“Golden Ages”: A Tale of the Labor Markets in China and the United States

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The peak age of the earnings profile in China declined from 55 in the 1990s to 35 in the 2010s, while in the United States it remained steady at around 50. Motivated by this and other facts, we propose and empirically implement a decomposition framework to infer from repeated cross-sectional earnings data the experience, cohort, and time effects. We find that China experienced a considerably larger intercohort human capital growth and increase in human capital rental price, but lower life-cycle human capital accumulation, compared to the United States. We use the inferred components to revisit several applications in macroeconomics and labor economics.

I. Introduction

The rapid growth of the Chinese economy in the last 40 years is undoubtedly the most important economic event of our time. China’s GDP per capita was USD 381 (in 2010 constant US dollars) when it started its

We would like to thank David Autor, Hal Cole, Dirk Krueger, Ernest Liu, Lance Lochner, Iourii Manovskii, Jun Nie, Nancy Qian, José-Víctor Ríos-Rull, Ke Shen, Michael Zheng Song, Feng Wang, Shang-Jin Wei, Yiqing Xu, Bernard Yeung, and Xiaodong Zhu; conference participants at the Chinese Economic Association Annual Conference (2019), National Bureau of Economic Research Chinese Economy Working Group (2020), Asian Bureau of Finance and Economic Research Annual Conference (2021), IZA/HSE Workshop (2021),

Electronically published November 3, 2023

Journal of Political Economy Macroeconomics, volume 1, number 4, December 2023.

https://doi.org/10.1086/726843

"Reform and Opening Up" in 1978, and it increased to USD 9,688 in 2018, which represents an astonishing 25-fold increase in 40 years. The GDP per capita of the United States, the world's leading economy, grew from USD 30,895 (also in 2010 constant US dollars) in 1978 to USD 59,822 in 2018, a slightly less than twofold increase in the same time span.[1] Numerous papers and books have been written about the Chinese economic growth experience. In this paper, we provide a novel perspective and examine the Chinese growth experience through the lens of the labor market, focusing on the evolving cross-sectional earnings distributions.[2] We contrast the labor market in China with that in the United States, and provide a tale of the two labor markets.

Specifically, the object of focus in this paper is the age-earnings profile. It is one of the most empirically examined objects in labor economics, dating back at least to Mincer (1974). A large and mature body of literature has confirmed the robust regularity of hump-shaped age-earnings profiles: earnings are low for young workers who have just entered the labor market, then rise with age, but at some point level off, and eventually decline after reaching the peak earnings age. In this paper, we call the age group that achieves the highest average earnings in a cross-sectional age-earnings profile the "golden age." For instance, the golden age in the United States has stayed at around 50 years old, meaning that 50-year-old workers tend to have the highest average earnings among all age groups in a cross-sectional labor market dataset.

In this paper, we start with a systematic comparison of the age-earnings profiles between the United States and China, the two largest economies in the world. We document three striking differences between the two labor markets during the last 30 years:

- The cross-sectional golden age stayed stable at around 45–50 years old in the United States but continuously decreased from 55 to 35 years old in China.
- Age-specific real earnings were almost stagnant in the United States but grew drastically in China.

Bank of Canada–Tsinghua People's Bank of China School of Finance–University of Toronto Conference on the Chinese Economy (2021), and China International Conference on Macroeconomics (2022); and seminar participants at Fudan University, Peking University, ShanghaiTech University, University of Southern California Marshall School of Business, and University of Pennsylvania for helpful comments and suggestions. This paper was edited by Joseph Vavra.

[1] Statistics for China and the United States are from https://fred.stlouisfed.org/series/NYGDPPCAPKDCHN and https://fred.stlouisfed.org/series/NYGDPPCAPKDUSA, respectively.

[2] This follows a long tradition in economics, as Smith (1776) noted in *The Wealth of Nations* that aggregate output would accrue to various original sources of production, one of which being labor; thus the evolving earnings distribution in the Chinese labor market can provide a useful lens to examine the underlying sources of economic growth.

- The cross-sectional and life-cycle age-earnings profiles look remarkably similar in the United States but differ substantially in China.

We then seek to uncover the causes of the above differences between the two labor markets. To this end, we first provide a framework to decompose the repeated cross-sectional age-earnings data nonparametrically into experience, cohort, and time effects, where experience effects capture human capital accumulation over the life cycle, cohort effects capture the intercohort human capital growth, and time effects capture the human capital rental prices at a given time, which of course may change over time.

As is well known (and we will show below), without further restrictions, these three factors cannot be separately identified. The identifying assumption we adopt in this paper is that there is no growth in experience effect in a worker's late career, as implied by the standard human capital investment theory (Ben-Porath 1967), which predicts no incentive to invest in human capital at the end of one's working life. This identification idea was exploited originally by Heckman, Lochner, and Taber (1998) and more recently also by Huggett, Ventura, and Yaron (2011), Bowlus and Robinson (2012), and Lagakos et al. (2018). Under this identifying assumption, we separately identify from repeated cross-sectional age-earnings profiles the experience, cohort, and time effects, which in turn allow us to simultaneously account for the three stylized facts regarding the differences in the evolution of the United States' and China's labor markets in the last 30 years.

First, the golden age in a cross-sectional age-earnings profile is determined by the race between the life-cycle human capital accumulation (the experience effect) and the intercohort human capital growth (the cohort effect). When the experience effect dominates, the golden age tends to be older; when the cohort effect dominates, the golden age tends to be younger. In China, rapid intercohort human capital growth has outpaced the experience effect, leading to a decline in the golden age. In contrast, in the United States, a high return to experience and minuscule intercohort human capital growth result in a relatively old golden age. Second, the rental price of human capital (the time effect) has increased much faster in China than in the United States over the past 30 years. Moreover, China has experienced much higher intercohort human capital growth (the cohort effect) than the United States. Both contribute to the much faster growth in age-specific earnings in China. Third, both cohort and time effects are minor in the United States compared to the large experience effects. As a result, both the cross-sectional and the life-cycle age-earnings profiles in the United States are close to the experience effect. In China, however, substantial cohort and time effects result in drastically different life-cycle and cross-sectional age-earnings profiles.

We then use our decomposition to revisit several important exercises in macroeconomics and labor economics. First, the decomposition delivers a measure of human capital quantity that accounts for both the experience and the cohort effects. Using this measure of human capital growth as input, we conduct a growth accounting and find a larger contribution of human capital and hence a smaller contribution of total factor productivity (TFP) to China's GDP per capita growth than standard estimates, mainly due to larger intercohort human capital growth revealed by our approach. Second, we apply the decomposition separately to high school– and college-educated workers and obtain an estimated series for skill-biased technical change. We find that the technical change is much more skill biased in China, without which the relative price of college human capital would have declined given such a rapid surge in the supply of college human capital. Third, we estimate cohort-specific returns to experience and find steepening experience profiles for later cohorts in China, suggesting that later cohorts not only have higher initial human capital but also accumulate more human capital over the life cycle. All these findings highlight the importance of intercohort human capital growth in understanding the evolution of China's labor market.

Related literature.—This paper relates to three strands of literature. First, we contribute to the large literature on age-earnings profiles. The literature is so large that we do not attempt to provide a comprehensive review but refer interested readers to Heckman, Lochner, and Todd (2006) and Lemieux (2006) for excellent surveys. We make three contributions to this literature. First, we document novel and empirically intriguing features of China's age-earnings profiles, including drastic changes in the shape of the profiles and the surprising decline in its golden ages, which are in stark contrast to the benchmark case of the United States. Second, we develop a simple pedagogical framework to clarify the determinants of the golden age and the difference between cross-sectional and life-cycle profiles and to transparently discuss the identification of the experience, time, and cohort effects. Moreover, the framework is empirically implementable by the identification strategy of Heckman, Lochner, and Taber (1998) and the procedure of Lagakos et al. (2018), and theoretically portable for embedding into richer models when we revisit classical applications. Third, our decomposition result demonstrates that in the case of China, all the experience, time, and cohort effects are relevant in driving the changes in the age-earning profiles; in contrast, ignoring the cohort or time effects in the US labor market, albeit conceptually problematic, turns out to be a good approximation in practice, because these two effects are relatively minor compared to the experience effect. This provides the empirical justification for the vast literature running Mincer regressions on the US labor market data to estimate returns to experience. The lesson is that we need to exercise caution on the identification issues for time, cohort, and experience effects in general, and especially so in fast-growing economies such as China, but such concerns are empirically less severe in more stationary environments such as the United States.

Second, we add to the literature concerning human capital measurements. It is common to measure human capital by years of schooling, as in the pioneering work on development accounting by Hall and Jones (1999) and Bils and Klenow (2000), among others. This approach, however, abstracts away from many other dimensions of human capital, which motivates Manuelli and Seshadri (2014) to consider a model of multiple human capital acquisition phases with early childhood development, schooling, and on-the-job training. Our measure goes beyond educational attainment to encompass all productive factors that contribute to wages—the defining feature of human capital—such as educational quality, experience, health, and match capital, to name a few. Instead of an inductive approach that constructs a human capital measure aggregating its various sources from the bottom up, we take a deductive approach by inferring from wage an index summarizing all productive factors. We are, therefore, ex ante agnostic about the sources of human capital and their weights, but our measure naturally captures all of them. The estimated series of human capital is thus a useful input to classical applications such as growth accounting and skill-biased technical change. In this aspect, the paper is closely related to Bowlus and Robinson (2012). We further decompose human capital into a cohort component and an experience component, revealing an important role of intercohort human capital growth in China.

Third, our paper offers a novel perspective for understanding China's growth experience through the lens of its evolving age-earnings profiles. The literature has examined the role of institutional foundations (Xu 2011; Qian 2017), political economy (Li and Zhou 2005), trade liberalization (Brandt et al. 2017), and internal trade and migration (Tombe and Zhu 2019), among others, in China's growth miracle.[3] The age-earnings profiles contain information on the income paid to a productive factor—human capital—and its distribution across cohorts and over time. Thus it provides a valuable lens for examining economic growth. Our results highlight the role of human capital, particularly the importance of intercohort human capital growth in China's development experience, an aspect that has not received as much attention as the commonly considered productivity growth assumed to apply uniformly to all. This is related to Porzio, Rossi, and Santangelo (2022), who similarly find an important role of cohort effects, although their paper focuses on the structural transformation in terms of a decline in agricultural employment.

The remainder of the paper is structured as follows. In section II, we describe the facts on age-earnings profiles in the United States and China.

[3] See Brandt and Rawski (2008) and Zhu (2012) for detailed reviews.

In section III, we present the framework and discuss identification issues. In section IV, we describe the main results from the decomposition. In section V, we apply the decomposition results: section V.A revisits the growth-accounting exercise by adjusting for human capital growth based on our decomposition; section V.B reconsiders skill-biased technical changes by accounting for different changes in human capital quantity and price across education groups; section V.C simulates the dynamics of golden ages in a counterfactual economy that starts to slow down after a fast-growing period; section V.D estimates cohort-specific experience profiles. Finally, in section VI, we conclude and discuss potential directions for future research.

