Effects of Cohort Size on College Premium: Evidence from China's Higher Education Expansion

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Abstract

In this paper, we document the lesser-known heterogeneous trends of college/non-college earnings premium across age groups from 1995 to 2013 in China. Specifically, the college premium in 2013 for the younger group (age 25-34) was about 30 percentage points, similar to the level in 1995, while the college premium in 2013 for the older group (age 45-54) increased to 50 percentage points, nearly double that of 1995. To attribute these divergent trends of the college premium to the changes in relative size of college workers, we use the model by Card and Lemieux (2001) which incorporates imperfect substitution between similarly educated workers in different age cohorts. Due to the distinctions of these trends in China, our identification is free of the overestimation issue that the existing studies suffer. Our results are similar to those in the U.S., U.K., Canada, and Japan. Holding the age cohort and survey year constant, a one unit increase in log relative size of college workers is associated with about 10 percentage points decrease in college/non-college premium and about 18 percentage points decrease in college/high school premium. We further find that the negative effect is much more substantial among the new entrants (age 25-29) than among the experienced workers (age 30-54). By this pattern, we not only demonstrate that the new labor market entrants are more sensitive to their own cohort size but also argue that the confounding ability composition effect should not be a serious issue.

Keywords: College Premium; Cohort Size Effect; Trends; Imperfect Substitution

JEL Classification Numbers: J11, J20, J31

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1 Introduction

As a leading proximate cause of rising overall earnings inequality since the 1980s in the U.S., the increase in the college/high school wage premium has been well documented. Authors such as Katz and Murphy (1992), Acemoglu (2002), and Autor et al. (2008) have explained the rise as the consequence of an accelerated rise in the relative demand for college graduates and an abrupt slowdown in the growth of the relative supply of college graduates.[1] These studies focus on the aggregate trend of the college wage premium that may conceal independent trends by age groups. Card and Lemieux (2001) argue that heterogeneous trends of college premium by age groups may arise if workers in different age groups within the same education group are imperfectly substitutable and the trends of the relative supply of college workers are heterogeneous by age groups. Using data from the United States, the United Kingdom and Canada, they demonstrate the imperfect substitution between age groups and attribute the observed relative rise in the college premium for younger workers since the early or mid 1980s to the stagnated growth of the relative supply of college educated workers among the young during the same periods.[2] However, little evidence from other countries has been added until recently. Kawaguchi and Mori (2016) reveal the heterogeneous trends of the college premium by age groups between 1986 and 2008 in Japan. Our paper adds evidence to this literature by documenting the divergent trends of college premium by age groups between 1995 and 2013 in China, and examines how the college premium is affected by the age group specific relative size of college educated workers.[3]

In the two studies of the U.S., U.K., Canada, and Japan, an important identification

[1]It is argued that the increase may have been driven by both skill-biased technological change (SBTC) featured by the computer revolution and the outsourcing of manufacturing. Katz et al. (1999) and Autor et al. (2008) support the idea of SBTC, and Feenstra and Hanson (2001) support the idea of outsourcing. The growth of college graduation rates stagnated for cohorts born in the early 1950s and entered labor market in late 1970s. See Card and Lemieux (2001) for details.

[2]The relative rise in college premium for younger workers commenced 5 years later in the U.K. and Canada than in the U.S.

[3]Considering that there exists certain amount of workers below high school education in China, we focus on the college premium with respect to non-college workers. Results for the college/high school premium will also be discussed and compared with existing studies.

issue arises, the relative size of the college educated population is likely responsive to the college premium. Identification typically rests upon exclusion restrictions for instruments. China presents a unique environment where the decision of who obtains a college degree is determined by a national test. In most time periods, far more students take the test than are admitted. However, since 1977, the government expanded admissions and allowed additional students to enter college. Hence the Chinese experience embeds a natural experiment allowing for arguably exogenous determination of college attainment. Further, the identification strategies for the four countries all rely on the relative rise in college premium for younger workers since early or mid 1980s and the associated relative slowdown in growth of relative supply of college workers among the young. This timing overlapped with the emergence of skill-biased technological change (SBTC) since the early 1980s with the onset of the computer revolution. And it is suggested that this computer driven technological change may increase the relative demand for college workers and further increase the college premium among the young in particular (Krueger, 1993; Card, 1999; Freeman and Katz, 2007).[4] Therefore, the negative effect of age group specific relative size on age group specific college premium may have been confounded by SBTC and overestimated for the four countries. The distinct trends of college premiums and relative size of college workers during our study period of 1995 to 2013 in China allows for a lower-bound of the estimated effects. Finally, China is also worth examining due to its large population and workforce.

Using China Household Income Project (CHIP) 1995, 1999, 2002, 2007, and 2013, five repeated cross-sectional surveys, we find that the trends of the college premium between 1995 and 2013 by age groups are substantially different. In figure 1(a), the college premium as measured by log earnings ratio was very similar for younger (age 25-34) and older (age 45-54) groups, about 25 percentage points in 1995. As of 2013, the college premium for the younger group was about 30 percentage points, similar to the level in 1995, while the college premium

[4]Card (1999) uses relative computer usage rates of college workers as a proxy indicator of the relative complementarity of college workers with new technology and finds little evidence supporting this hypothesis. However, we have no evidence to reject the hypothesis and it may be argued that the proxy indicator may have failed to fully capture the relative complementarity.

for the older group was about 50 percentage points, nearly double that of 1995. In figure 1(b), we present the age group specific trends of the relative supply of college workers measured as log employment ratio. The relative supply for the younger group was quite stable while that the for older group increased substantially during the same period. Comparing these two figures, the stagnation of the college premium for the younger group between 1995 and 2013 was potentially due to the fast growing relative supply of college workers. Figures 2 and 3 show that in the U.S. and Japan, unlike in China, the college premium for the older group decreased with respect to the younger group while the relative supply for the older group increased with respect to the younger group.[5] If technological progress positively affects the college premium for the younger group particularly as the literature argues, the negative age group specific supply effects will be overestimated for the U.S. and Japan, and underestimated for China. Thus, this paper provides a lower bound estimate of the negative effect.

The underlying cause of the heterogeneous trends of relative supply by age groups is the non-monotonic increase in the college attendance rate which was determined by college capacity and birth cohort size. The expansion of college attendance ended in 1965 in the U.S. and in 1975 in Japan.[6] Therefore, Card and Lemieux (2001) and Kawaguchi and Mori (2016) mainly study the post-expansion period for the U.S. and Japan.[7] In China, the growth in college attendance began in 1977 and did not slow down until 2008. This paper studies the period 1995-2013 which includes the expansion. Thus, this paper reveals the consequence of an ongoing college attendance expansion, supplementing previous studies on the consequence of past college attendance expansion.

In this paper, we follow the empirical strategy by Card and Lemieux (2001) to construct the college premium and relative supply by age and survey year, and to further regress the cell-specific college premium against the relative supply. The supply effect on the college

[5]These two figures are taken from the paper by Kawaguchi and Mori (2016) who compare the trends between the U.S. and Japan.

[6]The fast growth in college attendance rate ended for U.S. birth cohort 1947 and Japanese birth cohort 1957 approximately (Kawaguchi and Mori, 2016). And suppose college age is 18.

[7]Even though the period studied by Card and Lemieux (2001) is from 1959 to 1996, the identification relies on data in years later than 1975.

premium is estimated to be about -0.1 by our main specification. That implies, when holding the age cohort and survey year constant, a one unit increase in the log relative size of college workers is associated with about 10 percentage points decrease in the college premium. The more comparable result, by focusing on the college/high school earnings premium, is about -0.18 which is slightly lower than -0.2 in the U.S. and -0.23 in the U.K. while almost same as the results for Japan and Canada. That the negative supply effect in China is so close to the other four countries is remarkable in view of the very different economic development levels, trends of the college premiums and the relative supply, and higher education expansion phases between China and the other four countries. It is more interesting considering that the estimate of the supply effect should be a lower bound in China and upper bound in the other four countries.

We further examine the heterogeneous supply effects by age groups and find that the entrant group between ages 25 and 29 is more substantially affected by their own relative supply. This finding can be used to address the ability composition issue.[8] The ability effect is argued to be more substantial for the older group (Lillard, 1977), however, the estimated negative supply effects for the older groups are significantly lower than that for entrant group. This implies that the ability composition effect is not a dominant part in the estimated supply effect even if it may exist to some extent.

The rest of this paper is organized as follows. Section 2 presents the theoretical model by Card and Lemieux (2001). Section 3 discusses empirical strategy and potential identification issues. Section 4 introduces our data from China and describes the trends of college/non-college earnings gap and relative supply of college workers with details. Section 5 presents main results and section 6 reports a set of robustness checks. Finally, we conclude in section 7.

[8]It is argued that the increase in relative supply of college workers might be associated with a decrease in the average ability gap that leads to a decrease in the college premium.(Chay and Lee, 2000; Taber, 2001; Juhn et al., 2005; Carneiro and Lee, 2009, 2011) Thus, the negative supply effect tends to be overestimated.

2 Theoretical Framework

2.1 Model Setup

We start with a Cobb-Douglas aggregate production function that has been widely used in the macro-growth literature:

$$Y_t = A_t L_t^{\alpha} K_t^{1-\alpha} \tag{2.1}$$

where subscript t indexes year, Y_t is aggregate output, A_t is total factor productivity, L_t is aggregate labor force input, K_t is physical capital input and α is the share of income allocated to labor force.

Following the existing literature on the trend of wage differentials by education (Katz and Murphy, 1992; Autor et al., 2008), we assume the labor force input L_t in equation 2.1 follows a CES aggregation of college and non-college labor

$$L_t = [\sum_s (\theta_{st} L_{st}^{\rho})]^{1/\rho} \tag{2.2}$$

where subscript s indexes education level which takes c for college labor and n for non-college labor, θ_{st} is the technological efficiency parameter, and $-\infty < \rho \leq 1$ is a function of the elasticity of substitution σ_A between college and non-college labor force ($\rho = 1 - 1/\sigma_A$). The underlying assumption is that different age cohorts within the same education group are perfect substitutes. To explain the divergent trends of the college premiums across age cohorts, following Card and Lemieux (2001), we relax the assumption of perfect substitution across age cohorts and further assume the labor force of each education level is aggregated by age cohorts by CES functional form

$$L_{st} = [\sum_j (\alpha_{sjt} L_{sjt}^{\eta_s})]^{1/\eta_s} \tag{2.3}$$

where subscript j indexes age cohort, α_{sjt} is a relative efficiency parameter,[9] $-\infty < \eta_s \leq 1$ is a function of the elasticity of substitution σ_s among different age cohorts ($\eta_s = 1 - 1/\sigma_s$), and L_{sjt} is size of labor force for each education-age-year group.

2.2 Profit-Maximizing Wage

In this setup, assuming efficient utilization of labor force, we can derive the profit-maximizing wage of an average worker with education level s, among age cohort j, in year t as the value of corresponding marginal productivity in log form:

$$log(w_{sjt}) = log(\Phi_t) + log(\theta_{st}) + (\frac{1}{\sigma_s} - \frac{1}{\sigma_A})log(L_{st}) + log(\alpha_{sjt}) - \frac{1}{\sigma_s}log(L_{sjt}) \tag{2.4}$$

where

$$\Phi_t = \alpha A_t K_t^{1-\alpha} L_t^{\alpha-\rho}$$

According to equation 2.4, the age specific variation in wages is due to the age specific variation in the relative efficiency parameter α_{sjt} and the size of labor force L_{sjt}. The term $log(\Phi_t)$ represents a common year fixed effect across education levels while the terms $log(\theta_{st}) + (\frac{1}{\sigma_s} - \frac{1}{\sigma_A})log(L_{st})$ represents the year fixed effect for specific education level s. In this setup, the coefficient of $log(L_{sjt})$, $-1/\sigma_s$, should be negative unless the labor forces are perfectly substitutable across age cohorts ($\sigma_s = \infty$).

