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College Wage Premium and Computer Use in China

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Abstract: This paper explores the impacts of skill-biased technical change measured by computer use on college wage differentials in China over eight years from 2010 onwards. We find that expansion of computer use could significantly increase the college wage premium, especially when controlling industry heterogeneities and geographic factors. This pattern, using dynamic analysis in the long run, is mainly driven by complementary effects between capital structure and skilled workers, namely college educated workers. Moreover, the results are consistent when adopting propensity score matching methods, or in the case of over-education, or adopting alternative measures of technical change and wage earnings.
Key words: college wage premium; skill-biased technical change; computer use
JEL codes: I24, I26, J24, O33

1. Introduction

In recent years, China has experienced rapid economic development because the government introduced the Reform and Opening-up Policy in the late 1970s, making the transition from command economy to market economy. According to the statistics of International Monetary Fund (2020), China has ranked second after the USA in terms of nominal GDP in 2019, with an amount of approximately US $14.14 trillion.

However, wage inequality in China has also aroused the interests of labour economists. According to World Bank (2017), along with the dramatic expansion of aggregate income, the Gini index of China has reached 38.6 in 2017, which is higher than most developed countries in the world.

The theory of skill-biased technical change could provide a persuasive explanation for the source of wage inequality. With rapid technology updating in the past several years, people found statistical correlations between technical change and employment of skilled workers (Autor et al., 1998), leading to widening wage gap between skilled workers and unskilled workers within specific industries, which is called skill-biased technical change (SBTC).

This paper defines skilled workers as people who have received college education. In order to raise the potential of economic development, the Chinese government invested substantial amounts of money in education, which resulted in the explosion of high-skilled workers. Among developing countries, China has made an enormous contribution to the increase of world tertiary enrollment (Chi et al., 2013). From 1990 onwards, it is

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noticed that the dispersion of earnings and convergence of occupations between college graduates and non-college students has been driven by this college expansion (Chi et al., 2013). Simultaneously, the development of the Chinese economy has compelled the demand for higher educated workers, leading to more employment opportunities for college graduates (Li et al., 2008).

While a wide range of researches have observed widening income inequalities at the national level, concerns about detailed and differentiated analysis of contributors to the individual college wage differentials have so far been lacking, and that is why we focus on evidence in China. Nowadays, China has made a major breakthrough in technological development, but as one of the largest developing countries around the world, the monthly income of almost 0.6 billion people is still less than 1000 yuan (State Council of People's Republic of China, 2020). Compared with mechanisms about SBTC in other advanced countries, China's great technological progress can mainly be driven by catch-up effects at early stages of development, and now for some specific frontier research areas, China has already been able to participate in innovation process. For example, China has obtained leadership in the R&D process of 5G technology and COVID-19 vaccination. Therefore, with large-scale available dataset, the effects of technical changes on college premium in China could provide evidence for other early developing countries.

In this paper, we aim to investigate the contributions of skill-biased technical change measured by computer use on college wage differentials in China, and try to explore the economic mechanisms of college premium. Using CFPS (China Family Panel Studies) data whose sample ranges from 2010 to 2018, we find that expansion of computer use could significantly increase the college wage premium, especially when controlling industry heterogeneities and geographic factors.

This article contributes to the understanding of mechanisms behind SBTC, and provides a novel perspective of analysis on widening wage gaps. Different from other research based on macro level datasets, we successfully shed light on the contribution of technology on wage inequalities using micro evidence, which would pave the way for further research of applied micro-econometric studies.

The plan for the rest of this paper is organized as follows. In Section 2, we illustrate relevant literature, together with a brief discussion on several economic mechanisms to explain skill-biased technical change. In Section 3, we provide macro stylized facts about college premium regarding trend changes in employment as well as wage levels, and technical change. In Section 4, we propose a theoretical framework for econometric analysis. In Section 5, we undertake the quantitative framework, regression results, and IV estimates. In Section 6, we conduct robustness checks. In Section 7, we describe final conclusions and future implications. In an Appendix, we discuss details about derivations of the theoretical model.

2. Literature Review

According to the analysis of wage structure based on US census in the late 20th century, firms strongly favoured college graduates and females (Carneiro & Lee, 2011; Katz & Murphy, 1992), and empirical studies based on administrative data from Chile also suggests that people with college education were more likely to approach the top of income distribution (Zimmerman, 2019). Consequently, college educated workers tended to locate in cities with higher wages, local amenities, and productivities, while others were willing to pay in low amenity locations due to lower local rents (Diamond, 2016), which resulted in geographic reallocations in this area.

Moreover, given exogenous relative supply of skilled workers, only skill-biased technical change could contribute to changes in wage inequality (Card & DiNardo, 2002; Dolton & Makepeace, 2004; Jones & Yang, 2016; Kaplan & Rauh, 2013), and studies using World Health and Income database also described Pareto distribution of skill together with increasing skill returns (Jones & Kim, 2018). While for the influence of information technology on overall wage differentials between college students and non-college students, the expansion of computer use could account for roughly 60% of increasing education return (Krueger, 1993), and the effects could vary across different subjects of studies. Over the last two decades, it was skill demand shifts instead of non-market factors, such as episodic events or labour force composition changes, that played an increasingly significant role in wage structure variations among different education groups (Autor et al., 2008; Moreno-Galbis & Wolff, 2011).

This research contributes to the burgeoning literature on returns to college educations. Based on IEB (Integrated Employment Biographies) data file from the German social security system, decomposition of between-group wage differentials reveals that assertive matching between college educated workers and high-wage firms was attributable to 70% of widening wage premium (Card et al., 2013). While for evidence in China, throughout quantile regression analysis of wage differentials using CHIPs (China Household Income Project surveys) data spanning twenty years, decomposition of changes in earning inequalities suggests that changes in education returns had qualitatively similar effects, compared with changes in returns to working experience (Appleton et al., 2012). However, as time went by, this kind of substantial college wage premium declined quickly because more in-formation about workers' actual productivity would be obtained by employers (Demurger et al., 2019), and learning capabilities and labour market experience instead of higher education could play a relatively more substantial role in wage determination process several years later, especially for high-skill tasks (Stinebrickner et al., 2019). Without skill training and accumulation of working experience, such work interruptions as a long time of non-employment would lead to skill depreciation (Edin & Gustavsson, 2008; Polachek et al., 2015), thus reducing subsequent wages.

Regarding employment structure, pooling data of NSCG93 (National Survey of College Graduates for 1993) and ACS (American Community Survey) revealed that it was increasing returns to routine tasks that accounted for wage inequality across different occupations (Altonji et al., 2014). Controlling institutional differences and quality of peer groups, administrative data for Norway's centralized post-secondary education system showed labour market payoffs varied with different fields of studies (Kirkeboen et al., 2016). Theoretically, endogenizing assignment of skills and evolution of technology, technical change favouring skilled workers would substitute other skill groups' job tasks and reduce their real wages (Acemoglu & Autor, 2011). Unlike patterns of changes in developed countries, both declining fraction of routine manual occupations and increasing fraction of routine cognitive employment in developing countries are due to the rise of workers' education attainment and wide adoption of industrial robots (Ge et al., 2018). Therefore, the development of automation technology and college education could induce significant changes in employment structures (Autor et al., 2003).

Here not only do we study educational returns, especially college wage premium, but also the mechanisms of skill-biased technical change should be paid attention to. According to the Schumpeterian model, interactions between creative destruction by outside innovators and high efforts by heterogeneous entrepreneurs could determine inequality patterns (Kogan et al., 2017; Jones & Kim, 2018). Three principle channels have been identified from existing works of literature, namely substitution effects, complementary effects, and organizational structure.

Firstly, some people focused on substitution effects between skilled workers and unskilled workers within specific sectors. Based on Census data from the US, relative demand for skilled workers mainly came from rapid skill upgrading within industries (Autor et al., 1998), while the skill premium was not significant in the short run due to increase in the relative supply of skilled workers (Acemoglu, 1998; Li et al., 2017). However, in the long run, vast wage differentials would be generated due to crowd-out effects from skilled workers.

Secondly, others think it is capital-skill complementarity that accounts for wage inequality. With the development of manufacturing automation technology, many studies regarding NIPA (National Income and Product Accounts) data in the US indicated that the complementary effects between newly updated capital equipment and skilled labour are more extensive than those between machines and unskilled labour, especially for technologically advanced firms (Krusell et al., 2000; Lewis, 2011; Obiols-Homs & Sanchez-Marcos, 2018). Combining data on job requirements from DOT (Dictionary of Occupational Titles) issued by US department, advancing computer technology and declining price of computer capital could complement workers executing non-routine cognitive tasks such as problem-solving and sophisticated communication activities (Autor et al., 2003; Forman et al., 2012; Michaels et al., 2014), which was also supported by alternative empirical studies of broad Internet adoption policy using several Norwegian datasets (Akerman et al., 2015), and skill requirements across firms using BG (Burning Glass Technologies) dataset (Deming & Kahn, 2018). Therefore, unskilled workers have no choice but to reallocate themselves to service occupations, which requires fewer automation technologies (Autor & Dorn, 2013), contributing to wage and employment polarization. For profit incentives, firm owners tend to purchase cheaper capital equipment instead of unskilled workers (Acemoglu, 2002), especially within labour-intensive industries and occupations.

