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Return to Schooling in China
A Large Meta-Analysis*

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Abstract: In this study, we conducted a meta-analysis of 2,191 empirical results reported in 213 existing studies to estimate the Mincer-type return to schooling in China. The results revealed that the return to schooling showed a positive trend, and the effect size was medium in terms of the partial correlation coefficient. We also found that workers in non-state sectors and urban regions, urban *hukou* workers, and women tend to have higher returns to schooling than their counterparts. Furthermore, the results indicate that the return to schooling registered a significant increase over time.

JEL classification numbers: D31, I26, J31, P23, P36

Keywords: return to schooling, meta-analysis, publication selection bias, China

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1 Introduction

During the transition from a planned system to a socialist market economy, China witnessed a steady penetration of the market mechanism into the wage-setting process (Ma, 2018a). The private internal rate of return to schooling (hereafter return to schooling), which provides a measure of how increased years of schooling affect the wages earned by a worker, has received much attention in the field of education and labor economics, considering that it not only reflects how human capital is being compensated but also provides insights into the supply and demand for a highly educated workforce. Researchers conducting empirical studies in China have used the standard approach of estimating the return to schooling by employing the Mincer earnings function, as well as the theoretical standpoints of the human capital theory (Becker, 1964; Mincer, 1974) and the signaling hypothesis (Spence, 1973), both of which have been repeatedly tested and confirmed in studies of developed economies. Since the late 1990s, there has been a steady stream of published articles on China reporting the Mincer-type return to schooling, which is a coefficient derived from the estimation of a regression model in which wage levels are used as a dependent variable and years of schooling or a dummy variable of educational attainment as an independent variable (Meng, 1995; Maurer-Fazio, 1999; Huang et al., 2002; de Brauw and Rozelle, 2008; Messinis, 2013; Li, Wu, and Xing, 2018; Asadullah and Xiao, 2020). Most of the previous studies that do not focus on the effect of investments in schooling on wages recognize educational levels as an indispensable variable in the estimation of the Mincer earnings function, and often report the return to schooling as an estimate of a control variable. Therefore, we now have a plethora of empirical evidence on the return to schooling in China.

However, despite large volumes of academic outcomes, there are major gaps in this research. First, there has been a lack of scientific evaluation concerning the return to schooling in China during the transition period that began in 1978, when the “reform and opening-up policy” was introduced, which is ongoing. Although there is abundance of empirical evidence regarding the return to schooling in China, the heterogeneity in the results owing to marked differences in study conditions across the existing literature is so extensive that it is difficult to gauge whether there exists a consensus about the general return to schooling in China among researchers. This uncertainty appears more pronounced as empirical evidence builds, and it is recognized as a major issue in Chinese wage studies.

Second, considering that the Chinese government has undergone a gradual economic transition, the government or the Communist Party of China (CPC) has always underlain China's political system on one hand, while on the other, large-scale and aggressive marketization is being promoted to boost national economy. Consequently, various aspects of China's labor market are systematically segmented by institutions such as state and non-state sectors and urban and rural *hukou* (population registration) (Meng and Zhang, 2001; Cai, 2016; Ma, 2018a; Ma and Iwasaki, 2020). Although the segmentation of China's labor market is an important perspective that deserves the attention of researchers, and some empirical analyses have addressed how differences in the planned economy and market-oriented reform periods, *hukou*, and gender affect returns to schooling (Fleosher and Wang, 2005; Fu and Ren, 2010; Hannum, Zhang, and Wang, 2013), the evidence directly concerning the relationship between this phenomenon and the return to schooling is limited.

Third, there is a lack of evidence regarding changes in returns to schooling during the transition period. There is no denying that the penetration of market mechanism and meritocracy into economic activities has had major impacts on the wage-setting process in China. However, mainly due to data limitations, the overwhelming majority of previous studies covered only a specific year or very short periods of time, with only a few existing studies theoretically considering and empirically verifying a mid- to long-term tendency in the return to schooling in China. Constructing and analyzing a longitudinal dataset is one of the methods to address this problem. Tracing beyond three decades, however, is not a feasible option.

In this study, we attempt to offset these three research gaps by conducting a large-scale meta-analysis, which leverages the heterogeneity across existing studies, and is capable of answering questions that would otherwise be almost impossible to examine in standard empirical analyses. Although Fleisher et al. (2005), Liu and Zhang (2013), and Churchill and Mishra (2018) performed a meta-analysis on the topic, this study adds the following inputs: First, by using an approach similar to that of Iwasaki and Ma (2020) on the gender wage gap in China and that of Ma and Iwasaki (2021) on the wage premium of membership in the CPC, it presents and verifies a series of hypotheses regarding the differences in the return to schooling in China by sector (i.e., state-owned vs. privately-owned enterprises; urban vs. rural regions), by gender and by period, which were not considered in prior meta-analysis. These results can provide new evidence for better understanding the features of the Chinese labor market and the deficiency of the dualistic economy transition pattern. Second, all the previous studies used only English literature, while this study involves a large-scale meta-analysis using estimates derived from wide-ranging studies, including numerous research studies in Chinese. The 2,191 estimates derived from 213 existing papers (92 in English and 121 in Chinese) were used in this study, which exceeds the latest previous study (Churchill and Mishra 2018), which used only 53 papers in English. To the best of our knowledge, this study is the first to use Chinese literature published in mainland China. This can provide robustness-analyzed results. Third, previous studies used traditional regression models, including the fixed-effect and random-effects models, to perform meta-regression analyses. This study employed traditional as well as advanced meta-analysis methods to test the hypotheses (Doucouliagos, 2017; Stanley, Doucouliagos, and Ioannidis, 2017; Polák, 2019; Havranek and Sokolova, 2020), which may greatly complement previous studies.

The results show that the return to schooling in China is positive and of medium size through the transition period, in terms of the partial correlation coefficient (PCC). We also found that workers in the non-state sector, urban *hukou* workers, workers in urban regions, and women tend to register higher returns to schooling than workers in the state sector, rural *hukou* migrants, workers in rural regions, and men. The results indicate that the return to schooling in China shows a significant increasing trend over a period of time, suggesting that, in the transition period, the penetration of market mechanisms and technological development have considerably impacted wage levels in China.

The remainder of this paper is organized as follows: Section 2 presents testable hypotheses for meta-analysis, while Section 3 elucidates the procedures used to search and select the literature subject to the meta-analysis, and overviews the selected studies. Section 4 provides a meta-synthesis of the extracted estimates and Section 5 presents a meta-regression analysis (MRA) of heterogeneity among studies. Section 6 attempts to assess the publication selection bias. Finally, Section 7 summarizes the major findings of the meta-analysis and discusses their policy implications.

2 Return to Schooling in China: Hypothesis Development

Since December 1978, when the Third Plenary Session of the 11th CPC Central Committee adopted the "reform and opening-up policy" proposed by Deng Xiaoping (former Vice President of China), China's social and economic systems changed considerably. The education system was no exception. Two major changes introduced to the educational system in China deserve special mention. First, the *Decision Regarding* *the Reform and Advancement of Basic Education* issued in May 2001 to redress urban-rural disparities in access to compulsory education led to a nationwide effort to promote nine years of compulsory education for all children. The "two exemptions and one subsidy policy" (*Liangmian Yibu* in Chinese), implemented in September 2003, exempted all rural children from paying tuition and textbook fees, and other miscellaneous expenses, and provided a subsidy to help students pay for their boarding expenses. Consequently, the junior high school enrollment rate in China increased from 74.6% in 1990 to 98.8% in 2017 (Ministry of Education of the People's Republic of China, 1999, 2017). Second, before implementing the aforementioned measures to promote nationwide access to compulsory education, the Chinese government had introduced a policy to promote widespread access to higher education in 1999. In the earlier transition period, the intense competition for acceptance by prestigious universities has been described as "tens and millions of soldiers and horses trying to cross the only bridge there is," and only the selected elite successfully gained admittance to universities.[1] The implementation of the policy to promote widespread access to higher education in 1999 resulted in an increase in both universities and students, and the percentage of high school graduates advancing to universities rose from 3.5% in 1991 to 10.5% in 1999 and 45.7% in 2017 (Ministry of Education of the People's Republic of China, 1999, 2017). Undoubtedly, the promotion of nationwide access to compulsory education and the expansion of higher education, the two major features characterizing socio-economic changes that China witnessed since 1978, have drawn substantial interest from researchers seeking to identify how these features can impact educational levels and economic activities in the country.

Considering these facts and the major changes that have taken place in China since the implementation of the "reform and opening-up policy", including the transition to a market-oriented economy, rapid economic growth, and increasing emphasis on academic achievements, we propose six hypotheses to be tested by the meta-analysis in this study regarding returns to schooling in China, from the perspective of the human capital theory developed by Becker (1964) and Mincer (1974) and the signaling hypothesis proposed by Spence (1973).

Both the human capital theory and the signaling hypothesis are designed to predict

[1] In China, all students intending to advance to university must take the nationally standardized university entrance examination (*Gao Kao*) and achieve the score required by the university of their choice. This examination system was introduced in 1952, temporarily abolished in 1966 during the Cultural Revolution, and then reinstated in 1977.

the positive effects of schooling on wage levels. Even in China, where the market economy mechanism exerts a certain degree of control over the wage-setting process, these theories quite accurately describe the reality in the country, where there is undoubtedly a positive correlation between years of schooling and wage levels. What we need to know is the effect size of the return to schooling. According to Psacharopolos and Patrinos (2004), the return to schooling is generally higher in developing countries compared to developed nations, which is estimated to be approximately 10% in the Asian region. Conversely, the effect of a worker's schooling on his/her wage level in China during the transition period is likely to be only marginally higher than that in higher-income countries. [2] This conjecture can be explained by the following two circumstances: First, although the rapid growth of the economy has introduced technological advances in both industrial structure and corporate organizations and generated a high demand for highly educated workers, the level of technological advancement in China is still lower than in Europe, and developed countries like the USA and Japan (Japan Science and Technology Agency's Center for Research and Development Strategy, 2017). Second, China's marketization reform is not really thorough, with the government and the CPC organization still controlling large state-owned enterprises (SOEs) and party organizations exerting powerful influence on employment and wages in the state sector (Lin, Cai, and Li, 1994; Ma and Iwasaki, 2020). Accordingly, referring to the standard advocated by Doucouliagos (2011),[3] we propose the following hypothesis concerning the general effect size of the return to schooling through the transition period:

Hypothesis H_1: *The return to schooling in China is positive and of a medium size through the transition period*.

China has long been known for its persistent advocacy of gradual economic reform. During the transition period, reform has led to substantial growth of the non-state sector, while the CPC has tried to preserve and provide favorable treatment to the state sector (in particular, SOEs in key industry sectors) in an effort to maintain a certain degree of

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[2] In fact, although the return to schooling in China reported by recent empirical studies (including those of Sun (2004), Gao and Smyth (2015), and Ma and Zhang (2017)) varies greatly from 1.4% to 38.4%, a majority of the previous studies reported a return to schooling of about 10%.

[3] As described later in this paper, when effect sizes measured by PCC are to be categorized into three levels, i.e., "small," "medium," or "large," the effect of schooling on wage levels in China can be rated as "medium" based on these criteria (Doucouliagos, 2011).

control over the national economy (Lin, Cai, and Li, 1994; Ma, 2018a; Iwasaki, Ma, and Mizobata, 2020). Correspondingly, the division between the state and non-state sectors has become one of the most prominent features of the modern Chinese economy (Zhang and Xue, 2008; Ye, Li, and Luo, 2011; Ma, 2018b).

Presently, companies in the non-state sector (i.e., privately-owned enterprises: POEs; foreign-owned enterprises: FOEs) in China can determine the wage levels and employment conditions of individual workers at their own discretion as long as they abide by the regulations set forth in the relevant laws (i.e., the Labor Law and the Labor Contract Law), including requirements on the minimum wage levels and maximum working hours. To survive fierce competition in the domestic and overseas markets, companies in the non-state sector are increasingly setting wage levels based on market mechanisms. According to the human capital theory and the signaling hypothesis, it is expected that companies in the non-state sector would be willing to set higher wages for highly educated and skilled workers and that this tendency would be even more pronounced when they compete with the state sector for the best talent (Zhao, 2015; Zhang, 2018).

Meanwhile, despite the rules and regulations stipulated in the Labor Law and the Labor Contract Law, the base wages of SOE executives continue to be determined by the government, which strongly reflects the egalitarian ideology that was valued during the planned economy period. Accordingly, executives and managers of SOEs end up earning a lower salary than their counterparts working in the non-state sector, a trend that is prevalent even today. Considering that the wage disparities between individuals with different educational levels are relatively insignificant in the state sector, the return to schooling is likely to be lower in this sector than in the non-state sector. This notion led us to hypothesize the following:

Hypothesis H_2: *The return to schooling in the non-state sector is higher than that in the state sector*.

One of the segmentations of the Chinese labor market can be observed in the discrimination against rural migrants under the *hukou* system. This issue could trigger some of the difference in the returns to schooling of urban *hukou* workers (i.e., local urban workers who have urban *hukou*) and rural *hukou* migrants (migrant workers who have rural *hukou* and are working in urban areas).

