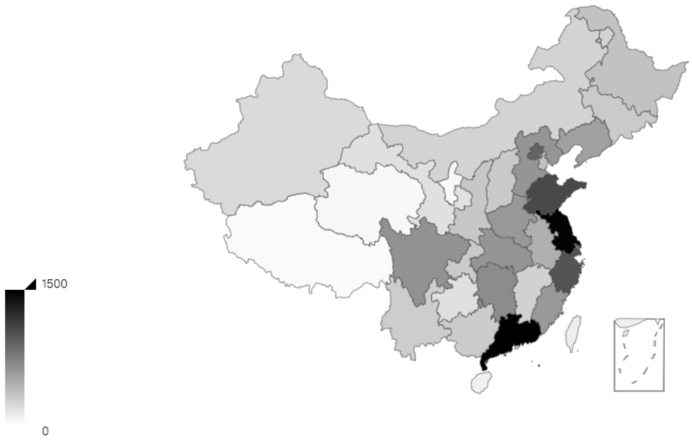
Value-added of the HS Sector in 2007 (billion Yuan)



Value-added of the HS Sector in 2013 (billion Yuan)



Value-added of the HS Sector in 2017 (billion Yuan)



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.

Table 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
	Transport, 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
	Residential 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.

Table 2: Summary Statistics

	CHIP Survey year			CFPS HS+	CFPS all
	2007	2013	2018	2014	2014
Panel A. Analysis Sample					
Age	32.93	34.56	35.00	35.56	37.99
Male (%)	60.38	56.66	57.96	58.33	61.86
Gaokao Z-score / Math Z-score					
Less than HS	.	.	.	.	-0.13
HS	-0.47	-0.63	-0.65	0.52	0.52
College	0.29	0.20	0.19	1.12	1.12
Hourly Wage	12.61	16.33	22.89	12.82	9.92
HS	7.67	11.91	15.20	10.03	10.03
College	14.75	17.48	24.49	15.43	15.43
HS (%)	30.32	20.61	17.16	48.40	20.71
College (%)	69.68	79.39	82.84	51.60	22.08
Observations	2,259	2,882	4,569	2,719	6,353
Panel B. Analysis Sample Inclusive of Observations Missing Gaokao Z-score or Math Z-score					
Age	34.85	37.23	37.00	34.84	37.29
Male (%)	60.36	57.99	57.93	58.60	62.40
Hourly Wage	10.67	14.52	19.87	13.07	10.00
HS	8.06	11.74	14.86	10.16	10.16
College	14.77	17.25	23.62	15.73	15.73
HS (%)	61.04	49.62	42.79	47.66	20.04
College (%)	38.96	50.38	57.21	52.34	22.01
Observations	8,239	8,863	11,600	3,053	7,261

Note: The five columns correspond to CHIP 2007, 2013 and 2018, the high school and above sample and the full sample of CFPS 2014, respectively. The analysis sample includes all full-time employees with hourly wages between 1 and 100 Yuan per hour (CPI-adjusted to constant 2007 Yuan), and non-missing information about the Gaokao score or math score, gender, age, years of schooling, province of residence, and sampling weights. High school includes ordinary high school, technical school and specialized secondary school (Zhong Zhuan). College includes 4-year college, 3-year college and graduate degrees. Panel B does not impose restrictions on the availability of Gaokao score or math score.

Table 3: Returns to Cognitive Skills and 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 in CHIP 2007, 2013 and 2018. The dependent variable is log hourly wage. 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 parentheses.