Thirdly, technology updating could lead to changes in organizational structure driven by decreasing communication costs (Aghion et al., 2017; Garicano & Rossi-Hansberg, 2004). Comparing US experience with European experience, which have similar occupational structure of skill distribution, it is different ways of information transformation due to institutional differences that contributed to various characteristics of wage inequalities (Hornstein et al., 2005). Besides, wage-setting institutions such as unionization and performance pay, could be viewed as an endogenous response to technical changes (Lemieux, 2008), which could contribute to continuing growth in top-end wage inequalities.

Nevertheless, there are few empirical interpretations about the mechanisms of college wage premium in China using the theory of skill-biased technical change. Due to the limitation of data about communication costs, this paper will only focus on the first two channels. Besides, the impacts of technical change on skill premium could be decomposed into changes in the supply side, namely conventional substitution effects, and demand side, namely directed technology effects or complementary effects (Acemoglu, 1998). In the short run, it is substitution effects between skilled workers and unskilled workers driven by the expansion of college graduates that dominate this process. While in the long run, the directed technology effects, especially skill-complementary technology, would be sufficiently strong, and increasing skill premium would induce further diffusion of new technology (Beaudry et al., 2010). Therefore, the college premium will shrink at first, and increase in the long run. Consequently, the first two mechanisms concerning the role of technical change could be synthesized into one episode. Theoretical derivations will be presented in section 4.

3. Macro Stylized Facts about College Wage Premium and Technical Change

3.1 Data Concerning Macro Stylised Facts

To explore whether college wage premium is driven by technology updating in recent years, we start our empirical analysis by establishing macro stylized facts concerning trends of college premium and technical change.

As for college premium, we use data from the Population Census of PRC conducted in 2000 and 2010[1], and China Labour Statistical Yearbook conducted in 2003-2006 and 2013-2017[2], to document time variation of overall employment after college education. Both these two institutions are under the governance of State Council of China and follow the same criteria of measurement when undertaking these two surveys. While data about changes in wage level are from NBSC (National Bureau of Statistics of China) urban household survey data, covering the years from 2000 to 2009.

As for technical change, data from the China Statistical Report on Internet Development conducted over the period from 2006 to 2019, could depict rapid computerization in recent decades. The overall scale of Internet users, along with the educational structure and occupational structure, will provide complete descriptions concerning the development of automation technologies, which could be treated as another aspect of technical change.

3.2 Evolution of College Premium

As seen in Table 1, the proportion of college-educated rose rapidly in recent years, while the proportion of those who did not receive primary school education has been decreasing dramatically over the past 18 years. Besides, the employment share of individuals who only received junior or senior high school education experienced fluctuations at first and remained steady from 2010 onwards. Despite that individuals who received high school diplomas still account for the majority of employed workers, we could not neglect the accelerating expansion of workers whose highest education level is college or more advanced education.

Table 2 illustrates a steady growth of future wage earnings among students with higher educational attainments. Not only did the starting payments of college graduates experience a considerable increase in the first ten years of the 21st century, but also the earnings growth rate has accelerated during the first several years after graduation.

It is widely acknowledged that during the 1990s, the profitability of the state-owned sector experienced a dramatic decline. As a consequence, many workers in state-owned enterprises were laid off and sent home with only initial payments, but remained on the payroll of their former employers, due to economic reforms in the urban sector, which is called *xiagang* in Chinese (Appleton et al., 2012; Brandt et al., 2014). Since the Fifth Plenary Session of the fourteenth Communist Central Committee held in 1995, the policies named *zhua da fang xiao* in Chinese, which aimed to privatize small and medium-sized state-owned enterprises and continue to control large enterprises, has been implemented (Feng et al., 2017). Therefore, such policies along with the shocks from financial crisis in 1998 accelerated the dramatic decline in employment, resulting in significant measurement

[1] According to National Bureau of Statistics of China (2010), the Population Census of People's Republic of China should be conducted every ten years, and only online data in 2000 and 2010 could be obtained from the website.

[2] According to Ministry of Human Resources Social Security of the Peoples Republic of China (2017), there are some measurement errors with the data in China Labour Statistical Yearbook from 2007 to 2012, and the officials should make some modifications. The new version will come out next year, so these data cannot be obtained from the website.

errors throughout the 1990s.

Table 1 Educational Composition of Employment (%), 2000-2017

	Illiterate	Primary School	Junior High	Senior High +Equivalent	College +Equivalent	Undergraduate	Graduate
2000	8.14	32.84	41.70	12.65	3.29	1.29	0.09
2003	7.80	30.00	43.20	13.10	4.30	1.60	0.20
2004	7.10	28.70	43.70	13.60	4.80	1.90	0.10
2005	6.20	27.40	45.80	13.40	5.00	2.10	0.13
2006	6.70	29.90	44.90	11.90	4.30	2.10	0.23
2010	3.41	23.86	48.80	13.87	5.96	3.71	0.39
2013	2.00	19.00	48.30	17.10	8.00	5.20	0.48
2014	1.90	18.50	47.90	17.10	8.50	5.50	0.51
2015	1.80	18.20	46.70	17.20	9.30	6.20	0.55
2016	2.80	17.80	43.30	17.30	10.60	7.50	0.70
2017	2.60	17.50	43.30	17.20	10.90	7.70	0.80

Notes: The data source is from the author's calculations based on data from Population Census of PRC by National Bureau of Statistics of China (2010) conducted in 2000 and 2010, and China Labour Statistical Yearbook conducted by Ministry of Human Resources Social Security of the Peoples Republic of China (2017) in 2003-2006 and 2013-2017. Senior high equivalent includes medium vocational education, and college equivalent includes high vocational education.

Table 2 Log Wage Earnings and Growth (%), 2000-2009

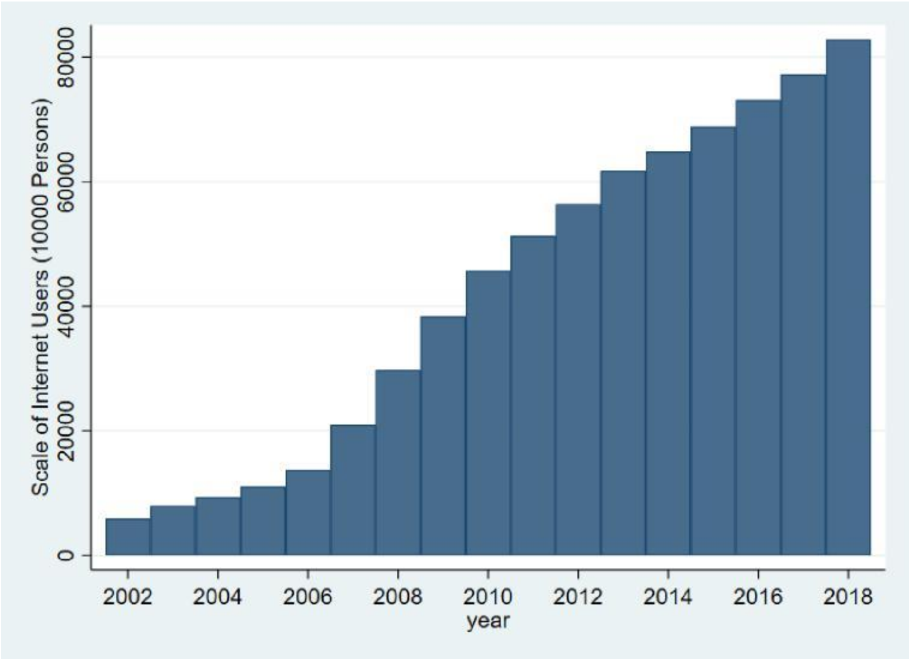
	Starting	1st Year	3rd Year	5th Year	Starting -3rd Year	Starting -5th Year	1st Year -3rd Year	1st Year -5th Year
2000	6.672	7.428	7.626	8.002	0.954	1.330	0.198	0.574
2001	6.866	7.416	7.774	8.111	0.908	1.245	0.358	0.695
2002	6.704	7.474	7.923	8.223	1.219	1.519	0.449	0.749
2003	6.841	7.652	8.014	8.375	1.173	1.534	0.362	0.723
2004	7.061	7.685	8.112	8.569	1.051	1.508	0.427	0.884
2005	7.044	7.845	8.264					
2006	7.265	8.022	8.421					
2007	7.437	8.055						
2008	7.401	8.242						
2009	7.491							

Notes: The data source is from Chi et al. (2013), and the original data before authors' calculation is from NBS urban household survey data. The authors did not have the data after 2009, so there are some missing cells in the table. Only data about annual earnings of graduates from 1989-2009 were reported in this article, and we cannot use data before 2000 owing to hyperinflation in the 1990s, so we only present the data in the 2000s.

Moreover, from 1990 onwards, college graduates should seek for jobs by themselves instead of being allocated by the labour bureau as before reforms (Chi et al., 2013). As a result, we cannot use data before 2000, owing to the transition to a genuine labour market.

