Life Cycle Wage Dynamics in Urban China *

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Abstract

This study explores the patterns of life cycle wage dynamics in the context of China's transition from a centrally planned labor market to a more market-oriented system. Conventional cross-sectional experience-wage profiles are found to be potentially misleading due to the changing compositions of workforce. This study therefore proposes a decomposition framework applied to repeated cross-sectional wage data, assessing life cycle human capital accumulation (experience effects), cohort-specific productivity (cohort effects), and human capital prices over time (time effects). Findings demonstrate a concave pattern of human capital accumulation, cohort-specific productivity fluctuations related to historical events, and a rise in human capital prices. These dynamics exhibit disparities across different employment ownership types and provincial development levels, underlining the complex interplay of factors shaping wage outcomes during China's labor market transformation.

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1 Introduction

Driven by a series of economic reforms, China's labor markets have undergone a substantial transformation over the past few decades, transitioning from a centrally planned towards a more market-driven system. The evaluation of this transformative process from the perspective of labor market outcomes is of considerable interest and importance. While most existing literature tends to focus on wage determination, centering on static wage differences (e.g., Zhang et al., 2005; Appleton, Song, and Xia, 2005; L. Wang, 2013; Ge and Yang, 2014; Gao and Smyth, 2015), this study aims to explore wage dynamics across life cycles. This approach allows for a deeper investigation into the complex interplay of factors that shape wage trajectories and offers a more dynamic perspective on the labor market.

Initiated in the late 1970s, China's reform and opening-up policies marked a significant shift towards economic liberalization and resulted in rapid economic growth. The Chinese economy, which prior to the reforms was a planned economy with most means of production owned and controlled by the state, underwent a substantial transformation into a socialist market economy. This major economic shift significantly reshaped the demand side of the labor market. On the one hand, changes in industrial composition catalyzed an evolution in the composition of labor demand. On the other hand, the growing economy amplified the need for skilled labor.

Throughout the 1990s and into the early 2000s, China embarked on an extensive restructuring of State-owned Enterprises (SOEs). A pivotal policy introduced in 1997, known as "grasping the large and letting the small go" aimed to maintain state control over the largest enterprises while smaller ones were either privatized or shut down. This shift led to a downsizing of the state sector and spurred the expansion of private enterprises, joint ventures, and foreign-owned firms.

Furthermore, China began embracing foreign investment, marked by the establishment of special economic zones. These zones, serving as testing grounds for market-oriented policies, provided incentives that attracted foreign businesses, further propelling the growth of the non-state sector. China's accession to the World Trade Organization (WTO) in 2001 further increased its participation in global trade and amplified the demand for a skilled and educated workforce.

Concurrently, the labor market itself was subjected to significant reforms, marked by major changes in labor policies. A significant milestone of this transition was the Labor Law implemented in 1995, which established a legal framework for employment contracts and other labor standards. First, the traditional system of lifelong employment, often referred to as the "iron rice bowl" guaranteeing job security but offering limited prospects for career advancement or change, was replaced by contract-based employment. Second, the government-assigned job system was replaced with a labor market mechanism where job positions and job seekers meet in the labor market. Third, the remuneration system underwent a shift from being seniority-based to performance-based, granting employers more discretion in determining wage levels.

On the supply side, several key changes also took place. The resumption of the National College Entrance Examination in 1977, along with the expansion of higher education initiatives starting from the 1980s, resulted in a significant increase in the pool of college-educated labor. Simultaneously, the relaxation of restrictions on rural-to-urban migration allowed a greater influx of individuals into urban labor markets, contributing to a more diverse and dynamic labor force.

This study focuses on the period from 2002 to 2009, a time when the labor market transition was well underway, and both the demand and supply for educated labor were increasing. Clear indications of higher education expansion and structural restructuring are evident in the data, along with disparities in the educational or sectoral composition of employees across different provinces. These factors contribute to complex labor market outcomes, making this period a valuable case for studying life cycle wage dynamics.

To measure these dynamics, this study starts with a straightforward approach: constructing cross-sectional experience-wage profiles where experience is measured as years of potential experience, defined as the period since the end of an individual's formal education. However, due to the changes in the educational composition of the workforce during this period, clear discrepancies are observed when comparing the experience-wage profiles of the total sample with those of individual educational groups. Furthermore, disparities in these profiles across employment ownership types and provincial groups, differentiated by development level, are also observed. At this point, determining the sources of these disparities—whether they stem from variations in education levels, differential returns to experience, or unique abilities inherent to each cohort of workers—remains elusive.

Therefore, I propose a framework that nonparametrically decomposes the repeated cross-sectional age-earnings data into experience, cohort, and time effects, while controlling for education. Experience effects capture life cycle human capital accumulation upon labor market entry; cohort effects reflect the inter-cohort productivity after accounting for education and experience; and time effects capture the prevailing human capital prices at a given time.

However, the estimation faces a well-known challenge due to the collinearity between potential experience (calculated as the calendar year, less the birth year and years of schooling), time (the calendar year), and birth cohort (the birth year). Although this issue is commonly referred to as the Age-Period-Cohort problem (Deaton, 1997), the analysis here focuses on working individuals who have completed their education, making it a fixed characteristic across the dataset. Consequently, education serves as a control rather than a variable in the main decomposition. The collinearity makes it impossible to separately identify the effect of experience from the effect of time or birth cohort without further restrictions. To address this challenge, this study adopts the identifying assumption that there are no wage gains due to experience—namely, no increase in experience effects—during an individual's final working years. This identification strategy was originally exploited by Heckman, Lochner, and Taber (1998) and has been more recently applied by Kuruscu (2006), Huggett, Ventura, and Yaron (2011), and Lagakos et al. (2018).

Applying this method, I uncover a pattern of concave human capital accumulation with experience, fluctuations in cohort-specific productivity tied to historical events, and rising rental prices of human capital. The findings hold under a variety of measurement assumptions. When examining different ownership types, the nonpublic sector reveals steeper increases in experience effects and growth in cohort effects, alongside flatter increases in time effects compared to its public sector counterparts. Similarly, clear disparities are observed based on provincial development levels. Developed provinces display steeper increases in experience effects and growth in cohort effects, and flatter increases in time effects, compared to their less developed counterparts.

These disparities in experience effects can be understood through the lens of human capital investment (Ben-Porath, 1967), on-the-job search (Burdett and Mortensen, 1998), and job matching models with learning (Jovanovic, 1979). In the nonpublic sector, the compensation system incentivizes stronger human capital investment, offers higher job mobility, and requires keeping pace with evolving market demands. Workers in developed provinces benefit from better access to learning resources, a broader range of job opportunities, and more efficient job matching mechanisms. On the other hand, the disparities in cohort effects can be attributed to selection effects and regional disparities, while the variations in time effects reflect the interplay between the demand for and supply of human capital.

2 Data

The data used in this study is drawn from eight consecutive years (2002 to 2009) of the Urban Household Survey (UHS). The UHS, conducted by China's National Bureau of Statistics (NBS), is the only nationally representative microdata source in China that spans consecutive years, starting from the late 1980s.

The NBS adopts a multistage, probabilistic sampling approach to select households triennially from various cities and towns within each province. The process initiates with the selection of cities and towns, advancing to districts, residential communities, and ultimately housing units. A final sample is subsequently determined through random selection from the initial sample, and those selected are asked to respond to surveys. To enhance data representativeness, one-third of the households in the final sample are annually replaced with alternative households from the initial sample. However, there have been inconsistencies in adhering to this design in certain years. The data prior to 2002 is known to overrepresent workers from state and collective enterprises whose response rates are systematically higher than those of workers in nonpublic sectors (see e.g., Ge and Yang, 2014; Feng, Hu, and Moffitt, 2017). Additionally, the UHS does not offer weights before 2002, and from 2002 onwards, it supplies weights that account for the probabilities of selecting a city of a particular size within a province. While the provided weights are not flawless, given that all individuals in similar-sized cities receive the same weight, this study concentrates on the 2002-2009 period and utilizes the available weights.

Due to the limited access to the UHS data, the sample includes only six provinces, which arguably present a representative snapshot of the nation through their geographically dispersed coverage. These provinces include Beijing, Liaoning, Zhejiang, Guangdong, Sichuan, and Shaanxi. Beijing is the capital city located in the north, while Guangdong and Zhejiang are dynamic, high-growth provinces in the southern coastal region. Liaoning is a heavy industrial province situated in the northeast, whereas Sichuan and Shaanxi are relatively less developed provinces located in the southwest and northwest, respectively. I acknowledge that national representativeness may be questionable, while provincial representativeness appears more reliable. As will be demonstrated in the analysis, the differences in wage patterns across provinces are significant.

The primary outcome variable in this study is an individual's wage, which, according to the UHS, encompasses basic wage, bonuses, subsidies, and other labor-related income. It is important to highlight that respondents report their wage income for the survey period, a span of the previous 12 months, irrespective of their actual duration of employment within this period. The dataset includes a variable denoting the number of months a respondent worked within the past year. However, this variable is prone to potential measurement errors. To address this concern and mitigate the potential impacts of extreme values, a systematic approach is employed. Initially, a subsample of respondents who worked for the full 12-month period is identified. For each year within this subsample, an interval is established by excluding the bottom and top 5% of wages. For respondents who worked less than 12 months, an equivalent annual wage is calculated. Observations with values outside the previously established interval, including those from the 12-month worker group, are then removed. This step effectively mitigates measurement errors and the effects of extreme wage values, resulting in a refined variable for the annual wage. Lastly, the nominal annual wage is transformed into the real annual wage using the Consumer Price Index (CPI)[1], with 2015 as the base year. Figure A1 plots the distributions of the log value of real annual wages, illustrating the effectiveness of our approach in handling the wage variable.

The survey data available for this study only provides information on the level of schooling attained. I construct measures for years of schooling, following Zhang et al. (2005)[2]. Labor market analyses often use potential experience as a proxy for actual work experience when data for the latter is unavailable. Potential experience, defined as the years since an individual's formal education ended, provides an estimate of possible workforce participation. In this study, potential experience is computed as the number of years elapsed since a worker finished schooling or turned 18, whichever is lesser[3]. This approach takes into account the minimum working age, ensuring a more accurate approximation of potential work experience.

The sample selection criteria used in this study align with standard practices in the literature on returns to education and experience (Murphy and Welch, 1990; Duflo, 2001; Lemieux, 2006). The sample is limited to employed males aged between 20 and 59 who have positive wages, as potential experience tends to serve as a more accurate proxy for actual experience for males. To fully capture the dynamics of wage evolution across a working life cycle, this study focuses on individuals who have completed their education and are actively engaged in the workforce. In China, the official retirement

[1]https://data.worldbank.org/indicator/FP.CPI.TOTL?locations=CN

[2]Assume the following years of schooling for different levels of education: primary education-6 years, lower secondary education—9 years, (vocational) upper secondary education—12 years, short-cycle tertiary education—15 years, Bachelor's level—16 years, and Master's level—17 years.

[3]Potential experience = age - schooling - 6 for individuals with more than 12 years of schooling, while for others, it is calculated as age - 18.

Table 1. Summary Statistics

	2002	2003	2004	2005	2006	2007	2008	2009	Total
N	7,207	7,955	9,330	10,382	10,216	10,992	12,753	12,675	81,510
Beijing (%)	9.5	10.4	9.5	10.5	10.5	10.5	8.2	9.0	9.7
Liaoning (%)	22.3	23.7	22.8	21.3	20.7	19.7	16.7	17.3	20.1
Zhejiang (%)	9.7	10.5	10.7	10.6	10.3	15.9	17.1	16.7	13.2
Guangdong (%)	26.2	23.0	23.9	24.4	24.4	24.3	28.2	26.3	25.2
Sichuan (%)	23.5	22.3	23.7	23.6	24.4	20.6	20.4	20.9	22.2
Shaanxi (%)	8.9	10.1	9.5	9.6	9.7	9.0	9.4	9.9	9.5
State-owned Units (%)	68.9	66.2	64.6	62.2	60.7	58.9	50.3	52.1	59.4
Urban Collective Units (%)	6.7	6.0	5.7	5.0	4.5	4.5	4.6	4.1	5.0
Joint Venture or Foreign-owned Firms (%)	10.7	11.8	13.6	14.7	16.7	18.2	15.7	16.3	15.1
Private Enterprises (%)	9.8	10.9	11.1	12.9	13.0	14.0	22.7	21.4	15.3
Other Ownership (%)	3.9	4.9	5.0	5.2	5.1	4.4	6.8	6.1	5.3
Primary Education or Below (%)	3.2	3.0	3.1	2.6	2.6	2.2	3.2	2.9	2.8
Lower Secondary Education (%)	27.5	26.6	25.2	25.9	24.3	21.6	23.2	21.7	24.2
Upper Secondary Education (%)	26.6	27.8	27.6	25.7	25.8	25.5	24.0	23.9	25.6
Vocational Upper Secondary Education (%)	11.2	11.6	11.3	10.7	10.5	9.5	9.0	9.2	10.2
Short-cycle Tertiary Education (%)	22.7	21.8	22.2	23.5	24.3	26.1	23.5	23.8	23.6
Bachelor's Level or Above (%)	8.7	9.1	10.6	11.6	12.6	15.1	17.2	18.6	13.5
Schooling (years)	12.0	12.0	12.1	12.2	12.3	12.6	12.5	12.6	12.4
Age (years)	42.0	42.5	42.8	42.8	43.1	42.7	41.8	42.6	42.6
Potential Experience (years)	23.0	23.5	23.7	23.6	23.9	23.3	22.3	23.2	23.3
Average Real Annual Wage (in 2015 RMB)	18,497.7	20,369.2	22,250.7	24,345.3	26,408.8	29,457.2	32,409.3	35,241.0	27,124.6

age for males is 60, setting an upper bound for the age range in the sample. The summary statistics of the sample are presented in Table 1.