Table 4: Trends in Returns to Cognitive Skills and College Degrees

	1	2	3	4	5
College	0.608	0.583	0.574	0.501	0.485
	(0.028)	(0.029)	(0.028)	(0.028)	(0.029)
College x Year2013	-0.279	-0.285	-0.277	-0.247	-0.248
	(0.040)	(0.042)	(0.039)	(0.039)	(0.041)
College x Year2018	-0.214	-0.280	-0.219	-0.173	-0.243
	(0.037)	(0.051)	(0.037)	(0.036)	(0.050)
Gaokao z-score	0.111	0.103	0.100	0.093	0.084
	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)
Gaokao x Year2013	-0.013	-0.016	-0.013	-0.017	-0.019
	(0.019)	(0.020)	(0.018)	(0.018)	(0.019)
Gaokao x Year2018	-0.003	0.009	-0.003	-0.001	0.008
	(0.018)	(0.024)	(0.017)	(0.017)	(0.023)
Year2013	0.510	0.523	0.501	0.498	0.501
	(0.034)	(0.037)	(0.034)	(0.034)	(0.036)
Year2018	0.760	0.761	0.759	0.731	0.733
	(0.033)	(0.046)	(0.032)	(0.032)	(0.045)
Male	0.156	0.138	0.147	0.149	0.127
	(0.012)	(0.015)	(0.012)	(0.012)	(0.015)
Maternal Education	No	Yes	No	No	Yes
Industry	No	No	Yes	No	Yes
Occupation	No	No	No	Yes	Yes
Province FEs	Yes	Yes	Yes	Yes	Yes
Observations	9,710	6,261	9,697	9,650	6,202
Adjusted R2	0.344	0.315	0.361	0.367	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 in CHIP 2007, 2013 and 2018. The dependent variable is log hourly wages. All regressions control for a quadratic function of potential experience. The omitted year category is 2007. Maternal education are dummy variables corresponding to below middle school education, middle school education, high school education and above higher education, respectively. Occupation and industry are identified essentially at the one-digit level. Industries include: Agriculture and mining; Electricity, gas & water; Manufacturing; Construction; Transport, storage, post and telecom & IT; Wholesale and retail trade and catering services; Finance and insurance; Real estate; Social services; Health, education, culture & research; and Party and Government organs and social organizations. Occupations include: Leading cadres; Professional and technical staff; Office workers; Service workers; and Production workers. Robust standard errors in parentheses.

Table 5: Comparison of Returns to Cognitive Skills Estimates from Different Data

Panel A. High School and Above Sample without Controls for College

	1	2	3	4	5	6	7	8
	OLS	OLS+Mother Edu	OLS+Occu	OLS+Indu	OLS+Sector	OLS+Occu, Indu, Sector, Mother edu	Col Degree	IV
Math z-Score (CFPS14)	0.153	0.140	0.084	0.133	0.133	0.071	0.086	0.199
	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)	(0.019)	(0.018)	(0.036)
Observations	2719	2578	2715	2677	2719	2537	2719	2719
Adjusted R2	0.187	0.195	0.291	0.207	0.221	0.312	0.239	0.087
Gaokao z-score (CHIP13)	0.137	0.124	0.105	0.121	0.113	0.083	0.094	
	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	
Observations	2882	2535	2834	2879	2878	2491	2882	
Adjusted R2	0.211	0.213	0.242	0.236	0.246	0.267	0.245	

Panel B. Full Sample Without Controls for Schooling

	OLS	OLS+Mother Edu	OLS+Occu	OLS+Indu	OLS+Sector	OLS+Occu, Indu, Sector, Mother edu	Edu Level	IV
Math z-Score (CFPS14)	0.170	0.163	0.086	0.147	0.132	0.079	0.062	0.200
	(0.011)	(0.012)	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)	(0.019)
Observations	6353	5890	6347	5914	6347	5483	6353	6353
Adjusted R2	0.195	0.205	0.289	0.213	0.228	0.307	0.251	0.114
Numeracy (PIAAC)	0.178	0.162	0.097	0.150			0.103	0.201
	(0.003)	(0.003)	(0.003)	(0.003)			(0.003)	(0.003)

Note: The sample includes full-time employees with hourly wages between 1 and 100 Yuan per hour in CFPS 2014 and CHIP 2013. Panel A restricts to the high school and above sample, and panel B uses the full sample. The bottom section of panel A report estimates from CHIP 2013; the bottom section of Panel B reproduces estimates of Hanushek et al. (2015). Column 1 reports the baseline OLS estimate controlling for gender, a quadratic function of potential experience, and province fixed effects. We add controls of maternal education, occupation, industry, and sector in columns 2-5 separately and jointly in column 6, and an indicator for college degree in column 7. Sectors include government agencies, public institutions, state-owned enterprises (SOEs), and firms and small business of all other ownerships. Column 8 reports the IV estimate using word test score as instrument for math score. Robust standard errors in parentheses.