[9]This relative efficiency parameter may be affected by labor complementarity with technology, skill composition, ability composition, etc. Card and Lemieux (2001) assume the relative efficiency parameter is constant over time. In our paper, we relax the strict assumption to allow for time variation which will be helpful to explain potential identification issues.

2.3 Age Specific Relative Size and College Premium

It is straightforward to derive the college premium by taking difference of the log wages between college and non-college labor force in terms of equation 2.4,

$$log(\frac{w_{cjt}}{w_{njt}}) = log(\frac{\theta_{ct}}{\theta_{nt}})+(\frac{1}{\sigma_c}-\frac{1}{\sigma_A})log(L_{ct})-(\frac{1}{\sigma_n}-\frac{1}{\sigma_A})log(L_{nt})+log(\frac{\alpha_{cjt}}{\alpha_{njt}})-\frac{1}{\sigma_c}log(L_{cjt})+\frac{1}{\sigma_n}log(L_{njt}). \quad (2.5)$$

To simplify our explanation of the age specific college premiums, we assume that the extent of substitution across age cohorts is the same for the college and non-college labor force. That is, we assume $\eta_c = \eta_n = \eta$ (which is equivalent to $\sigma_c = \sigma_n = \sigma$). This assumption will be tested empirically. We can rewrite equation 2.5 as:

$$log(\frac{w_{cjt}}{w_{njt}}) = log(\frac{\theta_{ct}}{\theta_{nt}}) + (\frac{1}{\sigma} - \frac{1}{\sigma_A})log(\frac{L_{ct}}{L_{nt}}) + log(\frac{\alpha_{cjt}}{\alpha_{njt}}) - \frac{1}{\sigma}log(\frac{L_{cjt}}{L_{njt}}) \quad (2.6)$$

where $log(\frac{\theta_{ct}}{\theta_{nt}})$ implies the year trend of the relative technological efficiency for college labor force, $log(\frac{L_{ct}}{L_{nt}})$ measures the relative size of aggregate college labor fore in year t, $log(\frac{\alpha_{cjt}}{\alpha_{njt}})$ is the age specific trend of relative efficiency of college workers, and $log(\frac{L_{cjt}}{L_{njt}})$ is the key variable of interest, the age specific relative size of college labor force.

Notice that the first two terms at the right-hand-side of equation 2.6 capture the year trend of the college premium common for all age cohorts. Thus, the heterogeneous trends of the college premium across age cohorts should be due to the last two terms. And, the negative effect of age specific relative size on the college premium is expected unless workers are perfectly substitutable across age cohorts (the substitution elasticity $\sigma = \infty$).

2.4 Birth Cohort Effects

The two age specific variables, $log(\frac{L_{cjt}}{L_{njt}})$ and $log(\frac{\alpha_{cjt}}{\alpha_{njt}})$, are actually measures for the birth cohort $t - j$. Thus, in addition to a fixed age profile and year fixed effect, $log(\frac{L_{cjt}}{L_{njt}})$ should capture birth cohort effects that reflect the variation in college attendance rate while $log(\frac{\alpha_{cjt}}{\alpha_{njt}})$ should capture birth cohort effects that mainly reflect the technological changes. We can decompose them into age cohort, year, and birth cohort fixed effects,

$$log(\frac{L_{cjt}}{L_{njt}}) = F_{t-j} + F_j + F_t \tag{2.7}$$

$$log(\frac{\alpha_{cjt}}{\alpha_{njt}}) = f_{t-j} + f_j + f_t. \tag{2.8}$$

Therefore, we can rewrite equation 2.6 as

$$log(\frac{w_{cjt}}{w_{njt}}) = F'_t + F'_j + f_{t-j} - \frac{1}{\sigma}F_{t-j} \tag{2.9}$$

where

$$F'_t = log(\frac{\theta_{ct}}{\theta_{nt}}) + (\frac{1}{\sigma} - \frac{1}{\sigma_A})log(\frac{L_{ct}}{L_{nt}}) + f_t - \frac{1}{\sigma}F_t$$

$$F'_j = f_j - \frac{1}{\sigma}F_j.$$

This implies that the college premium for age cohort j in year t can be decomposed into year, age and birth cohort fixed effects. Only in the case that workers are not perfectly substitutable across age cohorts ($\sigma < \infty$) can birth cohort effects in relative size, F_{t-j}, contribute to the birth cohort fixed effects in the college premium.

3 Empirical Approach

3.1 Construction of College Premium and Relative Cohort Size

Our primary goal in this paper is to estimate the effect of the age cohort specific relative size of college workers on the age cohort specific college premium. Since these two key variables are not directly observed in our data set, we need to construct measures of them prior to further analysis.

Following the standard approach in the literature on cohort size effects, we collapse individual data into cells based on single-year age and survey year. Then the age specific college premium in each survey year is estimated with the individual observations within corresponding cells by following specification,

$$y_i = \beta_0 + \beta_1 college_i + \varepsilon_i \tag{3.1}$$

where y_i is log annual earnings, β_0 is a constant, $college_i$ is a dummy variable that takes 1 for college workers and 0 for non-college workers, and β_1 is the college premium to be estimated. Some existing papers (Welch, 1979; Card and Lemieux, 2001; Brunello, 2010) on the effect of cohort size on earnings or the college premium use log weekly or hourly wages for analysis. However, in terms of equations 2.4 and 2.5, we believe that using weekly or hourly earnings is inappropriate unless the age specific relative size is measured using total working weeks per year or total working hours per year correspondingly. Due to the lack of information of working hours, we use log annual earnings for our analysis.

Accordingly, we build the measure of age specific relative size based on the number of workers.[10] The age-year cell specific relative size is just the log ratio of the number of college workers to the number of non-college workers within each cell.

Following Card and Lemieux (2001), we also record the standard errors of estimated cell specific college premiums. The corresponding inverse variances will be used as weights for the regression analysis to put more weight on those precisely estimated college premiums, and be used to construct goodness-of-fit tests for the null hypothesis that the relevant specification has no specification error.[11]

To improve the precision of the estimated college premiums and to reduce the sampling variation in relative size of college workers, we construct cells based on three-year age and

[10] Using annual earnings and number of workers to build measures for the college premium and relative size highlights that our estimated effects of cohort size on the college premium have slight different implications from those using weekly earnings or hourly earnings. Considering that working hours or working weeks are endogenously determined in the labor market, using them to measure relative size may suffer the identification issue of reverse causation.

[11] Essentially, it tests whether the recorded variances of the estimated college premiums are significantly different from the variances of the residual in relevant specification. See Card and Lemieux (2001) for details.

survey year alternatively at the expense of reducing the number of cells for regression analysis by two thirds. Nevertheless, this serves as a good robustness check.

3.2 Testing the Assumption: Equally Substitutable College and Non-College Labor

In section 2.3, we link age specific college premiums to age specific relative sizes by equation 2.6 based on the assumption that the substitution elasticity across age cohorts, σ_s, is the same among college and non-college groups. It is a hypothesis that needs to be tested. Following the profit-maximizing wage equation 2.4 for an average worker in age cohort j with education level s in year t, we decompose the unobserved three-way variable $log(\alpha_{sjt})$ into three two-way fixed effects (education level-year, education-age, and age-year fixed effects) and a conditional zero mean error term ε_{sjt}. Then we test the assumption by OLS estimation with the following specification:

$$log(w_{sjt}) = F_{st} + F_{sj} + F_{jt} + \beta_1 noncollege_s \times log(L_{sjt}) + \beta_2 college_s \times log(L_{sjt}) + \varepsilon_{sjt} \quad (3.2)$$

where the dependent variable $log(w_{sjt})$ is mean log earnings for j years old workers with education level s in year t, the education-year fixed effects F_{st} absorbs the terms $log(\Phi_t) + log(\theta_{st}) + (\frac{1}{\sigma_s} - \frac{1}{\sigma_A})log(L_{st})$ from equation 2.4 and the additional education-year fixed effect decomposed from $log(\alpha_{sjt})$, the education-age fixed effect F_{sj} captures the potentially different age-profile of earnings for college and non-college groups, the age-year fixed effect F_{jt} captures those unobserved factors that commonly affect both education groups, and $log(L_{sjt})$ is the age cohort size for education group s in year t. We allow for a different effect of cohort size on earnings by including the interaction terms between education group dummy and age cohort size, $college_s \times log(L_{sjt})$ and $noncollege_s \times log(L_{sjt})$. We test whether $\beta_1 = \beta_2$.

An equivalent test strategy as follows is based on equation 2.5,

$$log(\frac{w_{cjt}}{w_{njt}}) = F_t + F_j + \beta_1 log(L_{cjt}) + \beta_2 log(L_{njt}) + \varepsilon_{jt} \tag{3.3}$$

where dependent variable is estimated college premium for age cohort j in year t, the age-year fixed effect in equation 3.2 is canceled out by taking difference between log earnings of college workers and non-college workers. Noticing that β_1 and β_2 represent $-\frac{1}{\sigma_c}$ and $\frac{1}{\sigma_n}$ respectively, we test if $\beta_1 + \beta_2 = 0$.

Since both dependent variables in equations 3.2 and 3.3 are estimated first, the corresponding standard error can been obtained prior to the tests. Following the literature, we use inverse squared standard errors as weights to implement weighted-OLS estimation.

3.3 Estimating the Effect of Age Specific Relative Size on College Premium

Our basic specification to estimate the effect of age specific relative size on the college premium is based on the equation 2.6. We decompose the unobserved age-year log ratio of relative efficiency, $log(\frac{\alpha_{cjt}}{\alpha_{njt}})$, into age fixed effect, year fixed effect and age-year two-way variation. We use the following specification,

$$r_{jt} = F_t + F_j + \beta_1 log(\frac{L_{cjt}}{L_{njt}}) + \varepsilon_{jt} \tag{3.4}$$

where r_{jt} is the estimated college premium for age cohort j in year t, F_t captures all year specific factors, F_j is the age fixed effect decomposed from $log(\frac{\alpha_{cjt}}{\alpha_{njt}})$, $log(\frac{L_{cjt}}{L_{njt}})$ is relative size of college workers measured as log ratio of the number of college workers to the number of non-college workers within each age-year cell, and the error term ε_{jt} is assumed to be conditional zero mean to ensure the OLS estimate of β_1 identifies the relative size effect on the college premium.

However, a simple OLS estimate of β_1 may be biased through two ways. First, our specification is strictly based on the profit-maximizing wage functions which reflect only the demand side of the labor market, whereas the observed college premiums and age specific relative sizes represent the realized general equilibrium. Therefore, $log(\frac{L_{cjt}}{L_{njt}})$ may have been affected by the college premium through a supply channel. We use the predetermined variable, age-year cell specific log ratio of the number of college degree holders to the number of non-college degree holders (including both employed and unemployed individuals) as an instrumental variable for $log(\frac{L_{cjt}}{L_{njt}})$.