II. Facts

A. Cross-Sectional Age-Earnings Profiles and Golden Ages

We use the 1986–2012 waves of the March Current Population Survey (CPS) Annual Social and Economic (ASEC) Supplement extracted from Integrated Public Use Microdata Series (Flood et al. 2018) as the primary dataset for the United States. CPS is the official source of many labor market statistics, such as unemployment rate, wage growth, and worker flows. The sample period is chosen to facilitate the comparison with China, for which we only have access to data from 1986 to 2012.[4]

Figure 1*a* depicts the cross-sectional age-earnings profiles for male workers in the United States. Each curve represents a cross section that pools 5 or 4 adjacent years. To construct each curve, we first perform a nonparametric kernel regression of annual labor earnings on age separately for each cross section, where the Epanechnikov kernel function and rule-of-thumb bandwidth estimator are applied, and then display the smoothed values with the 95% confidence intervals. To avoid potential impacts of extreme values, we drop outliers defined as earnings in the top 2.5% and bottom 2.5% each year. We normalize earnings to the 2015 dollar using the Consumer Price Index. Individuals are weighted by the person-level ASEC weight. Figure 1*a* reveals that, first, the golden age in the United States has been relatively stable at around 50 years old during the past three decades; second, the United States has witnessed little growth in age-specific mean real earnings. That is, both the shape and the level of the age-earnings profiles are largely unchanged.

To study China's labor market, we use the Urban Household Survey (UHS) administered by the National Bureau of Statistics. UHS is the only nationally representative microdata source covering consecutive years

[4] Throughout this paper, a year refers to the year to which the income variable corresponds.

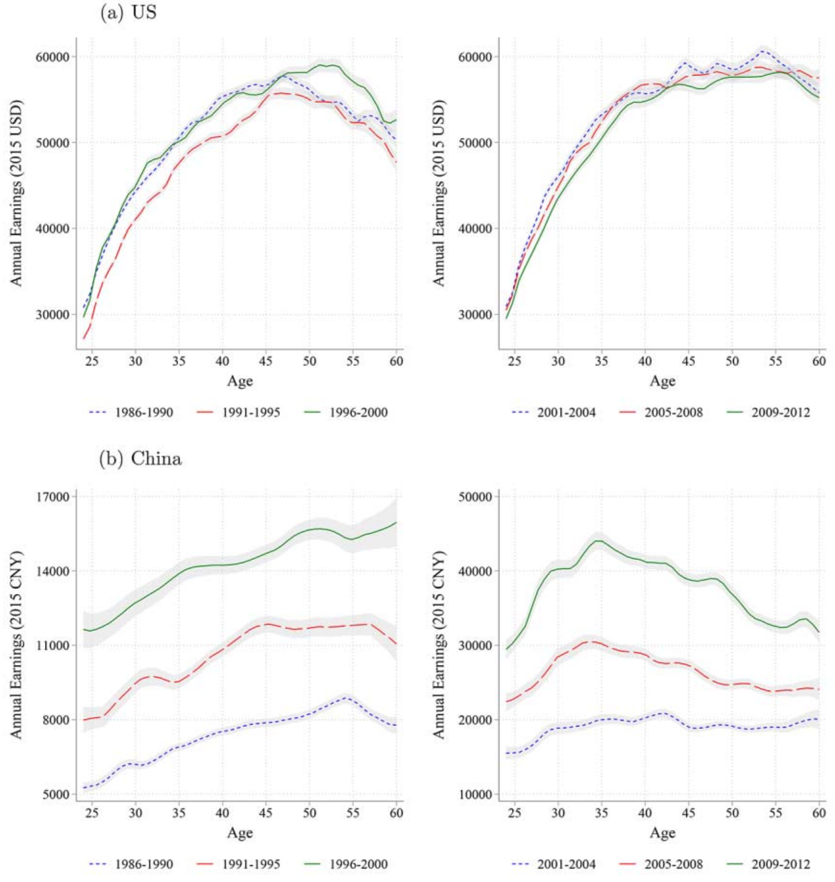

FIG. 1.—Cross-sectional age-earnings profiles. Panel *a* plots the cross-sectional age-earnings profiles of US male workers, using March CPS from 1986 to 2012. Panel *b* plots the cross-sectional age-earnings profiles of Chinese urban male workers, using UHS from 1986 to 2012. Each curve represents a cross section that pools adjacent years. The curves are kernel-smoothed values and the gray shaded areas are the 95% confidence intervals. Note that the vertical scale differs between the two graphs in panel *b*.

since the late 1980s. Although UHS is representative only of the population in urban China, it is the most comparable survey for China to CPS.

In figure 1*b*, we present the cross-sectional age-earnings profiles for Chinese male workers, using the same procedure as discussed before. A few striking contrasts between figure 1*a* and figure 1*b* emerge. First, Chinese workers have experienced a remarkable increase in real earnings over the past 30 years across all age groups, as evidenced by the large vertical upward shifts of the age-earnings profiles for later cross sections. Specifically, the earnings of urban Chinese male workers increased nearly

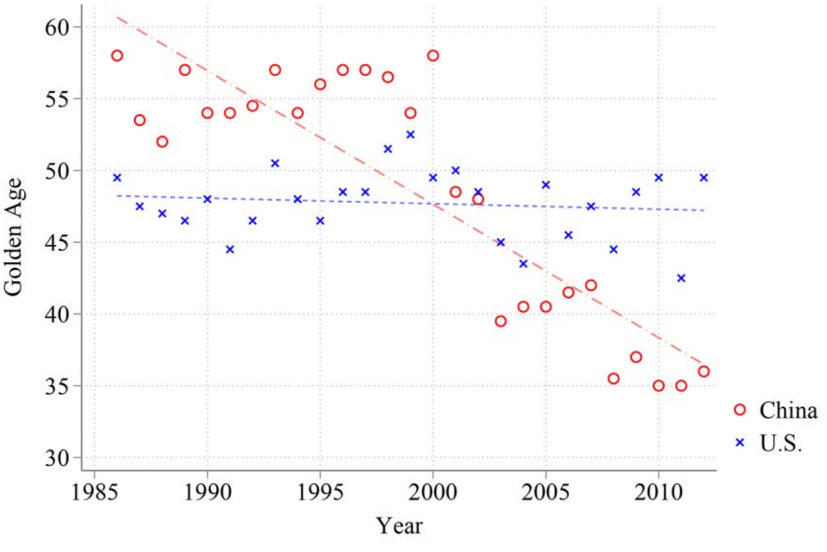

FIG. 2.—Evolution of cross-sectional golden age in the United States and China. The crosses denote the point estimate of the golden age in the US and the circles denote the point estimate of the golden age in China. The short-dashed line and the dash-dotted line are the respective linear time trends in the evolution of the golden age in each country.

sixfold, in marked contrast to the earnings stagnation observed in the United States. Second, while the shape of the cross-sectional age-earnings profiles and hence the corresponding golden ages have remained relatively constant in the United States, the golden age in China has continuously evolved to younger ages. Prior to 2000, the age-earnings profiles of China exhibited a familiar hump shape with the golden age around 55, although there were already some signs of a declining golden age between 1996 and 2000. Between 2001 and 2004, the age-earnings profile becomes almost flat and peaks around 40–45. After 2005, the golden age drops to 35 years old.[5]

To summarize, in the United States, workers in their fifties earn the highest labor income. In China, the same was true during the late 1980s and early 1990s, but since around 2010, it is the 35-year-old workers who earn the highest wages on average. Appendix A.1 (apps. A and B are available online) provides evidence that these findings are robust to various sample considerations. Moreover, figure A.2 (figs. A.1–A.11 are available online) suggests that hours worked are unlikely to have contributed to the striking changes in earnings profiles in China. Figure 2 fits a linear

[5] Song and Yang (2010) notice a flattening of age-earnings profiles in China. Cai et al. (2014) plot the earnings profiles in 2002 and 2007 using data from the Chinese Household Income Project, revealing an earlier arrival of the peak age in labor income.

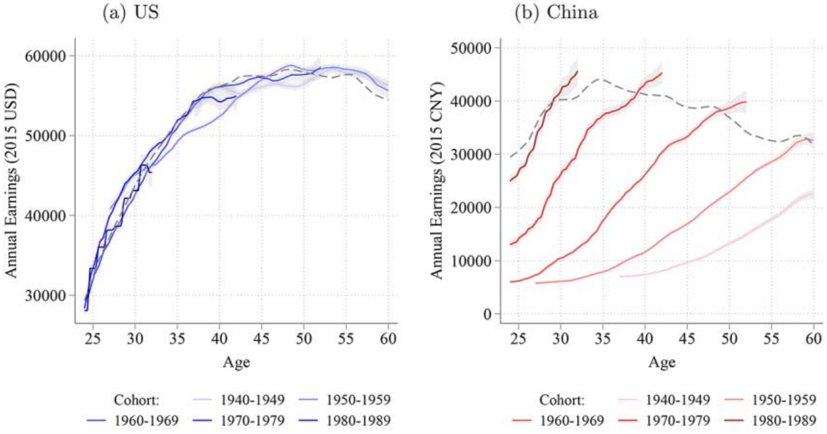

FIG. 3.—Life-cycle age-earnings profiles. Panel *a* plots the life-cycle age-earnings profiles for male workers of different birth cohorts in the United States, and panel *b* for urban China. Each solid line represents a 10-year cohort bin. Darker lines indicate more recent cohorts and lighter lines older cohorts. The gray dashed line in both panels reproduces the cross-sectional profile for 2009–12 from figure 1 for comparison.

time trend of the golden age for each country and shows a zero slope in the United States but a significantly negative slope in China.[6] In the United States, the golden age has remained relatively stable at around 50 years old over the past three decades, while in China, the golden age exhibits a striking downward trend during the same time, decreasing from 55 years old to just 35 years old.

B. *Cross-Sectional versus Life-Cycle Age-Earnings Profiles*

Conceptually, a *cross-sectional* age-earnings profile, which summarizes the earnings of workers of different ages at a given point in time, is distinct from the *life-cycle* earnings profile, which tracks the earnings of a given cohort over their life course. Thus, the two profiles are not expected to coincide. Figure 3 plots the life-cycle earnings paths of various birth cohorts, with each curve representing a 10-year cohort bin. Panel *a* corresponds to the United States and panel *b* to China. In addition, we include the cross-sectional profiles for 2009–12 reproduced from figure 1 as gray dashed lines for comparison.

In the United States (fig. 3*a*), cohorts born over a span of 50 years share remarkably similar life-cycle earnings paths. Moreover, the life-cycle profiles

[6] For each country and each year, we run a kernel regression of log earnings on age to predict age-specific earnings and obtain an estimated golden age in that year as the age with the maximal predicted earnings. We then fit a linear time trend of the golden age for each country.

bear a striking resemblance to the cross-sectional profile—the solid lines and the gray dashed line are almost on top of each other. In a stationary environment where the life-cycle profile remains constant across cohorts, the cross-sectional and life-cycle profiles would coincide. This implies that a typical 30-year-old worker who wants to predict his real earnings in 10 years could simply look at the contemporary earnings of a typical 40-year-old worker. This finding provides a justification for the voluminous prior research that has used cross-sectional profiles as approximations of life-cycle paths: although in theory, it is incorrect to interpret cross-sectional age-earnings profiles as life-cycle patterns, in practice, they are close to each other for the US case. In other words, stationarity is a reasonable assumption when examining the US earnings profiles.

However, as shown in figure 3*b*, the life-cycle patterns of different cohorts in China differ substantially. More recent cohorts experience both higher initial earnings and steeper life-cycle earnings growth. In contrast to the US case, these life-cycle profiles bear no resemblance to the cross-sectional profiles, despite being derived from the same underlying data.[7] It is perhaps not surprising that in a fast-growing economy such as China, stationarity is not a valid approximation. The next section provides a framework to organize the facts documented in this section.

