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cemmap working paper CWP02/09

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

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First draft: July 2007; This version: September 2008

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 8 percentage points in the college premium. The standard demand and supply framework (Katz and Murphy, 1992, Card and Lemieux, 2001) can qualitatively account for the trend in the college and age premia over this period, but the quantitative adjustments that need to be made to account for changes in quality are substantial. Furthermore, the standard interpretation of the supply effect can be misleading if the quality of college workers is not controlled for. To illustrate the importance of these adjustments, we reanalyze the problem studied in Card and Lemieux (2001), who observe that the rise in the college premium in the 1980s occurred mainly for young workers, and attribute this to the differential behavior of the supply of skill between the young and the old. Our results show that changes in quality are as important as changes in prices to explain the phenomenon they document.

1 Introduction

The college-high school wage differential in the US 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, because of the rapid expansion in college enrollment during this period, part of the changes in the college-high school wage differential could be compositional. The decline in the college premium in the 1970s may reflect not only an increase in the supply of college

*Email: p.carneiro@ucl.ac.uk and l.sokbae@ucl.ac.uk. We thank David Autor, Sami Berlinski, Richard Blundell, Hilary Hoynes, Fabian Lange, Jean-Marc Robin, Jeff Smith and participants in several seminars for very helpful comments and suggestions. We also thank Petra Todd for providing us the data on school quality. This research is supported in part by the Economic and Social Research Council (ESRC) Research Grant RES-000-22-2542. We also thank ESRC through the funding of the Centre for Microdata Methods and Practice (RES-589-28-0001). Lee thanks the Leverhulme Trust through the funding of the research programme *Evidence, Inference and Inquiry.* Carneiro also thanks the World Bank Research Group and Georgetown University for their generous hospitality.

graduates, but also of 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 novel 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 college worker quality with shifts in the proportion of college enrollment, even though the former are unobserved.[1]

Separating changes in the supply of college labor from changes in the quality of college graduates is a major empirical challenge, 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, and this 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 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 labor market, there is a clear negative relationship between the college premium and

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

the proportion in college in each individual's region of birth, which is confirmed by the regression line.[3] It shows that within similar labor markets, those workers with the lowest college premium were the ones born in regions of birth (and cohorts) where the college enrolment rate was the highest, and (presumably) the average quality of college students was the lowest.

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 8 percentage points in the college premium. Given that the college premium grew by 19 percentage points between these two 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., 2007; 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),

[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.

[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.

Acemoglu (2002), Juhn et al. (2005), Fortin (2006), among others. Very few empirical studies directly 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. (2007) and Moffitt (2008) show that using the marginal treatment effect (MTE) framework, marginal returns to college fall as more individuals go to college. Carneiro and Lee (2008) also use the MTE framework, 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 given. This is a limitation of the analysis, on which we have nothing

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

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 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. The 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:

$$W^k_{iatrb} = \Pi^k_{atr} U^k_{i,t-a,b}, \tag{1}$$

where W^k_{iatrb} is the wage, Π^k_{atr} 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 $U^k_{i,t-a,b}$ is the individual specific endowment of k-type

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

skill for those in cohort $t-a$ and in region of birth b. Taking logs:

$$w^k_{iatrb} = \pi^k_{atr} + u^k_{i,t-a,b}, \tag{2}$$

where $w^k_{iatrb} = \log W^k_{iatrb}$, $\pi^k_{atr} = \log \Pi^k_{atr}$ and $u^k_{i,t-a,b} = \log U^k_{i,t-a,b}$.[7]

Let S^k_i 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 $\omega^k_{atrb} = E\left[w^k_{iatrb}\middle| S^k_i = 1, A_{ita} = 1, M_{itrb} = 1\right]$ and $\nu^k_{atrb} = E\left[u^k_{i,t-a,b}\middle| S^k_i = 1, A_{ita} = 1, M_{itrb} = 1\right]$. It follows from (2) that

$$\omega^k_{atrb} = \pi^k_{atr} + \nu^k_{atrb}. \tag{3}$$

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^k_{atr} 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^k_{atrb} must come from variation in ν^k_{atrb}, 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^k_{atrb} 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.[8] Thus, our

[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] One possible reason for this is that individuals are heterogenous and marginal college entrants might be of lower quality than average college attendees. For example, see Carneiro et al. (2007) and Moffitt (2008). To illustrate this idea, consider a simple economic model of college enrolment. 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 ability. 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

variable of interest is the proportion of college-goers in cohort $t-a$ born in region b ($P_{t-a,b}$).

