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ICT Use, Cognitive and Non-cognitive Abilities, and Wages: Micro Evidence from China

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Abstract

On determining wages in the labor market, recent scholarly attention has been drawn toward individual abilities and external technological environment, in addition to conventional human capital theory. With the advancement of information and communication technologies (ICT), it is important to understand how individual abilities directly and jointly with ICT use affect wages at work. Using a unique Chinese micro panel data, the present study investigates the effects of both ICT use and cognitive and non-cognitive abilities on wages, and the potential complementary effect of ICT use in facilitating individual abilities in wage determination. The results show that cognitive and non-cognitive abilities are positively related to wages, and those who use ICT tend to earn more than those who do not. In addition, ICT use strengthens the positive relationship between cognitive and non-cognitive abilities and wages.

Keywords: Human Capital; ICT Use; Cognitive and Non-cognitive Abilities; Wages

INTRODUCTION

What determines an individual's income in the job market? This question has been under thorough scholarly scrutiny for decades. Human capital theory is among the most influential theories that offer answers to the question, with in-depth focus on the returns to experience, schooling and training. However, when wage polarization phenomenon first caught sight in the developed countries, scholars realized that the classic model only explains a limited portion of the variances, and started to look into the error term of the wage equation and discover the effects of cognitive and non-cognitive abilities on income determination (e.g., Cawley et al., 2001; Heckman & Rubinstein, 2001).

Meanwhile, a parallel stream of literature attempts to investigate how technological advancement is shaping the labor market and changing the wage structure. The findings suggest that the use of computer possibly increases worker's productivity and results in a premium in wages (Krueger, 1993). Information and communication technology (ICT) is complementing workers' non-routine abstract tasks and substituting routine tasks (Levy & Murnane, 1996; Autor, Levy, & Murnane, 2003; Akerman et al., 2015).

The two streams of literature combined suggest that both individual abilities and external technological environments in the workplace jointly affect workers' reward in the labor market. The two scholarly pathways can be linked together to explain skill formation and task completion for labor. In conjunction with the present practical context that new technology is setting off to carry out more tasks, it is important to understand how technology is complementing or replacing some of the roles that have been fulfilled relying upon workers' individual abilities.

To briefly review the history, very few would doubt that since the second half of the 20th century, ICT has been the most important technology that has pushed the world forward and reshaped the human lives in all aspects. Especially the popularization of personal computer and the development of the following internet technology have made vast impact on people's jobs and the workplace. Meanwhile, researchers in the fields of labor economics and human resources have noticed and studied these changes ever since the beginning of this ICT revolution.

China has a vast and growing population of internet users (see Figure1), which is the largest in the world and is taking leading position in several fields in the internet industry. But unlike in developed countries especially the United States, the changes brought by advanced technologies on the labor outcomes in China is still far from sufficient understanding in the academia.

[Insert Figure 1 about here]

In lieu of this academic deficiency, we attempted in the present study to deepen our understanding of how human intelligence is related to wages in the job market, and how ICT is influencing the wage structure in China. We linked the effects of cognitive and non-cognitive abilities on wages with the impact of ICT on labor market outcomes. Specifically, we explored the potential complementary effect of ICT use to cognitive and non-cognitive abilities. ICT development may change the labor market structure and the way workers are rewarded on top of cognitive and non-cognitive abilities. This phenomenon may soon turn prevalent in the labor market.

On the basis of the above introduction, the present study makes threefold contribution in the following aspects: Firstly, we provided extra evidence to how cognitive and non-cognitive abilities can influence wages in the Chinese transitional economy by utilizing the updated national micro survey data which can be seen as a representative sample. Secondly, we examined the comprehensive effects of ICT impact from the perspective of skill-biased technological change (SBTC), and found evidence supporting the positive labor market return to the use of information and communication technologies. Thirdly, we linked the effects of cognitive and non-cognitive abilities on wages to the impact of ICT on labor market outcomes. By connecting the two important research streams in human capital theory, we shed light on the potential complementary effect of ICT use.

THEORETICAL BACKGROUNDS

Cognitive and Non-cognitive Abilities in the Labor Market

Individual abilities are either reflected by education attainment, through the mechanisms of screening and signaling in the labor market (Stiglitz, 1975), or remain in the error term and regarded as a source of omitted variable biases that will result in over-estimation of return on education (Griliches & Mason, 1972). Although intelligence is mostly genetically inherited, and it tends to be quite stable in one's adulthood (Plomin et al., 1994), cognitive and non-cognitive abilities can be still significantly affected by family background and learning environment. The formation of these abilities is a dynamic process in one's life cycle, and educational investment in early years can greatly improve the outcomes in productivity and performance in the labor market in later years (Cunha & Heckman, 2008; Heckman & Corbin, 2016).

Related studies have been focusing on the developed countries, especially the United

States. For instance, Murnane, Willett and Levy (1995) found empirical evidence that basic cognitive ability affects wages and this impact has become larger in the mid-1980s than late 1970s, facilitated by data sets from two longitudinal surveys. Neal and Jonson (1996) found that one's cognitive ability level before entering labor market can explain the following wage gap between black and white young people. Some research has also shown that students' math grade in high school predicts their future annual earnings, and the effect is stronger for male than female (Murnane et al., 2000； Murnane et al., 2001). In addition to evidence from the United States, similar findings in Canada and Europe have shown that cognitive ability has positive impact on earnings for skilled workers (Green & Riddell, 2003; Lindqvist & Vestman, 2011).