III. Framework

Consider a competitive model of wage determination, where a worker's wage is the product of the *price* of human capital and the *quantity* of human capital the worker supplies. Denote by $W_{i,t}$ the wage of worker i at time t, $H_{i,t}$ the human capital supplied by worker i at time t, and P_t the rental price of human capital at time t. We have

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

Note that the rental price of human capital is allowed to vary over time but restricted to being the same across individuals. This formulation imposes a scalar representation of human capital.[8] Taking logarithms on both sides of equation (1), we have

[7] Note that the life-cycle and cross-sectional profiles are simply different ways to visualize the same underlying data. Suppose we keep track of a given time period, say, 2010, across different life-cycle profiles. That is, we connect the point of age 30 in the life-cycle profile for cohort 1980, age 40 for cohort 1970, age 50 for cohort 1960, and so on; then we are able to reproduce the cross-sectional profile for 2010, as illustrated by the dashed gray line, which is reproduced from the 2009–12 cross-sectional profile.

[8] To put it differently, worker heterogeneity is in the quantity of human capital, but not in the type of human capital. We consider an extension in sec. V.B that allows for different types of human capital. See Sanders and Taber (2012) for a review of the theoretical and empirical work on heterogeneous human capital in the context of life-cycle wage growth.

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

where for notational convenience we use lowercase letters for log values.

A cohort of workers is indexed by the year in which they enter the labor market. Define the human capital supplied by the "representative" worker of cohort c at time t as the average human capital among all workers of cohort c at time t,

$$h_{c,t} \coloneqq \mathbb{E}_i[h_{i,t}|c(i) = c, t].$$

By construction, the idiosyncratic component $\epsilon_{i,t} \coloneqq h_{i,t} - h_{c(i),t}$ has a conditional mean of zero (conditional on cohort c and time t). Therefore, we can rewrite equation (2) as

$$w_{i,t} = p_t + h_{c(i),t} + \epsilon_{i,t},$$

with $\mathbb{E}_i[\epsilon_{i,t}|c(i) = c, t] = 0$ for all c and t, where the expectation is taken over individual workers i, for a given pair of c and t.

Since both the price and quantity of human capital are unobservable, a nonidentification issue arises. It is worth noting that a normalization does not solve the problem because $\{p_t, h_{c,t}\}$ are not only observationally equivalent to $\{p_t + \lambda, h_{c,t} - \lambda\}$ for any constant λ ("normalization"), but also to $\{p_t + \lambda_t, h_{c,t} - \lambda_t\}$ for any arbitrary series of $\{\lambda_t\}$ ("nonidentification"). Therefore, without imposing further restrictions, we cannot determine how much of a wage difference is due to variation in human capital price versus human capital quantity.

We further decompose human capital into two components $h_{c,t} = s_c + r^c_{t-c}$, where $s_c \coloneqq h_{c,c}$ is the level of human capital of cohort c when they enter the labor market at year c, and $r^c_k \coloneqq h_{c,c+k} - s_c$ is the return to k years of experience for cohort c.[9] Using this notation, we can decompose log wages into time effects, cohort effects, and experience effects,

$$w_{i,t} = p_t + s_c + r^c_k + \epsilon_{i,t}, \tag{3}$$

with $\mathbb{E}_i[\epsilon_{i,t}|c(i) = c, t] = 0$, where (i) time effects p_t reflect the human capital prices, (ii) cohort effects s_c represent the cohort-specific human capital upon entry, and (iii) experience effects r^c_k are associated with the life-cycle human capital accumulation. Note that the perfect collinearity among year, cohort, and experience (since $k = t - c$) leads to nonidentification.

[9] We do not distinguish between age and experience; hence cohorts based on year of birth or year of labor market entry are interchangeable. In sec. V.B, we incorporate education heterogeneity, which consequently necessitates a distinction between age and experience as well as between birth cohort and entry cohort. In a robustness exercise in table 1, we also employ an alternative measure of experience as years since the first job, allowing workers from the same birth cohort to have different years of experience at a given age.

For ease of presentation, we follow the common practice in the literature to further impose the returns to experience to be the same across cohorts, that is, to restrict $r_k^c \equiv r_k, \forall\ c$, which gives rise to a variant of equation (3):

$$w_{i,t} = p_t + s_c + r_k + \epsilon_{i,t}. \tag{4}$$

This assumption has the advantage of allowing us to estimate a complete experience profile even if every cohort is only observed for part of their life cycle in the data. This restriction by itself does not resolve nonidentification, though. Even with this assumption, we still cannot disentangle time, cohort, and experience effects due to the perfect collinearity $k = t - c$. We adopt this usual restriction in the baseline analysis but relax it later in section V.D to allow for cohort-specific experience profiles.

A. *Cross-Sectional Age-Earnings Profiles and Golden Ages*

Suppose one has constructed cross-sectional age-earnings profiles as we have done in figure 1. Denote by $\{w(k;t)\}_{k=0}^{R}$ the cross-sectional age-earnings profile at time t, where k goes from 0 (labor market entry) to R (retirement).[10] The average log earnings of workers with experience k at time t is

$$w(k;t) \coloneqq \mathbb{E}_i[w_{i,t} | c(i) = t - k, t],$$

where the expectation is taken over individuals i for given time t and experience k (hence cohort $c = t - k$). The conditional mean zero property implies that the cross-sectional age-earnings profile can be written as

$$w(k;t) = p(t) + s(t-k) + r(k),$$

where we move the subscripts to inside the parentheses to emphasize that human capital price p is a function of time t, cohort-specific human capital s is a function of cohort $c = t - k$, and the return to experience r is a function of experience k.

Assuming differentiability, the slope of the cross-sectional age-earnings profiles at time t is given by

$$\frac{\partial}{\partial k} w(k;t) = \dot{r}(k) - \dot{s}(t-k), \tag{5}$$

[10] This paper focuses on the working-age population and abstracts from partial retirement transitions. See Casanova (2013) and Rupert and Zanella (2015), who focus on older workers around the retirement age and study such transitions.

which is positive if $\dot{r}(k) > \dot{s}(t-k)$ and negative if $\dot{r}(k) < \dot{s}(t-k)$.[11] Note that both r and s are in logarithms, so $\dot{r}$ and $\dot{s}$ are interpreted as the rate of life-cycle human capital growth and the rate of intercohort human capital growth, respectively. This observation immediately gives rise to the following characterization of the shape of a cross-sectional age-earnings profile:

Proposition 1. The cross-sectional age-earnings profile $\{w(k;t)\}_{k=0}^{R}$ is increasing (decreasing, respectively) in k when the rate of life-cycle human capital growth is greater (less, respectively) than the rate of intercohort human capital growth.

Though straightforward, proposition 1 helps clarify the determinants of the shape of cross-sectional age-earnings profiles. It states that the slope of a cross-sectional profile is a result of the race between life-cycle human capital growth (experience effects) and intercohort human capital growth (cohort effects). If life-cycle human capital growth dominates, older cohorts tend to have relatively higher earnings, resulting in steeper, upward-sloping cross-sectional age-earnings profiles. Conversely, if intercohort human capital growth is high, older cohorts tend to earn less relative to more recent cohorts, leading to flat or even downward-sloping cross-sectional age-earnings profiles. It is instructive to consider two extreme cases. First, consider an economy with no intercohort human capital growth, where each cohort is equally productive at any given age. In this case, the oldest workers earn the highest wages as long as returns to experience remain positive. Second, consider an economy with no returns to experience, but more recent cohorts are more productive. In this case, the youngest workers earn the highest wages.

The cross-sectional golden age at time t is defined as

$$k^*(t) \coloneqq \arg\max_{k\in[0,R]} w(k;t).$$

A characterization for the golden age follows immediately: the (interior) golden age of a cross-sectional profile at time t satisfies $\dot{s}(t-k^*) = \dot{r}(k^*)$. In other words, the cross-sectional golden age happens when the rate of intercohort human capital growth is balanced with the rate of life-cycle human capital growth.

B. *Cross-Sectional versus Life-Cycle Age-Earnings Profiles*

The simple framework also clarifies the difference between the cross-sectional and life-cycle profiles. Suppose one has constructed life-cycle age-earnings profiles as we have done in figure 3. Denote by $\{\tilde{w}(k;c)\}_{k=0}^{R}$

[11] We present the result in continuous time for notational simplicity. The logic easily carries to a discrete time formulation, mutatis mutandis. The dot notation refers to the first-order derivative with respect to the argument.

the life-cycle age-earnings profile for cohort c. The average log earnings of workers in cohort c with experience k is

$$\tilde{w}(k; c) \coloneqq \mathbb{E}_i[w_{i,t} | c(i) = c, t = c + k],$$

where the expectation is taken over individuals i for given cohort c and experience k (hence time $t = c + k$). The conditional mean zero property implies that the life-cycle age-earnings profile can be represented as

$$\tilde{w}(k; c) = p(c + k) + s(c) + r(k).$$

The slope of the life-cycle age-earnings profiles for cohort c is given by

$$\frac{\partial}{\partial k} \tilde{w}(k; c) = \dot{r}(k) + \dot{p}(c + k). \qquad (6)$$

Comparing equation (5) with equation (6) highlights the differences between cross-sectional and life-cycle profiles. If both intercohort human capital growth and human capital price increase are fast (i.e., both $\dot{s}$ and $\dot{p}$ are large, as will be shown to be the case for China), equations (5) and (6) suggest that the cross-sectional profiles tend to be flat and the life-cycle profiles steep. Conversely, if both intercohort human capital growth and human capital price changes are slow (i.e., both $\dot{s}$ and $\dot{p}$ are small, as will be shown to be the case for the United States), equations (5) and (6) suggest that the cross-sectional and life-cycle profile are close to each other, both approximating the returns to experience. Given the facts documented in section II, this narrative provides a promising candidate explanation of the dynamics of the two labor markets over the past three decades (and we show in sec. IV that it is indeed the case).

This section has outlined the role of the returns to experience $\dot{r}$, intercohort human capital growth $\dot{s}$, and human capital price changes $\dot{p}$ in shaping the cross-sectional and life-cycle profiles. Below we address the identification of these three components.

C. *Identification*

Suppose one has access to a repeated cross-sectional dataset on earnings, denoted by

$$\{w_{i,t}\}, \quad t = 1, 2, \ldots, T,$$

where i refers to an individual, and t time. The dataset covers individuals with different levels of experience, ranging from $k = 1$ to $k = R$. The sample of individuals can vary across periods. For convenience, we reproduce equation (4) here:

$$w_{i,t} = p_t + s_c + r_k + \epsilon_{i,t},$$

where p_t, s_c, and r_k indicate time, cohort, and experience effects with $k = t - c$. The residual satisfies the conditional mean zero property $\mathbb{E}_i[\epsilon_{i,t} | i \in c, t] = 0, \forall\ c, t$.

Two issues are worth noting. First, *normalization* (or nonidentification of levels). For each of the p_t, s_c, r_k vectors, we have to omit one group as the base, and focus on differences relative to that group. In the main analysis, we set the base group as 1935–39 for cohort, 1986 for time, and 0–4 for experience. The log earnings of the base group is loaded onto a constant term. Second, *nonidentification* (of first differences). Due to the perfect collinearity $k = t - c$, cohort, experience, and time effects cannot be separately identified without further restrictions.[12]

We adopt the identifying assumption that the growth of the experience effect is zero in the final years of one's working life, following the insights of Heckman, Lochner, and Taber (1998). This identifying assumption is theoretically justified by models of human capital investment à la Ben-Porath (1967), where the incentive to invest in human capital diminishes to zero as one approaches the end of working life.[13] In appendix B.1, we review the literature related to the age-cohort-time identification (Deaton 1997; McKenzie 2006; Lagakos et al. 2018; Schulhofer-Wohl 2018).