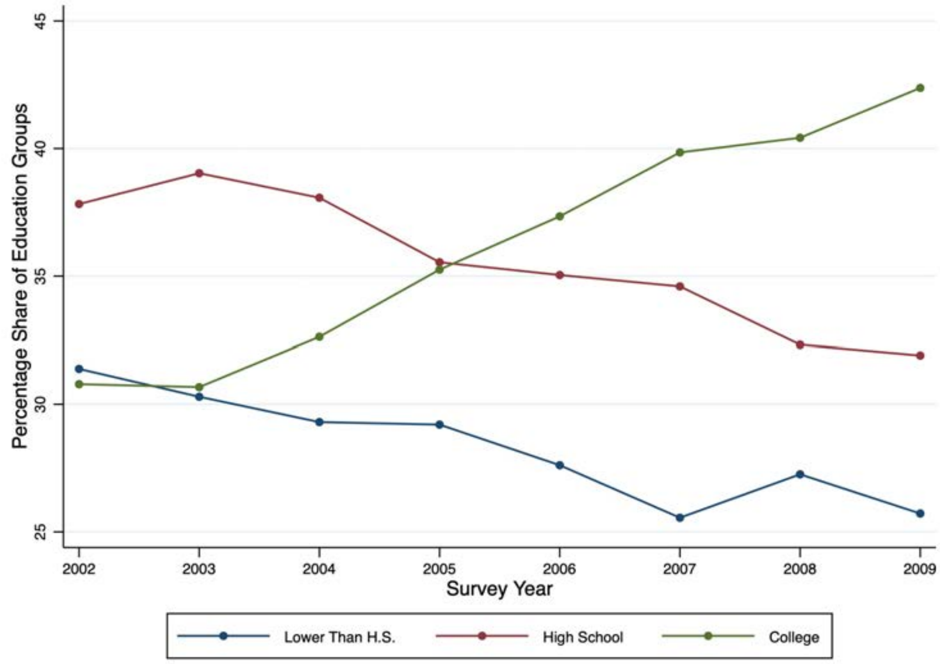
3 Sample Compositions

In order to develop a deeper understanding of our dataset and to provide necessary context for the forthcoming analyses, this section examines the sample compositions across various subgroups within the sample. The subgroups are based on key characteristics including education level, ownership type of employment, and province. Exploring these dimensions helps to uncover the inherent heterogeneity of the sample, which will later inform the examination of life cycle wage dynamics.

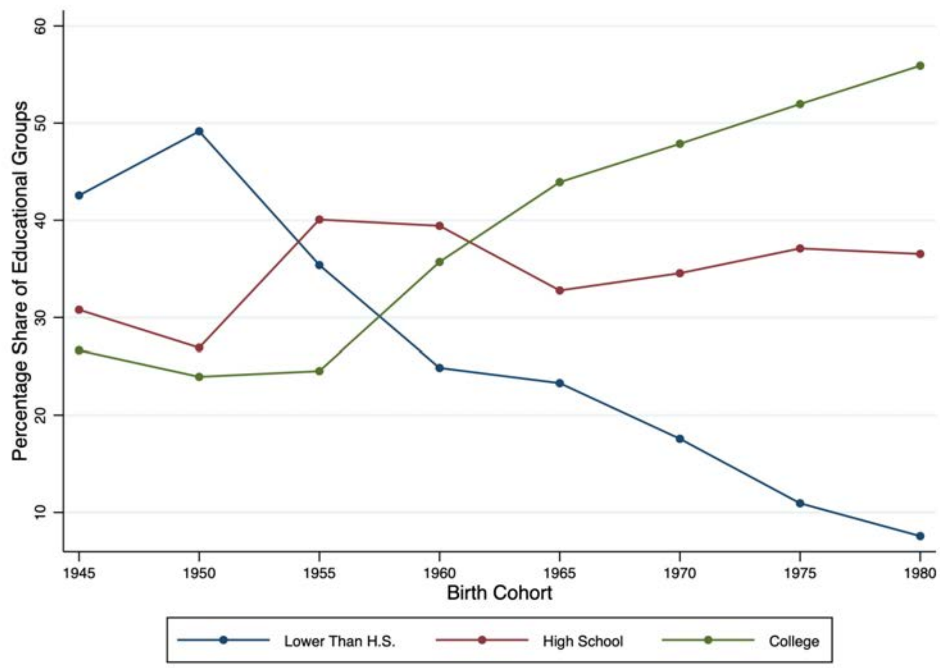
3.1 Sample Compositions by Educational Group

Education level is a key determinant of wage levels, as it often reflects the skills and qualifications that an individual brings to the labor market. To ensure sufficient sample sizes for each group, I divide the sample into three educational groups based on their attained education levels[4].

[4] The College group encompasses Short-cycle Tertiary Education, Bachelor's Level, and higher. The High School group includes Upper Secondary Education and Vocational Upper Secondary Education. The Lower than H.S. group comprises Lower Secondary Education and below.



(a) by Year



(b) by Birth Cohort

Figure 1. Sample Compositions by Year and Cohort, in Terms of Educational Groups

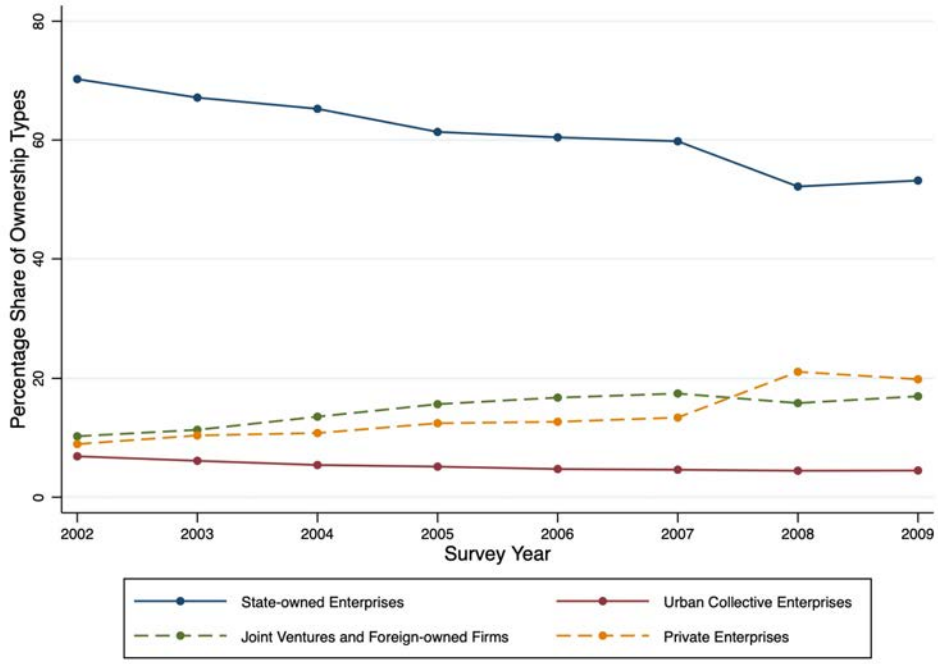
Figure 1a reveals an increasing proportion of college-educated workers in the sample, a trend that started from 2004. This trend becomes even more apparent when looking at cohort-based patterns, as illustrated in Figure 1b. Here, the proportion of college-educated individuals rose for cohorts born between 1960 and 1964 and thereafter. This increase aligns with significant educational policy changes in China, specifically the resumption of the National College Entrance Examination in 1977 and the subsequent expansion of access to higher education from the 1980s onwards. The steady proportion of high school-educated individuals within the sample suggests that the observed trend is not merely a reflection of growing aspirations for higher levels of education but is more likely to be driven by these policy changes.

3.2 Sample Compositions by Ownership Type

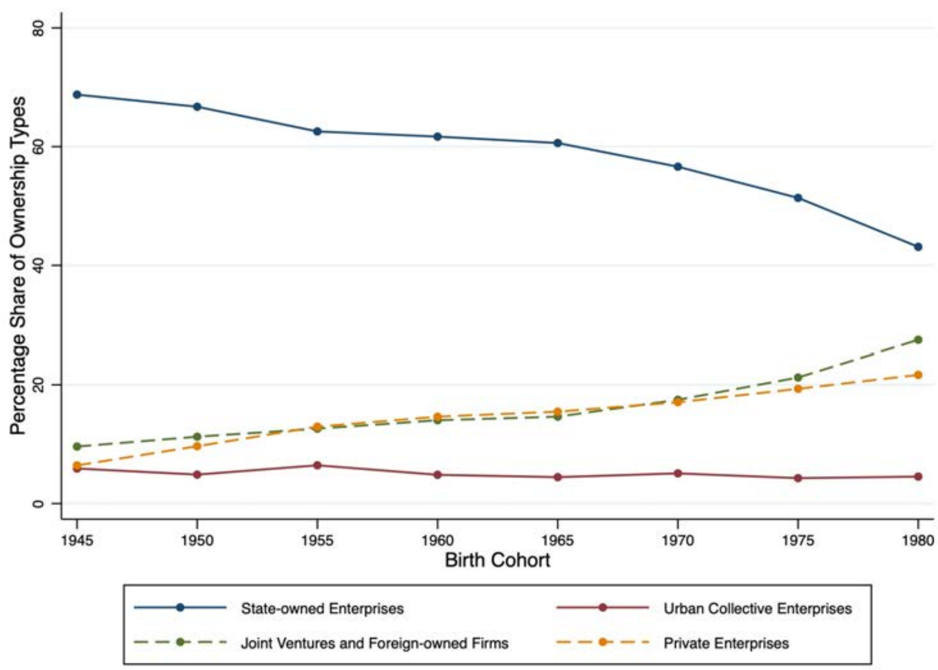
Ownership type in employment has also been identified as a crucial determinant of wage levels in China, particularly in the form of state-sector wage premium (see e.g., Meng, 2012; Ge and Yang, 2014).

Figure 2 provides evidence of the structural dynamics in China's labor market, characterized by the downsizing of SOEs, the expansion of nonpublic sectors including private enterprises and joint ventures and foreign-owned firms (JVFs), and the persistently low share of the urban collective sector. The comparison of year-by-year and cohort-based compositions reveals a trend: as younger cohorts entered the job market, they were increasingly likely to join the nonpublic sector, especially JVFs, over the traditionally dominant SOEs. As a result, there were more young workers in the nonpublic sector than in the public sector. Figure 3 provides more direct evidence of this trend, showing the age distributions across different ownership types. Thus, the downsizing of SOEs can be attributed to two primary factors. First, workers displaced by retrenchment transitioned into the nonpublic sector. Second, younger individuals were increasingly opting for nonpublic sector employment.

Figure 4 shows that workers in SOEs had the highest education levels, with the share of college-educated workers being 11% higher than in JVFs. Urban collectives followed, while private enterprises presented the lowest education levels. This can be understood through several key factors Firstly, during this period, employment in SOEs was still considered a desirable career path. Many positions within this sector demanded high levels of education and offered competitive wages, thus attracting a more educated workforce. Secondly, employment in JVFs was generally associated with high-skill roles, whereas jobs within private enterprises were often perceived as