Table 6: Heterogeneity By Gender and By Age

	1 Young Workers (age<35)	2 Older Workers (age>=35)	3 Male Workers	4 Female Workers
College	0.543	0.686	0.610	0.610
	(0.034)	(0.047)	(0.036)	(0.044)
College x Year2013	-0.330	-0.249	-0.318	-0.229
	(0.052)	(0.062)	(0.052)	(0.061)
College x Year2018	-0.249	-0.161	-0.275	-0.129
	(0.046)	(0.061)	(0.049)	(0.057)
Gaokao z-score	0.127	0.090	0.099	0.129
	(0.020)	(0.019)	(0.018)	(0.022)
Gaokao x Year2013	0.003	-0.018	0.000	-0.033
	(0.026)	(0.026)	(0.024)	(0.029)
Gaokao x Year2018	0.012	-0.016	-0.004	-0.001
	(0.024)	(0.025)	(0.023)	(0.027)
Year2013	0.546	0.491	0.552	0.448
	(0.046)	(0.052)	(0.045)	(0.054)
Year2018	0.786	0.706	0.816	0.678
	(0.041)	(0.053)	(0.043)	(0.049)
Male	0.156	0.147		
	(0.015)	(0.020)		
Observations	5,616	4,094	5,645	4,065
Adjusted R2	0.346	0.324	0.327	0.356

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 in CHIP 2007, 2013 and 2018. The dependent variable is log hourly wages. The four columns report estimates for young workers, senior workers, males and females, respectively. Young workers are those aged below 35 and older 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 function of potential experience. Robust standard errors in parentheses.

Table 7: Trends in Returns to Cognitive Skills and College Degrees By Region

	1	2	3	4	5
	Coastal	Inland	≥Median HS Share	<Median HS Share	BJ, SH, ZJ, GD
College	0.690	0.542	0.710	0.618	0.715
	(0.039)	(0.039)	(0.047)	(0.088)	(0.047)
College x Year2013	-0.238	-0.264	-0.307	-0.328	-0.141
	(0.061)	(0.053)	(0.066)	(0.109)	(0.081)
College x Year2018	-0.236	-0.172	-0.291	-0.310	-0.286
	(0.059)	(0.049)	(0.062)	(0.110)	(0.076)
Gaokao z-score	0.083	0.127	0.083	0.102	0.081
	(0.020)	(0.019)	(0.023)	(0.038)	(0.023)
Gaokao x Year2013	0.039	-0.048	0.070	-0.079	0.092
	(0.027)	(0.025)	(0.030)	(0.051)	(0.034)
Gaokao x Year2018	0.026	-0.013	0.021	-0.012	0.048
	(0.026)	(0.024)	(0.029)	(0.046)	(0.032)
Year2013	0.425	0.519	0.394	0.592	0.276
	(0.053)	(0.046)	(0.062)	(0.094)	(0.072)
Year2018	0.687	0.778	0.662	0.813	0.636
	(0.052)	(0.043)	(0.059)	(0.100)	(0.069)
Male	0.150	0.158	0.146	0.177	0.159
	(0.019)	(0.015)	(0.020)	(0.028)	(0.025)
Observations	3,729	5,981	3,559	1,978	2,320
Adjusted R2	0.371	0.301	0.334	0.261	0.375

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 in CHIP 2007, 2013 and 2018. The dependent variable is log hourly wage. All regressions control for province fixed effects, as well as a quadratic function of potential experience. The omitted year category is 2007. Columns 1 and 2 use samples of coastal and inland provinces 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. Columns 3-4 use samples of provinces with above- or below-median measures of economic development in the high-skilled sector in regional GDP, respectively. Column 5 use the sample of Beijing, Shanghai, Zhejiang and Guangdong. Robust standard errors in parentheses.

