Trends in Quality-Adjusted Skill Premia in the United States, 1960-2000

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Abstract

    This paper presents new evidence that increases in college enrollment lead to a decline in the average quality of college graduates between 1960 and 2000, resulting in a decrease of 6 percentage points in the college premium. We show that although a standard demand and supply framework can qualitatively account for the trend in the college and age premia over this period, substantial quantitative adjustments still need to be made to account for changes in quality.

1   Introduction

The college-high school wage differential in the US fluctuated dramatically since the 1960s. It declined in the 1970s, increased rapidly in the 1980s, and continued to rise in the 1990s, but at a slower pace (e.g., Katz and Murphy, 1992; Katz and Autor, 1999; Card and Lemieux, 2001; Autor et al., 2008). These movements are usually interpreted as reflecting changes in the prices of college and high school skill, brought on by shifts in demand and supply. However, changes in the composition of college and high school graduates resulting from an expansion in college enrollment can be equally important. The decline in the college premium in the 1970s may reflect not only an increase in the supply of college graduates, but also a decline in their average quality. Similarly, the rise in the college premium in the 1980s and 1990s could have been even more pronounced if the quality of college graduates was stable during these two decades.

    In this paper we present a decomposition of the trends in college and age premia into price and composition effects. Prices are determined by the interaction of the demand for skill with the *quantity* of skill supplied in the market, while composition is determined by the *quality* of individuals in each schooling level. Throughout the paper, we equate shifts in average quality of a particular cohort of college workers with shifts in the proportion of cohort-specific college enrollment by region of birth, even though the former are unobserved.[1]

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[1]Therefore, for most of the paper we use the terms quality and composition interchangeably. In Section 6, we

Our main empirical challenge is to separate changes in the supply of college labor from changes in the quality of college graduates. The is difficult because these two variables generally move together. In order to break this link we start by assuming that all individuals in a given age group working in the same regional labor market (in the same year) face the same skill prices, even if they were born and schooled in different regions. However, their wages differ because they have heterogeneous quantities of skill, which may be due to differences in composition across regions of birth. Therefore, by comparing (within labor market) wages of individuals born in regions with different fractions of college enrollment (and therefore, with a different average quality of college participants), we are able to identify the effect of quality on wages. We control for intrinsic differences across regions of birth using region of birth dummies, which are allowed to vary with year and with age.

Figure 1 illustrates the intuition behind our procedure. Using US Census data between 1960 and 2000, we group individuals into year-age-region of birth-region of residence cells. For each cell we compute the college premium, and we estimate the proportion of college participants for each cohort and region of birth, and the proportion of college participants for each year, age and region of residence.[2] Each line in the figure (and associated set of points) represents the relationship between the college premium in the region of residence and the proportion in college in the region of birth (our measure of composition) for a different set of labor markets. Labor markets are grouped according to the proportion of college workers in the region of residence (which is meant to represent supply). Within each set of similar labor markets (according to a supply indicator), there is a clear negative relationship between the college premium in the region of residence and the proportion in college in the region of birth, which is confirmed by the regression line.[3] Those workers with the lowest college premium are the ones born in regions of birth (and cohorts) where the college enrollment rate was the highest, and (presumably) the average quality of college students was the lowest.

There are two competing interpretations of our findings. First, marginal college students are

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present direct evidence of the decline in the quality of college workers due to the increase in the proportion of college enrollment.

[2]We consider white males aged 25-60 only, grouped into 5 year age groups. We consider 9 regions of residence and 9 regions of birth (Census regions). The college premium is the difference in average log wages of those with exactly 16 years of schooling and those with 12 years of schooling. The proportion of those in college is the proportion of individuals with at least some college. The same age groups and Census regions are also used in our main empirical work.

[3]Each observation is weighted by the inverse of the variance of the college premium in each cell. The slopes of all three lines are negative and statistically different from zero at the 5% level. We obtain a similar picture if, instead of using the college premium as the dependent variable, we use average college wages in each cell.

of lower quality than average college students. When there is an expansion in college attendance these marginal students are drawn into college, resulting in a decline in average quality. Second, the rise in college attendance means that resources have to be spread more thinly across students, resulting in a lower quality learning experience in college. We cannot separate the two, and leave this important topic for future research.

Our empirical strategy is analogous to the one used by Card and Krueger (1992) to estimate the effect of school quality on labor market outcomes, although its use is new in the present context. One concern with it is that selective migration may bias our estimates, as emphasized in Heckman et al. (1996). We address this concern by implementing a series of corrective procedures adapted from Heckman et al. (1996) and Dahl (2002). More importantly, we argue that selective migration would bias our estimates if changes in selective migration were correlated with changes in schooling (see section 5), and we present evidence that this is unlikely to drive our results. We also show that our results are robust to the inclusion of measures of school quality.

Much of the focus of the literature is on the college premium, but we devote similar attention to the age premium since changes in this parameter are as large as those in the college premium. We find that the decline in the quality of college graduates between 1960 and 2000 lead to a decrease of 6 percentage points in the college premium. Given that the college premium grew by 20 percentage points between over these 40 years, this quality effect is substantial. Our analysis of the age premium shows even more striking results. For college graduates, we can attribute much of the fluctuation in the age premium (its increase in the 1970s and its decline in the 1980s) to movements in the quality of college graduates. In contrast, the importance of quality changes on the average wage of high school graduates is negligible. The differential effects of worker quality for college and high school wages can be explained by a model with at least two types of ability, one specific to high school, and one specific to college. This provides a better description of the labor market than a single ability model (e.g., Willis and Rosen, 1979; Carneiro et al., 2009; Deschênes, 2007), and constitutes the basis of our empirical framework.

Composition effects of the type we discuss are often thought to be unimportant in the empirical literature on the college premium, although their existence is well recognized.[4] See Katz and Murphy (1992), Juhn et al. (1993), Hoxby and Long (1999), Gosling et al. (2000), Galor and Moav (2000), Acemoglu (2002), Juhn et al. (2005), Fortin (2006), among others. Very few empirical studies di-

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[4]Our composition effects are different from those of Lemieux (2006), who studies the role of composition effects in terms of explaining the increase of the variance of unobserved skills over time.

rectly searched for composition effects. For example, using the 1940-1990 US Census, Juhn et al. (2005) found that increases in college enrollment led to a lower college premium through composition effects, but their estimated effects were quite small (the procedure we use is quite different and is likely to provide better variation for identification of supply and quality effects).[5] Carneiro et al. (2009) and Moffitt (2008) show that marginal returns to college fall as more individuals go to college. Similarly, Carneiro and Lee (2009) estimate a selection model using data for the 1990s from the National Longitudinal Survey of Youth of 1979 (using the standard instruments in the literature for identification), and show that a model compatible with the magnitude of selection observed in that dataset implies the existence of large composition effects.

Our paper is also related to the literature which tries to separate the role of the return to schooling and return to ability in the evolution of college premium (Chay and Lee, 2000; Taber, 2001; Deschênes, 2006), and to the empirical literature estimating returns to schooling purged of selection bias. Their finding that selection bias is substantial and it is changing over time (even keeping composition fixed), reinforces the importance of studying changes in composition. The two problems are different sides of the same coin: if one believes that standard estimates of the college premium are biased because of self-selection (and one would like to correct the bias), then changes in self-selection (due to changes in composition) are bound to produce movements in the college premium. Indeed, the neglect of composition effects distorts our assessment of the economic drivers of inequality. In the last 40 years, changes in worker quality mask increases in the return to schooling larger than the ones we observe in the raw data, by exacerbating the role of increases in the supply and attenuating the role of increases in the demand for college workers.

Finally, our analysis has a close parallel with the study of selective unemployment and inequality. This literature shows that changes in unemployment rates dramatically change the evolution of inequality due to composition effects. See, for example, Keane et al. (1988), Blundell et al. (2003), Chandra (2003), Heckman and Todd (2003), Neal (2004), Blundell et al. (2007), Mulligan and Rubinstein (2008), Petrongolo and Olivetti (2008), among others.

A concern with our approach is that, as in most of the literature, we take changes in supply, demand and composition as exogenous. This is a limitation of the analysis, on which we have nothing new to add. Card and Lemieux (2001) suggest that cohort size may be an important driver of the trend in college participation, while Fortin (2006) emphasizes also the role of tuition

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[5]Rosembaum (2003) presents an alternative analysis reporting larger effects.

policy at the state level. In a different context, Acemoglu et al. (2004) consider the differential extent of mobilization for World War II across U.S. states as a source of plausibly exogenous variation in female labor supply.

The paper proceeds as follows. Section 2 discusses our empirical strategy. This is followed by a description of the data in Section 3. Section 4 presents estimation results and then Section 5 reports a number of sensitivity checks. Section 6 provides some direct evidence on the decline of college workers. Section 7 shows quality-adjusted trends in the college and age premia. Section 8 revisits the problem studied in Card and Lemieux (2001). Finally, we conclude in Section 9. Appendix A describes our method for estimating the model. In addition, the online appendix provides a more detailed description of data and some additional empirical results.

2 Econometric Framework

Section 2.1 presents a simple model of wage determination that allows for composition and price effects, together with a reduced form empirical strategy for distinguishing the two. Section 2.2 considers composition effects and price determination in a standard model of the labor market (Card and Lemieux, 2001).

2.1 A Simple Wage Structure

Each individual has schooling level $S = k$, where $k = H, C$ (denoting high school and college). There are separate labor markets for high school and college skills (e.g. Willis and Rosen, 1979; Heckman and Sedlacek, 1985). Suppose that the wage of each individual i, of age a, at time t, who is born and goes to school in region b,[6] and works in region r (which may or may not be equal to b), can be written as:

$$W_{iatrb}^{k} = \Pi_{atr}^{k} U_{i,t-a,b}^{k}, \tag{1}$$

where W_{iatrb}^{k} is the wage, Π_{atr}^{k} is the price of k-type skill for those with schooling level k, in age group a in year t working in region r, and $U_{i,t-a,b}^{k}$ is the individual specific endowment of k-type skill for those in cohort $t - a$ and in region of birth b. Taking logs:

$$w_{iatrb}^{k} = \pi_{atr}^{k} + u_{i,t-a,b}^{k}, \tag{2}$$

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[6]Hoxby and Long (1999) show that at least 75% of individuals attend university in their state of residence.

where $w_{iatrb}^k = \log W_{iatrb}^k$, $\pi_{atr}^k = \log \Pi_{atr}^k$ and $u_{i,t-a,b}^k = \log U_{i,t-a,b}^k$.[7]

Let S_i^k be an indicator which takes value 1 if the level of schooling is k, and 0 otherwise; A_{iat} takes value 1 if an individual belongs to age group a in year t; M_{itrb} takes value 1 if an individual who is born in region b lives in region r in year t. Define $\omega_{atrb}^k = E\left[w_{iatrb}^k \middle| S_i^k = 1, A_{ita} = 1, M_{itrb} = 1\right]$ and $\nu_{atrb}^k = E\left[u_{i,t-a,b}^k \middle| S_i^k = 1, A_{ita} = 1, M_{itrb} = 1\right]$. It follows from (2) that

$$\omega_{atrb}^k = \pi_{atr}^k + \nu_{atrb}^k. \tag{3}$$

This equation is the basis of our empirical models. It states that the average log wage of workers in each (k, a, t, r, b) cell is equal to the sum of the log price of k-type skill for age group a in labor market r at time t, and the average quality of workers in the corresponding cell. Therefore, differences in the average log wages within each (k, a, t, r) cell among individuals from different regions of birth (b) reflect differences in quality across individuals from different regions of birth.

We start by modelling π_{atr}^k as flexibly as possible, using full interactions between age, time and region of residence dummies for each schooling group. Once schooling, age, time, and region of residence are fully controlled for, the remaining variation in ω_{atrb}^k must come from variation in ν_{atrb}^k, allowing us to separate price and composition effects.

Another advantage of this procedure is that, within labor market $(t - a - r)$, differences in schooling across cells (b) are not endogenous responses to unobserved differences in prices, since prices are kept fixed. The only source of variation in wages is variation in worker quality. The drawback of this approach is that it does not allow us to understand the determinants of prices. We come back to this in section 2.2.

We conjecture that ν_{atrb}^k varies over cells because of changes in the college participation rate. For example, as more people go to college, the average ability of college-goers may fall. Thus, our variable of interest is the proportion of college-goers in cohort $t - a$ born in region b, denoted by $P_{t-a,b}$.

There exist at least two possible distinct reasons for declining quality of average college workers. First, individuals are heterogenous and marginal college entrants might be of lower quality than average college attendees. For example, see Carneiro et al. (2009) and Moffitt (2008).[8] Second, as

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[7]We can extend this framework to allow for individual specific price shocks due, say, to shocks to match productivity (as long as they are uncorrelated with individual skill). The potential advantage of such an extension is that it allows for changes in inequality even within (k, a, t, r, b) cells.

[8]To illustrate this idea, consider a simple economic model of college enrollment. Suppose that individuals enrol in college if returns $(\beta = X\gamma + U)$ are larger than costs $(C = Z\eta)$: $S = 1$ if $X\gamma - Z\eta + U > 0$, where U is unobserved

the proportion of individuals attending college increases, educational resources could be diluted, resulting in diminishing quality of average college attendees of the cohort.[9] These two interpretations have different policy implications; however, empirically, we would not be able to distinguish between them without further information about the production process in college. This is certainly an interesting and also challenging topic for future research, but in this paper, we focus on quantifying the gross effects of declining quality of college workers.

It is unlikely that $P_{t-a,b}$ is the only important factor determining differences in the average quality of workers across cells. Regions of birth differ in several other dimensions besides the cost of schooling. For example, school resources may vary across regions. Well endowed regions could have higher quality schools, which simultaneously lead to higher worker quality (independently of composition) and higher college enrollment. We account for this by using region of birth fixed effects as additional explanatory variables. Furthermore, we allow region of birth to affect both time trends and age profiles by including (region of birth)×(time) interactions and (region of birth)×(age) interactions. Finally, we show that our results are robust to the inclusion of direct measures of K-12 school quality.

Moreover, migration across US regions is substantial (Groen, 2004; Bound et al., 2004), and it is unlikely to be random (see, e.g., Heckman et al., 1996; Dahl, 2002). Individuals who migrate may not carry with them the average quality of their region of birth. However, it could happen that migrants are different from non-migrants due to self selection, but the quality of both groups changes with average college enrollment at the same rate, in which case our estimates would not be affected. This would imply that changes in selective migration are uncorrelated with changes in schooling. In Section 5, we argue and present evidence that in our basic specification (where we include a rich set of dummies as controls), the correlation between changes in selective migration and schooling is likely to be small, and unimportant for our results.

Still, we consider different corrective procedures. One alternative is to condition on migration probabilities as in Dahl (2002). Following Dahl (2002), one may estimate observed migration probabilities and staying probabilities for each cell and add them as additional control variables. These variables measure migration flows across regions, which are likely to capture changes in relative prices, and changes in the type of migrants. Another interpretation is that this procedure amounts

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ability that is independent of Z and X. It is possible to rewrite this model as: $S = 1$ if $P(X, Z) > V$, with $P(X, Z) = F_{-U}(X\gamma - Z\eta)$, $V = F_{-U}(-U)$, and $F_{-U}(.)$ is the c.d.f. of $-U$. Notice that $E(\beta|X, S = 1) = X\gamma + E(\beta|X, P > V)$. Changes in P result in changes in $E(\beta|X, S = 1)$ due to composition effects.