(a) by Year



(b) by Birth Cohort

Figure 2. Sample Compositions by Year and Cohort, in Terms of Ownership Types

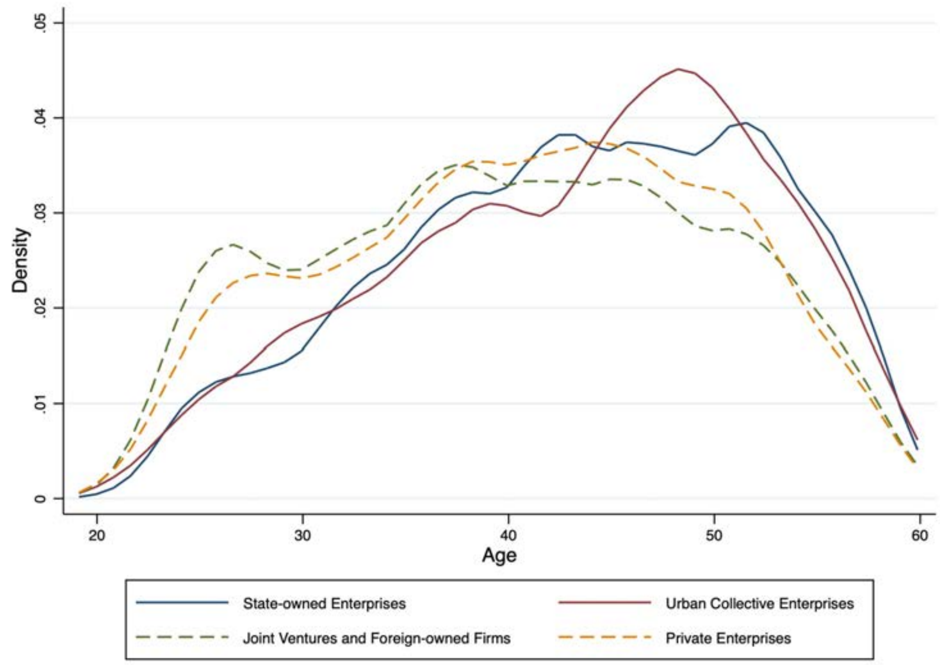


Figure 3. Age Distributions by Ownership Type

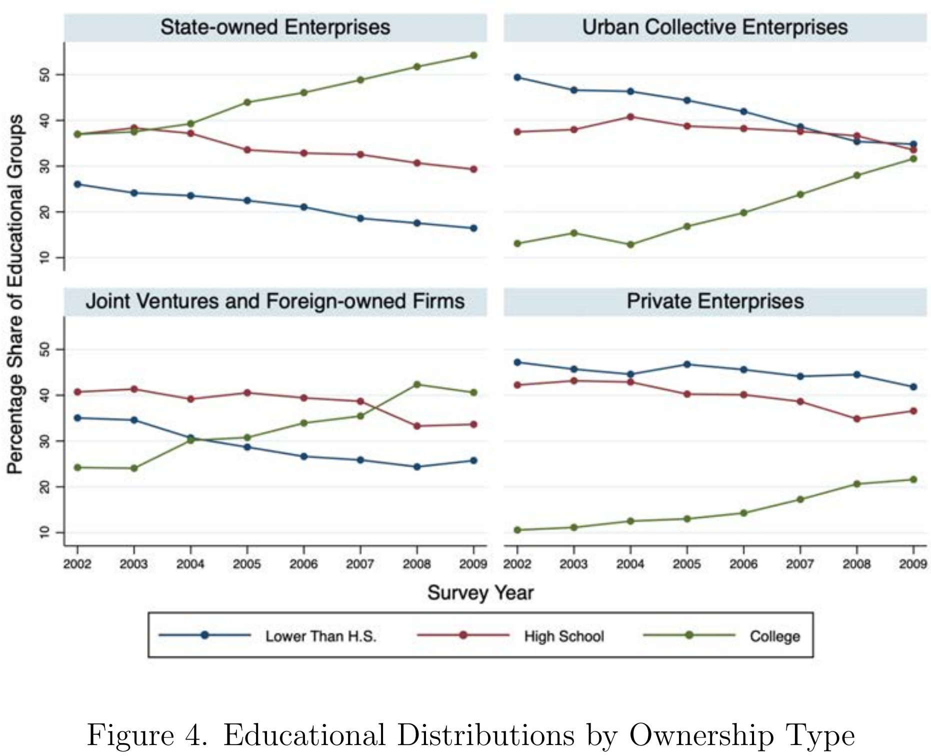


Figure 4. Educational Distributions by Ownership Type

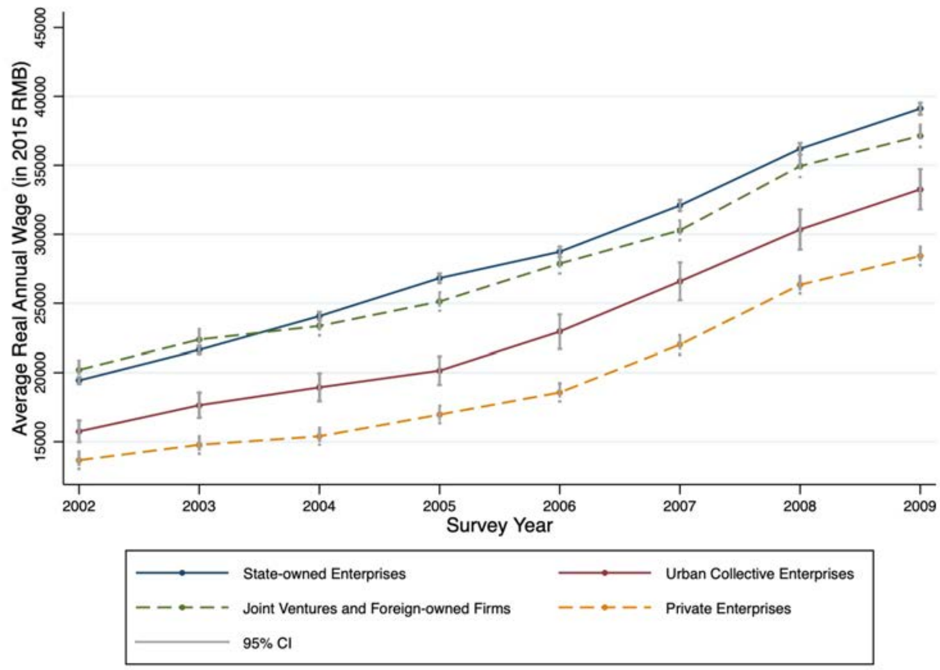


Figure 5. Trends in Average Real Annual Wage by Survey Year for Each Ownership Type

low-skill, explaining the differences in educational attainment across these sectors. Support for these reasonings can be found in Figure 5, which illustrates the patterns of average wages by ownership type.

3.3 Sample Compositions by Province

Given that the data in this study is more representative at the provincial level than at the national level, it is instructive to examine each province separately. Figure 6 shows that the average wages increased in each province, with clear distinctions in wage levels observed between provinces with differing development statuses. The more developed provinces—Beijing, Zhejiang, and Guangdong—showed higher wage levels compared to the less developed ones—Liaoning, Sichuan, and Shaanxi. This wage disparity aligns with the relative development status of these provinces, providing a rationale for dividing the provinces in the sample into two groups: developed provinces and less developed provinces. To better understand what factors contribute to these wage disparities, the distributions of education and ownership types are examined.

Figure 7a reveals that Beijing had high proportions of college-educated workers across all years and also experienced significant increases. Zhejiang and Guangdong,

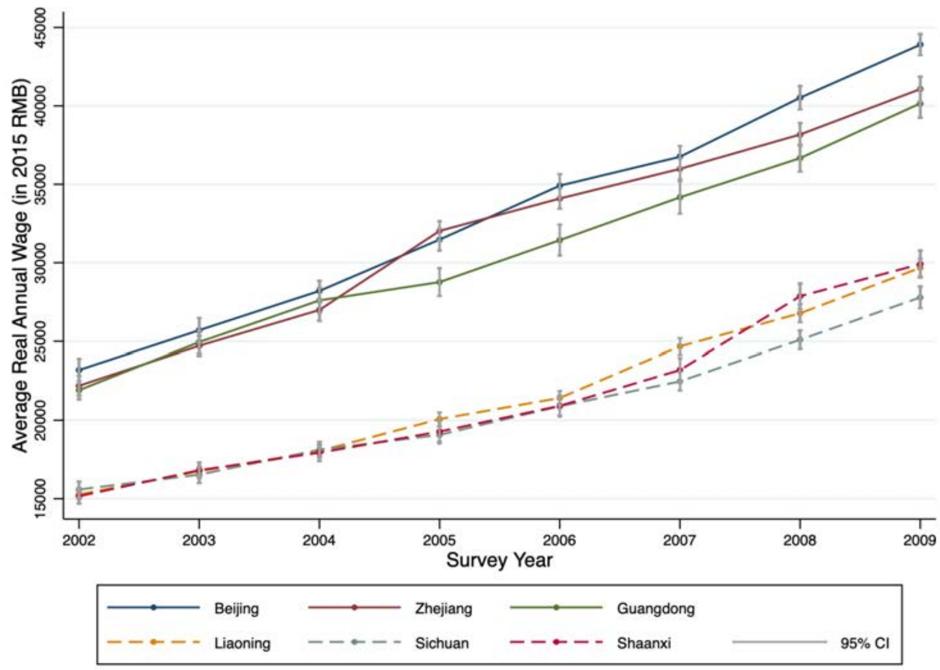
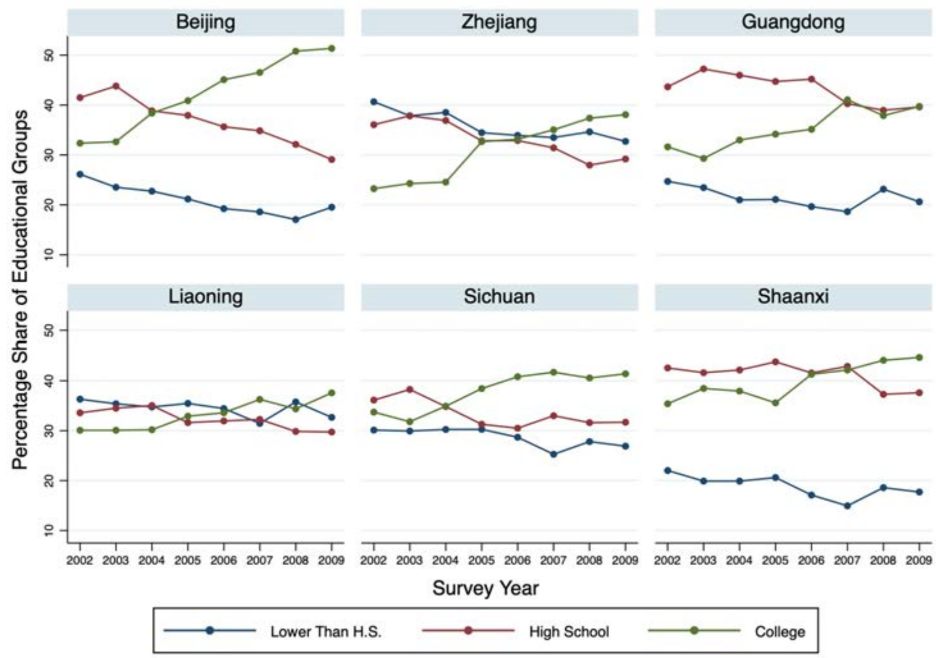


Figure 6. Trends in Average Real Annual Wage by Survey Year for Each Province

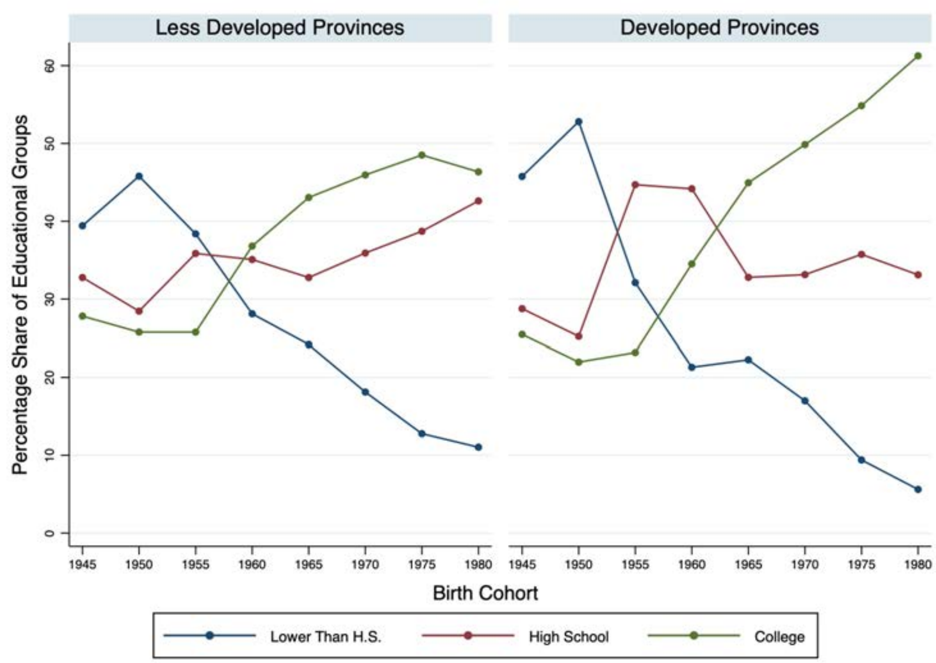
despite starting at lower levels of educational attainment, experienced a higher increase in the proportion of college-educated workers over the years than less developed provinces. Figure 7b provides further evidence, showing that the increase in the proportion of college-educated workers was more pronounced in developed provinces only for cohorts born after 1965. Although less developed provinces began with a proportion of college-educated workers similar to developed provinces in the earlier cohorts, they ended with a much smaller proportion in the more recent ones. This suggests that the effects of the expansion of higher education were particularly significant in developed provinces.

Figure 8a demonstrates that less developed provinces typically had a larger proportion of workers in SOEs and a smaller proportion in JVFs. Although both Beijing and Shaanxi had a dominant share of workers in SOEs, the proportion of workers in JVFs was significantly higher in Beijing. The representation of workers in JVFs in developed provinces was primarily driven by Zhejiang and Guangdong. Figure 8b provides clearer evidence that as more recent cohorts entered the nonpublic sector, those in less developed provinces were more likely to join private enterprises, while those in developed provinces were more likely to join JVFs.

The disparities observed can be traced back to the distinct provincial characteristics

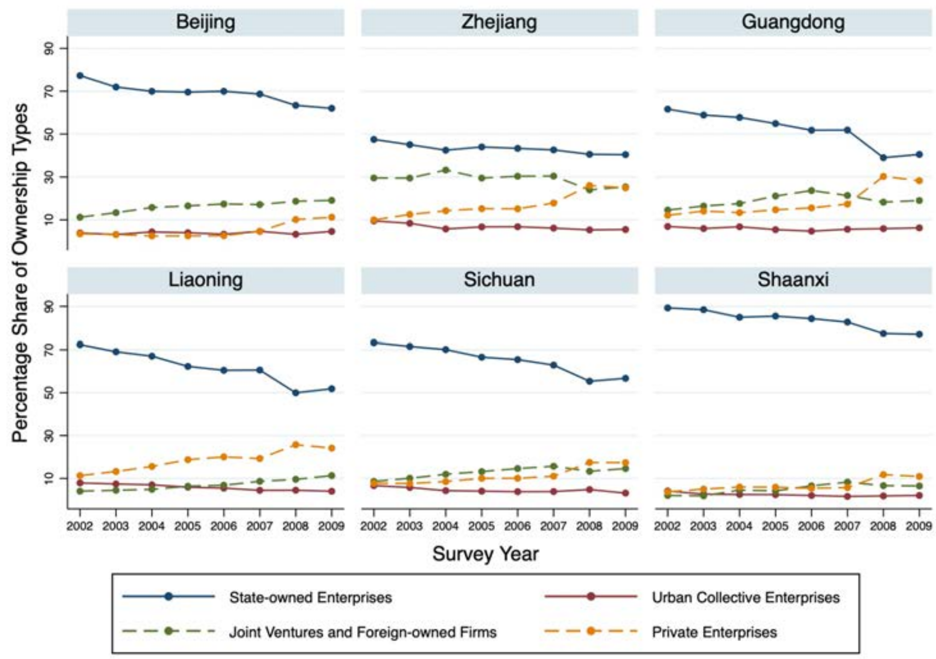


(a) by Year, for Each Province

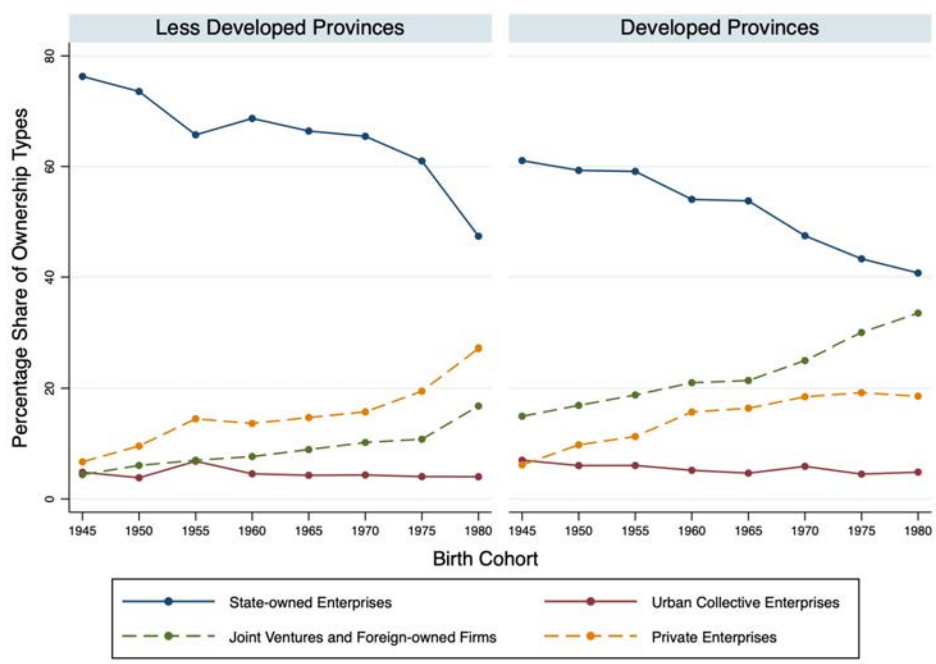


(b) by Birth Cohort, for Each Provincial Development Level

Figure 7. Education Distributions by Province or Provincial Development Level



(a) by Year, for Each Province



(b) by Birth Cohort, for Each Provincial Development Level

Figure 8. Ownership Type Distributions by Province or Provincial Development Level

that shaped each province's socio-economic landscape. Beijing, as the capital and administrative center of China, naturally received the largest allocation of resources. Furthermore, during the early stages of the reform and opening-up period, special economic zones were established as testing grounds for economic reforms. This led to advanced economic liberalization in Beijing, Zhejiang, and Guangdong. Benefiting from their coastal locations, Zhejiang and Guangdong had geographical advantages for attracting foreign investments and multinational firms. Coupled with superior infrastructure and preferential policies, these provinces had a higher share of workers in JVFs. Despite also attracting foreign investment, Beijing had a dominant presence of SOEs, largely due to its status as the capital, which resulted in a relatively smaller share of the nonpublic sector. SOEs typically hold a dominant position in sectors associated with natural resources and fundamental industries. This characteristic was particularly prominent in provinces such as Liaoning, Sichuan, and Shaanxi, where a significant proportion of workers were employed in SOEs. In addition, provinces with stronger economic potential, such as Beijing, Zhejiang, and Guangdong, received more government investment in education. This, in turn, led to a more significant effect of higher education expansion in these provinces.