Compared to cognitive ability, non-cognitive ability is relatively less explored due to lack of suitable measurement, but the literature is expanding because of its importance in determining one's earnings and success is no less than cognitive ability (Heckman & Rubinstein, 2001). Cognitive ability is a core indicator of human capability, and the introduction of non-cognitive ability gives more explanation to the economic return of the labor market (Heckman & Vytlacil, 2001; Heckman & Rubinstein, 2001). A series of studies conducted by scholars have confirmed that non-cognitive abilities such as motivation, personality traits, self-control, and social skills also have significant influences on wage income, education attainment, work performance and occupation choice (Heckman et al., 2006; Borghans et al., 2008). Higher cognitive ability is conducive to individual success and non-cognitive ability is conducive to prevention of failure in the labor market, which they both are good predictors in wage inequality (Cunha & Heckman, 2008; Lindqvist & Vestman, 2011).

The Impact of ICT Use on Incomes

Since the 1980s, wage structure in the United States has experienced some significant changes, mainly towards a more polarized structure. This phenomenon has been captured by a number of studies and attributed to two driving forces, one being skill-biased technological change and the other international competition and trade (Murphy & Welch, 1992). These two driving forces come across in the domain of computer and internet adaptation, causing spill-over effect to broader job scenarios. Following the computer revolution, some researchers have found that the wide utilization of computer has helped boost productivity in workplace and workers' efficiency (Krueger, 1993; Autor et al., 2003). Computer technology is considered to constitute a complement to abstract tasks and substitute for routine tasks, while the effects on manual tasks are ambiguous (Autor et al., 2003).

Krueger (1993) analyzed the impact of computer use in workplace on earnings, using micro data sets, and found that those who use computer at work earn 10 to 15 percent more than those who don't, and that computerization can explain one-third to one-half of the increase of educational return in the 1980s in the United States. In spite of unobserved individual heterogeneities, the use of computer has caused accelerating increase of wages in German labor market with similar pattern to the United States (DiNardo & Pischke, 1997). Later studies with improved methodology have further identified the premium to computer use remains significant and economically important (Autor, Katz, & Krueger, 1998; Dolton & Makepeace, 2004). Especially, computer skills can generate rewards in the labor market (Pabilonia & Zoghi, 2005). In general, research has supported the idea that the use of computer positively affects personal earnings in developed countries. However, the exact amount of premium still remains unclear.

The more recent wave of the widespread of internet use has drawn increasing scholarly attention to the ICT impact on income. Different from computer, the use of internet can be more universal and widely applied across industries and job types. For instance, musicians can garner premium by using online media to promote show ticket sale. Therefore, internet use has a more complex and multi-dimensional mechanism of influencing wages than computer; yet the phenomenon is still under researched. Lee and Kim (2004) analyzed the Current Population Survey (CPS) data from the United States and found that those using internet at work have higher wages than those who do not, but the premium decreases overtime with the increase of internet diffusion. DiMaggio and Bonikowski (2008) further discovered that not only internet use at work but also internet use at home is rewarded by increased earnings. With the changing scenario of income inequality, internet has gradually been acting as a skill-biased technology to complement skilled workers (Akerman, Gaarder, & Mogstad, 2015).

In this study, we incorporated both streams of research on cognitive and non-cognitive abilities and ICT use in explaining wage differences. Drawing upon literature mainly focus on the social economic environment of developed countries, we analyzed the present situation in a transitional economy, China, using a unique micro-level representative data set, the China Family Panel Studies (CFPS).

HYPOTHESIS DEVELOPMENT

The Effects of Cognitive & Non-Cognitive Abilities on Wages

It is a general impression that the more capable people earn more. And a great proportion of people's earning capability is from the abilities to understand, analyze and solve problems at work. Those who perform better in these areas are usually considered the more intelligent. Cognitive ability is the term in science today to indicate an individual's intelligence level. Therefore, it is rather intuitive to assume cognitive ability should be positively related to individual's wages. Given that general cognitive ability has been identified as the best predictor of job performance (for instance, Ree et al., 1994), it is rather safe to argue that, in most cases, wages largely reflect individual's within-job performance and that judgment can be applied across occupations. This fundamental understanding has been serving as the basic premise of human capital theory in explaining labor market outcomes.

In theory, the exact mechanism of how cognitive and non-cognitive abilities affect wages has two intuitive pathways. On the one hand, stemming from the human development perspective, skill formation is viewed as a dynamic process (Cunha & Heckman, 2008). People tend to use ability endowments including cognitive and non-cognitive abilities to form certain skills through learning, training and practice (Heckman & Corbin, 2016). People with stronger cognitive ability have stronger learning ability, thus more likely to become skilled labor and receive better income (Green & Riddell, 2003; Lindqvist & Vestman, 2011). In the meantime, non-cognitive abilities such as motivation, personality traits, self-control, and social skills also have significant influences on individual's job achievement (Heckman et al., 2006; Borghans et al., 2008). Furthermore, non-cognitive abilities are conducive to prevention of failure in the labor market (Cunha & Heckman, 2008; Lindqvist & Vestman, 2011). On the other hand, wages and earnings are seen as the outcomes of an exchange process. Tasks are units of activities that lead to outputs. As such, a worker applies her skill endowments to complete the tasks and consequently is rewarded with wages; therefore, wages are rather endogenously determined by the supply of skills and the use of technologies (Acemoglu & Autor, 2011). In summary, both pathways lead to positive expectations of cognitive and non-cognitive abilities on wages.

H1: Cognitive ability is positively related to wages.

H2: Non-cognitive ability is positively related to wages.