[9]We are grateful to an anonymous referee who emphasized this explanation as an important alternative.

to estimating a selection model, although the exclusion restrictions are left implicit.[10] A second alternative is to account for (region of birth)×(region of residence) interactions corresponding to (region of birth)×(region of residence) matches (Heckman et al., 1996). We apply both procedures, allowing for (region of birth)×(region of residence) interactions to be time-varying.

None of these corrections has a strong impact on our estimates. In section 5 we present evidence that changes in migration flows (reflecting the quantity of migration) and migration premia (reflecting the composition of migration) are uncorrelated with changes in schooling, which suggests that selective migration is unlikely to be driving our results.

It is plausible to think that *changes* in selection into migration and changes in schooling are uncorrelated, especially after accounting for all control variables (even though the levels of migration and schooling are highly correlated in the cross section). The reason is that they respond to different prices (at different points in time): while migration is driven by changes in relative prices, amenities, and travelling costs across *regions*, schooling is mostly driven by changes in relative prices and costs across *schooling levels*. Furthermore, much of the changes in prices are probably accounted for by our procedure. If there is any remaining correlation, the direction of the bias can theoretically go in different directions.

In view of concerns raised above, we write ν_{atrb}^k (average quality of workers in a cell) as:

$$\nu_{atrb}^k = \gamma_{kab} + \gamma_{ktrb} + \phi_k(P_{t-a,b}) + \lambda_k(P_{M,atrb}^k, P_{M,atrr}^k), \tag{4}$$

where γ_{kab} are region-of-birth fixed effects, interacted with age dummies and γ_{ktrb} are region-of-birth by region-of-residence fixed effects that are interacted with year dummies (capturing school quality or other unobserved variations), ϕ_k is a function of $P_{t-a,b}$ (capturing the effect of composition), and λ_k is a function of the proportion of individuals migrating from region r to region b ($P_{M,atrb}^k$, what we call observed migration probability), and the proportion of individuals working in the same region where they were born ($P_{M,atrr}^k$, what we call staying probability). Dahl (2002) proposed the use of the observed migration probability to account for selection, reinterpreting Lee (1983)'s

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[10]Migration probabilities (computed as the proportion of individuals in each cohort, time period and region of birth, who work in each region of residence r) have identifying variation because we exclude (cohort)×(region of residence)×(region of birth) interactions from the wage equations (as in Dahl, 2002). This procedure is justified if movements in migration probabilities are caused by changes in the cost of migrating (implicit in these omitted interactions) which are independent of wages, or changes in the benefits of migrating which are orthogonal to changes in schooling because, say, they are unobserved at the time of the schooling decision (Meghir and Whitehouse (1994) show that we can interpret our procedure as instrumenting migration probabilities with the omitted interactions). Unfortunately we do not have in the Census variables that can serve as explicit exclusion restrictions.

idea that in the presence of multiple alternatives, what matters is only the first-best choice (that is, the observed choice among multiple alternatives). Dahl (2002) calls this assumption "the index sufficiency" and provides a detailed discussion of this assumption. Dahl (2002) also suggests that staying probabilities should be used as additional controls since non-migrants can be substantially different from migrants.[11]

Putting equations (3) and (4) together, we can estimate our object of interest ($\phi_k(P_{t-a,b})$) from the following regression:

$$\omega_{atrb}^k = \gamma_{katr} + \gamma_{kab} + \gamma_{ktrb} + \phi_k(P_{t-a,b}) + \lambda_k(P_{M,atrb}^k, P_{M,atrr}^k) \tag{5}$$

where γ_{katr} are full interactions of age-time-region fixed effects. The functions $\phi_k(.)$ and $\lambda_k(.,.)$ are specified in the empirical section. Throughout the paper, we call equation (5) the "reduced form" model.

In summary, by comparing wages of individuals born in different regions but working in the same labor market we identify differences in worker quality. We can then relate these to differences in college participation across regions of birth, to determine how increases in college attainment affect average worker quality. This identification strategy is similar to the one used by Card and Krueger (1992) to study the impact of school quality on wages. While Card and Krueger (1992) relate wages with school quality variables, we relate them with the proportion of individuals going to college in each region. As noted before, it is unlikely that we are capturing school quality effects through our variable because of the set of controls we use (e.g., region of birth interacted with year and age). Furthermore, in the empirical section, we examine the robustness of our results to the inclusion of direct measures of school quality.

2.2   Skill Prices in Equilibrium: Supply and Demand Framework

The model of the previous section allows us to obtain robust estimates of composition effects, but leaves the modelling of prices unspecified. In order to compare the role of composition with the roles of supply and demand one needs a model for prices. We use the model in Card and Lemieux (2001), extending it to account for composition effects and regional labor markets.

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[11]In the sensitivity analysis reported in Section 5, we check the robustness of our main results.

2.2.1   Skill prices determination

We assume that skill prices $\left(\pi_{atr}^H, \pi_{atr}^C\right)$ are determined in equilibrium in a standard model of the labor market. Suppose the aggregate output in period t, say Y_t, is a sum of R regional outputs:

$$Y_t = G_t(Y_{t1}, \ldots, Y_{tR}) = \sum_{r=1}^R Y_{tr}, \tag{6}$$

where Y_{tr} is the aggregate output in region r and in period t, and R is the number of regions. In addition, we assume that output in region r and in period t is a function of region-specific aggregates of high-school and college labor, denoted by $\mathbf{L}_{tr}^C$ and $\mathbf{L}_{tr}^H$:

$$Y_{tr} = F_{tr}(\mathbf{L}_{tr}^C, \mathbf{L}_{tr}^H). \tag{7}$$

These two labor aggregates are in turn functions of sub-aggregates of age-group-specific high-school and college labor, denoted by $L_{1tr}^k, \ldots, L_{Atr}^k$ (age groups take values from 1 to A) for $k = C, H$:

$$\begin{aligned} \mathbf{L}_{tr}^k &= H_{tr}^k(L_{1tr}^k, \ldots, L_{Atr}^k), \\ L_{atr}^k &= N_{atr}^k Q_{atr}^k, \end{aligned} \tag{8}$$

where N_{atr}^k and Q_{atr}^k are (respectively) the number of workers and the average quality of those workers with schooling k, in age group a, in year t, and in region r. There is imperfect substitution between high school and college labor, and between workers of different ages (Card and Lemieux, 2001). The existing literature on this topic implicitly assumes that Q_{atr}^k does not change as the supply of college graduates varies.

We assume that Q_{atr}^k can be written as:

$$Q_{atr}^k = \sum_{b=1}^R \frac{N_{atrb}^k}{N_{atr}^k} E\left(U_{i,t-a,b}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1\right), \tag{9}$$

where N_{atrb}^k is the number of workers in sector k for age a in time t in region of residence r and in region of birth place b and $U_{i,t-a,b}^k$ is the same as in equation (1). The quality term is given by $E\left(U_{i,t-a,b}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1\right)$, the average level of k-type skill for individuals with schooling level k in age group a in year t in region of residence r and in region of birth b. This equation says that, for each (k, a, t, r) cell, the average worker quality in region r can be written as

the weighted average of the quality of workers born in different regions b, but working in region r. The weights are the proportion of workers in r born in region b.

A standard assumption in the literature is that labor markers are competitive, implying that skill prices equal corresponding marginal products:

$$\Pi_{atr}^k = \frac{\partial Y_t}{\partial L_{atr}^k} \equiv \frac{\partial G_t}{\partial Y_{tr}} \frac{\partial F_{tr}}{\partial \mathbf{L}_{tr}^k} \frac{\partial H_{tr}^k}{\partial L_{atr}^k},$$

so that by taking logs:

$$\pi_{atr}^k = \log \left[\frac{\partial G_t}{\partial Y_{tr}} \right] + \log \left[\frac{\partial F_{tr}}{\partial \mathbf{L}_{tr}^k} \right] + \log \left[\frac{\partial H_{tr}^k}{\partial L_{atr}^k} \right] \tag{10}$$

for each (k, a, t, r). By assumption, skill prices are specific to each (k, a, t, r) cell (which defines a labor market), but common to all individuals in that cell regardless of their region of birth b (individuals born in different regions are perfect substitutes).

2.2.2 Identification of the structural model

In this section we discuss identification of the parameters of the production function. There are two main issues to consider, although they are fairly standard, so our discussion is brief. Recall that, from the production function (for fixed output prices) we can derive the implied demand for each type of labor. It is useful to separate identification of the relative demand for older vs. young workers, and the relative demand for high school vs. college graduates.

We know that demand functions can be non-parametrically identified if i) the demand function is stable and, ii) supply shifts are exogenous. Assumption ii) is very strong but it is standard in this literature, and assumption i) is often found to be false. For example, Katz and Murphy (1992) show that the college premium and the relative supply of college graduates trend upwards over time, which means that the equilibrium cannot be moving along a stable demand curve. Therefore, they conjecture that the demand for skill is trending upwards, due to skill biased technical change. By analogy, it is natural to assume that the relative demand for older workers is not stable.[12]

The standard assumption (used throughout the paper) is that the demand for skill is stable up to an additively separable trend. Still, knowing the direction of the trend is not sufficient for identification; one also needs to know the magnitude of the annual shifts. For example, Katz and Murphy

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[12]Card and Lemieux (2001) assume away the existence of such trend in the experience premium, but not in the college premium.

(1992) consider different specifications, but the most popular one just has linear demand growth (perhaps with a break in the 1990s, as in Autor et al., 2008).

Even if the demand function is non-parametrically identified, it is well known that efficiency parameters and elasticities in (10) cannot be identified separately (see e.g. Diamond et al., 1978). A standard practice in the literature is to allow for factor-augmenting (time-varying) technological progress, while keeping the elasticity parameter fixed over time. We follow this convention and furthermore, as in Card and Lemieux (2001), we assume that both the production function, and the high-school and college labor sub-aggregates have the constant elasticity of substitution (CES) form:

$$Y_{tr} = \left[\theta_{Htr} \left(\mathbf{L}_{tr}^H \right)^\rho + \theta_{Ctr} \left(\mathbf{L}_{tr}^C \right)^\rho \right]^{\frac{1}{\rho}} \quad \text{and} \quad \mathbf{L}_{tr}^k = \left[\sum_{a=1}^A \beta_{at} \left(\alpha_{ka} L_{atr}^k \right)^{\eta_k} \right]^{1/\eta_k}, \tag{11}$$

where θ_{ktr} is a factor-augmenting technology efficiency parameter for schooling group k in time period t in region r, $\sigma \equiv 1/(1-\rho)$ (with $\rho \leq 1$) is the elasticity of substitution between college and high school labor, β_{at} is a factor-augmenting technology efficiency parameter for age group a in time period t, α_{ka}'s are time-constant, age-relative efficiency parameters for schooling group k, and $\sigma_k \equiv 1/(1-\eta_k)$ (with $\eta_k \leq 1$) is the elasticity of substitution between workers of different ages but with the same schooling k.

Let $\xi_{kat} = \log \beta_{at} + \eta_k \log \alpha_{ka}$ and let

$$\xi_{ktr} = (1-\rho) \log Y_{tr} + \log \theta_{ktr} + (\rho - \eta_k) \log \mathbf{L}_{tr}^k. \tag{12}$$

From equations (10) and (11) it follows that, in equilibrium:

$$\pi_{atr}^k = \xi_{ktr} + \xi_{kat} + (\eta_k - 1) \left[\log N_{atr}^k + \log Q_{atr}^k \right], \tag{13}$$

where ξ_{ktr} is the (year)×(region of residence) fixed effect (corresponding to the first two terms in the right hand side of equation (10)), and ξ_{kat} is the (possibly time-varying) age effect for each schooling group $k = H, C$. Equation (13) states that skill prices, π_{atr}^k, can be expressed as a separable function of a time varying region-of-residence effect (ξ_{ktr}), a time varying age effect (ξ_{kat}), and the quality-adjusted log supply of labor of schooling level k ($\log \left(N_{atr}^k Q_{atr}^k \right)$). Skill prices can change as quality (Q_{atr}^k) varies, even if labor supply (N_{atr}^k) is kept fixed. Therefore, composition has a direct effect on wages in each cell because it affects the average quality of workers in the cell,

but it also has an indirect effect through skill prices. We call equation (13) the "structural" model. The construction of N_{atr}^k and Q_{atr}^k are discussed below in the Data Section.

Putting (3), (4), (13) together with the model for Q_{atr}^k developed in Appendix A we can estimate η_k and $\phi_k(P_{t-a,b})$ from the following structural model:

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\begin{aligned}
\omega_{atrb}^k &= \xi_{ktr} + \xi_{kat} + (\eta_k - 1)\log\left(N_{atr}^k Q_{atr}^k\right) + \\
&\quad + \gamma_{kab} + \gamma_{ktb} + \phi_k(P_{t-a,b}) + \lambda_k(P_{M,atrb}^k, P_{M,atrr}^k).
\end{aligned}
\tag{14}
$$

Appendix A describes our method for estimating the structural model in detail (including a description of how Q_{atr}^k is constructed).

It is useful to discuss restrictions imposed in our CES model and to compare them with those of Card and Lemieux (2001). In our model, the efficiency parameter for the input L_{atr}^k is $\beta_{at}\alpha_{ka}^{\eta_k}$. In contrast, the efficiency parameters for the age-by-schooling labor inputs are time invariant parameters in Card and Lemieux (2001) ($\beta_{at} = \beta_a$ for all t). However, allowing β_{at} to have a time-trend means that technological change can affect the relative demand for older workers, as well as the relative demand for college graduates (θ_{ktr}). In the literature, skill-biased technological change typically refers to changes in ($\theta_{Ctr}/\theta_{Htr}$), although, in general, skills can be measured in multiple dimensions. For example, the skill-biased technological change can manifest itself in terms of changes in efficiency parameters for skills measured by age (increasing demand for experience).[13]

2.2.3 Two Alternative Specifications

There are several alternative ways to specificy equation (14). It is important to justify our choice against two of them in particular. In section 5 we show that our results are robust to the use of both of these alternative specifications.

First, one could think of defining the labor market for each schooling level k by $a - t - r - b$ instead of $a-t-r$. This alternative model would relax the assumption that workers born in different regions defined by b are perfect substitutes in each labor market defined by r (they just have different amounts of efficiency units of skill). Instead, this model allows for imperfect substitutability. In order to implement it we would define supply at the level of $a - t - r - b$ instead of $a - t - r$, and

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[13]In our empirical results, it turns out that this departure from the model of Card and Lemieux (2001) has little effect on our estimates of composition effects but it helps us with its overall fit.

we could then run the following regression:

$$\omega_{atrb}^k = \xi_{ktr} + \xi_{kat} + (\eta_k - 1) \log N_{atrb}^k +$$
$$+ \gamma_{kab} + \gamma_{ktb} + \phi_k(P_{t-a,b}) + \lambda_k(P_{M,atrb}^k, P_{M,atrr}^k). \tag{15}$$

Even though imperfect substitutability is a more general assumption than the one we use, we have good reasons not to estimate this model. One one end, the usual measure of supply in the literature on the college premium is the ratio of college to high school supplies (e.g., Katz and Murphy, 1992; Katz and Autor, 1999; Card and Lemieux, 2001; Autor et al., 2008). This is analogous but not exactly equal to our measure of $P_{t-a,b}$, which we use instead for measuring composition. In order to convince the reader that we are indeed able to separately identify supply and composition the variables we use to measure each of them vary at very different levels: supply varies at the level of the $a - t - r$ while composition varies at the level of the $a - t - b$.