Second, the error term ε_{jt} captures not only those plausible zero mean sampling error and specification error, but also the age-year two-way variation from the unobserved log relative efficiency ratio, $log(\frac{\alpha_{cjt}}{\alpha_{njt}})$. The simple OLS estimate of β_1 will be biased due to omission of relevant variables if $log(\frac{L_{cjt}}{L_{njt}})$ is correlated with the unobserved two-way varying $log(\frac{\alpha_{cjt}}{\alpha_{njt}})$. By the implication of the relative efficiency parameter α, we know it may be affected by relative labor complementarity with technology, relative skill composition, relative ability composition, etc. Since it has been discussed that the skill biased technological change favoring younger college workers allows for a lower bound of the estimates in the context of China, we focus on the potential ability composition effect and skill composition effect in this section.

3.3.1 Ability Composition Effect

It's widely believed that basic OLS estimates of college premium are biased due to unobserved ability or self-selection, which is reflected by the huge literature on isolating the returns to college from the returns to ability. However in the literature on the evolution of college premium, the change in the ability composition effect receives much less attention. Some studies find that the changes in ability composition or self-selection indeed contribute to the observed college premium evolution, even if the extents are found to be different (Chay and Lee, 2000; Taber, 2001; Juhn et al., 2005; Carneiro and Lee, 2009, 2011).[12]

[12] Among these studies, only Carneiro and Lee (2011) focus on isolating the ability composition effect within the age specific framework as we do in this paper, while others within aggregate framework.

Before presenting our empirical strategy to address the ability composition effect, it is necessary to explain how it may confound the estimate of the relative size effect in this paper. As we noted in section 2.4 and which will be empirically explored, the relative size $log(\frac{L_{cjt}}{L_{njt}})$ captures strong birth year fixed effects which drive the age-year two-way variation in $log(\frac{L_{cjt}}{L_{njt}})$. There has been an observed increase in college attainment along with the birth cohorts. And the observed increase stems from both demographic changes, and an expanding capacity of China's higher education. In China's strict test score-based college admission system, it's plausible that marginal college students have lower ability than the average college students. When the expansion of college capacity outpaced the demographic changes in China, the share of college students increased, marginal students entered college, and the average ability of college students was lowered. By the same logic, the average ability of non-college students also has been lowered. The lowered average abilities for both education groups result in difficulty in predicting the sign of the correlation between relative size $log(\frac{L_{cjt}}{L_{njt}})$ and relative average ability. However, some previous papers show that the ability effect on earnings for high school graduates is insignificant (Carneiro and Lee, 2011) and is less positive than that on college graduates (Lillard, 1977; Carneiro and Lee, 2011). This evidence implies that we should be careful that the negative correlation between relative size of college workers and the earnings gap effect of relative average ability may lead our estimated relative size effect on earnings gap to be downward biased. In the extreme case, what we estimated for β_1 by equation 3.4 may just be an ability composition effect rather than a relative size effect.

Our strategy is to explore the age pattern of the potentially confounded relative size effect by allowing for heterogeneity across age groups,

$$r_{jt} = r_t + r_j + \beta Agp_j \times log(\frac{L_{cjt}}{L_{njt}}) + \varepsilon_{jt} \tag{3.5}$$

where Agp_j is a vector of age group dummies, β is the corresponding vector of coefficients which captures the relative size effects on college premium across age groups, and ε_{jt} is suspected to include ability composition effects negatively correlated with $log(\frac{L_{cjt}}{L_{njt}})$. If the ability composition effects are significant and indeed negatively correlated with $log(\frac{L_{cjt}}{L_{njt}})$, by simple OLS estimation, we will obtain an estimated age group pattern of relative size effect dominated by the age group pattern of ability composition effects.

Lillard (1977) uses NBER-Th data[13] which includes measured ability (AFQT scores) and reveals that the earnings effect of measured ability increases as one ages and this increasing pattern is more significant for college graduates than for high school graduates.[14] More specifically, the ability effect is almost negligible or even slightly negative under age 35 and peaks around age 50. Taking this pattern as also true in China's context,[15] the estimated relative size effects will be more negative for older groups if the ability composition effects exist and are negatively correlated with $log(\frac{L_{cjt}}{L_{njt}})$. Therefore, if an opposite pattern is revealed by our estimation, we will be able to argue that the confounded ability composition effects are trivial, and the estimated effects for younger groups, especially those under age 35, should be uncontaminated by the ability composition effects at least. The opposite pattern can be explained as the younger groups tend to be affected by their own cohort relative size more substantially.[16]

3.3.2 Skill Composition Effects

We use occupation and industry composition to capture the skill composition approximately. The variation in age specific relative size, $log(\frac{L_{cjt}}{L_{njt}})$, is mainly driven by China's higher education expansion since 1977 when the national college entrance examination was restored. One year later, in 1978, China started "the open and reform" through which China

[13]NBER-Th sample was based on a sample of men who had volunteered for pilot, bombardier, and navigator programs of the Air Force during World War II. Thomas Juster organized a resurvey of a subset of these men in 1969 and built a data set providing information on education, income, AFTQ test scores and detailed information on various measures of family background.

[14]One explanation is that the more able tend to invest more in on-job training or choose more promising jobs.

[15]Even if there is no evidence from China's data, we believe the underlying logic also holds in China's labor market.

[16]Welch (1979) finds that the cohort size effects are more negative for entrant cohorts with data of the U.S.

switched from a central-planned economy to market-oriented economy gradually. Along with the transition, new labor market entrants with different education levels may have been reallocated into occupations and industries differently. Considering that the higher education expansion and economy transition took place during the same period, it is possible that the age-year variations in occupation and industry compositional differential between college and non-college groups are correlated with the age-year variation in college/non-college relative size. That means, in equation 3.6, the omitted occupation and industry compositional effects are possibly correlated with $log(\frac{L_{cjt}}{L_{njt}})$. Due to sample size limitation,[17] we are not able to control for these compositional effects consistently for each age-year cell. Therefore, we turn to regression with individual data directly by the following specification,

$$\begin{aligned} y_{ijt} = \beta_0 + \beta_1 college_{ijt} \times log(\frac{L_{cjt}}{L_{njt}}) + \beta_2 log(\frac{L_{cjt}}{L_{njt}}) \\ + F_t + F_j + college_{ijt} \times (F_t + F_j) + \gamma X_{ijt} \times F_t + \varepsilon_{ijt} \end{aligned} \tag{3.6}$$

where i, j, t denotes individual, and X_{ijt} includes a series of dummies for occupation and industry categories. We allow for the occupation and industry fixed effects vary across years by the interaction term $X_{ijt} \times F_t$. With this specification, the OLS estimate of β_1 is the relative size effect on the college premium conditional on occupation and industry. Dropping the interaction term $X_{ijt} \times F_t$ should result in an estimated β_1 close to those by specification 3.4 since the earnings gap by specification 3.6 can be expressed in the exactly same form:

$$E[Y_{ijt}|college_{ijt} = 1] - E[Y_{ijt}|college_{ijt} = 0] = \beta_1 log(\frac{L_{cjt}}{L_{njt}}) + F_t + F_j. \tag{3.7}$$

By controlling for these labor market destinations, we also alleviate another concern about the college majors composition effect since it is plausible that majors determine college graduates' occupation and industry destinations to a substantial extent.[18]

[17]On average, in our data set, each age-year cell contains about 90-210 individuals.

[18]Grogger and Eide (1995) reveal that the trend away from low-skill subjects such as education and toward high-skill subjects such as engineering accounts for one-fourth of the rise in the male college wage premium with the U.S. data. Majors information is not available in our data set that we can't directly control for them.

4 Data

Our data are drawn from five repeated cross-section nationally representative surveys - China Household Income Project (CHIP) 1995, 1999, 2002, 2007 and 2013.[19] As indicated by its name, CHIP surveys detailed household income, education, employment, and family background information, which makes it a widely used data source in the literature on earnings differential across education or other labor market-related topics in China.[20] In this paper, following the literature (Zhang et al., 2005; Ge and Yang, 2011; Wang, 2012; Wang et al., 2014) on China's college premium, we focus on the urban samples.[21] We further restrict our sample to males between 25-54. Only focusing on males avoids the selection issue due to intermittent female labor force participation.[22] The lower limit, age 25, is to make sure most college graduates have entered the labor market while the upper limit, age 54, is to drop those near retirement age who may decide to retire non-randomly (Brunello, 2010).

We define individuals who have a three-year college degree, a four-year college degree or above as college graduates, and all other individuals as non-college graduates. This broad definition has the advantage of covering all workers in the labor market and obtaining more precise estimates for earnings gaps by keeping more observations, but the disadvantage of bringing the contamination of composition effects. Therefore, we will also present results based on only 4-year college and high-school graduates as a robustness check.

We use annual earnings to estimate the college premiums due to limited consistent information on working weeks and hours. However, CHIP (2007) only provides monthly earnings information without working months available. Fortunately, the potential inconsistence in estimated college premiums for wave 2007 should be captured by a fixed year effect which

[19] CHIP 2008 surveys the same individuals in 2007, so we pool them together and notate it as CHIP2007 in this paper.

[20] For instance, Gustafsson et al. (2008) write a whole book using CHIP to explore inequality and public policy in China.

[21] The main reasons documented are that rural household income is generally indivisible, there is a relatively low share working in non-agriculture sectors, and there are few college graduates working in rural area.

[22] See Card and Lemieux (2001) and Brunello (2010). Even if this issue may not be as severe as that in western countries considering that female labor force participation is relatively high in China(Meng, 2012), we focus on males for comparing results with existing literature mainly on western countries.

will be controlled for in our empirical analysis.

We collapse the individuals between age 25-54 into 150 cells based on single-year age and survey year. For each cell, our estimated college premiums and the key explanation variable, relative size of college workers are further based on those employed individuals reporting positive annual earnings. The instrumental variable for relative size of college workers, as discussed in section 3.3, is based on both employed and unemployed individuals between 25-54, including females. This wide inclusion is to make sure we construct a predetermined variable only affected by the exogenous demographic change and higher education expansion.

4.1 Sample Summary

Before presenting a graphical description of cell-specific relative size and estimated college premium, we summary our filtered sample in Table 1. The number of observations in each survey year ranges between 2754 and 6461 and the variation is mainly due to the variation in sample size of original surveys. The average log annual earnings shows steady increase.[23] The share of college workers increased from 29% in 1995 to 45% in 2007 and drops slightly to 42% in 2013, even if the higher education expansion should have pushed up the college share. This reflects that men's share of college workers in urban areas has achieved a saturation level and more young college graduates have to stay in rural areas.[24] The age structure is stable during the covered period shown by the stable averages and standard deviations. By categorizing occupations into three levels (high-skill, mid-skill, and low-skill levels), we can see a decrease in high-skill share and increase in low-skill share.[25] Most industry shares are stable, except that manufacturing share decreased while service shares increased. The dominant industry by share of employment changed from manufacturing to service. As we discussed in section

[23]We use nominal annual earnings in this paper, so the increase captures both real income growth and inflation. Using nominal earnings does not affect our results since the inflation index is canceled out in the estimates of college/non-college earnings gap.

[24]By comparing the share of college graduates in rural area between 2007 and 2013 using CHIP rural surveys, we indeed find this trend.

