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Wage–Experience Profiles in China and Eastern Europe: A Large Meta-Analysis*

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Abstract: This paper conducts a comparative meta-analysis using 3098 estimates reported in 125 research works to explore the wage–experience profile in China and Eastern Europe as they experience a systemic transformation from the planned system to a market economy. The results indicate that the relationship between years of work experience and wage levels in China and Eastern Europe in the transition period was structured consistently with economic theories. It is also revealed that both China and Eastern Europe have experienced a flattening of their wage–experience profiles over time. These findings are statistically robust beyond issues of heterogeneity and publication selection bias in the literature.

JEL classification numbers: D31, I26, J16, J31, P23, P36
Keywords: wage–experience profile, research synthesis, meta-regression analysis, publication selection bias, China, Eastern Europe

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1 Introduction

The abandonment of the planned system and the pursuit over recent decades of building economic systems based on market principles have brought about significant changes in various aspects of the socio-economy in China and Eastern European countries (Dallago and Casagrande, 2022). The relationship between firms and workers is no exception. As a means of approaching the process of systemic transformation to a market economy and the accompanying social changes, technological progress, and other factors that affect labor relations in these countries, researchers have made numerous attempts to analyze the wage system. As a result, to the best of our knowledge, from 1990 until today, at least 700 wage studies have been published with respect to China and Eastern European countries; about one-third of these previous studies estimated wage functions using household/individual-level data. In other words, we now have a large number of estimation results of the wage function for China and Eastern Europe, including the Russian Federation and other European states of the former Soviet Union.

This rich evidence of the wage function not only provides us with an understanding of the actual situation in China and individual countries in Eastern Europe but also opens up the possibility of comparing them. While in China and Eastern Europe there are marked differences in the processes of economic transition, underlying institutions, histories and traditions, they share significant commonalities in the sense that they have both promoted the transition from the planned system to a market economy. Therefore, a comparison of the wage functions in China and Eastern Europe is expected to yield quite interesting findings, not only academically, but also practically and policy wise.

However, the empirical strategies of previous studies are so diverse that it is not easy to make comparisons between China and Eastern European states by simply reviewing them. In fact, there are almost no survey articles covering a wide range of wage studies targeting these countries. Meta-analysis enables us to synthesize and compare empirical results beyond the differences in the model specification, data type, estimation period, and other study conditions across studies, considering the possible influence of literature heterogeneity and publication selection bias on reported estimates (Borenstein et al., 2009; Stanley and Doucouliagos, 2012). Using these advantages of meta-analysis, Iwasaki et al. (2020, 2022) successfully compared China and Eastern Europe from the perspective of the impact of corporate ownership on managerial turnover and firm performance. This paper shares the same goal with these preceding meta-analyses.

The meta-analysis in this paper focuses on the wage–experience profile. As discussed later, along with education, work experience is an essential part of the so-called Mincer-type wage function in general and, needless to say, also for China and Eastern Europe (Gustafsson and Li, 2000; Gustafsson et al., 2000, 2001). However, we have other reasons for paying special attention to them, with the aim of comparing the two from the viewpoint of labor relations.

In China, the central government implemented gradual economic reforms while the Communist Party of China (CPC) maintained a one-party dictatorship. As a consequence, the state's influence on human resource management (HRM) remains strong (Lin et al., 1994, 2020). In addition, during the transition period, the Chinese labor market has been divided into public and private sectors. As a result, the employment and wage systems now differ greatly between the two (Sun et al., 2022). Thus, the effects of gradualism in economic transition and labor market segmentation on the wage seniority in all of China are quite unclear. At the same time, the country has been working to eliminate the rigid and sometimes economically irrational seniority system of the planned system era (Iwasaki and Ma, 2020; Ma and Iwasaki, 2021). It is likely that these historical facts have strongly influenced the wage–experience profile; therefore, a noteworthy time-series change may have occurred in it. In other words, to grasp the shape of the wage–experience profile and its historical changes from this perspective may serve to greatly help us understand the real impacts of regime change in China.

Transition countries in Eastern Europe moved from socialist personnel management, with a centralized corporate structure and socialistic corporate culture under strong state control, to decentralized Western-style HRM practices. However, as the meta-analysis by Horie and Kumo (2022) shows, socialist institutional legacies in HRM are still important in many Eastern European countries. This is especially true in the traditional manufacturing sector inherited from the period of socialism. On the other hand, as the new private sector and modern industries have grown over time and many countries deepened their integration with the European Union, the variety of HRM practices, including those related to employee motivation and remuneration, has greatly increased in Eastern Europe. Besides, after removing the major barriers to worker mobility between jobs within and outside a given post-socialist country, competition for talents intensified, and HRM practices aimed at attracting and retaining the best employees gained momentum. Therefore, we expect that the wage–experience profile has changed over time in response to substantial changes in HRM and that analyzing it can help us understand the peculiarities of economic transition in Eastern European countries.

Our meta-analysis, which employs 3098 estimates reported in 125 previous research works, indicates that the wage–experience profiles in China and Eastern Europe were structured consistently with economic theories after the end of the planned system. It also revealed that both China and Eastern Europe have experienced a flattening of their wage–experience profiles during the transition period. The meta-regression analysis and test for publication selection bias in this paper show that these findings are statistically robust beyond issues of heterogeneity and publication selection in the literature.

The remainder of the paper is structured as follows: The next section presents our hypotheses to be tested by meta-analysis. Section 3 describes the procedures used to search for and select literature for meta-analysis, and it overviews the collected estimates. Section 4 describes the methodology of meta-analysis applied in this paper. Section 5 reports the results. Lastly, Section 6 summarizes the major findings obtained from the meta-analysis and concludes the paper.

2 Hypothesis Development

In this section, we propose our hypotheses regarding the wage–experience profiles in China and Eastern Europe for testing by a meta-analysis of the extant literature. Our meta-analysis is conducted based on the estimation results of Mincer-type wage functions. A typical Mincer-type wage function is formulated in the following equation:

$$wage_i = \mu + \delta \cdot experience_i + \theta \cdot experience_i^2 + \vartheta \cdot schooling_i + \sum_{n=1}^{N} \psi_n \cdot z_n + \epsilon_{i,} \quad (1)$$

where $wage_i$, $experience_i$, and $schooling_i$ are wage level (log-transformed, in most cases), years of work experience, and years of schooling of the i-th worker, respectively. z_n is the other n-th wage determinant. μ is the constant term. ϵ is the error term. δ, θ, ϑ and ψ are parameters to be estimated.

As Eq. (1) indicates, the coefficient δ of the single term *experience* gauges the degree of wage seniority, while the coefficient θ of its squared term captures the curvature of the wage curve. These two factors form the so-called "wage–experience profile." Since, along with education, work experience is an indispensable variable for estimating the Mincer-type wage function, both Chinese and Eastern European studies commonly report estimates of δ and θ, thus providing a valuable opportunity to compare the two.

From the perspective of economic theory, two theories or hypotheses can explain the formation of the wage–experience profile. First, the human capital theory (Becker, 1964; Mincer, 1974) states that a worker's wage level is mainly determined by the individual's human capital that is directly related to labor productivity. Human capital consists of two types: (1) general human capital that is valued by all potential employers, and (2) firm-specific human capital that is more valuable to the firm where the worker is currently employed. In the Mincer-type wage function, years of schooling is a proxy for general human capital, while years of work experience (or tenure, if available) represent the accumulation of firm- or occupation-specific human capital, assuming that an individual has been working in either the same firm or a similar occupation. As valuable skills that improve labor productivity are acquired and accumulated with the passage of time, earnings tend to rise with more experience. Hence, the coefficient of variable δ in Eq. (1) is expected to have a positive value. Besides, the squared term of work experience is expected to have a negative coefficient θ, as earnings tend to increase at a decreasing rate throughout one's life until human capital depreciation exceeds its accumulation (Polachek, 2007).

Second, Lazear (1979, 1981) advocates for explaining the seniority-based wage system using the implicit contract hypothesis. According to this hypothesis, in an equilibrium path, the present value of a worker's wage stream over his/her lifetime (lifetime wages) is equal to the present value of the worker's marginal labor productivity over his/her lifetime. Then both employer and employee may find beneficial the system of pay over time so that a worker receives a wage lower than his/her productivity early in his/her career and higher than his/her productivity at an older age. Such a system increases employees' incentive to work industriously and longer within the same firm in order to qualify for the later overpayment. Following the Lazear hypothesis, the coefficient of years of work experience (δ) is expected to be positive, indicating the increase in wage level with seniority. As in the case of the human capital hypothesis, the coefficient of the squared term of years of work experience (θ) is expected to have a negative value, in line with the conventional assumption about the concavity of the wage–experience profile.

These standard economic theories have been repeatedly verified in numerous studies of earnings functions in China and Eastern European countries that have experienced a great transformation from a planned economy to a market-oriented system. For instance, Ma and Cheng (2023) found an inverted U-shaped relationship between wages and years of work experience in China using employer–employee survey data. Statistically significant concave returns to (potential) labor market experiences are found in the studies based on an analysis of household-level data in Eastern European countries, including, among many others, the Czech Republic (Münich et al., 2005), Poland (Rutkowski, 1997; Adamchik et al., 2003), Romania (Andrén et al., 2005), and Russia and Ukraine (Gorodnichenko and Sabirianova, 2005).

Therefore, we propose the following hypothesis:

Hypothesis H1: *In both China and Eastern Europe, the coefficients of years of work experience take on the theoretically predicted signs. Namely, coefficient δ in Eq. (1) is positive, while coefficient θ is negative.*

As mentioned in the Introduction, the specific issue that we would like to examine in this paper is the evolution of the wage–experience profile in China and Eastern Europe over the past decades. Below, we provide our arguments behind the second hypothesis regarding how parameters δ and θ could have changed since the start of the transition.

In China, during the planned economy period (1949–1977), the Chinese government instituted the "socialist movement," changing the ownership of entire corporations to state-owned enterprises (SOEs) or collectively-owned enterprises (COEs) by 1956. Both SOEs and COEs belonged to the public sector and were managed by the government. The unified graded wage system was established in the public sector and was extremely seniority based (Gustafsson et al., 2001; Yu, 2014; Tang, 2019).

Under the economic transition period (after 1978), the wage determination mechanism has changed with the progressive market-oriented economy reform (Meng and Kidd, 1997; Kwon et al., 2015). During the 1980s, the Chinese government promulgated the *Interim Regulation on the Contracted Management Responsibility System for Industrial Enterprises Owned by the Whole People* and the *Law of the People's Republic of China on Industrial Enterprises Owned by the Whole People*. These measures were taken to expand the authority and responsibility of managers in SOEs. However, the government continued to manage basic wage determinations, and SOEs retained the seniority wage system during that period (Meng and Kidd, 1997; Gustafsson et al., 2001; Yu, 2014; Tang, 2019). In the 1990s, the Chinese government promoted the reform of corporate governance in SOEs by adopting the stock system in large SOEs. In 1995, the Chinese government announced the "*hold large enterprises and let small enterprises go"* policy (*Zhuada Fangxiao*) to encourage the privatization of small and medium-sized SOEs. In 1998, the Chinese government set a "*three-year goal to overcome the predicament*" and continued to advance the reform of SOEs. Since the 2000s, the Chinese government has intensified corporate governance reforms in SOEs and promoted the growth of large SOEs. Additionally, starting in the 1980s, the Chinese government implemented an open-up policy to encourage foreign direct investment in the country. These market-oriented reforms have contributed significantly to the development of both privately owned enterprises (POEs) and foreign-invested enterprises (FIEs) during the transition period. The percentage of employees in POEs and FIEs to total enterprises (excluding those in the self-employment sector) in urban areas increased from 0.68% in 1990 to 45.50% in 2010 and 65.35% in 2021 (National Bureau of Statistics of China, 2022).