ICT Use and Wages

Early research has mainly focused on how the use of computer potentially increases the worker's productivity and results in a 15-20 percent premium in wages (Krueger, 1993; Autor, Katz, & Krueger, 1998). But some studies argued that the return on computer use merely reflects unobserved heterogeneity associated with specific job positions (DiNardo & Pischke, 1997; Spitz-Oener, 2008). In more recent literature (e.g., Dolton & Makepeace, 2004; Pabilonia & Zoghi, 2005), scholars from different parts of the world used different methods and data sets to deal with the potential heterogeneity issue, and re-confirmed Krueger's (1993) findings. The most widely accepted explanation is that wage premium on computer use would reflect the increase of marginal productivity of labor; that is, computer may free the worker from some repetitive tasks and let the worker devote more time and energy towards challenging tasks such as problem solving, innovation and interpersonal activities, which will enhance the overall productivity of individuals (Pabilonia & Zoghi, 2005).

Following the computerization trend, internet use has become prevalent in the workplace across jobs and occupations around the globe. As another crucial part of ICT, the use of internet has shown its great power to change and reshape people's work and life. Scholars have found evidence that, like computer use, internet use also has impact on one's real income return (e.g., Goss & Phillips, 2002; Lee & Kim, 2004; DiMaggio & Bonikowski, 2008). While the explanations for the causes of wage premium from internet use share some common grounds with that of computer use, there are differences too. Internet is taken as a skill-biased technology for complementing skilled workers (Akerman, Gaarder & Mogstad, 2015). Considering today's widespread of internet access on mobile devices, the barriers and costs are substantially lower compared to computer use. Also the internet is a powerful communication system that can revolutionize organizations and dictate how things should be done within the organization. As such, it has substantial potential in terms of improving productivity in innovative ways, which consequently leading to higher wages as a return.

H3: ICT use is positively related to wages.

The Moderating Effect of ICT Use

Advanced technology may have two kinds of effect on workers. One may be the complementary effect on skilled workers, and the other one may be the substituting effect on unskilled workers. In the case of complementary effects, the use of technology may increase the wage differentials according to different levels of skills, while in the case of substitution, the wage differences brought about by skills would be compressed (Krueger, 1993). Cognitive and non-cognitive abilities predict wages through skill formation. The wage differential may be widened due to the complementary effect of ICT use to the better-endowed skilled workers. In the meantime, the wage differential may be compressed due to the substitution effect of ICT use on unskilled workers.

ICT is believed to complement workers in non-routine abstract tasks such as problem solving and complex interactive tasks, and substitute workers in routine tasks that follow certain clear, unambiguous and orderly procedures (Autor et al., 2003; Akerman et al., 2015). These discussions are all task-based, because by far technology is still only able to take over certain types of work that has specific features. However, more recent literature starts to argue that there are new versions of tasks created with the development of technologies where human labor has a comparative advantage (Acemoglu & Restrepo, 2017). Under such circumstances, ICT use may facilitate the effects of cognitive and non-cognitive abilities on wages.

In the meantime, abilities like creativity and problem solving are not automated and possessed by artificial technologies yet. Therefore, people with strong abilities in these dimensions could benefit from the complementing effect of ICT. In this case, some non-cognitive abilities may even become more valuable along with increasingly powerful technologies, compared to situations in simple and routine task environment. Lindqvist and Vestman (2001) already found in an empirical study that non-cognitive abilities are rewarded with a higher return than cognitive abilities for unskilled workers and managers. And there is the possibility of continuous value appreciation of non-cognitive ability against cognitive ability in the labor market along with the development of ICT. Facing that time being of artificial intelligence, the understanding of how technology and people's ability endowments interact with each other in determining labor market outcomes is definitely crucial. Therefore, when considering the external technology environment in addition to focusing on conscious individual choice, we proposed the hypothesis as follows:

H4: ICT use strengthens the positive relationship between cognitive ability and wages.

H5: ICT use strengthens the positive relationship between non-cognitive ability and wages.

METHODS

Data Source and Sample Selection

The data source for the present study is Chinese Family Panel Studies (CFPS), a large national and comprehensive longitudinal survey conducted by the Institute of Social Science Survey, Peking University. The purpose of the project is to provide researchers with a most detailed data describing contemporary China. It tracks three levels of data: individual, family and community. The survey covers family relationships, family economy, immigration, job and income, educations, health, marriage and so on. The pilot test was conducted in 2010 and it tracks every two years. The data is from 25 provinces and regions in mainland China, covering 95% of the national population; thus it can be regarded representative of the whole population of China (Xie & Zhou, 2014). We used the data from traced individuals of the 2010 wave and the 2014 wave to construct a panel data set for the empirical study.

The total size of the original data set for 2010 and 2014 is over 30,000 individuals, respectively. The following filters are applied: (1) the sampled individuals have to be employed in the year surveyed; (2) individuals can be traced from 2010 to 2014 to make the panel balanced; (3) those with important variable data missing were also excluded, important variables include dependent variable, independent variables, and crucial control variables. After the filtering, 10,574 observations remained in the final sample.

Dependent Variable

Wage is defined as personal wage income. It is a computed data from the data set, which is the sum of wage incomes from all jobs in the year of the person interviewed. The log form of wage is computed according to the Mincer's wage equation (1974), which is widely used in studying wages. It has the advantage of being closer to normal distribution (Heckman & Polachek, 1974) and easy to be interpreted. This study chooses to use the annual earning instead of the more rigorous hourly wage, because the data regarding working hours/weeks/ months in the data set suffer substantial missing and abnormal information. In order to maintain a sufficient sample size and avoid additional selection biases caused by arbitrary data processing, alternative measure is used.