[25]High-skill level includes principals and professional technicians, mid-skill level includes clerical/office staff and low-skill level includes the other occupations.

3.3.2, if these changes in occupation and industry shares were different between education groups and age groups, our estimated effect of the relative size on the college premium would be contaminated by occupation and industry compositional effects.

4.2 Relative Sizes and Estimated College Premiums

For each age-year cell, we can estimate a college premium by equation 3.1, and measure the corresponding relative size of workers as the log ratio of the number of college workers to the number of non-college workers. Figure 4 provides pairs of these two variables. Due to the year fixed effects and the intrinsic age profile, it shows no clear linear relationship between the college premium and the relative size of college workers. Nevertheless, figure 4 reveals substantial variations in the two variables, which makes it possible for us to identify the potential relationship by regression analysis.

By exploring the changing age profiles of college premium and relative size, we can reveal the relationship between them graphically. To make sure our graphs suffer less estimation variation, we use 30 broader cells of five-year age and survey year. Figures 5 and 6 present the age profiles of the college premium and the relative size respectively across survey years. As the downward age profile of the relative size turned much steeper form 1995 to 2013 in figure 6, the age profile of the college premium departed from flat pattern to a upward pattern in figure 5. The opposite switching age profiles of relative size and the college premium is a reflection of the negative relationship.

4.3 Relative Size, College Premium and Higher Education Expansion

As we discussed in section 2.4, the relative size for college workers in age cohort j and year t is measuring those born in year t-j, which implies that it should have captured strong birth year effects in addition to a fixed age profile and year fixed effect. To graphically illustrate the birth cohort effects, we plot the share of college workers against birth year groups in figure 8. Even if the profiles shifts up and down across years and may also have absorbed intrinsic age structure, it is clearly revealed that there are steady rises in the share of college workers from birth year group 1953-1958 to 1984-1988. Considering that high school students usually take the national college entrance examination (NCEE) at about 18 years old, the rising birth year trends coincide with the restored NCEE and the expansion of higher education since 1977 as figure 7 shows.[26] The positive correlation implies that the rise in relative size of college workers across birth years was mainly driven by the higher education expansion.

We also check if the college premiums also show strong birth year fixed effects, which would serve as preliminary evidence of the effect of the relative size on the college premium as we discussed in section 2.4. Due to the more substantial variations in the college premium across years and age cohorts, the graph for the college premium suffers greater noise than the graph for shares of college workers. Therefore, we turn to regressions based on equations 2.7 and 2.9 which decompose relative size and college premium for age cohort j in year t into year, age and birth cohort fixed effects.

Table 2 presents results of the decompositions. We take survey year 1995 and birth group 1941-1958 as reference groups.[27] In column 1, we decompose college premiums by basic OLS estimation. In column 2 we weight our regression by the inverse sampling variance of estimated college premium with the χ^2 statistic for testing specification error reported.[28] Since the results are just different slightly between basic OLS and Weighted OLS estimation, we focus on the weighted-OLS results following the literature. Year fixed effects on the college premium increased by 38.3 percentage points from 1995 to 2013, and about half of the increase happens between 1995 and 1999. The estimated birth year fixed effects show a

[26]This figure depicts the nationwide trend including both urban and rural while figure 8 is based on CHIP's urban samples only. The absolute shares of college workers are much higher than those in figure 8. This implies that more college students are from urban areas or stay in urban areas.

[27]Considering that most high school students apply for college at about 18 years old, those born before 1958 arrived at college age before 1977 when the NCEE was restored. We do not divide our sample evenly into birth groups due to the uneven year gaps of our surveys.

[28]The null hypothesis is that there is no specification error conditional on included fixed effects. See Card and Lemieux (2001) for details.

steady decreasing trend for those born after 1958. Specifically, comparing with those born in 1941-1958, the college premium for the recent birth cohorts 1984-88 decreased by almost 39 percent. As the χ^2 static 111.07 and its p-value 0.45 indicate, we fail to reject the null hypothesis that there is no specification error in our model. The dependent variable in column 3 is the share of college workers while the dependent variable in column 4 is relative size of college workers which is also the explanatory variable in our main specification 3.4 to be estimated in next section. Estimated year fixed effects capture both sampling variation and overall relative employment across survey years. As the results in column 3 show, comparing with 1995 conditionally, about 3.5 percent more college workers were employed in 1999 and 9.6 percent less college workers were employed in 2013. The estimated birth year fixed effects show a steady rising trend for those born after 1958, which reveals a negative correlation with the estimated fixed effects on college premium in column 2. The predicted birth group fixed effects on the share of college workers and college premium, standardized to age 40 and year 2013, are plotted in figures 9 and 10. The contrasting trends together with the higher education expansion in figure 7 provide preliminary evidence that higher education expansion drove the rise in share of college workers which further compressed the college premium.

By exploring the decomposed birth year fixed effects on the two key variables, we can find that their age-year two-way variations are mainly captured by the birth cohort fixed effects and our identification of the effect of relative size on earnings gap relies just on these two-way variations. Therefore, if any other birth cohort specific factors affecting college premium are correlated with the birth cohort specific variation in relative size of college workers, our identification of the relative size effect will fail. As we discussed in section 3.4, the main contaminating factors are potentially correlated compositional effects due to the birth cohort specific variations in ability, occupation and industry compositions.

5 Results

In table 3, we present our basic estimates of the effect of age specific relative size of college workers on the college premium based on specification 3.4 which regresses the age specific college premium against age and year fixed effects and the age specific relative size of college workers. The results by weighted/unweighted OLS estimation in columns 1 and 2 do not show significant differences. The estimated effects of the relative size of college workers on the college premium, -0.08 and -0.078 are quite similar and significant at the 5% level. They imply that, holding year and age constant, a one unit increase in the relative size of college workers leads to about 8 percentage points decrease in the college premium. By the model implication, these estimates represent that the elasticity of substitution across age cohorts is about 12.5. The estimated year fixed effects show that the college premium increased steadily until 2007 and then fell slightly in 2013, which indicates that the macro conditions may have favored college workers relatively during the covered period.

As we discussed in section 3.4, basic OLS estimation may suffer the issue of simultaneous causation which makes it biased. We use the predetermined variable, log ratio of the number of college graduates to the number of non-college individuals (including both male and female, employed and unemployed), as an instrumental variable for our independent variable based only on male workers. The corresponding results are presented in column 3 and 4. The magnitudes of the estimated relative size effects increase by about 30 percent, even if these increases are not statistically significant. The slightly attenuated OLS estimates imply that the relative size of college workers might be positively affected by the college premium simultaneously. In other words, higher college premium induces relatively more college graduates to seek employment, which is consistent with basic intuition even if this is not empirically studied in this paper.

However, our results above may still suffer bias due to omission of relevant variables as we discussed in section 3.4, such as ability, occupation and industry compositional factors which may be correlated with the relative size of college workers. To address the potential ability compositional effects, we explore the age group pattern of the relative size effect on the college premium based on equation 3.5. The corresponding results are presented in table 4. In column 1 of table 4, we divide ages into 6 groups evenly: 25-29, 30-34, 35-39, 40-44, 45-49 and 50-54. The estimated effects are significant only for the new entrants between age 25 and 29, -.142, at the 1% level. Thus, we alternatively divide ages into two groups, new entrants 25-29 and all other ages 30-54. Corresponding results are presented in column 2. The estimated effect for the new entrant group is still negative and significant, -0.156, while for all other ages is insignificantly negative, at -0.049. The F statistic implies that the effects are different significantly at the 5% level. The magnitudes of IV estimates in column 3 increase slightly, which reveals a similar pattern that new entrants are more substantially affected by their own relative size than the older group (age 30-54). If our estimates are dominated by the ability composition effect, the revealed pattern should be the opposite showing a smaller negative effect for new entrants because the conditional ability effects are more substantial for older workers by Lillard (1977) as we discussed in section 3.4.1. Our estimated pattern is also consistent with the findings by Welch (1979) that entrant cohorts are more easily affected by the cohort size effect. As Welch (1979) argues, in the early career phase, workers as learners accumulate skills gradually. Due to the substantial variance of the skills possessed, entrant workers are less easily substituted with each other, therefore, more easily affected by their own cohort size. As they enter later career phases and accumulate enough skills to fulfill different tasks, they are more substitutable and less easily affected by the cohort size.

In the specifications for our main findings above, we define the college premium and relative size of college workers based on broadly defined college workers including three-year college graduates or above and corresponding non-college graduates. We believe this definition has the advantage in covering all workers in the labor market and keeping as many observations as possible to obtain precisely estimated college premium for further analyzing the relative size effect on the college premium. However, the estimated college premium by our definition is different from the college premium referring to the earnings gap between 4-year college and high-school graduates, which leads our analysis to be less relevant to the huge literature on college premiums and less comparable to several studies on the effect of relative size on college premium (Card and Lemieux, 2001; Carneiro and Lee, 2009; Kawaguchi and Mori, 2016). Another disadvantage is that the potential varying average years of schooling for broadly defined college and non-college groups may bring in additional sources of variation in the estimated college premium.[29]

Therefore, we measure relative size of college workers and estimate college premium based on the sample including only four-year college workers and high-school workers. Results are presented in table 5. The magnitudes of our OLS and IV estimates presented in columns 1 to 4 increase slightly but the increases are not significant compared with the results by the broader definition of college and non-college. To make our results more comparable with Card and Lemieux (2001) using data from the U.S., U.K., and Canada, we follow their method for measuring relative size. They use the college premium (earnings gap between 4-year college and high-school) as the dependent variable while using a relative size measure based on all education levels as independent variable.[30] We follow their measure for relative size notated as LRS in table 5. The estimated effect, -0.178, in column 5 is much larger by magnitude than -0.101 in column 1 and becomes very similar to the results by Card and Lemieux (2001), -0.203 for the U.S., -0.233 for U.K. and -0.165 for Canada.[31] That the negative supply effect in China is so close to these three countries is remarkable in view of the very different economic development levels, trends of the college premiums and the relative supply, and higher education expansion phases between China and the other three countries.

[29]The average year of schooling for non-college group increased substantially because of family income growth and China's nine-year compulsory education program implemented since 1985.

[30]To account for differences in the effective labor supply by different education levels, they also assign a weight to each level with the average earnings. However, we have to point that they use hourly wage rates and annual working hours to construct their college premium and relative size. In our data, information about working hours is not available.

[31]The larger estimated absolute effects by this alternative measure LRS comes from its high correlation with the basic measure and its smaller variation. A one unit change in this alternative measure is associated with about 1.5 units change in the basic measure.

It is more interesting considering that the estimate of the supply effect should be a lower bound in China and upper bound in the other three countries.

6 Robustness Checks

In this section, we first test the underlying assumption of our main specification 3.4. After presenting the positive results for the assumption that college workers and non-college workers are equally substitutable across age cohort, we use several alternative specifications to check the robustness of the effect of age specific relative size of college workers on the age specific college premium.