On the one hand, POEs and FIEs have established their wage determination systems based on market mechanisms to address the challenges posed by fierce domestic and global competition. Due to the high turnover or exit rate in POEs and FIEs, especially for female workers, corporations do not pay much attention to investing in corporate–special human capital (e.g., employee training). Therefore, the influence of work experience on wage levels in POEs and FIEs is small. On the other hand, in SOEs, with their progressive reform, education's impact as a wage determinant has become greater than in the past (Bargain et al., 2009; Kwon et al., 2015). Meanwhile, the influence of years of work experience may decrease with the transformation of the wage determination system from a seniority-based wage system to a performance payment system. Consequently, it is predicted that although the seniority-based wage system still is implemented in the public sector due to a sort of institutional inertia, the wage return to years of work experience has decreased with the development of private sector and progressive SOE reform in China. This means that wage–experience profiles have flattened over the economy's transition period.

In Eastern Europe, the advancement of market-oriented reforms since the late 1980s and the development of a new dynamic private sector caused a gradual shift from the centralized wage-setting system, which often rewarded seniority in line with a predetermined wage grid, to a more flexible and decentralized wage-determination system. However, the pace of labor market reforms and the transformation of labor market institutions differed across countries (Roaf et al., 2014), causing great diversity in wage-setting systems across and within countries in the region. Besides, the restructuring of transition economies and the emergence of new industries and occupations increased rewards for younger and more adaptive people with modern skills. At the same time, sector-, occupation-, and firm-specific human capital accumulated in the old socialist system often became obsolete in the new economic environment. As a result, average returns to labor market experience in Eastern European countries were relatively small, and the wage–experience profiles were flatter as compared to those of

Western economies (Gevorkyan, 2023). In Russia, even after the year 2000, the trajectory of the wage–experience profile remains flat (Chernina and Gimpelson, 2023). Besides, returns to experience have fallen from the late 1980s to the mid-1990s in many Eastern European countries (Rutkowski, 1997; Flanagan, 1998; Adamchik et al., 2003; Gorodnichenko and Sabirianova, 2005). However, this is not the case in Romania (Andrén et al., 2005), where returns to experience increased in the 1990s as compared to the pre-transition period, and in the Czech Republic (Münich et al., 2005), where the wage–experience profile did not change from communism to the transition. Given this heterogeneity between countries found in country-level studies, it would be particularly interesting to test the hypothesis about the flattening of wage–experience profiles in Eastern Europe in our meta-analysis.

Hypothesis H2: *In both China and Eastern Europe, wage–experience profiles have flattened over the past decades. Namely, coefficients δ and θ approach zero over time both for China and Eastern Europe.*

In the following sections, we examine the above two hypotheses by performing a meta-analysis of wage studies in China and East European countries.

3 Literature Selection and Overview of Estimates Included in Meta-Analysis

This section describes how we searched for and identified papers to be included in the meta-analysis in this paper. It then provides an overview of the estimates extracted from selected research works.[1]

As the first step in searching for studies in which coefficients δ and θ obtained as outcomes from regression estimation of a Mincer-type wage function in China and Eastern Europe are available, we utilized the electronic literature databases of EconLit and Web of Science and accessed the websites of major academic publishers to identify relevant research works. The search covered the period from 1990 to the winter of 2022.[2] We conducted an AND search for article titles using the term "*wage*" in combination with one of the terms "*emerging markets*," "*Central Europe*," "*Eastern Europe*," or "*China*" and the name of one of the Eastern European countries. We obtained

[1] The literature selection and meta-analysis in this paper were carried out in general conformity with the guidelines described in Havránek et al. (2020).

[2] The publishers include Emerald Insight, Oxford University Press, Sage Journals, ScienceDirect, Springer Link, Taylor & Francis Online, and Wiley Online Library. The final literature search was conducted in December 2022.

approximately 680 articles. We then inspected each of these collected works and narrowed the literature to those studies that reported target estimates. As a result, we selected 86 papers on China and 39 papers on Eastern European countries.[3]

From the 125 selected research works, we extracted a total of 3098 estimates.[4] The mean (median) of the number of collected estimates per study is 24.8 (20). Both coefficients δ and θ reported in Chinese studies account equally for 1126, while those two in Eastern European studies account equally for 423, implying that each coefficient δ (i.e., estimate of a single term of *experience*) always accompanies its corresponding coefficient θ (i.e., estimate of a squared term of *experience*). We checked each of the collected estimates to see whether they captured semi-elasticities. If not, we made the necessary transformations, referring the mean of the wage variable used in regression estimation of the variable in question. Hereinafter, we call collected estimates of coefficients δ and θ studies of wage seniority and the wage curve, respectively.

Table 1 shows the descriptive statistics of the collected estimates, as well as the results of a *t*-test of means by study type and period. **Figure 1** illustrates the corresponding kernel density estimation results. To examine Hypothesis H2, we computed the descriptive statistics and estimated the kernel density by dividing the collected estimates into three different time periods, consisting of (1) 1995 or before, (2) 1996–2005, and (3) 2006 or later, in addition to those for all studies, to test Hypothesis H1.

According to **Table 1**, the means of the estimates extracted from studies of wage seniority are statistically significantly different from zero and take a positive value, while those from studies of the wage curve are statistically significantly negative, irrespective of the difference in target country/region. In addition, **Figure 1** displays a highly skewed distribution of estimates of coefficient δ toward the positive side in Panels (a) and (b); in contrast, Panels (c) and (d) of the figure shows that estimates of coefficient θ tend to be skewed toward the negative side, although the bulk of the estimates are concentrated near zero. These observations are highly consistent with Hypothesis H1, which predicts the presence of a concave wage–experience profile in both China and Eastern Europe. The mean and distribution of the estimates by period share the same

[3] **Appendix Table A1** lists the 125 selected studies. The literature included in the meta-analysis in this paper covers only studies in English in order to avoid a kind of selection bias that arises from the fact that we understand only Chinese and some Eastern European languages.

[4] Estimates of interaction terms of the years of work experience and other independent variables are not included in the meta-analysis in this paper.

result with those of the whole period, suggesting that this fact has remained true throughout past decades.

Furthermore, the descriptive statistics by period and their univariate comparison by the analysis of variance (ANOVA) and the Kruskal-Wallis rank-sum test in **Table 1** indicate that the absolute values of coefficients δ for both China and Eastern Europe and those of coefficients θ for China tend to diminish as the time period approaches the present, which is in line with Hypothesis H2. Meanwhile, the absolute values of coefficients θ for Eastern Europe show an upward trend from the period of 1995 or before to the period of 1996–2005 and then a downward trend in the period of 2006 or later. This indicates an inverse U-shape time-series change as a whole. Panel (a) of **Figure 1** also demonstrates a similar time trend of coefficient δ for China. We cannot say, however, that Panels (b), (c), and (d) strongly back up the observations in **Table 1**.

Overall, the descriptive statistics and kernel density distributions of the collected estimates in **Table 1** and **Figure 1**, respectively, support our predictions concerning the wage–experience profiles in China and Eastern Europe. However, we must interpret these findings with caution because the simple aggregation of the reported empirical results and an illustration of their distribution may lead us to a false conclusion. In other words, we should synthesize and compare the collected estimates, taking into account their precision and heterogeneity, as well as the possible influence of publication selection bias. The next section briefly introduces meta-analytic techniques for dealing with these critical issues from the viewpoint of research synthesis.

4 Meta-Analysis Methodology: A Brief Note

According to Stanley and Doucouliagos (2012) and Iwasaki (2020), a meta-analysis conventionally consists of three steps: (a) meta-synthesis of collected estimates, (b) meta-regression analysis (MRA) of heterogeneity across studies, and (c) testing for publication selection bias. This paper follows this standard procedure.[5]

To synthesize the collected estimates, we utilize the unrestricted weighted least squares average (UWA), and the weighted average of the adequately powered (WAAP) in addition to the conventional meta fixed-effect and random-effects methods. According to Stanley and Doucouliagos (2017) and Stanley et al. (2017), the UWA is

[5] The methodological description of the meta-analysis presented in this paper is kept to a minimum due to space limitations. For more details, see Borenstein et al. (2009) and Stanley and Doucouliagos (2012).

less subject to influence from excess heterogeneity than is the meta fixed-effect model. 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 Eq. (2), in which there is no intercept term, and the coefficient, α, is utilized as the synthesized value of the collected estimates in question:

$$t_k = \alpha(1/SE_k) + \varepsilon_k, \quad (2)$$

where SE_k is the standard error of the k-th estimate, and ε_k is a residual term. In theory, α in Eq. (2) is consistent with the estimate of the meta fixed-effect model.

Table 1. Descriptive statistics and univariate tests of collected estimates by study type and period

Study type and period	Number of estimates (K)	Mean	Median	S.D.	Max.	Min.	t- test [a]
Studies of wage seniority in China [b]	1126	0.02772	0.02600	0.01954	0.09600	-0.02900	47.610 ***
1995 or before	265	0.03444	0.03200	0.01977	0.09358	-0.02900	28.349 ***
1996–2005	474	0.02776	0.02500	0.02108	0.09600	-0.01990	28.664 ***
2006 or later	387	0.02306	0.02200	0.01573	0.08000	-0.02900	28.850 ***
Studies of wage seniority in Eastern Europe [c]	423	0.01688	0.01500	0.01699	0.11410	-0.04800	20.432 ***
1995 or before	99	0.02350	0.02200	0.02245	0.11410	-0.04800	10.414 ***
1996–2005	222	0.01591	0.01300	0.01446	0.06300	-0.03100	16.402 ***
2006 or later	102	0.01255	0.01300	0.01399	0.05000	-0.02700	9.061 ***
Studies of the wage curve in China [d]	1126	-0.00574	-0.00060	0.01476	0.04140	-0.11000	-13.044 ***
1995 or before	265	-0.01057	-0.00070	0.02296	0.00200	-0.11000	-7.492 ***
1996–2005	474	-0.00517	-0.00050	0.01157	0.01800	-0.06300	-9.722 ***
2006 or later	387	-0.00314	-0.00053	0.00936	0.04140	-0.05300	-6.591 ***
Studies of the wage curve in Eastern Europe [e]	423	-0.02455	-0.00800	0.03924	0.04720	-0.23000	-12.868 ***
1995 or before	99	-0.02454	-0.01500	0.03745	0.01200	-0.23000	-6.519 ***
1996–2005	222	-0.03404	-0.02260	0.04381	0.04720	-0.17400	-11.576 ***
2006 or later	102	-0.00392	-0.00039	0.01566	0.03000	-0.10700	-2.528 **

Note:

[a] *** and ** denote that null hypothesis that mean is zero is rejected at the 1% and 5% levels, respectively.