4 Cross-sectional Evidence on Life Cycle Wage Dynamics

In this section, I present cross-sectional evidence on life cycle wage dynamics. I focus on experience-wage profiles rather than age-wage profiles. As pointed out by Murphy and Welch (1990), the profiles appear more vertically parallel across groups with different education levels when arranged based on experience rather than age, thus supporting Mincer's emphasis on experience over age. The underlying rationale is that age combines years of schooling and work experience, and thus experience-wage profiles provide a cleaner source of life cycle wage dynamics. The composition of China's workforce in terms of education levels has significantly evolved due to the expansion of higher education, a point that will be substantiated in the following sections. This change introduces additional biases when using age-wage profiles to understand wage dynamics. Therefore, focusing on experience-wage profiles offers a more accurate exploration of wage dynamics.

The experience-wage profile is generated by computing the average wage for each 5-year experience bin. To more clearly depict wage dynamic patterns, I also present the percent difference from the average wage of the lowest experience bin (1-5 years of experience).

4.1 Results by Year

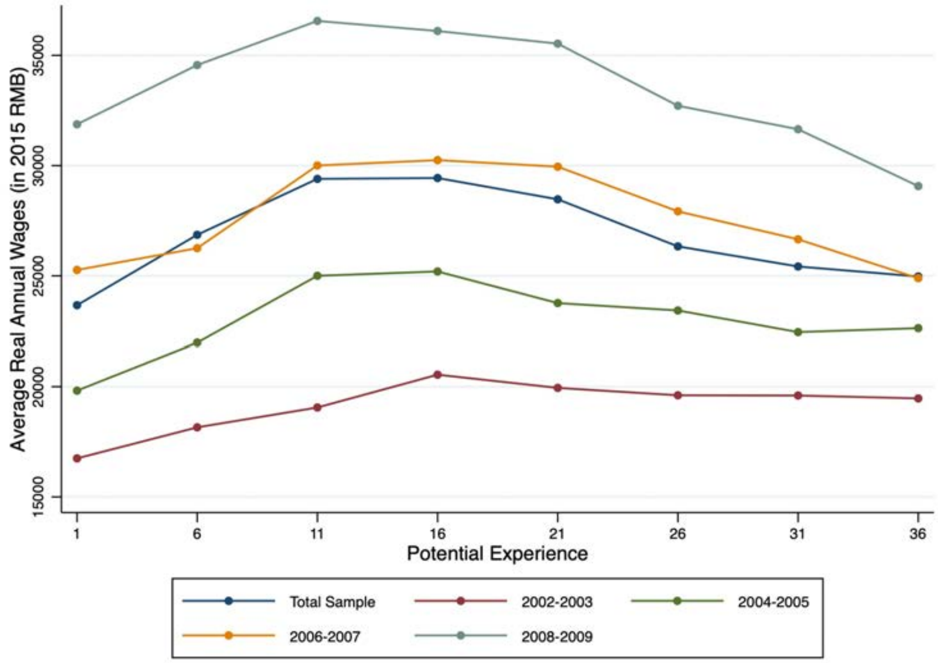
Figure 9 displays experience-wage profiles for each year group (comprising two consecutive years) and for all years in the sample. First, the figure shows an increase in real annual wages by years for all experience bins, which is evident in the significant vertical upward shifts for later cross sections. Second, on average, the profiles exhibit growth until reaching 11-15 years of potential experience, at approximately 24% higher wages, before declining afterward. This decline is more significant for later cross sections (post-2006), resulting in an average wage at the end of the career that is similar to the wage at the beginning. The peak of the cross-sectional experience-wage profiles here is reached earlier and demonstrates a lower level of increase compared to the developing countries studied in Lagakos et al. (2018). However, it is perhaps not entirely accurate, to conclude that one's wages start to decline just after acquiring 11-15 years of experience.

4.2 Results by Educational Group

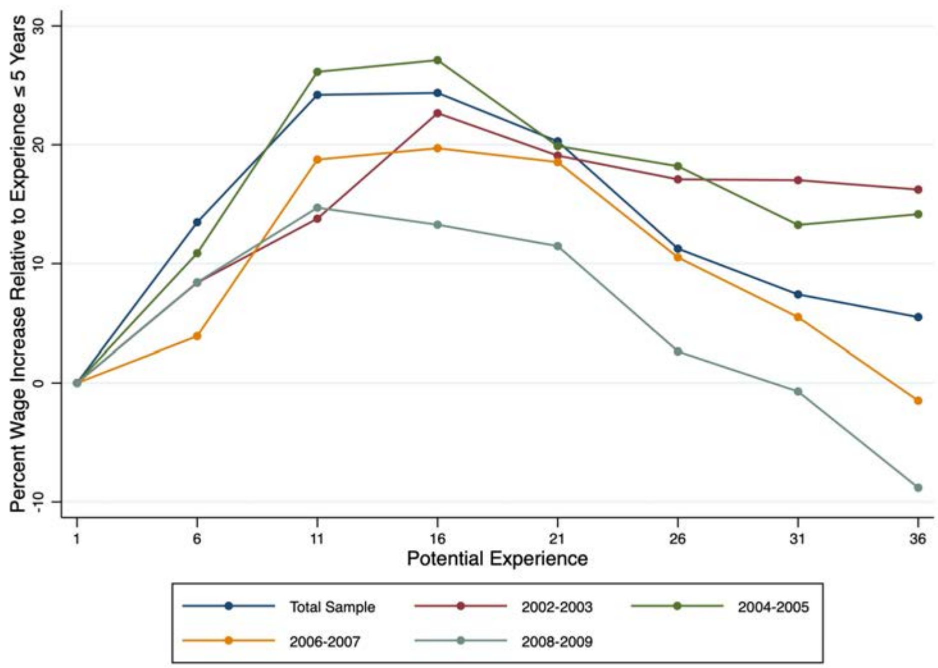
Mincer (1974) introduced a critical empirical innovation in studying the age-earnings profile and its association with education. Thus, it is relevant to conduct a similar analysis in this study.

Figure 10 presents experience-wage profiles for each educational group. As anticipated, higher levels of education corresponded to higher average wages across all experience bins. College-educated individuals began their careers with significantly higher wages compared to their counterparts in other groups and exhibited a smaller percentage increase until reaching 21-25 years of experience. None of the groups exhibited a sustained decline during the final 20 years of experience.

At first glance, it may seem counterintuitive that the profile for the total sample exhibited a smaller percentage increase than each of the three educational groups, and that it declined earlier and more markedly. However, Figure 11 shows that the proportion of college-educated individuals in the sample steadily decreased with the years of experience. Conversely, the proportion of individuals with education levels lower than high school continuously increased, while the proportion of high school-educated individuals remained relatively stable. Given that the average wage level for more-educated individuals was substantially higher for all experience bins, a

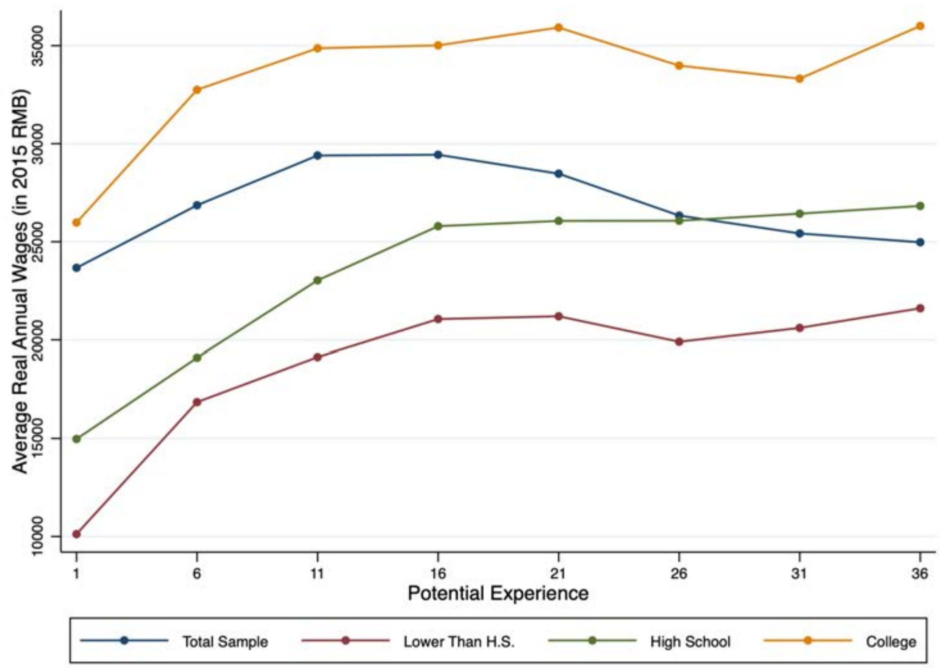


(a) Level

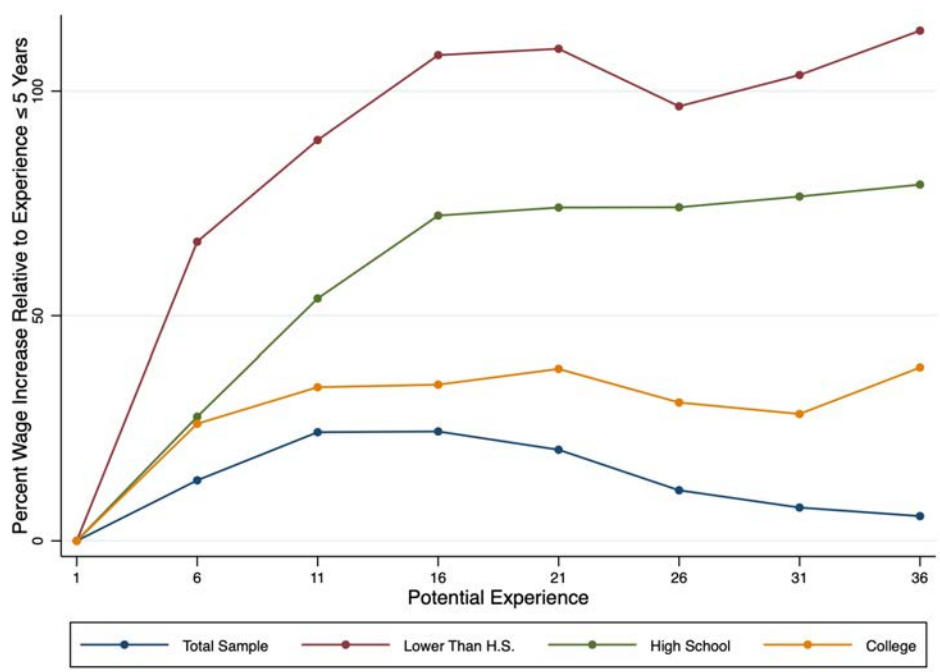


(b) Percent Difference

Figure 9. Cross-sectional Experience-wage Profiles by Year Group



(a) Level



(b) Percent Difference

Figure 10. Cross-sectional Experience-wage Profiles by Educational Group

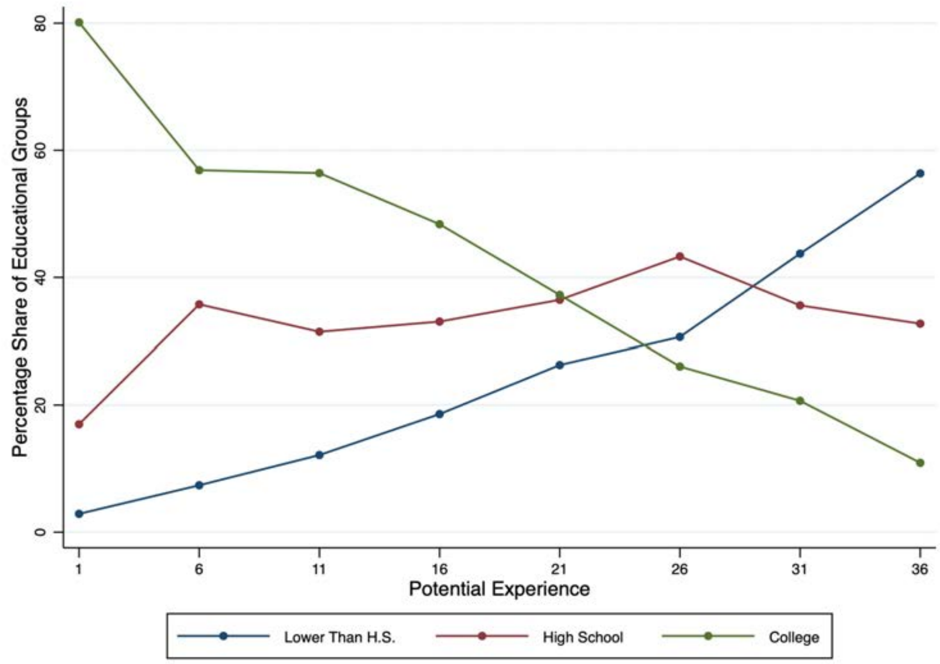


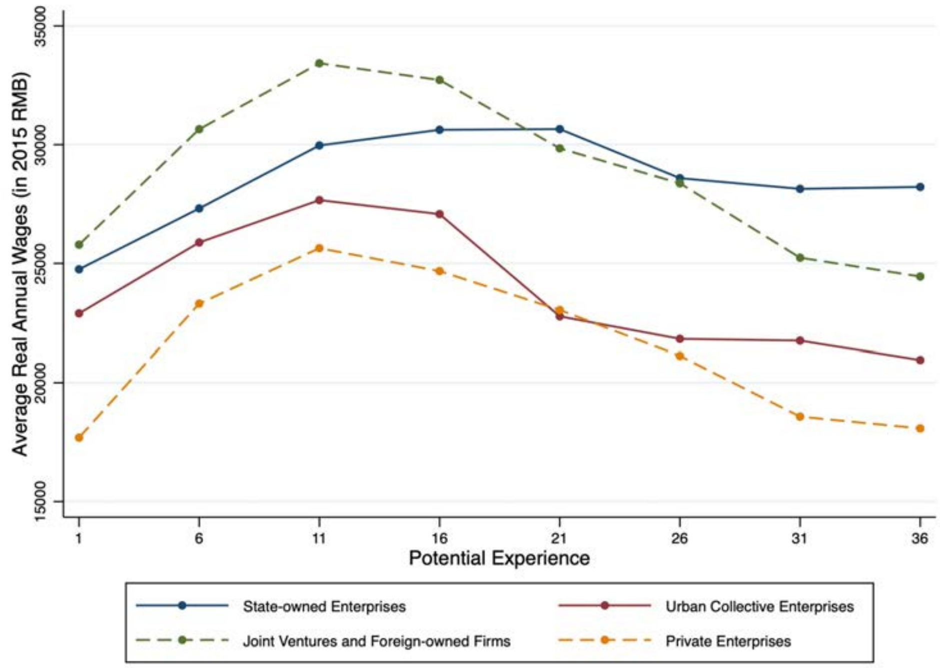
Figure 11. Sample Compositions by Potential Experience, in Terms of Educational Groups

composition effect could lead to a situation where the profile for the total sample may exhibit a decrease despite the increasing trend in profiles for each educational group.