Furthermore, our strategy for identifying composition effects is robust to misspecification of the production function, as we can see from the reduced form model. We are able to identify composition effects keeping prices fixed in a very flexible way, which do not rely on imposing a structure for the production function (apart from the assumption that individuals coming from different regions b are perfect substitutes within a given labor market r).

Second, notice that Q_{atr}^k in equation (14) is a function of $P_{t-a,b}$, which can be seen from equation (9). If we were very flexible in the way we specify Q_{atr}^k and $\phi_k(P_{t-a,b})$ in equation (14), it would not be possible to identify $\phi_k(P_{t-a,b})$. Therefore, one may think of dropping $P_{t-a,b}$ from the structural model, estimating the following equation instead:[14]

$$\omega_{atrb}^k = \xi_{ktr} + \xi_{kat} + (\eta_k - 1) \log \left(N_{atr}^k Q_{atr}^k \right) +$$
$$+ \gamma_{kab} + \gamma_{ktb} + \lambda_k(P_{M,atrb}^k, P_{M,atrr}^k). \tag{16}$$

One would think that we are able to include $\phi_k(P_{t-a,b})$ together with Q_{atr}^k in equation (14) only because of the parametric structure we assume. Although that may be true, notice that it is possible to separately identify these two components using a two step estimator. In the first step we would estimate $\phi_k(P_{t-a,b})$ from the reduced form model which bypasses the specifiation of Q_{atr}^k. In the second step we would estimate the structural model after subtracting the role of composition

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[14]We would like to thank the editor for suggesting us this type of the alternative model.

from wages:

$$
\omega_{atrb}^k - \phi_k(P_{t-a,b}) = \xi_{ktr} + \xi_{kat} + (\eta_k - 1)\log\left(N_{atr}^k Q_{atr}^k\right) +
$$
$$
+ \gamma_{kab} + \gamma_{ktb} + \lambda_k(P_{M,atrb}^k, P_{M,atrr}^k).
$$

Therefore, we choose to estimate equation (14) as our baseline model, which explicitly preserves the tight link between the reduced form and the structural models.

3 Data

We use data from the 1960, 1970, 1980, 1990 and 2000 US Censuses (1% sample).[15] We focus on white males, ages 25 to 60, and we aggregate them into 7 age groups: 25-30, 31-35, 36-40, 41-45, 46-50, 51-55, 56-60. We consider 9 regions of birth and 9 regions of residence,[16] and we drop from the sample those individuals who are foreign born. We group individuals into cells defined by five variables: schooling (high school or college), year, age group, region of residence, and region of birth. The reason we do not use the state as the geographical unit is that the resulting cell sizes would be too small for our estimates to be reliable.[17]

For each cell we compute the relevant average weekly log wages for full-time/full-year workers, log total weeks worked (a measure of labor supply) and the proportion of individuals in college (a measure of composition). Full-time/full-year workers are individuals who work at least 35 hours a week and 40 weeks a year. In order to construct hours worked per week we use usual hours worked in a week for the year of 1980, 1990 and 2000, and hours worked the week before the interview for 1960 and 1970. We exclude farm workers from the group of full-time/full year workers. The construction of wages and weeks worked described in this section is based on Card and Lemieux (2001). Weekly wages for high school graduates are obtained by taking only white males with exactly 12 years of schooling and dividing annual income from wages by annual weeks worked. Weekly wages for college graduates are obtained in an analogous way, but considering individuals

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[15]Our data was extracted from `http://www.ipums.umn.edu/` (see Ruggles et al., 2004)

[16]We use the regions defined by the Census: New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont), Middle Atlantic (New Jersey, New York, Pennsylvania), East North Central (Illinois, Indiana, Michigan, Ohio, Wisconsin), West North Central (Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota), South Atlantic (Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia), East South Central (Alabama, Kentucky, Mississippi, Tennessee), West South Central (Arkansas, Louisiana, Oklahoma, Texas), Mountain (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming), Pacific (Alaska, California, Hawaii, Oregon, Washington). Different regions have different sizes, but we do not see this as a major problem for our analysis.

[17]Our attempts to do so resulted in imprecise estimates.

with exactly 16 years of schooling.[18] Unfortunately, for the 1960 and 1970 US Censuses weeks worked are only available in intervals: 1 to 13, 24 to 26, 27 to 39, 40 to 47, 48 to 49, 50 to 52. For these two years we take the midpoint of each interval as our estimate of weeks worked.

We now describe the construction of log weeks worked (N_{atr}^k) for high school and college equivalents. Log weeks worked by high school equivalents are a weighted sum of weeks worked by white males in each region of residence, who can be high school dropouts, high school graduates, and individuals with some college. Log weeks worked by college equivalents are a weighted sum of weeks worked by white males with some college, a college degree, or post-graduate studies.

The weights for these sums are defined as follows. Each high school dropout week is only a fraction of a regular high school graduate week. This fraction corresponds to the relative wage of high school dropouts and high school graduates. Similarly, each week worked by an individual with a post-graduate degree has a larger weight than a week worked by a college graduate, and the weight is given by the relative wage of post-graduates and college graduates. Finally, in order to construct the weights for some college weeks, we first look at the difference between high school graduate and college graduate wages. If the difference between some college wages and high school graduate wages is say, one third of the difference between college and high school wages, then we assign one third of some college weeks to high school, and two thirds to college. We allow these weights to vary across age groups, but not across year or region.

We have one additional variable relative to those considered in Card and Lemieux (2001): composition. Composition is measured by (a function of) the proportion of individuals with some college or more in each cell. This proportion should vary only with cohort and region of birth. However, empirically it varies over time, even within cohort-region of birth cells, because individuals acquire more education as they age (during their adult years), or because of (time varying) sampling error or measurement error. Therefore, in order to get a measure of composition which is fixed within cohort and cohort-region of birth cell, we average this number across years using as weights the proportion of people in each cell.

The quality-adjusted log weeks ($\log N_{atr}^k Q_{atr}^k$) can be constructed by the sum of log weeks worked ($\log N_{atr}^k$) and log average quality ($\log Q_{atr}^k$). The average quality of workers in (9) is not directly observable and hence, it is necessary to develop a model for $\log Q_{atr}^k$. In Appendix A, we provide alternative models for $\log Q_{atr}^k$. Our main model is based on the idea that the average quality of

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[18]Notice that in order to get measures of wages for clearly defined and relatively homogeneous groups of individuals we ignore high school dropouts, those with some college, those with post-graduate studies.

workers in a regional labor market can be linked to some aggregate measure of the composition of workers and also some aggregate measure of selective migration. See Appendix A for more details.

In order to have a clear idea of the sources of identification in the model, it is helpful to understand the level of variation of different variables. Wages vary across schooling-year-age-region of residence-region of birth cells (unrestricted variation). Weeks worked vary across schooling-year-age-region of residence, and are constructed by adding weeks across regions of birth (therefore they are constant across cells corresponding to different regions of birth but the same region of residence). Composition varies across cohort-region of birth (constant across regions of residence, for the same region of birth). The definition of these variables conforms with the reasoning behind our identification strategy: skill prices are constant within region of residence and are affected by total labor supply in the region of residence, while composition is constant within region of birth (subject to assumptions on migration, which we further discuss in Sections 4 and 5).

In our setup, a migrant is an individual who resides in a region different from the region he was born in. Migration proportions are constructed simply by counting the number of individuals of schooling group k, age a, year t, born in b and residing in r, and dividing by the total number of individuals of schooling group k, age a, year t, born in b, independently of their region of residence.

Figure 2 shows the basic features of our data, which we present after grouping the nine Census regions into four more aggregate regions: Northeast (New England + Middle Atlantic), North Central (East North Central + West North Central), South (South Atlantic + East South Central + West South Central), and West (Mountain + Pacific). The first panel shows that the trend in the college premium, measured by the average difference in log wages of college and high school graduates, is qualitatively similar across regions, although there are differences in the levels. The college premium rises in the 1960s, declines in the 1970s, accelerates in the 1980s and continues growing in the 1990s but at a slower rate, except in the Northeast where the growth in the college premium in the 1990s is comparable to that in the 1980s.

The college age premium (shown in the second panel), measured by the difference in average log wages of 51-55 and 31-35 year old college graduates, increases in the 1970s in all regions, and declines in the 1990s in all regions. It is stable during the 1980s in the northern regions, but it declines during this decade both in the South and in the West. The high school age premium (shown in the third panel) increases throughout the 1970s and 1980s for all regions, and then it seems to stagnate or decline slightly. Notice also that the movements in the age premium we document are

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of the same magnitude as the movements in the college premium. Between 1960 and 2000, the college premium increased by 17% in our data, while the 5, 10 and 20 year age premia (relative to the 31-35 year old age group) grew respectively by 7%, 7% and 6% among college graduates, and 6%, 8%, and 17% among high school graduates.

Finally, the last panel of the figure shows the evolution of the proportion of college attendees in each region. Even though there are clear regional differences in the levels of this variable, with the South presenting lower numbers than the other three regions, the trends are the same across the US: college enrollment increases over time, but it grows at a lower rate starting in the 1980s.

These basic trends are well documented in the literature. It is interesting to see that there are strong commonalities across different regions.

4   Empirical Results

Table 1 reports estimation results that are obtained by implementing the econometric framework described in Section 2. All regressions in the table are weighted by the inverse of the sampling variance of average log wages in each cell and robust standard errors are reported in brackets, clustered by schooling, region of residence, and year.

In column (1) of Table 1, we estimate the reduced-form model of equation (5). In this model π_{atr}^k is not modeled explicitly. Instead, we control for skill prices using full interactions between year, age and region of residence dummies in separate regressions for college and high school. In doing so, we estimate the role of composition by putting as little structure as possible on price determination. In the empirical implementation of (5), we assume that ϕ_k is linear in the odds of proportion in college ($\tilde{P}_{t-a,b} := P_{t-a,b}/(1 - P_{t-a,b})$). This functional-form choice is arbitrary, but it gives a convenient parameterization (it is a strictly increasing function of $P_{t-a,b}$ and can vary from 0 to ∞).[19] In addition, λ_k in (5) is modeled as a second-order expansion of migration probabilities: that is, linear and quadratic terms of $P_{M,atrb}^k$ and $P_{M,atrr}^k$ and the interaction between the two. All regressions include region of birth dummies interacted with year and age, separately.[20]

Column (1) of Table 1 shows that the coefficient on $\tilde{P}_{t-a,b}$ is significantly negative and quantitatively large for the college equation, but insignificantly negative and quantitatively small for the

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[19]We carried out estimation of the reduced-form model of equation (5) using alternative specifications of ϕ_k. The main qualitative results of the paper are similar regardless of the specification of ϕ_k. See the online appendix for details.

[20]Therefore, we control for region of birth specific cohort trends, as well as time-varying region-of-birth by region-of-residence effects. Recall that these dummies were denoted by γ_{kab} and γ_{ktrb} in (5).

high school equation.[21] This means that, for fixed prices, log college wages respond substantially to changes in college enrollment, but that is not the case with log high school wages. We estimate that when the proportion of college participants increases from 50% to 60% ($\tilde{P}_{t-a,b}$ increases from 1 to 1.5) average college wages decline by 4.3%. We interpret this as a decline in average worker quality.

Composition plays a much smaller role in the high school sector than in the college sector. This is an interesting result which may happen for several reasons. For example, the skills that determine selection into college may be less valued in high school type occupations than in college type occupations. This is possible in a model of the labor market in which there are two or more types of skills, as opposed to a model with a single type of skill. Individuals are differentiated in terms of a college skill and select on this skill when enrolling in college, but this is a skill that is not valued in high school occupations.

Alternatively, in a model where the quality of college workers declines not because of an influx of lower quality workers, but because of a potential decrease in available educational resources per capita in college (but not in high school), this is precisely what we would expect.[22] The cohort crowding hypothesis implies that a quality decline should only be visible among college workers, and not among high school workers.

From Table 1 we can also infer the role of composition for the trend in the college premium, one of the main goals of our paper. Since the college premium at time t is defined as $E\left(w_t^C|S^C=1\right) - E\left(w_t^H|S^H=1\right)$, this requires subtracting the college and high school wage equations and averaging across all ages, regions of birth and regions of residence. Given that our specification of the high school and college wage equations is linear in all variables, in order to compute the effect of composition on the college premium we just need to take the difference between the coefficients on $\tilde{P}_{t-a,b}$ in the college and high school equations. In column (1) of Table 1, this difference is equal to -0.054, implying that the college premium would decline by 2.7% if college enrollment went from 50% to 60%.[23] Our estimate also implies that an increase of college enrollment from 30% to 60% (the magnitude similar to that observed between 1960 and 2000) leads to about a 6% decline of college premium. One important implication of our findings is that estimates of the trend in the

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[21]In the online appendix, we show that the main results are basically unchanged even when we include measures of within group composition (the within odds of proportion in dropout, the within odds of proportion in some college, and the odds of proportion in post college enrollment).

[22]This was pointed out to us by a referee.

[23]In the online appendix, we report the effects of declining quality of marginal college graduates on their average log wages for different specifications of the model, and at different levels of P.

college premium are contaminated by composition effects, an issue we explore in Section 7.

In column (2) of Table 1, we estimate the structural model where π_{atr}^k is modeled explicitly as in (14). For comparison, in column (3) of Table 1, we estimate a model without $\log Q_{atr}^k$ in (13). This corresponds to the standard model in the literature where we ignore changes in the quality of workers and interpret fluctuations in wages as being driven exclusively by changes in prices. In both columns (2) and (3) of Table 1, the age effect ξ_{kat} is modeled as an interaction of a linear time trend with age specific dummies that are common between schooling groups.[24] The exact specifications of columns (2) and (3) are described in Appendix A.

In column (2), we can see that the coefficients on $\tilde{P}_{t-a,b}$ in the college and high school equations are not very different from those in the more general model of column (1). Specifically, in column (2), the difference between two coefficients is -0.069, which is similar to -0.054 in column (1). Thus, our estimation results are robust to alternative models for π_{atr}^k. In the college equation, the coefficient for the quality-adjusted log weeks $(\eta_C - 1)$ in (13) is -0.11, which implies that the elasticity of substitution between workers of different ages in college is $\sigma_C = 1/(1 - \eta_C) = 1/0.11 \approx 9.1$. In the high school equation, the corresponding coefficient $(\eta_H - 1)$ is -0.09 and, therefore, the elasticity of substitution is about 11.1. Thus, our estimates indicate that different age groups are slightly closer substitutes in high school than in college (equivalently, high school wages are slightly less sensitive to labor supply than college wages). However, their difference is not statistically significant at any conventional level.

Looking at column (3), we see that the coefficients for (quality-unadjusted) log wages in college and high school are -0.188 and -0.090, respectively, implying that the elasticities of substitution are about 5.3 and 11.1 in college and high school, respectively. Hence, failing to adjust for changes in the quality of labor supply has a substantial effect on our estimate of the elasticity of substitution across age groups in college (σ_C). Movements in the number of weeks worked by college graduates confound changes in the supply of college labor and changes in the composition of college labor. The two effects go in the same direction, and therefore the estimate of the effect of college labor on college wages is upward biased (in absolute value) if quality is not controlled for. However, there is no difference between the two estimates in the high school equation, which is not surprising since the composition effect is not important in high school.