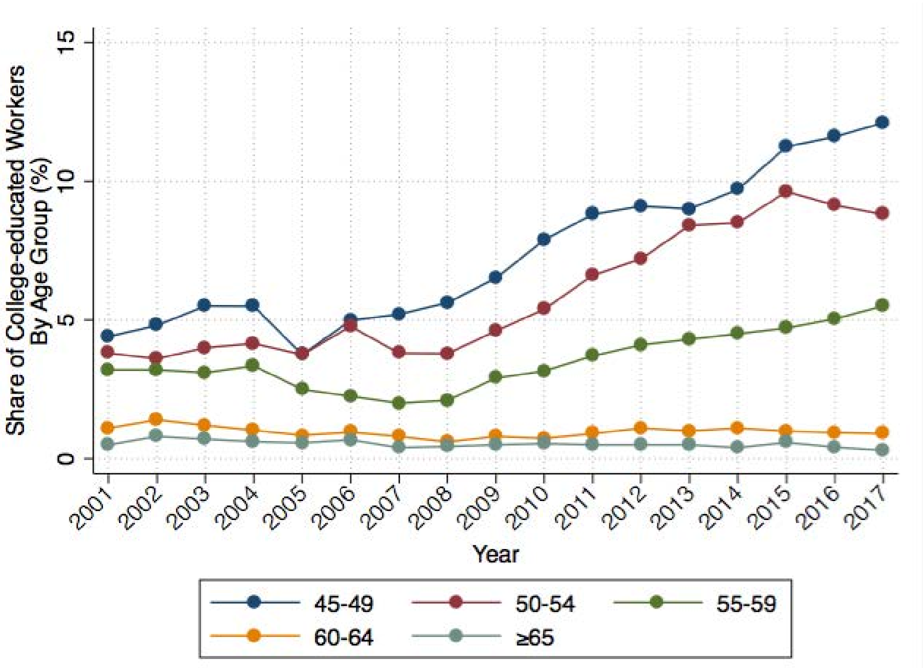
Table 8: Education attainment of adults (aged 16-65) in different regions

	inland		**coastal**		**Beijing, Shanghai, Guangdong, Zhejiang**	
	all non-full time student residents	full-time working residents	all non-full time student residents	full-time working residents	all non-full time student residents	full-time working residents
Panel A: 2005 census						
<= primary school	0.416	0.420	0.274	0.254	0.259	0.236
middle school	0.409	0.408	0.463	0.478	0.447	0.462
high school	0.116	0.108	0.174	0.169	0.192	0.187
>= 3 year college	0.058	0.064	0.089	0.099	0.102	0.114
Panel B: 2010 census						
<= primary school	0.305	0.297	0.214	0.192	0.198	0.174
middle school	0.475	0.483	0.497	0.512	0.456	0.471
high school	0.136	0.129	0.170	0.166	0.194	0.188
>= 3 year college	0.084	0.091	0.120	0.130	0.153	0.167
Panel C: 2015 census						
<= primary school	0.265	0.247	0.194	0.165	0.189	0.154
middle school	0.465	0.472	0.467	0.477	0.425	0.434
high school	0.165	0.161	0.188	0.186	0.210	0.207
>= 3 year college	0.105	0.120	0.150	0.172	0.177	0.205

Notes: This table reports the education attainment of adults (aged 16-65) residing in different regions of China calculated from the 2005, 2010, and 2015 censuses. Numbers in each column in each panel add up to 1. Coastal provinces are Liaoning, Hebei, Beijing, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Hainan; all other provinces are inland provinces.