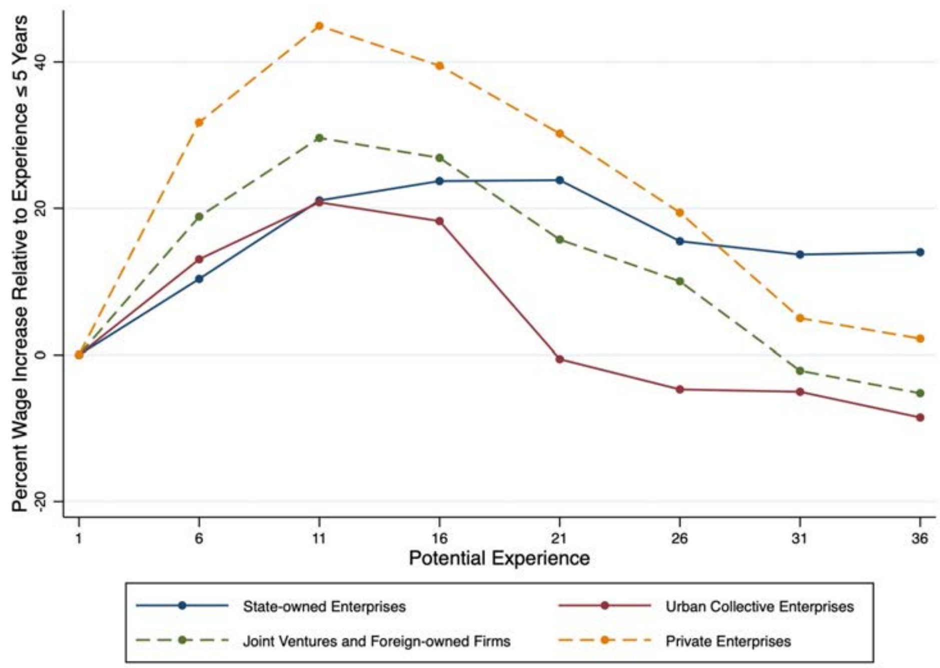
Regarding the shifting workforce composition in terms of education levels, one could argue that this pattern arises from the potential experience calculation and the inherent characteristics of cross-sectional data, particularly the brief observation period relative to the duration of a career. However, evidence from patterns within cohorts (Figure 1b) confirms that the observed shift in workforce composition is largely attributable to the expansion of higher education in China. This change, combined with large disparities in experience-wage profiles among different educational groups, exerts significant composition effects on the overall sample profile. This suggests that using the cross-sectional experience-wage profile as a measure of life cycle wage dynamics in the context of China may be misleading.

4.3 Results by Ownership Type

Figure 12 presents the experience-wage profiles for each ownership type separately. Workers in private enterprises had the lowest average wage levels among the four groups, which could be attributed to their low education levels and low skill requirements of



(a) Level



(b) Percent Difference

Figure 12. Cross-sectional Experience-wage Profiles by Ownership Type

their work. These workers experienced the steepest increase in wages before 30 years of experience, primarily because their starting wages were quite low. Workers in SOEs consistently maintained high wage levels, except for those with fewer than 20 years of experience, where they were surpassed by JVFs. This provides a dynamic perspective on the wage premium associated with different sectors of employment, and reveals the existence of a premium for young workers employed in JVFs.

When comparing the decline in wages at the end of careers in SOEs and JVFs, it is challenging to determine whether this is due to later cohorts in JVFs possessing lower education levels or lower abilities, or whether the experience effects in JVFs for workers approaching the end of their careers are genuinely low. This aspect will become clearer in subsequent sections.

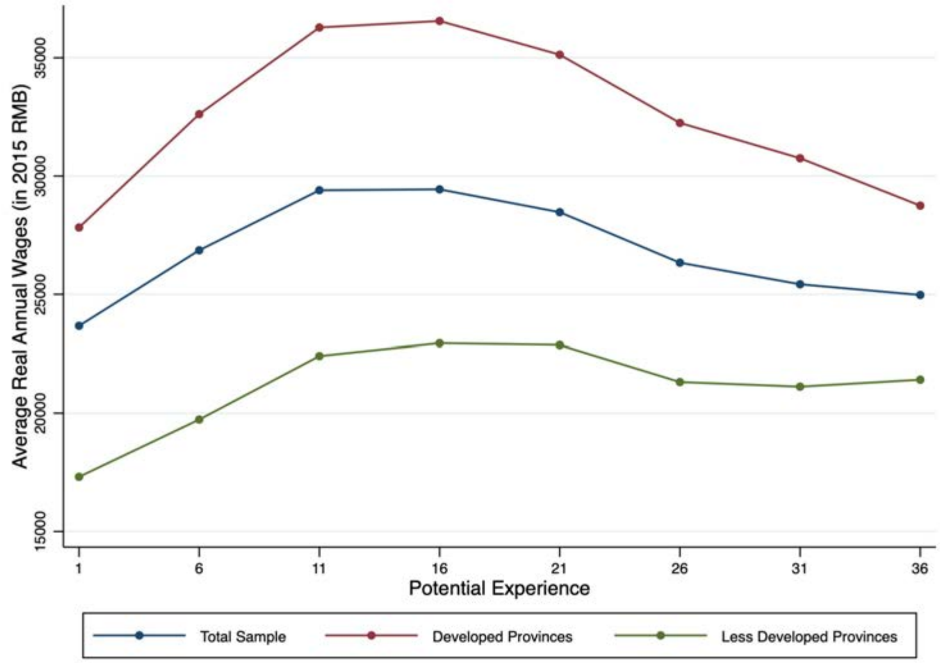
4.4 Results by Provincial Development Level

Figure 13 illustrates that the cross-sectional experience-wage profiles for developed provinces exhibit higher levels, with a slightly steeper increase in the initial 20 years and a steeper decrease thereafter. Given the higher proportion of college-educated and JVFs workers in developed provinces, it could be expected that the wage profiles for these workers were generally higher. Conversely, due to the lower education levels of workers and a higher share of workers in SOEs in less developed provinces, wage profiles there were lower with slightly flatter increases. The composition effects, in terms of education level and ownership type, could account for the higher levels in wage profiles in developed provinces, particularly for younger workers. This complexity makes it challenging to understand how experience in isolation impacted wages across different provinces.

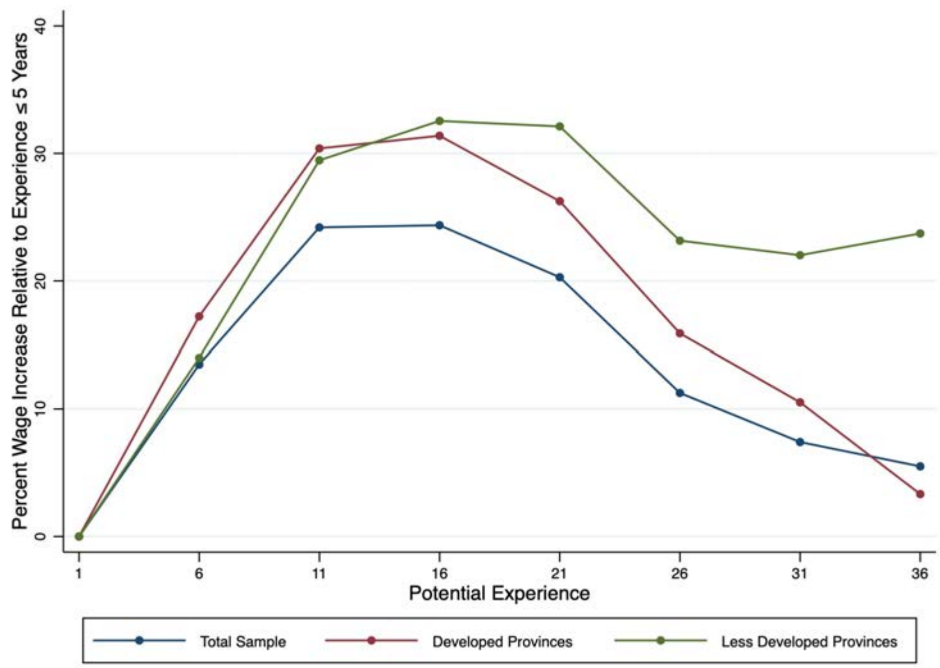
5 Decomposition Framework

The cross-sectional experience-wage profile serves as a valuable starting point for understanding life cycle wage dynamics, as it imposes minimal structure on the data. However, it has been demonstrated that such profiles can be misleading due to the changing compositions of workforce.

Furthermore, it is important to distinguish between a cross-sectional experience-wage profile—which summarizes wages of workers with varying experience levels at a specific point in time—and a life cycle profile, which outlines the trajectory of wages for an individual throughout their career. In the absence of panel data, a life cycle profile



(a) Level



(b) Percent Difference

Figure 13. Cross-sectional Experience-wage Profiles by Provincial Group

could be approximated by tracking a cohort. In a stationary environment, where life cycle profiles remain constant across cohorts, these two types of profiles coincide. However, in a dynamic context such as China, variations in profiles across cohorts are expected, rendering these two profiles distinct. Consequently, disentangling cohort effects is essential to accurately comprehend life cycle wage dynamics. The following sections will start by explaining the construction of the decomposition framework, which is designed to facilitate comprehension of the underlying intuition.

5.1 Setup

According to both human capital theory and a competitive market interpretation, a worker's wage is the product of the price and quantity of human capital. This relationship can be represented as:

$$W_{i,t} = P_t H_{i,t} \tag{1}$$

where $W_{i,t}$ denotes the wage of individual i observed at time t. $H_{i,t}$ represents the quantity of their human capital (measured in efficiency units), and P_t refers to the rental rate (the price of efficiency units) at time t. This formulation assumes that there exists a single price, P_t, and the sole source of heterogeneity among workers lies in the quantity of human capital they possess. Applying the logarithm transformation to both sides of Equation 1 results in:

$$w_{i,t} = p_t + h_{i,t} \tag{2}$$

For simplicity, uppercase letters indicate level values, while lowercase letters represent their corresponding logarithmic values.

Define $h_{c,t}$ as the average log value of human capital held by workers from birth cohort $c(i) = c$ at time t:

$$h_{c,t} \equiv \mathbb{E}\left[h_{i,t} | c(i) = c, t\right]$$

Consequently, Equation 2 can be rewritten as

$$w_{i,t} = p_t + h_{c,t} + \epsilon_{i,t} \tag{3}$$

where c is the birth cohort of individual i and the idiosyncratic component $\epsilon_{i,t} \equiv$

$h_{i,t} - h_{c,t}$ has a zero conditional mean, $\mathbb{E}\left[\epsilon_{i,t}|c(i) = c, t\right] = 0$.

As education and work experience are essential components of human capital and can be potentially observed, I further decompose human capital into three elements:

$$h_{c,t} = h_{c,s} + h_{c,x} + h_{c,c}$$

where $h_{c,s}$ and $h_{c,x}$ are the quantities of human capital acquired through s years of schooling and x years of work experience, respectively. $h_{c,c}$ represents the cohort-specific human capital that is not directly attributable to education or work experience.

It is common to further impose that the accumulation effects of schooling and experience are the same across cohorts, with the notation $h_{c,s} \equiv \alpha_s$, $h_{c,x} \equiv \beta_x$, and $h_{c,c} \equiv \gamma_c$. Consequently, the log value of wages can be decomposed into time effects, schooling effects, experience effects, and cohort effects as follows:

$$w_{i,t} = p_t + \alpha_s + \beta_x + \gamma_c + \epsilon_{i,t} \tag{4}$$

Time effects p_t represent the rental prices of human capital, reflecting macroeconomic factors and shifts in labor market conditions that influence overall wage levels. Schooling effects α_s represent the accumulated human capital from schooling. Experience effects β_x capture the life cycle human capital accumulation that occurs after entering the job market. Cohort effects γ_c account for cohort-specific productivity after controlling for schooling and experience. Cohort differences may arise due to variations in labor market conditions encountered by distinct age groups or other factors influencing productivity across cohorts.

5.2 Identification

Suppose a repeated cross-sectional dataset on log wages $w_{i,t}, t = 1, 2, \ldots, T$ is available, where i denotes an observation and t represents the observed time. For each observation i, the corresponding schooling s, experience x, and cohort c are provided. Typically, the dataset does not include the actual year of work experience; instead, potential experience, calculated as $x = t - c - s$, is used, assuming that the worker remains employed upon completing school. In this context, time dummies, schooling dummies, experience dummies, and cohort dummies would be utilized to capture $p_t, \alpha_s, \beta_x, \gamma_c$ in Equation 4. For each indicator vector, one category must be omitted to serve as the reference group. All estimates for the indicator vector are relative to this reference group. The log wage of the reference group will be incorporated into a constant term.