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[24]We have chosen this specification instead of a more flexible one because we are concerned about overparameterization of the model and also unrestricted interactions between age and time dummies for each schooling group lead to imprecise coefficients in quality-adjusted and unadjusted log weeks in columns (2) and (3), respectively.

Our estimates in column (3) are of comparable magnitude (especially in the college equation) to the estimates in Card and Lemieux (2001, Column (1) of Table VII), where the preferred estimates are -0.201 for high school and -0.204 for college. What is remarkable is that after correcting for the role of composition the college estimate drops dramatically to -0.11, which means that the elasticity of substitution across age groups increases dramatically once we account for quality. We come back to this point in section 8.

5 Sensitivity Analysis

We start this section by discussing two alternative specifications of the structural model, shown above in equations (15) and (16). In the model of equation (15) we consider a labor market for each (k, a, t, r, b) cell and to take N_{atrb}^k as supply and $P_{t-a,b}$ as a measure of composition (or quality). Column (2) of Table 2 provides the corresponding estimation results. It can be seen that the results are qualitatively similar to those in column (1), which are our baseline structural results in column (2) of Table 1.

In addition, we consider an alternative structural model without the composition term $\phi_k(P_{t-a,b})$, as in equation (16). Column (3) Table 2 shows estimation results when $\phi_k(P_{t-a,b})$ is dropped from column (1). It is interesting to note that there is almost no change in estimates. This suggests that $N_{atr}^k Q_{atr}^k$ and $\phi_k(P_{t-a,b})$ are at most very weakly correlated, given other control variables. This is a bit surprising, and probably due to the fact that Q_{atr}^k includes $P_{t-a,b}$ weighted by $\frac{N_{atrb}^k}{N_{atr}^k}$, whereas $\phi_k(P_{t-a,b})$ does not weight $P_{t-a,b}$ by any quantity.

Since the main focus of our paper is the magnitude of composition effects and they can be estimated from the reduced form model, we focus the remaining of our sensitivity analysis on the reduced form model.[25] Table 3 presents estimation results for the college wage equation with alternative specifications and samples. Comparable results for the high school wage equation are not shown here but given in the online appendix, since there is no composition effect for high school graduates across different specifications.

We do not know what should be the correct functional form for $\phi_k(P_{t-a,b})$ in equation (5). Therefore, in the first panel of Table 3 we experiment with four alternatives. The first column

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[25] Table 12 in Appendix A reports estimation results of the structural model with alternative specifications of $\ln Q_{atr}^k$ in (22).

corresponds to the original specification:

$$\phi_k(P_{t-a,b}) = \psi \frac{P_{t-a,b}}{1 - P_{t-a,b}},$$

where ψ is the parameter we report. In the second column,

$$\phi_k(P_{t-a,b}) = \psi_1 \frac{P_{t-a,b}}{1 - P_{t-a,b}} + \psi_2 \left(\frac{P_{t-a,b}}{1 - P_{t-a,b}} \right)^2,$$

and we report ψ_1, ψ_2, and the p-value of the test of joint significance of these two parameters. In the third column,

$$\phi_k(P_{t-a,b}) = \psi P_{t-a,b},$$

and in the fourth column,

$$\phi_k(P_{t-a,b}) = \psi_1 P_{t-a,b} + \psi_2 P^2_{t-a,b}.$$

The first panel of the table corresponds to the original sample of white males, and show that we find strong effects of composition for alternative specifications of $\phi_k(P_{t-a,b})$.[26]

In the remaining panels of this table we show the sensitivity of our results to different samples. The middle panel corresponds to a sample of white females. The main reason why we chose to focus on males rather than females was that female non-employment rates in our sample are, on average, three to four times higher than male non-employment rates. If that is the case, we need to worry not only about shifts in the composition of schooling, but also shifts in the composition of employment (Blundell et al., 2003; Mulligan and Rubinstein, 2008). There is no significant result here, suggesting that further research is needed to distinguish changes in the composition of schooling from the changes in the composition of employment. In the bottom panel, we group males and females together in the same sample. Results are similar to the original ones, especially in column 3.

One purpose of this section is also to study the potential confounding role of selective migration and school quality in our empirical work. If migration is selective then migrants may not carry with

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[26]In addition, our quantitative results are robust to the use of an alternative measure of composition. In particular, the coefficient for $P_{t-a,b}$ for the college wage equation (column (3) in the top panel of Table 3) is -0.517. The corresponding coefficient for the high school equation is -0.295 (the full table is available in the online appendix). This implies that if we use the level of proportion in college rather than the odds of proportion in college, the college premium would decline by 2.2% if college enrollment increases by 10% $(0.10 * [-0.517 - (-0.295)] = 0.0222)$. This change is comparable to 2.7%, which we obtained using the odds of proportion in college when college enrollment changed from 50% to 60%.

them the average quality of their region of birth. Recall that our reduced form model includes: year×age×region of residence, year×region of birth, and age×region of birth (on top of migration flows, which we ignore for now). Therefore, our estimates would be biased if, within region of birth, cohort changes in selective migration are correlated with cohort changes in composition. In theory this is a possibility, but the question is whether it is empirically important.

In our search for valid correction criteria, we studied this question in detail. Based on three different sets of results that will be discussed below, we conclude that it is unlikely that selective migration explains our findings. Without a valid model for migration (identified with a valid instrument) this is an untestable proposition, and therefore each of these results on its own is merely suggestive of our claim. However, taken together, they provide a strong case for it.

First, we show that the inclusion of alternative sets of controls for selective migration does not affect our basic results. The reason is not that these variables do not affect wages, but that these variables (given the set of controls) are uncorrelated with changes in schooling. Table 4 summarizes these results. In this table, we experiment alternative specifications for column (1) of Table 1, where prices are modeled as full interactions between year, age and region of residence dummies (reduced form model). Column (1) of Table 4 considers the simplest specification, where we add as controls region of birth interacted with year and age, to account for omitted variable bias caused by heterogeneity across regions of birth. This is the base specification in this table, against which it is useful to compare the remaining columns. Column (2) expands the set of region of birth effects by adding a region of birth specific nonlinear cohort effect.[27] This amounts to including a quadratic "cohort trend" in the model, as a parametric way of accounting for region of birth specific cohort effects that evolve smoothly across cohorts (for example, trends in local labor markets affecting the decision to migrate of individuals in different cohorts). The resulting change in the coefficients of interest both in high school and college is quite small.

In Column (3) we attempt to control for selective migration more explicitly by including region of residence and region of birth interactions, and allowing them to vary with year. With these variables we intend to capture match specific shocks that can be time varying, and changes in the quality of (region of birth)-(region of residence) migrants over time. Relative to Column (1), there is a decline in the coefficient of interest in college but again it is small, and almost no change in high school.

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[27] A linear cohort effect, (Cohort)×(Region of Birth), is implicitly included since (Cohort) = (Year) - (Age).

Relatively to Column (1), in column (4), we add a basic set of migration probabilities, as discussed above. In particular, for each (k, a, t, r, b) cell we include the proportion of individuals born in r and residing in r (staying probability), the proportion born in b and residing in r (observed migration probability), their squares and an interaction between the two (Dahl, 2002). What is most striking about this column is that the results are similar to Column (1), although the coefficients on the migration proportion are highly significant (jointly). This suggests that changes in migration flows are uncorrelated with changes in schooling in our basic specification, an issue we explore below.

Column (5) is the main specification of the paper (and replicates Column (1) of table 1). In Column (5) we join the specifications in (3) and (4). The remaining columns present variants of these first five specifications. In column (6) we take the specification in column (4) but estimate it only for migrant cells (cells for whom $b \neq r$). This column shows that our results are not driven by differences between migrant and non-migrant cells. Instead, they seem to be driven by variation in composition across migrant cells.

Finally, in column (7), we add school quality variables as additional controls compared to the basic specification. The included school quality variables are pupil-teacher ratio, average term length, and relative teacher salary, as in Card and Krueger (1992) and Heckman et al. (1996).[28] One concern with the basic specification in column (5) is that we may be capturing school quality effects through the proportion in college. It can be seen that differences between estimates in columns (5) and (7) are small, indicating that our results are robust to inclusion of school quality variables. We conjecture that this is because variation in school quality is already accounted for by the set of controls we use in the basic specification (region of birth interacted with year and age).

Our second set of results builds on the comparison between Columns (1) and (4) (and (5)) above, which show that the inclusion or exclusion of migration flows as control variables does not change our main results. This means that changes in migration flows and changes in schooling across cohorts are orthogonal. Therefore, it is unlikely that selective migration varies with schooling because migration flows (as opposed to schooling flows) are roughly constant over time, although the composition of migrants could still be correlated with schooling. We explore these two issues more formally next.

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[28] Petra Todd kindly provided us with these variables for several states and years. For each individual in the Census, we gathered the values of each school quality variable for the state he was born in, and for the years in which he was between 6 and 17 years of age, and we averaged them. We assigned this as the level of school quality for each individual in the data, and then we averaged these values within each (k, a, t, b) cell.

In Table 5, we examine differences between including and excluding migration probabilities in our basic specification. In column (1), we reproduce estimates for the college sector from column (4) of Table 4, but we present coefficients for the migration probabilities as well. In column (2), we show the estimate of odds in proportion in college without controlling for selective migration (hence, this is the same as the specification in column (1) of Table 4). In column (3), we show the estimates for migration probabilities without controlling for proportion in college. In columns (4)-(6), we show corresponding estimates for the high school sector. The coefficients for proportion in college are almost identical whether or not migration probabilities are controlled for. Similarly, coefficients for migration probabilities change only a little if we do not control for proportion in college. This confirms our assertion that migration flows are orthogonal to changes in schooling.

In order to examine this more directly, in columns (1) and (2) of Table 6, we regress the proportion of individuals not migrating in each cell on the odds of proportion in college. We use only non-migrant cells. In column (1), no control variable is used and in column (2), (Year)×(Age), (Year)×(Region of Birth), and (Age)×(Region of Birth) dummies are controlled for (as in our base specification). There is no significant correlation between schooling and migration flows in college. The regression coefficient in high school is significant even after including the full set of controls, but its magnitude is very small. Similarly, in columns (3) and (4), we use only migrant cells to test whether the odds in proportion in college is correlated with the observed migration probability. In column (3), no variable is controlled for and in column (4), the basic set of control variables is used. Once again, after including the full set of controls, there is no evidence of any correlation between migration flows and college attainment. In columns (1)-(4), all regressions are weighted by the inverse of the sampling variance of the dependent variable using the fact that the dependent variable is a probability in each column.

These results show that migration flows respond very little to schooling, which means that selective migration is unlikely to vary with schooling. However, it is possible that the composition of migrants is correlated with variation in schooling, even if the size of the migration flows is not. If this were true, we might expect changes in the raw migration premium (the average difference between logs wages for migrants and those for stayers) to be correlated with changes in college attainment, since this parameter will be sensitive to changes in the composition of migrants. In order to check this possibility, in columns (5)-(7), we regress the migration premium on the odds of proportion in college. In these columns, all regressions are weighted by the same weights used

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in Table 1. In column (5) when no variable is controlled for, there is a significant negative effect of college attainment on the migration premium; however, this effect disappears in columns (6) and (7) when we introduce our basic set of controls. Therefore it is unlikely that changes in schooling are correlated with changes in the composition of migrants.

Selective migration is undoubtedly important and may be present in our data even after including our set of controls. However, we believe that, taken together, the results of Tables 4, 5, and 6 provide convincing evidence that selective migration does not substantially affect our results.

In the online appendix we present additional specification checks (unrelated to migration). First, we examine how results change when we drop one of the nine regions at a time from the sample, to check whether results are driven by one region alone as opposed to being a national phenomenon. Second, we examine the sensitivity of our results to dropping one year at a time. Third, since we aggregate individuals into two levels of schooling only, one may worry that changes in college attainment also lead to changes in composition within each of these aggregates (between dropouts and high school graduates, those with some college and college graduates, or those between college graduates and post-college-educated workers). We show that our basic results are unchanged even when we include measures of within group composition (the odds of proportion in dropout within the high school sector, the odds of proportion in some college within the college sector, and the odds of proportion in post college enrollment).[29]

6 Direct Evidence on Declining Quality of College Workers

In this section we study the relationship between cognitive test scores of college attendees and the proportion attending college across regions of the US.

We first examine average scores on the SAT by state. As illustrated in Figure 3, test taking rates vary widely across states, and states with a large proportion of SAT takers have low average test results, because they test more students from the bottom of the distribution of student quality. For example, in 2004 New York had the sixth lowest average verbal SAT score (497) and the highest proportion of high school graduates taking the SAT (92%), while North Dakota had the fifth highest verbal score (590) and the lowest SAT test taking rate in the US (4%). Figure 3 does not control for other possible confounding factors. For example, some states use mainly the SAT,

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[29]One way to interpret these results is as saying that the most important margin for the phenomenon studied here is the college enrolment margin, and not the college graduation margin.

whereas other states use mainly the ACT. To carry out a more formal analysis, we have collected average verbal and math SAT scores for high school seniors graduating in each state from 1993 to 2004. Our main explanatory variable is the proportion of high school seniors taking the SAT in each state and year (as opposed to the proportion of college graduates among those graduating from high school, since we observe SAT scores for those taking the SAT, regardless of whether they attend college or not). For the years we are analyzing, the proportion of SAT takers is very strongly correlated with the fraction of high school graduates graduating from four year colleges, but not as much correlated with the fraction graduating from two year college (perhaps because the SAT is needed for enrollment in four but not two year colleges).

Using this dataset, we run a regression of SAT math and verbal test scores on the percentage of high school seniors taking the test. Our specification is quite demanding, since we control for both year and state dummies. The estimation results reported in Table 7 show exactly the same pattern reported in figure 3. We find that an increase in the proportion of high school seniors taking the SAT is significantly associated with lower math and verbal scores. This provides additional direct evidence that increases in college attainment lead to declines in the quality of college attendees.

Second, we consider the International Adult Literacy Survey (IALS), which is a literacy survey administered in several OECD countries. The US sample consists of a random sample of adults aged 16-65 surveyed in 1994-1995. Three literacy tests were administered: Quantitative, Document and Prose. The survey also collects data on individual schooling attainment, among many other variables (see OECD, 2000). We restrict our analysis to the quantitative score of individuals aged 25-60 (our results are not sensitive to the test we use). We standardize the score so that it has mean 0 and variance 1. The quantitative test measures individual proficiency in basic quantitative tasks: "the knowledge and skills required to apply arithmetic operations, either alone or sequentially, to numbers embedded in printed materials, such as balancing a checkbook, calculating a tip, completing an order form, or determining the amount of interest on a loan from an advertisement".

For each cohort, we group individuals into two schooling groups: high school or less, and some college or more. Then for each cohort, we compute the percentage of individuals with some college or above, which we call P. Table 8 reports the coefficients of a regression of quantitative literacy on age, age squared and P, for the high school and college groups separately, and for the whole sample together. The coefficient on P is negative and strong for college, and insignificant for high school. The third column of Table 8 shows what happens when we run the regression for the whole sample,

including an indicator for college attendance (because college attendance may affect literacy). The coefficient on P is zero, indicating that there are no intrinsic differences in the ability distribution across cohorts, except differences in composition.[30]

The online appendix provides additional direct evidence on declining quality of college workers by analyzing data from the original cohorts of the National Longitudinal Survey of Young Males (NLS66), the National Longitudinal Survey of Youth of 1979 (NLSY79), and the National Longitudinal Survey of Youth of 1997 (NLSY97). In short, we have used data from the NLS66, NLSY79, NLSY97, SAT, and IALS to show that empirical results from several different sources are all consistent with our main hypothesis.