Independent Variable: Cognitive and Non-cognitive Abilities

Due to data availability, the use of measurements of cognitive and non-cognitive abilities varies in prior studies. In studies of developing countries, the tests are more simplified, which can be as basic as numeracy and literacy tests (e.g., Nordman et al., 2015, a study about Bangladesh). Some empirical studies of developed countries use single literacy test as well, but the test itself is designed in a more complicated and layered way (e.g., Green & Riddell, 2003, a study about Canada).

The CFPS data set includes tests for cognitive ability, which is very rare in social surveys from developing countries. Though cognitive tests are already very common in developed countries, due to technical and budget limitations, such data remains rare in China. The literacy test consists of 24 Chinese characters, from easy to difficult, and the score is the number of the most difficult character the interviewee recognized. The numerical test consists of 34 math problems, from easy to difficult, and the score is the number of the most difficult problems the interviewee could solve. We constructed the index measurement for cognitive ability from numeracy and literacy test scores using PCA (Principal Component Analysis) method in the model and then standardized. And then for the non-cognitive ability variable, the interviewer observed the interviewee and gave scores from 1 to 7 for each item of the five-dimension evaluation during the interview: comprehension, expression, courteousness, cooperation and reliability. We constructed the measurement of non-cognitive ability from the five items using the PCA method, and then standardized as well.

Independent Variable: ICT Use

The *ICT Use* variable is a dichotomous variable measuring the frequency of the interviewee's use of Internet. The original question in survey asks *"In general, how frequently do you use Internet to work/ study/ social/ entertainment?"* There are 7 choices from most frequent (every day) to least frequent (never). To keep it straightforward and consistent, the original data is recorded as a dichotomous variable measuring whether or not the person is using Internet.

Control Variables

There are three types of control variables in this study: generic control variables which are used by mainstream literature about wages worldwide; China-specific variables which are unique factors to consider under the circumstances of China; and dichotomous variables controlling for regional and year fixed effects.

Education year is a continuous variable measuring how many years of education the person received, which is the central element of Mincer's equation of earnings. It is directly from the original data and imputed by the provider of CFPS data. This measurement is more precise than computing from highest education degree, because CFPS has factored in different education systems and dropouts.

Female is common knowledge that women usually earn less than men, and in the literature plenty of research can be found regarding this topic. According to a meta-analysis on gender wage gap conducted by Weichselbaumer and Winter-Ebmer (2005), internationally the raw wage gap has fallen, but the major reason is attributed to better labor market endowments for women.

Married is marriage status that affects wages conditional on gender. Generally speaking, married male have family responsibility thus tend to work harder and earn more, while married female focus more on family and tend to earn less in jobs.

Employed in public sector is variable with Chinese characteristics which are used by previous literature. Due to China's system, employees in the public sector may receive more non-money rewards and benefits than employees in the private sector.

Urban is measured for living in urban or rural area which is not exactly a China-specific factor to influence wages, but China is known for urban-rural gap. This variable is measured by Census Bureau's definition according to CFPS.

Region dummies are notable because of the existence of income gap across regions, especially from eastern coasts to middle and western areas. It is valuable to compare between results controlling and not controlling for region dummies.

The variable description is listed in Table 1. Table 2a shows the descriptive statistics of the main variables. The percentage of internet users is 30.5 percent in 2010, and 40.1 percent in 2014. If compared to the data in the United States, the internet penetration rate in 2014 is similar to that in 2001 in the United States, which is 38 percent in the workplace and 52 percent among the whole population (DiMaggio & Bonikowski, 2008).

[Insert Tables 1 and 2 about here]

The measurements for cognitive and non-cognitive abilities are standardized, but the original coding can give a more straightforward idea. The maximum value of components of cognitive ability, i.e., the word and math test scores, are the full score of the tests. Similarly, the maximum value of components of non-cognitive ability is the full score of the tests. The mean value of math test score is less than half of the full score, while the mean value of literacy test is well above the half point. As for the statistic of dependent variable, the mean value of natural logarithm of wages is 9.57, which is around 24,000 RMB, and this mean value is different from the mean value calculated directly from wages. Another notable number is the mean value of education year, which is 9.37 years suggesting the average education level of the sample is between middle school and high school.

Regression Models

The model is based on the Mincer equation (1974), consistent with the mainstream body of literature. To test the interactive effects of hypotheses, we built the following model:

$$\ln(\mathrm{Wage}) = \alpha + \beta_1 \times \text{cognitive ability} + \beta_2 \times \text{noncognitive ability} + \beta_3 \times \text{internet use} + \beta_4 \times \text{internet use} * \text{cognitive ability} + \beta_5 \times \text{internet use} * \text{noncognitive ability} + \sum_{i=6}^{n} \beta_i \times \text{control}_i + \varepsilon_i$$

In this model, the dependent variable is the log of wage, with cognitive ability and non-cognitive ability as the independent variables, and internet use as the moderator. Control variables include education years, gender dummy, marital status dummy, employed in the public sector dummy, urban dummy, region dummy, and year fixed effects.

RESULTS AND DISCUSSION

Table 3 presents the basic results using OLS regression. As shown in Table 3, when cognitive ability is measured by the integration of math and word test scores, the coefficient is positive and significant at 1% level from Column 1 and Column 4, supporting Hypothesis 1. In Column 1, log of wage is regressed on the cognitive ability, with control variables including years of education, gender dummy, marital status dummy, the interaction term of female and married, area and year fixed effects. The significant positive effect of cognitive ability suggests that Hypothesis 1 holds. In Column 4, non-cognitive ability and internet use are included, the coefficient of cognitive ability is still significantly positive ($p<1\%$).