6.1 Testing the Assumption: Equal Education-Specific Elasticity of Substitution

As we discussed in section 2.3, to directly link the relative size of college workers and the college premium like equation 2.6 entails the assumption of identical elasticity of substitution across age cohorts for college and non-college groups. The testing results are presented in table 6. In column 1, we estimate a model based on equation 3.2 without controlling for the age-year two-way fixed effects. The estimated effect of college workers' size on college workers' average earnings is significantly negative, -0.146, while that for non-college workers is insignificantly positive, 0.04. By the high F statistic with nearly zero p-value, we have to reject the null hypothesis of identical effects. However, we can reject the hypothesis of no specification error at the 1% level as the corresponding χ^2 statistic indicates. After we control for the age-year two-way fixed effects in the specification for column 2, we find that the age-specific size effects for college workers and non-college workers are similar, and we can't reject the null hypothesis of identical effects by the corresponding F statistic, 0.41 with p-value 0.522. Meanwhile, the χ^2 statistic testing the hypothesis that there is no specification error reduces substantially from 409.86 in column 1 to 120.64 with p-value 0.313. The comparison implies that there exists a common age-year fixed effect on average earnings for both college and non-college workers. In column 3, the equivalent specification to that for column 2 is based on equation 3.3, which leads to estimates with almost identical magnitudes. The opposite signs of the estimated effects are consistent with the model implication since the dependent variable is the estimated college premium instead of education-specific average earnings. The corresponding F and χ^2 statistics have large p-values, which indicates that we can't reject the null hypothesis of identical effects and the null hypothesis of no specification error.

6.2 Controlling for Occupation and Industry

To deal with the potential confounding factors due to occupation and industry compositions, we directly control for these factors with individual data based on equation 3.6. Results are presented in table 7. In columns 1 and 2, we present results without controlling for occupation or industry as a comparison with the results by structural specifications in which these composition effects are not controlled for. As expected, we obtain very similar results of the effects of relative size on the college premium. The estimated average effect over all ages is -0.074 in column 1, while the effect is -0.191 for entrant group and -0.044 for older group in column 2. After controlling for year-varying fixed effects of occupation, industry and province, the results change slightly and the changes are not significant. This implies that these suspected confounding composition effects are not a serious issues. In columns 5 and 6 we present IV estimates which are very similar with corresponding estimates in tables 3 and 4.

6.3 Results for Women only and Pooled Women and Men

Focusing on men only is only appropriate conditional on a strong assumption that men and women in the same age cohort, education level, and survey year are not substitutable. Therefore, we first replicate our analysis for women only and then for pooled women and men under the assumption that men and women in same age cohort, education level and survey are perfect substitutable. For the sake of brevity, we only present OLS estimates in table 8. The results with women only in columns 1 and 2 are not only smaller by magnitude but also less precise than those with men only while the results with both men and women are very similar. Another interesting finding comes from the difference in year trends between women and men. Comparing the estimated fixed year effects in column 1 of table 8 and column 2 in table 3, we can find that men's college premium increased more rapidly than women's from 1995 to 2013.

6.4 Several Other Specification Checks

We have performed several other specification checks of which the results are presented in table 9.

Firstly, we notice that CHIP 1999 and 2007 draw samples from provinces that are partially different from those in CHIP 1995, 2002 and 2013 even though each wave is nationally representative. Therefore, it is naturally to check the robustness using CHIP 1995, 2002 and 2013 only to keep the province composition constant.[32] The corresponding results are presented in columns 1 and 2.

Secondly, by checking individual's rural-urban migration status, we find that the proportion of rural-urban migrants increased steadily from about 18 percent in 1999 to about 32 percent in 2013.[33] Considering that including rural-urban migrants may introduce an added source of variation in the college premium due to endogenous self-section, we focus on those non-migrants to check the robustness of relative size effect on the college premium and present the results in columns 3 and 4.

Lastly, to reduce sampling variations, we also construct broader cells based on three-year age and survey year at the expense of reducing number of cells by two thirds, from 150 to 50.

[32] Even though we have controlled for province fixed effects in our previous specification with individual data, we perform the estimation with structural model as a double check.

[33] We define those born with rural residence registration changed to urban residence registration. In CHIP 1995, we can't accurately identify the migration status that we only use the waves 1999, 2002, 2007 and 2013

The corresponding results are presented in columns 5 and 6.

Even if the OLS and IV estimates in columns 1-4 are less precise than our previous main results due to the drop of CHIP 1995 (or both 1995 and 2007), their magnitudes are similar. The results with broader cells shown in column 5 and 6 are significantly negative with similar magnitudes. Overall, these alternative specifications show robust results of the relative size effects on college premium.

7 Conclusion

In this paper, we document the divergent trends of the college premiums across age groups from 1995 to 2013 in China. Comparing with the well-studied increasing overall trend during the same period, this divergence has received little attention. Specifically, the college premium in 2013 for the younger group (age 25-34) was about 30 percentage points, similar to the level in 1995, while the college premium in 2013 for the older group (age 45-54) increased to 50 percentage points nearly double that of 1995. To attribute these divergent trends of college premium to the changes in relative size of college workers, we use the model by Card and Lemieux (2001) which incorporates imperfect substitution between similarly educated workers in different age cohorts. Due to the distinctions of these trends in China, our identification is free of the overestimation issue due to the technological progress which possibly favored younger college workers in particular. Our results are similar to those in the U.S., U.K., Canada, and Japan. Holding the age cohort and survey year constant, a one unit increase in relative size of college workers is associated with about 10 percentage points decrease in college/non-college premium and about 18 percentage points decrease in college/high school premium. That the negative supply effect in China is so close to the other four countries is remarkable in view of the very different economic development levels, trends of the college premiums and the relative supply, and higher education expansion phases between China and the other four countries.

We further find that the negative effect is much more substantial among the new entrants (age 25-29) than among the experienced workers (age 30-54). By this pattern, we not only demonstrate that the new labor market entrants are more sensitive to their own cohort relative size but also argue that the confounding ability composition effect should not be a serious issue.

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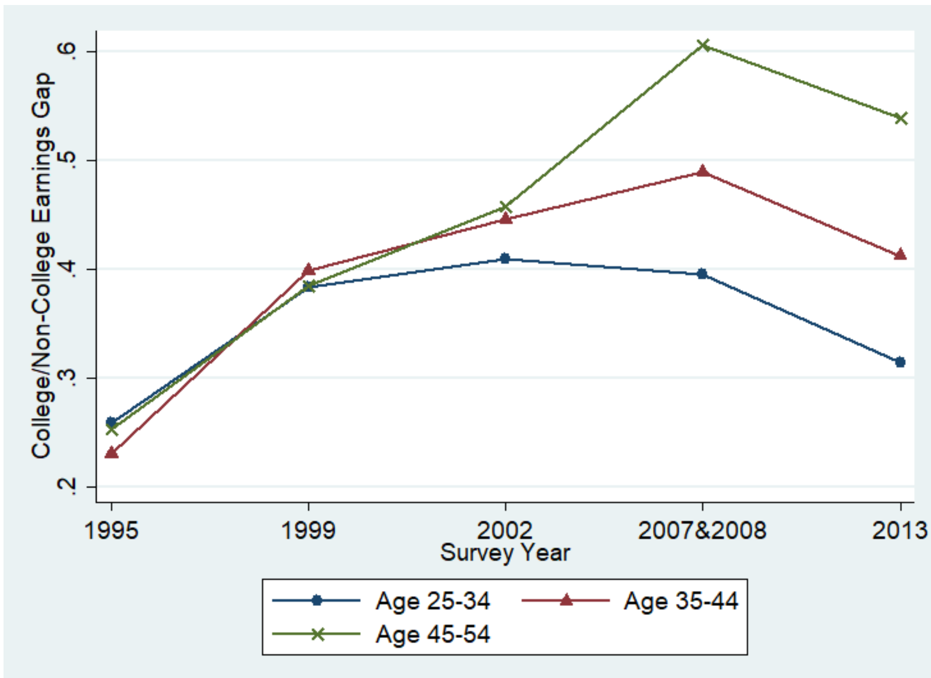
8 Figures

Figure 1: Trends of College Premium and Relative Supply of College Workers by Age Groups: China

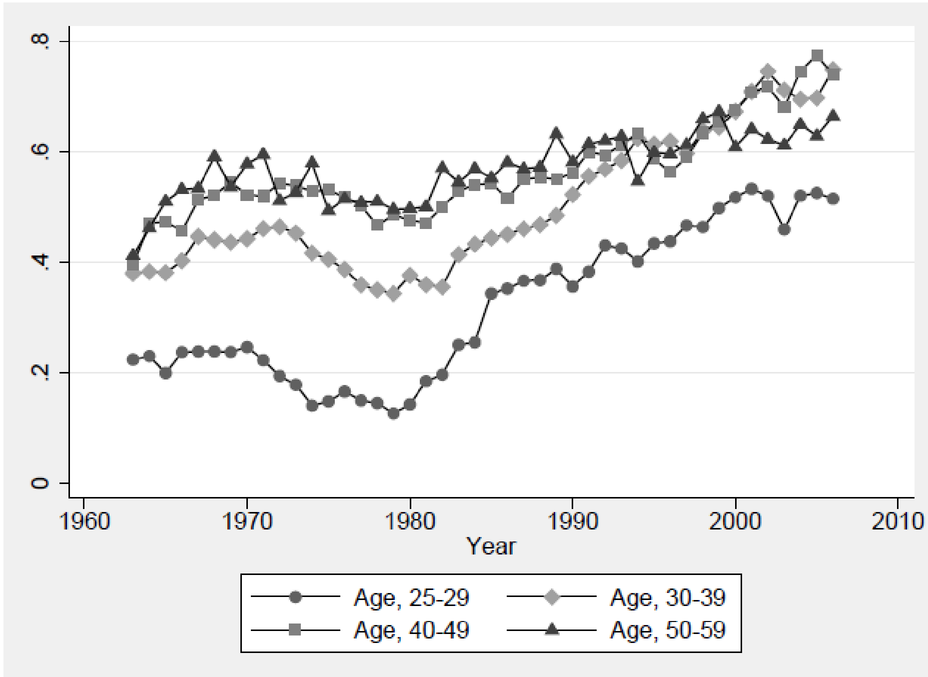
(a) Log College/Non-College Earnings by Age Groups



(b) Log College/Non-College Supply by Age Groups

Figure 2: Trends of College Premium and Relative Supply of College Workers by Age Groups: The U.S.