Therefore, the objective is to estimate the following equation:

$$w_{i,t} = w_0 + \alpha_s + \beta_x + p_t + \gamma_c + \epsilon_{i,t} \tag{5}$$

where $\alpha_s, \beta_x, p_t, \gamma_c$ are vectors of schooling dummies, experience dummies, time dummies, and cohort dummies; $\epsilon_{i,t}$ is a mean zero error term.

This equation follows the common assumption that schooling and experience contribute to the log value of wage in a linearly additive manner, without accounting for potential interactions between these two factors. Compared to Lagakos et al. (2018), this approach allows the relationship between schooling and wages to be more flexible, as it accounts for the possibility that returns to years of schooling may not be linear. This flexibility is particularly relevant for the data in this study, where the observed relationship between years of schooling and wages does not follow a linear pattern (Figure A2).

The identification problem concerning the effects of age (or potential experience), time, and birth cohort is well-known in the literature. Education is typically treated as a separate component rather than being integrated into the main decomposition. This is because the focus is on working individuals who have completed their education, making it a fixed characteristic across the dataset. Despite not being a direct component of the decomposition, controlling for education is essential for a more accurate estimation of the other three terms. With s fixed, collinearity persists among x, t, c. The objective is to understand wage dynamics; however, any trend in the data can be arbitrarily reinterpreted as due to time effects, or alternatively, as due to experience or cohort effects. Without further restrictions, these three terms, experience, time, and cohort effects, cannot be separately identified.

To solve the identification problem, I adopt the method used by Lagakos et al. (2018), which was first proposed in Heckman, Lochner, and Taber (1998). The identifying assumption is that there are no wage gains due to experience, i.e. no increase in experience effects, in the last few years of an individual's working life. This assumption aligns with the theoretical predictions of human capital investment (Ben-Porath, 1967), on-the-job search (Burdett and Mortensen, 1998), and job matching models with learning (Jovanovic, 1979)[5]. As individuals approach the end of their working lives, the incentives to invest in human capital formation or to search for better job matches are believed to diminish, effectively reaching zero. Compared to

[5]Rubinstein and Weiss (2006) provide a literature review on life cycle wage dynamics and explain the three mechanisms in detail.

the approach by Deaton (1997) , which attributes all labor productivity growth to cohort effects and uses year dummies to capture only cyclical fluctuations, the HLT approach offers several benefits. Firstly, it draws on economic theories to motivate restrictions on time and cohort effects. Secondly, it preserves the interpretation of each term, allowing for a better understanding of the underlying mechanisms.

Intuitively, by tracking a fixed cohort across multiple cross-sectional observations during the final years of their working lives, both cohort effects (by design) and experience effects (by assumption) can be excluded, leaving only time effects. Next, experience effects can be estimated by tracking a fixed cohort who are not approaching the end of their life cycle, as cohort effects are ruled out and time effects have been obtained. Finally, comparing across cohorts allows for the estimation of cohort effects, since the other two effects have already been estimated.

The HLT identification approach requires an assumption about the flat region of experience, which is a period where there is no growth in the experience effect. Bowlus and Robinson (2012) proposed benchmark flat age ranges of 50–59 for college graduates, 48–57 for some college, 46–55 for high school graduates, and 44–53 for high school dropouts. These ranges roughly correspond to the last 10 years of experience, once the years of schooling have been deducted. Following Lagakos et al. (2018), I examine the assumption of no growth in experience effects during the last 10 or 5 years of a worker's career and present the results adopting the 10-year flat region in the main analysis. In addition, as observed in this study and aligning with the findings of Fang and Qiu (2021), the peak of cross-sectional experience-wage profiles in China occurs much earlier than in other countries. Therefore, I also extend the analysis to explore the flat region of the last 15 years of a career. This approach has the added benefit of allowing for an initial increase followed by a decrease in the final 5 years, which naturally accounts for the depreciation of human capital.

5.3 Algorithm

In practice, I generally follow Lagakos et al. (2018), grouping experience and cohorts into 5-year bins. Equation 5 is then transformed to

$$w_{i,t} = w_0 + \sum_{s \in S} \alpha_s D^s_{i,t} + \sum_{x \in X} \beta_x D^x_{i,t} + \sum_{c \in C} \gamma_c D^c_{i,t} + gt + \tilde{p}_t + \epsilon_{i,t} \tag{6}$$

where $D^s_{i,t}$ is a dummy for education level; $D^x_{i,t}$ is a dummy for experience group $x \in X = 6 - 10, 11 - 15, \ldots, 36 - 40$; and $D^c_{i,t}$ is a dummy for cohort group $c \in C =$

$1945-1949, 1950-1954, \ldots, 1980-1984$. $\tilde{p}_t$ represents fluctuations orthogonal to a linear time trend such that $\sum_t \tilde{p}_t = 0$ and $\sum_t t\tilde{p}_t = 0$. In this way, the time series p_t is represented as a linear trend gt plus fluctuations $\tilde{p}_t$.

The advantage of this approach is that for a given value of time trend g, the procedure of Deaton (1997) can be applied to the deflated wage $\tilde{w}_{i,t} \equiv w_{i,t} - gt$, generating estimates corresponding to this specific g. The problem then becomes determining the value of g, which is pinned down by the HLT assumption in this case. The process begins with an initial g guess, followed by the estimation of the corresponding experience effects. If these effects do not satisfy the HLT assumption, an update to the g guess is made by considering the annualized experience effect in the specified flat region from the current iteration, moderated by a damping factor. This iterative process continues until the experience effects satisfy the HLT assumption.

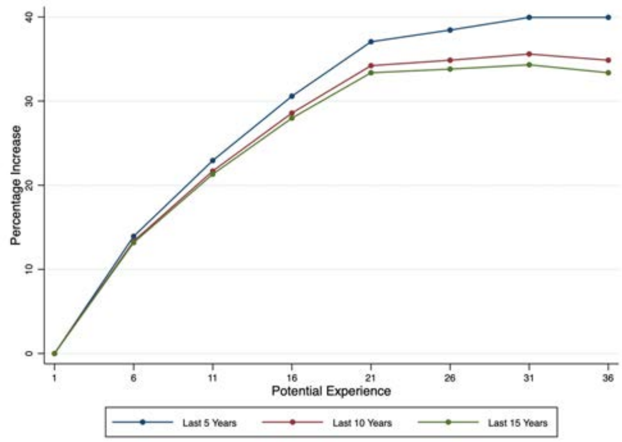
After obtaining the estimates for each term, I employ a series of transformations to facilitate a more intuitive interpretation. I convert β_x into $\mathrm{B}_x = 100[\exp(\beta_x) - 1]$, which is interpreted as the percentage change in accumulated human capital quantity for a given experience group x, relative to the reference group (1-5 years of experience). Likewise, I transform γ_c into $\Gamma_c = 100[\exp(\gamma_c) - 1]$, representing the percentage change in cohort-specific productivity for group c compared to the reference cohort (those born in 1940-1944). Lastly, I compute the rental prices of human capital at time t as $\mathrm{P}_t = \exp(gt + \tilde{p}_t)$. These transformations enable a direct interpretation of the coefficients in terms of wage levels, which better aligns with the study's objectives compared to interpreting coefficients in the context of log-transformed wages.

6 Decomposition Results

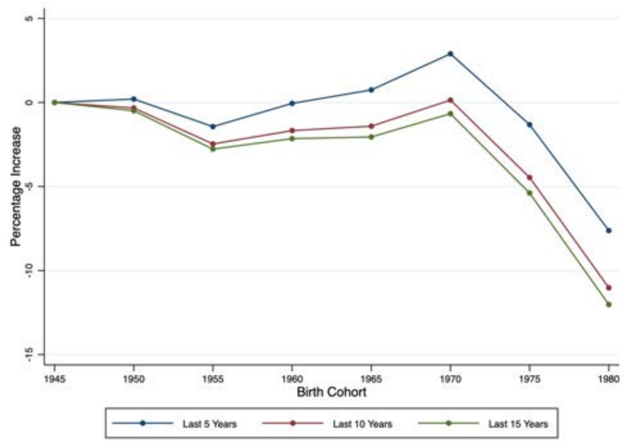
6.1 Baseline Results

Figure 14 presents the results from the decomposition of earnings into experience, cohort, and time effects under the assumption that there is no growth in experience effects during the last 5, 10 or 15 years of a worker's career. The profiles across these assumptions share similar shapes, revealing heightened experience and cohort effects when adopting the 5-year flat region. Variations in the levels across these profiles are observed due to the fact that as the number of years with assumed no growth increases, the experience-wage profiles mechanically become flatter.

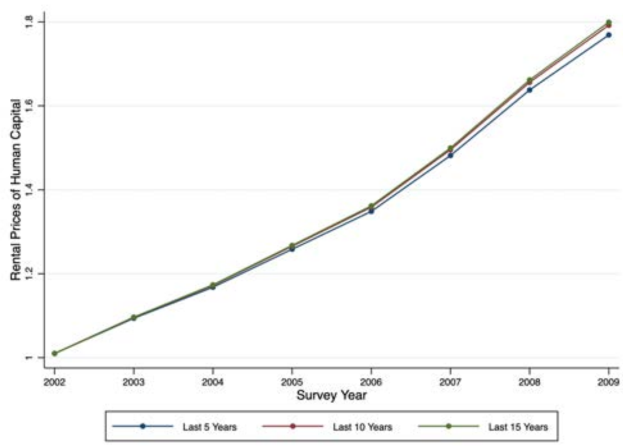
After controlling for education, cohort, and time, the estimated experience-wage profiles were concave and exhibited an increase of approximately 35% by 26-30 years of



(a) Experience Effects



(b) Cohort Effects



(c) Time Effects

Figure 14. Decomposition Results for Varying Assumption Parameters

Table 2. Experience, Cohort, Time Decomposition

Flat Region	Spefication	Experience Effects		Cohort Effects		Time Effects	
		16-20	36-40	1960-1964	1980-1984	2005	2009
Last 5 Years	Baseline	30.58	39.95	-0.06	-7.62	1.26	1.77
	Ownership FE	34.49	47.06	1.57	-0.27	1.27	1.81
	Province FE	38.88	50.31	3.80	-4.82	1.24	1.69
	Approximate Experience	32.89	48.81	10.77	5.47	1.15	1.42
Last 10 Years	Baseline	28.57	34.86	-1.67	-11.03	1.27	1.79
	Ownership FE	32.36	41.53	-0.13	-4.04	1.27	1.83
	Province FE	35.47	41.64	1.11	-10.38	1.25	1.72
	Approximate Experience	27.80	31.82	1.75	-9.39	1.23	1.66
Last 15 Years	Baseline	27.97	33.37	-2.15	-12.02	1.27	1.80
	Ownership FE	30.51	36.86	-1.59	-7.22	1.28	1.85
	Province FE	35.14	40.82	0.86	-10.91	1.25	1.72
	Approximate Experience	26.46	27.59	-0.55	-13.01	1.25	1.73

experience. That is, the quantity of human capital accumulated by workers with 26-30 years of experience was 35% greater than that for workers in the first 1-5 years upon labor market entry. The rental prices of human capital increased continuously, reaching a level 80% higher in 2009 than it was in 2002. The increase became notably steeper after 2006, a trend largely attributable to the increased demand for human capital in the face of globalization and technological advancements, despite a concurrent rise in supply.

The fluctuations in cohort-specific productivity were relatively small. The 1950-1959 cohort faced significant challenges during their formative years, as they experienced both the Great Famine (1959-1961) in their childhood and the Cultural Revolution (1966-1976) in their adolescence. The widespread social chaos during this period severely impacted the opportunities available to this generation. Following these events, improved health conditions and labor market conditions led to inter-cohort human capital growth. Then there was a significant decrease starting from the 1970-1974 cohort. This may be attributable to the higher education expansion. As more people enrolled in college, the range of abilities among students likely became more diverse Consequently, a larger proportion of college graduates may not have exhibited the same productivity levels as their counterparts from earlier cohorts, when access to higher education was more limited.

6.2 Robustness

Before delving into the decomposition results for different subgroups, I present a robustness check of the decomposition result using alternative specifications, as listed in Table 2.

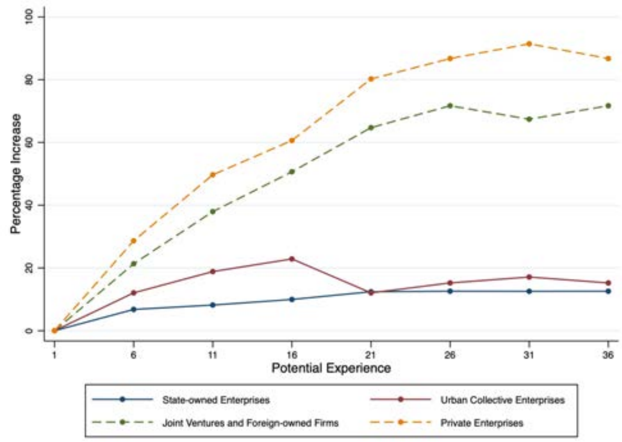
First, under all specifications, the levels of experience effects and cohort effects are smaller when the number of years with assumed no growth is higher. However, these differences are relatively minor, indicating the robustness of the findings to alternative restrictions imposed by the HLT method.

Under each flat region assumption, I control for the fixed effects of ownership type and province in the second and third rows, respectively. However, these fixed effects only account for the level differences in wage determination. Seeing a similar pattern to the baseline does not necessarily mean there are no differences across ownership types or provinces.

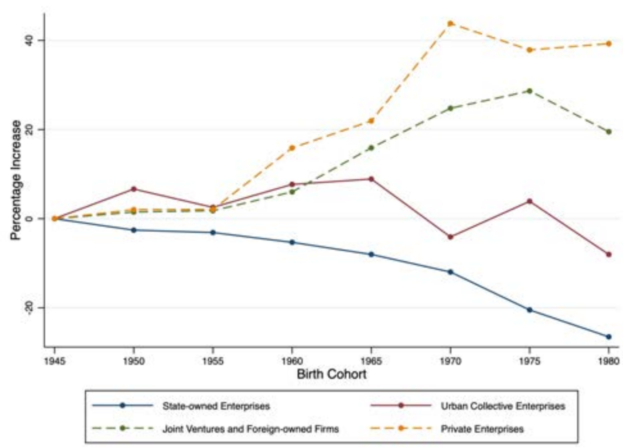
Moreover, I consider an alternative measure for experience. In the baseline model, potential experience is computed as $\min\{\text{age} - \text{edu} - 6, \text{age} - 18\}$. The UHS provides data on the year the respondent started their first job. I calculate the difference between the survey year and the year of the first job, defining it as approximate experience. This could represent actual experience if the respondent has been continuously employed since entering the job market. The results are more robust when assuming that there is no growth in the experience effect in the last 10 years, further supporting the choice of the assumption used in the main analysis.