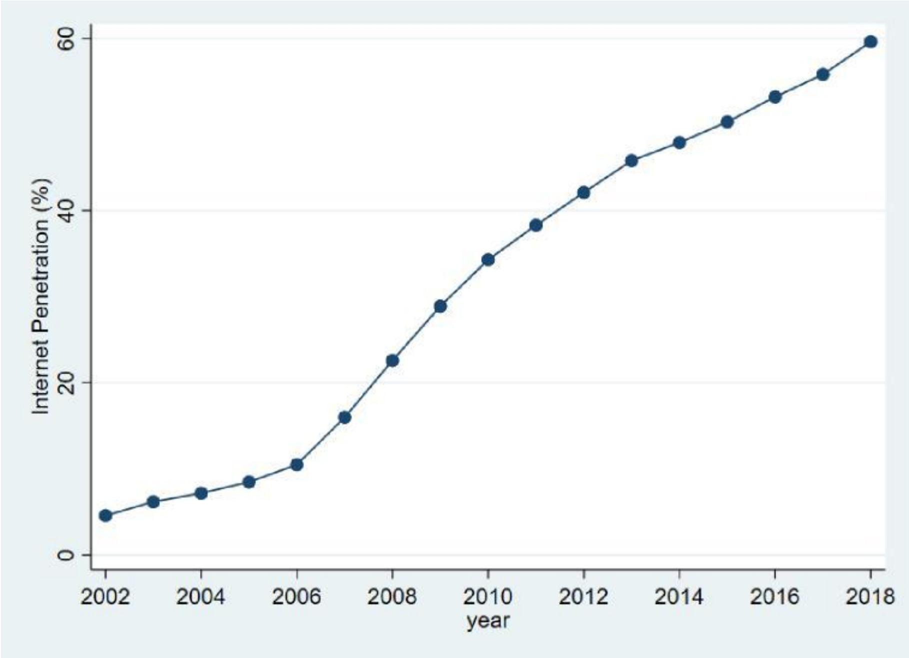
3.3 Trends of Technical Change

Regarding evidence about information technologies, the rapid development of computerization has been witnessed in China. Up to 2018, the number of Internet users in China has reached 828.5 million, and Internet penetration has risen sharply to roughly 60%, as is shown in Figure 1 and Figure 2. Also, the steady growth of the scale of Internet users could reflect the popularity of computer use and other computerization equipments in modern societies.



Notes: The data source is from China Internet Network Information Center (2019). Overall scale of Internet users refers to netizens per 10000 persons in the whole population.

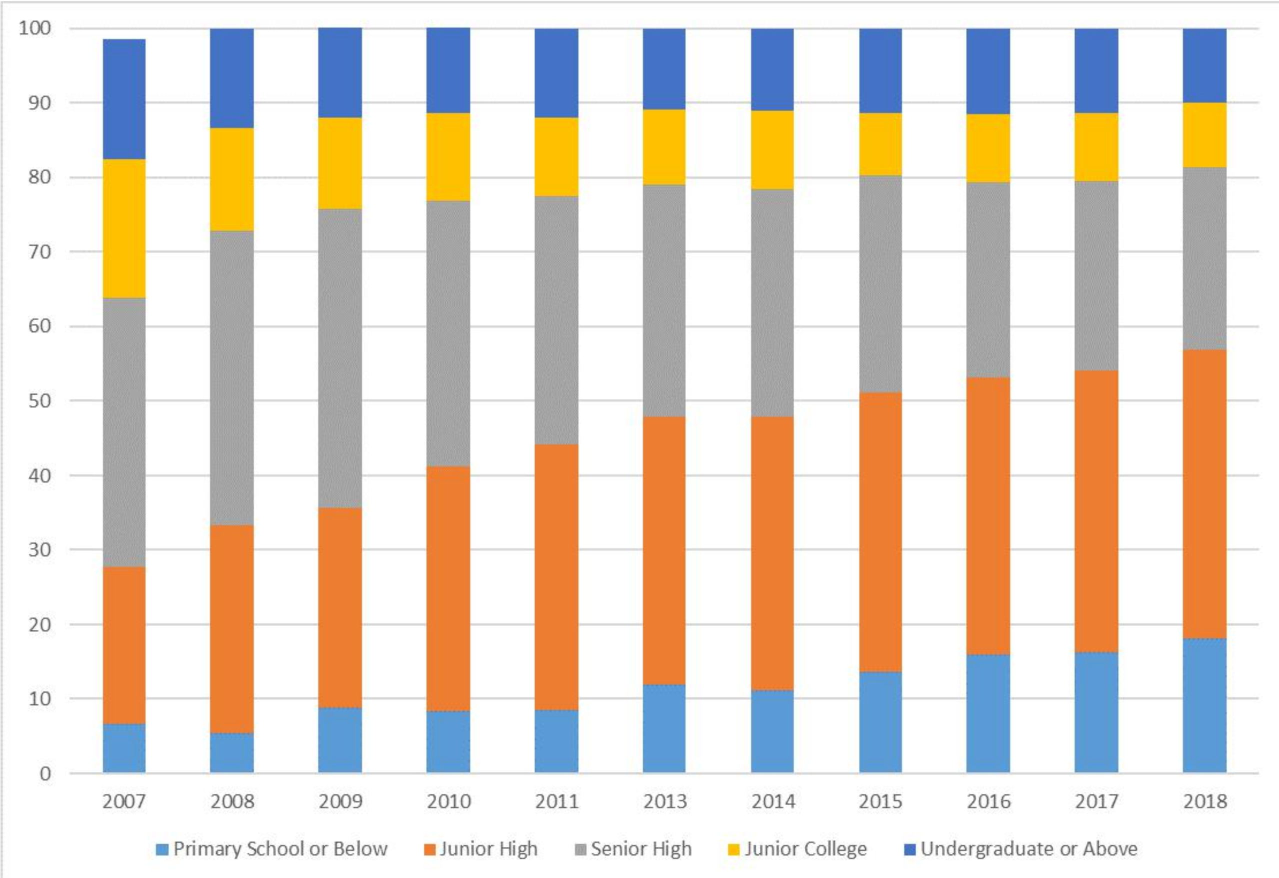
Figure 1 Overall Scale of Internet Users in China



Notes: The data source is from China Internet Network Information Center (2019).

Figure 2 Internet Penetration (%) in China

According to Figure 3, Internet users with high school education levels, including junior high and senior high, constitute a substantial fraction of overall Internet users. Working with computers has played an increasingly important role in workers with all educational levels, while the occupational structure of Chinese netizens remained stable. It could be observed from Table 3 that student is the largest group among overall Internet users. Nowadays, computer use becomes an essential skill in varieties of fields of work.



Notes: The data source is from China Internet Network Information Center (2019).

Figure 3 Education Structure of Chinese Internet Users

Table 3 Occupational Structure of Chinese Internet Users (%)

	2011	2012	2013	2014	2015	2016	2017
Student	30.2	25.5	23.8	25.2	25	25.4	25.4
Institutions (Leaders)	0.7	0.5	0.5	0.4	0.4	0.5	0.2
Institutions (General Stuff)	5.2	4.3	3.4	4.9	4.3	2.9	2.6
Enterprises (Executives)	0.8	0.4	0.6	0.5	0.5	0.5	0.6
Enterprises (Management)	3.2	2.1	2.2	2.3	2.3	1.9	2.2
Enterprises (Employees)	9.9	11.4	14.2	12.4	11.9	12.2	10.1
Technicians	8.3	6.6	5.8	5.5	4.8	4.8	5.2
Workers in Commercial Service	3.5	3.8	3.9	4.2	4.4	4.3	5.2
Manufacturing Workers	3.5	3.5	3.7	2.6	4.5	3.5	3.8
Others	34.7	41.9	41.9	42	41.9	44	44.7

Notes: The data source is from China Internet Network Information Center (2019).

4. Theoretical Model Specification

In this section, we only consider a basic model with one firm sector and four-factor aggregate production function. We first outline the four-factor production model developed by Krusell et al. (2000), and explain the assumptions and main results. Then the second part is concerned with the firm's static profit maximization using the method by Acemoglu (1998), to imply the substitution effects between skilled workers and unskilled workers in the short run. Finally, long-run analysis using a dynamic system can be adopted to illustrate complementary effects.

4.1 Preliminaries and Outline

Suppose that firms in a closed-economy are utilizing four factors to produce goods: capital structure k_s, capital equipment k_e, unskilled worker u, and skilled worker s. It bears note that the capital equipment k_e only captures physical properties of capital investment, while capital structure k_s refers to the abstract components. For example, the capital equipment of one computer is the physical materials, such as steel and plastic, which could complement with unskilled labour, and capital structure refers to intangible components such as copyright of such inventions. In order to highlight that the factors have constant returns to scale technology, the production function is Cobb-Douglas over k_e and the other three remaining factors. Besides, the relationship between k_s, u and s is constructed using CES specification, so that the substitution elasticities between every two factors are constant (Autor et al., 1998; Card & DiNardo, 2002; Krusell et al., 2000). Therefore, the primary aggregate production function is given below:

$$Y = Ak_e^{\alpha}\left\{\mu u^{\sigma} + (1-\mu)\left[\lambda k_s^{\rho} + (1-\lambda)s^{\rho}\right]^{\frac{\sigma}{\rho}}\right\}^{\frac{1-\alpha}{\sigma}} \tag{1}$$

In this specification, μ, λ, ρ, σ are parameters with $0 < \rho < \sigma < 1$. We denote wage premium, which is equal to the ratio between the marginal product of skilled workers and unskilled workers, by p_s, and this can be expressed as:

$$p_s = \frac{(1-\mu)(1-\lambda)}{\mu}\left[\lambda\left(\frac{k_s}{s}\right)^{\rho} + (1-\lambda)\right]^{\frac{\sigma-\rho}{\rho}}\left(\frac{s}{u}\right)^{\sigma-1} \tag{2}$$