(a) Log College/HS Wage by Age Groups



(b) Log College/HS Supply by Age Groups

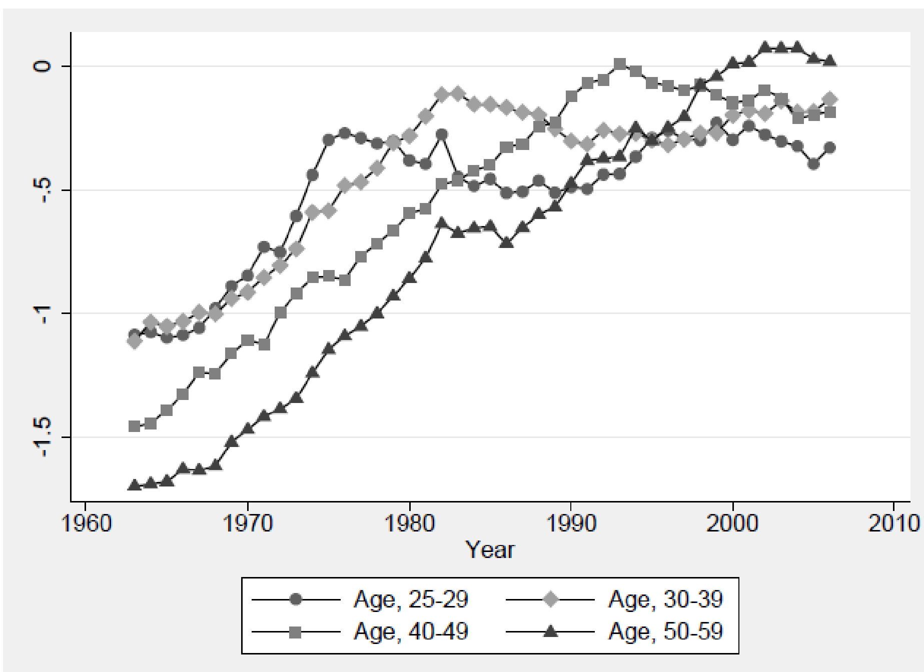
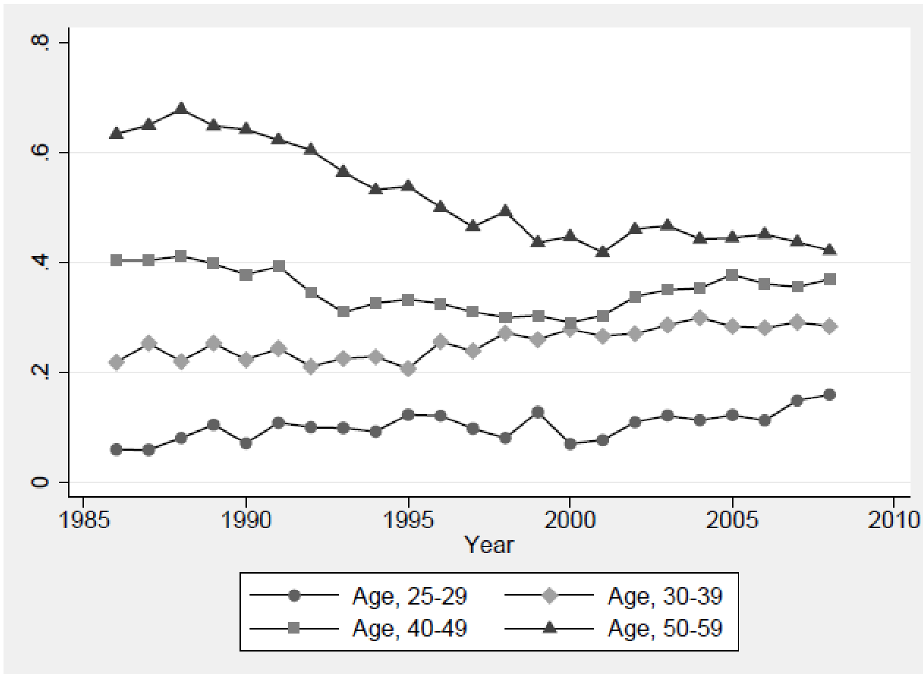


Figure 3: Trends of College Premium and Relative Supply of College Workers by Age Groups: Japan

(a) Log College/HS Wage by Age Groups



(b) Log College/HS Supply by Age Groups

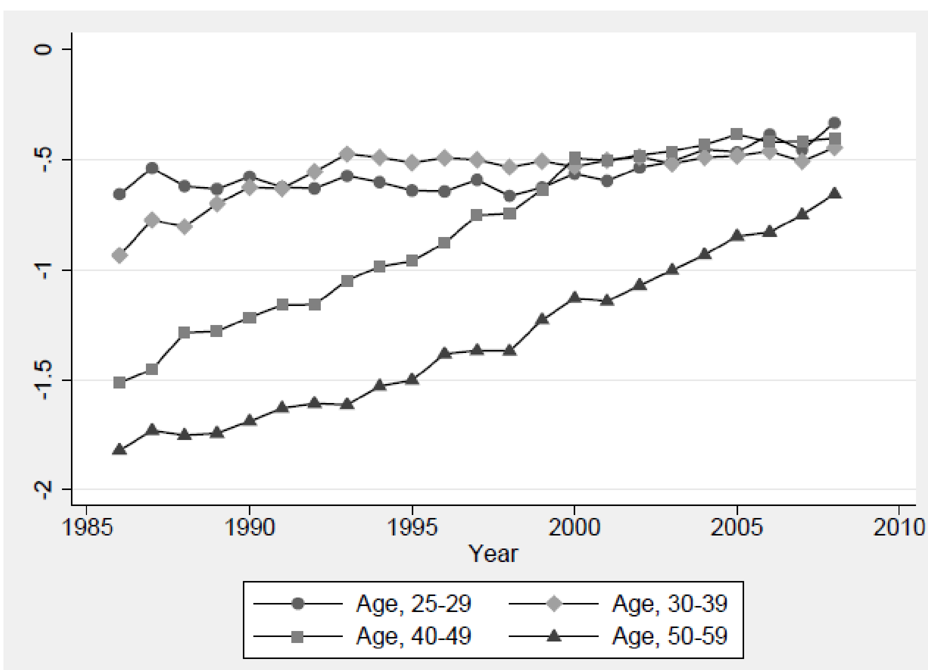


Figure 4: Age-Year Cell Specific Log Relative Sizes and Estimated College Premiums