[b] Comparison of three periods: ANOVA: F = 27.93, p = 0.000; Bartlett's test: χ^2 = 36.2046, p = 0.000; Kruskal-Wallis rank-sum test: χ^2 = 64.356, p = 0.0001

[c] Comparison of three periods: ANOVA: F = 11.75, p = 0.000; Bartlett's test: χ^2 = 34.9742, p = 0.000; Kruskal-Wallis rank-sum test: χ^2 = 18.678, p = 0.0001

[d] Comparison of three periods: ANOVA: F = 21.27, p = 0.000; Bartlett's test: χ^2 = 309.1526, p = 0.000; Kruskal-Wallis rank-sum test: χ^2 = 17.720, p = 0.0001

[e] Comparison of three periods: ANOVA: F = 22.71, p = 0.000; Bartlett's test: χ^2 = 104.5057, p = 0.000; Kruskal-Wallis rank-sum test: χ^2 = 68.654, p = 0.0001

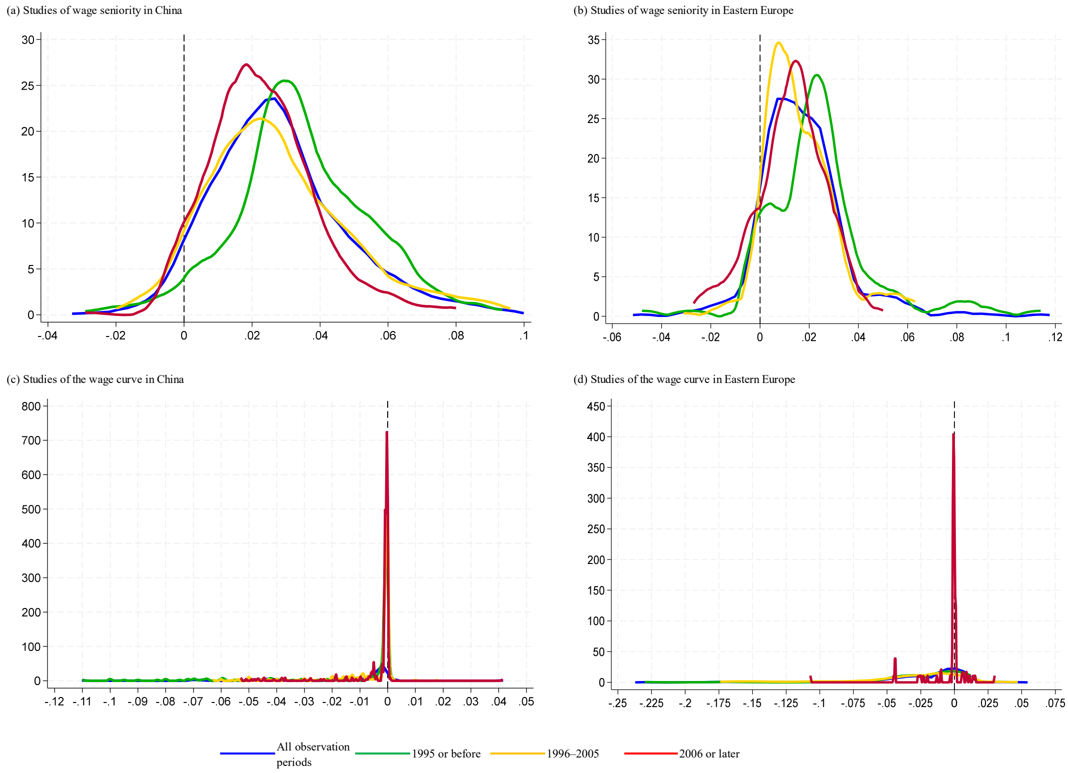

Figure 1. Kernel density estimation of collected estimates by study type and period

Note: The vertical axis is the kernel density. The horizontal axis is the semi-elasticities coefficient of collected estimates. See Table 1 for the descriptive statistics of estimates.

Further, Stanley et al. (2017) proposed conducting a UWA of estimates, the statistical power of which exceeds the threshold of 0.80, and called this estimation method “the weighted average of the adequately powered (WAAP).” They stated that WAAP synthesis has less publication selection bias than the traditional meta random-effects model. Accordingly, we adopt the WAAP estimate as the best synthesis value whenever available. Otherwise, the traditional synthesized effect size is used as the second-best reference value.

Following the synthesis of collected estimates, we conduct an MRA to explore the factors causing heterogeneity between the selected studies. More concretely, we estimate a meta-regression model:

$$y_k = \beta_0 + \sum_{n=1}^{N} \beta_n x_{kn} + \beta_{SE} SE_k + e_k, \quad (3)$$

where y_k is the k-th estimate, β_0 is the constant, x_{kn} denotes a meta-independent variable (also known as a moderator) that captures the relevant characteristics of an empirical study and explains its systematic variation from other empirical results in the literature, β_n denotes the meta-regression coefficient to be estimated. β_{SE} expresses the coefficient of SE, and e_k is the meta-regression disturbance term.

There is no clear consensus among meta-analysts about the best model for estimating Eq. (3) (Iwasaki et al., 2020, 2022; Ono and Iwasaki, 2022). Hence, to check the statistical robustness of coefficient β_n, we perform an MRA using the following six estimators: (1) the cluster-robust weighted least squares (WLS), which clusters the collected estimates by study, computes robust standard errors, and is weighed by the inverse of standard error ($1/SE$) as a measure of estimate precision; (2) the cluster-robust WLS weighed by the degrees of freedom to account for sample-size differences among the studies; (3) the cluster-robust WLS weighed by the inverse of the number of estimates in each study to avoid the domination of the results by studies with large numbers of estimates; (4) the multi-level mixed-effects RLM estimator; (5) the cluster-robust random-effects panel generalized least squares (GLS) estimator; and (6) the cluster-robust fixed-effects panel least squares dummy variable (LSDV) estimator. We report either a random-effects panel model or a fixed-effects panel model, according to the Hausman test of model specification. In this paper, we assume that meta-independent variables that are statistically significant and have the same sign in at least three of five models constitute robust estimates.

As Havranek and Sokolova (2020) and Zigraiova et al. (2021) argued, MRA involves the issue of model uncertainty, in the sense that the true model cannot be identified in advance. In addition, there is a high risk that the simultaneous estimation of multiple meta-independent variables could lead to multicollinearity. Accordingly, we estimate the posterior inclusion probability (PIP) and t value of each meta-independent variable other than the variables needed for hypothesis testing and the standard error of collected estimates using the Bayesian model averaging (BMA) estimator and the weighted-average least squares (WALS) estimator, respectively. We do this while adopting a policy of employing variables for which the estimates have a PIP of 0.50 or more in the BMA analysis and a t value of 1.00 or more in the WALS estimation as selected moderators in Eq. (3).

As the final stage of meta-analysis, we examine publication selection bias using a funnel plot and by performing an MRA test procedure consisting of a funnel-asymmetry test (FAT), a precision-effect test (PET), and a precision-effect estimate with standard error (PEESE) approach, which were proposed by Stanley and Doucouliagos (2012) and have been used widely in previous meta-studies.

A funnel plot is a scatter plot with the effect size (in the case of this paper, coefficients δ and θ) on the horizontal axis and the precision of the estimate (in the case of this paper, $1/SE$) 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 size. 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 must look like an inverted funnel. In other words, 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 and/or are statistically significant) are more frequently published.

The FAT and PET have been developed to test publication selection bias and the presence of genuine evidence in a more rigid manner: FAT can be performed by regressing the t value of the k-th estimate on $1/SE$ using Eq. (4), thereby testing the null hypothesis that the intercept term γ_0 is equal to zero:

$$t_k = \gamma_0 + \gamma_1(1/SE_k) + v_k, \quad (4)$$

where v_k is 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. (4). The rejection of the null hypothesis implies the presence of a genuine effect. γ_1 is the coefficient of precision; therefore, it is called a PET.

Furthermore, Stanley and Doucouliagos (2012) also stated that an estimate of the publication selection bias–adjusted effect size can be obtained by estimating the following equation (5), which has no intercept. If the null hypothesis of $\varphi_1 = 0$ is rejected, then the nonzero true effect does actually exist in the literature, and the coefficient φ_1 can be regarded as its estimate.

$$t_k = \varphi_0 SE_k + \varphi_1(1/SE_k) + w_k, \quad (5)$$

where w_k is the error term. This is the PEESE approach.

To test the robustness of the coefficients obtained from the above FAT–PET–PEESE procedure, we estimate Eqs. (4) and (5) using not only the unrestricted WLS estimator, but also the WLS estimator with bootstrapped standard errors, the cluster-robust WLS estimator, and the unbalanced panel estimator for a robustness check. In addition to these four models, we also run an instrumental variable (IV) estimation with the inverse of the square root of the number of observations used as an instrument of the standard error, because "the standard error can be endogenous if some method choices affect both the estimate and the standard error. Moreover, the standard error is estimated, which causes attenuation bias in meta-analysis" (Cazachevici et al., 2020, p. 5).

In recent years, some advanced techniques for estimating the publication selection bias–corrected effect size have been developed that are comparable to the PEESE approach. They include the selection model, developed by Andrews and Kasy (2019), which tests for publication selection bias using the conditional probability of publication as a function of a study's results; the endogenous kinked model, innovated by Bom and Rachinger (2019), which presents a piecewise linear meta-regression of estimates of their standard errors, with a kink at the cutoff value of the standard error below which publication selection bias is unlikely; and the *p*-uniform method, introduced by van Aert and van Assen (2021), which is grounded on the statistical theory that the distribution of *p*-values is uniform conditional on the population effect size. In this paper, we apply these three methods to provide alternative estimates of the publication selection bias–corrected effect size and compare them with the PEESE estimates for a robustness check.

5 Results

This section reports the results obtained from a meta-analysis conducted in accordance with the procedure and methodology described in the previous section.

5.1 Meta-Synthesis

Table 2 presents the meta-synthesis results. As in **Table 1** and **Figure 1**, **Table 2** shows the results by study type and by period.

In Column (b) of **Table 2**, Cochran's Q test of homogeneity rejects the null hypothesis at the 1% significance level, and the I^2 and H^2 statistics strongly suggest the presence of heterogeneity across studies in all 16 cases. Therefore, the synthesized effect sizes of the meta random-effects model in Column (a) are preferred to those of the meta fixed-effect model. With respect to the results of the UWA and WAAP estimations in Column (c), a considerable number of estimates whose statistical power exceeds the threshold of 0.80 are secured for all cases. Accordingly, we adopt the WAAP synthesis values, which are more reliable than those of the UWA and the meta random-effects model.

As shown in the first row in Column (c) of **Table 2**, the synthesized effect sizes for all studies of wage seniority in China and Eastern Europe using the WAAP approach are statistically significant at the 1% level and take positive values of 0.02457 for China and 0.02112 for Eastern Europe, implying that an increase of one year of work experience increases wages by 2.5 percentage points in China and by 2.1 percentage points in Eastern Europe. This result suggests that, throughout the entire observation period, economically meaningful wage seniority existed in both China and Eastern Europe, as Hypothesis H1 predicts.

Table 2. Synthesis of collected estimates by study type and period

Study type and period	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's 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
Studies of wage seniority in China	1126	0.02536 *** (209.79)	0.02674 *** (50.99)	18123.21 *** (0.00)	93.22	14.75	0.02475 *** (41.20)	682	0.02457 *** (32.97)	0.00636	0.974
1995 or before	265	0.03479 *** (160.15)	0.03289 *** (31.85)	3296.76 *** (0.00)	93.83	16.21	0.03716 *** (28.28)	192	0.03686 *** (23.84)	0.00853	0.992
1996–2005	474	0.02287 *** (113.07)	0.02639 *** (30.67)	7227.42 *** (0.00)	93.11	14.51	0.01956 *** (23.26)	255	0.02274 *** (21.46)	0.00615	0.889
2006 or later	387	0.01927 *** (91.98)	0.02321 *** (29.55)	4715.91 *** (0.00)	90.84	10.92	0.01956 *** (24.70)	216	0.01892 *** (19.70)	0.00607	0.897
Studies of wage seniority in Eastern Europe	423	0.01837 *** (184.87)	0.01589 *** (24.21)	13305.89 *** (0.00)	97.23	36.07	0.02232 *** (15.04)	331	0.02112 *** (13.38)	0.00400	1.000
1995 or before	99	0.01928 *** (113.66)	0.01884 *** (13.75)	4500.25 *** (0.00)	97.87	46.87	0.01950 *** (10.39)	66	0.01998 *** (8.71)	0.00400	0.998
1996–2005	222	0.01869 *** (126.16)	0.01593 *** (17.62)	6627.70 *** (0.00)	96.94	32.64	0.02498 *** (9.63)	200	0.02424 *** (8.84)	0.00400	1.000
2006 or later	102	0.01616 *** (74.02)	0.01306 *** (9.99)	2042.28 *** (0.00)	96.40	27.78	0.02127 *** (8.29)	71	0.01614 *** (13.73)	0.00409	0.999
Studies of the wage curve in China	1126	-0.00067 *** (-38.67)	-0.00329 *** (-11.13)	6699.01 *** (0.00)	99.46	185.73	-0.00099 *** (-8.88)	150	-0.00061 *** (-12.27)	0.00600	0.036
1995 or before	265	-0.00082 *** (-18.47)	-0.00735 *** (-6.31)	4172.53 *** (0.00)	99.82	555.83	-0.00172 *** (-4.17)	54	-0.00069 *** (-8.84)	0.00500	0.053
1996–2005	474	-0.00056 *** (-16.84)	-0.00064 *** (-8.16)	1278.87 *** (0.00)	48.21	1.93	-0.00109 *** (-5.72)	44	-0.00055 *** (-5.12)	0.00900	0.033
2006 or later	387	-0.00068 *** (-29.90)	-0.00087 *** (-13.72)	1224.22 *** (0.00)	70.68	3.41	-0.00075 *** (-7.14)	66	-0.00061 *** (-8.29)	0.00500	0.035
Studies of the wage curve in Eastern Europe	423	-0.01008 *** (-57.11)	-0.01846 *** (-13.93)	9590.82 *** (0.00)	95.82	23.91	-0.01349 *** (-11.67)	91	-0.01079 *** (-6.09)	0.04000	0.052
1995 or before	99	-0.02130 *** (-49.90)	-0.02452 *** (-9.72)	2095.69 *** (0.00)	93.75	16.00	-0.03069 *** (-8.69)	39	-0.03095 *** (-6.35)	0.02600	0.218
1996–2005	222	-0.02647 *** (-72.34)	-0.02521 *** (-12.33)	2541.71 *** (0.00)	90.61	10.65	-0.02621 *** (-15.33)	45	-0.02780 *** (-11.15)	0.05900	0.065
2006 or later	102	-0.00047 ** (-2.06)	-0.00430 ** (-3.03)	487.39 *** (0.00)	94.67	18.76	-0.00328 *** (-3.82)	15	-0.00040 ** (-2.64)	0.01000	0.051