The intuition of identification is the following. First, the time effect is identified by comparing the wages of a given cohort in the final years of their working life, where the experience effect is assumed to be zero. By repeating this procedure for other cohorts, a series of time effects is determined. Next, the experience effect is identified by comparing the wages of a given cohort in the earlier years of their working life and removing the associated time effect, which is now known from the first step. Finally, the cohort effect is identified by comparing the wages of workers of different

[12] In practice, there may be cases in which cohort, experience, and time are not perfectly collinear. For instance, some surveys provide information on individuals' entire employment history, which can be used to construct the actual years of experience by subtracting nonemployment periods. Variation in employment history can break the perfect collinearity such that individuals with the same labor market entry year may have different levels of experience at a given time. Even in these cases, however, we are still typically faced with an issue of near multicollinearity. As a result, the standard OLS estimator will generate imprecise estimates. Moreover, the actual experience is an endogenous labor market outcome, so controlling for it may instead contaminate the estimates.

[13] The same identification assumption has also been adopted by Huggett, Ventura, and Yaron (2011), Bowlus and Robinson (2012), and Lagakos et al. (2018). In fact, this assumption is also consistent with other prominent models of wage dynamics, such as search theories with on-the-job search (Burdett and Mortensen 1998) and job matching models with learning (Jovanovic 1979). We view match capital as one source of human capital broadly defined. Rubinstein and Weiss (2006) provide a review on these three classes of models of investment, search, and learning that explain life-cycle wage growth. Bagger et al. (2014) find that human capital accumulation is quantitatively the most important source of life-cycle wage growth. Kuruscu (2006) infers the value of training investments from the flattening of wages toward the end of working life.

experience in the same year and removing the associated experience effect, which is now known from the second step.

To illustrate the idea more concretely, we provide a constructive explanation of the identification. Suppose that there is no human capital accumulation, say, from $R-1$ to R years old. First, comparing the wages of $(R-1)$-year-old workers in year $t-1$ and R-year-old workers in year t identifies the time effect from $t-1$ to t. This is because (1) by comparing the same cohort, the cohort effect does not contribute to the difference, and (2) according to the identifying assumption, the experience effect does not contribute to the difference either.

Second, comparing the wages of $(a-1)$-year-old workers in year $t-1$ and a-year-old workers in year t allows us to identify the experience effect from $(a-1)$ to a. This is because (1) again by comparing the same cohort, the cohort effect does not contribute to the difference, and (2) the time effect from $t-1$ to t has already been obtained from the first step and can be removed.

Third, comparing the wages of $(a-1)$-year-old workers and a-year-old workers in the same year t allows us to identify the cohort effect from cohort $c=t-a$ to cohort $c+1$. This is because (1) by focusing on the same year, the time effect does not contribute the difference, and (2) the experience effect from $(a-1)$ to a has already been obtained from the second step and can be removed.

This section aims to provide a clear intuition of the identification strategy for transparency. The actual implementation is more sophisticated, so we relegate the details of the estimation algorithm to appendix B.2.

IV. Decomposition

A practical issue is specifying a “flat spot” where there is assumed to be no growth in the experience effect. In the baseline specification, we follow Lagakos et al. (2018) by considering 40 years of experience and assuming no growth in experience effects in the last 10 years. This choice largely overlaps with the preferred flat spot by Bowlus and Robinson (2012), who attempt to determine the flat spot more carefully. We have also investigated an extensive set of alternative specifications below to address various concerns.

A. *Results*

Figure 4 presents the decomposition of earnings into experience, cohort, and time effects. We estimate experience effects (relative to the first 0–4 years since labor market entry) in 5-year bins, cohort effects (relative to 1935–39 birth cohorts) in 5-year bins, and time effects (relative to 1986) year by year. The main messages emerge clearly: First, Chinese workers’

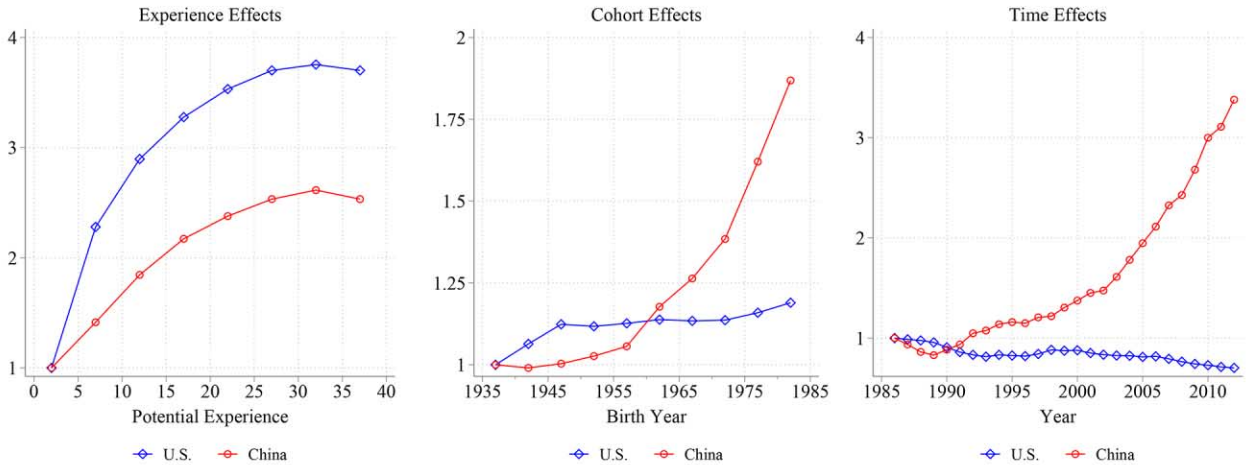

FIG. 4.—Decomposition results of experience, cohort, and time effects in the United States (*diamonds*) and China (*circles*) under the baseline specification.

human capital increases by 150% over 40 years of working experience, while the corresponding life-cycle human capital growth for US workers is 270%, nearly twice as high. Second, in China, intercohort human capital growth was almost 90% over 50 years of cohorts, most of which happened since the 1960 cohort. In contrast, there was only a 20% increase in cohort-specific human capital over 50 years of cohorts in the United States, most of which happened between cohort 1935 and 1950. Third, the time effect shows that human capital price grew more than threefold in China from 1986 to 2012, whereas it was virtually unchanged in the United States (and if anything, it declined at a rate of about 1% per year).

Robustness of the decomposition results.—The decomposition result is robust to alternative specifications as summarized by table 1. First, the patterns are not driven by regional differences of specific locations. This is demonstrated in row 2 by controlling for state fixed effect for the United States and province fixed effect for China. Additionally, in row 3, the analysis is restricted to the four provinces that are covered by the UHS sample throughout all years. The results are close to the baseline results reported in row 1.

TABLE 1
Experience, Cohort, and Time Decomposition for the United States and China

	Experience Effect (0–39 Years)		Cohort Effect (1935–84)		Time Effect (1986–2012)	
	United States	China	United States	China	United States	China
1. Baseline	3.70	2.53	1.19	1.87	.70	3.38
2. State/province fixed effects	3.71	2.53	1.19	1.78	.71	2.96
3. Four provinces		2.37		1.79		3.27
4. Experience = age − 20	3.24	2.55	1.20	1.84	.85	3.56
5. Years since first job		2.31		1.71		3.92
6. Alternative flat spot	4.10	3.18	1.36	2.52	.65	2.82
7. Depreciation rate	2.87	2.22	.86	1.57	.86	3.76
8. 35 years of experience	3.46	2.10	1.03	1.38	.76	4.15
9. Median regression	3.91	2.11	1.21	1.42	.60	3.65
10. Controlling education	3.39	2.35	1.04	1.47	.84	3.64
11. Hourly wage	1.84		1.03		.80	

Note.—This table reports various robustness results of the experience, cohort, and time decomposition for the United States and China. Row 1 reports the baseline result. Row 2 controls for state fixed effect for the United States and province fixed effect for China, and row 3 focuses on the four provinces covered by the UHS sample throughout all years. Alternative definitions for potential experience are considered in rows 4 and 5, using age minus 20 and years since the first job (available in UHS but not in CPS), respectively. Rows 6–8 consider alternative flat-spot specifications, including a flat spot in the last 5 years (row 6), a 1% human capital depreciation rate in the last 5 years (row 7), and a flat spot in the last 5 years out of 35 years of experience (row 8). Row 9 performs a quantile regression at the median. Row 10 controls for years of schooling. Row 11 considers hourly wages for full-time workers in the United States.

Second, we examine alternative definitions for potential experience. In the baseline, potential experience is defined as $\min\{\text{age} - \text{education} - 6, \text{age} - 18\}$. That is, workers with more than 12 years of schooling are assumed to start schooling at 6 years old and enter the labor market after completing their education, and workers with fewer than 12 years of schooling are assumed to enter the labor market at 18 years old. We consider a simpler definition for potential experience as (age – 20) in row 4. Since UHS provides information on the actual labor market entry year when the respondent started the first job, we also consider experience measured as (current calendar year – year of first job) for China in row 5.

Third, we investigate the robustness of our results to alternative identifying assumptions. In row 6, we consider an alternative flat spot, assuming no growth in the experience effect in the last 5 years. In the baseline analysis, we assume a zero human capital depreciation rate following Heckman, Lochner, and Taber (1998), but in row 7, we allow for a human capital depreciation rate of 1% per year in the last 5 years. In row 8, we drop older samples, restrict attention to up to 35 years of experience, and assume a flat spot in the last 5 years. Although the magnitude of experience effects varies somewhat across specifications as recognized by Lagakos et al. (2018), the general patterns of interest in terms of the comparisons between the United States and China remain unchanged.

Fourth, we look at median earnings. Medians are less sensitive than means to outliers and less likely to be influenced by changes in the tails of the earnings distribution. Furthermore, focusing on median earnings also helps mitigate concerns about differences in hours worked, to the extent that a median worker is likely to be working full time. In row 9, we perform a quantile regression analysis to estimate the experience, cohort, and time effects on median earnings.

Fifth, we include years of schooling as a control variable in row 10. The estimated cohort effect in China becomes smaller in this specification. This is expected since part of intercohort human capital growth is due to increased education. However, we still find large cohort effects even after controlling for education. This provides evidence for intercohort human capital growth within education groups, in addition to the composition changes between education groups. We will revisit the role of different education groups in section V.B.

Finally, due to the lack of information on hours worked in UHS, we also focus primarily on annual earnings for the United States to ensure a fair comparison. Nevertheless, we report in row 11 of table 1 and in figure A.6 the decomposition result using hourly wages for full-time male workers in CPS. The experience effects are smaller than previous specifications based on earnings, because very young workers tend to increase hours (or transition from part-time to full-time work) during the first few years after entering the labor market (see fig. A.1). The estimated cohort and time effects remain largely consistent with other specifications. See also appendix A.1 for a related discussion on hours.

B. *Discussion*

1. Experience Effect: Life-Cycle Human Capital Accumulation

Figure 4 (*left*) shows that the experience effects are higher in the United States than in China. Specifically, an average male worker in the United States has accumulated nearly 4 times the amount of human capital by the end of his working life than he had at the start of his career, while the most experienced male workers in China have only about 2.5 times the human capital of the least experienced ones.

The finding is consistent with the recent finding documented by Lagakos et al. (2018) that developed countries have higher returns to experience than developing countries. This positive correlation between returns to experience and economic development has been further confirmed by Jedwab et al. (2023), who use a global sample from 145 countries. It would be interesting to investigate why returns to experience are steeper in the United States than in China, or more generally, in developed countries than in developing countries, in future research.