However, 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 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 enrolment 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 implement different corrective procedures. One alternative is to condition on migration probabilities as in Dahl (2002). Following Dahl (2002), we 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 to estimating a selection model, although the exclusion restrictions are left implicit.[9] A second

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. An alternative explanation that could also be consistent with the decline of the average quality of college workers is that as a larger proportion of individuals go to college, educational resources could be diluted, resulting in diminishing quality of average college attendees of the cohort. These two interpretations contain different policy implications; however, empirically, we would not be able to distinguish between them without further information about the skill production process at college. We are grateful to an anonymous referee who suggested the latter explanation.

[9] 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

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, but we use the former as our base case.

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^k_{atrb} (average quality of workers in a cell) as:

$$\nu^k_{atrb} = \gamma_{kab} + \gamma_{ktb} + \phi_k(P_{t-a,b}) + \lambda_k(P^k_{M,atrb}, P^k_{M,atrr}), \tag{4}$$

where γ_{kab} and γ_{ktb} are region-of-birth fixed effects which are separately interacted with age dummies and year dummies (capturing school quality or other unobserved variation across regions of birth), 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 ($P^k_{M,atrb}$, what we call observed migration probability), and the proportion of individuals working in the same region where they were born ($P^k_{M,atrr}$, what we call staying probability). Dahl (2002) proposed the use of the observed migration probability to account for selection, reinterpreting Lee (1983)'s 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

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.

be used as additional controls since non-migrants can be substantially different from migrants.[10]

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

$$\omega^k_{atrb} = \gamma_{katr} + \gamma_{kab} + \gamma_{ktb} + \phi_k(P_{t-a,b}) + \lambda_k(P^k_{M,atrb}, P^k_{M,atrr}) \tag{5}$$

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.

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 (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 start from the model in Card and Lemieux (2001), which we extend to account for composition effects and regional labor markets.

2.2.1 Skill prices determination

We assume that skill prices $\left(\pi^H_{atr}, \pi^C_{atr}\right)$ 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:

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

[10]In the sensitivity analysis reported in Section 5, we check the robustness of our main results without imposing index sufficiency (by conditioning on all possible migration probabilities).

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 $\mathbf{U}_{tr}^C$ and $\mathbf{U}_{tr}^H$:

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

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

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

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 in the sense that skill prices equal corresponding marginal products:

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

so that by taking logs:

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

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 model for skill prices

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.[11]

The standard assumption (use 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 (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 technological progress, while keeping the elasticity parameter fixed over time. We follow this convention and furthermore, as in

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

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:

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

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

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

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 ($\log\left(N_{atr}^{k}Q_{atr}^{k}\right)$). This implies that 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.

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 U_{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 tipically 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).[12]

2.2.3 Estimation of the model

This section describes our method for estimating the model. It is difficult to estimate wage equations based on (13). To see this, notice that Q^k_{atr} is given by,

$$Q^k_{atr} = \sum_{b=1}^{R} \frac{N^k_{atrb}}{N^k_{atr}} E\left(U^k_{i,t-a,b}|S^k_i = 1, A_{ita} = 1, M_{itrb} = 1\right).$$

Therefore, the most direct solution would be to model $E\left(U^k_{i,t-a,b}|S^k_i = 1, A_{ita} = 1, M_{itrb} = 1\right)$ as functions of $P_{i,t-a,b}$, for all b. This procedure would require including nine different $P_{i,t-a,b}$ (non-linearly) in the regression (corresponding to nine different regions of birth), which could lead to problems of multicolinearity.

Our solution to this difficulty is to use the wage structure assumed in (1) to reduce the number of variables ($P_{i,t-a,b}$) 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:

$$\frac{E\left(U^k_{i,t-a,b'}|S^k_i = 1, A_{ita} = 1, M_{itrb} = 1\right)}{E\left(U^k_{i,t-a,b''}|S^k_i = 1, A_{ita} = 1, M_{itrb} = 1\right)} = \frac{E\left(W^k_{iatrb'}|S^k_i = 1, A_{ita} = 1, M_{itrb} = 1\right)}{E\left(W^k_{iatrb''}|S^k_i = 1, A_{ita} = 1, M_{itrb} = 1\right)}, \tag{14}$$

since workers living in the same region face the same skill prices (Π^k_{atr} is non-random conditional on $S^k_i = 1, A_{ita} = 1, M_{itrb} = 1$). Notice that the left-hand side of (14) is unobservable, but the right-hand side is observable from the data. Equation (14) provides the basis for our estimation method.