Notes: *** and ** denote statistical significance at the 1% and 5% levels, respectively.
[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 the number of estimates with a statistical power of 0.80 or more, which is computed by referring to the UWA of all collected estimates

With respect to Hypothesis H2, WAAP synthesis values by period indicate that the degree of wage seniority in China declined gradually through the three periods. Actually, the synthesized effect size takes a value of 0.03686 in the period of 1995 or before, while in the years of 1996–2005 and the period of 2006 or later, the values are estimated to be 0.02274 and 0.01892, respectively, which is consistent with Hypothesis H2. Additionally, the synthesized effect size for studies of the wage curve in Eastern Europe can be considered as supporting evidence, demonstrating that it declines from -0.03095 in the period of 1995 or before to -0.02780 in the years of 1996–2005, and further to -0.00040 in the period of 2006 or later. These results also support Hypothesis H2.

Furthermore, the synthesis results for studies of wage seniority in Eastern Europe and studies of the wage curve in China demonstrate a U-shaped change in the effect size through the three periods, although they do not deny our expectation of the flattening tendency of the wage–experience profile from the era of the planned system to the present.

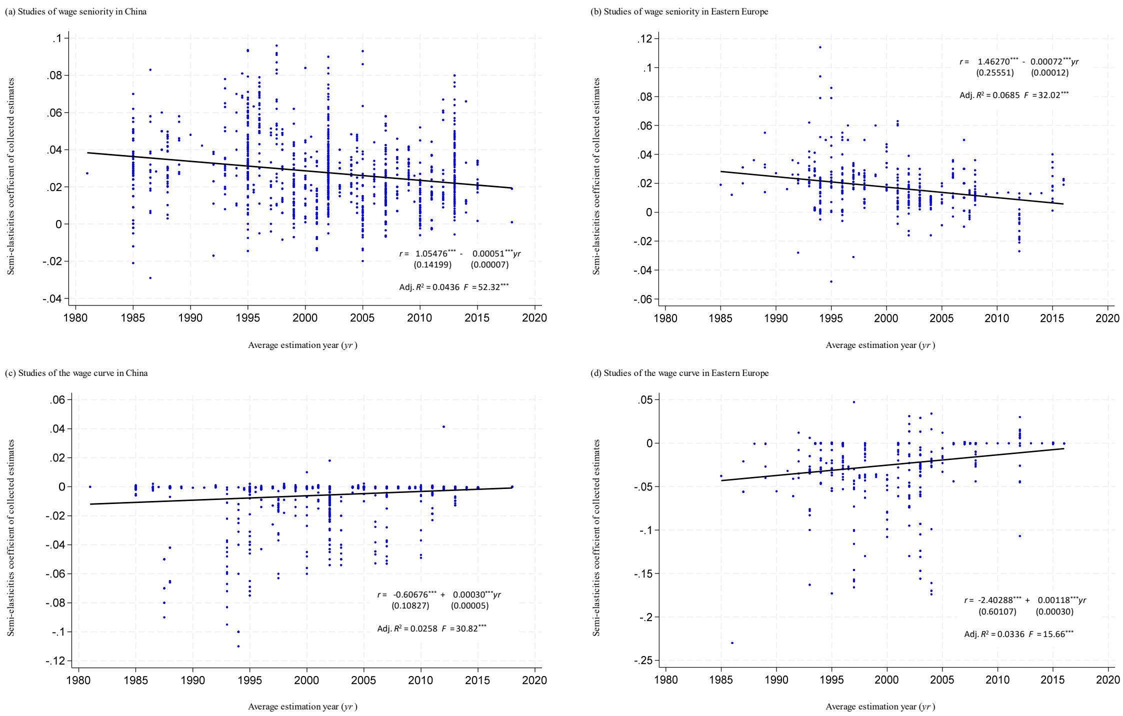

Figure 2. Chronological order of collected estimates by study type

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

It is possible that the coarse division of the observation periods may mislead us. Hence, to examine the reliability of the synthesis results by period in **Table 2**, we examined changes over time of coefficients δ and θ through a more detailed subdivision of collected estimates. **Figure 2** shows the results. In all panels of the figure, the slopes of the approximate line are estimated to be statistically significant at the 1% level with the predicted sign. In fact, corresponding with Hypothesis H2, Panels (a) and (b) display that, as the average estimation year approaches the present year by year, the degree of wage seniority decreases toward zero in both China and Eastern Europe; moreover, Panels (c) and (d) show that the wage curve shrinks not only in China but also in Eastern

Europe. In other words, our prediction is more strongly supported when the data are pooled together.

5.2 Meta-Regression Analysis

The meta-synthesis presented in the previous subsection enables explicit hypothesis testing by providing point estimates as synthesized effect sizes. Nevertheless, it fails to sufficiently consider the influence of heterogeneity across the selected studies on their reported estimates. Therefore, this subsection examines the credibility of synthesis results by estimating a multivariate meta-regression model in which diversity in study conditions and attributes is simultaneously controlled for.

As meta-independent variable x_{kn}, in addition to the variable of the average estimation year that is a key to hypothesis testing, we employed a series of moderators—length of estimation period, target region, target firm ownership, data type, survey data used, estimation of independent variable in question with an intercepted variable(s), estimator, presence of control for selection bias and endogeneity, and selection of control variables with potentially significant impact on the reported estimates. As expounded in the previous section, the meta-independent variables are estimated along with the standard errors of the collected estimates using six different estimators.[6]

Estimation results of Eq. (3), with moderators selected through a BMA analysis and a WALS estimation using estimates available in studies of wage seniority in China as the dependent variable, are reported in Panel (a) of **Table 3**. As shown in this panel, five meta-independent variables—from *Rural region* to *Trade union*—were chosen as moderators for this study type by the BMA–WALS estimation procedure.[7] Further, this table reports the cluster-robust random-effects panel GLS model as Model [5] because the Hausman test did not reject the null hypothesis that the errors are uncorrelated with the independent variables ($\chi^2 = 10.36$, $p = 0.1692$).

In Panel (a) of **Table 3**, average estimation year, the key variable for testing Hypothesis H2, shows a negative coefficient with statistical significance at the 5% level

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[6] The names, definitions, and descriptive statistics of the meta-independent variables are provided in **Appendix Table A2**. To avoid the multicollinearity that can arise from the simultaneous estimation of a large number of independent variables, we have inspected the correlation matrix and variance inflation factor (VIF) of all of the coded variables. As a result, we narrowed down the variables to the 25 listed in this table that fully met the criteria of a correlation coefficient of less than 0.7 and a VIF of less than 10.

[7] See the corresponding panel of **Appendix Table A3** for the procedure for selecting moderators.

or less in four of five models. This implies that the effect size of a single term of *experience* reported in Chinese wage studies tends to decrease by 0.00033–0.00061 per year through the observation period, *ceteris paribus*. This result corresponds well with the synthesis results in **Table 2** as well as the single regression analysis in **Figure 2**. Thus, our expectation of the diminishing time trend of wage seniority in China is strongly reinforced.

We repeated the same MRA procedure for the other three study types, in addition to that subject to studies of wage seniority in China mentioned above. Panels (b), (c), and (e) of **Table 3** exhibit estimates of average estimation year obtained from these additional MRA trials. From these panels, we find that the variable of average estimation year is given a statistically robust coefficient with a predicted sign in all three cases. Actually, in Panel (b), average estimation year shows a significant negative estimate in three models, and, in Panels (c) and (e), the variable provides a significant positive estimate in three and five models, respectively, which is in line with Hypothesis H2. In addition to Panel (a), these estimation results also satisfy the robustness criteria.

Table 3. Meta-regression analysis of literature heterogeneity by study type

(a) Studies of wage seniority in China

Estimator (Analytical weight in brackets)[a]	Cluster-robust WLS [Precision]	Cluster-robust WLS [Sample size]	Cluster-robust WLS [Study size]	Multilevel mixed-effects RML	Cluster-robust random-effects panel GLS
Meta-independent variable (default category)/model	[1]	[2]	[3]	[4]	[5][b]
Estimation period					
Average estimation year	-0.00050***	-0.00061***	-0.00030	-0.00033**	-0.00033**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Selected moderators					
Rural region	-0.01093***	-0.00876**	0.00108	-0.00566**	-0.00575**
	(0.0041)	(0.0038)	(0.0063)	(0.0026)	(0.0026)
Cross-sectional data	-0.00688	-0.01070	-0.02323**	-0.00505	-0.00469
	(0.0049)	(0.0074)	(0.0096)	(0.0052)	(0.0050)
Control for selection bias	0.02743**	0.02191	0.01435	0.01718	0.01704
	(0.0115)	(0.0163)	(0.0173)	(0.0162)	(0.0162)
Health	-0.00370	-0.00596*	-0.00904**	-0.00663*	-0.00642*
	(0.0039)	(0.0033)	(0.0038)	(0.0034)	(0.0035)
Trade union	-0.00774**	-0.00878*	-0.00529	-0.00638**	-0.00624**
	(0.0031)	(0.0051)	(0.0038)	(0.0030)	(0.0030)
SE	0.06672	0.00039	0.00289***	0.00285***	0.00285***
	(0.0555)	(0.0015)	(0.0004)	(0.0003)	(0.0003)
Intercept	1.03331***	1.26005***	0.65334*	0.70012**	0.69466**
	(0.3618)	(0.3678)	(0.3855)	(0.3167)	(0.3224)
K	1126	1126	1126	1126	1126
R^2	0.140	0.158	0.133	-	0.125

(b) Studies of wage seniority in Eastern Europe

Estimator (Analytical weight in brackets)[a]	Cluster-robust WLS [Precision]	Cluster-robust WLS [Sample size]	Cluster-robust WLS [Study size]	Multilevel mixed-effects RML	Cluster-robust fixed-effects panel LSV
Meta-independent variable (default category)/model	[6]	[7]	[8]	[9]	[10][c]
Estimation period					
Average estimation year	-0.00040	-0.00096 **	-0.00044 **	-0.00028 *	-0.00013
	(0.0003)	(0.0004)	(0.0002)	(0.0002)	(0.0003)
Selected moderators					
Rural region	0.05504	0.03102 ***	0.03674 ***	0.02906 ***	-0.04695 **
	(0.0436)	(0.0106)	(0.0054)	(0.0022)	(0.0186)
Original household survey	-0.00671 **	0.00735	-0.00428	-0.00261	dropped
	(0.0030)	(0.0071)	(0.0036)	(0.0036)	
OLS	0.00545 **	0.00025	0.00652 **	0.00455 **	0.00472 **
	(0.0024)	(0.0029)	(0.0026)	(0.0022)	(0.0022)
Control of endogeneity	-0.01647 ***	-0.03794 ***	-0.01992 ***	-0.01960 ***	dropped
	(0.0033)	(0.0092)	(0.0035)	(0.0035)	
Occupation	-0.00413	0.01076 ***	-0.00580 *	-0.00298	0.00150
	(0.0034)	(0.0029)	(0.0033)	(0.0028)	(0.0012)
Industry fixed effects	-0.00906 ***	-0.01086	-0.01051 ***	-0.00806 ***	0.00034
	(0.0026)	(0.0069)	(0.0030)	(0.0031)	(0.0008)
SE	0.00451	-0.01216	0.03431 ***	0.01359	-0.27374 ***
	(0.1450)	(0.0362)	(0.0120)	(0.0180)	(0.0892)
Intercept	0.81213	1.94329 **	0.89360 **	0.58623	-0.24355
	(0.5065)	(0.7321)	(0.4250)	(0.3961)	(0.5688)
K	423	423	423	423	423
R^2	0.323	0.246	0.276	-	0.050