In 1958, the Chinese government introduced the *hukou* system, which basically bans all individuals, except state officials who have been sent by the government to work in different regions, from migrating from rural to urban regions in search of jobs. In the 1980s, the government began relaxing its restrictions, which resulted in an exodus of labor force to urban areas, leading to a gradual increase in the number of rural *hukou* migrants (Minami and Ma, 2010). According to the 2018 Migrant Workers Monitoring Survey Report and the China Statistical Yearbook (National Bureau of Statistics, 2018, 2019), the total number of migrant workers reached 288.36 million in 2018, accounting for 69.2% of all urban workforce (416.49 million). Although relaxing labor migration regulations helped rural *hukou* workers greatly expand their presence in the urban labor market, it simultaneously gave rise to the wage gap between rural *hukou* migrants and urban *hukou* workers. In essence, the average wage of the former decreased dramatically from 76.9% in 1995 to 56.6% in 2010 of the average wage of the latter.

The human capital theory and the hypothesis regarding discriminatory preferences held by employers (Becker, 1957) attributed the wage gap between rural *hukou* migrants and urban *hukou* workers to differences in human capital or discriminatory treatment against employees by employers. In China, public and household investments in education are considerably higher in urban regions than in rural regions, leading to a pronounced difference in educational attainment between rural *hukou* migrants and urban *hukou* workers. Moreover, exploiting the vulnerable position in which migrants from rural areas are placed owing to the institutional and social barriers they face, companies in urban regions might practice blatant discrimination against rural *hukou* migrants by providing them with poor working conditions, something that has been repeatedly highlighted in the literature (Meng and Zhang, 2001; Cai, 2016; Ma, 2018b).

It is worth noting that discriminatory practices in the treatment of workers are the only factor that can potentially lead to differences in the return to schooling by the *hukou* system. Only when companies in urban areas pay lower wages to rural *hukou* migrants than to urban *hukou* workers with similar educational attainment can empirical analysis capture differences in returns to schooling between the two. Research by Meng and Zhang (2001), Messinis (2013), and Zhu (2016), which are among the few available studies that address the relationship between the segmentation of the Chinese labor market by the *hukou* system and the return to schooling in China, found that employers tend to underestimate the educational attainment of rural *hukou* migrants. These observations lead us to the following hypothesis:

Hypothesis H_3: *The return to schooling of rural hukou migrants is limited compared to urban* hukou *workers.*

The disparity between urban and rural regions is also an important aspect of the segmentation of the Chinese labor market. These regional disparities in return to schooling are strongly related to differences in ownership structures and technological levels between rural companies (typically township and village enterprises (TVEs)) and their urban counterparts (mainly large SOEs, POEs, and FOEs). Two factors are noteworthy in this regard.

First, due to differences in the corporate ownership structure and average company size, employment/wage systems vary greatly between rural and urban companies. In rural regions, TVEs and other small companies that are mainly run on the basis of collective ownership are characterized by a unique management system that is often described as "familistic," where social capital symbolized by community-based human resource relationships and egalitarianism stemming from a strong sense of community (i.e., factors unrelated to education, work experience, or other aspects of human capital) play a significant role in the wage-setting process (Iwasaki and Ma, 2020). Conversely, urban companies are strongly guided by market mechanisms that focus on maximizing profits, which motivate them to operate employment/wage systems that place great importance on human capital.

Second, rural and urban companies pursue different technological levels, which translates into vastly diverse demands for highly educated and skilled workers. Since the 1980s, TVEs, which achieved growth by absorbing the surplus labor force in rural regions, were not entitled to the same protection that the majority of SOEs in urban regions received from the central government to procure the funds and materials necessary to make substantial investments in production facilities or to run long-term innovation projects (Lin, Cai, and Li, 1994). Starting from the 2000s, the gap between rural and urban companies widened even further, as urban enterprises successfully incorporate advanced information technology and management know-how acquired from developed countries to upgrade their management and production systems. What used to be a novel phenomenon in Shenzhen, China's Silicon Valley — the active and willing hiring of high-tech companies of young graduates of universities or graduate schools at high salaries — has now become a common practice for many companies in urban regions. Therefore, such differences between rural and urban companies may manifest as differences in the return to schooling between rural and urban regions. This notion enables us to predict the following:

Hypothesis H_4: *The return to schooling in urban regions is higher than that in rural regions.*

The fourth factor possibly contributing to the segmentation of the labor market is gender. Theoretically, two factors are responsible for gender differences in returns to schooling.

The first is sexual discrimination against women that is simply unreasonable or that arises from traditional thinking. According to Becker's hypothesis regarding discriminatory preferences (Becker, 1957), when a group of employers, managers, or other influential individuals in the labor market discriminates against women without legitimate reasons, they would set lower wages for women even when female workers have attained the same educational levels as their male counterparts, resulting in lower returns to schooling among women than men. In addition, the hypothesis regarding the household economics of gender roles and the division of market work and housework (Becker, 1985) suggests that when it becomes customary for men to specialize in work and women in household duties in order to maximize household utility, it becomes more unlikely for women than men to choose and continue market work. This gives companies an excuse to set higher wages for male workers, who are more likely to provide continuous service to the firm, than for female workers, who are likely to leave their jobs after a short time, as described by the statistical discrimination theory (Arrow, 1972; Phelps, 1973).

The second factor responsible for the gender diversity in returns to schooling is the difference in the signaling effect of educational attainment. In China, many people, especially those in rural regions, do not question the notion that men are inherently superior to women. Consequently, parents tend to invest much more in their sons' education compared to their daughters. This tendency has manifested as a gender gap in the percentage of high school graduates advancing to universities in China. In fact, the share of females among all university students was 24.1% in 1978, which only increased by slightly more than 10 percentage points during the transition period (Liu, 2008). Although the Chinese government's promotion of access to higher education has succeeded in greatly reducing the gender difference in the percentage of high school graduates advancing to universities, the scarcity of highly educated individuals is still much more prominent among females than among males when workers of all ages are taken into consideration. This suggests that the signaling effect of educational attainment may be stronger for women than for men.

As described above, general theories do not allow us to make accurate predictions about gender differences in returns to schooling in China. Furthermore, a few existing studies that have compared the returns to schooling between men and women in China have yielded mixed, largely inconsistent results.[4] However, we can surmise that Chinese women have become increasingly willing to participate in the labor market, as implied by the recent increase in the number of women delaying marriage and having fewer children, and that stereotypes about women like those proposed by the hypothesis regarding household economics of the division of market work and housework may have lost much of their influence over the last few decades. Meanwhile, despite their heightened willingness to participate in the labor market, Chinese women have had limited educational opportunities when compared to men throughout the transition period, resulting in female workers being much more affected by the signaling effect of educational attainment than their male counterparts. Accordingly, in this study, we test the following hypothesis regarding the gender gap in return to schooling:

Hypothesis H_5: *The return to schooling is higher for women than for men.*

The last hypothesis is related to the possible changes in returns to schooling during the transition period. Theories suggest the following three possibilities:

First, the return to schooling is expected to increase with economic development, which is accompanied by technological advancements. This kind of qualitative transformation of the industrial structure can increase the demand for highly educated and skilled workers; in turn, this could lead to improved returns to schooling (Solow, 1957). China's economic growth during the transition period has undoubtedly been a rapid catch-up process with remarkable advancements in science and technology, during which the return to schooling could have increased significantly.

Second, progress in marketization can also improve returns to schooling. It is easy to imagine that the penetration of market mechanisms in the national economy and the expansion of the non-state sector would drive more employers to provide wages that are appropriate to the marginal productivity of workers. The marketization reforms over the past 30 years have essentially overthrown the old wage-setting traditions adopted in the

[4] For instance, Chen and Gu (2004) and Ma and Zhang (2017) concluded that women in China surpass men in terms of the return to schooling. According to Ma (2018c), however, although the return to schooling for women working for SOEs exceeded that of their male counterparts by 1.6% in 2002, which is also pointed out by Chen, Démurger, and Fournier (2005) and Ma and Zhang (2017), in 2013, the return to schooling for men surpassed that for women by 0.9%.

planned system, which was characterized by a false sense of equality that came at the cost of efficiency. Thus, it can be presumed that the reforms have led to a gradual increase in the positive association between schooling and wage levels.

Third, there could be a negative association between schooling and wage levels. Two reasons have been proposed to explain this phenomenon. First, in a high-income society, most households tend to invest heavily in their children's education, which leads to a significant proportion of high school graduates advancing to universities. This inevitably causes the return to schooling to decline, which might be exactly what is happening in China, where a one-child policy adopted as a measure to control the population has driven households to invest heavily in the education of their only child, and, as a result, highly educated individuals may no longer be rare in China.[5] Second, when individuals with higher education do not have the skills required by companies, the return to education may decline (i.e., skill/education attainment mismatch).

Summarily, the prediction of how the progress of market-oriented reforms in China over the past 30 years can affect the return to schooling depends upon how we interpret the balance between the positive effect brought about by the advancement of industrial technology and marketization, the negative effect generated by heavy investment in education, and the mismatch between the supply and demand of highly educated laborers. The following four observations are noteworthy in this regard: (1) To this day, there is still much room for further technological advancement in the Chinese economy; (2) the market-oriented reforms have contributed greatly to redressing the inefficient wage-setting system that was prevalent during the planned system period; (3) although the percentage of high school graduates advancing to universities has increased significantly in recent years, it is still relatively low compared to developed countries;[6] and (4) there is not enough scientific evidence to support that the mismatch between the supply and demand of highly educated laborers is so great that it can reduce the benefits of investing in higher education. These observations lead us to the following assumptions:

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[5] Actually, Wu and Zhao (2010), Chang and Xiang (2013), and Gao and Smyth (2015) reported that, as a result of the implementation of the higher education expansion policy, the employment rate has become lower for many university graduates recently, and their starting salaries are showing a downward trend.

[6] According to data published by UNESCO, the percentage of high school graduates advancing to universities in 2018 was 88.2% in the USA, 70.3% in Germany, 63.6% in Japan, and only 50.6% in China (http://uis.unesco.org/).

Hypothesis H_6: *The return to schooling increased over time during the transition period*.

In the following sections, we conduct a meta-analysis of the extant literature to verify the six hypotheses proposed in this section.

3 Literature Selection and Overview of Selected Works for Meta-Analysis

This section first describes the procedure for searching and selecting literature suitable for testing the hypotheses proposed in the previous section, and then outlines the studies selected for the meta-analysis.

A large volume of empirical studies has analyzed the wage determinants in China, and a vast proportion of these studies employed educational attainment as an independent variable in the wage function. Accordingly, we adopted a policy of searching for and selecting literature by collecting as many empirical studies as possible on the wage structure in China and extracting estimates suited to the meta-analysis in this study. Specifically, using the electronic academic literature databases of EconLit and Web of Science as well as the websites of leading academic publishers for English language literature [7] and the Chinese National Knowledge Infrastructure (CNKI) database, which is the largest academic literature database in China for Chinese language literature, we first searched for relevant studies published from 1990 to the first half of 2020. In these databases and websites, we carried out an AND search for article titles using "*China*" and "*wage*" as keywords, obtaining 212 papers in English and 163 in Chinese on wage empirical studies from China.[8] Subsequently, we closely examined the contents of these 375 studies and selected those that actually report returns to schooling by estimating a wage function. Finally, we selected 92 and 121 studies in English and Chinese, respectively.[9]

A breakdown of the 213 selected works by publication year shows that 6 papers (2.8% of the total) were published during the 1990s, 52 (24.4%) during the 2000s, 144 (67.6%) in the 2010s, and 11 (5.2%) in 2020, constructively reflecting the growth of empirical analysis in Chinese economic studies over the last decade. This fact implies

[7] They refer to the following six publishers: Emeraldinsight(https://www.emeraldinsight.com), Sage Journals (http://journals.sagepub.com), ScienceDirect (http://www.sciencedirect.com), Springer Link (https://link.springer.com), Taylor and Francis Online (https://www.tandfonline.com), and Wiley Online Library (https://onlinelibrary.wiley.com).

[8] The final literature search was conducted in July 2020.

[9] A bibliography of the 213 selected works is available upon request.

that the meta-analysis in this study is largely based on empirical evidence generated from advanced econometric analyses conducted from the 2010s. This is important for pursuing the true effect of the return to schooling in China through the transition period, which is the subject of Hypothesis H_1.

To test Hypotheses H_2 to H_5 regarding the variance of return to schooling from the viewpoint of company ownership, *hukou*, region, and gender, it is essential to include empirical results in which the corresponding sample groups have been analyzed individually. The selected studies satisfied this requirement. That is, 13 of the 213 studies have reported estimates of a schooling variable for the state or non-state sectors, 70 for rural *hukou* migrants or urban *hukou* workers, 147 for urban or rural regions, and 68 for women or men.

The selected studies are also useful for testing hypothesis H_6, which concerns the return to schooling in the transition period and its time-series dynamics. This is representative because the periods subject to research in these 213 works cover the 34-year period from 1985 to 2018, with the exception of 1994. The vast majority of estimates reported in the extant literature are empirical results of the return to schooling during specific years. This factor is advantageous for testing Hypothesis H_6.

From the 213 selected studies, we extracted 2,191 estimates overall. The mean (median) of the number of collected estimates per study was 10.3 (6). All of these are single-term estimates of the years of schooling variables.[10]

Furthermore, to correspond to the difference in the units of estimation results in the selected studies, we employ the PCC of a corresponding estimate in the meta-analysis. The PCC is a measure of the association between a dependent variable and the independent variable in question when other variables are held constant. When t_k and df_k denote the t value and the degree of freedom of the k-th estimate, respectively, PCC (r_k) is calculated using the following equation:

$$r_k = \frac{t_k}{\sqrt{t_k^2 + df_k}}\ , \qquad k = 1, 2, \ldots, K. \ (1)$$

The standard error (SE_k) of r_k is given by $\sqrt{(1 - r_k^2)/df_k}$.