Similarly, the price ratio between capital structure and unskilled workers is presented as:

$$p_{k_s} = \frac{(1-\mu)\lambda}{\mu}\left[\lambda + (1-\lambda)\left(\frac{s}{k_s}\right)^{\rho}\right]^{\frac{\sigma-\rho}{\rho}}\left(\frac{k_s}{u}\right)^{\sigma-1} \tag{3}$$

4.2 Static Analysis in the Short Run

We can simplify the analysis by normalizing the wage of unskilled workers to 1, then the price of skilled workers, namely wage premium, become p_s, and p_{k_s} can be regarded as the price of capital structure. Suppose k_e can only be determined by exogenous shock instead of other internal factors, then the cost of purchasing capital equipments could be treated as fixed costs. The firm aims to maximize profits π by choosing an appropriate combination of the other three factor inputs:

$$\max_{s,u,k_s} \pi = p_y Y$$
$$\boldsymbol{s.t.}\ m = p_s s + u + C_{k_e} + p_{k_s}k_s \tag{4}$$

In this specification, exogenous parameter p_y represents the price of final goods, and total wealth of the firm could be expressed in exogenous parameter m. Following steps presented in Appendix, we can calculate substitution effects between skilled workers and unskilled workers:

$$\frac{ds}{du} = -\frac{\sigma\left[\lambda k_s^{\rho}+(1-\lambda)s^{\rho}\right]+(1-\sigma)}{\sigma(1-\lambda)\rho u s^{\rho-1}} < 0 \tag{5}$$

It is obvious that $\frac{ds}{du}$ is negative, indicating that substitution effects between skilled workers and unskilled workers indeed exist. Similarly, we can also calculate the complementary effects:

$$\frac{ds}{dk_s} = -\frac{\lambda k_s^{\rho-1}}{(1-\lambda)s^{\rho-1}} < 0 \tag{6}$$

$$\frac{du}{dk_s} = -\frac{\sigma\lambda u k_s^{\rho-1}}{\sigma\left[\lambda k_s^{\rho}+(1-\lambda)s^{\rho}\right]+(1-\sigma)} < 0 \tag{7}$$

Equations (6) and (7) suggest that both $\frac{ds}{dk_s}$ and $\frac{du}{dk_s}$ are negative, indicating that complementary effects between skilled workers and capital equipment and those between unskilled workers and capital equipment do not exist.

From the static analysis above, in the short run, it is substitution effects between skilled workers and unskilled workers driven by the expansion of college graduates that dominate this process.

4.3 Dynamic Analysis in the Long Run

In the long run, a dynamic system of capital accumulation should be taken into considerations. Besides direct effects on total output, skilled workers could also contribute to the accumulation of organizational capital (Valletta, 2016). To simplify our analysis, we assume that organizational capital is a subset of capital structure k_s, then our value function could be modified into:

$$\max_{s,u,k_s} \pi = p_y Y$$
$$\boldsymbol{s.t.}\ m = p_s s + u + C_{k_e} + p_{k_s} k_s$$
$$\dot{k_s} = s + \delta k_s \tag{8}$$

In this specification, the evolution of capital equipment with time t is denoted as $\dot{k_s} = \frac{dk_s}{dt}$, and the depreciation rate is δ. Also, the evolution of skilled workers and unskilled workers could be defined as $\dot{s} = \frac{ds}{dt}$ and $\dot{u} = \frac{du}{dt}$. Here it is assumed that the growth of skilled workers is faster than that of unskilled workers, namely $\frac{\dot{s}}{\dot{u}} > 1$. Then we can solve this problem by following the steps presented in Appendix:

$$\frac{\omega}{\dot{u}} = \frac{(1-\mu)\sigma\mu\Omega^{\frac{\sigma+\rho}{\rho}}u^{\sigma-1}}{(1-\sigma)(1-\mu)^2\Omega^{\frac{2\sigma}{\rho}}+\sigma\mu^2u^{2\sigma}+(3\sigma-1)(1-\mu)\mu u^{\sigma}\Omega^{\frac{\sigma}{\rho}}} > 0 \tag{9}$$

$$\Omega = \lambda k_s^{\rho} + (1-\lambda)s^{\rho} \tag{10}$$

$$\omega = \lambda k_s^{\rho-1}\dot{k_s} + (1-\lambda)s^{\rho-1}\dot{s} \tag{11}$$

After some algebra, we can combine Equations (9) and (11), and finally explore the relationship between the evolution of skilled workers and unskilled workers:

$$\frac{\dot{s}}{\dot{u}} = \frac{\omega}{\dot{u}} \times \frac{\dot{s}}{\omega} = \frac{\omega}{\dot{u}} \times \frac{\dot{s}}{\lambda k_s^{\rho-1}\dot{k_s}+(1-\lambda)s^{\rho-1}\dot{s}} > 0 \tag{12}$$

As is suggested in Equation (12), the evolution of unskilled workers and that of skilled workers moves along the same directions, so there are no substitution effects between skilled workers and unskilled workers in this dynamical system.

$$\frac{\dot{k_s}}{\dot{u}} = \frac{\omega}{\dot{u}} \times \frac{\dot{k_s}}{\omega} = \frac{\omega}{\dot{u}} \times \frac{\dot{k_s}}{\lambda k_s^{\rho-1}\dot{k_s}+(1-\lambda)s^{\rho-1}\dot{s}} > 0 \tag{13}$$

$$\frac{\dot{k_s}}{\dot{s}} = \frac{\dot{k_s}}{\dot{u}} \times \frac{\dot{u}}{\dot{s}} > \frac{\dot{k_s}}{\dot{u}} > 0 \tag{14}$$

Taking Equations (13) and (14) into accounts, the complementary effects indeed exist, and those between skilled workers and capital equipment are larger than those between unskilled workers and capital equipment.

Overall, the theoretical framework derivations above imply that the impacts of technical change vary across different periods. Because our data could cover the changes of technology updating and wage differentials for eight years, and the main regressors are time variant, it is appropriate to conduct the dynamic analysis based on the complementary effects in the long run. Below is the long-run econometric analysis.

5. Empirical Analysis

5.1 Data Concerning Micro-Econometric Analysis

We now use micro data to examine whether technical change is a primary cause for the observed college wage premium. All the data related to individual characteristics are from CFPS (China Family Panel Studies) database, covering the years 2010, 2012, 2014, 2016, and 2018. We can find computer use, the highest educational degree received by individuals and monthly salaries here. Because our research question is about college wage premium, the sample is restricted to 44505 adults whose ages are above 25 years old, apart from retired[3] and unemployed, and self-employed individuals together with those out of labour force. Overall, workers which reports situation of computer use accounts for approximately 91% of efficient sample.

The CFPS database was launched in 2010 by Peking University. This nationally representative survey focuses on current Chinese society, covering several topics such as individual and family information, educational performances, and economic activities, etc. Due to follow-up strategy in the practice of fieldwork, all the family members including their infants will be tracked in the future, making it appropriate for us to conduct panel survey studies (Xie & Hu, 2014). Besides, the application of telephone or Web interviews could better solve sample attrition problems.

5.2 Variables

To measure changes in wage earnings, the dependent variable in our model is the natural logarithm of monthly salaries ($\ln wage$), so that we can avoid the noises from other components of individual income such as housing rents and financial interests. For people from rural areas, especially those in agricultural sector, it is hard for us to precisely calculate their monthly wages since they only receive their earnings after selling agricultural produced. Hence we will discuss about that in the Robustness Check section. The highest level of education received by individuals (college and noncollege) and computer use (computer) along with their interactions can be constructed as the main explanatory variables.

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[3] According to Ministry of Human Resources Social Security of the Peoples Republic of China (2017), the statutory retirement age for male workers is 60 years old, while that for female workers is 55 years old.

Based on the results in both theoretical and empirical studies, the covariates include gender (male), household address (urban), marital status (marry), housing registration status (agri), province locations (province)(, ethnicity (han), industrial heterogeneities (industry), scores from word and maths test (word and math)(, individual working experience (exp) and experience squared (exp^2). Individual characteristics such as gender, marital status, ethnicity, and working experience (linear and squared terms) could account for individual heterogeneities (Mincer, 1974).

Table 4 Description of Variables

	Symbol	Description
Explained Variable	In wage	Natural logarithm of monthly salaries after tax (yuan).
Main Explanatory Variables	College	Dummy variable. 1 if individual has received college education (including those who has received bachelor's degree ormaster's degree), and 0 if not.
	Noncollege	Dummy variable. 1 if individual has not received college education (including those who has received bachelor's degree or master's degree), and 0 if individual has received college education.
	Computer	Dummy variable. 1 if individual uses computer at any time including at work and at home, and 0 if not.
Control Variables	Male	Dummy variable. 1 if individual is male, and 0 if female.
	Urban	Dummy variable. 1 if live in urban area, and 0 if rural area.
	Marry	Dummy variable. 1 if individual is married or cohabitation, and 0 if never married, divorced, or widowed.
	Agri	Dummy variable. 1 if housing registration status is agriculture, and 0 if non-agriculture.
	Han	Dummy variable. 1 if individual is Han nationality, and 0 if other ethnicities.
	Exp.	Working experience of individuals.
	Exp^2	Experience squared.
	industry	A set of dummy variables, which refer to industry type of jobs.
	province	A set of dummy variables, which refer to provincial-level administrative region in China mainland.
	word	Score of word test.
	math	Score of maths test.