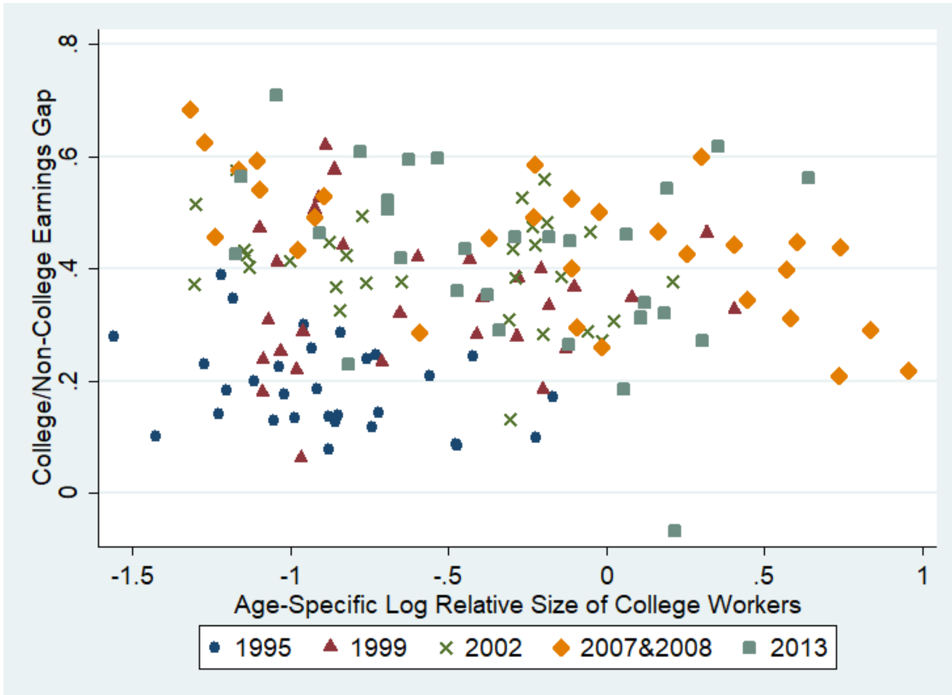


Figure 5: Male Workers' Age Profiles of the College Premium Across Years

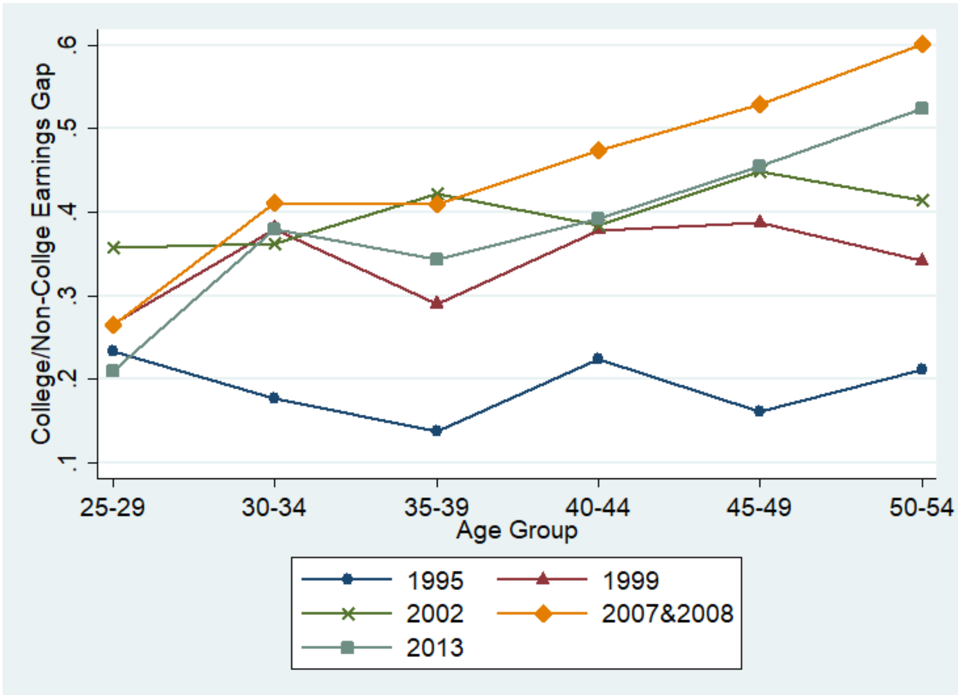


Figure 6: Male Workers' Age Profiles of Relative Size Across Years

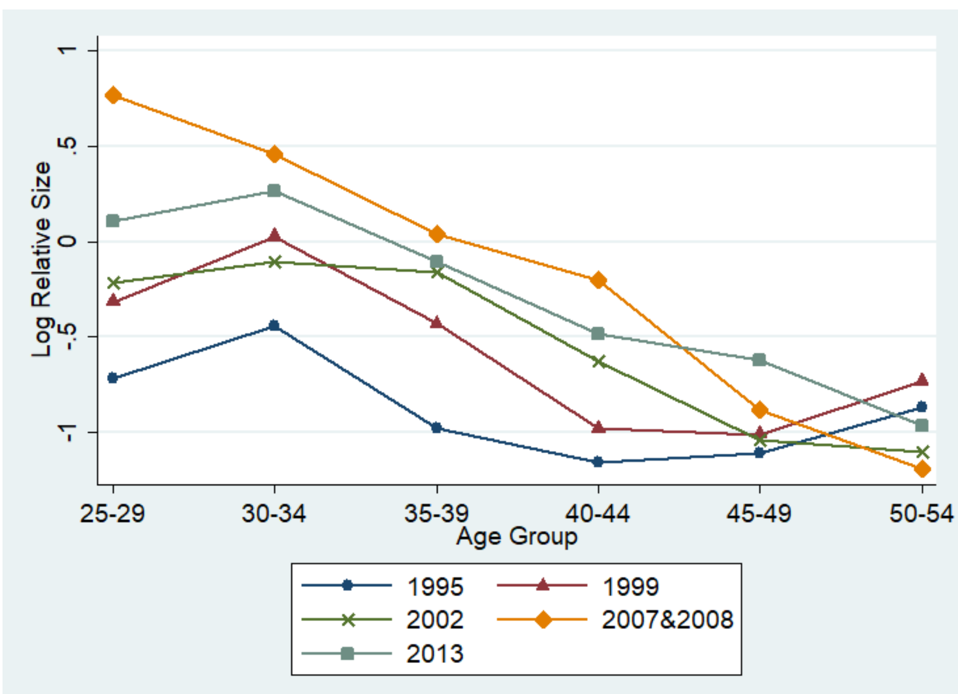


Figure 7: Demographical Change and Higher Education Expansion in China

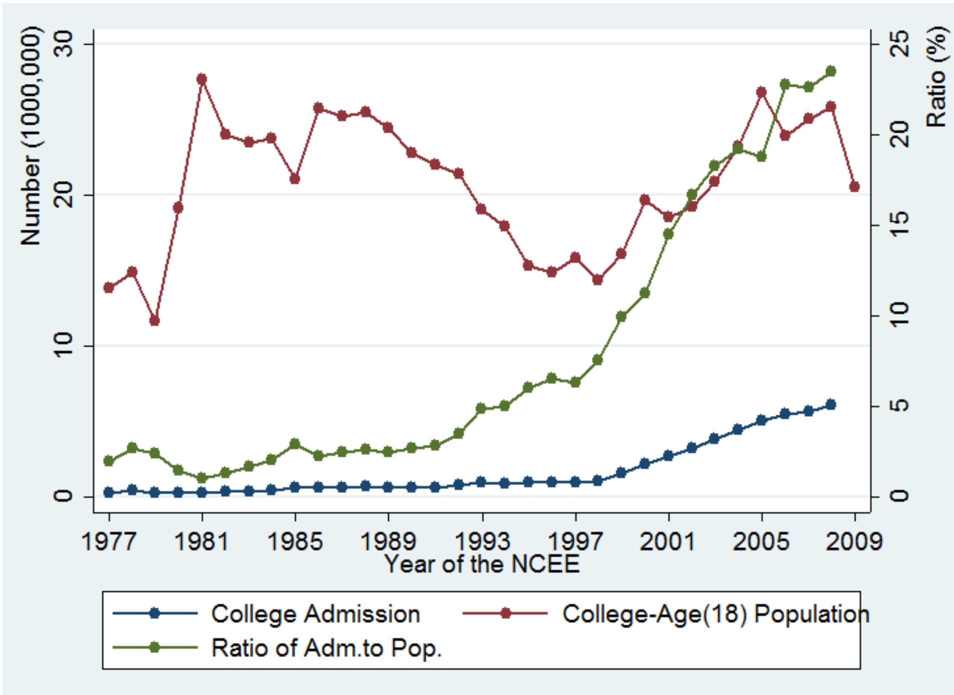


Figure 8: Birth Year Profiles of the Share of College Workers

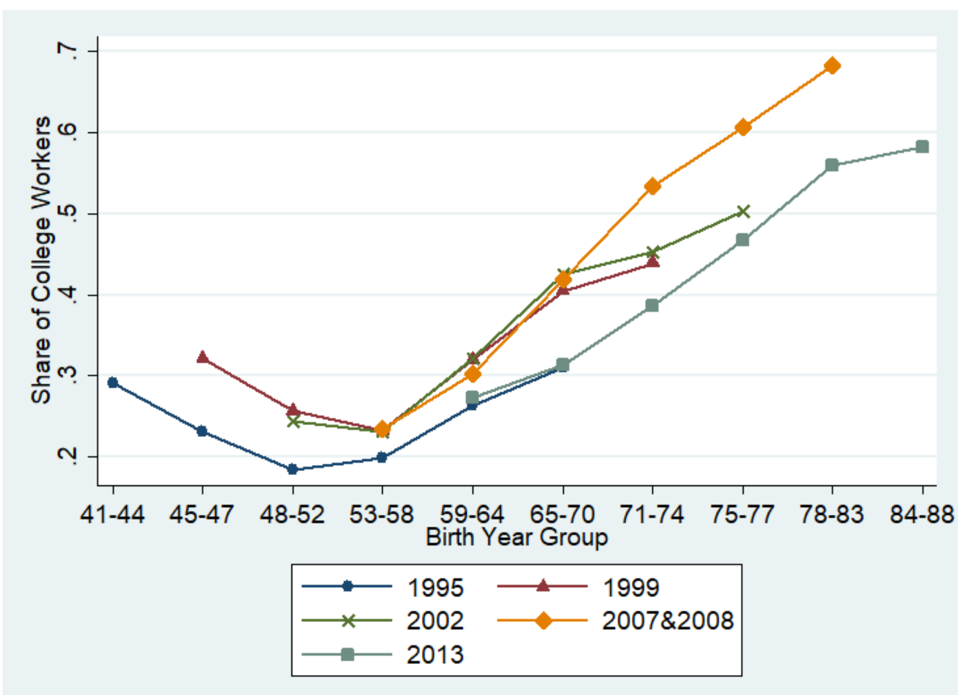


Figure 9: Predicted Birth Group Fixed Effects on the College Premium

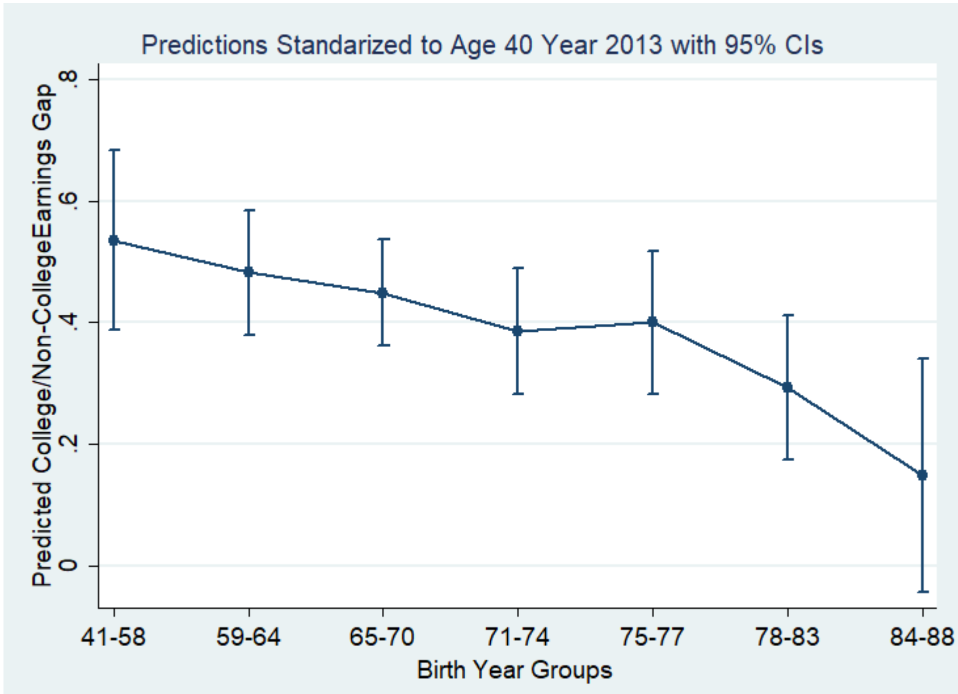
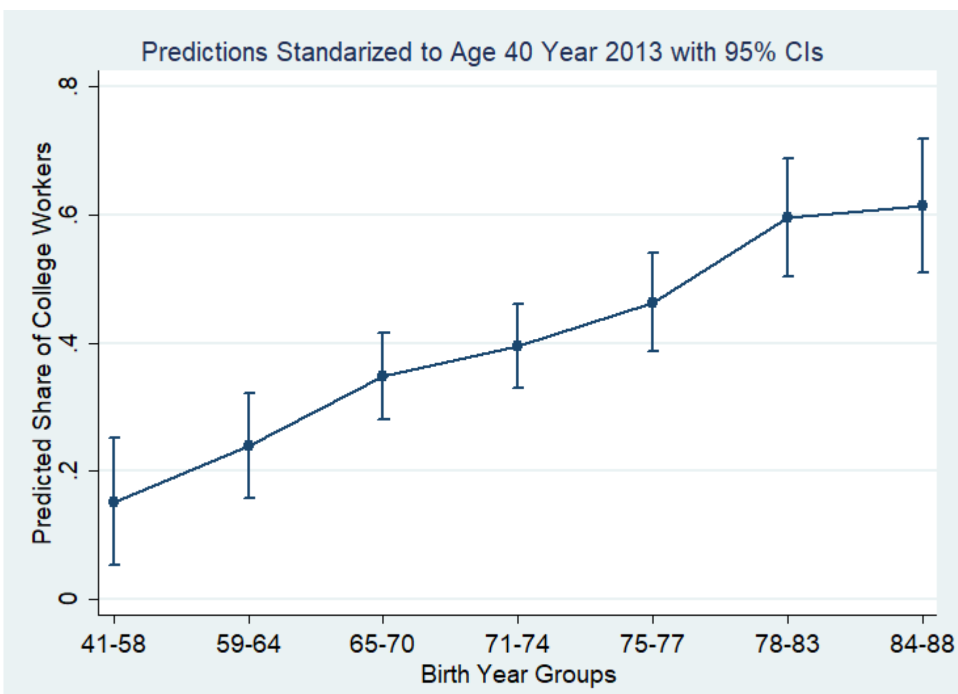


Figure 10: Predicted Birth Group Fixed Effects on the Share of College Workers



9 Tables

Table 1: Summary Statistics: Male Workers Only

CHIP	1995	1999	2002	2007	2013
Log Annual Earnings	8.76	9.07	9.32	10.21	10.50
	(0.55)	(0.57)	(0.62)	(0.69)	(0.71)
College	0.29	0.35	0.36	0.45	0.42
	(0.45)	(0.48)	(0.48)	(0.50)	(0.49)
Age	39.84	40.59	41.41	40.48	40.74
	(7.70)	(7.52)	(7.62)	(8.28)	(8.18)
High-Skill Occ.	0.40	0.41	0.40	0.34	0.25
	(0.49)	(0.49)	(0.49)	(0.47)	(0.43)
Mid-Skill Occ.	0.20	0.16	0.18	0.22	0.18
	(0.40)	(0.37)	(0.38)	(0.41)	(0.39)
Low-Skill Occ.	0.40	0.43	0.42	0.45	0.57
	(0.49)	(0.50)	(0.49)	(0.50)	(0.50)
Agriculture	0.02	0.01	0.01	0.01	0.02
	(0.14)	(0.11)	(0.11)	(0.10)	(0.14)
Mining	0.01	0.04	0.03	0.01	0.04
	(0.11)	(0.18)	(0.17)	(0.10)	(0.21)
Construction	0.03	0.05	0.04	0.05	0.07
	(0.18)	(0.22)	(0.20)	(0.21)	(0.26)
Manufacturing	0.43	0.32	0.27	0.20	0.15
	(0.49)	(0.47)	(0.45)	(0.40)	(0.36)
Transportation etc.	0.06	0.16	0.14	0.16	0.14
	(0.24)	(0.37)	(0.35)	(0.37)	(0.35)
Trade	0.12	0.08	0.10	0.11	0.10
	(0.33)	(0.27)	(0.30)	(0.31)	(0.30)
Finance	0.05	0.03	0.04	0.08	0.06
	(0.22)	(0.17)	(0.19)	(0.28)	(0.24)
Service	0.13	0.20	0.23	0.29	0.28
	(0.34)	(0.40)	(0.42)	(0.45)	(0.45)
Public Institutions	0.14	0.11	0.14	0.09	0.13
	(0.35)	(0.32)	(0.34)	(0.29)	(0.33)
Observations	4978	2754	4900	6461	4335