As the evaluation criterion of the correlation coefficient, Cohen (1988) suggested using the values of 0.10, 0.30, and 0.50 as cut-offs to distinguish small, medium, and

[10] Estimates of the interaction terms of schooling years and other independent variables are not included in the meta-analysis in this study. In addition, although some literature used educational attainment dummy variables in empirical analysis, these estimates are also not used in this research.

large effects, respectively. However, this criterion is set with a zero-order correlation, which is the correlation coefficient with no control variables. It is relatively rigid in economics research, in which a large number of control variables are usually employed in empirical studies. Therefore, Doucouliagos (2011) proposed 0.048, 0.112, and 0.234 as the lowest thresholds of small, medium, and large effects, respectively, as the new general standard in labor economics research (ibid., **Table 3**, p. 11). In this study, we evaluated the return to schooling in China in accordance with this standard.

4 Meta-Synthesis

A meta-analysis generally consists of three steps: (1) meta-synthesis of collected estimates, (2) meta-regression analysis (MRA) of heterogeneity among the literature, and (3) testing for publication selection bias (Iwasaki, 2020a).[11] We followed this standard procedure to examine the hypotheses on the return to schooling in China. Accordingly, in this section, as the first step of the meta-analysis, we synthesized 2,191 estimates collected from the 213 selected works using their PCCs after observing their distribution.

Table 1 shows the descriptive statistics of the PCCs of the collected estimates and the results of the *t*-test and the Shapiro-Wilk normality test, while **Figure 1** displays their kernel density estimations. To match the six hypotheses proposed in Section 2, both of these are presented not only for all studies but also for cases in which collected estimates are divided by corporate sectors, *hukou*, region, gender, and periods.

According to **Table 1**, the mean and median of the PCCs for all studies are positive, and Panel (a) of **Figure 1** shows a skewed distribution toward the positive side. Specifically, the vast majority of empirical results reported in the selected literature indicate that there exists a positive relationship between schooling years and wage levels in China. In fact, 2,135 (97.4%) of the 2,191 collected estimates had a positive sign. Moreover, according to the Doucouliagos standard, 668 (31.3%) of these 2,135 estimates show a large effect of schooling on wages, while 800 (37.5%) and 448 (21.0%) indicate medium and small effects, respectively, and the remaining 219 (10.3%) denote that the return to schooling is insignificant. In sum, most of the collected estimates suggest that the wage effect of schooling has an economically meaningful size, in line with Hypothesis H_1.

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[11] For detailed descriptions of the meta-analysis method, see Borenstein, Hedges, Higgins, and Rothstein (2009), Stanley and Doucouliagos (2012), and Iwasaki (2020b, Chapter 1).

As demonstrated in **Table 1** and **Figure 1**, the distributions of collected estimates categorized based on target *hukou*, region, and gender also support Hypotheses H_3, H_4, and H_5. The distributions of estimates of the return to schooling are more heavily weighted toward the positive side for urban *hukou* workers, urban, and female worker groups than those for rural *hukou* migrant, rural, and male worker groups, respectively. Similarly, there is an apparent difference in the distribution of the estimates by period. Although the estimates for the 2000s are similar to those for the 2010s, looking through four periods, estimates for the 2010s are more strongly deflected to the positive side than those for the 2000s and earlier periods, which corresponds with Hypothesis H_6. However, with regard to the estimates by target corporate sector, it is difficult to say that there remains a large difference between the state and non-state sectors.

Table 2 reports the results of the meta-synthesis. In this table, together with synthesis results using the traditional fixed-effect and the random-effects model,[12] we also performed synthesis using the unrestricted weighted least squares average (UWA) method, which is less subject to influence from excess heterogeneity than the fixed-effect model and has less publication selection bias than the random-effects model, and UWA synthesis of estimation results with statistical power of more than 0.80 — that is, the weighted average of the adequately powered (WAAP) synthesis (Stanley and Doucouliagos, 2017; Stanley, Doucouliagos, and Ioannidis, 2017).[13] **Table 2** also provides results specialized for each hypothesis.

With respect to the traditional synthesis results reported in Column (a) of **Table 2**,

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[12] The fixed-effect model regards the integrated effect size of the weighted average by using the reciprocal number of the variance of each observation value as the weights, based on the assumption that the parameters of the estimation results to be integrated are common. On the contrary, the random-effects model is regarded as a method that integrates the estimates by using the moment method, based on the assumption that there is a non-negligible heterogeneity between the estimates, and the error is a probability variable—the mean value of error is zero, and the variance is τ^2 (Iwasaki, 2020b).

[13] The UWA method regards as the synthesized effect size, a point estimate obtained from the regression that takes the standardized effect size as the dependent variable and the estimation precision as the independent variable. Specifically, we estimate the following equation, in which there is no intercept term, and the coefficient α is utilized as the synthesized value of the PCCs:

$$t_k = \alpha_1(1/SE_k) + \varepsilon_k,$$

where ε_k is a residual term. In theory, α is completely consistent with the estimated value in a traditional fixed-effect model. Its standard error, however, is more robust to publication selection bias.

since in each case Cochran's Q test of homogeneity rejects the null hypothesis at the 1% significance level, and the I^2 and H^2 statistics also suggest the presence of heterogeneity in Column (b) of this table, the estimates of the random-effects model are adopted as reference values of the synthesized effect size. Concerning the new UWA synthesis results in Column (c) of **Table 2**, given that a considerable number of estimates in which the statistical power is 0.8 or more are secured, WAAP synthesis values, considered more reliable, are used as reference values for comparison with those generated by the random-effects model.

The overall results showed that the random-effects model produced a synthesis value of 0.175, while WAAP estimation yielded a value of 0.164. According to the Doucouliagos standard, it could be said that the return to schooling in China would be of medium size through the transition period, irrespective of the synthesis method. Hence, the results strongly support Hypothesis H_1. Similarly, Hypotheses H_3, H_4, and H_5 are also supported by both the random effects and WAAP synthesis results. However, the results for Hypothesis H_2 differ between the two models. The random-effects estimates indicate that the return to schooling in the non-state sector falls below that in the state sector, while the WAAP values show a reverse relationship. Therefore, we will make a final judgment regarding Hypothesis H_2, referring to the MRA results as well as the test results of publication selection bias and the presence of genuine empirical evidence in the selected literature.

Regarding Hypothesis H_6, the random-effects model produced results that the return to schooling tends to increase from the early period to the current years. However, the WAAP synthesis results indicate a U-shaped time trend in which the effect size in the 1990s was smaller than that in the 1980s or earlier. The disagreement between the two models may be due to the coarse division of the periods. To test this possibility, we looked at changes over time in the scale of the return to schooling with a more detailed subdivision of collected estimates. The results are shown in **Figure 2**. The slope of the approximate line in this figure is estimated to be positive and statistically significant at the 1% level, and its coefficient implies that, as the average estimation period approaches the present time year by year, the return to schooling increases by 0.0025 in terms of the PCC. As demonstrated in **Figure 2**, Hypothesis H_6 is supported when the estimation period is divided into single-year units.

5 Meta-Regression Analysis

While the meta-synthesis carried out explicit hypothesis testing by providing a point estimate of the return to schooling as a synthesized effect size, it has the drawback of largely excluding the consideration of heterogeneity among the literature. Accordingly, this section verifies the reliability of the synthesis results in the previous section by estimating a multivariate meta-regression model that simultaneously controls for various study conditions among the selected studies. Specifically, we estimate a regression equation in the form of

$$y_k = \beta_0 + \sum_{n=1}^{N-1} \beta_n x_{kn} + \beta_N se_k + e_k, \quad k = 1, \cdots, K, \quad (2)$$

where y_k is the PCC, β_0 is the intercept, β_n denotes the meta-regression coefficient to be estimated, x_{kn} denotes a meta-independent variable that captures the relevant characteristics of an empirical study and explains its systematic variation from other empirical results in the literature, se_k is the standard error of the k-th estimate of the PCC, and e_k is the meta-regression disturbance term. For x_{kn}, in addition to the focused research attributes consisting of the target corporate sector, *hukou*, region, gender, and period, a series of variables are introduced to capture the differences in survey data, wage type, estimator, presence of control for selection bias, presence of addressing the endogeneity problem between years of schooling and wages, and other factors that may affect the results. The names, definitions, and descriptive statistics of these independent variables are presented in **Table 3**.[14]

It should be noted that there is currently no consensus among meta-analysts on the best estimator to control for literature heterogeneity (Iwasaki, Ma, and Mizobata, 2020). Therefore, following the guidelines of Stanley and Doucouliagos (2012), to verify the statistical robustness of coefficient β_n, we performed the MRA using the following six estimators: the cluster-robust weighted least squares (WLS) estimator, which clusters the collected estimates by study and computes robust standard errors, using (1) the inverse of the standard error (1/*SE*); (2) the degree of freedom (*df*); or (3) the inverse of the number of estimated results extracted from literature (1/*EST*) as an analytical weight;

[14] In addition to the series of research conditions listed in **Table 3**, we also investigated the influence of the age cohort of the sample population, the wage-level percentile, the data sources and types of empirical data, the wage payment period, basic unit of wage variable, simultaneous estimation with interaction term, and the presentation language on extracted estimates, and found that the control for these factors was not statistically significant.

(4) the multilevel mixed-effects RLM estimator; (5) the cluster-robust random-effects panel GLS estimator; and (6) the cluster-robust fixed-effect panel LSDV.

Table 4 presents the results of the estimation. It shows that the differences in *hukou*, region, and estimation period strongly impact the estimates of return to schooling in China, in line with Hypotheses H_3, H_4, and H_6, which is robust even after controlling for a series of study conditions from wage type to standard errors. The variable of rural *hukou* migrants is estimated to be significant and negative in all six models, while the variable of urban *hukou* workers is not significant. Compared with urban *hukou* workers, the return to schooling for rural *hukou* migrants is smaller within a range of 0.0382 to 0.0675 in terms of PCC, *ceteris paribus*. Furthermore, the rural region variable is estimated with a significant and negative coefficient in all models, indicating that the return to schooling in rural areas is limited compared to urban areas within a range of 0.0432 to 0.0687. Moreover, the average estimation year is projected to be significant and positive in all six models; its coefficients imply that, as the estimation period approaches the current time year by year, the return to schooling increases within a range of 0.0036 to 0.0044. This result is significantly consistent with the estimation results of the approximate line shown in **Figure 2**.

In contrast with the above results, the corporate sector variables do not show significant estimates and, thus, do not support Hypothesis H_2. The findings that the female gender variable is estimated to be positive and significant, while the male gender variable is insignificant in Models [1] to [3], correspond to Hypothesis H_5. However, similar results were not reproduced in Models [4] to [6]. Hence, the reliability of hypothesis testing remains somewhat questionable for Hypothesis H_5.

Lastly, as emphasized by Bayesian meta-analysts such as Polák (2019) and Havranek and Sokolova (2020), MRA faces the so-called "model uncertainty" problem, which implies that the true model cannot be identified in advance (Ugur et al., 2020). It is also likely that the simultaneous estimation of a large number of meta-independent variables can result in multicollinearity. To address these issues, following the approach employed by Brada et al. (2020), we conducted Bayesian model averaging (BMA) by taking the variables used for hypothesis testing from the non-state corporate sector to the average estimation year, and the standard errors of the PCCs as focus regressors and the remaining 21 independent variables as auxiliary regressors to extract posterior inclusion probabilities (PIPs) of the latter 21 variables. We subsequently estimated a meta-regression model that introduces only those auxiliary regressors with 0.80 or a PIP (i.e., selected moderators), with focus regressors on the right-hand side.[15] The results presented in **Table 5** show that the variables of rural *hukou* migrants, rural areas, and average estimation year are given a significant estimate in all six models, in agreement with **Table 4**. In summary, a robustness check, which considers model uncertainty and multicollinearity, also strongly supports Hypotheses H_3, H_4, and H_6.

6 Testing for Publication Selection Bias

As mentioned above, the results of both the meta-synthesis and MRA strongly support Hypotheses H_3, H_4, and H_6, and provide conditional support for Hypothesis H_5. In contrast, Hypothesis H_2 is not empirically supported. However, the reliability of these results cannot be established if the selected studies did not contain genuine evidence due to publication selection bias. Accordingly, as the final stage of the meta-analysis, in this section, we test for publication selection bias and the presence of the true effect. Accordingly, in addition to visual examination using a funnel plot, we conducted a funnel asymmetry test (FAT), a precision-effect test (PET), and a precision-effect estimate with standard error (PEESE), which were proposed by Stanley and Doucouliagos (2012) and have been used widely in previous meta-analyses.

Publication bias means that the results of only a part of the research actually conducted are published; therefore, a problem, in that the evaluation of effect size and statistical significance based on the published results deviates from the true value, may occur (Iwasaki, 2020a). A funnel plot is a scatter plot with the effect size (in the case of this study, the PCC) on the horizontal axis and the precision of the estimate (in this case, the inverse of the standard error $1/SE$) on the vertical axis. In the absence of publication selection bias, effect sizes reported by independent studies vary randomly and symmetrically around the true effect. Moreover, according to the statistical theory, the dispersion of effect sizes is negatively correlated with the precision of the estimate. Therefore, the shape of the plot resembles an inverted funnel. If the funnel plot is not bilaterally symmetrical but is deflected to one side, then an arbitrary manipulation of the study area in question is suspected, in the sense that estimates in favor of a specific conclusion (i.e., estimates with an expected sign) are more frequently published (Stanley and Doucouliagos, 2012; Iwasaki, 2020b).