(c) Studies of the wage curve in China

Estimator (Analytical weight in brackets)[a]	Cluster-robust WLS [Precision]	Cluster-robust WLS [Sample size]	Cluster-robust WLS [Study size]	Multilevel mixed-effects RML	Cluster-robust fixed-effects panel LSV
Meta-independent variable (default category)/model	[11]	[12]	[13]	[14]	[15][d]
Estimation period					
Average estimation year	0.00005	0.00052 **	0.00022	0.00058 **	0.00070 **
	(0.0000)	(0.0002)	(0.0001)	(0.0003)	(0.0003)
Selected moderators					
State enterprise	0.00037	0.00945 ***	0.00665 ***	0.00059	-0.00126
	(0.0009)	(0.0033)	(0.0023)	(0.0009)	(0.0011)
Private firm	0.00081	0.00807 ***	0.00495 ***	0.00055	-0.00133
	(0.0006)	(0.0017)	(0.0017)	(0.0009)	(0.0011)
OLS	0.00421	0.01676 ***	0.01153 ***	0.00038	-0.00172
	(0.0025)	(0.0046)	(0.0044)	(0.0013)	(0.0017)
Control for selection bias	0.00318	0.01594 ***	0.00521	-0.00161	-0.00210
	(0.0021)	(0.0051)	(0.0062)	(0.0015)	(0.0015)
Age	0.00161	0.00385	0.00592 *	0.00984 ***	0.01394 ***
	(0.0010)	(0.0027)	(0.0035)	(0.0032)	(0.0041)
Trade union	0.00074	0.00020	0.00438 ***	-0.00004	-0.00044
	(0.0008)	(0.0020)	(0.0015)	(0.0011)	(0.0006)
Industry fixed effects	-0.00032	-0.00690 **	-0.00272	-0.00170 *	-0.00095
	(0.0006)	(0.0032)	(0.0025)	(0.0010)	(0.0007)
SE	-0.15370 *	-0.00361 ***	-0.00283 **	-0.00156	-0.00158
	(0.0814)	(0.0007)	(0.0012)	(0.0014)	(0.0014)
Intercept	-0.10070	-1.07041 **	-0.45109	-1.17057 **	-1.40439 **
	(0.0821)	(0.4720)	(0.2787)	(0.5545)	(0.6469)
K	1126	1126	1126	1126	1126
R^2	0.069	0.231	0.127	-	0.020

(d) Studies of the wage curve in Eastern Europe

Estimator (Analytical weight in brackets)[a]	Cluster-robust WLS [Precision]	Cluster-robust WLS [Sample size]	Cluster-robust WLS [Study size]	Multilevel mixed-effects RML	Cluster-robust random-effects panel GLS
Meta-independent variable (default category)/model	[16]	[17]	[18]	[19]	[20][e]
Estimation period					
Average estimation year	0.00095 ***	0.00117 ***	0.00123 ***	0.00149 ***	0.00152 **
	(0.0003)	(0.0004)	(0.0004)	(0.0006)	(0.0006)
Selected moderators					
Length of estimation period	0.00053	-0.00102	0.00088	0.00086	0.00076
	(0.0006)	(0.0008)	(0.0009)	(0.0007)	(0.0007)
Urban region	-0.02435	-0.01891	-0.02068 **	-0.01835 *	-0.01716 *
	(0.0150)	(0.0113)	(0.0090)	(0.0097)	(0.0101)
Original household survey	0.00409	-0.01790	-0.01189	-0.01329 **	-0.01333 **
	(0.0066)	(0.0109)	(0.0076)	(0.0066)	(0.0066)
Control of endogeneity	0.02259 ***	0.03987 ***	0.03558 ***	0.03732 ***	0.03693 ***
	(0.0055)	(0.0100)	(0.0081)	(0.0078)	(0.0080)
Occupation	-0.00125	-0.00158	-0.01169	-0.01922 **	-0.01997 ***
	(0.0054)	(0.0027)	(0.0094)	(0.0076)	(0.0078)
Firm size	0.00693	-0.00079	0.00372	0.00718	0.00683
	(0.0057)	(0.0046)	(0.0074)	(0.0051)	(0.0049)
Trade union	-0.01738	-0.00769	-0.01767	-0.01367 **	-0.01090 *
	(0.0167)	(0.0258)	(0.0197)	(0.0062)	(0.0062)
Industry fixed effects	0.01216 ***	-0.00434	0.00969	0.00970	0.00870
	(0.0042)	(0.0079)	(0.0067)	(0.0061)	(0.0061)
SE	0.07594 **	0.03344	0.01942 *	0.01506	0.01280
	(0.0299)	(0.0229)	(0.0098)	(0.0100)	(0.0111)
Intercept	-1.91561 ***	-2.35106 ***	-2.47173 ***	-2.99271 ***	-3.05710 **
	(0.6159)	(0.7320)	(0.8193)	(1.1202)	(1.2032)
K	423	423	423	423	423
R^2	0.339	0.715	0.193	-	0.203

Notes: Figures in parentheses beneath the regression coefficients are robust standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Appendix Table A2 for definitions and descriptive statistics of the meta-independent variables. Selected moderators denote meta-independent variables with a PIP of 0.50 or more in the Bayesian model averaging (BMA) estimation and with a t value of 1.00 or more in the weighted-average least squares (WALS) estimation as reported in Appendix Table A3.

[a] Precision: inverse of the standard error; Sample size: degree of freedom; Study size: inverse of the number of reported estimates

[b] Hausman test: $\chi^2 = 10.36, p = 0.1692$

[c] Hausman test: $\chi^2 = 55.67, p = 0.0000$

[d] Hausman test: $\chi^2 = 37.36, p = 0.0000$

[e] Hausman test: $\chi^2 = 7.56, p = 0.4779$

To sum up, the results of MRA in **Table 3** provide strong support for the meta-synthesis findings in the previous subsection.

5.3 Test for Publication Selection Bias

As the final step of meta-analysis, this subsection tests for publication selection bias and the presence of genuine evidence in the literature.

Figure 3 illustrates a funnel plot by study type and period. As explained in the previous section, in the absence of publication selection bias, reported estimates vary randomly and symmetrically around the true effect size; as a consequence, the shape of the plot must look like an inverted funnel. If the true effect is assumed to be zero, as the dotted line in the figure depicts, it is clear that no study type has so-called "funnel symmetry" at all. If the WAAP synthesis value reported in **Table 2** is assumed to be the approximate value of the true effect, as drawn by the solid line, Panels (a) and (b) seem to form an ideal distribution of collected estimates from the viewpoint of statistical theory. In contrast, the funnel plots in Panels (c) and (d) of **Figure 3** cannot rule out the risk of publication selection bias in these two study types even if the WAAP synthesis value is assumed as the true effect size.

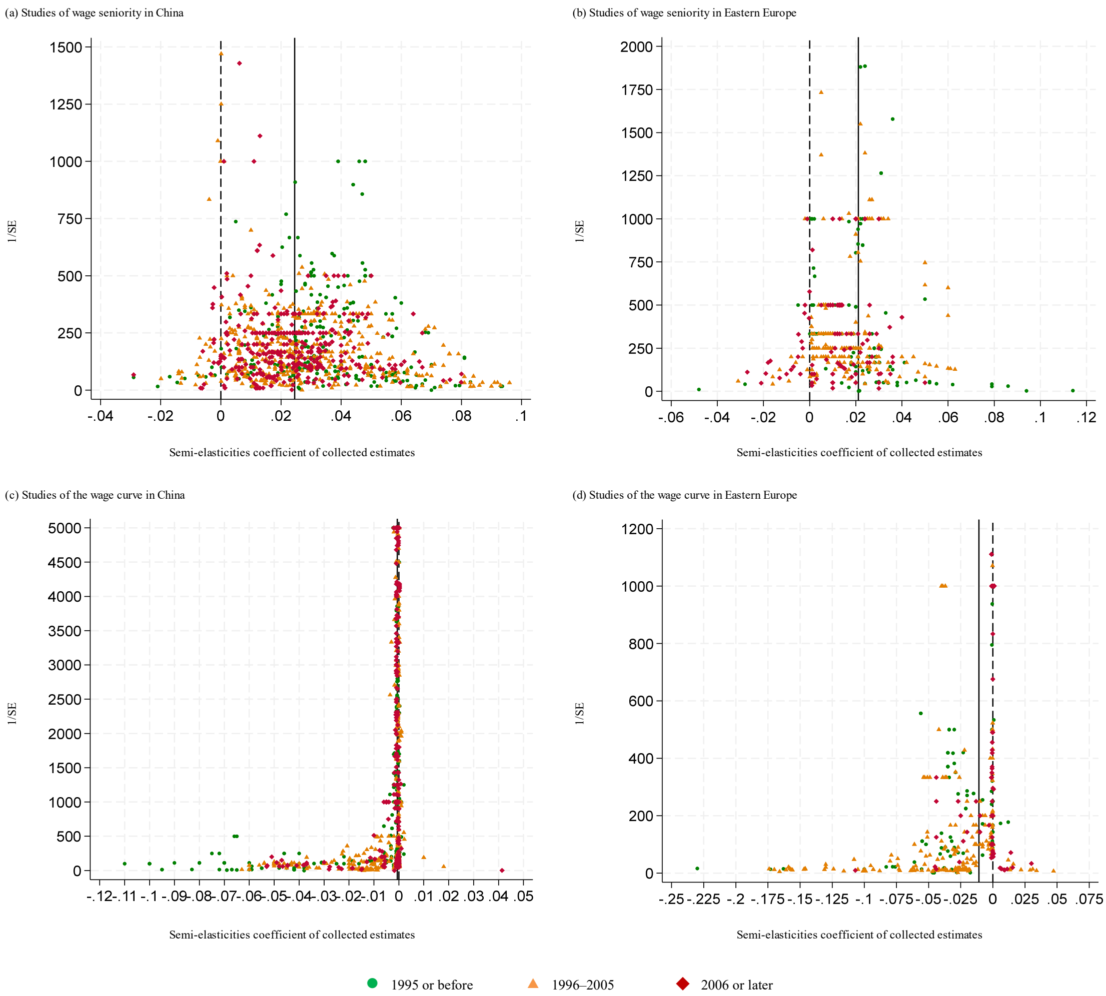

Figure 3. Funnel plot of collectes estimates by study type and period

Note: The solid line indicates the synthesized effect size of all collected estimates by WAAP estimation by study type as reported in Table 2.

Test results of publication selection bias using the FAT–PET–PEESE procedure for studies of wage seniority in China are reported in **Table 4**. Panel (a) of the table shows that the null hypothesis that the intercept γ_0 is zero is rejected by the FAT in all five models. This suggests that publication selection bias is highly likely to occur in this study type, despite the visual impression obtained from the funnel plot in Panel (a) of **Figure 3**. Furthermore, the PET rejects the null hypothesis that the coefficient of the inverse of the standard errors (γ_1) is zero in all five models, meaning that the collected estimates do contain evidence of a nonzero true effect of wage seniority in China. Also, the PEESE approach in Panel (b) shows that the coefficient φ_1 is statistically significantly different from zero in five models, implying that the real scale of wage seniority should be in a range from 0.01520 to 0.02579 during the entire observation period.