2. Cohort Effect: Intercohort Human Capital Growth

Figure 4 (*middle*) reveals China's remarkable intercohort human capital growth. While US workers' human capital has increased by only about 20% over 50 years of cohorts, the most recent cohort in China has more than doubled the human capital of their older counterparts born 50 years earlier.[14] The result underscores the importance of intercohort human capital growth in understanding labor market transformations in China. Note that while the increase in educational attainment among subsequent cohorts is an apparent source of intercohort human capital growth, other factors, such as higher education quality, better health conditions, and sorting into better matches, may also contribute to it.

The rapid intercohort human capital growth in China, however, is not evenly distributed across cohorts. The growth is concentrated among cohorts born after 1960, while an earlier generation experienced little human

[14] The framework defines the cohort effect as the intercohort growth in initial human capital upon entry into the labor market. In the baseline analysis where experience effects are assumed to be invariant across cohorts, intercohort growth in initial human capital is equivalent to intercohort growth in lifetime human capital.

capital growth. This lost generation lived through the Great Famine of 1959–61 during childhood and experienced the Cultural Revolution (1966–76) during adolescence. These historical events, with the suspension of higher education and social chaos, stunted human capital accumulation for an entire generation.

3. Time Effect: Human Capital Rental Price Changes

Figure 4 (*right*) plots the time effects, or changes in the rental price of human capital over time. The human capital price in 2012 increased to about 3.5 times its level in 1986 in China, while there was little change in the United States. If anything, the human capital price in the United States declined at a rate of around 1% per year from 1986 to 2012.

How should we interpret changes in the human capital price? We clarify that the human capital price is related but not equivalent to productivity. While a formal analysis requires the framework detailed below in section V.A, here we provide a brief explanation. Consider a standard Cobb-Douglas production function as in equation (7). The competitive human capital price equals its marginal product

$$P_t = (1 - \alpha_t)A_t(k_t/h_t)^{\alpha_t},$$

where A_t denotes the total factor productivity at time t, k_t the physical capital per worker, h_t the human capital per worker, and α_t the factor share of physical capital. Human capital price changes are a combination of changes in human capital supply, which depresses its marginal product, and TFP and physical capital, both of which increase the marginal product of human capital. The contribution of a changing factor share is negligible.

In both countries, all three elements—human capital, physical capital, and TFP—are growing, as shown in figure 5 in section V.A. The two components, experience and cohort effects, both contribute to aggregate human capital accumulation, which, ceteris paribus, would have caused a decline in human capital prices. In China, however, physical capital and TFP are growing so fast that they more than compensate for the downward pressure on human capital price induced by aggregate human capital accumulation. In the United States, however, the growth of TFP and physical capital effectively balances out the accumulation of human capital, resulting in little change in the human capital price.

Although we will turn to a more detailed discussion of TFP in the following section, we note that the takeoff in the estimated time effects in China at around 2000 corresponds to the rapid rise in the estimated TFP growth. The timing coincides with historical events such as the state-owned enterprise reform initiated in 1998, China's accession to the World

Trade Organization in 2001, and the massive internal migration since the early 2000s.

4. Connection to Evolution of Earnings Profiles

We use the decomposition results to shed light on the empirical facts documented in section II regarding the evolution of earnings profiles.

First, section III.A demonstrates that the golden age occurs when returns to experience, $\dot{r}$, and intercohort human capital growth, $\dot{s}$, are balanced. If returns to experience are high and intercohort human capital growth is low, the golden age tends to be old. If returns to experience are low and intercohort human capital growth is high, the golden age tends to be young. The decomposition finds large experience effects and small cohort effects for the United States, and oppositely, small experience effects and large cohort effects for China, which explains the old golden age in the United States and the young golden age in China. The fast intercohort human capital growth in China manifests as unusual behavior in cross-sectional age-earnings profiles.

Second, equation (5) shows that the slope of a cross-sectional profile is the difference between returns to experience and intercohort human capital growth (i.e., $\dot{r} - \dot{s}$), and equation (6) shows that the slope of a life-cycle profile is the sum of returns to experience and changes in human capital price over time (i.e., $\dot{r} + \dot{p}$). If both cohort and time effects are small, the two profiles are both similar to $\dot{r}$. The decomposition finds that this is the case for the United States. If, however, both cohort and time effects are large, the two profiles differ. The decomposition finds that this is the case for China.

Third, the large time effects in China suggest that the returns to human capital have been increasing over time, and the large cohort effects indicate that later cohorts are more productive. This accounts for why age-specific earnings grow drastically in substantially. In contrast, both time and cohort effects are minor in the United States, resulting in stagnant age-specific earnings.

V. Applications and Extensions

This section considers a few applications and extensions of the decomposition results. First, section V.A revisits the growth-accounting exercise by adjusting for human capital changes based on our estimates. Second, section V.B incorporates education differences and revisits skill-biased technical changes. Third, section V.C simulates a counterfactual economy that starts to slow down after the period of fast growth. Finally, section V.D extends the baseline framework to allow for cohort-specific experience profiles.

A. *Growth Accounting*

Consider a Cobb-Douglas aggregate production function

$$Y_t = A_t K_t^{\alpha_t} H_t^{1-\alpha_t}, \tag{7}$$

where Y_t is the aggregate output, K_t the aggregate physical capital, H_t the aggregate human capital, A_t the total factor productivity (TFP), and α_t the factor share distribution parameter. Note that all variables are allowed to depend on time t. Let lower case letters denote the corresponding variables in per worker terms, that is, $x := X/L$, where $X \in \{Y, K, H\}$ and L is the total number of workers. The output per worker can be expressed as $y_t = A_t k_t^{\alpha_t} h_t^{1-\alpha_t}$.

First, as is standard, we can directly measure y_t, k_t, and α_t from the data. Specifically, we obtain four annual data series for each country: (1) real GDP Y_t, (2) capital stock K_t, (3) number of persons engaged L_t, and (4) share of labor compensation in GDP, from the Penn World Table 9.0 (Feenstra, Inklaar, and Timmer 2015).[15] We divide the real GDP Y_t and capital stock K_t by the number of workers L_t to construct output per worker y_t and capital stock per worker k_t for each year t. Under the competitive framework, the labor share is equal to $1 - \alpha_t$, which we set to the observed share of labor compensation in GDP.

Second, we use estimates from the decomposition in section IV to construct human capital changes; this is the new part. Specifically, we construct the average human capital at time t (up to a normalization) as the weighted average of the human capital of each cohort group and experience group

$$h_t = \sum_c \sum_k \exp(s_c + r_k)\omega(c, k; t),$$

where $\omega(c, k; t)$ is the employment share of workers of cohort c and experience k at time t, and estimates for each cohort's human capital s_c and returns to experience r_k are obtained from our decomposition in section IV. We can therefore get an estimated series for changes in human capital per worker.[16]

[15] The Penn World Table 9.0 is available on the Federal Reserve Bank of St. Louis website: https://fred.stlouisfed.org/categories/33402. The series on the share of labor compensation in GDP for China starts from 1992. We therefore are forced to impute the labor share between 1986 and 1991 to the same level as in 1992.

[16] For our estimated series from male earnings data to apply to the national growth accounting, one needs to assume that the human capital changes (not necessarily levels) are the same for males and females. This assumption may not hold if, e.g., female human capital growth has outpaced male human capital over the past three decades. In such a case, relying exclusively on male human capital growth would understate overall human capital growth. Correcting for this bias would result in an even lower estimate of TFP growth than the one that does not adjust for human capital. Future research is needed to better deal with the selection issue in female labor force participation to study labor market changes for females.

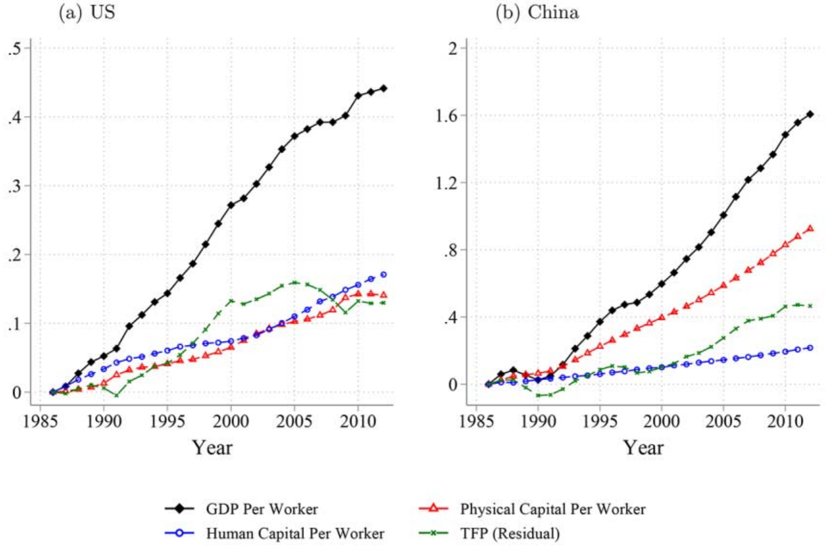

FIG. 5.—Growth accounting. The graph decomposes the growth in GDP per worker (*diamonds*) into contributions of physical capital per worker (*triangles*), human capital per worker (*circles*), and TFP residual (*crosses*). Note that the scales differ in the two figures.

TFP changes are then obtained as a residual from

$$d\ln \tilde{A}_t = d\ln y_t - \alpha_t d\ln k_t - (1-\alpha_t)d\ln h_t, \tag{8}$$

where $d\ln \tilde{A}_t \coloneqq d\ln A_t + (\ln k_t - \ln h_t)d\alpha_t$. Note that our decomposition only delivers differences relative to the base group and therefore does not provide the levels of h_t.[17]

1. Sources of Growth

We visualize the contributions of physical capital per worker, human capital per worker, and the residual to the growth of GDP per worker in figure 5. We find that all three sources contribute almost equally to the US growth, with human capital contributing slightly more than the other two. The picture is quite different in China. Although the absolute level of the growth in human capital is higher in China than in the United States, the relative contribution of human capital turns out to be the least important to China's growth. This is due to the even faster growth of physical capital

[17] As a result, we cannot isolate $d\ln A_t$ from $(\ln k_t - \ln h_t)d\alpha_t$. In practice, such disparity is typically ignored in growth accounting, as the annual labor share change $d\alpha_t$ is small. Elsby, Hobijn, and Şahin (2013) find that observed changes in the labor share barely affect the results of a growth-accounting exercise.

and TFP in China. Specifically, physical capital is responsible for almost 60% of the growth in GDP per worker, and TFP for almost another 30% in China.

This exercise can be viewed as a refinement of the usual growth-accounting analyses by providing a more "under the hood" examination of the "black box" TFP growth. This is achieved by incorporating intercohort human capital growth and the life-cycle human capital accumulation into our growth-accounting procedure. While TFP is a model-based concept so we do not expect our TFP estimates to be identical to previous estimates, it is reassuring that our TFP estimates track the broad movements over time as in other prominent TFP estimates. For example, figure 5*a* shows little TFP growth in the United States since the mid-2000s, which is consistent with the productivity slowdown during the same period according to estimates by Fernald (2014). For China, figure 5*b* shows that TFP increased by almost 60% from 1986 to 2012, almost all of which occurred since 2000. This is consistent with the estimates by Zhu (2012), who also finds a much larger TFP growth after the late 1990s.[18] This is a period when many prominent economic reforms have happened, such as the privatization of the state-owned enterprises (SOEs) in the late 1990s, the trade liberalization following China's joining the World Trade Organization in 2001, and the massive internal migration amid the nationwide temporary residence permit reform in 2003.[19]

2. Relationship to Literature

There is an existing related approach to accounting for human capital. The classical work by Hall and Jones (1999) measures human capital as $\exp\{\phi(e)\}$, where e is educational attainment and ϕ' is the estimated return to schooling from a standard Mincerian regression. Bils and Klenow (2000) further enrich this framework by including the Mincerian return to experience and spillover from older cohorts. Human capital disciplined by Mincerian returns is then aggregated across narrowly defined cells. This Mincer-based approach has since then become the standard approach to measuring human capital in growth and development accounting. There are two potential caveats. First, the Mincer-based approach implicitly assumes that one additional year of schooling contains

[18] Zhu (2012) estimates the average annual total factor productivity growth in the nonagricultural sector to be 2.17% and 0.27% for the nonstate and state sectors during 1988–98, but 3.67% and 5.50% for nonstate and state sectors during 1998–2007.