The FAT–PET–PEESE procedure was developed to test publication selection bias and the presence of genuine evidence in a more rigid manner, and it can be performed

[15] The BMA estimation results are provided in **Appendix Table A1**.

by regressing the *t* value of the *k*-th estimate on the inverse of the standard error (1/*SE*) using Eq. (3), thereby testing the null hypothesis that the intercept term γ_0 is equal to zero.

$$t_k = \gamma_0 + \gamma_1(1/SE_k) + v_k, \qquad (3)$$

where v_k denotes the error term. When the intercept term γ_0 is statistically significantly different from zero, we can interpret that the distribution of the effect sizes is asymmetric. Even if there is publication selection bias, a genuine effect may exist in the available empirical evidence. Stanley and Doucouliagos (2012) proposed examining this possibility by testing the null hypothesis that the coefficient γ_1 is equal to zero in Eq. (3). The rejection of the null hypothesis implies genuine empirical evidence. γ_1 is the coefficient of precision; therefore, it is called PET.

Stanley and Doucouliagos (2012) also stated that an estimate of the publication-selection-adjusted effect size can be obtained by estimating Eq. (4), which had no intercept. If the null hypothesis of $\gamma_1 = 0$ is rejected, then the non-zero true effect exists in the literature, and the coefficient γ_1 can be regarded as its estimate.

$$t_k = \gamma_0 SE_k + \gamma_1(1/SE_k) + v_k. \qquad (4)$$

This was the PEESE approach. To test the robustness of the regression coefficients obtained from the above FAT–PET–PEESE procedure, we estimated Eqs. (3) and (4) using not only the unrestricted WLS estimator, but also the other four models to address the literature heterogeneity problem.

A funnel plot of all the studies is shown in **Figure 3**, which exhibits a strongly skewed distribution of the PCCs of return to schooling toward the positive side. The assessment of the presence of publication bias and its extent depends on the assumption that the true value is equal to zero, or whether it takes a positive value. The univariate test results for this point are reported in the top row of **Table 6**. If the true value is assumed to be zero, as the dotted line in **Figure 3** demonstrates, the ratio of positive to negative estimates is 2135:56; therefore, the null hypothesis that the number of positive estimates equals the number of negative estimates is strongly rejected (z=44.415, p=0.00). If the synthetic value of the WAAP model is assumed to be the true effect size, as indicated by the solid line in **Figure 3**, the collected estimates are divided into a ratio of 1062:1129 with a value of 0.164 as the threshold, and the null hypothesis that the ratio of estimates below the WAAP value versus those over it is 50:50 is not rejected (z=1.431, p=0.15). In **Table 6**, similar results are obtained from 9 of 16 cases when the collected estimates are classified by target corporate sector, *hukou*, region, gender, and period. In summary, the assessment of publication selection bias relies heavily on assumptions about the true effect size, and no conclusion can be drawn from the visual verification using the funnel plot and the univariate test results discussed above. Therefore, we leave the final judgment to the FAT–PET–PEESE procedure.

The results are listed in **Table 7**. In Panel (a) of the table, FAT rejects the null hypothesis that the intercept (γ_0) is zero for all five models, implying that the collected estimates lack funnel symmetry due to strong publication selection bias. However, even in the presence of publication selection bias, genuine evidence may exist in the selected literature. As reported in Panel (a) of **Table 7**, PET rejects the null hypothesis that the coefficient (γ_1) of the inverse of the standard error ($1/SE$) is zero in all five models and, accordingly, proves that the collected estimates do contain empirical evidence regarding the true effect size. The results of the PEESE approach in Panel (b) of the table show that, in all five models, the coefficients (γ_1) of $1/SE$ are estimated to be statistically significant; therefore, the true value of the return to education in China should be in the range of 0.1430 to 0.1604 in terms of the PCC.[16] From these results, we conclude that the return to schooling throughout the transition period in China measured by the PCC is at a medium level, which is in accordance with the Doucouliagos standard, as predicted in Hypothesis H_1.

We also performed the FAT–PET–PEESE procedure separately by the target corporate sector, *hukou*, region, gender, and period. These results, as well as those of the studies, are summarized in **Table 8**. As shown in this table, FAT detects publication selection bias in nine of the 16 cases. However, in all 16 cases, PET indicates the presence of genuine empirical evidence, and the PEESE method generates a statistically significant non-zero publication-selection-bias-corrected effect size irrespective of the FAT results. The estimated true effects are greater for the non-state sector, urban *hukou* workers, urban regions, and women than for their counterparts; this fact supports Hypotheses H_2, H_3, H_4, and H_5. The PEESE estimates also verify that the return to schooling increases steadily from the 1990s to the 2010s, which is in line with Hypothesis H_6. Combining this result with the results from **Figure 2**, which shows an upward chronological order of the collected estimates and the meta-regression analysis

[16] It is noteworthy that the publication-selection-bias-adjusted effect size generated by the PEESE method is closer to the WAAP synthesis value (0.164) than the random-effects one (0.175), according to **Table 2**. This result supports the statement by Stanley, Doucouliagos and Ioannidis (2017) that, as compared with the traditional random-effects model, the WAAP method is more robust to publication selection bias.

in **Tables 4** and **5**, which gives a robust and positive coefficient to the variable of average estimation year, we can judge that Hypothesis H_6 was also consistently supported through this and previous sections.

7 Conclusions

In this study, we conducted a meta-analysis of 2,191 estimates derived from 213 previous studies to estimate the Mincer-type return to schooling in China during the transition period. We also examined possible variances in the return to schooling from the viewpoints of corporate ownership, *hukou*, region, gender, and period.

The results obtained from the meta-analysis in Sections 4 to 6 can be summarized as follows: Hypothesis H_1, that the general return to schooling in China through the transition period is positive and of medium size is strongly supported by both the meta-synthesis result and the publication selection bias test result. With respect to Hypothesis H_2 on the gap in the return to schooling between the state and non-state sectors, although neither meta-synthesis nor MRA supports it, PEESE estimates of the publication-selection-bias-adjusted effect size suggest that the return to schooling in the non-state sector tends to exceed that in the state sector, which corresponds with our expectation. Hypotheses H_3, H_4, and H_5 — that urban *hukou* workers, workers in urban regions, and women enjoy a higher return to schooling than rural *hukou* migrants, workers in rural regions, and men, respectively, — are largely proven by all means of meta-analysis. Lastly, Hypothesis H_6 — that the return to schooling increases over time during the transition period — also receives considerable support from the meta-analysis, especially when the estimation period is subdivided into single years.[17] These findings are novel and, hence, greatly contribute to a deeper understanding of the labor market and wage system in China.

Finally, based on the results of the meta-analysis, we establish the following three policy implications:

First, the general return to schooling during the transition period, which is proven to be of medium size in terms of the PCC, confirms that the expansion and penetration

[17] Estimation results that introduced a squared term of average estimation year into the regression equation in **Fig.2** and **Table 4** also indicated that the return to schooling tends to increase monotonically over time. Actually, the results turned out that, while the single term of average estimation year was significant and positive, the squared term was estimated to be either statistically insignificant or significant but with an extremely small coefficient.

of market mechanisms in China have reached levels equivalent to those seen in neighboring developing countries. This finding provides a positive evaluation of the marketization reform that has taken place in the country over the last 30 years. From the standpoint of the return to schooling, there is no doubt that the wage-setting mechanism in China has been drastically rationalized as compared to that adopted in the planned economy. Continuous reform efforts are required to ensure further improvements in the wage system.

Second, a rapid increase in the return to schooling from the 1990s to the 2000s and from the 2000s to the 2010s strongly suggests the possibility of a critical shortage of highly educated and skilled labor forces due to the huge progress made in the advancement of technology in Chinese industry sectors. To ensure an ample supply of highly skilled labor forces, the Chinese government and the CPC have implemented various policies to promote education, science, and technology, including the establishment and expansion of higher education research institutions and the active promotion of study abroad experiences. However, these policies have likely failed to sufficiently produce the highly educated labor force sought by the industry. The inability to supply a sufficient number of highly educated workers can seriously hamper further development of the Chinese economy. Appropriate policy responses are imperative in this respect.

Third, the segmentation of the Chinese labor market, manifesting as disparities in the returns to schooling between the state and non-state sectors, urban *hukou* workers vs. rural *hukou* migrants, those living in urban versus rural regions, and men vs. women, is just as serious an issue as the critical shortage of highly educated labor in China. The Chinese government's persistent advocacy for gradual reform is, in fact, no more than an excuse to preserve large SOEs while, simultaneously, promoting the development of the non-state sector. This reform strategy is referred to as the multiplication reform (*Zeng Liang Gaige* in Chinese). Researchers have debated whether greater priority should be given to market or ownership reform. Policymakers, including high-ranking state officials and the Communist Party leadership, are so keen to maintain their control over economic activities by exercising their authority over SOEs that they are reluctant to implement radical ownership reform. The radical reform of large SOEs, along with the deregulation of the *hukou* system, is an important measure that can provide an effective solution to the segmentation of the labor market; now is the right time for these reforms. In addition, regional and gender differences in the return to schooling are deep-rooted issues associated with egalitarianism stemming from a strong sense of community and

Confucianism's traditional notion that men are superior to women, which cannot be resolved overnight. Nevertheless, policymakers should pay more attention to this issue because neglecting the problem can cause instability in Chinese society.

Finally, although we conducted a large meta-analysis using 2,191 empirical results reported in 213 existing studies to estimate the Mincer-type return to schooling in China for a longer term, this study has several limitations. First, although we used different models to perform robustness checks, for example, we also conducted a BMA to select robust moderators and estimated a meta-regression model that introduces only those selected moderators with the key variables, we could not address the uncertainty problem in the meta-analysis completely. To develop the meta-analysis method to address the problem has become a future research issue. Second, although we attempted to control the moderators that might affect the estimated results, such as analyzed objects, econometric methods including models and data, variables used in studies, and analyzed periods, there might have been a heterogeneity problem in this study owing to other factors, such as the heterogeneity of characteristics of authors and the editor of journals, the change in published criteria and preferences of both authors and journals by period. In particular, when performing a meta-analysis from a long-term perspective, the results should be interpreted with consideration of these drawbacks. To address the heterogeneity problem in meta-analysis is still an important issue that should be addressed in the future. Despite these limitations, we believe that the current study, with respect to China's labor market segmentation and the change of return to education as the progressive of the market-oriented economy reform and economic development in China, provides new insights for understanding the role of education in the individual income and income inequality problem in China.

References

Arrow, K. J. (1973). The theory of discrimination. In: Asehenfelter, O. A., and Rees, A. (eds.), *Discrimination in Labor Market*, Princeton, N.J.: Princeton University Press, 3-42.

Asadullah, M., Asadullah, N., and Xiao, S. (2020). The changing pattern of wage returns to education in post-reform China. *Structural Change and Economic Dynamics,* 53, 137-148.

Becker, G. S. (1957). *The economics of discrimination*. Chicago: University of Chicago Press.

Becker, G. S. (1964). *Human capital: A theoretical and empirical analysis, with special reference to education*. New York: Columbia University Press.

Becker, G. S. (1985). Human capital, effort, and the sexual division of labor. *Journal of Labor Economics*, 3(1), S33-58.

Brada, J. C., Drabek, Z., and Iwasaki, I. (2021). Does investor protection increase foreign direct investment? A meta-analysis. *Journal of Economic Surveys*, 35(1), 34-70.

Borenstein, M., Hedges, L.V., Higgins, P. T., and Rothstein, H. R. (2009). *Introduction to meta-analysis*. Chichester: John Wiley and Sons.

Cai, F. (2016). *China' economic growth prospects: form demographic dividend to reform dividend*. Beijing: Social Sciences Academy Press.

Chang, J., and Xiang, J. (2013). Higher education expansion and returns to college education. *Chinese Journal of Population Science*, 3,104-111 (in Chinese).

Chen, L., and Gu, G. (2004). Empirical Ssudy on the gender gap of the Mincer-type return to schooling. *Education Review of Beijing University*, 2(3), 40-45 (in Chinese).

Chen, Y, Démurger, S., and Fournier, M. (2005). Earnings differentials and ownership structure in Chinese enterprises. *Economic Development and Cultural Change,* 53(4), 933-958.

Churchill, S. A., and Mishra, V. (2018) Returns to education in China: A meta-analysis. *Applied Economics*, 50(54), 5903-5919.

de Brauw, A., and Scott, R. (2008). Reconciling the returns to education in off-farm wage employment in rural China. *Review of Development Economics*, 12(1), 57–71.

Doucouliagos, H. (2011). How large is large? Preliminary and relative guidelines for interpreting partial correlations in economics. *School Working Paper No. SWP 2011/5*, School of Accounting, Economics and Finance, Faculty of Business and Law, Deakin University: Melbourne.

Fleisher, B. M., Sabirianova, K., and Wang, X. (2005). Returns to skills and the speed of reforms: Evidence from Central and Eastern Europe, China, and Russia. *Journal of Comparative Economics*, 33(2), 351–370.