Notes: The data source is from Institute of Social Science Survey (ISSS). In China, most people do not care about the amount of taxation, and they only know their wages after tax. Therefore, it is hard to get information on monthly salaries before tax during this survey period, and that is why we use natural logarithm monthly salaries after tax as dependent variable. And for exp, according to Mincer (1974), it is assumed that people started schooling at the age of 6 and get employed immediately after graduation, so we can obtain$exp = age - educ - 6$

As for other dummy variables, industry dummies[4] can be adopted to analyse industry heterogeneities. Moreover, due to migration restrictions named hukou policy in China (Au & Henderson, 2006), different types of household address and housing registration status could play a key role in rural-urban wage inequalities. In addition, the combination of static gains associated with big cities, accumulated valuable experience by working, as well as skilled workers' self-selection could together contribute to higher individual earnings in big cities (Roca & Puga, 2016), and that is why we try to use province dummies to take account of regional economic development.

[4] We use industry dummies in our analysis, including mining; manufacturing; production and supply of electricity; construction; transportation; storage and postal service; information transmission and computer service; wholesale and retail; hotel and catering service; finance; real estate; rental and commercial service; scientific research and technical service; water resource, environment and public service; residential and other service industry; education; health, social security and public welfare; culture, sports and recreation; public administration and social organisation.

As for other continuous variables, cognitive skills measured by the scores from word and maths test during survey period could reflect individual abilities, which would tackle endogenous problems from omitted abilities problems (Deming, 2017; Heckman et al., 2018; Kottelenberg & Lehrer, 2019; Malamud & Pop-Eleches, 2011; Nybom, 2017; Polachek et al., 2015), and they can also affect educational choices and outcomes.

Table 4 explains the dependent variable and essential explanatory variables in our analysis.

5.3 Descriptive Statistics

Table 5 displays means for the explained variable and main regressors in this paper, which are separately presented for workers who have received college educations and those who have not, and those who use computer or not, accompanied with t-statistics for the hypothesis that the means are equal between these two groups.

According to the Table 5, the monthly wage of college educated workers is significantly higher than that of other groups, and the proportion of workers who can use computers in the college educated group is 43.4% higher than that in non-college educated group. In addition, the monthly wage of workers who use computers are 22.9% higher than those without computers.

Table 5 Means of Key Variables

Variable	Non-College	College	Difference	Non-Computer	Computer	Difference
Panel A: Total sample						
ln wage	8.038 (0.007)	8.898 (0.009)	-0.859*** (0.012)	7.860 (0.007)	8.089 (0.008)	-0.229*** (0.013)
Computer	0.152 (0.002)	0.586 (0.005)	-0.434*** (0.004)			
Panel B: Individuals Whose Age Between 25 and 40						
ln wage	8.145 (0.010)	8.861 (0.013)	-0.715*** (0.012)	7.930 (0.007)	8.084 (0.009)	-0.154*** (0.014)
Computer	0.289 (0.004)	0.791 (0.005)	-0.502*** (0.007)			
Panel C: Individuals Whose Age Between 40 and 60						
ln wage	8.015 (0.011)	8.828 (0.013)	-0.814*** (0.017)	7.872 (0.010)	8.089 (0.015)	-0.217*** (0.024)
Computer	0.085 (0.002)	0.379 (0.007)	-0.293*** (0.005)			
Panel D: Individuals in Manufacturing Sectors						
ln wage	7.622 (0.010)	7.971 (0.009)	-0.350*** (0.024)	7.610 (0.010)	7.878 (0.017)	-0.268*** (0.020)
Computer	0.193 (0.005)	0.637 (0.015)	-0.444*** (0.014)			
Panel E: Individuals in Non-Manufacturing Sectors						
ln wage	8.129 (0.010)	8.948 (0.009)	-0.819*** (0.013)	7.864 (0.010)	8.118 (0.008)	-0.254*** (0.015)

Computer	0.181 (0.002)	0.581 (0.005)	-0.400*** (0.005)			

Notes: The variable description is given in Table 4. Panel B refers to individuals whose age are exactly 25 and those whose age are exactly 40 are included. Panel C refers to individuals whose age are exactly 40 are excluded, and those whose age are exactly 60 are included. Robust standard errors are presented in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

As for age differences, the wage gap is more significant among workers who are older than 40, and the college educated workers whose ages range from 40 to 60 are more likely to use computers than those who did not receive college education. For differences across industries, both variations in monthly wage levels and computer use are larger among workers in non-manufacturing sectors than those in manufacturing sectors. Overall, the results suggest that age and experience effects, and industry heterogeneities should be taken into accounts when conducting econometric analysis.

Therefore, we put forward the hypothesis that on average, college educated workers could earn more salaries than other groups, which is due to differences in computer use. The impacts vary across different industries and different age groups with different experiences.

5.4 Regression Model

Below is the basic model specification based on panel data. Assuming little indirect components of educational return from continuation values (Heckman et al., 2018), this article only focuses on direct components. We aim to explore the impacts of technical change measured by computer use on college wage premium, and our interest centres on β_2 and β_3 in this model, which could reveal the relationship between computer use and college wage differentials. Therefore, the main evidence in favour of this assumption is that, β_2 is expected to be significantly larger than β_3, indicating that the complementary effects between college educated workers and computer use are supposed to be larger than those between non-college educated workers and computer use.

$$\ln \mathrm{wage}_{it} = \beta_0 + \beta_1 \times \mathrm{college}_i + \beta_2 \times \mathrm{college}_i \times \mathrm{computer}_{it} + \beta_3 \times \mathrm{noncollege}_i \times \mathrm{computer}_{it} + X_{it}^{'}\delta + \alpha_i + \varepsilon_{it} \quad (15)$$

In Equation (15), $\ln wage_{it}$ and $computer_{it}$ refers to time-varying[5] explained and explanatory variables of each individual i at year t, while $college_i$ and $noncollege_i$ refer to time-invariant regressors of each individual i, with detailed descriptions listed in Table 4. X_{it} includes all the covariates in Table 4. The individual specific effects α_i and idiosyncratic error ε_{it} constitute the unobserved error term in this equation. This panel data structure is unbalanced with random missing values for some respondents.

In addition, to further establish the difference between the complementary effects for college workers and non-college educated workers, namely to test whether $\beta_2 - \beta_3$ in Equation (15) is significantly positive, we also conduct another regression displayed below.

$$\ln wage_{it} = \gamma_0 + \gamma_1 \times college_i + \gamma_2 \times computer_{it} + \gamma_3 \times college_i \times computer_{it} + X_{it}^{'}\delta + \alpha_i + \varepsilon_{it} \quad (16)$$

Clearly, γ_2 in Equation (16) measures the wage differentials of computer use for non-college workers, and γ_3 tells the gap between the complementary effects for college workers and non-college educated workers.

Because college educated workers are not the majority of labour force, an increasing number of young

[5] $computer_{it}$ is a time-varying variable because some people start to learn to use computer at work.

skilled workers is associated with increasing the marginal product of senior skilled workers (Card & DiNardo, 2002; Li et al., 2017). Therefore, we have to pay attention to the coefficients of experience. Since individual experience can be treated as a combination of initial intrinsic ability and time trend, which could enable us to capture macro shocks, we do not need to add year dummies. Moreover, the impacts of technical change vary across different industries (Altonji et al., 2014), which indicates the importance of adding industry dummies into the regression model.

5.5 Basic Regression Results

In this section, we estimate Equation (15) and (16) for the overall sample and investigate whether computer use could contribute to wage differentials between college educated workers and others in Table 6. We prefer to use GLS estimator, to better identify the impacts of time-invariant components from college education and computer use.

Table 6 provides estimates of the effects on individual monthly wages. Working experience always has significant impacts on individual monthly wages. Considering industry heterogeneities, Column (1) reveals that computer use could significantly increase the college wage premium. On average, for college educated workers, the wage gap when using computers is 15.5% higher than that without using computers, while for non-college counterparts, the monthly wage when using computers is only 12.7% higher than that without using computers. After adding province dummies in Column (2), which could reflect regional effects, it is computer use that makes the wage premium significantly 11.8% higher than that without using computers, compared with 11.5% for non-college counter-parts. However, the results in Column (3) and (4) indicate that the difference between impacts of computer use for college and non-college educated workers are positive but not significant, implying that computer use could contribute to wage premium for both of the two groups. Detailed analysis regarding the magnitudes and significance level of our estimations results will be exhibited in the next section.