Table 4. Meta-regression analysis of publication selection bias: Studies of wage seniority in China

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

Estimator	Unrestricted WLS	WLS with bootstrapped standard errors	Cluster-robust WLS	Cluster-robust fixed-effects panel LSDV	IV
Model	[1]	[2]	[3]	[4][a]	[5]
Intercept (FAT: H_0: $\gamma_0 = 0$)	1.58167 ***	1.58167 ***	1.58167 ***	2.63452 ***	-1.42271 ***
	(0.4316)	(0.3816)	(0.5400)	(0.7238)	(0.4997)
$1/SE$ (PET: H_0: $\gamma_1 = 0$)	0.02006 ***	0.02006 ***	0.02006 ***	0.01464 ***	0.03554 ***
	(0.0026)	(0.0023)	(0.0038)	(0.0037)	(0.0024)
K	1126	1126	1126	1126	1126
R^2	0.304	0.304	0.304	0.304	0.123

(b) PEESE approach (Equation: $t = \varphi_0 SE + \varphi_1(1/SE) + w$)

Estimator	Unrestricted WLS	WLS with bootstrapped standard errors	Cluster-robust WLS	Random-effects panel ML	IV
Model	[6]	[7]	[8]	[9]	[10]
SE	0.09381 *	0.09381	0.09381	-0.12126	0.08771
	(0.0550)	(0.8089)	(0.0578)	(0.2189)	(0.3666)
$1/SE$ (H_0: $\varphi_1 = 0$)	0.02475 ***	0.02475 ***	0.02475 ***	0.01520 ***	0.02579 ***
	(0.0015)	(0.0017)	(0.0026)	(0.0007)	(0.0013)
K	1126	1126	1126	1126	1126
R^2	0.601	0.601	0.601	-	-

Notes: Figures in parentheses beneath the regression coefficients are standard errors. Models [3], [4], and [8] report standard errors clustered by study. Models [5] and [10] use the inverse of the square root of the number of observations as an instrument of the standard error. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

[a] Hausman test: $\chi^2 = 2.88$, $p = 0.0896$

As pointed out in the previous section, in addition to the PEESE approach, three advanced meta-analytic techniques exist for estimating a genuine effect beyond publication selection bias. For a robustness check, therefore, we performed these alternative estimations of the publication selection bias–corrected effect size. **Table 5** shows the results. Although the synthesis value varies depending on the method applied, all of the estimates demonstrate the existence of a statistically significant and economically meaningful effect of work experience on wage levels in China corresponding with Hypothesis H1, as the FAT–PET–PEESE approach suggests.

Table 5. Alternative estimates of publication selection bias–corrected effect size: Studies of wage seniority in China

Method	Selection model [a]	Endogeneous kink model [b]	*p* -uniform [c]
Model	[1]	[2]	[3]
Publication selection bias–corrected effect size	0.02300 ***	0.01129 ***	0.02373 ***
	(0.0010)	(0.0049)	(0.0008)
K	1126	1126	1126

Notes: Figures in parentheses are standard errors. *** denotes that the coefficient is statistically significantly different from zero at the 1% level.

[a] Test for publication selection bias using the conditional probability of publication as a function of a study's results (Andrews and Kasy, 2019)

[b] Piecewise linear meta-regression of estimates on their standard errors, with a kink at the cutoff value of the standard error below which publication selection bias is unlikely (Bom and Rachinger, 2019)

[c] Method based on the statistical theory that the distribution of *p* -values is uniform conditional on the population effect size (van Aert and van Assen, 2021)

We carried out the same test procedure subject to studies of wage seniority in China using collected estimates divided by the period and the other three study types. The FAT–PET results are summarized in **Table 6**. As shown in the table, although publication selection bias was detected by the FAT in most cases, the PET confirmed the existence of a genuine effect beyond the potential contamination from publication selection bias for all cases in addition to that of wage seniority in China. Furthermore, **Figure 4** illustrates the PEESE and alternative estimates of the true effect size by study type and period. Overall, all panels in the figure provide evidence supporting both Hypotheses H1 and H2, except for the PEESE estimates in Panel (b), which indicate a significant U-shaped time-series change in the wage seniority effect size in Eastern Europe.

In sum, although there is one exceptional case, irrespective of methodology, the test results of publication selection bias generally support our predictions, as the meta-synthesis and the MRA did in the previous subsections.

Table 6. Summary of the FAT-PET results by study type and period

Study type and period	Number of estimates (K)	Test results	
		Funnel asymmetry test (FAT) (H_0: $\gamma_0 = 0$)	Precision-effect test (PET) (H_0: $\gamma_1 = 0$)
Studies of wage seniority in China	1126	**Rejected**	**Rejected**
1995 or before	265	**Rejected**	**Rejected**
1996–2005	474	**Rejected**	**Rejected**
2006 or later	387	**Rejected**	**Rejected**
Studies of wage seniority in Eastern Europe	423	**Rejected**	**Rejected**
1995 or before	99	Not rejected	**Rejected**
1996–2005	222	Not rejected	**Rejected**
2006 or later	102	Not rejected	**Rejected**
Studies of the wage curve in China	1126	**Rejected**	**Rejected**
1995 or before	265	**Rejected**	**Rejected**
1996–2005	474	**Rejected**	**Rejected**
2006 or later	387	**Rejected**	**Rejected**
Studies of the wage curve in Eastern Europe	423	**Rejected**	**Rejected**
1995 or before	99	Not rejected	**Rejected**
1996–2005	222	**Rejected**	**Rejected**
2006 or later	102	**Rejected**	**Rejected**

Note: This table reports that the null hypothesis is rejected when more than three of five models show a statistically significant estimate. Otherwise not rejected.

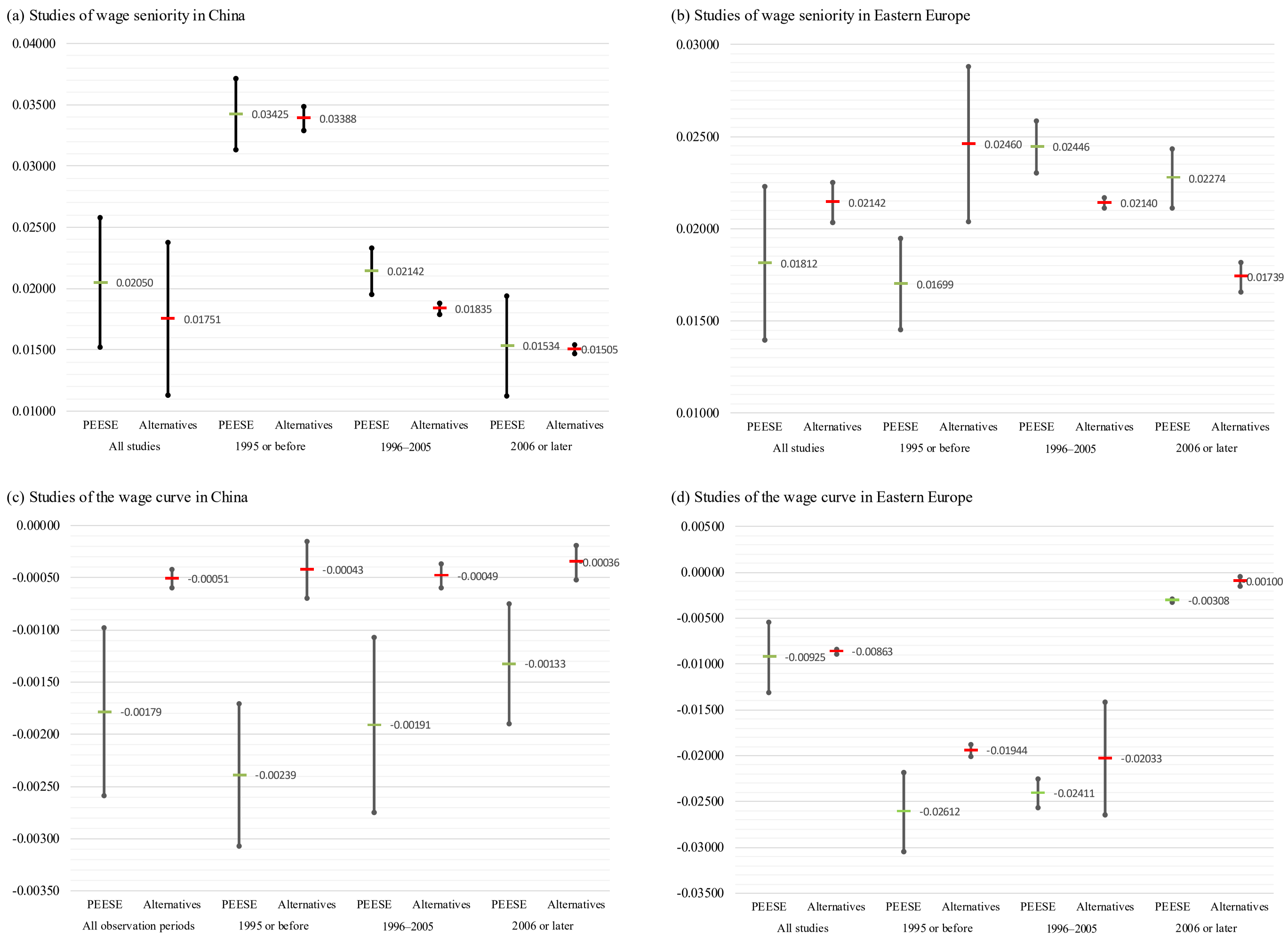

Figure 4. Illustrated comparison of publication selection bias–corrected effect size using the PEESE approach and alternative estimations methods by study type and period

Notes: The straight lines in the figure show the maximum and minimum ranges of the estimated publication selection bias–adjusted effect size, with their intermediate values indecated by a bar.

6 Conclusions

In this paper, we explored the wage–experience profiles in China and Eastern Europe from the viewpoint of the impacts of work experience on wage levels through a meta-analysis using 3098 estimates reported in 125 previous research works.

The results indicate that, after the end of the planned economic system, the relationship between work experience and wage levels both in China and Eastern Europe was structured consistently with standard economic theories. In fact, the meta-synthesis results in **Table 2** reveal that Chinese and Eastern European workers experienced a wage increase of more than 2 percentage points for each year of work experience throughout the transition period. Nevertheless, it is also revealed that their wage–experience profiles changed dynamically through the previous decades. Actually, we found that China and Eastern Europe have experienced a flattening of their wage–experience profiles, implying that the impact of work experience on wage level was gradually diminishing, and, as a consequence, the seniority-based wage system was dissolving over time. This evolutionary diversity of the wage–experience profile is likely driven by the process of systemic national-scale transformation toward a market economy after the end of the planned system era. In this sense, the process of economic transition in China and Eastern Europe has one common feature in the wage system.

In this regard, it is of great importance to point out that, in the transition period, China and Eastern Europe showed quite contrasting changes in the wage effects of education and gender. In fact, our preceding meta-analyses discovered that the impacts of education and gender on wage levels in China have been gradually increasing toward the present (Iwasaki and Ma, 2020; Ma and Iwasaki, 2021), while those in Eastern Europe have been declining remarkably (Horie and Iwasaki, 2023; Iwasaki and Satogami, 2023). How can we understand this coexistence of the commonality in the wage–experience profile and the heterogeneity in returns to education and the gender wage gap observed in the wage systems of China and Eastern Europe?

Since the 1990s, the economic systems of both China and Eastern Europe have undergone significant changes. Their economies have become more market oriented, globalization has progressed, and technological innovation—including digitalization—has advanced to a level comparable to that in developed countries. As well as significantly increased competition in the market, market transition policies have been accompanied by early retirement, the accelerated obsolescence of traditional skills, and accelerated early turnover due to the hardening budget constraints of firms, all of which may have worked to flatten their wage–experience profiles. However, significant disparities in the economic development of China and Eastern Europe become apparent from 2000 onward.