Fleisher, B. M., and Wang, X. J. (2005) Return to schooling in China under planning and reform. *Journal of Comparative Economics*, 33(2), 265–277.

Fu, Q., and Ren, Q. (2010). Educational inequality under China' rural-urban divide: the hukou system and return to education. *Environment and Planning A*, 42(3), 592-610.

Gao, W., and Smyth, R. (2015). Education expansion and returns to schooling in urban China, 2001–2010: Evidence from three waves of the China urban labor survey. *Journal of the Asia Pacific Economy*, 20(2),178-201.

Hannum, E., Zhang,Y. P., and Wang, M. Y. (2013). Why are return to education higher for women than for men in urban China? *China Quarterly*, 215, 616-640.

Havranek, T., and Sokolova, A. (2020). Do consumers really follow a rule of thumb? Three thousand estimates from 144 studies say “probably not.” *Review of Economic Dynamics*, 35, 97-122.

Huang, X., Caldas, J. V., and Rebelo, J. (2002). Returns to education during the reform of state-owned enterprises in Hunan People's Republic of China. *Labour*, 16(3),513-535.

Iwasaki, I. (2020a). Meta-analysis of emerging markets and economies: An introductory note for the special issue. *Emerging Markets Finance and Trade*, 56(1), 1-9.

Iwasaki, I. ed. (2020b). *The economics of transition: Developing and reforming emerging economies*. Abingdon and New York: Routledge.

Iwasaki, I., and Ma, X. (2020). Gender wage gap in China: A large meta-analysis. *Journal for Labour Market Research*, 54, Article 17.

Iwasaki, I., Ma, X., and Mizobata, S. (2020). Corporate ownership and managerial turnover in China and Eastern Europe: A comparative meta-analysis. *Journal of Economics and Business* (in press).

Japan Science and Technology Agency (2017). International comparison of science and technology capabilities based on R and D view report (2017): Macroscopic consideration of the scientific and technological capabilities of each country. G-Tec Report No. CRDS-FY2017-CR-01(in Japanese).

Li, S., Wu, S., and Xing, C. (2018). Education development and wage inequality in urban China. *Asian Economic Papers*, 17(2), 140-151.

Lin, Y., Cai, F., and Li, Z. (1994). *Chinese miracle: Development strategy and economic reform*, Shanghai Branch of SDX Joint Publishing Company (in Chinese).

Liu, Z. (2008). Why is the return to schooling higher for women than men? An analysis from discrimination perspective. *Economic Science*,2,119-128 (in Chinese).

Liu, E., and Zhang, S. (2013). A meta-analysis of the estimates of returns to schooling in China. Working Paper No. 201309855, Department of Economics, University of Houston: Houston.

Ma, X., and Zhang, C. (2017). Return to education in China during the 2000s: Evidence from CGSS. *International Journal of Financial Research*, 8(3),85-104.

Ma, X. (2018a). *Economic transition and labor market reform in China*, Singapore: Palgrave Macmillan.

Ma, X. (2018b). Labor market segmentation by industry sectors and wage gaps between migrants and local urban residents in urban China. *China Economic Review*, 47, 96-115.

Ma, X. (2018c). Ownership sector segmentation and gender wage gap in urban China during the 2000s.*Post-Communist Economies*, 30(6),775-804.

Ma, X., and Iwasaki, I. (2021). Does party membership bring a wage premium in China? A meta-analysis. *Journal of Chinese Economic and Business Studies*. (Early View: https://doi.org/10.1080/14765284.2020.1842987)

Maurer-Fazio, M. (1999). Earnings and education in China’s transition to a market economy: Survey evidence from 1989 and 1992. *China Economic Review,* 10(1),17–40.

Messinis, G. (2013). Return to education and urban-migrant wage differentials in China: IV quantile treatment effects. *China Economic Review,* 26, 39-55.

Meng, X. (1995). The role of education in wage determination in China's rural industrial sector. *Education Economics*, 3(3),235-247.

Meng, X., and Zhang, J. (2001). The two-tier labor market in urban China: Occupational segregation and wage differentials between urban residents and rural migrants in Shanghai. *Journal of Comparative Economics*, 29(3), 485-504.

Minami, R., and Ma, X. (2010) The Lewisian turning point of Chinese economy: Comparison with Japanese experience. *China Economic Journal*, 3(2), 165-181.

Mincer, J. (1974). *Schooling, experience and earning*, New York: Columbia University Press.

Ministry of Education of the People's Republic of China (1999). *China education statistics yearbook 2009,* China Statistics Press (in Chinese).

Ministry of Education of the People's Republic of China (2017). *China education statistics yearbook 2009*, China Statistics Press (in Chinese).

National Bureau of Statistics (2018). *Migrants supervision survey report 2018*, China Statistics Press (in Chinese).

National Bureau of Statistics (2019). *China statistics yearbook 2019*, China Statistics Press (in Chinese).

Polák, P. (2019). The Euro's trade effect: A meta-analysis. *Journal of Economic Surveys*, 33(1), 101-124.

Psacharopoulos, G., and Patrinos, H. A. (2004). Returns to investment in education: A further update. *Education Economics*, 12(2),111-134.

Phelps, E. S. (1972). The statistical theory of racism and sexism. *American Economic Review*, 62(4),659-661.

Ren, W., and Miller, P. W. (2012). Gender differentials in the payoff to schooling in rural China. *Journal of Development Studies*, 48(1),133-150.

Solow, R. M. (1956). A contribution to the theory of economic growth. *Quarterly Journal of Economics*, 70(1), 65-94.

Spence, M. (1973). Job market signaling. *Quarterly Journal of Economics*, 87(3), 354-374.

Stanley, T. D., and Doucouliagos, H. (2012). *Meta-regression analysis in economics and business*, London and New York: Routledge.

Stanley, T. D., and Doucouliagos, H. (2017). Neither fixed nor random: Weighted last squares meta-regression. *Research Synthesis Method*, 8(1), 19-42.

Stanley, T. D., Doucouliagos, H., and Ioannidis, J. P. A. (2017). Finding the power to reduce publication bias. *Statistics in Medicine*, 6(10), 1580-1598.

Sun, Z. (2004). Studies on return to schooling in China: Survey and policy implications. *Chinese Journal of Population Science*, 5, 5-80(in Chinese).

Ugur, M., Churchill, S. A., and Luong, H. M. (2020). What do we know about RandD spillovers and productivity? Meta-analysis evidence on heterogeneity and statistical power. *Research Policy,* 49, Article 103866.

Wu,Y., and Zhao, Q. (2010). Higher education expansion and employment of college graduates. *Economic Research Journal*, 9, 93-108 (in Chinese).

Ye, L., Li, S., and Luo, C. (2011). Industrial monopoly, ownership and enterprises wage inequality: An empirical research based on the First National Economic Census of

Enterprises data. *Management World*, 4, 26-36 (in Chinese).
Zhang, J., and Xue, X. (2008). State and non-state sector wage differentials and human capital contribution. *Economic Research Journal*, 4,15-25 (in Chinese).
Zhang, H. (2018). Differences of human resource management between public sector and private sector under the background of talent competition. *Labor Security World*, 21, 5.
Zhao, Y. (2015). How does the public sector gain an advantage in the talent competition? *Productivity Research*, 2, 93-95 (in Chinese).
Zhu, R. (2016). Wage differentials between urban residents and rural migrants in urban China during 2002-2007: A distributional analysis. *China Economic Review*, 37, 2-14.

Table 1. Descriptive statistics of the partial correlation coefficients, *t* test and Shapiro–Wilk normality test of collected estimates

Study type	Number of estimates (*K*)	Mean	Median	S.D.	Max.	Min.	Kurtosis	Skewness	*t* test [a]	Shapiro-Wilk normality test (*z*) [b]
All studies—Hypothesis H_1	2191	0.175	0.167	0.111	0.566	-0.234	2.711	0.312	73.760 ***	7.645 †††
Target corporate sector—Hypothesis H_2										
Non-state corporate sector	90	0.149	0.153	0.109	0.371	-0.073	2.330	-0.050	12.928 ***	0.685
State corporate sector	37	0.162	0.171	0.098	0.386	-0.033	2.490	0.016	10.083 ***	-0.364
Corporate sector unspecified	2064	0.176	0.168	0.111	0.566	-0.234	2.706	0.329	72.027 ***	72.027 †††
Target *hukou* —Hypothesis H_3										
Urban *hukou* worker	223	0.165	0.153	0.104	0.420	-0.067	2.386	0.368	23.607 ***	3.680 †††
Rural *hukou* migrant	335	0.142	0.125	0.092	0.439	-0.049	2.877	0.622	28.271 ***	4.995 †††
Hukou unspecified	1633	0.183	0.180	0.114	0.566	-0.234	2.709	0.217	64.812 ***	6.044 †††
Target region—Hypothesis H_4										
Urban region	1238	0.182	0.176	0.110	0.566	-0.234	2.707	0.338	58.115 ***	6.655 †††
Rural region	311	0.123	0.106	0.105	0.514	-0.134	3.318	0.529	20.770 ***	3.601 †††
Region unspecified	642	0.187	0.184	0.109	0.476	-0.226	2.596	0.214	43.381 ***	5.057 †††
Target gender—Hypothesis H_5										
Woman	353	0.200	0.199	0.107	0.486	-0.067	2.518	0.174	34.959 ***	2.288 ††
Man	351	0.185	0.178	0.113	0.566	-0.134	3.166	0.276	30.703 ***	1.095
Gender unspecified	1487	0.167	0.153	0.111	0.514	-0.234	2.672	0.364	58.203 ***	7.694 †††
Target period—Hypothesis H_6										
Before the 1990s	116	0.112	0.082	0.128	0.528	-0.130	3.564	0.828	9.384 ***	3.369 †††
1990s	497	0.152	0.142	0.101	0.486	-0.134	2.967	0.424	33.463 ***	4.084 †††
2000s	971	0.190	0.186	0.112	0.566	-0.234	2.706	0.252	53.077 ***	6.590 †††
2010s	607	0.182	0.180	0.107	0.480	-0.045	2.417	0.311	41.716 ***	5.113 †††

Notes:

[a] *** denotes that null hypothesis that mean is zero is rejected at the 1% level.

[b] ††† and †† denote that null hypothesis of normal distribution is rejected at the 1% and 5% levels, respectively.

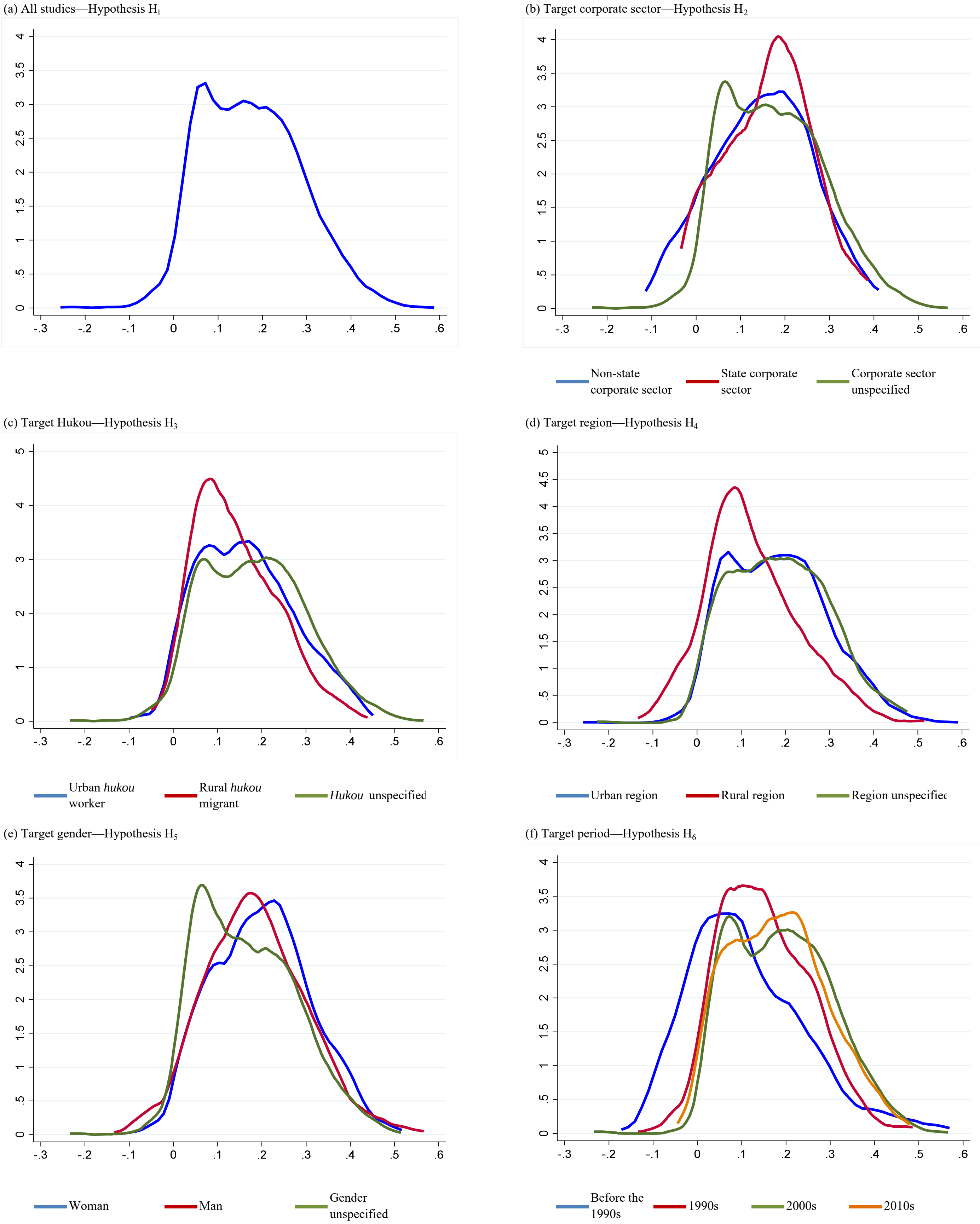

Figure 1. Kernel density estimation of collected estimates

Notes : The vertical axis is the kernel density. The horizontal axis is the variable value.