[19] Chen et al. (2021) address the selection issue in the privatization of SOEs and find that privatization leads to productivity gains. Brandt et al. (2017) provide evidence that trade liberalization—both input tariff cuts and output tariff cuts—raises firms' productivity. Tombe and Zhu (2019) quantify that the reduction in internal trade and migration costs accounts for 28% of China's growth.

the same quality of human capital across countries or over time, which may not be suitable for studying countries at very different development stages and economic transitions in fast-growing periods. Second, those constructions conceptually focus only on one dimension of human capital, namely, education attainment, and exclude other prominent examples of human capital such as health (Grossman 1972) and noncognitive skills (Heckman, Stixrud, and Urzua 2006). Essentially, the standard measurement approach boils down to a composition adjustment procedure based on observable demographic characteristics, but assumes away changes within categories. Our approach addresses these caveats by treating human capital as an index summarizing all productive factors manifested in wages. To facilitate comparison with the existing benchmark, we report the results using the Mincer-based approach in appendix A.2. While the two approaches produce relatively similar estimates of human capital growth for the United States, our methodology reveals a larger role of human capital (and hence a smaller role of TFP) for China compared to the Mincer-based approach. Nevertheless, both methods confirm that human capital contributes the most to growth relative to physical capital and TFP in the United States but the least in China.

Motivated by a similar concern about the measurement of human capital, Manuelli and Seshadri (2014) adopt a model-based approach that calibrates a model of human capital acquisition with early childhood development, schooling, and on-the-job training to calculate human capital stocks. Our approach combines the strengths of both the model-based and regression-based methods: it incorporates all productive factors in the notion of human capital while maintaining simplicity of the procedure. The closest to our exercise is Bowlus and Robinson (2012), who are the first to apply the insight of Heckman, Lochner, and Taber (1998) in the context of growth accounting. We further separate the role of experience accumulation and intercohort improvements in the aggregate human capital growth, which we discuss next.

3. Decomposing Human Capital into Experience and Cohort Effect

We calculate the contribution of experience (respectively, cohort) to aggregate human capital by fixing the cohort (respectively, experience) effect at its base group level.[20] Figure 6*a* shows that human capital per worker increased by almost 30% in the United States from 1986 to 2012, primarily due to experience rather than cohort effects. This is not surprising given the small cohort effect and large experience effect estimated for the

[20] The “experience” series in fig. 6 is calculated as $h_t^{\text{experience}} = \Sigma_c \Sigma_k \exp(r_k)\omega(c, k; t)$ and the “cohort” series as $h_t^{\text{cohort}} = \Sigma_c \Sigma_k \exp(s_c)\omega(c, k; t)$.

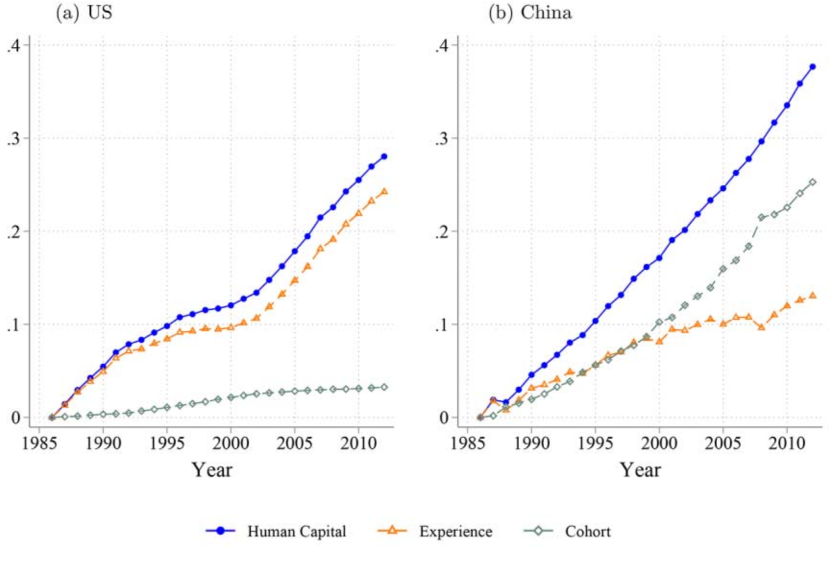

FIG. 6.—Decomposition of the average human capital growth (*circles*) into contributions of the experience effect (*triangles*) and the cohort effect (*diamonds*).

United States. In an aging workforce, productivity gains from experience would be large if life-cycle human capital accumulation is fast. Figure 6*b* shows that, in China, human capital per worker increased by almost 40% during the same period, with intercohort human capital growth accounting for two-thirds of the overall human capital growth and experience the remaining one-third. These results highlight the importance of intercohort human capital growth in understanding China's growth miracle. Figure A.9 presents the same decomposition using the Mincer-based approach, which attributes a much smaller growth of human capital due to rising education for China than the role of intercohort human capital growth reported in figure 6*b*. Nevertheless, the two methods agree that experience plays a more important role in the human capital growth in the United States, while intercohort human capital growth is more important for China.

B. *The Canonical Model of Skill Premium*

1. Heterogeneous Human Capital by Education Groups

In the baseline analysis, we assume homogeneity in skill types so that workers' human capital quantity is represented by a single index indicating the level of efficiency units. The framework can easily be extended to allow for different types of human capital. For example, college and high school graduates may possess different types of skills that are not perfect substitutes. In this case, we perform the decomposition discussed in section IV separately for college and high school workers, who would be allowed to have different paths of life-cycle human capital accumulation, different intercohort human capital growth, and different time series of human capital price changes. The only restriction is that for both college and high school workers, there is no additional experience accumulation toward the end of working life. We set potential experience such that college and high school workers enter the labor market at 22 and 18 years old, respectively. This is largely overlapped with the "flat spot" proposed by Bowlus and Robinson (2012).[21]

The results are presented in figure 7. First, within each education group, the returns to experience are still higher in the United States than in China. Within a country, the experience effects are larger for college workers than for high school workers. This is consistent with, for instance, Bagger et al. (2014), who find that workers with more education experience faster life-cycle human capital accumulation. The difference in experience profiles between the two education groups, however, is much smaller than the difference in the cohort effects, which will be discussed next.

Second, the education-specific cohort effects exhibit distinct patterns between China and the United States. In the United States, we find a large and positive intercohort human capital growth for college graduates but a negative growth for high school graduates. This finding echoes the "fanning out" phenomenon in wage inequality, as summarized by Acemoglu and Autor (2011), that real earnings declined significantly for low-skill workers. Our result provides a new cohort-based perspective as opposed to the traditional time-series perspective. In China, both education groups exhibit positive intercohort human capital growth, especially for college graduates. We also observe that the cohort effect declines for the 1980–84 birth cohort of college graduates in China. The Chinese government expanded college enrollment massively in 1999, doubling the number of students admitted to colleges in 2 years, and continued expansion after that. As a significantly larger fraction of this cohort could enroll in college than of previous cohorts, such a rapid expansion of higher education also implies a decrease in college selectivity, which likely led to a downward shift in the distribution of ability among college students for this cohort.

[21] After careful investigation of the US data, they conclude that a reasonable range for the flat spot is 50–59 for college graduates and 46–55 for high school graduates. Our specification effectively assumes a flat spot of 52–61 for college graduates and 48–57 for high school graduates.

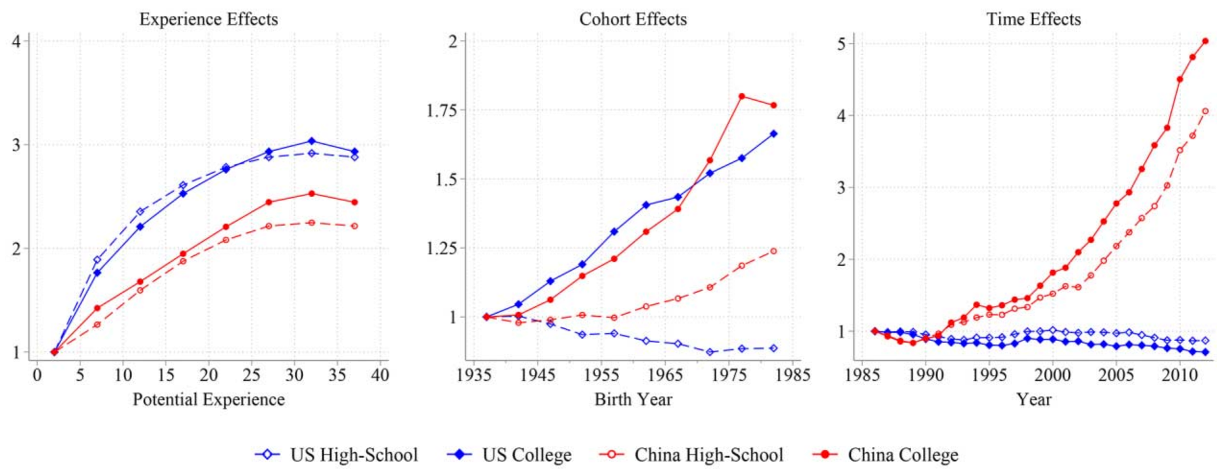

FIG. 7.—Decomposition for college and high school workers. The figure shows the decomposition results of experience, cohort, and time effects in the United States (*diamonds*) and China (*circles*), separately for college workers (*solid lines and filled symbols*) and high school workers (*dashed lines and open symbols*).

Finally, the time effects are broadly similar across education groups. In China, the rental price of human capital increases rapidly for both education groups, with a somewhat faster increase for college graduates than for high school. In the United States, there is not much change in human capital prices for either group, but college workers experience a slight decrease.

2. Decomposing College Premium

The wage gap between college graduates and high school graduates is often interpreted as the relative price between college skills and high school skills. Consequently, changes in the college wage premium are interpreted as changes in the relative skill prices. This interpretation, however, implicitly assumes that the relative quantity of human capital between education groups remains constant. To see this, suppose the average wage of each education group $e \in \{s, u\}$ at time t is $W_t^e = P_t^e H_t^e$, where P_t^e is the rental price to the human capital of education group e at time t, and H_t^e is the average human capital for workers of education group e at time t. Note that

$$\frac{W_t^s}{W_t^u} = \frac{P_t^s}{P_t^u} \times \frac{H_t^s}{H_t^u}.$$

Only under the assumption of constant relative amount of human capital, that is, $\xi_t \coloneqq H_t^s/H_t^u \equiv \xi, \forall\ t$, can we interpret the changes in the college premium over time as reflecting entirely the changes in the relative price of college and high school human capital. Under this implicit assumption, the observation that a remarkable increase in the supply of college workers in the United States coincides with a rising college wage premium motivates the literature on skill-biased technical changes (see Violante [2008] and Acemoglu and Autor [2011] for excellent overviews).