7   Quality-Adjusted Trends in the College and Age Premia

In this section, we construct quality-adjusted trends in the college and age premia. In order to do so, for each year we need to construct average college and age premia across age, region of birth and region of residence cells. We define the college premium, denoted by CP_t, as the difference between average log college and high school wages. A particular age premium for each schooling k, denoted by AP_t^k, is defined as the difference between average log wages of old workers and those of young workers. Formally:

$$
\begin{aligned}
CP_t &= \sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{b=1}^{R}\omega_{atrb}^{C}f_t^{C}\left(a,r,b\right) - \sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{b=1}^{R}\omega_{atrb}^{H}f_t^{H}\left(a,r,b\right) \quad \text{and} \\
AP_t^k &= \sum_{r=1}^{R}\sum_{b=1}^{R}\omega_{atrb}^{k}f_t^{k}\left(a,r,b\right)\Big|_{a=o} - \sum_{r=1}^{R}\sum_{b=1}^{R}\omega_{atrb}^{k}f_t^{k}\left(a,r,b\right)\Big|_{a=y},
\end{aligned}
\tag{17}
$$

where o and y denotes old and young workers, respectively, and $f_t^k\left(a,r,b\right)$ is the proportion of individuals in cell (a,r,b) for each schooling group k and time t. There does not exist a natural definition of young and old workers. In our empirical work, we set young workers to be those in age group 25-30 and consider three different age premia using age groups, 36-40, 46-50, and 56-60 as old workers.

In order to define quality-adjusted college and age premia, recall that average log wages for

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[30]In order to explore further this issue, we estimated the quantiles of literacy conditional on age and age squared, and a third order polynomial in P. We find that the decline in literacy is mainly at the bottom of the college distribution.

each cell are modeled as:

$$\omega_{atrb}^{k} = \pi_{atr}^{k} + \gamma_{kab} + \gamma_{ktb} + \phi_k(P_{t-a,b}) + \lambda_k(P_{M,atrb}^{k}, P_{M,atrr}^{k}). \tag{18}$$

We fix the proportion in college $P_{t-a,b}$ at the 1960 level and regard the following as quality-adjusted average log wages:

$$\omega_{atrb}^{k,Q} = \pi_{atr}^{k} + \gamma_{kab} + \gamma_{ktb} + \phi_k(P_{1960-a,b}) + \lambda_k(P_{M,atrb}^{k}, P_{M,atrr}^{k}). \tag{19}$$

Then quality-adjusted college and age premia are defined as in (17) (after substituting in ω_{atrb}^{k}):

$$CP_t^Q = \sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{b=1}^{R}\omega_{atrb}^{C,Q}f_t^C(a,r,b) - \sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{b=1}^{R}\omega_{atrb}^{H,Q}f_t^H(a,r,b) \quad \text{and}$$

$$AP_t^{k,Q} = \sum_{r=1}^{R}\sum_{b=1}^{R}\omega_{atrb}^{k,Q}f_t^k(a,r,b)\Big|_{a=o} - \sum_{r=1}^{R}\sum_{b=1}^{R}\omega_{atrb}^{k,Q}f_t^k(a,r,b)\Big|_{a=y}, \tag{20}$$

where $\omega_{atrb}^{k,Q}$ corresponds to the average wage that we would observe in each cell if the average worker quality was kept fixed at its 1960 level. Variation in $\omega_{atrb}^{k,Q}$ over time is purely due to changes in prices, which are caused by fluctuations in the demand and supply of skill. $\omega_{atrb}^{k,Q}$ is an abstract construction since it is impossible to vary the supply of labor without changing its composition, unless selection into schooling is random.

Notice that the *level* of $\omega_{atrb}^{k,Q}$ is still affected by selection. This happens because we fix quality of type k at the level of the average worker who self-selected into schooling level k in 1960 (thus, not a random worker in the economy). Therefore, the difference between ω_{atrb}^{k} and $\omega_{atrb}^{k,Q}$ is that, while selection is time varying for the former, it is fixed for the latter at 1960 levels (so that $\omega_{a1960rb}^{k} = \omega_{a1960rb}^{k,Q}$). In this paper we do not intend to estimate measures of ω_{atrb}^{k}, and of the college and age premia, purged of selection. Our more modest goal is to keep selection fixed, so that we can interpret movements in wages as reflecting solely movements in prices. The reason why we do not try to purge the *level* ω_{atrb}^{k} completely from selection is that we do not have enough variation in $P_{t-a,b}$, which would have to have support over the entire unit interval in our data for the selection correction to work. If that were the case we would be able to observe groups of individuals for whom $P_{t-a,b} = 1$ (everyone goes to college) and $P_{t-a,b} = 0$ (nobody goes to college), allowing us to compute college and high school wages free from selection.

Before we present any of our decompositions it is important to comment on the fit of the model. If the fit is poor, then this exercise would not be as interesting. In the online appendix, we show that the reduced-form model fits almost perfectly the evolution of the college premium from 1960 to 2000, as well as the evolution of the college and high school age premia.[31]

Figure 4 shows trends in quality-adjusted and unadjusted college and age premia using the estimation results reported in column (1) of Table 1 (corresponding to the robust reduced form model). In the top-left panel of the figure, the solid line correspond to CP_t in (17), while the dashed lines correspond to CP_t^Q in (20). This panel shows that the college premium increased by 20% between 1960 and 2000, but the quality adjusted college premium increased by 26%.[32] There is a substantial difference of 6 percentage points shown in the top-right panel (the solid line plots the difference between the two lines in the previous panel), which is due to the large increase in college enrollment during this period, also shown in the top-right panel (dashed line). The largest decline in quality from 1970 to 1980 corresponds to the largest increase in college enrollment in the same period and relatively modest decreases in quality in both 1980-1990 and 1990-2000 are associated with a slowdown in the growth in college attainment in those periods.

The three bottom-left panels show a dramatic difference between adjusted and unadjusted trends in the age premium in the college sector. For example, if we look at the unadjusted trends from 1980 to 1990, then there is a large decrease of about 10% in the age premium between age groups 25-30 and 36-40. On the other hand, the quality-adjusted trends show a decrease of only 4%. This suggests that from 1980 to 1990, the quality of college workers in age group 36-40 declined substantially relative to that of those in age group 25-30. Interestingly, if we look at changes from 1990 to 2000, there is a larger increase in the unadjusted age premium than in the quality-adjusted age premium. This implies that from 1990 to 2000, the quality of college workers in age group 36-40 increased substantially relative to that of those in age group 25-30. If we look at the age premia of age groups 46-50 and 56-60 relative to the age group 25-30, then there is a decrease in the unadjusted age premia from 1980 to 1990. However, there is an increase in the quality-adjusted age premia for the same period. The three bottom-right panels show that there is virtually no quality change over time in the age premium in the high school sector. This is because composition plays little role (if any at all) in explaining high school wages.

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[31]The fit of the college age premia is relatively poor for 1960s and 1970s. Thus, when we compare the quality-adjusted and unadjusted college age premia, we focus on the period of 1980-2000.

[32]In the figure, the lines are based on fitted values from the reduced-form model, i.e. column (1) of Table 1.

What remains to be shown is the set of changes in supply and composition across age groups that drive the results we just discussed. Figure 5 shows us the main drivers of composition and supply effects in the age premium. The three left panels of the figure show the evolution of the proportion in college over time for old and young workers, as well as their relative proportion over time (rescaled to fit the figure). The decrease and increase of the relative proportion in college coincides with our interpretation that the quality of old college workers (age group 36-40) decreased relatively (with respect to young college workers, age group 25-30) from 1980 to 1990 and increased relatively from 1990 to 2000. In addition, the largest increase of the relative proportion in college for age groups 46-50 and 56-60 (that is, the largest quality decline for those age groups) coincides with the reversal of trends (decreasing trends in the unadjusted premia vs. increasing trends in the adjusted premia) from 1980 to 1990. It is also clear from the figure that changes in quality cannot possibly explain fluctuations in the age premium in high school. The three right panels of the figure show the labor supply of old workers relative to young workers for both college and high school (measured in log weeks worked in each year). It appears that changes in relative labor supply do not mimic the changes in age premia, especially in the college age premium (age premia are shown in Figure 4). This suggests that changes in demand play an important role explaining trends in age premia as well, just like the college premium.

We now move to our estimates of relative demands for college workers and older workers after adjusting for quality. The trend in the relative demand for college skill is given by $\log(\theta_{Ctr}/\theta_{Htr})$. It is well known that, without additional assumptions, one cannot identify this trend separately from ρ (see equations (11) and (12)).[33] Therefore, one alternative is to take an estimate of ρ from the literature, and compute the implied series for $\log(\theta_{Ctr}/\theta_{Htr})$. Card and Lemieux (2001) who, like us, use a sample of males only, estimate ρ to be close to 0.673 (table IV, column 3, shows that $1 - \rho = 0.327$). This is the number we take for our calculations. Given ρ, we compute the implied series for $\log(\theta_{Ctr}/\theta_{Htr})$.[34]

In order to get the trend in the relative demand for older workers we just need to estimate

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[33]If suitable identifying assumptions are placed on demand growth then the parameter ρ can be estimated in a second-stage procedure with estimates of η_k, β_{at}, α_{ka}, Φ_k, and ϕ_k as inputs to the second-stage estimation.

[34]In detail, we start by constructing $\mathbf{L}_{tr}^k = \left[\sum_{a=1}^A \beta_{at} \left(\alpha_{ka} L_{atr}^k\right)^{\eta_k}\right]^{1/\eta_k}$ using parameter estimates. Since we include a general trend in the model, it is only possible to identify β_{at} relative to this general trend. Therefore, we normalize $\beta_{25t} = 1$ (where $a = 25$ is the youngest age group). Then we compute

$$R_{atrb}^k = \omega_{atrb}^k - (\rho - \eta_k) \log \mathbf{L}_{tr}^k - (\eta_k - 1) \left[\log N_{atr}^k + \log Q_{atr}^k\right] - \phi_k(P_{t-a,b}) - \lambda_k(P_{M,atrb}^k, P_{M,atrr}^k).$$

Finally, we approximate $\log(\theta_{Ctr}/\theta_{Htr})$ as the average of $(R_{atrb}^C - R_{atrb}^H)$ over (a, b), weighted by the cell sizes.

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the changes in $\log(\beta_{at})|_{a=old} - \log(\beta_{at})|_{a=young}$, where β_{at} is given in (11). In general, this can be derived from the series of ξ_{kat} from equation (13), but in our paper we just assumed this trend to be linear. The identifying assumption is that the trend in the demand for older workers does not vary across regions. If it did, we would have the same identification problem as above, and we would not be able to distinguish this trend from η_k.

We could have used a different specification, but we believe that the choices we made are adequate. First, since there are already several estimates of ρ in the literature and we have nothing to add to its estimation, the most natural way to proceed is to use one of them in our calculations (although it is possible that quality adjustments, absent from the literature so far, affect the estimate of ρ).[35] Second, there is hardly any discussion in the literature about the trend in the demand for older workers, and therefore we wanted to be as simple as possible in our specification without compromising the estimation of η_k. Our assumption produces estimates of η_k that are similar to other estimates in the literature, giving us confidence in our procedure.

Table 9 shows demand estimates for college using the estimation results reported in columns (2) and (3) of Table 1. In particular, it shows percentage changes in the relative demands for all regions as well as four large Census regions. First of all, the trend in demand is shown to be qualitatively the same regardless of the quality-adjustment: it increases in the 1960s, slows down in the 1970s, accelerates in the 1980s, slows down again the 1990s. Estimated trends are also quite similar across the four large regions. Controlling for the quality of college workers is quantitatively important. The quality adjusted trend in the demand for college workers (a measure of skill biased technological progress) is 10 percentage points higher than the unadjusted trend. This magnitude is comparable to 6 percentage points difference in the college premium, as reported in Figure 4. Regional demand estimates show that adjusted trends are higher than unadjusted trends for each region, although they are quite different quantitatively.

Table 10 shows relative demand estimates for old workers using the estimation results reported in columns (2) and (3) of Table 1. As in Table 9, it shows percentage changes in the relative demands for the youngest worker group (25-30) and two old worker groups (46-50, 56-60) with respect to the workers of prime age (36-40).[36] Recall that we used the linear time trend specification of $\log(\beta_{at})$, thereby resulting in identical changes in the relative demand for older workers for each

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[35] We are grateful to David Autor for suggesting this.

[36] Originally we were using the younger group as base, but a referee rightly pointed out to us that a much clearer picture emerged if we used prime-age workers as the reference group in the table.

decade. The most striking results are (1) the relative demands for prime age workers relatively to the youngest workers increased substantially from 1970 to 2000, (2) the demand for older workers increased relatively to prime age workers, and (3) the quality adjustment plays a relative minor role (as opposed to the previous table).

8   Can Declining Quality of Old Workers Explain the Rising College Premium for Young Workers?

In this section, using the estimation results reported in Section 4, we revisit the analysis of Card and Lemieux (2001), who explain the rising college premium for young workers (but not for old workers) by a fall in the supply of young college workers relative to old workers. In contrast, we show in this section that changes in quality are important factors to explain the phenomenon they document.

Table 11 summarizes our analysis. In column (1) we show changes from 1980 to 1990 in the raw college premium (data), composition-fixed (or quality-fixed) college premium, and proportion in college for the two age groups considered in Card and Lemieux (2001). In this table, the composition-fixed college premium is constructed using the reduced-form model (i.e. column (1) of Table 1). The difference in the growth of the raw college premium between those aged 25-60 and those aged 45 - 60 is 9.5%, which Card and Lemieux (2001) attribute to a falling relative supply of young college workers. An interesting thought experiment is the following: what would be this difference if the quality of both age groups of workers were fixed? According to our estimates, the difference would be just 6%. That is, about 37% of observed increase in the college premium for young workers relatively to old workers can be attributed to the declining quality of old college workers relative to young college workers. In column (2), we carry out the same analysis for changes from 1990 to 2000. Unlike the previous decade, the change in the college premium is small and therefore quality adjustment is less important in this decade.

9   Conclusion

In this paper we make the following points.[37] First, increases in college attainment cause adverse compositional shifts that mask the rising college demand during the 1990s. Composition shifts affect average college wages, but not average high school wages. As a result, the composition-adjusted college premium rose by 26% over 1960-2000 rather than 20% as OLS estimates suggest. Second, these compositional shifts also lead to overestimates of the effect of supply on the change in the college premium in the same interval, since more than a third of changes in the college premium for young workers from 1980 to 1990 are due to favorable compositional shifts rather than changes in the position of the relative supply curve. Third, compositional shifts also change our estimates of the trend in the demand for college graduates. Fourth, this paper uncovers a rising trend in the demand for older relatively to younger workers. Fifth, this paper cannot assess whether the adverse effect of composition on the college premium is due to a reduction in quality at the margin or a reduction in quality on average (say, due to college crowding). The distinction is important for policy since the latter is readily remediable with additional college resources whereas the former may be much harder to address. Distinguishing these hypotheses is a critical direction for future research.