China has succeeded in creating a major manufacturing base as the world's factory on the back of its low-wage labor force. This success has led to an increasingly sophisticated industrial structure and a level of competitive innovation that has caused economic friction between the United States and China. In fact, the economic growth rate in the 2000s was remarkably high, although it declined slightly after the 2008 global economic crisis. Economic growth has led in parallel to higher education levels, with human capital bringing higher remuneration to workers and higher skills to firms, which has further encouraged increased human capital investment (Fang, 2019). However, while the vast Chinese market has expanded the skilled and highly qualified labor sphere with accumulated human capital, industries that rely on unskilled and semi-skilled labor also have been preserved. Women's share of total employment in labor-intensive sectors such as agriculture, services and distribution, and the textile industry is high, which preserves the gender gap (Dasgupta et al., 2015).

Eastern Europe achieved economic growth after the transformational recession in the 1990s, but the growth could not continue stably. Since the global economic crisis, growth in these countries has slowed. Even though the market transition, the EU Eastern enlargement, and globalization have led to higher levels of education and greater qualifications, there has not been sufficient demand for highly qualified labor under the international division of labor in Europe, which is biased toward labor-intensive sectors (Ikemoto and Shimuta, 2022), resulting in over-education or labor outflows of highly educated workers.

As discussed above, the findings reported in this paper and our previous meta-analyses of wage studies reveal both remarkable commonalities and heterogeneities in the wage systems of China and Eastern Europe during the transition period. Comparing China and Eastern Europe in a standard empirical analysis is usually difficult due to data limitations and other technical reasons, as is the case with wage structure studies. As demonstrated in this paper, however, comparative meta-analysis has the potential to overcome such difficulties and provide new findings for deeper understanding of Eurasian emerging markets.

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Appendix Table A1. List of selected studies on wage-experience profiles in China and Eastern Europe for meta-analysis

(a) Chinese Studies

No.	Author(s) (Publication year)	Publication media	Estimation period		Number of estimates collected
			From	To	
1	Gregory and Meng (1995)	Journal of Comparative Economics	1985	1985	52
2	Meng (1995)	Education Economics	1985	1985	24
3	Meng (1996)	Applied Economics	1985	1985	44
4	Meng and Kidd (1997)	Journal of Comparative Economics	1981	1987	4
5	Meng (1998)	Applied Economics	1995	1995	14
6	Meng (1998)	Labour Economics	1986	1987	36
7	Maurer-Fazio (1999)	China Economic Review	1989	1992	24
8	Liu (2001)	Applied Economics Letters	1988	1988	4
9	Meng and Zhang (2001)	Journal of Comparative Economics	1995	1996	8
10	Zhao (2001)	China Economic Review	1996	1996	16
11	Dong and Bowles (2002)	China Economic Review	1998	1998	28
12	Ho et al. (2002)	Economics of Transition	1999	1999	40
13	Huang et al. (2002)	LABOUR	1995	1998	36
14	Li (2003)	Economics of Education Review	1996	1996	32
15	Heckman and Li (2004)	Pacific Economic Review	2000	2000	4
16	Li and Luo (2004)	Pacific Economic Review	1995	1995	20
17	Appleton et al. (2005)	Journal of Comparative Economics	1988	2002	16
18	Bishop et al. (2005)	Economics of Transition	1988	1995	46
19	Chen et al. (2005)	Economic Development and Cultural Change	1996	1996	20
20	Dong (2005)	Journal of Comparative Economics	1994	2001	44
21	Lui and Wong (2005)	Applied Economics Letters	2000	2000	4
22	Zhang et al. (2005)	Journal of Comparative Economics	1988	2001	28
23	Knight and Li (2006)	China Economic Review	2000	2000	6
24	de Brauw and Rozelle (2008)	Review of Development Economics	2000	2000	10
25	Ma and Ng (2008)	Applied Economics	1997	1997	6
26	Qian and Smyth (2008)	Post-Communist Economies	2005	2005	42
27	Wang and Cai (2008)	Review of Development Economics	2001	2001	16
28	Zhang et al. (2008)	China & World Economy	2005	2005	4
29	Appleton et al. (2009)	Journal of Development Studies	1988	1999	12
30	Bargain et al. (2009)	Review of Income and Wealth	1987	2004	48
31	Deng and Li (2009)	CESifo Economic Studies	1988	2002	6
32	Guo and Hammitt (2009)	Envrionment Resource Economics	1995	1995	16
33	Gao and Smyth (2010)	Journal of Development Studies	2005	2005	8
34	Qiu and Hudson (2010)	Economic Change and Restructuring	1989	2000	8
35	Cai and Du (2011)	China Economic Review	2001	2010	12
36	Gao and Smyth (2011)	Applied Economics Letters	2007	2007	10
37	Li and Dong (2011)	Contemporary Economic Policy	1995	2001	80
38	Mukhopadhyay et al. (2011)	Chinese Economy	2007	2007	12
39	Zhong (2011)	China Economic Review	2002	2002	66
40	Demurger et al. (2012)	China Economic Review	2002	2007	20

41	Kang and Peng (2012)	Post-Communist Economies	1989	2009	20
42	Lee (2012)	China Economic Review	2005	2005	12
43	Mishra and Smyth (2012)	Journal of Environmental Planning and Management	2007	2007	26
44	Ren and Miller (2012)	Journal of Development Studies	2006	2006	16
45	Jia and Dong (2013)	Cambridge Journal of Economics	1990	2005	88
46	Xiu and Gunderson (2013)	LABOUR	1995	2002	84
47	Zuo (2013)	Australian Economic Review	2006	2006	4
48	Mishra and Smyth (2014)	Review of Development Economics	2007	2007	14
49	Xing (2014)	Economics of Transition	2002	2002	20
50	Xue et al. (2014)	China Economic Review	2005	2010	12
51	Cai and Liu (2015)	Journal of Comparative Economics	2002	2002	24
52	Gao and Smyth (2015)	Journal of the Asia Pacific Economy	2001	2010	36
53	Kwon et al. (2015)	Pacific Economic Review	1988	2007	18
54	Mishra and Smyth (2015)	Economic Modelling	2007	2007	8
55	Wang et al. (2015)	China Economic Review	2009	2009	26
56	Hare (2016)	China Economic Review	1991	2011	8
57	Qi and Dong (2016)	Feminist Economics	2008	2008	12
58	Zhang et al. (2016)	China Economic Review	2007	2007	10
59	Zhu (2016)	China Economic Review	2002	2007	32
60	Liu (2017)	Asian Economic Journal	2008	2008	24
61	McLaughlin (2017)	Journal of Comparative Economics	1988	2002	42
62	Qu and Zhao (2017)	China Economic Review	2002	2007	24
63	Li et al. (2018)	Asian Economic Papers	1995	2013	16
64	Ma (2018)	China Economic Review	2002	2013	48
65	Ma (2018)	Post-Communist Economies	2002	2013	42
66	Wang and Lien (2018)	China Economic Review	2013	2013	60
67	Yao et al. (2018)	China Economic Review	2009	2009	20
68	Lyu and Chen (2019)	Urban Studies	2011	2011	12
69	MacDonald and Hasmath (2019)	International Labour Review	2011	2011	36
70	Pan et al. (2019)	China Economic Review	2002	2013	56
71	Peng (2019)	Journal of the Asia Pacific Economy	2010	2010	24
72	Qu et al. (2019)	Economic Research—Ekonomska Istrazivanja	2010	2014	64
73	Wang et al. (2019)	China Agricultural Economic Review	2004	2015	56
74	Zhao et al. (2019)	Economic Research—Ekonomska Istrazivanja	2013	2013	16
75	Asadullah and Xiao (2020)	Structural Change and Economic Dynamics	2010	2015	20
76	Chou et al. (2002)	Economic Research—Ekonomska Istrazivanja	2011	2011	28
77	Gustafsson and Wan (2020)	China Economic Review	1988	2013	20
78	Su et al. (2020)	North American Journal of Economics and Finance	1989	2011	36
79	Zhang (2020)	Australian Journal of Agricultural and Resource Economics	1990	2010	80
80	Hu (2021)	Asian Geographer	2013	2013	30
81	Ma (2021, Chapter 4)	In Ma, Xinxin, Female Employment and Gender Gaps in China	2002	2013	4
82	Ma and Cheng (2021)	Emerging Markets Finance & Trade	2013	2015	6
83	Sun et al. (2021)	Economic and Political Studies	1988	2013	20
84	Li and Zhang (2022)	Economic Research—Ekonomska Istrazivanja	2004	2013	48
85	Liu and Kawata (2022)	Applied Economics	2008	2008	12
86	Ma and Li (2022)	China & World Economy	2013	2018	12

(b) Eastern European studies

No.	Author(s) (Publication year)	Publication media	Estimation period		Number of estimates collected
			From	To	
1	Flanagan (1995)	IMF Staff Papers	1988	1994	12
2	Rutkowski (1996)	Economics of Transition	1987	1993	12
3	Rutkowski (1997)	MOST-MOST	1987	1996	16
4	Bedi (1998)	Journal of Development Studies	1996	1996	8
5	Newell and Socha (1998)	Economics of Transition	1996	1996	24
6	Noorkoiv et al. (1998)	Economics of Transition	1989	1995	20
7	Paternostro and Sahn (1999)	World Bank Policy Research WP No. 2113	1994	1994	8
8	Deloach and Hoffman (2002)	American Economic Journal	1994	1996	12
9	Adamchik et al. (2003)	International Journal of Manpower	1994	2001	48
10	Delteil et al. (2004)	Journal of Comparative Economics	1989	1998	24
11	Falaris (2004)	Journal of Comparative Economics	1995	1995	8
12	Andren et al. (2005)	Journal of Comparative Economics	1990	2000	32
13	Co et al. (2005)	Review of Development Economics	1993	1993	20
14	Gorodnichenko and Sabirianova (2005)	Journal of Comparative Economics	1985	2002	40
15	Munich et al. (2005)	Review of Economics and Statistics	1991	1996	40
16	Ogloblin and Brock (2005)	Economic Systems	2000	2002	4
17	World Bank (2005)	World Bank Ukraine Jobs Study	2003	2004	88
18	Brown et al. (2006)	Journal of Comparative Economics	1997	2003	10
19	Pastore and Verashchagina (2006)	Comparative Economic Studies	1996	2001	24
20	Earle and Telegdy (2007)	In Bender et al. eds., The Analysis of Firms and Employees	1992	2003	6
21	Kazakova (2007)	Economics of Transition	1996	2002	24
22	Csengodi et al. (2008)	Review of World Economics	1992	2001	10
23	Dohmen et al. (2008)	Journal for Labour Market Research	1997	2002	52
24	Krillo and Masso (2010)	Research in Economics and Business: Central and Eastern Europe	1997	2007	8
25	Nestic (2010)	Croatian Economic Survey	1998	2008	32
26	Bouton et al. (2011)	World Bank Policy Research WP No. 5764	2006	2006	14
27	Eriksson and Pytlikova (2011)	Economics of Transition	2006	2006	4
28	Holscher et al. (2011)	Post-Communist Economies	2007	2007	52
29	Kecmanovic and Barrett (2011)	Comparative Economic Studies	2001	2005	32
30	Kovacheva (2011)	Post-Communist Economies	1995	2003	20
31	Pastore and Verashchagina (2011)	Economics of Transition	1996	2006	24
32	Kecmanovic (2012)	Economic Systems	2001	2005	8
33	Mysikova (2012)	Prague Economic Papers	2008	2008	16
34	Tiwari et al. (2015)	World Bank Policy Research WP No. 7291	2006	2010	2
35	Balcar and Gottvald (2016)	Ekonomicky casopis	2008	2014	14
36	Bezeredi and Urban (2016)	Financial Theory and Practice	2012	2012	28
37	Kossova et al. (2020)	Journal of Economic Studies	2016	2016	6
38	Karabchuk et al. (2021)	In Karabchuk et al. eds., Gendering Post-Soviet Space	2000	2015	24
39	Laparsek et al. (2021)	Economic Systems	2015	2015	20

Notes: Estimation period may differ depending on target country. Deteiled bibliographic information of the selected research works is available upon request.