Our decomposition allows us to estimate changes in the relative human capital of college and high school workers, as well as the relative price of college and high school skills. We construct relative human capital quantity series based on both experience and cohort effects, as we do in section V.A. We then decompose the evolution of the average college premium into changes in the relative price and quantity of these two types of human capital.

The results are plotted in figure 8. The college premium is defined as the relative log earnings among prime-age male workers between 25 and 54 years old, and we normalize the series to obtain changes relative to the 1986 level. As is shown in panel *a*, in the United States, the relative price between college human capital and high school human capital is actually declining. The rising college premium in the United States results from an increased relative quantity of college human capital. That is, an average

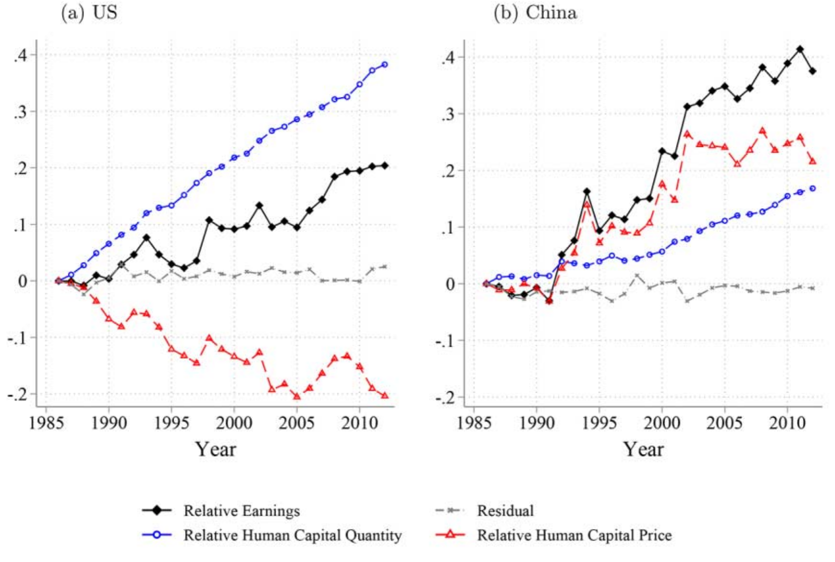

FIG. 8.—Decomposition of changes in college premium (*diamonds*) into changes in relative human capital price (*triangles*) and changes in relative human capital quantity (*circles*). The line with no symbols plots the residual of the decomposition.

college worker's human capital increases faster than an average high school worker's. In fact, the relative human capital quantity increases more than enough to offset the declining relative human capital price so that the college premium still increases. Figure 8*b* shows that in China, the rise in the college wage premium is driven by increases in both the relative price and relative quantity of college human capital to noncollege human capital. Quantitatively, the relative price changes play a slightly more important role. Note that the residual plotted with the gray dashed line is tightly around zero in both figures, indicating that the decomposition provides a good fit to the data.

3. Decomposing Relative Prices and Revisiting Skill-Biased Technical Change

The finding of increasing relative college human capital quantity and declining relative college human capital price in the United States is consistent with Bowlus and Robinson (2012). At first glance, this may seem to contradict the idea of skill-biased technical changes. Our findings below confirm the presence of skill-biased technical changes in both countries, without which the relative price of college human capital in the United States would have declined even more, given the rapid rise in the relative quantity of college human capital.

We augment the canonical model (e.g., Katz and Murphy 1992; Acemoglu and Autor 2011) by accounting for changes in human capital quantity. Contemporaneous work by Bowlus et al. (forthcoming) takes a similar approach and focuses on the US labor market. Consider an aggregate production function that exhibits constant elasticity of substitution over college and high school human capital:

$$Y_t = \left[(A_t^s H_t^s)^{(\sigma-1)/\sigma} + (A_t^u H_t^u)^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)}, \tag{9}$$

where H^s and H^u are the aggregate human capital quantity of college and high school workers, A^s and A^u the skill-augmenting technology specific to each group, and $\sigma > 0$ the elasticity of substitution between college and high school human capital.[22] Assuming skills are paid by their marginal product, we can express the relative price of the two skill types as follows (dropping time subscripts):

$$\ln\left(\frac{p^s}{p^u}\right) = \frac{\sigma - 1}{\sigma}\ln\left(\frac{A^s}{A^u}\right) - \frac{1}{\sigma}\ln\left(\frac{h^s}{h^u}\right) - \frac{1}{\sigma}\ln\left(\frac{L^s}{L^u}\right), \tag{10}$$

where h^s and h^u represent human capital quantity per worker for each education group, and L^s and L^u the total number of workers such that the aggregate human capital is given by $H^s = h^s L^s$ and $H^u = h^u L^u$. The first term on the right-hand side captures the contribution of the skill-biased technical changes to the relative price changes. The second term reflects the impact of changes in the relative quantity of human capital per worker. The last term is the head counts of workers.

As long as $\sigma > 1$, an increase in A^s/A^u (i.e., skill-biased technical change) increases p^s/p^u, while an increase in either h^s/h^u or L^s/L^u (i.e., an increasing relative supply of college human capital) decreases p^s/p^u. Our experience-cohort-time decomposition delivers changes in the relative price p^s/p^u and the relative human capital quantities per worker h^s/h^u. Since the relative labor supply L^s/L^u is observed, the contributions of skill-biased technical changes can thus be obtained as a residual. Figure 9 decomposes the evolution of relative human capital prices into the contributions of relative labor supply, relative human capital per worker, and

[22] We simplify the exposition by making two abstractions. First, we do not explicitly model capital in the production function. Krusell et al. (2000) explain skill-biased technical changes through capital-skill complementarity. Here the role of capital is captured by A^s/A^u in a reduced-form fashion. Second, we assume perfect substitution across age groups. While Card and Lemieux (2001) advocate for incorporating such imperfect substitution, recent research by Carneiro and Lee (2011) finds strong substitutability across age groups; they report an elasticity of substitution across groups of 9.1 for college workers and 11.1 for high school workers. In addition, Bowlus et al. (forthcoming) also conclude that imperfect substitution across age groups is not needed to explain the different paths of relative wages by age, which was raised as a potential issue by Card and Lemieux (2001), once the evolution of relative skill price and quantity is accounted for.

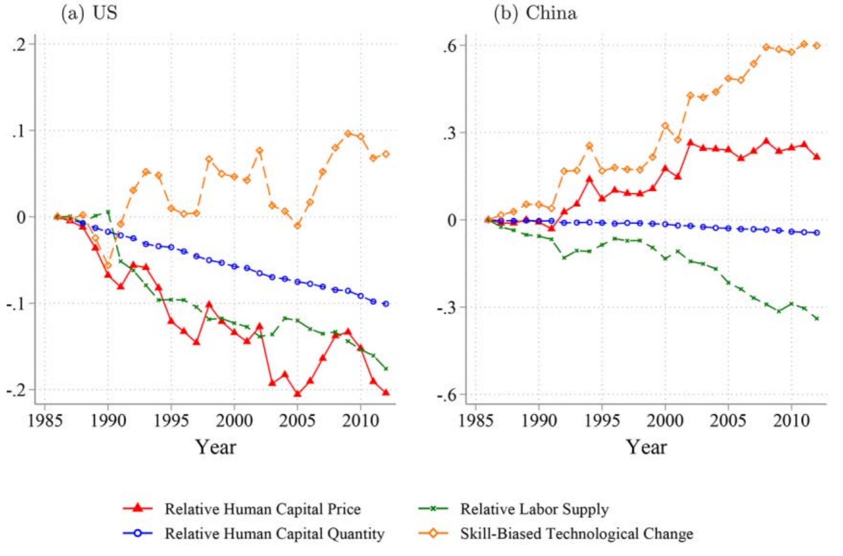

FIG. 9.—Decomposition of changes in relative human capital prices (*triangles*) into relative labor supply (*crosses*), relative human capital quantity per worker (*circles*), and skill-biased technical change (*diamonds*), with $\sigma = 3.8$.

skill-biased technical change, where σ is calibrated to 3.8, the value estimated by Bowlus et al. (forthcoming) on the canonical model using the Bowlus and Robinson (2012) series of human capital prices and quantities. As a robustness check, we also report in figure A.10 the results with alternative values for σ, ranging from as low as 1.4, the benchmark value estimated by Katz and Murphy (1992), to as high as 5, a large elasticity suggested by the new approaches developed by Bowlus et al. (forthcoming). We find that in both the United States and China, the relative quantity of college human capital grows rapidly, which would have led to sharp declines in the relative price of college human capital. Due to skill-biased technical changes (SBTCs), the relative price of college human capital in the United States declined less and in China actually increased over the past 30 years. Quantitatively, we find smaller SBTC, because previous estimates of SBTC do not separate out changes of relative human capital quantity. See appendix B.3 for a formal illustration.

C. *"New Normal" and the Golden Ages in China*

The fast growth in China is expected to slow down in the future. Between 1986 and 2012, the average intercohort human capital growth rate in China is 1.40% ($= 1.87^{1/45} - 1$) per year, and the average growth rate of human capital prices in China is 4.80% ($= 3.38^{1/26} - 1$) per year. Both are astonishing rates of growth, while the two growth rates are both close to 0 for the United States. However, the spectacular growth in China over the last 40 years is not expected to last forever; in fact, since 2010, the growth rate in China has slowed down significantly, and many analysts expect the "new normal" growth rate in China to converge to rates similar to those in the United States (Barro 2016). In this section, we perform a simple experiment that both the cohort effects and time effects still grow but start to uniformly decelerate in 30 years to a stationary environment of zero growth in cohort and time effects (approximately the US case), with the experience effects fixed at China's current estimated level.

In figure 10, we show that under this scenario, the vertical gaps between two consecutive cross-sectional age-earnings profiles will be shrinking, showing the slowdown in the time effects. Notably, the golden age, which was around 30–35 in 2010, would become older and to 45–50 years old in 2035. Recall proposition 1 and its corollary that the position of the golden age is essentially a race between experience effects and cohort effects. The golden age becoming older is a result of the slowdown in the intercohort human capital growth rate. If the Chinese economy indeed slows down and converges to the "new normal" growth rates similar to those of a more mature developed economy such as the United States in the next 30 years, our simulation suggests that the cross-sectional age-earning profiles over time will exhibit older golden ages, and reverse the pattern of ever-lowering golden ages in the next 30 years.

Is this a realistic prediction? Only history will tell for sure, but interestingly, figure 11 shows that such a pattern of increasing golden ages actually happened in Korea during the past 10 years, using data from the Korean Labor and Income Panel Study (KLIPS). Korea experienced its

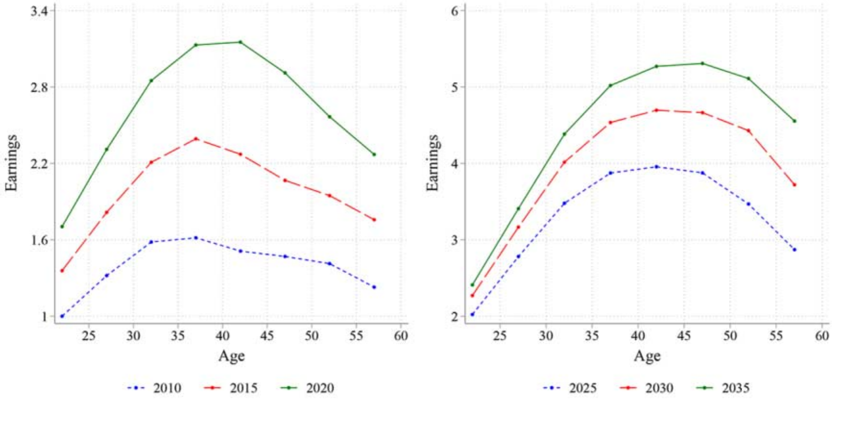

FIG. 10.—Plot of the hypothetical scenario for age-earnings profiles if China's cohort effects and time effects start to uniformly decelerate to a stationary environment in 30 years.