In Column 2, the log of wage is significantly positive with the non-cognitive ability ($p<0.01$) which supports Hypothesis 2. In Column 4, the coefficient of non-cognitive ability is still positive at the significant level of 10% when adding cognitive ability and internet use. Overall, Hypothesis 2 that non-cognitive ability positively affects wages holds.

In Column 3, internet use is included in the model, testing Hypothesis 3 that ICT use has a positive effect on the wages. The estimate suggests that Hypothesis 3 is supported with the significance level of 1%, suggesting a significantly positive return to ICT use. In column (4), we considered cognitive ability, non-cognitive ability and internet use in the same model. The result shows that internet use is still positively related to wages with similar magnitude at the significance level of 1%.

We put the interaction of cognitive ability and internet use and the interaction of non-cognitive ability and internet use in Column 5. Both interactions are significantly positive with wages and shows that internet use has moderating effect on the relationship between cognitive and non-cognitive abilities and wages. The result shows that the interaction of cognitive ability is positive at the significant level of 1%, supporting Hypothesis 4. And the interaction of non-cognitive ability and internet use is positive at the significant level of 10%, which marginally supports Hypothesis 5.

[Insert Table 3 about here]

The moderating effect of internet use on the relationship of cognitive ability and wages are illustrated in Figure 2 and the moderating effect of ICT use on the relationship of non-cognitive ability and wages are illustrated in Figure 3. We can tell from figure 2 that the slope of cognitive ability is steep and positive with the high level of internet use, while the slope is less steep and even negative with low level of internet use. Therefore, internet use has a positive moderating effect on the relationship between cognitive ability and wages, supporting Hypothesis 4. Similarly, from Figure 3, we can identify that internet use has a positive moderating effect on the relationship between non-cognitive ability and wages, suggesting that Hypothesis 5 holds. Both figures demonstrate the estimates in Column 5 of Table 3 for cognitive and non-cognitive abilities, respectively.

[Insert Figures 2 and 3 about here]

For robustness check, we first applied the regressions by using the independent variables and control variables tested in 2010 and dependent variable in 2014 dataset. Since individual's test scores of cognitive ability tend to be stable in adulthood (Plomin et al., 1994), similar results are expected if the models are robust. By including lagged wages, it helps to correct for endogeneity resulted from the possibility that wages and internet use are simultaneously related with a third factor. DiMaggio and Bonikowsi (2008) first adopted this method in their study for internet use. Table 4 shows the robust regression result. The sample size shrunk to 5287 after the same data processing with the 2010 and 2014 survey information. Nevertheless, it shows that using 2014 wages regressed on the 2010 independent variables generates similar results. The coefficients of cognitive ability are still positive with wages. The wage return to the ICT use is significantly positive at 1% level, and the coefficient of non-cognitive ability is positive and significant at 5% level. The moderation effect of ICT use on the relationship of cognitive ability and wages is still positive but insignificant. Meantime, the moderation effect of ICT use on the relationship of non-cognitive ability and wages is marginally significant at 10% level.

[Insert Table 4 about here]

We also included extended tests considering industry difference and gender difference. We selected most represented industry group and gender groups to run regressions using these subsample. The industry we selected is manufacturing industry and transportation industry. Observations in the subsample of manufacturing industry and transportation industry account for nearly 30% of the full sample at CFPS. The complementing effects of ICT use may vary across industry because different industries are involved with different tasks and require different skills. Table 5 shows that, for the group of manufacturing industry and transportation industry, the estimates of the interaction terms are very similar to those of the full sample. It is understandable that non-cognitive ability is not significantly positive with the wages. As this industry need more technical skills which require more cognitive ability to deal with.

[Insert Table 5 about here]

The gender difference was shown by dividing the full sample in male subsample and female subsample. The results of female subsample are presented in Table 6. The coefficient of cognitive ability on wages is significant with the wages in Column 1, similarly to the result of basic results. The coefficient of non-cognitive ability in Column 2 and internet use in Column 3 are also significant positive with the wages. As we put them together in Columns 4 and 5, the coefficient of internet use is still significant and the interaction showed the complementary effect of internet use on the cognitive and non-cognitive abilities.

For male subsample showed in Table 7, the results are different with those of female subsample. In Columns 1 and 4, the coefficient of cognitive ability on wages is significantly positive, which supports Hypothesis 1. The coefficient of non-cognitive ability is significantly positive in Column 2, but becomes insignificant in Columns 4 when considering the internet use. The estimate of return to internet use is similar with basic results, showing the significantly positive relationship. As for the terms of interaction, the moderation effect of ICT use on the relationship of cognitive ability and wages is positive at the significant level of 1%. But the coefficient of interaction between non-cognitive ability and ICT use is not significant.

[Insert Tables 6 and 7 about here]

CONCLUSIONS

By using Chinese recent cross-sectional survey micro data CFPS, we examined the effect of cognitive and non-cognitive abilities, and the impact of ICT use on wages, as well as the moderating effect of ICT use on the relationship between cognitive and non-cognitive abilities and wages. The results show that cognitive and non-cognitive abilities are positively related to wages. It confirms the conclusion by previous literature in this field. As for ICT use, it suggests that those who use ICT tend to earn more than those who do not. This finding confirms the results of ample literature using data in developed countries (Krueger, 1993; Lee and Kim, 2004). The wage premium estimated in 2010s China is higher than that in 1990s the United States, which suggests that China still needs substantial effort to promote ICT use in the workplace to harness the benefits of technologies for enhancing productivity on a larger scale. The results also show that there is a positive moderating effect of ICT use on the relationship between cognitive and non-cognitive abilities and wages, accounting for variations of sampling. It suggests that technologies act as complement to cognitive and non-cognitive abilities of workers in general.