Appendix Table A2. Name, definition, and descriptive statistics of meta-independent variables by study type

Variable name	Definition	Descriptive statistics											
		Studies of wage seniority						Studies of the wage curve					
		Chinese studies			Eastern European studies			Chinese studies			Eastern European studies		
		Mean	Median	S.D.	Mean	Median	S.D.	Mean	Median	S.D.	Mean	Median	S.D.
Average estimation year	Average estimation year	2001.759	2002	8.030	2000.597	2001	6.250	2001.763	2002	8.033	2000.597	2001	6.250
Length of estimation period	Years of estimation period	2.158	1	3.628	1.943	1	3.042	2.158	1	3.628	1.943	1	3.042
Nationwide	1 = if the target region is unspecified, 0 = otherwise	0.141	0	0.348	0.936	1	0.245	0.141	0	0.348	0.936	1	0.245
Urban region	1 = if the target region is urban, 0 = otherwise	0.689	1	0.463	0.059	0	0.236	0.689	1	0.463	0.059	0	0.236
Rural region	1 = if the target region is rural, 0 = otherwise	0.170	0	0.375	0.005	0	0.069	0.170	0	0.375	0.005	0	0.069
All firms	1 = if the target firm is unspecified, 0 = otherwise	0.866	1	0.341	0.842	1	0.366	0.866	1	0.341	0.842	1	0.366
State enterprise	1 = if the target firm is a state enterprise, 0 = otherwise	0.042	0	0.200	0.057	0	0.232	0.042	0	0.200	0.057	0	0.232
Private firm	1 = if the target firm is a private firm, 0 = otherwise	0.092	0	0.290	0.102	0	0.303	0.092	0	0.290	0.102	0	0.303
Panel data	1 = if panel data is employed for empirical analysis, 0 = otherwise	0.073	0	0.260	0.147	0	0.354	0.073	0	0.260	0.147	0	0.354
Cross-sectional data	1 = if cross-sectional data is employed for empirical analysis, 0 = otherwise	0.927	1	0.260	0.853	1	0.354	0.927	1	0.260	0.853	1	0.354
Official household survey	1 = if the results of an official household survey are used as the data source, 0 = otherwise	0.016	0	0.125	0.586	1	0.493	0.016	0	0.125	0.586	1	0.493
Original household survey	1 = if the results of an original household survey are used as the data source, 0 = otherwise	0.984	1	0.125	0.414	0	0.493	0.984	1	0.125	0.414	0	0.493
With intercepted variable	1 = if the independent variable in question is estimated with an intercepted variable(s), 0 = otherwise	0.036	0	0.185	0.035	0	0.185	0.027	0	0.161	0.035	0	0.185
Non-OLS	1 = if an estimator rather than OLS is used for estimation, 0 = otherwise	0.240	0	0.427	0.236	0	0.425	0.240	0	0.427	0.236	0	0.425
OLS	1 = if OLS is used for estimation, 0 = otherwise	0.760	1	0.427	0.764	1	0.425	0.760	1	0.427	0.764	1	0.425
Control for selection bias	1 = if the sample selection bias of employment is controlled for, 0 = otherwise	0.091	0	0.287	0.087	0	0.283	0.091	0	0.287	0.087	0	0.283
Control of endogeneity	1 = if endogeneity between wage variable and the independent variable in question is controlled for, 0 = otherwise	0.003	0	0.052	0.014	0	0.118	0.003	0	0.052	0.014	0	0.118
Occupation	1 = if the estimation simultaneously controls for occupation, 0 = otherwise	0.240	0	0.427	0.395	0	0.489	0.238	0	0.426	0.395	0	0.489
Age	1 = if the estimation simultaneously controls for age or age group, 0 = otherwise	0.066	0	0.248	0.260	0	0.439	0.066	0	0.248	0.260	0	0.439
Health	1 = if the estimation simultaneously controls for health conditions, 0 = otherwise	0.139	0	0.346	0.064	0	0.245	0.139	0	0.346	0.064	0	0.245
Firm size	1 = if the estimation simultaneously controls for the size of firms to which workers belong, 0 = otherwise	0.090	0	0.286	0.407	0	0.492	0.090	0	0.286	0.407	0	0.492
Trade union	1 = if the estimation simultaneously controls for the presence of trade unions, 0 = otherwise	0.102	0	0.303	0.095	0	0.293	0.102	0	0.303	0.095	0	0.293
Location fixed effects	1 = if the estimation simultaneously controls for location fixed effects, 0 = otherwise	0.513	1	0.500	0.546	1	0.498	0.512	1	0.500	0.546	1	0.498
Industry fixed effects	1 = if the estimation simultaneously controls for industry fixed effects, 0 = otherwise	0.334	0	0.472	0.461	0	0.499	0.334	0	0.472	0.461	0	0.499
SE	Standard error of partial correlation coefficient	0.027	0.006	0.419	0.010	0.004	0.043	0.028	0.006	0.417	0.059	0.040	0.095

Note: The variables of nationwide, all firms, panel data, official household survey, and non-OLS are default categories.

Appendix Table A3. Meta-regression analysis of model uncertainty and multicollinearity for the selection of moderators

(a) Studies of wage seniority in China

Estimator	Bayesian model averaging (BMA)				Weighted-average least squared (WALS)		
Meta-independent variables/Model	[1]				[2]		
	Coef.	S.E.	*t*	PIP	Coef.	S.E.	*t*
Focus regressors							
Average estimation year	-0.0005	0.0001	-6.38	1.00	-0.0005	0.0001	-6.02
SE	0.0030	0.0013	2.35	1.00	0.0029	0.0013	2.31
Auxiliary regressors							
Length of estimation period	0.0000	0.0001	-0.14	0.04	0.0000	0.0002	-0.12
Urban region	0.0001	0.0008	0.16	0.05	0.0028	0.0018	1.58
Rural region	-0.0083	0.0020	-4.23	0.98	-0.0046	0.0022	-2.14
State enterprise	0.0003	0.0013	0.23	0.08	0.0030	0.0024	1.25
Private firm	0.0000	0.0004	0.07	0.03	0.0001	0.0018	0.07
Cross-sectional data	-0.0161	0.0024	-6.74	1.00	-0.0133	0.0029	-4.64
Original household survey	-0.0026	0.0051	-0.51	0.25	-0.0102	0.0048	-2.12
With intercepted variable	0.0000	0.0006	0.05	0.03	0.0001	0.0035	0.04
OLS	-0.0017	0.0025	-0.67	0.37	-0.0036	0.0014	-2.53
Control for selection bias	0.0085	0.0037	2.29	0.90	0.0049	0.0025	2.00
Control of endogeneity	0.0070	0.0122	0.57	0.29	0.0187	0.0094	1.99
Occupation	0.0000	0.0003	0.10	0.04	0.0013	0.0013	1.03
Age	0.0001	0.0009	0.16	0.05	0.0009	0.0025	0.34
Health	-0.0055	0.0023	-2.40	0.92	-0.0052	0.0016	-3.26
Firm size	-0.0001	0.0009	-0.07	0.04	-0.0021	0.0025	-0.82
Trade union	-0.0084	0.0022	-3.81	0.99	-0.0054	0.0023	-2.29
Location fixed effects	0.0000	0.0002	0.04	0.03	0.0005	0.0011	0.43
Industry fixed effects	-0.0003	0.0009	-0.37	0.15	-0.0023	0.0012	-1.92
K	1126				1126		

(b) Studies of wage seniority in Eastern Europe

Estimator	Bayesian model averaging (BMA)				Weighted-average least squared (WALS)		
Meta-independent variables/Model	[1]				[2]		
	Coef.	S.E.	*t*	PIP	Coef.	S.E.	*t*
Focus regressors							
Average estimation year	-0.0006	0.0001	-3.75	1.00	-0.0006	0.0001	-3.95
SE	0.0511	0.0220	2.33	1.00	0.0718	0.0221	3.25
Auxiliary regressors							
Length of estimation period	0.0000	0.0001	0.02	0.05	-0.0006	0.0005	-1.23
Urban region	-0.0002	0.0014	-0.15	0.07	-0.0103	0.0061	-1.69
Rural region	0.0300	0.0174	1.72	0.83	0.0234	0.0119	1.97
State enterprise	-0.0001	0.0009	-0.14	0.06	-0.0036	0.0031	-1.16
Private firm	-0.0003	0.0011	-0.24	0.09	-0.0032	0.0024	-1.33
Cross-sectional data	-0.0002	0.0012	-0.18	0.08	-0.0090	0.0051	-1.77
Original household survey	-0.0048	0.0026	-1.82	0.85	-0.0029	0.0017	-1.67
With intercepted variable	-0.0023	0.0042	-0.53	0.28	-0.0081	0.0038	-2.15
OLS	0.0067	0.0022	3.06	0.97	0.0056	0.0021	2.68
Control for selection bias	-0.0001	0.0012	-0.09	0.06	-0.0001	0.0032	-0.03
Control of endogeneity	-0.0120	0.0099	-1.21	0.67	-0.0111	0.0066	-1.69
Occupation	-0.0043	0.0028	-1.54	0.79	-0.0040	0.0019	-2.09
Age	-0.0006	0.0016	-0.34	0.15	-0.0017	0.0021	-0.82
Health	0.0004	0.0016	0.23	0.09	0.0040	0.0030	1.35
Firm size	0.0013	0.0023	0.55	0.29	0.0030	0.0019	1.53
Trade union	0.0000	0.0007	0.01	0.05	-0.0008	0.0026	-0.31
Location fixed effects	-0.0007	0.0015	-0.45	0.22	-0.0027	0.0017	-1.56
Industry fixed effects	-0.0103	0.0018	-5.60	1.00	-0.0081	0.0018	-4.59
K	423				423		

(c) Studies of the wage curve in China

Estimator	Bayesian model averaging (BMA)				Weighted-average least squared (WALS)		
Meta-independent variables/Model	[1]				[2]		
	Coef.	S.E.	*t*	PIP	Coef.	S.E.	*t*
Focus regressors							
Average estimation year	0.0003	0.0001	6.17	1.00	0.0004	0.0001	6.15
SE	-0.0014	0.0009	-1.45	1.00	-0.0014	0.0009	-1.50
Auxiliary regressors							
Length of estimation period	0.0000	0.0000	0.00	0.03	0.0003	0.0002	1.77
Urban region	0.0001	0.0005	0.19	0.06	0.0028	0.0014	1.95
Rural region	0.0000	0.0004	0.09	0.04	0.0035	0.0018	1.96
State enterprise	0.0050	0.0031	1.64	0.80	0.0054	0.0019	2.82
Private firm	0.0065	0.0015	4.44	1.00	0.0058	0.0014	4.14
Cross-sectional data	0.0004	0.0012	0.34	0.13	0.0055	0.0022	2.51
Original household survey	-0.0016	0.0034	-0.46	0.22	-0.0081	0.0039	-2.08
With intercepted variable	0.0021	0.0033	0.63	0.34	0.0042	0.0029	1.43
OLS	0.0154	0.0012	13.04	1.00	0.0130	0.0012	10.55
Control for selection bias	0.0091	0.0019	4.87	1.00	0.0073	0.0019	3.93
Control of endogeneity	0.0000	0.0014	0.03	0.03	0.0009	0.0073	0.12
Occupation	-0.0001	0.0004	-0.18	0.06	-0.0001	0.0010	-0.09
Age	0.0085	0.0022	3.87	0.99	0.0064	0.0019	3.42
Health	0.0000	0.0003	0.13	0.04	0.0006	0.0012	0.50
Firm size	0.0012	0.0022	0.54	0.27	-0.0004	0.0020	-0.21
Trade union	0.0032	0.0026	1.23	0.67	0.0052	0.0019	2.79
Location fixed effects	-0.0001	0.0003	-0.17	0.05	-0.0005	0.0009	-0.55
Industry fixed effects	-0.0047	0.0009	-5.20	1.00	-0.0036	0.0009	-4.21
K	1126				1126		