Table 6 Basic Regression Results

	ln wage				Computer	
	(1)	(2)	(3)	(4)	(5)	(6)
College	0.212*** (0.041)	0.220*** (0.041)	0.212*** (0.041)	0.220*** (0.041)	0.681*** (0.042)	0.668*** (0.043)
Computer			0.127*** (0.019)	0.115*** (0.019)		
College × computer	0.155*** (0.040)	0.118*** (0.040)	0.028 (0.044)	0.003 (0.044)		
Noncollege × computer	0.127*** (0.019)	0.115*** (0.019)				
Exp	0.016**	0.016**	0.016**	0.016**	-0.060**	-0.059***

	* (0.002)	* (0.002)	* (0.002)	* (0.002)	* (0.005)	(0.006)
Industry dummies	√	√	√	√	√	√
Province dummies		√		√		√
N	16605	16605	16605	16605	18740	18740

Notes: The variable description is given in Table 4. Apart from individual experience, other covariates included in regressions are not displayed here. The estimation results in Column (5) and (6) are marginal effects based on probit model. Robust standard errorsare presented in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Furthermore, college workers who already learned advanced skills usually self-select themselves into jobs requiring computer use, resulting in complementary effects between computer use and college education (Autor et al., 2003). In thinking about these questions, we also regress computer use on college education based on probit model, and report estimation results in Column (5) and (6). Consistent with our expectations, the percentage of computer use for college educated workers is almost 66.8% higher than non-college counterparts. Therefore, these results suggest the existence of complementary effects, and a much more careful illustration for differences between complementary effects of two groups is required in the following sections.

5.6 IV Estimates

Treating college education and computer use as endogenous variables, we next turn to IV estimates. Although $computer$ refers to the situation of computer use at workplace, which to some extent could not be influenced by total income, we still regard it as an endogenous variable, because people with high abilities have strong propensities to obtain college degree and self-select themselves into occupations which require computer use. The omitted abilities in Equations (15) and (16) could lead to upward biased estimates of the impacts of college education. Therefore, instrumental variables which could only affect monthly wage earnings through college education and computer use are required.

In this section, we use heteroscedasticity based estimation provided by Lewbel (2012), which requires the product of mean deviation of internal exogenous instruments and generated residuals, to estimate the effects of computer use on college wage differentials. If we regress monthly wages on all the covariates except for any variables containing college education and computer use, they must have common unobserved error terms with Equation (15) and (16), which could satisfy the assumptions by Baum & Lewbel (2018), including first stage requirements, namely strong correlation between heteroscedastic error structure and individual monthly wages. Besides, unobserved abilities have been eliminated from the IV construction. Therefore, we are confident that Lewbel (2012) estimator could only affect individual monthly wages through college education and computer use.

To increase the confidence of robustness and accuracy, higher education expansion policy ($expansion$) could act as an instrumental variable outside the equation to conduct feasible GMM estimation. In 1999, the State Council approved the proposal about higher education expansion policy by Department of Education. Aiming at raising tertiary education enrolment rate, they encourage universities and other equivalent colleges to improve hardware and software conditions and increase student-teacher ratio (Ma, 2019). In the subsequent period of time, it is observed that the implementation of various strategies has successfully raise the possibility of receiving college education. Therefore, the exogenous higher education expansion policy could satisfy the requirements of instrumental variables.

The results of estimates using Lewbel (2012) estimation along with external IV ($expansion$) are listed in

Column (1) and (2) of Table 7. Instrumented with mean deviation of internal exogenous instruments and generated residuals along with exogenous higher education expansion policy, it is evident that college education has significant impacts on monthly wage earnings, and the monthly wage gap of college educated workers when using computers is 27.5% higher than that of other workers, while for non-college counterparts, the monthly wage when using computers is only 8% higher than that without using computers. Column (2) also shows that the difference between impacts of computer use for college and non-college educated workers is 19.6%, indicating the complementary effects between college educated workers and computer use are higher than non-college educated counterparts, after tackling endogenous problems. Taking potential abilities into considerations, Column (7) suggests a more substantial magnitudes of intermediary effects, and the percentage of computer use for college educated workers is almost 24.3% higher than non-college counterparts, implying that college education could reinforce individual computer use. Based on Stock-Yogo weak identification test, accompanied with the null hypothesis that the equation is weakly identified (Chao & Swanson, 2005; Stock & Yogo, 2005), the Cragg-Donald Wald F statistics[6] is 5803.846, so we can reject the null hypothesis and conclude that the strength of instrument variables could ensure the consistent estimation.

Table 7 IV Estimates of the Effects of Computer Use on College Wage Premium

	ln wage						computer
	Whole		Agriculture		Non-Agriculture		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
College	0.025 (0.023)	0.025 (0.023)	0.031 (0.028)	0.031 (0.028)	0.049 (0.055)	0.049 (0.055)	0.243*** (0.009)
Computer		0.080*** (0.022)		0.018 (0.025)		0.226*** (0.051)	
College × computer	0.275*** (0.025)	0.196*** (0.030)	0.158*** (0.039)	0.139*** (0.043)	0.275*** (0.044)	0.049 (0.066)	
Noncollege × Computer	0.080*** (0.022)		0.018 (0.025)		0.226*** (0.051)		
N	29646	29646	19278	19278	10360	10360	38049

Notes: The variable description is given in Table 4. Higher education expansion policy ($expansion$) and other generated variables based on heteroscedastic error structure are instruments for $college$, $college \times computer$ and $noncollege \times computer$. ($expansion$) is a dummy variable, and $expansion = 1$ for workers who are less than 18 years old in 1999, and $expansion = 0$ if others. Column (3) and (4) is regression results only for workers with agricultural *hukou*, and Column (5) and (6) is regression results only for workers with non-agricultural *hukou*. Other covariates included in regressions are not displayed here. Variation of observations results from randomly missing value of instrument variables. Robust standard errors are presented in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Because there remains discrimination against migrants from rural areas owing to hukou system (Au &

[6] We use Stock-Yogo weak identification test to justify the significance of college, college × computer, and noncollege×computer, which is assumed to be endogenous in GMM-IV estimation. The 5% maximal IV relative bias is 20.54, and 10% maximal IV size is 11.04. Cragg-Donald Wald F statistic is more extensive than both two critical values, indicating that we can reject the null hypothesis and concluded that the strength of instrument variables could ensure the consistent estimation.

Henderson, 2006; Ma, 2019), the monthly wage levels of rural migrants fall behind those of local urban residents. Therefore, we estimate the heterogeneous effects of computer use on college wage premium using Lewbel (2012) estimation by hukou identities. Column (3) and (4) of Table 7 suggest that computer use could contribute to significantly more substantial wage gaps between college educated workers and others for workers with agricultural hukou, and the differences between such complementary effects are significantly positive due to relatively lower penetration rates of advanced facilities.

The difference between impacts of computer use for college and non-college educated workers is 13.9% for rural migrants, indicating that the technical change represented by computer use could be useful for workers with agricultural *hukou* to step up the economic ladder and achieve promising future lives. Since local urban residents are easily exposed to computer use, the magnitudes of complementary effects between college educated workers and computer use for workers with non-agricultural *hukou* are still significantly larger than urban counterparts. As summarised in Column (5) and (6), computer use could be attributable to college premium. And the monthly wage gap of college educated workers when using computers is 27.5% higher than that of other workers, while for non-college counterparts, the monthly wage when using computers is only 22.6% higher than that without using computers.

Overall, as illustrated in Table 7, IV estimates based on heteroscedastic error structure and external instruments could mitigate upward biased estimates from Section 5.5, and shed light on the explanation of differences between complementary effects of two groups.

6. Robustness Check

6.1 Propensity Score Matching Methods

The goal of this section is to check the robustness of econometric results using propensity score matching methods. Because a simple comparison of wage earnings between college educated workers and individuals from other education groups may not only reflect the impact of computer use, but also results from differences in other covariates, we adopt propensity score matching methods (Dehejia & Wahba, 2002), which use the probability of receiving college education conditional on other covariates, to alleviate the bias due to different specification of function forms and interruptions from noises.

We prefer to choose caliper matching methods in this section, where the probabilities of getting college education for all the non-college educated workers are within a predefined propensity score radius. As a method of matching with replacement, every college educated worker can be matched to the nearest comparison unit, thus would reduce the bias of the estimation, though less efficient in contrast with matching without replacement.

In this section, we regress $\ln wage$ on $college$, and other covariates with detailed descriptions listed in Table 4, for workers who use computer at work or not. Columns (1) and (2) of Table 8 exhibits results after controlling industry heterogeneities and geographic factors, indicating that college education has significant positive impacts on monthly wage earnings, especially for workers who can use computers, while Column (4) and (5) reveal that the effects of college premium for workers who do not use computer at work are insignificant. Therefore, results are consistent with the initial results in Table 6.

For columns (3) and (6) of Table 8, we turn attention to the results of fitting Equation (15) with different propensity score radius. On average, the college premium of those who can use computers is around 18.1% than that of others.

To sum up, the results above imply that our findings are not driven by the effects of other covariates, which imply the significant impacts of computer use on college wage premium.