There are a few implications that can be drawn from this study. Theoretically, it linked the effect of cognitive and non-cognitive abilities on wages and the impact of ICT on labor market outcome together, and shed new light on the possible complementary effect of ICT use to the benefits of cognitive and non-cognitive abilities. This angle is becoming increasingly relevant with the recent development of artificial intelligence and the interest of the business world of applying AI technologies to the workplace. Practically, the implications are more likely to be found on the policy making side. The study offers evidence that ICT use increases individual productivity, which promotes the application of information and communication technologies in the major industries. At the same time, it is worth noting that technologies may increase the wage gap between workers with high cognitive ability and workers with low cognitive ability. Policy makers should take actions to help those who fail to share the benefits from development and popularization of ICT.

This paper also has some limitations. First, the measurement of cognitive ability is confined by data availability, since the cognitive ability data is financially and technically challenging to acquire especially in national scale surveys. The limitation of using such measurements is that the effects tend to be somewhat mixed with years of education and the examination into the complementary effect of ICT use and cognitive ability is restricted from going deeper. Second, the empirical studies on ICT use and wages are sensitive to the endogeneity issue brought by unobserved individual heterogeneity, which is a problem that most of literature face. The methodology controls for some level of unobserved individual heterogeneity, but far from being a thorough solution. Future studies should employ better instrument variables to address the endogeneity issue. Finally, future studies should exam this topic more closely by differentiating the purposes or motivations of using ICT.

In fact, there are theories in psychology that are emphasizing on multiple aspects or forms of the mental ability of our humans already. For example, Sternberg (1985) categorized intelligence into three fundamental aspects: analytic, creative, and practical. Out of these three, only the first one is measured properly by mainstream tests, and this aspect is also the one that perhaps will be substituted the most if artificial intelligence becomes prevalent. Perhaps it is the right time to review these theories by present evidence and shed new light on them for labor studies, which is what the present study attempts to do.

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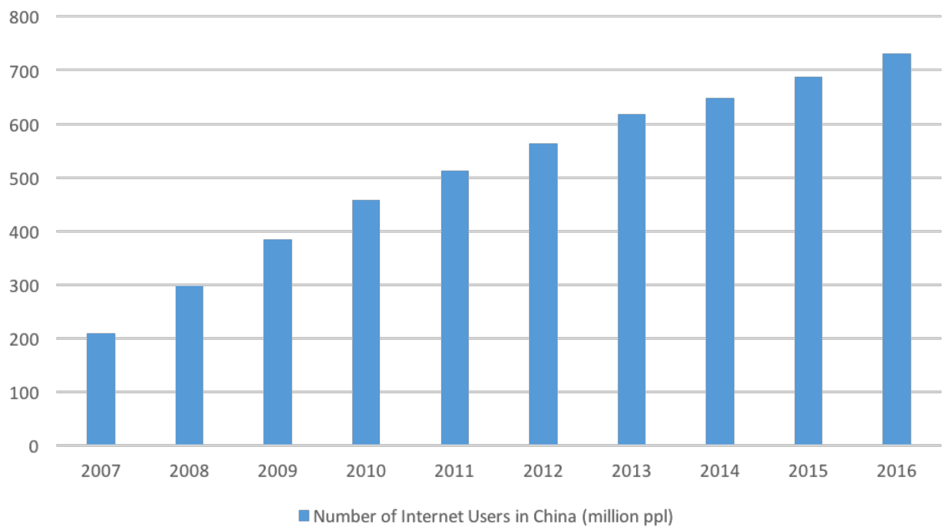
Figure 1 Number of Internet Users in China