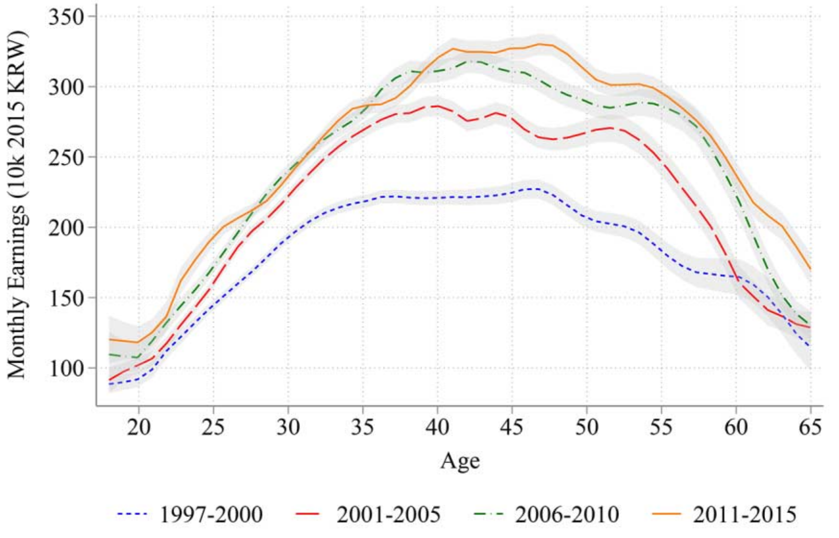

FIG. 11.—Plot of the cross-sectional age-earnings profiles of Korean male workers, using KLIPS data from 1997 to 2015. Each curve represents a cross section that pools adjacent years. The curves are kernel-smoothed values and the gray shaded areas are the 95% confidence intervals.

fastest growth from the 1960s to 1990s. After that, it began to slow down. Figure A.7 depicts the decomposition for Korea, together with the decomposition for the United States and China. It is worth noting that the cohort effects are particularly large from cohort 1945 to cohort 1960, but start to decelerate afterward. This is consistent with our explanation of the golden age as a result of the race between intercohort human capital growth and life-cycle human capital growth. As intercohort human capital growth starts to give way to experience in Korea, the golden age comes back to older ages, as in our hypothetical scenario in figure 10.

D. *Cohort-Specific Experience Profiles*

In the analysis thus far, the life-cycle human capital accumulation path is restricted to be invariant across cohorts. We rely on this assumption to overcome the data limitation of partial life cycles for different cohorts, and the assumption is irrelevant to the identification argument. Nevertheless, this section extends the baseline decomposition framework to allow for cohort-specific experience profiles.

Imposing cohort-invariant experience effects enables econometricians to pool data from different cohorts and estimate experience profiles that span an entire working life. Without such pooling of data, it would be impossible to estimate the complete experience profiles, as the available data cover a shorter period than the entire life cycle of any given cohort. To see this, let the experience effect, denoted by r_k^c, depend on cohort c. To estimate the entire experience profile $\{r_k^c\}_{k=1}^{40}$ for a given cohort c, we would need to observe the cohort's entire 40-year working life in the data. However, since our data span only 27 years from 1986 to 2012, the cohort with the longest coverage is observed for 27 years in the data, shorter than a 40-year working life. For instance, the cohort born in 1960 was 26 years old in 1986 and 52 years old in 2012. Other cohorts only have equal or shorter coverage. Obviously, we cannot infer a complete experience profile without even observing the full working life. This highlights the benefit of restricting the returns to experience to being constant across cohorts in the baseline analysis; we can still estimate a complete path of life-cycle human capital accumulation, despite the lack of data covering the whole life cycle for any given cohort.

While restricting the experience profiles to being invariant across cohorts is a standard practice in the literature, one might be concerned about the validity of this assumption, especially in the context of China's economic transformations. For example, as an economy develops rapidly, it is reasonable to expect that the human capital investment behavior would respond and hence differ across cohorts. To address this concern, we extend the baseline analysis to allow for cohort-specific experience profiles.

To do so, we deviate from the implementation by Lagakos et al. (2018) of the flat-spot identification of Heckman, Lochner, and Taber (1998) that restricts cohort-invariant experience effects. The identifying assumption is preserved that there is no human capital accumulation in the flat spot. We first identify the human capital price, or the time effects, by comparing wages of a given cohort across adjacent years in the flat spot. Subtracting the corresponding log prices series from the observed cohort-specific life-cycle log earnings profiles, we then obtain the cohort-specific paths of life-cycle human capital accumulation. See appendix B.4 for the details of the procedure. We then normalize the human capital quantity of the 1960s cohort between age 20 and 25 to be 1.

Figure 12 plots the cohort-specific experience profiles, where darker lines are for more recent cohorts and lighter lines for older cohorts.[23] The figure reveals a couple of findings. First, the pattern that the United States exhibits higher returns to experience than China is not altered, and the overall magnitude is comparable to that in the baseline analysis. This further gives confidence to our results in the previous sections. Moreover, figure A.11 shows that the estimated human capital price series in this specification is very similar to that in the baseline specification,

[23] See also Kambourov and Manovskii (2009), Kong, Ravikumar, and Vandenbroucke (2018), and Guvenen et al. (2022), who document changes in the raw life-cycle earnings profiles across cohorts in the United States.

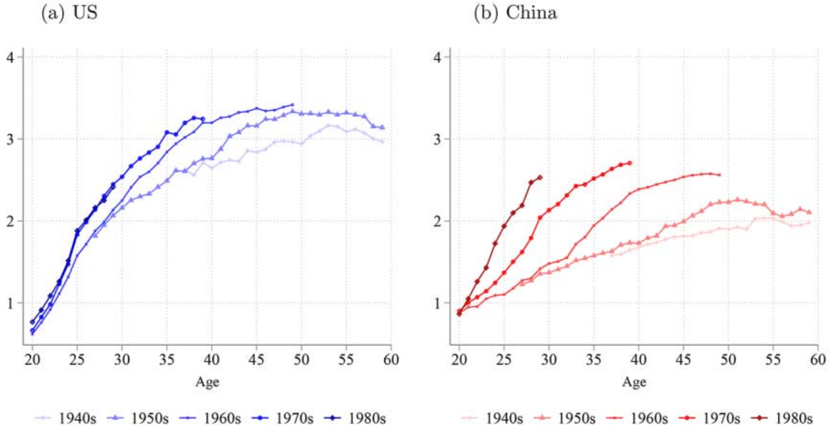

FIG. 12.—Plot of cohort-specific experience profiles for the United States (*a*) and China (*b*). Darker lines indicate more recent cohorts and lighter lines older cohorts. We normalize the average human capital quantity of the 1960s cohort between ages 20 and 25 to be 1.

indicating little bias in our previous analysis that involves disentangling price and quantity. Second, as one may expect, while the assumption of cohort-invariant experience profiles is not be a bad one for the United States, where the experience profiles for different cohorts are reasonably close to each other, it is clearly violated in the case of China. In particular, the experience profiles are shifting counterclockwise, meaning that returns to experience are getting higher for later cohorts.

The second finding of steepening experience profiles in China is particularly noteworthy. As documented by Lagakos et al. (2018), the experience profiles tend to be steeper in developed countries than in the developing countries. If we extrapolate this cross-sectional pattern to the time dimension, we would naturally expect a fast-growing economy to see steepening experience profiles as the economy develops. Our results confirm that this is indeed true, at least in the case of China's development.

What may explain the steepening experience profiles for later cohorts in China? A cohort-specific experience profile captures the life-cycle human capital accumulation for a given cohort. Individuals make human capital investment decisions by taking into account (the expectation of) the future path of returns to human capital. The significant increase in the rental price of human capital in China, as we document in section IV, provides a stronger incentive for later cohorts to invest in human capital, which in turn leads to steeper experience profiles. A quantitative analysis that incorporates this channel to study China's growth would be an interesting avenue for future research.

VI. Conclusion

In this paper, we document stark differences in the age-earnings profiles between the United States and China, the two largest economies in the world, over the past 30 years. We find that, first, the peak age in cross-sectional age-earnings profiles, which we refer to as the "golden age," stayed almost constant at around 50 years old in the United States but decreased sharply from 55 to around 35 years old in China; second, the age-specific real earnings grew drastically in China, but stayed almost stagnant in the United States; and third, the cross-sectional and life-cycle age-earnings profiles looked remarkably similar in the United States, but differed substantially in China.

To account for these differences, we propose and empirically implement a decomposition framework to infer from repeated cross-sectional earnings data the life-cycle human capital accumulation (the experience effect), the intercohort human capital growth (the cohort effect), and the human capital price changes over time (the time effect), under an identifying assumption that the growth of the experience effect stops at the end of one's working career. The decomposition suggests that China has experienced a much larger intercohort human capital growth and a higher increase in the rental price to human capital compared to the United States, but the return to experience is higher in the United States.

We then apply the inferred components to revisit several important and classical questions in macroeconomics and labor economics. Those exercises highlight the importance of intercohort human capital growth in understanding the evolution of China's labor market. First, we find a larger contribution of human capital and hence a smaller contribution of TFP to China's GDP per capita growth than previous estimates, mainly due to larger intercohort human capital growth revealed by our approach. Second, the technical change is much more skill biased in China than in the United States, without which the relative price of college human capital would have declined given the rapid increase in college human capital. Third, a simple simulation exercise suggests that as the Chinese economy slows down to a "new normal" growth rate—similar to that of the United States—the golden ages of the cross-sectional age-earnings profile in China will start to shift toward older ages, similarly to what has happened in Korea over the past two decades. Fourth, we find steepening returns to experience for later cohorts in China, suggesting that later cohorts not only have higher initial human capital but also accumulate more human capital over the life cycle.

The mostly descriptive findings in this paper suggest many potential directions for future research. First, identify the extent to which the rapid intercohort human capital growth in China is a result of the newer generations having the skills to operate on the latest technology, which would shed light on the broader intergenerational implications of technological advances. Second, connect the decomposition results to specific institutions and reforms, and quantify their contributions. For example, the 1999 college expansion in China may contribute to the intercohort human capital growth, while SOE reforms may improve the overall efficiency of the economy and increase the rental price to human capital. Third, investigate why returns to experience are higher in developed economies than in less developed economies, and why they steepen as an economy develops. Fourth, examine the implications of the rapid intercohort human capital growth and human capital price increase in China on other programs such as the social security system.[24] The drastically changing earnings profile and the surprisingly young golden age may also have significant ramifications for saving motives and relate to China's puzzling high saving rates. Finally, in this paper we focused on the United States and China. They are the two largest economies in the world, and the labor market dynamics in these two countries are likely to play an outsized influence on the global economy, but the decomposition framework can be fruitfully applied in other countries.

Data Availability

Data and code replicating results in this article can be found in Fang and Qiu (2023) in the Harvard Dataverse, https://doi.org/10.7910/DVN/FTVDNH.

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[24] For example, see Fang, Qiu, and Zhang (2022) for an exploratory study on the relationship between intercohort productivity growth and pension reform, particularly the delay of retirement age, in China.

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