6.3 Results by Ownership Type

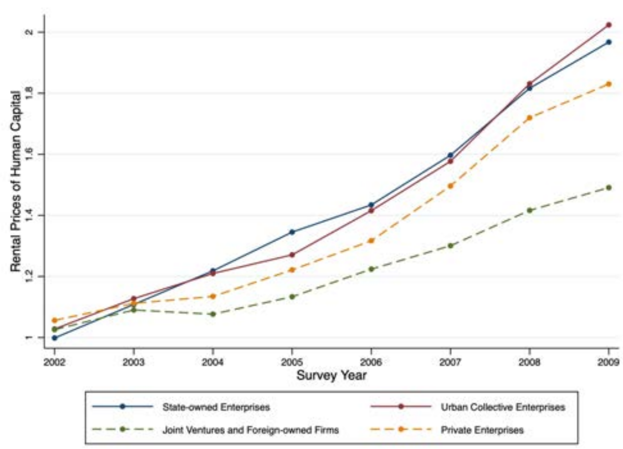
The decomposition results by ownership type, as displayed in Figure 15, provide more explicit evidence of the impact of China's restructuring process. While it has been shown that the experience-wage profiles of workers in JVFs and private enterprises are significantly different in terms of levels and do not exhibit similar rates of increase (Figure 12), these profiles appear much more similar after the decomposition process. Likewise, the experience effects and cohort effects for SOEs and urban collectives are comparable. The decomposition process reveals more pronounced differences between the experience effects and cohort effects of workers in public and nonpublic sectors, highlighting the distinction between these two groups.



(a) Experience Effects



(b) Cohort Effects



(c) Time Effects

Figure 15. Decomposition Results by Ownership Type

A. Experience Effects

Workers in the nonpublic sector showed a more significant accumulation of human capital throughout their careers. In contrast, their counterparts in the public sector experienced relatively modest growth, around 15% over 40 years of experience.

A crucial aspect of China's labor market transition during this period was the shift from a seniority-based to a performance-based compensation system. The nonpublic sector, influenced more significantly by market forces, aligned more closely with this latter model where compensation was tied to employee productivity. This structure provided a strong incentive for workers in the nonpublic sector to invest in their human capital, consistent with Ben-Porath (1967) model of human capital investment, as they could directly reap the benefits of improved performance through higher wages.

Moreover, new labor laws promoting contract-based employment were more aggressively implemented in the nonpublic sector. This system offered increased job mobility, thus facilitating more frequent "on-the-job" searches, as outlined in Burdett and Mortensen (1998). This dynamic environment motivated workers to proactively develop their skills and knowledge, preparing them for the pursuit of improved opportunities. The process of seeking and transitioning between jobs provided invaluable learning experiences, exposing them to a variety of roles, tasks, and work environments. These experiences not only bolstered their current work performance but also cultivated adaptability and preparedness for future roles, thus contributing to a more pronounced growth in their human capital. In contrast, jobs in the public sector were transitioning more gradually towards the new system, still offering a degree of lifelong job security, stable income, and benefits. As a result, job mobility in the public sector was somewhat restricted, which in turn limited the opportunities for skill enhancement and human capital accumulation.

Finally, work in the nonpublic sector tended to be within a context characterized by intense competition, evolving market demands, and progressive technological advancements. These dynamics necessitated employees not only to continuously acquire new skills in line with technological advancements, but also to adapt their roles and responsibilities to meet the changing market demands and competitive forces. This consistent learning and adaptation significantly contributed to their human capital growth. In contrast, work in the public sector generally offered a more stable and predictable environment, with less emphasis on frequent skill enhancements or role adaptations. This stability potentially limited opportunities for continuous learning and human capital accumulation As a result, the experience effect, reflecting human capital accumulation over time, was less pronounced in the public sector.

B. Cohort Effects

Cohort-specific productivity for workers within the nonpublic sector showed a significant growth as birth cohorts became more recent. Conversely, it demonstrated a decline for workers within the public sector. A plausible interpretation of this pattern leans toward selection effects.

The performance-based compensation systems of the nonpublic sector inherently attracted more productive individuals. This effect was amplified for the more recent cohorts, typically better educated and provided with more opportunities, enabling them to discern and leverage these advantages. Consequently, this resulted in an uplift in the average productivity of these recent cohorts within the nonpublic sector.

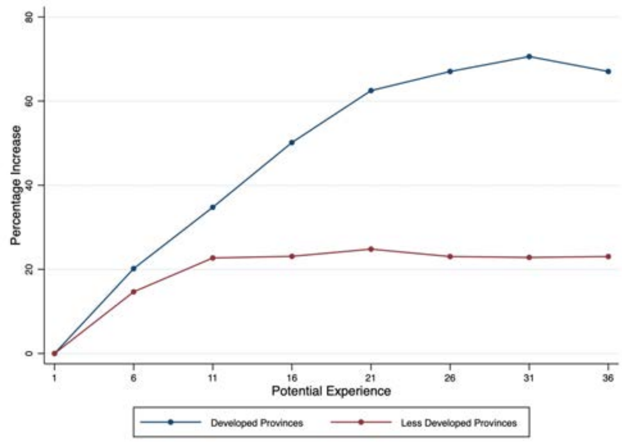
On the other hand, during the period of economic restructuring, those who retained employment post-retrenchment in the public sector generally had relatively high productivity. However, the younger cohorts opting to enter the public sector were not necessarily the most productive individuals. This led to a decrease in cohort-specific productivity within the public sector, especially SOEs.

C. Time Effects

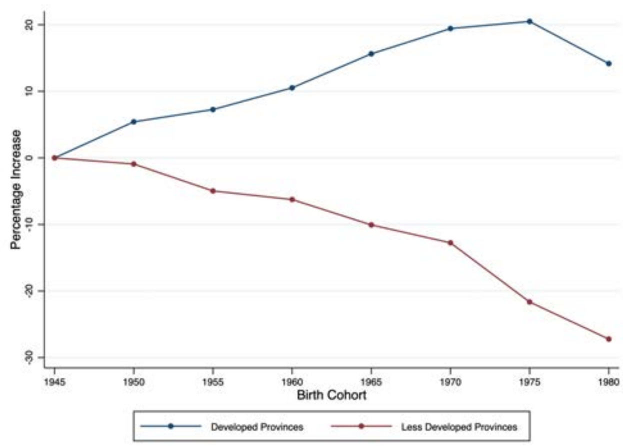
The prices of human capital are a reflection of the equilibrium between demand and supply. The prices in SOEs and urban collective enterprises were found to be similar and slightly higher than those in private enterprises, while significantly higher than those in JVFs. These groups followed an upward trend similar to that of the total sample, with a more pronounced rise post-2006. The relatively slower trend for JVFs can be attributed to a higher increase in the supply of human capital.

6.4 Results by Provincial Development Level

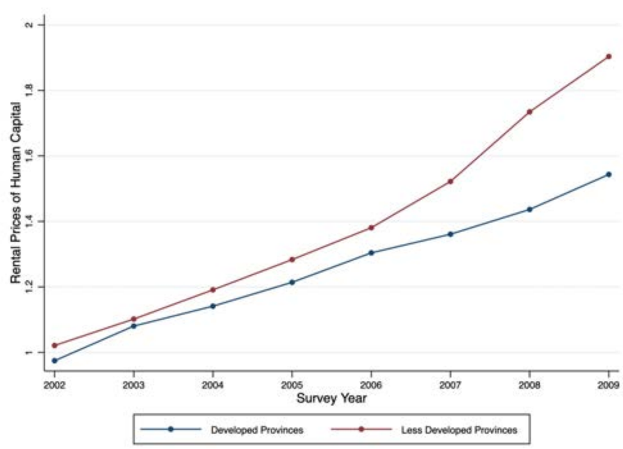
Figure 16, which presents the decomposition results by provincial development level, reveals significant disparities between developed and less developed provinces, particularly in terms of experience and cohort effects. This analysis provides a comprehensive understanding of regional disparities, offering insights beyond those derived from the sample measure using experience-wage profiles. Much like in the simple measure case, a composition effect in terms of ownership type could contribute to these disparities.



(a) Experience Effects



(b) Cohort Effects



(c) Time Effects

Figure 16. Decomposition Results by Provincial Development Level

However, these disparities could also be interpreted through in light of the distinct characteristics that differentiate these two groups of provinces.

A. Experience Effects

The experience profiles for workers in developed provinces reflected a 67% increase by 26-30 years of experience. In contrast, those in less developed provinces showed only a 22% increase by 11-15 years of experience, remaining flat thereafter.

In developed provinces, workers typically had better access to resources, training opportunities, and knowledge networks, which enabled greater investment in their human capital. Workers in less developed provinces often faced constraints in accessing such resources, impeding the accumulation of human capital throughout their careers.

Additionally, the job market in developed provinces generally offered a more diverse array of opportunities and efficient job matching mechanisms, facilitating frequent job transitions. Each job transition exposed individuals to novel environments, tasks, technologies, and networks, presenting opportunities for learning and skill acquisition, thereby boosting their human capital. On the other hand, in less developed provinces, the scarcity of job opportunities and inefficient job matching mechanisms could limit workers' exposure to varied work environments and opportunities for skill acquisition, slowing down their human capital growth.

The efficient matching mechanisms in developed provinces also enhanced the probability of job matches aligning well with workers' skills and preferences. A good job match fostered a conducive environment for skill development and human capital accumulation, as workers were likely to be more engaged and motivated to learn when their skills were well-aligned with their job requirements. Conversely, in less developed provinces, the limited job opportunities and inefficient matching mechanisms might have resulted in workers remaining in poor job matches for longer periods, leading to slower human capital growth.

B. Cohort Effects

In terms of cohort-specific productivity, it continuously declined in less developed provinces while increasing in developed provinces up to the 1975-1979 cohort. These diverging patterns could be explained in light of regional disparities during the transitional period.

Productivity, after accounting for education and experience, can be seen as a reflection of these factors: access to resources, technological advancement, efficiency

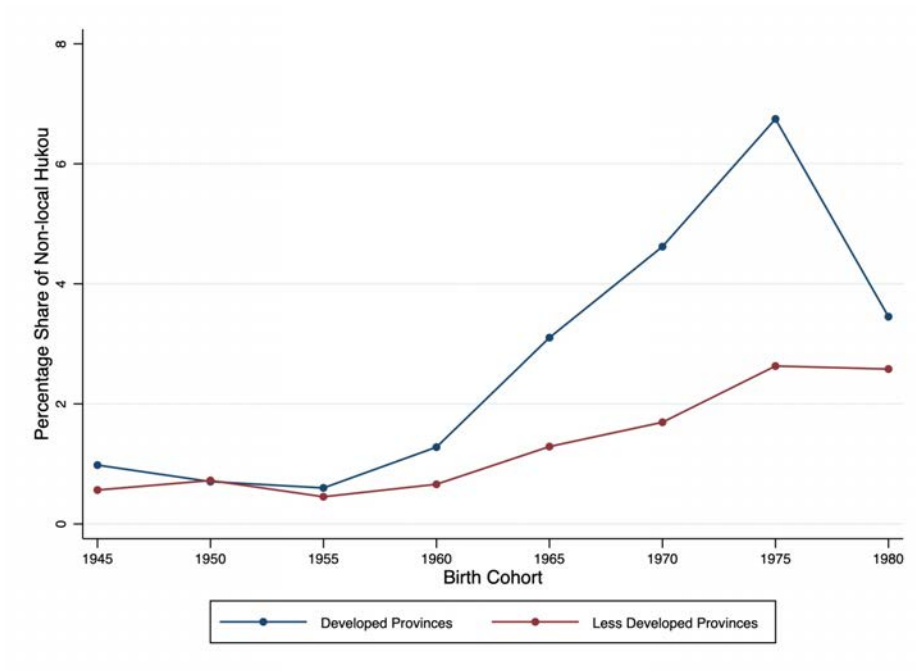


Figure 17. Proportion of Sample with Non-local Hukou for Each Provincial Group

of market structures, and institutional frameworks. In developed provinces, superior infrastructure and stronger economic potential provided a better platform for attracting resources and accessing technology. More recent cohorts in these provinces were able to reap and effectively utilize these advantages, leading to increased productivity. This trend indicated an inter-cohort productivity growth among workers in these provinces. Conversely, less developed provinces faced more formidable challenges during the transitional period. Their limited access to these critical resources and technology, compounded by potentially less efficient market structures and institutional frameworks, likely led to a decrease in the productivity of their younger cohorts. Consequently, these provinces witnessed a relative decline in cohort-specific productivity.

Furthermore, the economic reforms in China that encouraged labor mobility across provinces created a selection effect. More capable and skilled workers were inclined to move to developed provinces, thus driving higher cohort-specific productivity growth. This gap was particularly significant for the younger cohort, as they faced fewer mobility barriers. Figure 17 illustrates an upward trend in the proportion of the sample with non-local Hukou (household registration), beginning from the 1960-1964 cohort, except for the final cohort group. Although actual labor mobility might be higher due to potential Hukou transfers, such instances were likely rare during the period studied. Therefore, the non-local Hukou proportion can serve as a useful proxy for labor mobility. The observed trend indicates an increase in labor mobility, particularly towards developed provinces. However, despite this upward trend, the overall proportion of non-local Hukou within all cohorts and years remained relatively low. Thus, while selection effects were present, their impact on the results presented here was likely limited.

C. Time Effects

The prices of human capital across provinces followed an almost parallel trajectory before 2006. After this point, less developed provinces experienced a steeper upward trend compared to developed provinces. While the demand for human capital rose steeply across all of China, likely more so in developed provinces, the concurrent substantial increase in supply in these developed provinces tempered the upward pressure on its price.

7 Conclusion

This study presents experience-wage profiles for subgroups differentiated by education level, ownership type of employment, and provincial development level. For each educational group, average real wages generally increased with potential experience, despite minor fluctuations. The changing compositions in terms of education level, primarily driven by the expansion of higher education, contributed to the unique pattern observed in the total sample, where a notable decline followed after 11-15 years of experience. These findings suggest that relying solely on the simple measure of experience-wage profiles could potentially misinterpret the dynamics of life cycle wages in China.