Source : See Table 1 for the number of observations and descriptive statistics.

Table 2. Synthesis of estimates

Study type	Number of estimates (K)	(a) Traditional synthesis		(b) Heterogeneity test and measures			(c) Unrestricted weighted least squares average (UWA)				
		Fixed-effect model (z value)[a]	Random-effects model (z value)[a]	Cochran Q test of homogeneity (p value)[b]	I^2 statistic[c]	H^2 statistic[d]	UWA of all estimates (t value)[a e]	Number of the adequately powered estimates[f]	WAAP (weighted average of the adequately powered estimates) (t value)[a]	Median S.E. of estimates	Median statistical power
All studies—Hypothesis H_1	2191	0.164 *** (465.81)	0.175 *** (74.01)	96654.76 *** (0.00)	97.66	42.69	0.164 *** (70.12)	2052	0.164 *** (67.91)	0.022	1.000
Target corporate sector—Hypothesis H_2											
Non-state corporate sector	90	0.183 *** (53.69)	0.149 *** (13.16)	953.12 *** (0.00)	89.55	9.57	0.183 *** (16.41)	63	0.185 *** (14.18)	0.044	0.985
State corporate sector	37	0.163 *** (67.78)	0.163 *** (9.99)	1831.72 *** (0.00)	97.74	44.23	0.163 *** (9.50)	37	0.163 *** (9.50)	0.013	1.000
Corporate sector unspecified	2064	0.163 *** (457.75)	0.176 *** (72.19)	93838.25 *** (0.00)	97.74	44.22	0.163 *** (67.87)	1955	0.163 *** (66.08)	0.022	1.000
Target *hukou* —Hypothesis H_3											
Urban *hukou* worker	223	0.158 *** (160.42)	0.165 *** (23.28)	14038.94 *** (0.00)	97.92	48.07	0.158 *** (20.17)	207	0.159 *** (19.44)	0.020	1.000
Rural *hukou* migrant	335	0.151 *** (174.90)	0.139 *** (27.59)	12402.02 *** (0.00)	96.73	30.55	0.131 *** (28.70)	294	0.131 *** (26.89)	0.022	1.000
Hukou unspecified	1633	0.167 *** (401.21)	0.183 *** (65.48)	69901.94 *** (0.00)	97.66	42.71	0.167 *** (61.30)	1547	0.167 *** (59.74)	0.022	1.000
Target region—Hypothesis H_4											
Urban region	1238	0.172 *** (381.83)	0.181 *** (57.65)	55478.28 *** (0.00)	97.83	46.05	0.172 *** (57.02)	1170	0.172 *** (55.43)	0.021	1.000
Rural region	311	0.110 *** (106.14)	0.122 *** (22.03)	6974.74 *** (0.00)	96.05	25.30	0.110 *** (22.38)	216	0.109 *** (18.82)	0.028	0.972
Region unspecified	642	0.167 *** (250.90)	0.186 *** (43.36)	31171.11 *** (0.00)	97.49	39.77	0.167 *** (35.98)	615	0.167 *** (35.19)	0.023	1.000
Target gender—Hypothesis H_5											
Woman	353	0.186 *** (170.20)	0.198 *** (34.90)	8340.82 *** (0.00)	96.02	25.13	0.186 *** (34.97)	337	0.189 *** (34.20)	0.027	1.000
Man	351	0.178 *** (172.05)	0.185 *** (31.05)	8847.71 *** (0.00)	96.84	31.61	0.178 *** (34.22)	333	0.172 *** (33.40)	0.025	1.000
Gender unspecified	1487	0.158 *** (399.00)	0.167 *** (58.38)	78676.83 *** (0.00)	97.96	48.94	0.158 *** (54.83)	1386	0.158 *** (52.97)	0.021	1.000
Target period—Hypothesis H_6											
Before the 1990s	116	0.162 *** (92.29)	0.117 *** (9.73)	3789.08 *** (0.00)	97.59	41.48	0.162 *** (16.08)	86	0.164 *** (14.17)	0.037	0.993
1990s	497	0.133 *** (182.74)	0.150 *** (33.61)	15431.01 *** (0.00)	97.19	35.60	0.133 *** (32.76)	461	0.132 *** (31.56)	0.022	1.000
2000s	971	0.174 *** (319.30)	0.182 *** (52.86)	45281.53 *** (0.00)	97.54	40.57	0.174 *** (46.73)	922	0.174 *** (45.51)	0.023	1.000
2010s	607	0.174 *** (274.84)	0.187 *** (41.28)	29730.81 *** (0.00)	97.85	46.58	0.174 *** (39.24)	577	0.183 *** (38.26)	0.020	1.000

Notes : *** denotes statistical significance at the 1% level.

[a] Null hypothesis: The synthesized effect size is zero.

[b] Null hypothesis: Effect sizes are homogeneous.

[c] Ranges between 0 and 100% with larger scores indicating heterogeneity.

[d] Takes zero in the case of homogeneity

[e] Synthesis method advocated by Stanley and Doucouliagos (2017) and Stanley et al. (2017)

[f] Denotes number of estimates with statistical power of 0.80 or more which is computed referring to the UWA of all collected estimates.

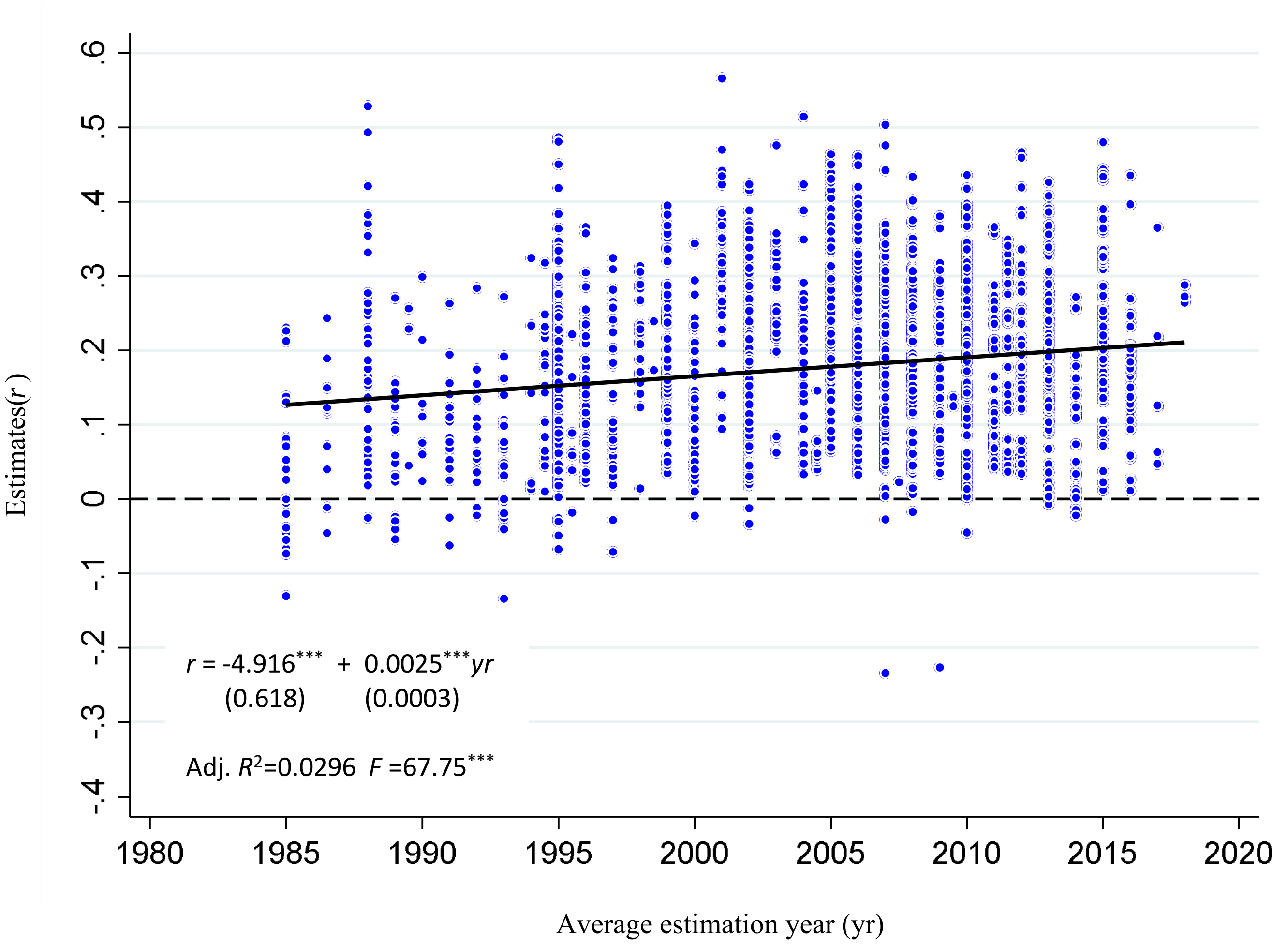

Figure 2. Chronological order of partial correlation coefficients (K=2191)

Notes: The values in parentheses below the coefficients in the equation are robustness standard errors. *** denotes statistical significance at the 1% level.

Table 3. Name, definition, and descriptive statistics of meta-independent variables

Variable name	Definition	Descriptive statistics		
		Mean	Median	S.D.
Non-state corporate sector	1 = if the sample is limited to workers of non-state companies, 0 = otherwise	0.041	0	0.199
State corporate sector	1 = if the sample is limited to workers of state companies, 0 = otherwise	0.017	0	0.129
Urban *hukou* worker	1 = if the sample is limited to workers with urban *hukou* , 0 = otherwise	0.102	0	0.302
Rural *hukou* migrant	1 = if the sample is limited to migrant workers with rural *hukou* , 0 = otherwise	0.153	0	0.360
Rural region	1 = if the target region is rural region, 0 = otherwise	0.142	0	0.349
Region unspecified	1 = if the target region is unspecified, 0 = otherwise	0.293	0	0.455
Woman	1 = if the sample is limited to female workers, 0 = otherwise	0.161	0	0.368
Man	1 = if the sample is limited to male workers, 0 = otherwise	0.160	0	0.367
Average estimation year	Average estimation year	2003.878	2005	7.577
Regular wage	1 = if regular wage/income is employed for empirical analysis, 0 = otherwise	0.683	1	0.465
Bonus wage	1 = if bonus wage is employed for empirical analysis, 0 = otherwise	0.003	0	0.052
CHNS	1 = if the survey results of the China's Health and Nutrition Survey (CHNS) are used as the data source, 0 = otherwise	0.130	0	0.336
CGSS	1 = if the survey results of the Chinese General Social Survey (CGSS) are used as the data source, 0 = otherwise	0.123	0	0.329
Other household survey	1 = if the results of a household survey other than CHIP, CHNS, or CGSS are used as the data source, 0 = otherwise	0.215	0	0.411
Enterprise survey	1 = if the results of an enterprise survey are used as the data source, 0 = otherwise	0.069	0	0.253
Natiional survey	1 = if the results of an national survey are used as the data source, 0 = otherwise	0.041	0	0.197
OLS	1 = if OLS estimator is used for estimation, 0 = otherwise	0.782	1	0.413
IV/2SLS/3SLS	1 = if IV, 2SLS, or 3SLS estimator is used for estimation to deal with possible endogeneity between the wage variable and a dependent variable, 0 = otherwise	0.091	0	0.288
Control for selection bias	0 = if the sample selection bias of employment is controlled for, 0 = otherwise	0.084	0	0.278
Control for endogeneity	1 = if the endogeneity between education and wage level is controlled for, 0 = otherwise	0.071	0	0.257
Occupation	1 = if the estimation simultaneously controls for occupation, 0 = otherwise	0.285	0	0.451
Age/age group	1 = if the estimation simultaneously controls for age or age group, 0 = otherwise	0.174	0	0.379
Work experience/tenure	1 = if the estimation simultaneously controls for work experience and/or tenure, 0 = otherwise	0.822	1	0.383
Regular/irregular	1 = if the estimation simultaneously controls for the difference between regular and irregular employment, 0 = otherwise	0.027	0	0.163
Health condition	1 = if the estimation simultaneously controls for the health condition of workers, 0 = otherwise	0.153	0	0.360
Firm size	1 = if the estimation simultaneously controls for the size of firms to which workers belong, 0 = otherwise	0.068	0	0.251
Trade union	1 = if the estimation simultaneously controls for the trade union, 0 = otherwise	0.037	0	0.188
Location fixed effects	1 = if the estimation simultaneously controls for location fixed effects, 0 = otherwise	0.489	0	0.500
Industry fixed effects	1 = if the estimation simultaneously controls for industry fixed effects, 0 = otherwise	0.356	0	0.479
Time fixed effects	1 = if the estimation simultaneously controls for time fixed effects, 0 = otherwise	0.022	0	0.148
S.E.	Standard error of patial correlation coefficient	0.027	0.022	0.023