Appendix

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

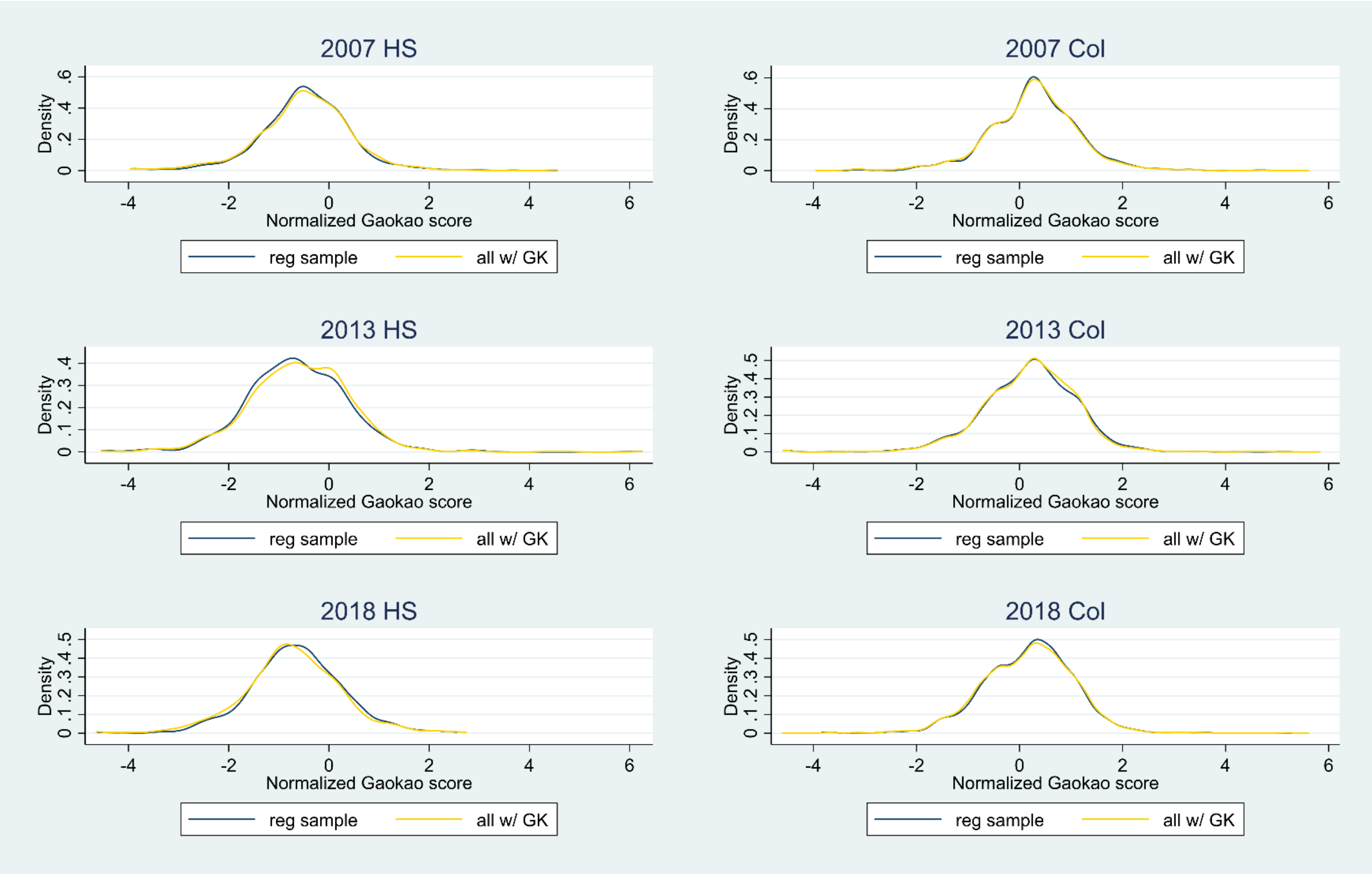


Note: The figure depicts the share of employed workers with a college degree or above for age groups 45-49, 50-54, 55-59, 60-64, and 65 and above from 2001 to 2017. Data comes from the China Labor Statistics Yearbook.

Figure A2: Wage Distribution of Analysis Sample and Full-Time Working Sample Missing Gaokao Z-Score by Education Level

Note: The figure presents kernel densities of the hourly wage of the analysis sample and the full-time working sample in CHIP for each education level in each year. The analysis sample includes all full-time employees with hourly wages between 1 and 100 Yuan per hour (CPI-adjusted to constant 2007 Yuan), and non-missing information about the Gaokao score, gender, age, and province of residence. The full-time working sample are otherwise identical to the analysis sample except for no requirements on non-missing gaokao z-score.