Table 8 Regression Results Under Propensity Score Matching Methods

	computer = 1			computer = 0		
	(1)	(2)	(3)	(4)	(5)	(6)
College	0.180*** (0.024)	0.181*** (0.024)	0.181*** (0.024)	−0.076 (0.051)	−0.076 (0.051)	−0.076 (0.051)
Industry dummies	√	√	√	√	√	√
Province dummies		√	√		√	√
N	4044	4042	4042	12561	12558	12558

Notes: The variable description is given in Table 4. Other covariates included in regressions are not displayed here. Coefficients of college refer to average treatment effect on the treated. Treatment in this section refers to whether or not receive college education. Results are only for "matched" samples. Number of observations refers to individuals within predefined propensity score radius (caliper). Propensity score radius in columns (3) and (6) are 0.001, and those in other columns are 0.01. Robust standard errors are presented in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6.2 Over-Education

Alternative explanations could also be proposed to account for factors of college wage premium. The analysis above assumes that there is no educational mismatching. However, as the largest developing country in the world, over-education must exist in China due to market frictions, which is defined as a type of skill mismatch where workers have more education years than requirements (Groot, 1996). Therefore, skilled workers tend to search intensively and pursue job reallocation (Bagger & Lentz, 2019). The wage loss of over-educated workers with tertiary education is significantly massive, while over-education has no significant impacts on workers with high school education (Wu & Wang, 2018). In terms that over-education is unevenly distributed across different groups (Deming & Kahn, 2018), we have to conduct regressions based on over-educated workers in different occupations.

In order to establish whether individuals are over-educated, two main measures can be taken into consideration. One is "objective", which is designed to make comparisons between education level and self-evaluated educational requirement. The other one is "subjective", where we make contrasts between an individual's educational level and mean value of job dataset (Baert et al., 2013; Ng, 2001). This paper will first adopt the subjective measure to investigate the degree of over-education, which is not restricted by shortages of self-reported data. If the gap between an individual's educational level and the mean value of this group is more extensive than one standard deviation, then the person is over-educated (Bauer, 2002).

Table 9 provides the estimates of the effects of computer use on college wage differentials for those who are over-educated. As exhibited in Column (1), on average, college wage differentials of workers who can use computers are significantly 12.8% higher than those without computer use when controlling for industry heterogeneities and geographic factors, while for non-college educated workers, computer use could only increase wage gap by 11.6%, though Column (2) expresses insignificant impacts of differences between complementary effects of two groups due to potential ability bias illustrated before. Using IV estimation based on exogenous heteroscedastic structure, the difference between impacts of computer use for college and non-college educated workers is 16.2%, implying significant gap between complementary effects of two groups. Column (5) shows the intermediary effects of college education on computer use are more substantial, implying over-educated workers who have received college education are more inclined to occupations which require computer use.

Table 9 Regression Results in the Case of Over-Education

	ln wage		ln wage(IV)		computer
	(1)	(2)	(3)	(4)	(5)
College	0.211*** (0.051)	0.211*** (0.051)	0.111** (0.051)	0.111** (0.051)	0.668*** (0.057)
Computer		0.128*** (0.030)		0.119*** (0.043)	
College × computer	0.128*** (0.030)	0.012 (0.051)	0.282*** (0.037)	0.162*** (0.056)	
Noncollege × computer	0.116*** (0.041)		0.119*** (0.043)		
Industry dummies	√	√	√	√	√
Province dummies	√	√	√	√	√
N	8566	8566	8566	8566	9499

Notes: The variable description is given in Table 4. Other covariates included in regressions are not displayed here. The estimation results in Column (5) are marginal effects based on probit model. Robust standard errors are presented in parenthesis.
* p < 0.1, ** p < 0.05, *** p < 0.01.

Therefore, the results above are broadly consistent with estimates of computer use and college wage premium in Section 5.5, and reveal that even in the case of over-education, our findings are still robust to account for the significant impacts of computer use on college wage premium.

6.3 Measures of Technical Change and Earnings

As noted earlier, we adopt computer use as a measure of technical change. However, this could not adequately reflect an individual's skillfulness in computer use, since people could also operate other technologically advanced machines to raise production efficiencies. Based on German data, people found statistically significant associations between wage differentials and the use of other "white-collar" tools such as calculator, telephone and manual writing materials, and the magnitude was similar to the correlation between computer use and wage gaps (DiNardo & Pischke, 1997). Adopting our considerably more detailed information in CFPS database, we turn to analyze another "white-collar" tool named email use (email), which would deliver different interpretations of impacts of technical change on college wage differentials. As illustrated in Section 4, college wage differentials could arise from complementary effects between capital equipment and college educated workers. Specifically, studies illustrate that electronic mail is the most highly rewarded among a variety of computer tasks (Krueger, 1993). Furthermore, it is still popular for people engaging in business and productive activities to use email in China, which is relevant to earnings determination, though most people mainly use *WeChat* to communicate with each other (South China Morning Post, 2017). In terms that email use might also proxy for computer use (DiNardo & Pischke, 1997), we also regress monthly wage earnings on computer use and email use simultaneously.

Table 10 Regression Results using Alternative Measures of Technical Change

	ln wage			ln wage (IV)	
	(1)	(2)	(3)	(4)	(5)
College	0.198*** (0.047)	0.198*** (0.047)	0.022 (0.091)	-0.051 (0.049)	-0.051 (0.049)
Email		0.181*** (0.025)			-0.049 (0.079)
College × email	0.135*** (0.039)	0.054 (0.046)	0.112*** (0.037)	0.185*** (0.053)	0.234*** (0.079)
Noncollege × email	0.181*** (0.025)		0.084*** (0.026)	-0.049 (0.079)	
College × computer			0.204*** (0.073)		
Noncollege × computer			-0.010 (0.028)		
Industry dummies	√	√	√	√	√
Province dummies	√	√	√	√	√
N	4683	4683	4683	8326	8326

Notes: The variable description is given in Table 4. Email refers to email use, which is a dummy variable. Other covariates included in regressions are not displayed here. Robust standard errors are presented in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10 documents estimates of the effects of the combination of email use and computer use on college wage differentials. It is observed from Column (1) and (2) that college wage differentials of workers who can use email are significantly 13.5% higher than those without email use when controlling for industry heterogeneities and geographic factors, while for non-college educated workers, computer use could only increase wage gap by 8.1%, though the differences with each complementary effects are not significantly large. Through IV estimation based on exogenous heteroscedastic structure, the difference between impacts of email use for college and non-college educated workers is 23.4%, implying significant gap between complementary effects of two groups. Unlike primary regression results in Table 6, Column (3) reveals that the coefficients of noncollege computer tend to diminish later for non-college educated workers, indicating weak complementary effects between email use and computer use within specific occupations.

Moreover, wage earnings constitute the majority of income for urban Chinese residents, so income inequality could be regarded as an alternative measure of wage differentials (Appleton et al., 2012; Demurger et al., 2019). Also, only adopting monthly wages to measure college premium could induce substantial measurement errors for people from rural areas, since they usually obtain their earnings from agricultural produces on annual or quarter basis, making it hard to identify individual wage level for people located in rural areas.

Table 11 documents estimates of the effects of computer use on college income differentials. On average, college income differentials of workers who can use computers are significantly 20.1% higher than those without computer use when controlling for industry heterogeneities and geographical factors, while for non-college educated workers, computer use could only increase wage gap by 19.9%, and the insignificant differences between two complementary effects are attributable to individual potential abilities. Subgroup estimations listed on Column (5) and (6) also provide similar results, and the impacts of computer use are more substantial for workers from urban areas, and the magnitudes of differences are lower for workers from rural areas.

Therefore, the results above suggest that even with alternative measures of technical change and wage earnings, our findings are still robust to account for the significant impacts of technical change on college wage premium.

Table 11 Regression Results using Alternative Measures of Earnings

	Whole		Whole (IV)		Urban	Rural
	(1)	(2)	(3)	(4)	(5)	(6)
College	0.355*** (0.036)	0.355*** (0.036)	0.365*** (0.026)	0.365*** (0.026)	0.411*** (0.039)	0.111 (0.087)
Computer		0.201*** (0.021)		0.398*** (0.023)		
College × computer	0.201*** (0.021)	0.002 (0.038)	0.398*** (0.023)	0.034 (0.034)	0.205*** (0.025)	0.289*** (0.089)
Noncollege × computer	0.199*** (0.032)		0.364*** (0.029)		0.192*** (0.035)	0.231*** (0.040)
Industry dummies	√	√	√	√	√	
Province dummies	√	√	√	√	√	
N	17197	17197	30385	30385	8873	8324

Notes: The variable description is given in Table 4. Dependent variable is natural logarithm of total income for all jobs (ln income). Other covariates included in regressions are not displayed here. Column (5) is regression results only for workers from urban areas, and Column (6) is regression results only for workers from rural areas. Robust standard errors are presented in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

7. Conclusion

From the perspective of skill-biased technical change, studies of the contributions of technology upgrading measured by computer use on college wage differentials in China have attracted people's attentions in recent years. Evidence about college premium, including the evolution of employment and wage levels, and technical change such as the proportion of R&D workers and computer use, actively supports the views that widening wage gap within specific industries could result from statistical correlation between technical change and employment of skilled workers.

Throughout the theoretical framework of the four-factor production model concerning relationship among capital structure, capital equipment, skilled workers and unskilled workers, our results discover that the complementary effects in dynamical system between skilled workers and capital structure are more significant than those between unskilled workers and capital structure, which is a direct consequence of wage premium in the long run.

Besides stylized macro evidence, the micro-econometric analysis based on CFPS database in China could also provide evaluations of the central hypothesis derived from our model. These findings suggest that computer use could significantly increase the college wage premium, especially when controlling industry heterogeneities and geographic factors.

Also, a wide range of alternative specifications are presented to check the robustness of our conclusions. Even when adopting propensity score matching methods, or in the case of over-education, or adopting alternative measures of technical change and wage earnings, the results still exhibit significant impacts from technical change on college wage premium.