Table 2: Birth Year Fixed Effects on College Premium and Relative Size

	(1) College Premium	(2) College Premium	(3) College Share	(4) Log Relative Size
Year Fixed Effects:				
1999	0.187***	0.183***	0.035**	0.159**
	(0.031)	(0.032)	(0.016)	(0.072)
2002	0.257***	0.252***	0.014	0.059
	(0.031)	(0.028)	(0.016)	(0.073)
2007	0.351***	0.349***	0.020	0.064
	(0.045)	(0.043)	(0.026)	(0.119)
2013	0.399***	0.383***	-0.096**	-0.427**
	(0.067)	(0.062)	(0.038)	(0.175)
Birth Fixed Effects:				
1959-64	-0.066	-0.053	0.088***	0.416***
	(0.043)	(0.038)	(0.025)	(0.114)
1965-70	-0.112*	-0.086	0.196***	0.894***
	(0.062)	(0.056)	(0.033)	(0.151)
1971-74	-0.184**	-0.149**	0.244***	1.098***
	(0.079)	(0.073)	(0.043)	(0.199)
1975-77	-0.151*	-0.135	0.312***	1.389***
	(0.090)	(0.085)	(0.051)	(0.236)
1978-83	-0.283***	-0.243**	0.443***	1.950***
	(0.108)	(0.098)	(0.064)	(0.292)
1984-88	-0.441***	-0.388***	0.462***	2.033***
	(0.150)	(0.137)	(0.076)	(0.349)
χ^2(p-value)		111.07(0.45)		
Observations	150	150	150	150
R-squared	0.943	0.951	0.985	0.910

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Reference year is 1995, reference birth group is 1941-1958. Age fixed effects are not shown. Weights used in specification 2 are inverse variances of estimated college premiums.

Table 3: Basic Estimates for Effects of Age Specific Relative Size of College Workers on College Premiums

Dependent Variable: College Premium	(1) OLS	(2) Weighted-OLS	(3) IV	(4) Weighted-IV
Log Relative Size	-0.080**	-0.078***	-0.111***	-0.103***
	(0.032)	(0.030)	(0.032)	(0.029)
Year Effects:				
1999	0.187***	0.188***	0.197***	0.195***
	(0.029)	(0.031)	(0.026)	(0.027)
2002	0.245***	0.246***	0.256***	0.254***
	(0.027)	(0.023)	(0.024)	(0.020)
2007	0.316***	0.328***	0.338***	0.345***
	(0.031)	(0.030)	(0.029)	(0.028)
2013	0.277***	0.293***	0.295***	0.307***
	(0.032)	(0.031)	(0.028)	(0.028)
F Statistic			447.17	655.04
χ^2(p-value)		115.85(0.46)		113.28(0.53)
Observations	150	150	150	150
R-squared	0.938	0.949	0.938	0.949

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable for all specifications is the college premiums by age and year. All specifications also include age fixed effects not reported. The instrumental variable for log relative size is log ratio of the number of college degree holders (including both male and female, employed and unemployed) to the number of non-college degree holders. Weights for specifications in columns 2 and 4 are the inverse sampling variance of estimated college premiums. Reference year is 1995.

Table 4: Heterogeneous Relative Size Effects across Age Groups

Dependent Variable: College Premium	(1) Weighted-OLS	(2) Weighted-OLS	(3) Weighted-IV
Log Relative Size:			
Age 25-29 (New Entrants)	-0.142***		
	(0.050)		
Age 30-34	0.007		
	(0.060)		
Age 35-39	0.015		
	(0.055)		
Age 40-44	-0.064		
	(0.059)		
Age 45-49	-0.075		
	(0.090)		
Age 50-54	-0.172		
	(0.099)		
Age 25-29 (New Entrants)		-0.156***	-0.190***
		(0.047)	(0.044)
Age 30-54		-0.049	-0.069**
		(0.033)	(0.033)
F statistic(p-value)		4.51(0.04)	6.62(0.01)
χ^2(p-value)	107.74(0.54)	111.73(0.54)	109.41(0.52)
Observations	150	150	150
R-squared	0.953	0.951	0.951

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variables for all specifications are estimated college premiums by age and year. All specifications also include age and year fixed effects not reported. The instrumental variable for log relative size is log ratio of the number of college degree holders (including both male and female, employed and unemployed) to the number of non-college degree holders. All specifications are weighted by the inverse sampling variance of estimated college premiums.

Table 5: The Results to Sample including only High-School and 4-Year College Workers

Dependent Variable: College Premiums	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) OLS	(6) OLS
Log Relative Size	-0.101***		-0.128***			
	(0.028)		(0.028)			
Log Relative Size (Age 25-29)		-0.219***		-0.225***		
		(0.045)		(0.040)		
Log Relative Size (Age 30-54)		-0.081***		-0.099***		
		(0.029)		(0.029)		
LRS (Alternative Measure)					-0.178***	
					(0.043)	
LRS (Age 25-29)						-0.323***
						(0.067)
LRS (Age 30-54)						-0.147***
						(0.045)
Year Fixed Effects:						
1999	0.257***	0.252***	0.264***	0.257***	0.267***	0.258***
	(0.040)	(0.039)	(0.036)	(0.035)	(0.039)	(0.040)
2002	0.319***	0.318***	0.325***	0.321***	0.358***	0.351***
	(0.033)	(0.032)	(0.029)	(0.028)	(0.035)	(0.035)
2007	0.560***	0.565***	0.589***	0.582***	0.588***	0.580***
	(0.048)	(0.048)	(0.045)	(0.045)	(0.050)	(0.052)
2013	0.359***	0.353***	0.383***	0.369***	0.399***	0.386***
	(0.043)	(0.044)	(0.039)	(0.040)	(0.048)	(0.050)
Observations	150	150	150	150	150	150
R-squared	0.929	0.933	0.928	0.933	0.930	0.932

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variables for all specifications are the estimated college premiums by age and year. All specifications also include age fixed effects not reported. In column 3 and 4, the instrumental variable for log relative size is log ratio of the number of all college degree holders (including both male and female, employed and unemployed) to the number of non-college degree holders. Weights for specifications in columns 2 and 4 are the inverse sampling variance of estimated college premiums. To compare with the result by Card and Lemieux (2001), the alternative measure for log relative size, LRS in columns 5 and 6 is constructed based on all education levels rather than only high-school and 4-year college. Reference year is 1995.

Table 6: Testing Assumption: Identical Elasticity of Substitution for College and Non-College Workers

	(1) Average Earnings	(2) Average Earnings	(3) College Premium
Log Size of College Workers	-0.146*** (0.029)	-0.096** (0.037)	0.093*** (0.035)
Log Size of Non-College Workers	0.040 (0.031)	-0.067 (0.042)	-0.062 (0.039)
F Statistic testing "Identical Effects"	28.95 (0.000)	0.41 (0.522)	0.47 (0.495)
χ^2 Statistic testing "No Specification Errors"	409.86 (0.000)	120.64 (0.313)	115.39 (0.446)
$Age \times Year$ Fixed Effects	NO	YES	NO
Observations	300	300	150
R-squared	0.989	0.997	0.949

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions are weighted by the inverse sampling variance of the corresponding dependent variable. Specifications in column 1 and 2 also include a set of year and age effects fully interacted with college dummy variable. Specification in column 3 also includes age and year fixed effects.

Table 7: Results Using Individual Data Controlling for Province, Occupation and Industry

Dependent Variable: Log Annual Earnings	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) IV
$College \times LogRelativeSize$	-0.074**		-0.083***		-0.106***	
	(0.031)		(0.028)		(0.031)	
$College \times LogRelativeSize$ (Age 25-29)		-0.191***		-0.177***		-0.208***
		(0.049)		(0.044)		(0.047)
$College \times LogRelativeSize$ (Age 30-54)		-0.044		-0.057*		-0.069**
		(0.034)		(0.031)		(0.034)
$LogRelativeSize$	0.166***	0.296***	0.144***	0.243***	0.184***	0.281***
	(0.019)	(0.034)	(0.017)	(0.031)	(0.019)	(0.034)
$LogRelativeSize \times$ 1[Age 30-54]		-0.170***		-0.128***		-0.128***
		(0.036)		(0.033)		(0.036)
(Province,Occupation,Industry)$\times$Year	NO	NO	YES	YES	YES	YES
Observations	23,428	23,428	23,428	23,428	23,428	23,428
R-squared	0.573	0.573	0.653	0.653	0.653	0.654

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications also include college, age, and year fixed effects, the interaction between college and year fixed effects, and the interaction between college and age fixed effects.

Table 8: Robustness of The Results to Female Sample and Pooled Sample including both Male and Female

Dependent Variable: College Premiums	(1) Women Only	(2) Women Only	(3) Men and Women	(4) Men and Women
Log Relative Size	-0.044		-0.071**	
	(0.042)		(0.028)	
Log Relative Size (Age 25-29)		-0.128***		-0.161***
		(0.045)		(0.033)
Log Relative Size (Age 30-54)		-0.016		-0.034
		(0.041)		(0.026)
Year Fixed Effects:				
1999	0.132***	0.124***	0.175***	0.165***
	(0.039)	(0.037)	(0.023)	(0.022)
2002	0.178***	0.172***	0.226***	0.216***
	(0.042)	(0.041)	(0.023)	(0.023)
2007	0.243***	0.233***	0.307***	0.295***
	(0.055)	(0.053)	(0.030)	(0.029)
2013	0.205***	0.193***	0.273***	0.255***
	(0.056)	(0.054)	(0.030)	(0.030)
Observations	150	150	150	150
R-squared	0.955	0.957	0.972	0.975

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variables for all specifications are estimated college premiums by age and year. All specifications also include age fixed effects not reported. All specification are weighted by the inverse sampling variance of the estimated college premiums.

Table 9: Robustness of The Results to Several Alternative Specifications

Dependent Variable: College Premium	(1) Same Provinces	(2) Same Provinces	(3) Non-Migrants Only	(4) Non-Migrants Only	(5) 3-Age-Year Cells	(6) 3-Age-Year Cells
Panel A: OLS Estimates:						
Log Relative Size	-0.069		-0.069		-0.101***	
	(0.045)		(0.043)		(0.026)	
Log Relative Size (Age 25-29)		-0.290**		-0.132*		-0.158***
		(0.117)		(0.071)		(0.030)
Log Relative Size (Age 30-54)		-0.045		-0.041		-0.077**
		(0.041)		(0.052)		(0.031)
R-squared	0.955	0.959	0.956	0.956	0.986	0.987
Panel B: IV Estimates:						
Log Relative Size	-0.090**		-0.113**		-0.109***	
	(0.046)		(0.045)		(0.022)	
Log Relative Size (Age 25-29)		-0.302***		-0.191***		-0.172***
		(0.089)		(0.061)		(0.029)
Log Relative Size (Age 30-54)		-0.053		-0.074		-0.084***
		(0.042)		(0.055)		(0.026)
R-squared	0.955	0.959	0.955	0.956	0.986	0.987
Observations	90	90	120	120	50	50

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variables for all specifications are estimated college premiums for by age and year (or by 3-age and year). All specifications also include age and year fixed effects not reported. All specification are weighted by the inverse sampling variance of the estimated college premiums. The instrumental variable for log relative size is log ratio of the number of college degree holders (including both male and female, employed and unemployed) to the number of non-college degree holders.