Recognizing this potential pitfall, this study further implements a decomposition framework, using repeated cross-sectional wages data to infer life cycle human capital accumulation (experience effects), inter-cohort productivity changes (cohort effects), and human capital price changes over time (time effects). This approach is based on the identifying assumption that there is no growth in experience effects at the end of one's working life.

The decomposition results reveal pronounced human capital accumulation among workers in the nonpublic sector and developed provinces, relative to those in the public sector and less developed provinces. These disparities, rooted in distinct characteristics, can be effectively interpreted through the lens of three main theoretical frameworks: human capital investment, on-the-job search, and job matching with learning. Divergent cohort-specific productivity trends are observed, characterized by growth in the nonpublic sector and developed provinces, and decline in the public sector and less developed provinces. These trends are primarily attributed to selection effects and regional disparities. Moreover, the increase in human capital rental prices is less steep in the nonpublic sector and developed provinces, suggesting a balance between demand and supply. By illuminating these complex dynamics, this study offers valuable insights into understanding wage dynamics in urban China within the context of its structural economic transformations.

Future research could benefit from using a more extensive dataset covering a longer time period and a wider geographic area. This would allow for a broader understanding of the trends and disparities identified in this study. Further exploration of other potentially influential factors, such as the role of different industries or the impacts of exogenous policy changes, would also be informative.

An intriguing possibility is to link these labor market dynamics to international trade patterns, for example, examining whether China's advantage of low labor cost still persists(e.g., Huang, Sheng, and G. Wang, 2021). Additionally, the decomposition framework could be applied in other countries, particularly in examining the development processes of other emerging economies. More cross-country studies could be conducted to enhance our understanding of the global labor market.

This study did not explicitly plot cohort-based life cycle wage profiles nor examine the peak age of these profiles due to the limited scope of the time frame. While the peak age from these profiles should be later than that from the cross-sectional wage profiles, a relatively earlier peak age in comparison to other countries might still be observed due to age discrimination (Webster, 2011). Therefore, utilizing a dataset with an extended time range or panel data would be advantageous for studying this pattern.

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Appendix

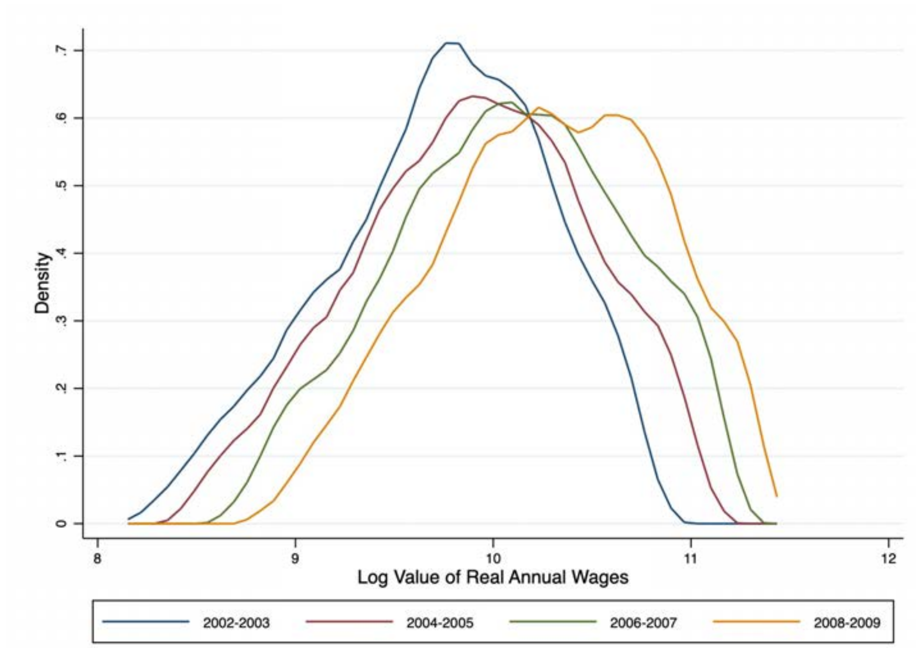


Figure A1. Distribution of Log Value of Real Annual Wages for Each Year Group

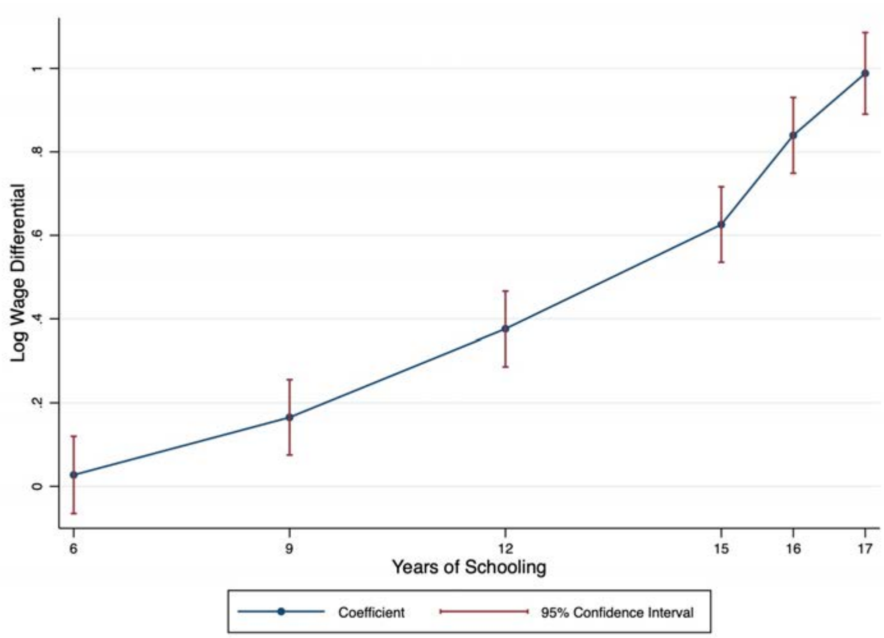
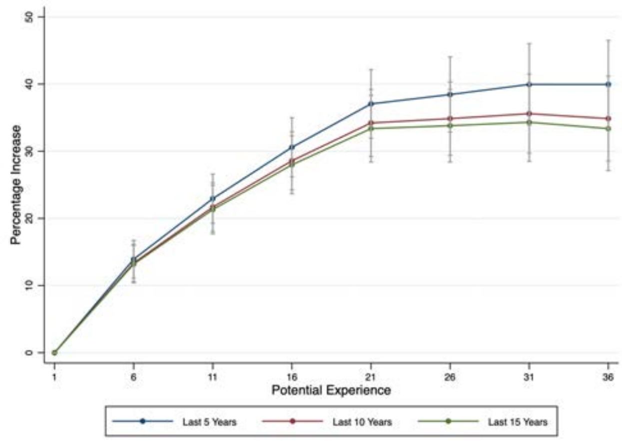
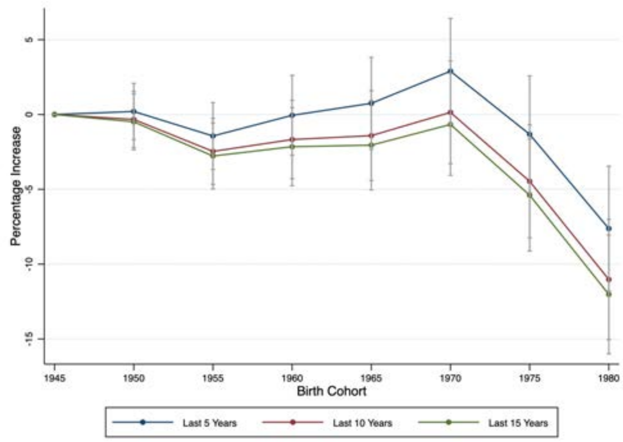


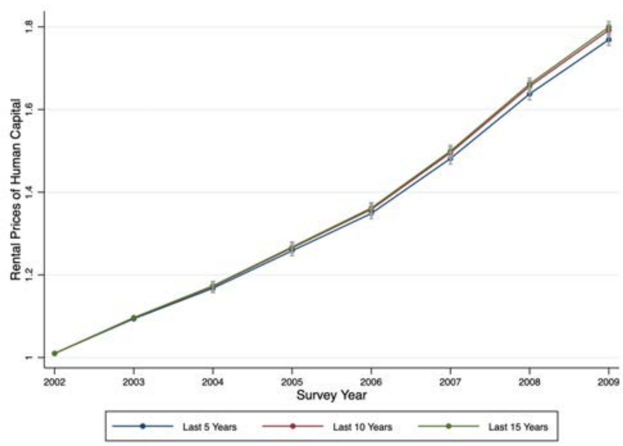
Figure A2. Returns to Years of Schooling



(a) Experience Effects

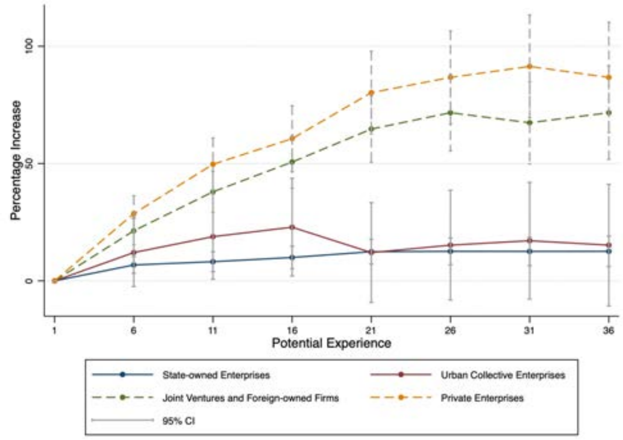


(b) Cohort Effects

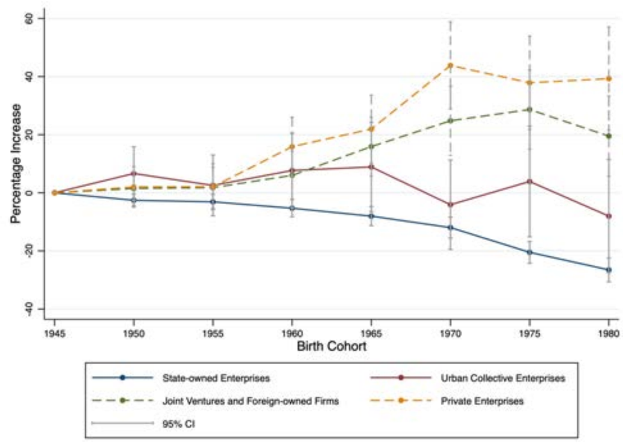


(c) Time Effects

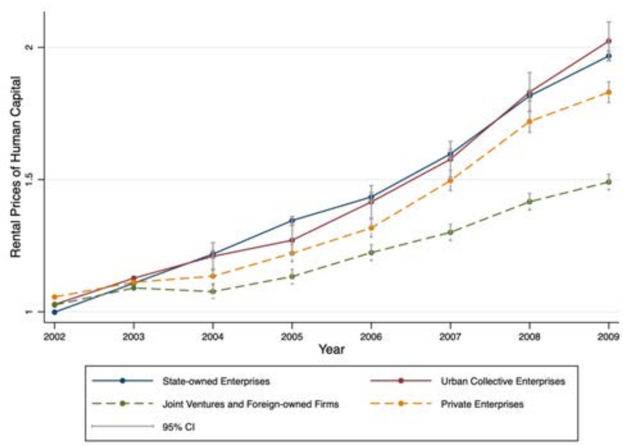
Figure A3. Decomposition Results for Varying Assumption Parameters with Confidence Intervals



(a) Experience Effects

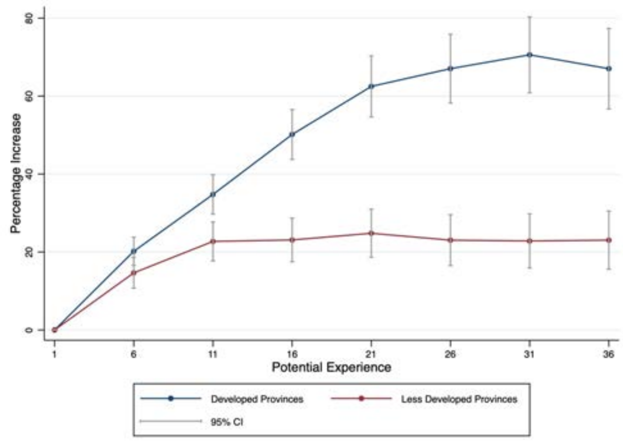


(b) Cohort Effects

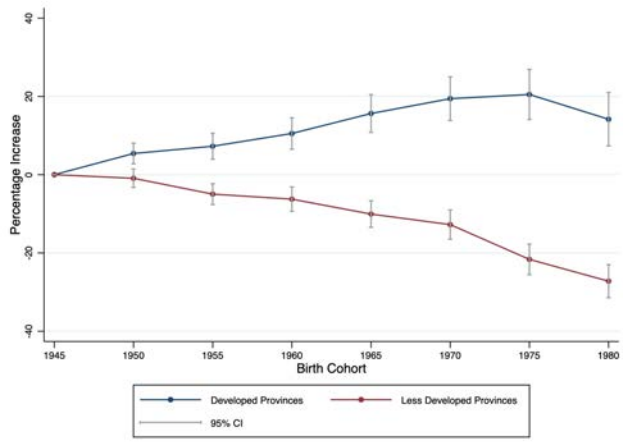


(c) Time Effects

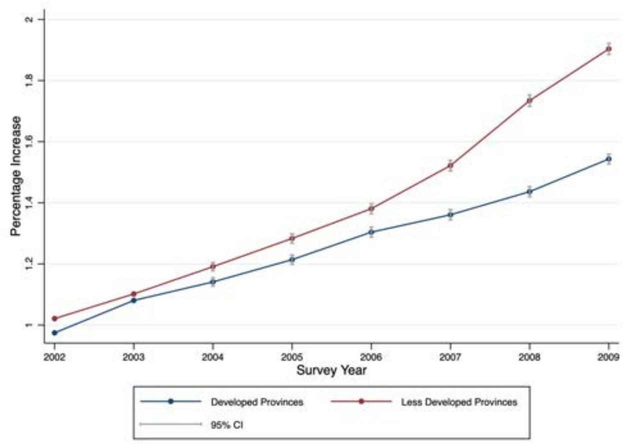
Figure A4. Decomposition Results by Ownership Type with Confidence Intervals



(a) Experience Effects



(b) Cohort Effects



(c) Time Effects

Figure A5. Decomposition Results by Provincial Development Level with Confidence Intervals