Data source: China Statistical Yearbook

Figure 2 Moderating Effect of ICT Use on Cognitive Ability and Wages

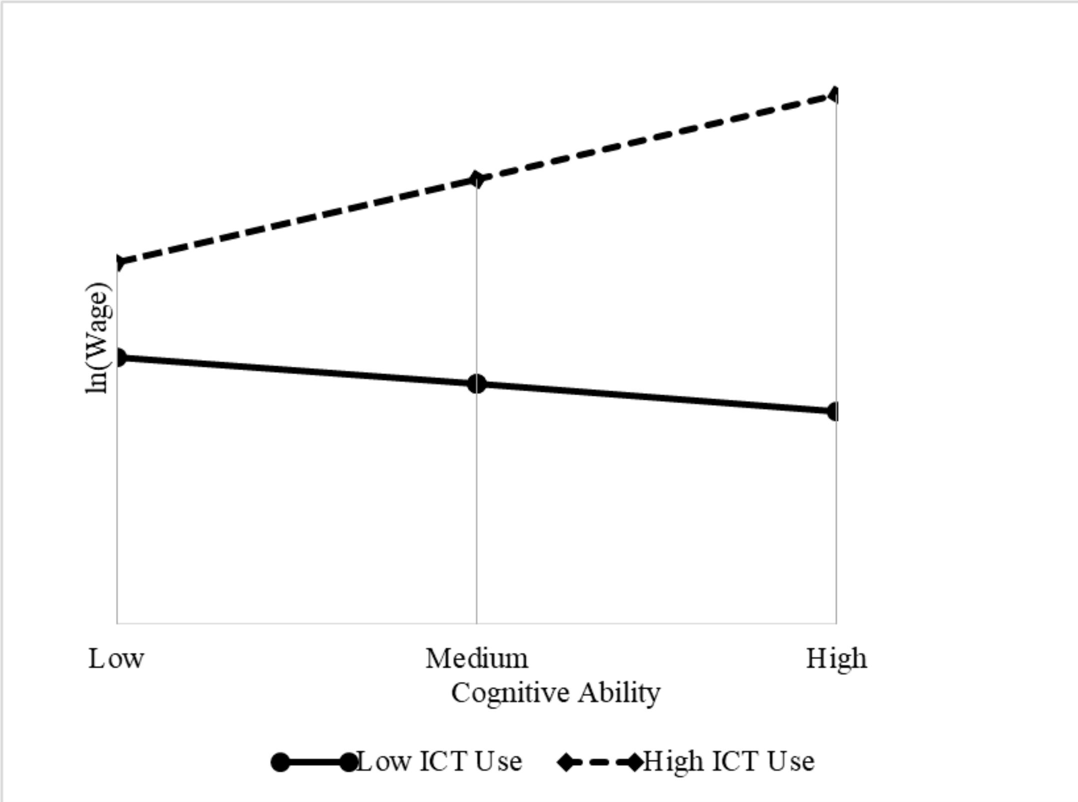


Figure 3 Moderating Effect of ICT Use on Non-cognitive Ability and Wages

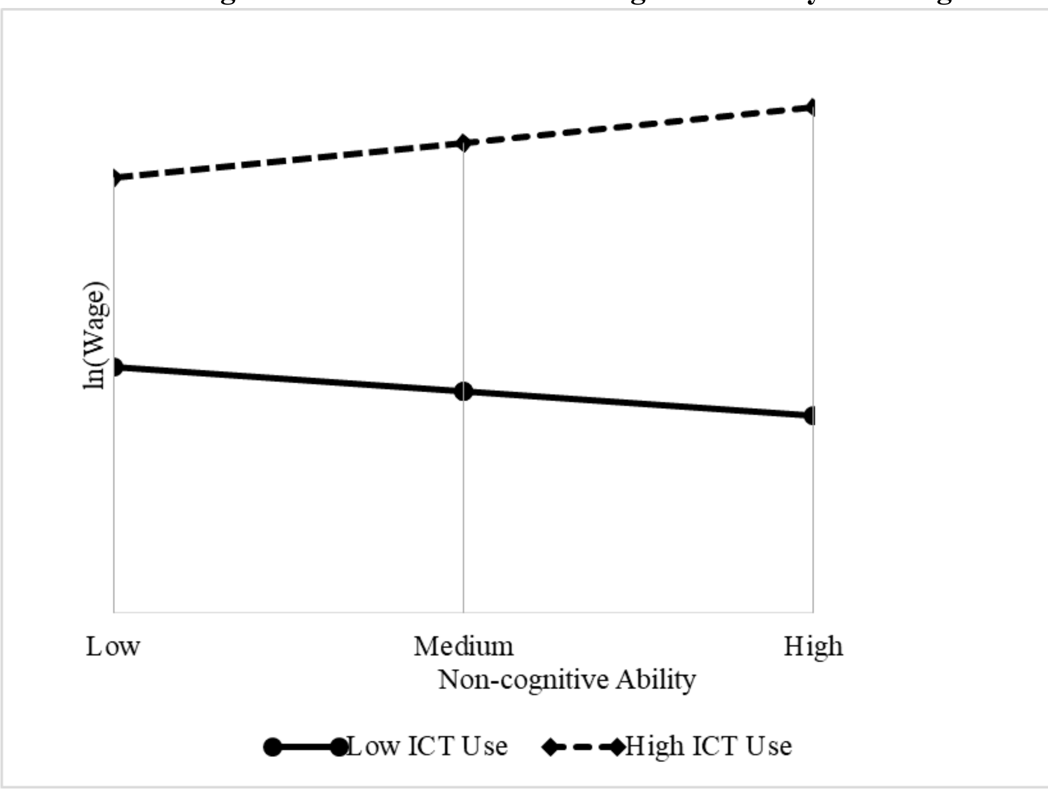


Table 1 Variables Description

	Name	Measurements
Dependent variable	ln(wage)	The natural logarithm of individual's personal wage income in RMB from all jobs in the year surveyed
Independent variables	Cognitive ability	Constructed from word and math test scores using PCA (Principal Component Analysis), standardized in the model
	Non-cognitive ability	Constructed from comprehension, expression, courteousness, cooperation and reliability using PCA (Principal Component Analysis), standardized in the model
Independent & moderating variables	Internet use	Internet=1 if use internet to work, study, social, entertainment, etc.
Control variables	Years of education	Years of education
	Female	female=1 if female
	Married	married=1 if in marriage
	Employed in public sector	empl_pub=1 if employer is government or SOE
	Urban	urban=1 if living in urban area (census bureau definition)
	Region dummies	Dummies to control for regional effects The central China is treated as the reference group

Table 2a Descriptive Statistics of Main Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent Variable					
ln(Wage)	10,574	9.571	1.143	0	13.00
Independent Variable					
Cognitive Ability	10,574	0.394	0.833	-1.525	1.967
Math Test Score	10,574	11.24	5.958	0	24
Word Test Score	10,574	21.29	9.215	0	34
Non-cognitive Ability	10,574	0.212	0.913	-4.210	1.520
Comprehension	10,574	5.534	1.185	1	7
Expression	10,574	5.469	1.163	1	7
Courteousness	10,574	5.561	1.088	1	7
Cooperation	10,574	5.782	1.104	1	7
Reliability	10,574	5.679	1.094	1	7
Moderator					
Internet Use	10,574	0.354	0.478	0	1
Control Variable					
Years of education	10,574	9.373	4.113	0	19
Female	10,574	0.373	0.484	0	1
Married	10,574	0.871	0.335	0	1
Employed in public sector	10,574	0.238	0.426	0	1
Urban	10,574	0.580	0.494	0	1
Region_east	10,574	0.581	0.493	0	1
Region_mid	10,574	0.225	0.417	0	1
Region_west	10,574	0.195	0.396	0	1

Notes: As for correlations, all coefficients are below 0.6 except the one between non-cognitive ability and education years (the result of Pearson correlation analysis of main variables is shown in Table 2b). The correlation between cognitive ability and non-cognitive ability is 0.446 which is very less than 0.5.