A   Appendix: Estimation of the Structural Model

This appendix describes our method for estimating the structural model. In order to estimate an equation based on (13) we need to specify a model for $\ln Q_{atr}^k$, where (repeating equation (9)):

$$Q_{atr}^k = \sum_{b=1}^{R} \frac{N_{atrb}^k}{N_{atr}^k} E\left(U_{i,t-a,b}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1\right).$$

If we were to model $E\left(U_{i,t-a,b}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1\right)$ in a general way we would make it a flexible function of $P_{t-a,b}$ and $(P_{M,atrb}^k, P_{M,atrr}^k)$, for all b and r. The problem with this approach is one of potential multicollinearity, since all these variables appear elsewhere in the regression (in the term defined by equation (4)). In this appendix we explore alternative methods for constructing Q_{atr}^k.

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[37]This set of conclusions is taken, almost *ipsis verbis*, from the report of an incredibly generous and thoughtful referee.

One possibility is to model $\ln Q_{atr}^k$ directly using a reduced-form specification, and restrict the way $P_{t-a,b}$, $P_{M,atrb}^k$, and $P_{M,atrr}^k$ enter the estimating equation. To break the collinearity problem mentioned above, we restrict all $P_{t-a,b}$ and $P_{M,atrb}^k$ to influence $\ln Q_{atr}^k$ through the following indices: $\widetilde{P}_{atr} = \sum_{b=1}^{R} \frac{N_{atrb}^k}{N_{atr}^k} \frac{P_{t-a,b}}{1-P_{t-a,b}}$ and $P_{M,atr}^k = \sum_{b=1}^{R} \frac{N_{atrb}^k}{N_{atr}^k} P_{M,atrb}^k$. Then we specify $\ln Q_{atr}^k$ as:

$$\ln Q_{atr}^k = \zeta_1^k \widetilde{P}_{atr} + \zeta_2^k P_{M,atr}^k + \zeta_3^k \left(P_{M,atr}^k\right)^2 + \zeta_4^k P_{M,atrr}^k + \zeta_5^k \left(P_{M,atrr}^k\right)^2, \tag{21}$$

where $(\zeta_1^k, \ldots, \zeta_5^k)$ are unknown parameters for each schooling group k. The idea behind (21) is again similar to those in (4) and (25): the aggregate quality of average workers in a regional labor market can differ because of aggregate composition of workers $\widetilde{P}_{atr}$ and selective migration $P_{M,atr}^k$. We use this as our baseline specification of $\ln Q_{atr}^k$ and we report baseline estimation results in column (2) of Table 1.

We now describe the exact specifications of columns (2) and (3) of Table 1. Note that ζ_4^k and ζ_5^k cannot be separately identified from the terms in λ_k in (4), so we just absorb them in λ_k. When estimating column (3), quality-unadjusted log weeks ($\log N_{atr}^k$) are used instead of the quality-adjusted log weeks, and all the quality-related variables ($\tilde{P}_{t-a,b}$, $\widetilde{P}_{atr}$, and $P_{M,atr}$) are excluded from the regression.

The functional form used in (21) is arbitrary and is meant to approximate $\ln Q_{atr}^k$ in a parsimonious way. The advantage of using a parsimonious specification of $\ln Q_{atr}^k$ is simplicity, but its cost is that it is restrictive and can be misspecified. The remaining models of $\ln Q_{atr}^k$ in this appendix will be used to check the robustness of our results to different specifications for $\ln Q_{atr}^k$.

One natural alternative to break the collinearity problem is based on the fact that when modeling Q_{atr}^k, the probabilities ($P_{t-a,b}$, $P_{M,atrb}^k$, and $P_{M,atrr}^k$) always enter interacted with $\frac{N_{atrb}^k}{N_{atr}^k}$. In view of this, we could think of the following simple reduced-form model for $\ln Q_{atr}^k$:

$$\ln Q_{atr}^k = \sum_{b=1}^{R} \left[\Omega_1^{bk} \left(\frac{N_{atrb}^k}{N_{atr}^k}, P_{t-a,b} \right) + \Omega_2^{bk} \left(\frac{N_{atrb}^k}{N_{atr}^k}, P_{M,atrb}^k \right) + \Omega_3^{bk} \left(\frac{N_{atrb}^k}{N_{atr}^k}, P_{M,atrr}^k \right) \right], \tag{22}$$

where we specify $\Omega_1^{bk} \left(\frac{N_{atrb}^k}{N_{atr}^k}, P_{t-a,b} \right) = \chi_1^{bk} \frac{N_{atrb}^k}{N_{atr}^k} \frac{P_{t-a,b}}{1-P_{t-a,b}}$, $\Omega_2^{bk} \left(\frac{N_{atrb}^k}{N_{atr}^k}, P_{M,atrb}^k \right) = \chi_2^{bk} \frac{N_{atrb}^k}{N_{atr}^k} P_{M,atrb}^k$, and $\Omega_3^{bk} \left(\frac{N_{atrb}^k}{N_{atr}^k}, P_{M,atrr}^k \right) = \chi_3^{bk} \frac{N_{atrb}^k}{N_{atr}^k} P_{M,atrr}^k$ and $\{(\chi_1^{bk}, \ldots, \chi_3^{bk}) : b = 1, \ldots, R\}$ are unknown parameters we estimate. Column (2) of Table 12 reports estimation results of the structural model with the specification of $\ln Q_{atr}^k$ in (22).

It is also possible to consider alternatives which are more consistent with the original model

we specify. For example, we can use the wage structure assumed in (1) to reduce the number of variables $(P_{t-a,b})$ that we need to include in the regression. Notice that (1) implies that for any two different regions of birth, say b' and b'', the relative quality across different groups of individuals in the same labor market is proportional to their relative wages:

$$\frac{E\left(U_{i,t-a,b'}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1\right)}{E\left(U_{i,t-a,b''}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1\right)} = \frac{E\left(W_{iatrb'}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1\right)}{E\left(W_{iatrb''}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1\right)}, \quad (23)$$

since workers living in the same region face the same skill prices (Π_{atr}^k is non-random conditional on $S_i^k = 1, A_{ita} = 1, M_{itrb} = 1$). Notice that the left-hand side of (23) is unobservable, but the right-hand side is observable from the data. Then, re-write (9) as

$$Q_{atr}^k = \tilde{Q}_{atr}^k E\left(U_{i,t-a,b}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1\right)\Big|_{b=r}, \quad (24)$$

where

$$\tilde{Q}_{atr}^k = \sum_{b=1}^R \frac{N_{atrb}^k}{N_{atr}^k} \frac{E\left(U_{i,t-a,b}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1\right)}{E\left(U_{i,t-a,\tilde{b}}^k | S_i^k = 1, A_{ita} = 1, M_{itr\tilde{b}} = 1\right)\Big|_{\tilde{b}=r}}.$$

In words, we normalize Q_{atr}^k by the quality of the group of workers who were born in region r, and we call this quantity $\tilde{Q}_{atr}^k$. Then as in (23), we have

$$\frac{E\left(U_{i,t-a,b}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1\right)}{E\left(U_{i,t-a,\tilde{b}}^k | S_i^k = 1, A_{ita} = 1, M_{itr\tilde{b}} = 1\right)\Big|_{\tilde{b}=r}} = \frac{E\left(W_{iatrb}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1\right)}{E\left(W_{iatr\tilde{b}}^k | S_i^k = 1, A_{ita} = 1, M_{itr\tilde{b}} = 1\right)\Big|_{\tilde{b}=r}}.$$

Therefore,

$$\tilde{Q}_{atr}^k = \sum_{b=1}^R \frac{N_{atrb}^k}{N_{atr}^k} \frac{E\left(W_{iatrb}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1\right)}{E\left(W_{iatr\tilde{b}}^k | S_i^k = 1, A_{ita} = 1, M_{itr\tilde{b}} = 1\right)\Big|_{\tilde{b}=r}},$$

which can be estimated directly by sample analogs using Census data. To complete the description of Q_{atr}^k in (24), we assume that

$$E\left(U_{i,t-a,\tilde{b}}^k | S_i^k = 1, A_{ita} = 1, M_{itr\tilde{b}} = 1\right) = \exp\left[\Gamma_{k\tilde{b}} + \Phi_k(P_{t-a,\tilde{b}}) + \Lambda_k(P_{M,atr\tilde{b}}^k, P_{M,atrr}^k)\right], \quad (25)$$

where $\Gamma_{k\tilde{b}}$ is region-of-birth fixed effects, Φ_k is a function of $P_{t-a,\tilde{b}}$ (composition), and Λ_k is a function of $P_{M,atr\tilde{b}}^k$ and $P_{M,atrr}^k$ (migration). The exponential function is used to ensure that the conditional expectation on the left-hand side of (25) is always positive. We assume that Φ_k in (25)

is linear in the odds of proportion in college. It is not necessary to specify the term Λ_k separately because when $b = r$, Λ_k is only a function of $P^k_{M,atrr}$ and can be absorbed into λ_k in (4). The underlying ideas behind (25) are the same as in (4): the average quality of workers can differ because of region-of-birth fixed effects, differences in composition captured by $P_{t-a,b}$, and selective migration.[38]

One problem with this approach is that Q^k_{atr} is modeled as a function of ratios of the dependent variable, which can cause an endogeneity problem if the model is misspecified. We tackle this problem by obtaining lagged values of $\left. \frac{E\left(W^k_{iatrb}|S^k_i=1,A_{ita}=1,M_{itrb}=1\right)}{E\left(W^k_{iatr\tilde{b}}|S^k_i=1,A_{ita}=1,M_{itr\tilde{b}}=1\right)}\right|_{\tilde{b}=r}$ (for each census, the lag can be constructed using the previous census, 10 years before) and using them as instruments. Column (3) of Table 12 reports ordinary-least-squares estimation results of the structural model with the third specification of Q^k_{atr} and column (4) reports instrumental-variables estimation results. Again, these alternative estimation results are quite similar to baseline results, which are reproduced in column (1) of Table 12. It is assuring that all of alternative estimation results are in line with the baseline results. We conclude that our main results are robust to alternative specifications of Q^k_{atr}.

References

Daron Acemoglu. Technical change, inequality and the labor market. *Journal of Economic Literature*, 40(1):7–72, 2002.

Daron Acemoglu, David H. Autor, and David Lyle. Women war and wages: The impact of female labor supply on the wage structure at mid-century. *Journal of Political Economy*, 112(3):497–551, 2004.

David H. Autor, Lawrence F. Katz, and Melissa S. Kearney. Trends in U.S. wage inequality: Revising the revisionists. *Review of Economics and Statistics*, 90(2):300–323, 2008.

Richard Blundell, Howard Reed, and Thomas. M Stoker. Interpreting aggregate wage growth: The role of labor market participation. *American Economic Review*, 93(4):1114–1131, 2003.

Richard Blundell, Amanda Gosling, Hidehiko Ichimura, and Costas Meghir. Changes in the distribution of male and female wages accounting for employment composition using bounds. *Econometrica*, 75(2):323–363, 2007.

John Bound, Jeffrey Groen, G. Gabor Kezdi, and Sarah Turner. Trade in university training: cross-state variation in the production and stock of college-educated labor. *Journal of Econometrics*, 121(1-2):143–173, 2004.

David Card and Alan Krueger. Does school quality matter? returns to education and the characteristics of public schools in the United States. *Journal of Political Economy*, 100(1):1–40, 1992.

David Card and Thomas Lemieux. Can falling supply explain the rising return to college for younger men? a cohort based analysis. *Quarterly Journal of Economics*, 116(2):705–746, 2001.

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[38]Notice that Γ_{kb} and Λ_k are different from γ_{kab}, γ_{ktb}, and λ_k. Strictly speaking, (25) is not directly compatible to (4) since in general, $E[\log Y|X] \leq \log E[Y|X]$ for random variables Y and X (Jensen's inequality).

Pedro Carneiro and Sokbae Lee. Estimating distributions of potential outcomes using local instrumental variables with an application to changes in college enrollment and wage inequality. *Journal of Econometrics*, 149(2):191–208, 2009.

Pedro Carneiro, James J. Heckman, and Edward Vytlacil. Estimating marginal returns to education. unpublished manuscript, Department of Economics, University College London, 2009.

Amitabh Chandra. Is the convergence of the racial wage gap illusory? *NBER Working Paper*, (No. 9476), 2003.

Kenneth Y. Chay and David S. Lee. Changes in relative wages in the 1980s: Returns to observed and unobserved skills and black-white wage differentials. *Journal of Econometrics*, 99(1):1–38, 2000.

Gordon B. Dahl. Mobility and the return to education: Testing a Roy model with multiple markets. *Econometrica*, 70(6):2367–2420, 2002.

Olivier Deschênes. Unobserved ability, comparative advantage, and the rising return to college in the United States, 1979-2002. unpublished manuscript, Department of Economics, University of California, Santa Barbara, 2006.

Olivier Deschênes. Estimating the effect of family background on the return to schooling. *Journal of Business and Economic Statistics*, 25(3):265–277, 2007.

Peter Diamond, Daniel McFadden, and Miguel Rodriguez. *Production Economics: A Dual Approach to Theory and Applications Volume II: Applications of the Theory of Production*, chapter Measurement of the Elasticity of Factor Substitution and Bias of Technical Change, pages 125–147. Amsterdam: North-Holland, 1978.

Nicole M. Fortin. Higher education policies and the college premium: Cross-state evidence from the 1990s. *American Economic Review*, 96(4):959–987, 2006.

Oded Galor and Omer Moav. Ability-biased technological transition, wage inequality, and economic growth. *Quarterly Journal of Economics*, 115(2):469–497, 2000.

Amanda Gosling, Stephen Machin, and Costas Meghir. The changing distribution of male wages in the U.K. *Review of Economic Studies*, 67(4):635–66, 2000.

Jeffrey Groen. The effect of college-location on migration of college-educated labor. *Journal of Econometrics*, 121(1-2):125–142, 2004.

James J. Heckman and Guilherme Sedlacek. Heterogeneity, aggregation and market wage functions: An empirical model of self-selection in the labor market. *Journal of Political Economy*, 93(6): 1077–1125, 1985.

James J. Heckman and Petra Todd. Understanding the contribution of legislation, social activism, markets and choice to the economic progress of african americans in the twentieth century. unpublished manuscript, Department of Economics, University of Pennsylvania, 2003.

James J. Heckman, Anne Layne-Farrar, and Petra Todd. Human capital pricing equations with an application to estimating the effect of schooling quality on earnings. *Review of Economics and Statistics*, 78(4):562–610, 1996.

Caroline M. Hoxby and Bridget T. Long. Explaining rising income and wage inequality among the college educated. *NBER Working Paper*, (No. 6873), 1999.

Chinhui Juhn, Kevin M. Murphy, and Brooks Pierce. Wage inequality and the rise in returns to skill. *Journal of Political Economy*, 101(3):410–442, 1993.

Chinhui Juhn, Dae Il Kim, and Francis Vella. The expansion of college education in the United States: Is there evidence of declining cohort quality? *Economic Inquiry*, 43(2):303–315, 2005.

Lawrence F. Katz and David H. Autor. *Handbook of Labor Economics, Volume 3A*, chapter Changes in the Wage Structure and Earnings Inequality, pages 1463–1555. Amsterdam: North-Holland, 1999.

Lawrence F. Katz and Kevin M. Murphy. Changes in relative wages, 1963-1987: Supply and demand factors. *Quarterly Journal of Economics*, 107(1):35–78, 1992.

Michael Keane, Robert Moffitt, and David Runkle. Real wages over the business cycle: Estimating the impact of heterogeneity with micro data. *Journal of Political Economy*, 96(6):1232–1266, 1988.