Table 4. Meta-regression analysis of literature heterogeneity

Estimator	Cluster-robust WLS [1/*SE*]	Cluster-robust WLS [*df*]	Cluster-robust WLS [1/*EST*]	Multi-level mixed effects RML	Cluster-robust random-effects panel GLS	Cluster-robust fixed-effects panel LSDV
Meta-independent variable (default study type)/model	[1]	[2]	[3]	[4]	[5] [a]	[6] [b]
Target corporate sector (corporate sector unspecified)—Hypothesis H_2						
Non-state corporate sector	-0.0111	-0.0100	-0.0131	-0.0097	-0.0097	-0.0082
	(0.025)	(0.025)	(0.022)	(0.021)	(0.021)	(0.025)
State corporate sector	-0.0070	-0.0065	-0.0068	-0.0168	-0.0168	-0.0160
	(0.027)	(0.027)	(0.018)	(0.023)	(0.023)	(0.028)
Target region (*hukou* unspecified)—Hypothesis H_3						
Urban *hukou* worker	-0.0251	-0.0248	-0.0260	-0.0066	-0.0066	-0.0048
	(0.023)	(0.023)	(0.018)	(0.011)	(0.012)	(0.013)
Rural *hukou* migrant	-0.0389 **	-0.0382 **	-0.0424 ***	-0.0620 ***	-0.0620 ***	-0.0675 ***
	(0.018)	(0.018)	(0.015)	(0.012)	(0.012)	(0.015)
Target region (urban region)—Hypothesis H_4						
Rural region	-0.0687 ***	-0.0670 ***	-0.0458 **	-0.0465 **	-0.0465 **	-0.0432 *
	(0.018)	(0.018)	(0.019)	(0.022)	(0.022)	(0.026)
Region unspecified	0.0003	0.0005	-0.0041	0.0025	0.0026	0.0001
	(0.018)	(0.018)	(0.016)	(0.011)	(0.011)	(0.010)
Sample gender (gender unspecified)—Hypothesis H_5						
Woman	0.0267 *	0.0268 **	0.0209 *	0.0121	0.0120	0.0087
	(0.014)	(0.014)	(0.012)	(0.010)	(0.011)	(0.012)
Man	0.0198	0.0198	0.0143	-0.0028	-0.0029	-0.0064
	(0.013)	(0.013)	(0.013)	(0.009)	(0.010)	(0.011)
Target period—Hypothesis H_6						
Average estimation year	0.0036 ***	0.0036 ***	0.0040 ***	0.0043 ***	0.0043 ***	0.0044 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Wage type (total wage)						
Regular wage	0.0203	0.0196	0.0287 **	0.0253 **	0.0252 **	0.0027
	(0.015)	(0.015)	(0.014)	(0.012)	(0.013)	(0.005)
Bonus wage	-0.1370 ***	-0.1354 ***	-0.1003 ***	-0.1474 ***	-0.1475 ***	-0.1532 ***
	(0.034)	(0.034)	(0.030)	(0.021)	(0.021)	(0.022)
Survey data used (CHIPS)						
CHNS	-0.0560 **	-0.0554 **	-0.0297	-0.0431 **	-0.0431 **	
	(0.024)	(0.024)	(0.021)	(0.020)	(0.020)	
CGSS	0.0185	0.0182	0.0303	-0.0277	-0.0281	-0.0848 **
	(0.026)	(0.025)	(0.022)	(0.030)	(0.030)	(0.012)
Other household survey	0.0020	0.0022	-0.0058	-0.0034	-0.0035	
	(0.020)	(0.020)	(0.017)	(0.017)	(0.017)	
Enterprise survey	0.0387	0.0362	0.0080	0.0058	0.0059	
	(0.042)	(0.042)	(0.037)	(0.035)	(0.035)	
National survey	0.0210	0.0198	0.0556 **	0.0341	0.0341	
	(0.036)	(0.035)	(0.027)	(0.029)	(0.029)	

(Continued)

(Table 4 continued)

Estimator	Cluster-robust WLS [1/*SE*]	Cluster-robust WLS [*df*]	Cluster-robust WLS [1/*EST*]	Multi-level mixed effects RML	Cluster-robust random-effects panel GLS	Cluster-robust fixed-effects panel LSDV
Meta-independent variable (default study type)/model	[1]	[2]	[3]	[4]	[5] [a]	[6] [b]
Estimator						
OLS (estimators other than OLS)	0.0087	0.0089	0.0202	0.0142	0.0141	0.0116
	(0.021)	(0.020)	(0.019)	(0.021)	(0.021)	(0.022)
IV/2SLS/3SLS	0.0068	0.0074	-0.0035	-0.0375 ***	-0.0375 ***	-0.0396 ***
	(0.033)	(0.033)	(0.028)	(0.012)	(0.012)	(0.013)
Control for selection bias and endogeneity						
Control for selection bias	-0.0334	-0.0330	-0.0211	-0.0452 **	-0.0452 **	-0.0536 **
	(0.028)	(0.027)	(0.024)	(0.021)	(0.022)	(0.024)
Control for endogeneity	-0.0412	-0.0404	-0.0483	-0.0436 **	-0.0435 **	-0.0423 **
	(0.035)	(0.035)	(0.032)	(0.019)	(0.019)	(0.020)
Control variable						
Occupation	-0.0253 **	-0.0243 *	-0.0253 **	-0.0490 ***	-0.0490 ***	-0.0569 ***
	(0.013)	(0.012)	(0.011)	(0.011)	(0.011)	(0.015)
Age/age group	-0.0465 *	-0.0467 *	-0.0120	-0.0186	-0.0187	-0.0580
	(0.027)	(0.026)	(0.022)	(0.024)	(0.024)	(0.074)
Work experience/tenure	-0.0065	-0.0064	0.0098	0.0085	0.0085	0.0044
	(0.023)	(0.022)	(0.022)	(0.019)	(0.019)	(0.028)
Regular/irregular	-0.0016	-0.0009	0.0028	-0.0211	-0.0213	-0.0761 ***
	(0.029)	(0.029)	(0.023)	(0.025)	(0.025)	(0.026)
Health condition	-0.0378	-0.0382 *	-0.0076	-0.0023	-0.0022	-0.0045
	(0.023)	(0.023)	(0.020)	(0.009)	(0.009)	(0.005)
Firm size	0.0038	0.0045	0.0248	0.0313	0.0312	-0.0312
	(0.023)	(0.023)	(0.018)	(0.025)	(0.025)	(0.025)
Trade union	-0.0060	-0.0054	0.0113	-0.0460	-0.0464	-0.1852 ***
	(0.039)	(0.039)	(0.029)	(0.049)	(0.049)	(0.001)
Location fixed effects	0.0033	0.0032	0.0049	-0.0024	-0.0025	-0.0127
	(0.013)	(0.013)	(0.012)	(0.010)	(0.010)	(0.015)
Industry fixed effects	-0.0108	-0.0101	-0.0153	-0.0281 ***	-0.0281 ***	-0.0311 **
	(0.013)	(0.013)	(0.011)	(0.011)	(0.011)	(0.014)
Time fixed effects	-0.0459	-0.0455	-0.0513	-0.0231	-0.0230	-0.0152
	(0.037)	(0.036)	(0.034)	(0.015)	(0.015)	(0.015)
Standard error of patial correlation coefficient						
S.E.	0.5091	0.4973	0.4881	0.4102 **	0.4103 **	0.4170 *
	(0.433)	(0.427)	(0.306)	(0.202)	(0.203)	(0.224)
Constant	-7.0506 ***	-6.9578 ***	-7.9413 ***	-8.5062 ***	-8.5079 ***	-8.6064 ***
	(1.944)	(1.923)	(1.859)	(1.545)	(1.558)	(1.797)
K	2191	2191	2191	2191	2191	2191
R^2	0.202	0.201	0.204	-	0.120	0.028

Notes:

[a] Breusch-Pagan test: χ^2=2839.72, p=0.0000

[b] Hausman test: χ^2=50.01, p=0.0045

Figures in parentheses beneath the regression coefficients are robust standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: See Table 3 for the definitions and descriptive statistics of meta-independent variables.

Table 5. Meta-regression analysis of literature heterogeneity: Estimation with selected moderators for robustness check

Estimator	Cluster-robust WLS [1/*SE*]	Cluster-robust WLS [*df*]	Cluster-robust WLS [1/*EST*]	Multi-level mixed effects RML	Cluster-robust random-effects panel GLS	Cluster-robust fixed-effects panel LSDV
Meta-independent variable (default study type)/model	[1]	[2]	[3]	[4]	[5] [a]	[6] [b]
Target corporate sector (corporate sector unspecified)—Hypothesis H_2						
Non-state corporate sector	-0.0153	-0.0145	-0.0098	-0.0088	-0.0088	-0.0046
	(0.017)	(0.017)	(0.018)	(0.021)	(0.021)	(0.028)
State corporate sector	-0.0165	-0.0159	-0.0111	-0.0161	-0.0161	-0.0137
	(0.022)	(0.022)	(0.017)	(0.023)	(0.023)	(0.029)
Target region (*hukou* unspecified)—Hypothesis H_3						
Urban *hukou* worker	-0.0185	-0.0186	-0.0129	-0.0030	-0.0030	-0.0064
	(0.021)	(0.021)	(0.019)	(0.012)	(0.012)	(0.014)
Rural *hukou* migrant	-0.0332 *	-0.0324 *	-0.0358 **	-0.0571 ***	-0.0572 ***	-0.0685 ***
	(0.019)	(0.018)	(0.015)	(0.012)	(0.012)	(0.016)
Target region (urban region)—Hypothesis H_4						
Rural region	-0.0688 ***	-0.0675 ***	-0.0507 ***	-0.0460 **	-0.0460 **	-0.0433 *
	(0.018)	(0.017)	(0.017)	(0.022)	(0.022)	(0.026)
Region unspecified	0.0045	0.0044	0.0079	0.0017	0.0017	-0.0001
	(0.019)	(0.018)	(0.017)	(0.011)	(0.011)	(0.010)
Sample gender (gender unspecified)—Hypothesis H_5						
Woman	0.0221	0.0223	0.0173	0.0122	0.0122	0.0087
	(0.014)	(0.014)	(0.013)	(0.010)	(0.010)	(0.012)
Man	0.0153	0.0154	0.0111	-0.0027	-0.0028	-0.0065
	(0.013)	(0.013)	(0.013)	(0.010)	(0.010)	(0.011)
Target period—Hypothesis H_6						
Average estimation year	0.0031 ***	0.0030 ***	0.0037 ***	0.0041 ***	0.0041 ***	0.0040 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Selected moderators						
Bonus wage	-0.1462 ***	-0.1445 ***	-0.1337 ***	-0.1618 ***	-0.1618 ***	-0.1648 ***
	(0.019)	(0.019)	(0.016)	(0.001)	(0.001)	(0.000)
CHNS	-0.0624 ***	-0.0617 ***	-0.0365 *	-0.0340 *	-0.0340 *	
	(0.021)	(0.021)	(0.020)	(0.018)	(0.018)	
Control for selection bias	-0.0336	-0.0334	-0.0299 *	-0.0535 ***	-0.0536 ***	-0.0625 ***
	(0.021)	(0.021)	(0.017)	(0.013)	(0.013)	(0.014)
Control for endogeneity	-0.0413 **	-0.0400 **	-0.0547 ***	-0.0790 ***	-0.0790 ***	-0.0799 ***
	(0.020)	(0.020)	(0.019)	(0.018)	(0.018)	(0.018)
Occupation	-0.0297 **	-0.0284 **	-0.0303 **	-0.0603 ***	-0.0604 ***	-0.0726 ***
	(0.013)	(0.012)	(0.012)	(0.010)	(0.010)	(0.012)
Age/age group	-0.0484 **	-0.0489 **	-0.0227	-0.0229	-0.0230	-0.0502
	(0.024)	(0.023)	(0.016)	(0.018)	(0.018)	(0.077)
Standard error of patial correlation coefficient						
S.E.	0.7870 **	0.7701 **	0.6895 **	0.4125 **	0.4123 **	0.3898 *
	(0.380)	(0.378)	(0.310)	(0.196)	(0.197)	(0.216)
Constant	-5.9425 ***	-5.8540 ***	-7.3158 ***	-7.9438 ***	-7.9438 ***	-7.8252 ***
	(2.015)	(1.986)	(1.770)	(1.654)	(1.663)	(1.995)
K	2191	2191	2191	2191	2191	2191
R^2	0.174	0.174	0.160	-	0.144	0.120

Notes: Figures in parentheses beneath the regression coefficients are robust standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Selected moderators denote the meta-independent variables having a PIP of 0.80 or more in the Bayesian model averaging estimation reported in Appendix Table A1.

[a] Breusch-Pagan test: χ^2=2953.06, p=0.0000

[b] Hausman test: χ^2=19.81, p=0.1793

Figures in parentheses beneath the regression coefficients are robust standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: See Table 3 for the definitions and descriptive statistics of meta-independent variables.