An exciting extension for future work would be to incorporate institutional factors into this framework of analysis. As the largest developing country in the world, we cannot ignore the impacts of state capacity on resource allocations in China. Also, information costs could contribute to wage differentials across varieties of firms. Therefore, proper measurements about communication costs and institutional variations could make it convenient for future analysis.

A second area for future research is the trend analysis based on a broad span of a period. Because of political factors and measurement errors, we cannot quickly get access to macro data before the 21st century. Consequently, macro data which covers a long time could better reflect the evolution of skill-biased technical change.

Our detailed investigation takes a step towards the analysis of wage differentials from the perspective of skill-biased technical change, which could provide alternative explanations on wage inequalities. If this interpretation could be generalized into other areas and other periods, it has potentially significant implications for future policy makings. Regarding human capital accumulations, technology updating could strengthen the advantages of college educated workers and provide more wage promotion opportunities for them. Therefore, the policy named "Develop the Country through Science and Education" could better enhance sustainable economic development in China.

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Appendix: Technical Details

A.1 Derivation of Static System in the Short Run

As illustrated in Section 4.2, our value function could be expressed as Equation (4):

$$\max_{s,u,k_s} \pi = p_y Y$$
$$\boldsymbol{s.t.}\, m = p_s s + u + C_{k_e} + p_{k_s} k_s \tag{4}$$

All the variables and parameters are as described in the text. Under Karush–Kuhn–Tucker (KKT) conditions, we can solve this problem by substituting Equation (1), (2) and (3) into Equation (4) and obtain the results:

$$= \frac{\sigma}{1-\sigma} u\left[\lambda k_s^{\rho} + (1-\lambda)s^{\rho}\right] \tag{A1}$$

Then we can find total derivatives of the Equation (A1):

$$\left\{\frac{\sigma}{1-\sigma} u\left[\lambda k_s^{\rho} + (1-\lambda)s^{\rho}\right] + 1\right\} du + \frac{\sigma}{1-\sigma}\lambda\rho u k_s^{\rho-1} dk_s + \frac{\sigma}{1-\sigma}(1-\lambda)\rho u s^{\rho-1} ds = 0 \tag{A2}$$

After some algebra, we can figure out the relationship between ds, dk_s, and du, whichcould be represented as the Equation (5), (6), and (7).

A.2 Derivation of Dynamical System in the Long Run

As mentioned in Section 4.3, our value function could be modified into Equation (8):

$$\max_{s,u,k_s} \pi = p_y Y$$
$$\boldsymbol{s.t.}\, m = p_s s + u + C_{k_e} + p_{k_s} k_s$$
$$\dot{k_s} = s + \delta k_s \tag{8}$$

All the variables and parameters are as described in the text. Under Karush–Kuhn–Tucker (KKT) conditions and Euler Formula[7], we can substitute Equation (1), (2) and (3) into Equation (8) and rearrange the results:

$$\begin{aligned}
&\left[(1-\mu)(1-\sigma)\Omega^{\frac{\sigma}{\rho}} - \sigma\mu u^{\sigma}\right]\Omega\left\{\left[\lambda k_s^{\rho-1} + \delta(1-\lambda)s^{\rho-1}\right]\left[\mu u^{\sigma} + (1-\mu)\Omega^{\frac{\sigma}{\rho}}\right]\right. \\
&\qquad\left. + (1-\lambda)s^{\rho-2}\left[\mu u^{\sigma} + (1-\mu)\Omega^{\frac{\sigma}{\rho}}\right](1-\rho)\dot{s}\right\} \\
&= (1-\lambda)s^{\rho-1}\left(\sigma\Omega\left[\mu u^{\sigma} + (1-\mu)\Omega^{\frac{\sigma}{\rho}}\right]\left[(1-\mu)(1-\sigma)\Omega^{\frac{\sigma-\rho}{\rho}}\omega - \sigma\mu u^{\sigma-1}\dot{u}\right]\right. \\
&\qquad\left. - \left[(1-\mu)(1-\sigma)\Omega^{\frac{\sigma}{\rho}} - \sigma\mu u^{\sigma}\right]\left\{\sigma\Omega\left[\mu u^{\sigma-1}\dot{u} + (1-\mu)\Omega^{\frac{\sigma-\rho}{\rho}}\omega\right] + \left[\mu u^{\sigma} + (1-\mu)\Omega^{\frac{\sigma}{\rho}}\right]\omega\right\}\right)
\end{aligned} \tag{A3}$$

$$\Omega = \lambda k_s^{\rho} + (1-\lambda)s^{\rho} \tag{A4}$$

$$\omega = \lambda k_s^{\rho-1}\dot{k_s} + (1-\lambda)s^{\rho-1}\dot{s} \tag{A5}$$

Obviously, whether the left-hand side is positive or negative is determined by the sign of $\left[(1-\mu)(1-\sigma)\Omega^{\frac{\sigma}{\rho}} - \sigma\mu u^{\sigma}\right]$[8], and as noted before, $(1-\lambda)s^{\rho}$ must be positive. Therefore, the product of$\left[(1-\mu)(1-\sigma)\Omega^{\frac{\sigma}{\rho}} - \sigma\mu u^{\sigma}\right]$ on the left hand side and the third components of the right-hand side must be non-negative, then we can rearrange into the inequality below:

$$\begin{aligned}
&\left[(1-\mu)(1-\sigma)\Omega^{\frac{\sigma}{\rho}} - \sigma\mu u^{\sigma}\right]\left[(1-\sigma)(1-\mu)^2\Omega^{\frac{2\sigma}{\rho}} + \sigma\mu^2 u^{2\sigma} + (3\sigma-1)(1-\mu)\mu u^{\sigma}\Omega^{\frac{\sigma}{\rho}}\right]\omega \\
&\geq \left[(1-\mu)(1-\sigma)\Omega^{\frac{\sigma}{\rho}} - \sigma\mu u^{\sigma}\right](1-\mu)\sigma\mu\Omega^{\frac{\sigma+\rho}{\rho}} u^{\sigma-1}
\end{aligned} \tag{A6}$$

---

[7] Assume $x$evolves with time t, and let $\dot{x} = \frac{dx}{dt}$, then for a general function $f(x, \dot{x}, t)$, we can obtain $\frac{df}{dx} - \frac{d}{dt}\left(\frac{df}{dx}\right) = 0$.

[8] According to Equation (A4), $\Omega$is weighted average of two non-negative variables k_s and s, so $\Omega > 0$.Similarly, $\left[\lambda k_s^{\rho-1} + \delta(1-\lambda)s^{\rho-1}\right] > 0$, and $\left[\mu u^{\sigma} + (1-\mu)\Omega^{\frac{\sigma}{\rho}}\right] > 0$, so all the components except for $\left[(1-\mu)(1-\sigma)\Omega^{\frac{\sigma}{\rho}} - \sigma\mu u^{\sigma}\right]$ should be positive.

We aim to find the relationship between $\dot{u}$and ω, which could pave the road for exploring the relationship among $\dot{u}$,$\dot{s}$and $\dot{k_s}$, namely the relative changes among skilled workers, unskilled workers, and capital structure. By moving $\dot{u}$and ω to the left-hand side, we yield:

$$\frac{\omega}{\dot{u}} \geq \frac{(1-\mu)\sigma\mu\Omega^{\frac{\sigma+\rho}{\rho}}u^{\sigma-1}}{(1-\sigma)(1-\mu)^2\Omega^{\frac{2\sigma}{\rho}} + \sigma\mu^2u^{2\sigma} + (3\sigma-1)(1-\mu)\mu u^{\sigma}\Omega^{\frac{\sigma}{\rho}}} \tag{A7}$$

Therefore, whether the right-hand side is positive or negative is determined by the sign of $(1-\sigma)(1-\mu)^2\Omega^{\frac{2\sigma}{\rho}} + \sigma\mu^2u^{2\sigma} + (3\sigma-1)(1-\mu)\mu u^{\sigma}\Omega^{\frac{\sigma}{\rho}}$ since it is apparent that $(1-\mu)\sigma\mu\Omega^{\frac{\sigma+\rho}{\rho}}u^{\sigma-1}$is the products of several non-negative components. Then we can treat the ambiguous part as a quadratic function of Ωsrand construct a new function:

$$f\left(\Omega^{\frac{\sigma}{\rho}}\right) = (1-\sigma)(1-\mu)^2\Omega^{\frac{2\sigma}{\rho}} + (3\sigma-1)(1-\mu)\mu u^{\sigma}\Omega^{\frac{\sigma}{\rho}} + \sigma\mu^2u^{2\sigma} \tag{A8}$$

Since $\Omega^{\frac{\sigma}{\rho}} = \left[\lambda k_s^{\rho} + (1-\lambda)s^{\rho}\right]^{\frac{\sigma}{\rho}} \geq \min\left\{k_s^{\rho}, s^{\rho}\right\}$, we can easily obtain that $f\left(\Omega^{\frac{\sigma}{\rho}}\right) \geq 0$ for any $f\left(\Omega^{\frac{\sigma}{\rho}}\right) \in \left(\min\left\{k_s^{\rho}, s^{\rho}\right\}, \infty\right)$. Therefore, Equation (A7) must be positive, and the relationship of three factors could be easily obtained.