Lung-Fei Lee. Generalized econometric models with selectivity. *Econometrica*, 51(2):507–512, 1983.

Thomas Lemieux. Increasing residual wage inequality: Composition effects, noisy data, or rising demand for skill? *American Economic Review*, 96(3):461–498, 2006.

Costas Meghir and Edward Whitehouse. The evolution of wages in the United Kingdom: Evidence from micro data. *Journal of Labor Economics*, 14(1):1–25, 1994.

Robert Moffitt. Estimating marginal treatment effects in heterogeneous populations. *Annales dEconomie et de Statistique,* forthcoming, 2008.

Casey B. Mulligan and Yona Rubinstein. Selection, investment, and women's relative wages over time. *Quarterly Journal of Economics*, 123(3):1061–1110, 2008.

Derek A. Neal. The measured black-white wage gap among women is too small. *Journal of Political Economy*, 112:S1–S28, 2004.

OECD. *Literacy in the Information Age: Final Report of the International Adult Literacy Survey.* OECD Publishing, 2000.

Barbara Petrongolo and Claudia Olivetti. Unequal pay or unequal employment? a cross-country analysis of gender gaps. *Journal of Labor Economics*, 26(4):621–654, 2008.

Dan T. Rosembaum. Ability, educational ranks, and labor market trends: The effects of shifts in the skill composition of educational groups. unpublished manuscript, Department of Economics, University of North Carolina at Greensboro, 2003.

S. Ruggles, M Sobek, T Alexander, C. Fitch, R. Goeken, P. Hall, M. King, and C. Ronnander. *Integrated Public Use Microdata Series: Version 3.0 [Machine-readable database].* Minneapolis, MN: Minnesota Population Center [producer and distributor], 2004.

Christopher R. Taber. The rising college premium in the eighties: Return to college or return to unobserved ability? *Review of Economic Studies*, 68(3):665–691, 2001.

Robert J. Willis and Sherwin Rosen. Education and self-selection. *Journal of Political Economy*, 87(5, Pt2):S7–36, 1979.

Table 1: Regression of Wages on Labor Supply and the Odds of Proportion in College

	(1) Reduced-Form Model (Controlling for Quality)	(2) Structural Model (Controlling for Quality)	(3) Structural Model (Without Controlling for Quality)
Panel A - College			
Odds of Proportion in College	-0.086 [0.036]**	-0.092 [0.032]***	
Quality-Adjusted Log Weeks		-0.110 [0.022]***	
Log Weeks			-0.188 [0.019]***
Observations	2598	2598	2598
Panel B - High School			
Odds of Proportion in College	-0.032 [0.022]	-0.023 [0.024]	
Quality-Adjusted Log Weeks		-0.091 [0.012]***	
Log Weeks			-0.090 [0.012]***
Observations	2692	2692	2692
Included Explanatory Variables			
(Year)×(Age)×(Region of Residence)	√		
(Year)×(Region of Residence)×(Region of Birth)	√	√	√
(Age)×(Common Linear Time Trends)		√	√
(Year)×(Region of Birth)	√	√	√
(Age)×(Region of Birth)	√	√	√
(Observed Migration Probability)	√	√	√
(Observed Migration Probability)^2	√	√	√
(Staying Probability)	√	√	√
(Staying Probability)^2	√	√	√
(Observed Migr. Prob.)×(Staying Prob.)	√	√	√

Notes: The dependent variable is log weekly wage in each cell. The variable "Odds of Proportion in College" is the odds of going to college for cohort $t - a$ born in region b. The variable "Quality-Adjusted Log Weeks" is the logarithm of the labor supply multiplied by the average quality. All regressions are weighted by the inverse of the sampling variance of average log wages in each cell. Robust standard errors in brackets, clustered on the region of residence-schooling-year cell. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 2: Alternative Estimates of the Structural Model

	(1) Controlling for Quality	(2) N_{atrb}^{k} as supply and $P_{t-a,b}$ as composition	(3) Drop $P_{t-a,b}$ from column (1)
Panel A - College			
Odds of Proportion in College	-0.092 [0.032]***		
Proportion in College ($P_{t-a,b}$)		-0.097 [0.014]***	
Quality-Adjusted Log Weeks	-0.110 [0.022]***		-0.109 [0.022]***
Log Weeks (N_{atrb}^{C})		-0.069 [0.023]***	
Observations	2598	2598	2598
Panel B - High School			
Odds of Proportion in College	-0.023 [0.024]		
Proportion in College ($P_{t-a,b}$)		-0.004 [0.007]	
Quality-Adjusted Log Weeks	-0.091 [0.012]***		-0.091 [0.012]***
Log Weeks (N_{atrb}^{H})		-0.078 [0.010]***	
Observations	2692	2692	2692

Notes: The dependent variable is log weekly wage in each cell. The variable "Odds of Proportion in College" is the odds of going to college for cohort $t-a$ born in region b. The variable "Quality-Adjusted Log Weeks" is the logarithm of the labor supply multiplied by the average quality. All regressions are weighted by the inverse of the sampling variance of average log wages in each cell. Included explanatory variables are the same as in Table 1. Robust standard errors in brackets, clustered on the region of residence-schooling-year cell. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3: Sensitivity Analysis: Alternative Specifications and Samples

	(1)	(2)	(3)	(4)
The Dependent Variable: Log College Wages				
White Males (Original Sample)				
Odds of Proportion in College	-0.086 [0.036]**	-0.106 [0.087]		
(Odds of Proportion in College)^2		0.005 [0.021]		
Proportion in College			-0.517 [0.255]**	0.923 [0.598]
(Proportion in College)^2				-1.13 [0.487]**
Observations	2598	2598	2598	2598
P-value	0.02	0.06	0.05	0.04
White Females				
Odds of Proportion in College	-0.028 [0.036]	-0.006 [0.112]		
(Odds of Proportion in College)^2		-0.005 [0.022]		
Proportion in College			0.077 [0.367]	0.871 [0.909]
(Proportion in College)^2				-0.732 [0.691]
Observations	2097	2097	2097	2097
P-value	0.44	0.62	0.84	0.57
Both White Males and Females				
Odds of Proportion in College	-0.06 [0.040]	-0.189 [0.101]*		
(Odds of Proportion in College)^2		0.034 [0.025]		
Proportion in College			-0.526 [0.241]**	-0.109 [0.721]
(Proportion in College)^2				-0.359 [0.604]
Observations	2662	2662	2662	2662
P-value	0.14	0.13	0.03	0.12

Notes: Robust standard errors in brackets, clustered on the region of residence-schooling-year cell. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4: Estimation Results of Sensitivity Analysis (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A - College							
Odds of Proportion in College	-0.093	-0.086	-0.086	-0.096	-0.086	-0.086	-0.080
	[0.038]**	[0.049]*	[0.032]**	[0.041]**	[0.036]**	[0.055]	[0.043]*
Observations	2598	2598	2598	2598	2598	2283	2517
Panel B - High School							
Odds of Proportion in College	-0.014	0.032	-0.029	-0.019	-0.032	-0.038	0.000
	[0.028]	[0.034]	[0.022]	[0.028]	[0.022]	[0.030]	[0.031]
Observations	2692	2692	2692	2692	2692	2377	2611
Included Explanatory Variables							
(Year)×(Age)×(Region of Residence)	✓	✓	✓	✓	✓	✓	✓
(Age)×(Region of Birth)	✓	✓	✓	✓	✓	✓	✓
(Year)×(Region of Birth)	✓	✓	✓	✓	✓	✓	✓
$(\text{Cohort})^2 \times (\text{Region of Birth})$		✓					
(Year)×(R. of Res.)×(R. of Birth)				✓		✓	
Basic Migration Probabilities				✓	✓	✓	✓
Only Migrant Cells						✓	
School Quality Variables							✓

Notes: The dependent variable is log weekly wage in each cell. All regressions are weighted by the inverse of the sampling variance of average log wages in each cell. Robust standard errors in brackets, clustered on the region of residence-schooling-year cell. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5: Differences between Inclusion and Exclusion of Migration Probabilities

	(1)	(2)	(3)	(4)	(5)	(6)
	Log College Wages			Log High School Wages		
Odds of Proportion in College	-0.086 [0.036]**	-0.093 [0.038]**		-0.032 [0.022]	-0.014 [0.028]	
Staying Probability	0.004 [0.910]		-0.042 [0.917]	-0.164 [0.580]		-0.149 [0.585]
(Staying Prob.)^2	-0.305 [0.705]		-0.269 [0.710]	-0.082 [0.424]		-0.068 [0.435]
Observed Migration Probability	-0.451 [0.322]		-0.538 [0.331]	-0.023 [0.264]		-0.049 [0.273]
(Observed Migr. Prob.)^2	0.517 [0.535]		0.393 [0.550]	-0.709 [0.367]*		-0.738 [0.383]*
(Observed Migr. Prob.) ×(Staying Prob.)	0.379 [0.644]		0.580 [0.648]	1.047 [0.299]***		1.095 [0.311]***
Observations	2598	2598	2598	2692	2692	2692
Included Explanatory Variables						
(Year)×(Age)×(Region of Residence)	√	√	√	√	√	√
(Year)×(Region of Birth)	√	√	√	√	√	√
(Age)×(Region of Birth)	√	√	√	√	√	√

Notes: The dependent variable is log weekly wage in each cell. All regressions are weighted by the inverse of the sampling variance of average log wages in each cell. Robust standard errors in brackets, clustered on the region of residence-schooling-year cell. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: Relationship between Proportion in College and Migration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	Staying Probability		Observed Migration Probability		Migration Premium		
Panel A - College							
Odds of Proportion in College	0.01	-0.011	0.001	0.000	-0.022	-0.006	-0.006
	[0.016]	[0.015]	[0.001]	[0.002]	[0.052]	[0.032]	[0.033]
Observations	310	310	2430	2430	2283	2283	2283
Panel B - High School							
Odds of Proportion in College	0.034	-0.027	-0.005	0.002	-0.235	-0.005	-0.008
	[0.013]***	[0.014]*	[0.002]***	[0.003]	[0.049]***	[0.031]	[0.032]
Observations	310	310	2496	2496	2377	2377	2377
Included Explanatory Variables							
(Year)×(Age)		✓					
(Year)×(Age)×(Region of Residence)				✓		✓	✓
(Year)×(Region of Birth)		✓		✓		✓	✓
(Age)×(Region of Birth)		✓		✓		✓	✓
Basic Migration Probabilities							✓

Notes: Robust standard errors in brackets, clustered on the region of residence-schooling-year cell. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7: Regression of SAT Scores on the Percentage of High School Graduates Taking SAT, with Year and State Dummies - 1993/2004 (except 1995 and 1998)

	(1)	(2)
	SAT Math	SAT Verbal
Percentage of High School Graduates Taking SAT	-16.503 [7.275]**	-26.268 [6.629]***
Observations	510	510
R-squared	0.99	0.99
Included Dummy Variables		
(Year)	√	√
(State)	√	√

Notes: Robust standard errors in brackets, clustered on the region of residence-schooling-year cell. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8: Regression of Quantitative Literacy on Proportion in College

Variable	(1) College	(2) High School	(3) All
Proportion in College	-1.248 [0.581]**	0.604 [0.533]	-0.112 [0.384]
College			0.977 [0.047]***
Age	0.101 [0.024]***	0.001 [0.019]	0.037 [0.013]***
Age Squared	-0.001 [0.000]***	0.000 [0.000]	0.000 [0.000]***
Constant	-0.794 [0.416]*	-0.651 [0.444]	-1.050 [0.295]***
Observations	962	1503	2465
R-squared	0.03	0.00	0.22

Notes: The dependent variable is the standardized quantitative literacy score of individuals aged 25-60 in the US sample of the International Adult Literacy Survey. Proportion in college is the percentage of individuals with some college or more and is computed for each cohort. The variable "College" is a dummy variable for individuals with some college or more. Robust standard errors in brackets, clustered at the cohort level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9: Changes in the Relative Demands for College Graduates

	Relative Demand	(1) 1960-1970	(2) 1970-1980	(3) 1980-1990	(4) 1990-2000	(5) 1960-2000
All Regions	Quality-Adjusted	17.83	11.10	23.95	13.01	65.89
	Unadjusted	16.22	6.38	21.93	11.31	55.84
Northeast	Quality-Adjusted	16.70	8.85	25.39	16.27	67.21
	Unadjusted	14.04	2.84	22.47	13.02	52.37
Midwest	Quality-Adjusted	16.70	9.78	24.49	13.33	64.30
	Unadjusted	14.70	3.37	21.25	10.73	50.05
South	Quality-Adjusted	20.52	11.64	21.37	11.99	65.52
	Unadjusted	17.97	9.12	20.48	11.06	58.63
West	Quality-Adjusted	19.91	14.26	22.66	12.41	69.24
	Unadjusted	21.24	9.07	21.05	11.57	62.93

Notes: The reported numbers are one hundred times the changes in weighted averages of estimates of $\log(\theta_{Ctr}/\theta_{Htr})$, where θ_{ktr} is a factor-augmenting technology efficiency parameter for schooling group k in time period t in region r and is given in (11) in the main text. The weights are based on proportions of the sample for each cell.

Table 10: Changes in the Relative Demands for Older Workers

| Age Group	Relative Demand	(1) 1960-1970	(2) 1970-1980	(3) 1980-1990	(4) 1990-2000	(5) 1960-2000
25-30 vs.	Quality-Adjusted		-2.47			-12.33
36-40	Unadjusted		-2.69			-13.43
46-50 vs.	Quality-Adjusted		1.47			7.35
36-40	Unadjusted		1.52			7.58
56-60 vs.	Quality-Adjusted		3.01			15.05
36-40	Unadjusted		3.23			16.16

Notes: The reported numbers are one hundred times the changes in estimates of $\log(\beta_{at})|_{a=old} - \log(\beta_{at})|_{a=young}$, where β_{at} is a factor-augmenting technology efficiency parameter for age group a in time period t and is given in (11) in the main text. The changes are identical over decades because of the linear time trend specification of $\log(\beta_{at})$.

Table 11: Changes in the College Premium between Young and Old Workers

|	(1) Changes from 1980 to 1990	(2) Changes from 1990 to 2000
Age Group: 25 - 30		
Raw College Premium	0.179	0.041
Composition-Fixed College Premium	0.165	0.061
Proportion in College	-0.041	0.058
Age Group: 45 - 60		
Raw College Premium	0.084	0.014
Composition-Fixed College Premium	0.105	0.051
Proportion in College	0.115	0.139
Differences between Two Age Groups		
Raw College Premium	0.095	0.027
Composition-Fixed College Premium	0.060	0.010

Notes: The first column of the table shows changes from 1980 to 1990 in the raw college premium (data), in composition-fixed (or quality-fixed) college premium, and in proportion in college for two age groups: 25-30 and 45-60. The second column shows changes from 1990 to 2000.