Table 2b Pearson Correlation Analysis of Main Variables

		1	2	3	4	5	6	7	8	9	10	11
1	**Ln(wage)**	1										
2	**Internet Use**	0.252***	1									
3	**Cognitive Ability**	0.199***	0.234***	1								
4	**Non-cognitive Ability**	0.156***	0.266***	0.446***	1							
5	**Education Year**	0.298***	0.246***	0.493***	0.732***	1						
6	**Female**	-0.184***	-0.001	0.057***	0.022**	0.033***	1					
7	**Married**	0.069***	-0.032***	-0.213***	-0.100***	-0.101***	0.015	1				
8	**Employed in Public Sector**	0.236***	0.119***	0.224***	0.270***	0.365***	-0.021**	0.023**	1			
9	**Urban**	-0.235***	-0.134***	-0.300***	-0.369***	-0.476***	-0.060***	0.033***	-0.399***	1		
10	**Region_east**	0.146***	0.015	0.052***	0.038***	0.048***	0.058***	-0.035***	-0.020**	-0.101***	1	
11	**Region_west**	-0.118***	-0.069***	-0.080***	-0.094***	-0.112***	-0.050***	0.016	0.004	0.148***	-0.579***	1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (two-tailed)

Table 3 Main Regression Results

	(1)	(2)	(3)	(4)	(5)
	ln_wage	ln_wage	ln_wage	ln_wage	ln_wage
std_cognitive	0.104***			0.066***	0.050***
	(0.02)			(0.02)	(0.02)
std_noncognitive		0.037***		0.018*	0.008
		(0.01)		(0.01)	(0.01)
internet			0.289***	0.268***	0.180***
			(0.02)	(0.02)	(0.03)
it_cog					0.097***
					(0.03)
it_noncog					0.043*
					(0.02)
Full set of controls	Y	Y	Y	Y	Y
N	10574	10574	10574	10574	10574
r2_a	0.252	0.250	0.260	0.261	0.262

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (two-tailed)

Table 4 Robustness Regression Results

	(1) ln_wage	(2) ln_wage	(3) ln_wage	(4) ln_wage	(5) ln_wage
std_cognitive	0.068^{***}			0.041	0.038
	(0.03)			(0.03)	(0.03)
std_noncognitive		0.032^{**}		0.017	0.003
		(0.01)		(0.01)	(0.02)
internet			0.266^{***}	0.256^{***}	0.156^{**}
			(0.03)	(0.03)	(0.07)
it_cog					0.081
					(0.06)
it_noncog					0.067^{*}
					(0.04)
控制变量	Y	Y	Y	Y	Y
N	5287	5287	5287	5287	5287
r2_a	0.147	0.147	0.156	0.157	0.157

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (two-tailed)

Table 5 Regression Results in Manufacturing Industry and Transportation Industry

	(1) ln_wage	(2) ln_wage	(3) ln_wage	(4) ln_wage	(5) ln_wage
std_cognitive	0.062^{***}			0.039	0.016
	(0.02)			(0.02)	(0.03)
std_noncognitive		0.016		0.003	0.001
		(0.01)		(0.02)	(0.02)
internet			0.185^{***}	0.175^{***}	0.105^{**}
			(0.03)	(0.03)	(0.05)
it_cog					0.095^{**}
					(0.04)
it_noncog					0.013
					(0.03)
Full set of controls	Y	Y	Y	Y	Y
N	2951	2951	2951	2951	2951
r2_a	0.208	0.207	0.215	0.215	0.216

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (two-tailed)

Table 6 Regression Results in Female Group

	(1)	(2)	(3)	(4)	(5)
	ln_wage	ln_wage	ln_wage	ln_wage	ln_wage
std_cognitive	0.067^{**}			0.035	0.017
	(0.03)			(0.03)	(0.04)
std_noncognitive		0.039^{*}		0.025	-0.001
		(0.02)		(0.02)	(0.02)
internet			0.258^{***}	0.246^{***}	0.133^{**}
			(0.05)	(0.05)	(0.06)
it_cog					0.107^{*}
					(0.06)
it_noncog					0.094^{**}
					(0.05)
Full set of controls	Y	Y	Y	Y	Y
N	3941	3941	3941	3941	3941
r2_a	0.226	0.226	0.232	0.232	0.233

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (two-tailed)

Table 7 Regression Results in Male Group

	(1)	(2)	(3)	(4)	(5)
	ln_wage	ln_wage	ln_wage	ln_wage	ln_wage
std_cognitive	0.115^{***}			0.075^{***}	0.059^{***}
	(0.02)			(0.02)	(0.02)
std_noncognitive		0.033^{***}		0.013	0.014
		(0.01)		(0.01)	(0.01)
internet			0.298^{***}	0.273^{***}	0.202^{***}
			(0.03)	(0.03)	(0.04)
it_cog					0.101^{***}
					(0.04)
it_noncog					-0.004
					(0.03)
Full set of controls	Y	Y	Y	Y	Y
N	6633	6633	6633	6633	6633
r2_a	0.220	0.217	0.230	0.232	0.233

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (two-tailed)