Figure A3: Gaokao Z-score Distribution of Analysis Sample and Overall Sample with Non-Missing Gaokao Z-Score by Education Level



Note: The figure presents kernel densities of Gaokao z-score of the analysis sample and the sample of all adults with non-missing Gaokao z-score regardless of their working status in CHIP for each education level in each year. The analysis sample includes all full-time employees with hourly wages between 1 and 100 Yuan per hour (CPI-adjusted to constant 2007 Yuan), and non-missing information about the Gaokao score, gender, age, and province of residence.

Table A1: Value-added of HS Sector By Providence in 2007, 2013, and 2017

Province	Year		
	2007	2013	2017
Beijing	368.3	641.4	917.3
Tianjin	95.7	233.5	370.8
Hebei	199.2	356.3	621.8
Shanxi	103.4	210.1	316.3
Inner Mongolia	82.3	164.6	258.7
Liaoning	226.6	443.9	559.4
Jilin	99.6	207.2	310.8
Heilongjiang	124.0	241.9	360.2
Shanghai	367.9	651.1	1003.6
Jiangsu	442.4	941.7	1478.8
Zhejiang	363.0	656.8	1008.1
Anhui	152.7	278.7	471.0
Fujian	193.0	364.6	597.8
Jiangxi	84.6	162.2	270.8
Shandong	366.6	725.1	1072.5
Henan	180.8	384.4	603.9
Hubei	201.9	384.7	622.6
Hunan	194.8	397.4	674.1
Guangdong	709.1	1245.2	1930.8
Guangxi	104.3	196.2	303.4
Hainan	25.7	61.3	90.1
Chongqing	91.0	195.8	309.6
Sichuan	209.6	427.3	640.1
Guizhou	53.8	114.7	187.8
Yunnan	101.9	194.8	295.1
Tibet	9.9	19.2	29.3
Shaanxi	99.6	210.9	329.7
Gansu	56.7	122.2	184.2
Qinghai	16.1	30.1	45.2
Ningxia	15.3	27.7	42.9
Xinjiang	77.1	143.1	215.0

Note: The table reports the value-added of HS sector (in billion Yuan) by province in 2007, 2013 and 2017. All monetary values are adjusted to the 2000 price level. Data comes from the National Bureau of Statistics.

Table A2: Returns to Cognitive Skills and College Degrees by Year, No Sample Restrictions on the Availability of Gaokao Z-score

	1	2	3	4	5	6	7	8	9
Year	2007	2007	2007	2013	2013	2013	2018	2018	2018
College	0.609	0.567	0.511	0.388	0.343	0.285	0.481	0.414	0.342
	(0.013)	(0.014)	(0.017)	(0.013)	(0.014)	(0.017)	(0.012)	(0.014)	(0.016)
Gaokao z-score		0.116	0.109		0.096	0.098		0.109	0.110
		(0.013)	(0.014)		(0.012)	(0.013)		(0.010)	(0.011)
1(missing GK z-score)		-0.050	-0.045		-0.075	-0.071		-0.114	-0.104
		(0.015)	(0.016)		(0.014)	(0.014)		(0.013)	(0.013)
PE	0.036	0.036	0.036	0.034	0.035	0.035	0.040	0.041	0.041
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
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	0.142	0.139	0.139	0.195	0.193	0.193	0.175	0.171	0.172
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Constant	1.314	1.374	1.415	2.150	2.211	2.262	2.307	2.398	2.461
	(0.027)	(0.030)	(0.031)	(0.029)	(0.030)	(0.031)	(0.029)	(0.030)	(0.032)
Observations	8,239	8,239	8,239	8,863	8,863	8,863	11,600	11,600	11,600
Adjusted R2	0.333	0.341	0.339	0.200	0.209	0.209	0.197	0.210	0.209

Note: The sample includes all full-time employees with hourly wages between 1 and 100 Yuan per hour in CHIP 2007, 2013 and 2018. The dependent variable is log hourly wage. 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. 1(missing GK z-score) is a dummy variable indicating missing Gaokao z-score. Columns 2, 5, and 8 impute missing gaokao z-score as the average gaokao z-score by year group in full sample (basically 0). Columns 3, 6, and 9 impute missing gaokao z-score as the average gaokao z-score by education-year group. All regressions control for province fixed effects. Robust standard errors in parentheses.