Figure 1: College Premium in Region of Residence as a Function of Proportion College in Region of Birth
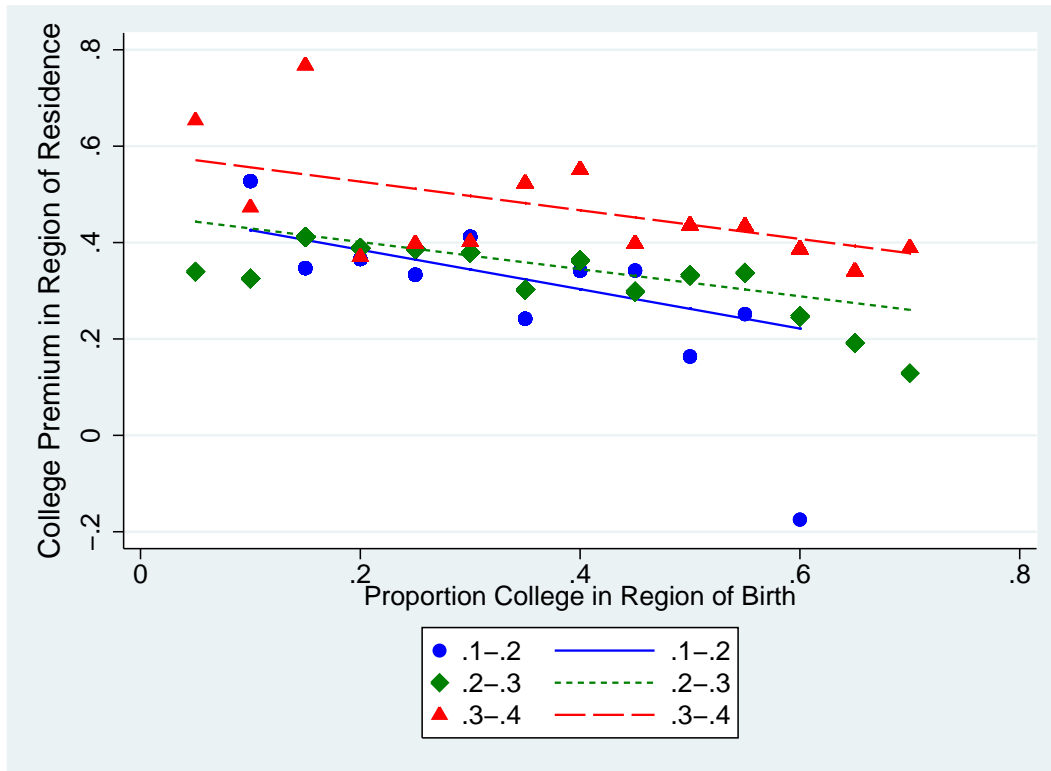
Notes: Using US Census data between 1960 and 2000, the figure graphs the college premium in each (year)×(age)×(region of birth)×(region of residence) cell against the proportion in college by cohort and region of birth, after grouping individuals into three sets of regional labor markets: those with a high share of college educated workers (30-40%), those with a medium share (20-30%), and those with a low share (10-20%).

Figure 2: Description of Data
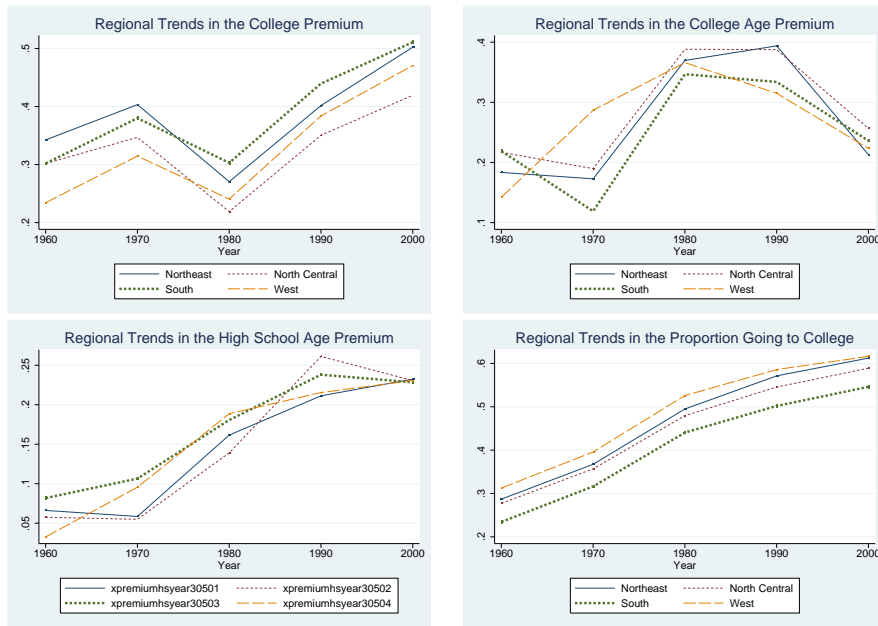
Notes: This figure shows regional trends in skill premia and changes in the proportion of going to college.

Figure 3: SAT Scores and Participation Rates
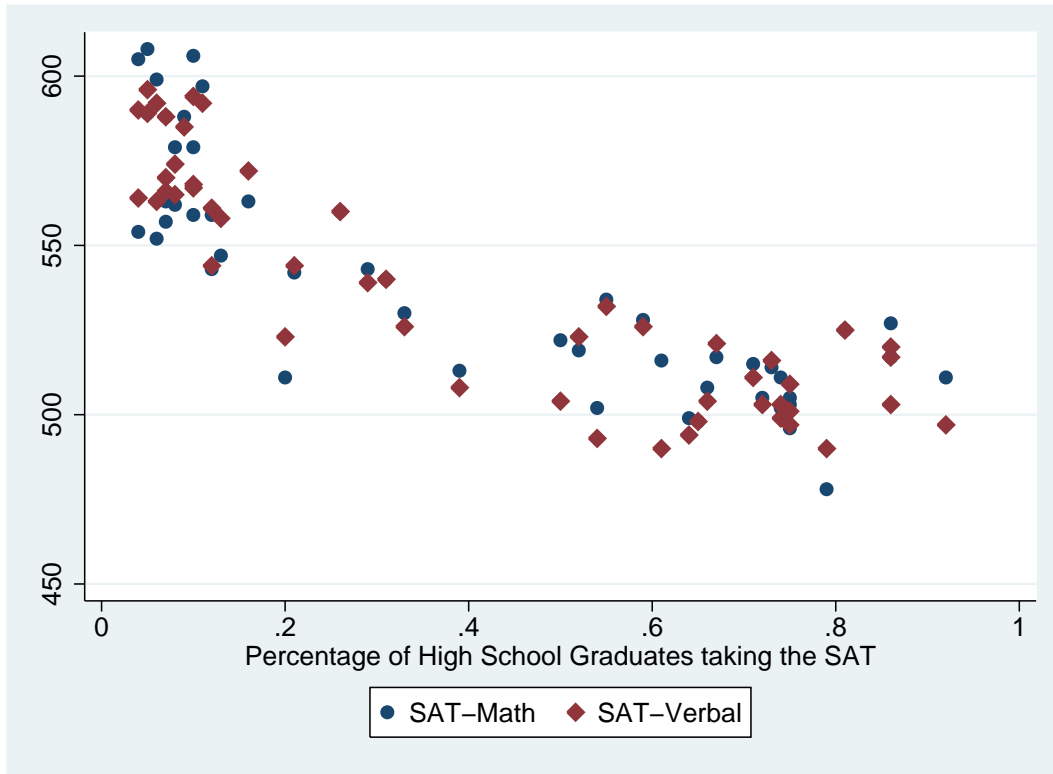
Notes: The figure displays average verbal and math SAT scores by state (in 2004) against the percentage of high school graduates who take the SAT in each state.

Figure 4: Quality-Adjusted College and Age Premia
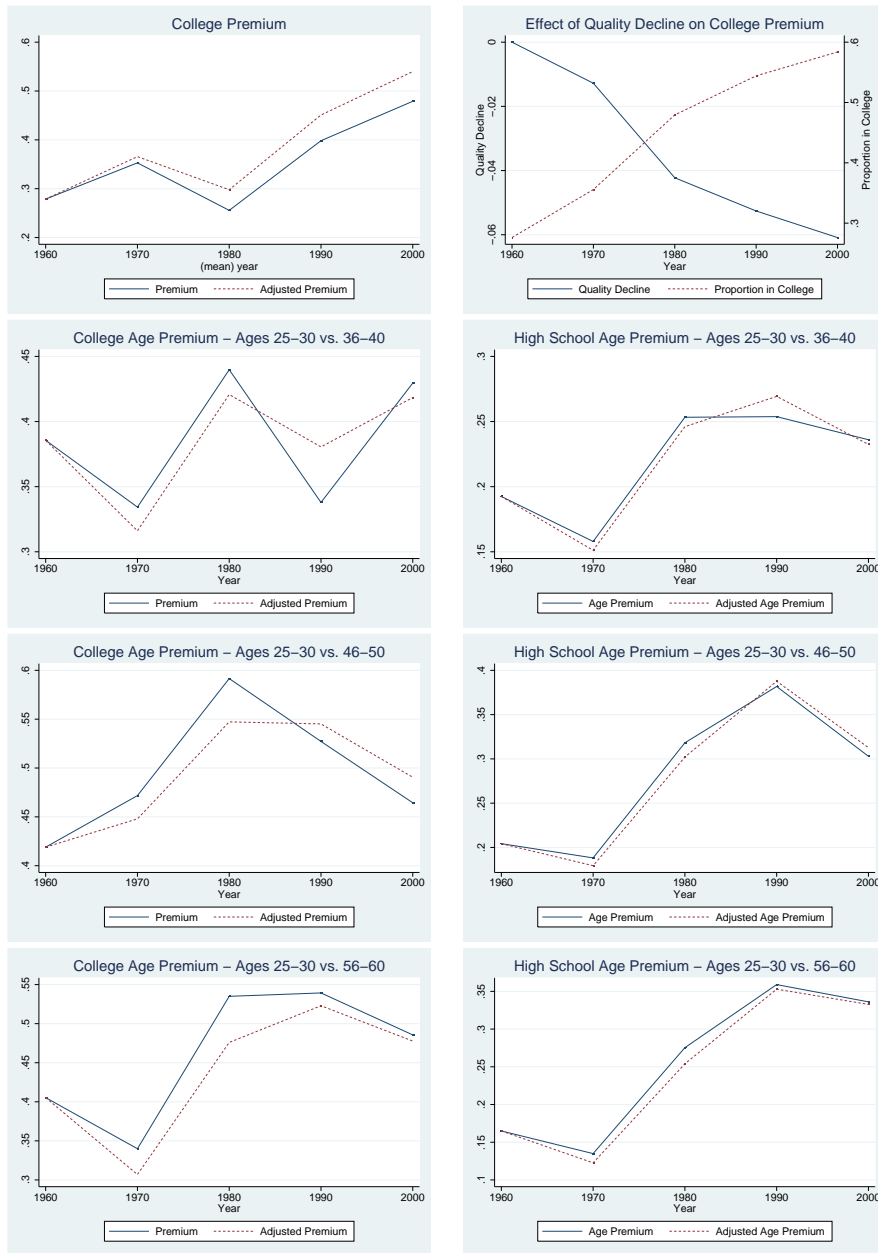
Notes: This figure shows quality-adjusted and unadjusted college and age premia.

Figure 5: Changes in the Relative Composition and Relative Labor Supply
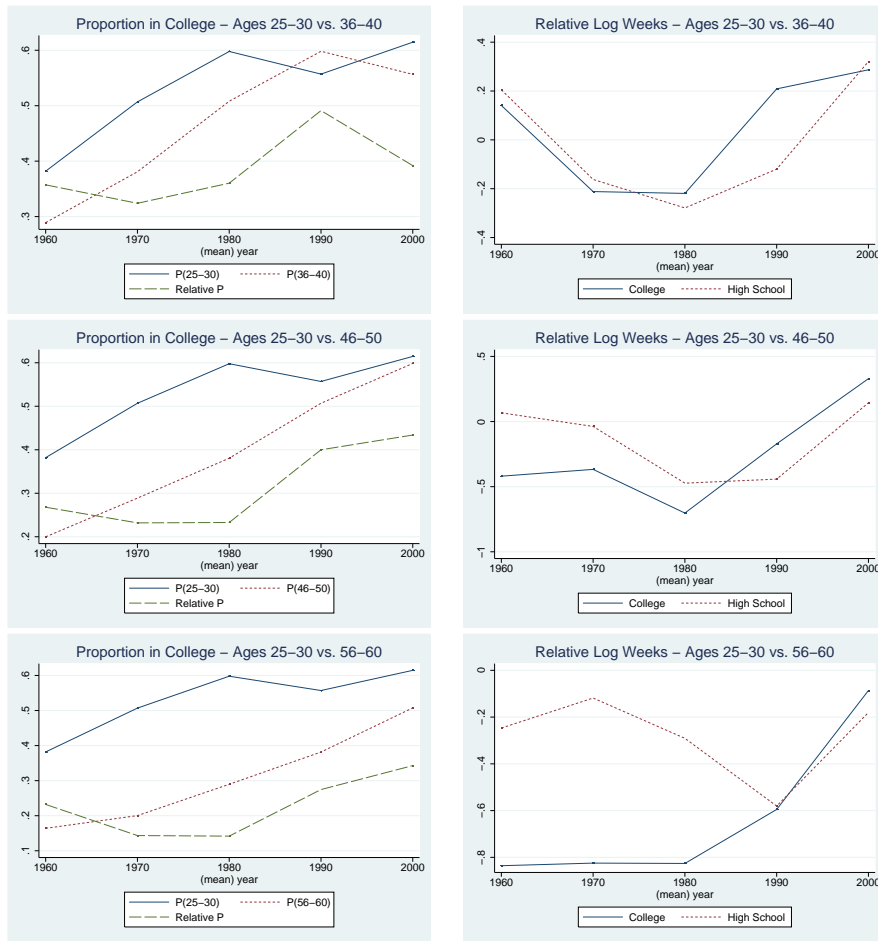
Notes: The top left panel of the figure shows changes in proportion in college and their relative ratio for age groups 25-30 and 36-40. The middle and bottom left panels, respectively, show corresponding lines for older age groups 46-50 and 56-60 along with the baseline young age group, 25-30. The three figures on the right panel of the figure show the labor supply of old workers relative to young workers for both college and high school, measured in log weeks worked in each year.

Table 12: Appendix Table: Alternative Estimates of the Structural Model

	(1) Baseline (Aggregate $\tilde{P}_{atr}$)	(2) Interacting $P_{t-a,b}$ with N_{atrb}^k	(3) Using the Wage Ratios	(4) Using the Lagged Wage Ratios
Estimation Method	OLS	OLS	OLS	IV
Panel A - College				
Odds of Proportion in College	-0.092	-0.099	-0.100	-0.093
	[0.032]***	[0.035]***	[0.024]***	[-0.023]***
Quality-Adjusted Log Weeks	-0.110	-0.130	-0.110	-0.155
	[0.022]***	[0.020]***	[0.021]***	[0.019]***
Panel B - High School				
Odds of Proportion in College	-0.023	-0.030	-0.034	-0.029
	[0.024]	[0.022]	[0.024]	[0.021]
Quality-Adjusted Log Weeks	-0.091	-0.084	-0.090	-0.125
	[0.012]***	[0.015]***	[0.011]***	[0.013]***

Notes: The dependent variable is log weekly wage in each cell. The variable "Odds of Proportion in College" is the odds of going to college for cohort $t-a$ born in region b. The variable "Quality-Adjusted Log Weeks" is the logarithm of the labor supply multiplied by the average quality. All regressions are weighted by the inverse of the sampling variance of average log wages in each cell. Included explanatory variables are the same as in Table 1. Robust standard errors in brackets, clustered on the region of residence-schooling-year cell. * significant at 10%; ** significant at 5%; *** significant at 1%.