Table 6. Univariate test of publication selection bias

Study type	Number of estimates (K)	Under the assumption that the true effect size is zero			Under the assumption that the true effect size is the WAAP estimate (x)		
		Number of estimates		Goodness-of-fit z test (p value)[a]	Number of estimates		Goodness-of-fit z test (p value)[b]
		PCC_k<0	PCC_k>0		PCC_k<x	PCC_k>x	
All studies—Hypothesis H_1	2191	56	2135	44.415 *** (0.00)	1062	1129	1.431 (0.15)
Target corporate sector—Hypothesis H_2							
Non-state corporate sector	90	12	78	6.957 *** (0.00)	52	38	-1.476 (0.14)
State corporate sector	37	1	36	5.754 *** (0.00)	17	20	0.493 (0.62)
Corporate sector unspecified	2064	43	2021	43.538 *** (0.00)	996	1068	1.585 (0.11)
Target *hukou* —Hypothesis H_3							
Urban *hukou* worker	223	3	220	14.531 *** (0.00)	116	107	-0.603 (0.55)
Rural *hukou* migrant	335	7	328	17.538 *** (0.00)	198	137	-3.333 *** (0.00)
Hukou unspecified	1633	46	1587	38.134 *** (0.00)	757	876	2.945 *** (0.00)
Target region—Hypothesis H_4							
Urban region	1238	19	1219	34.105 *** (0.00)	601	637	1.023 (0.31)
Rural region	311	32	279	14.006 *** (0.00)	159	152	-0.397 (0.69)
Region unspecified	642	5	637	24.943 *** (0.00)	291	351	2.368 ** (0.02)
Target gender—Hypothesis H_5							
Woman	353	5	348	18.256 *** (0.00)	160	193	1.756 * (0.08)
Man	351	14	337	17.241 *** (0.00)	176	175	-0.053 (0.96)
Gender unspecified	1487	37	1450	36.643 *** (0.00)	759	728	-0.804 (0.42)
Target period—Hypothesis H_6							
Before the 1990s	116	25	91	6.128 *** (0.00)	83	33	-4.642 *** (0.00)
1990s	497	19	478	20.589 *** (0.00)	226	271	2.019 ** (0.04)
2000s	971	7	964	30.712 *** (0.00)	448	523	2.407 ** (0.02)
2010s	607	5	602	24.232 *** (0.00)	292	315	0.934 (0.35)

Notes :

[a] Null hypothesis: The ratio of the positive versus negative values is 50:50

[b] Null hypothesis: The ratio of estimates below x versus those over x is 50:50.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

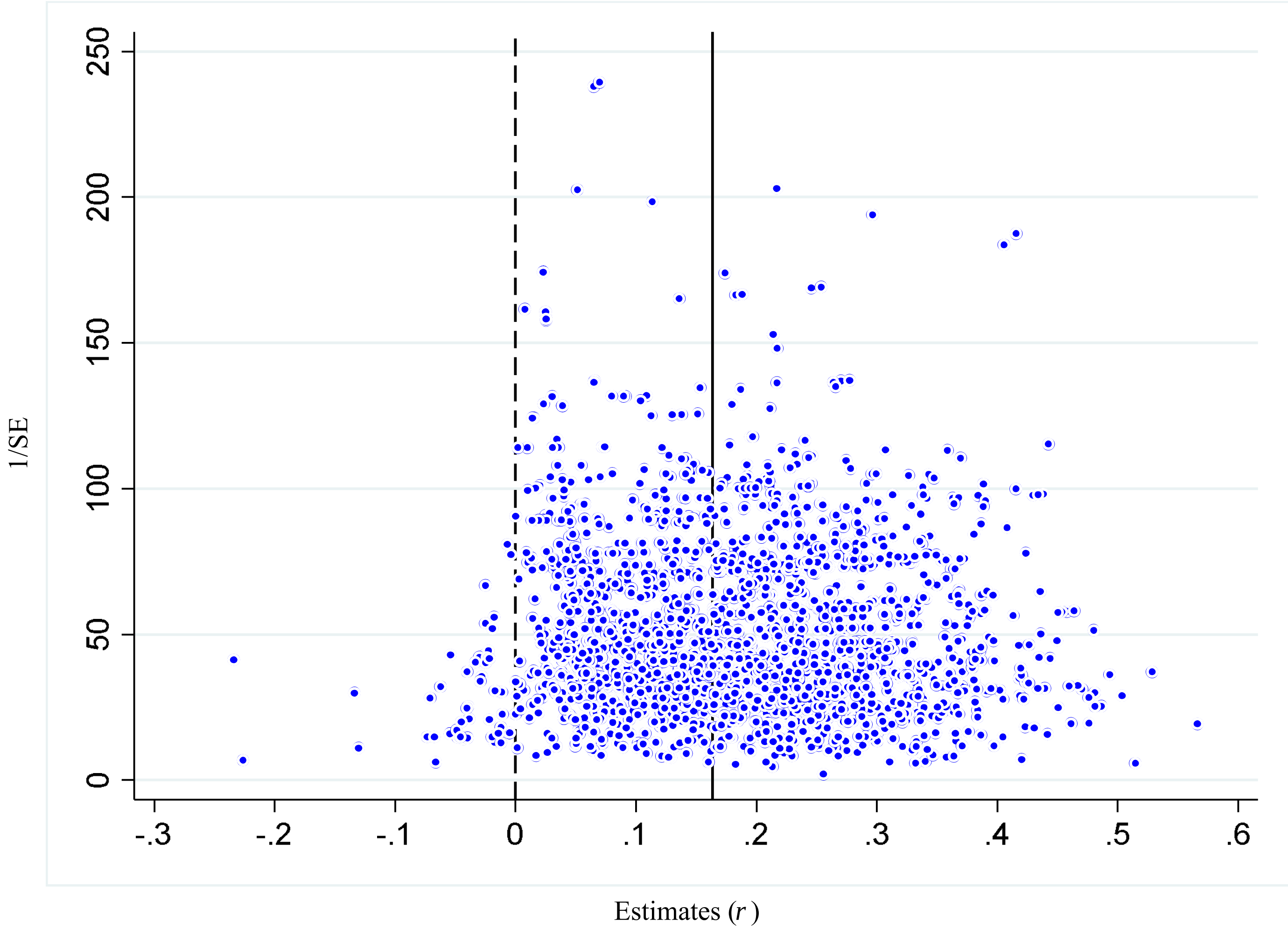

Figure 3. Funnel plot of patial correlation coefficients (*K* =2191)

Note : The solid line indicates the synthesized effect size by WAAP estimation reported in Table 2.

Table 7. Meta-regression analysis of publication selection bias

(a) FAT-PET test (Equation: $t = \gamma_0 + \gamma_1 (1/SE) + v$)

Estimator	Unrestricted WLS	Cluster-robust unrestricted WLS	Multi-level mixed-effects RML	Cluster-robust random-effects panel GLS	Cluster-robust fixed-effects panel LSDV
Model	[1]	[2]	[3]	[4] [a]	[5] [b]
Intercept (FAT: H_0: $\gamma_0 = 0$)	1.3268 ***	1.3268 *	2.3009 ***	2.3111 ***	2.4235 ***
	(0.401)	(0.769)	(0.823)	(0.827)	(0.907)
$1/SE$ (PET: H_0: $\gamma_1 = 0$)	0.1447 ***	0.1447 ***	0.1295 ***	0.1293 ***	0.1239 ***
	(0.009)	(0.145)	(0.016)	(0.016)	(0.017)
K	2191	2191	2191	2191	2191
R^2	0.309	0.309	-	0.309	0.309

(b) PEESE approach (Equation: $t = \gamma_0 SE + \gamma_1 (1/SE) + v$)

Estimator	Unrestricted WLS	Cluster-robust unrestricted WLS	Multi-level mixed-effects RML	Random-effects panel ML	Population-averaged panel GEE
Model	[6]	[7]	[8]	[9]	[10]
SE	11.5649 ***	11.5649	7.6767	7.6767	12.7319 **
	(3.498)	(7.436)	(4.792)	(5.857)	(5.294)
$1/SE$ (H_0: γ_1=0)	0.1604 ***	0.1604 ***	0.1430 ***	0.1430 ***	0.1531 ***
	(0.005)	(0.011)	(0.013)	(0.005)	(0.011)
K	2191	2191	2191	2191	2191
R^2	0.693	0.693	-	-	-

Notes : Figures in parentheses beneath the regression coefficients are standard errors. Except for Model [9], robust standard errors are estimated. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

[a] Breusch-Pagan test: χ^2=3553.64, p=0.0000

[b] Hausman test: χ^2=6.08, p=0.0136

Table 8. Summary of publication selection bias test

Study type	Number of estimates (K)	Test results [a]		
		Funnel asymmetry test (FAT) (H_0: γ_0=0)	Precision-effect test (PET) (H_0: γ_1=0)	Precision-effect estimate with standard error (PEESE) (H_0: γ_1=0) [b]
All studies—Hypothesis H_1	2191	**Rejected**	**Rejected**	**Rejected (0.1430/0.1604)**
Target corporate sector—Hypothesis H_2				
Non-state corporate sector	90	**Rejected**	**Rejected**	**Rejected (0.1997/0.2208)**
State corporate sector	37	Not rejected	**Rejected**	**Rejected (0.1516/0.1638)**
Corporate sector unspecified	2064	**Rejected**	**Rejected**	**Rejected (0.1393/0.1596)**
Target *hukou* —Hypothesis H_3				
Urban *hukou* worker	223	Not rejected	**Rejected**	**Rejected (0.1483/0.1605)**
Rural *hukou* migrant	335	**Rejected**	**Rejected**	**Rejected (0.1120/0.1323)**
Hukou unspecified	1633	**Rejected**	**Rejected**	**Rejected (0.1442/0.1613)**
Target region—Hypothesis H_4				
Urban region	1238	**Rejected**	**Rejected**	**Rejected (0.1546/0.1696)**
Rural region	311	**Rejected**	**Rejected**	**Rejected (0.0816/0.1073)**
Region unspecified	642	**Rejected**	**Rejected**	**Rejected (0.1383/0.1650)**
Target gender—Hypothesis H_5				
Woman	353	Not rejected	**Rejected**	**Rejected (0.1685/0.1826)**
Man	351	Not rejected	**Rejected**	**Rejected (0.1563/0.1740)**
Gender unspecified	1487	**Rejected**	**Rejected**	**Rejected (0.1460/0.1563)**
Target period—Hypothesis H_6				
Before the 1990s	116	Not rejected	**Rejected**	**Rejected (0.1409/0.1705)**
1990s	497	**Rejected**	**Rejected**	**Rejected (0.1022/0.1261)**
2000s	971	Not rejected	**Rejected**	**Rejected (0.1688/0.1744)**
2010s	607	Not rejected	**Rejected**	**Rejected (0.1804/0.1866)**

Notes :
[a] The null hypothesis is rejected when more than three of five models show a statistically significant estimate. Otherwise not rejected.
[b] Figures in parentheses are PSB-adjusted estimates. If two estimates are reported, the left and right figures denote the minimum and maximum estimat respectively.

Appendix Table A1. Bayesian model averaging analysis of model uncertainty

Moderator	Coef.	S.E.	*t* value	PIP
Focus regressors				
Non-state corporate sector	-0.02310	0.01208	-1.91	1.00
State corporate sector	-0.02069	0.01732	-1.19	1.00
Urban hukou worker	-0.03273	0.00818	-4.00	1.00
Rural hukou migrant	-0.04625	0.00698	-6.63	1.00
Rural region	-0.06547	0.00699	-9.37	1.00
Region unspecified	0.00085	0.00657	0.13	1.00
Woman	0.02938	0.00620	4.74	1.00
Man	0.01789	0.00621	2.88	1.00
Average estimation year	0.00302	0.00037	8.23	1.00
S.E.	0.48621	0.10607	4.58	1.00
Auxiliary regressors				
Regular wage	0.00023	0.00152	0.15	0.04
Bonus wage	-0.13618	0.05631	-2.42	0.92
CHNS	-0.05327	0.00898	-5.93	1.00
CGSS	0.01517	0.01339	1.13	0.63
Other household survey	0.00341	0.00689	0.49	0.23
Enterprise survey	0.00401	0.00985	0.41	0.17
Natiional survey	0.00260	0.00841	0.31	0.11
OLS	0.00113	0.00414	0.27	0.09
IV/2SLS/3SLS	-0.00001	0.00259	0.00	0.02
Control for selection bias	-0.02442	0.01259	-1.94	0.86
Control for endogeneity	-0.04909	0.00912	-5.38	1.00
Occupation	-0.02724	0.00509	-5.36	1.00
Age/age group	-0.05120	0.00644	-7.95	1.00
Work experience/tenure	0.00015	0.00151	0.10	0.03
Regular/irregular	0.00024	0.00271	0.09	0.03
Health condition	-0.00192	0.00546	-0.35	0.14
Firm size	0.00693	0.01164	0.60	0.31
Trade union	0.00049	0.00383	0.13	0.04
Location fixed effects	-0.00196	0.00476	-0.41	0.18
Industry fixed effects	-0.00014	0.00117	-0.12	0.03
Time fixed effects	-0.00320	0.01033	-0.31	0.11
K		2191		
Model space		2,097,152		

Notes : S.E. and PIP denote standard errors and posterior inclusion probability, respectively. The variables used for hypothesis testing from the non-state corporate sector to average estimation year as well as standard errors of partial correlation coefficients are included in the estimation as focus regressors. Therefore, the PIP of these key variables is
Source : See Table 3 for the definitions and descriptive statistics of meta-independent variables.