To be more specific about our implementation, re-write (9) as

$$Q^k_{atr} = \tilde{Q}^k_{atr} E\left(U^k_{i,t-a,b}|S^k_i = 1, A_{ita} = 1, M_{itrb} = 1\right)\Big|_{b=r}, \tag{15}$$

[12] 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.

where

$$\tilde{Q}^k_{atr} = \sum_{b=1}^{R} \frac{N^k_{atrb}}{N^k_{atr}} \frac{E\left(U^k_{i,t-a,b} | S^k_i = 1, A_{ita} = 1, M_{itrb} = 1\right)}{E\left(U^k_{i,t-a,b} | S^k_i = 1, A_{ita} = 1, M_{itrb} = 1\right)\Big|_{b=r}}.$$

In words, we normalize Q^k_{atr} by the quality of the group of workers who were born in region r, and we call this quantity $\tilde{Q}^k_{atr}$. Then as in (14), we have

$$\frac{E\left(U^k_{i,t-a,b} | S^k_i = 1, A_{ita} = 1, M_{itrb} = 1\right)}{E\left(U^k_{i,t-a,b} | S^k_i = 1, A_{ita} = 1, M_{itrb} = 1\right)\Big|_{b=r}} = \frac{E\left(W^k_{iatrb} | S^k_i = 1, A_{ita} = 1, M_{itrb} = 1\right)}{E\left(W^k_{iatrb} | S^k_i = 1, A_{ita} = 1, M_{itrb} = 1\right)\Big|_{b=r}}.$$

Therefore,

$$\tilde{Q}^k_{atr} = \sum_{b=1}^{R} \frac{N^k_{atrb}}{N^k_{atr}} \frac{E\left(W^k_{iatrb} | S^k_i = 1, A_{ita} = 1, M_{itrb} = 1\right)}{E\left(W^k_{iatrb} | S^k_i = 1, A_{ita} = 1, M_{itrb} = 1\right)\Big|_{b=r}},$$

which can be estimated directly by sample analogs using Census data.

To complete the description of Q^k_{atr} in (15), suppose that

$$E\left(U^k_{i,t-a,b} | S^k_i = 1, A_{ita} = 1, M_{itrb} = 1\right) = \exp\left[\Gamma_{kb} + \Phi_k(P_{t-a,b}) + \Lambda_k(P^k_{M,atrb}, P^k_{M,atrr})\right], \quad (16)$$

where Γ_{kb} is region-of-birth fixed effects, Φ_k is a function of $P_{t-a,b}$ (composition), and Λ_k is a function of $P^k_{M,atrb}$ and $P^k_{M,atrr}$ (migration). The exponential function is used to ensure that the conditional expectation on the left-hand side of (16) is always positive. The underlying ideas behind (16) 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.[13] Finally:

$$Q^k_{atr} = \tilde{Q}^k_{atr} \exp\left[\Gamma_{kb} + \Phi_k(P_{t-a,b}) + \Lambda_k(P^k_{M,atrb}, P^k_{M,atrr})\right]\Big|_{b=r}. \quad (17)$$

Using this expression of Q^k_{atr}, one can estimate a model of the demand for skill based on (13).

Putting (3), (4), (13) and (17) together we can estimate η_k and $\phi_k\left(P_{t-a,b}\right)$ (as well as β_{at}, α_{ka}, and $\Phi_k\left(P_{t-a,r}\right)$) from the following model:

$$\begin{aligned} \omega^k_{atrb} &= \xi_{ktr} + \xi_{kat} + (\eta_k - 1)\log\left(N^k_{atr}\tilde{Q}^k_{atr}\right) + \\ &\quad + (\eta_k - 1)\left[\Gamma_{kb} + \Phi_k(P_{t-a,b}) + \Lambda_k(P^k_{M,atrb}, P^k_{M,atrr})\right]\Big|_{b=r} \\ &\quad + \gamma_{kab} + \gamma_{ktb} + \phi_k(P_{t-a,b}) + \lambda_k(P^k_{M,atrb}, P^k_{M,atrr}) \end{aligned} \quad (18)$$

[13] Notice that Γ_{kb} and Λ_k are different from γ_{kab}, γ_{ktb}, and λ_k. Strictly speaking, (16) 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).

We are left with the estimation of ρ, which is subsumed in ξ_{ktr} (see equation (12)). If 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. Another alternative is to take an estimate of ρ from the literature and then back out the trend in demand.

3 Data

We use data from the 1960, 1970, 1980, 1990 and 2000 US Censuses (1% sample).[14] 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,[15] 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 regional unit is that the resulting cell sizes would be too small for our estimates to be reliable.

For each cell we compute the relevant average weekly log wages, log total weeks worked (a measure of labor supply) and the proportion of individuals in college (a measure of composition). 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 with exactly 16 years of schooling.[16] 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.

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

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

[15] 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.

[16] 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.

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.

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 as large as the movements in the college premium. More generally, changes in age premia are as important as changes in the college premium for the evolution of inequality. In other words, movements in the age premia are of the same order of magnitude as 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.[17]

Finally, the last panel of the figure shows the evolution of the proportion of college graduates 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 reassuring to see that our data replicates these well known patterns, and it is interesting to see that there are strong commonalities across different regions.

[17] We could have picked another age contrast as our main example. A full study of the age premium is available on request from the authors, and is omitted here for brevity.

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 on the schooling-region of residence-year cell.

In column (1) of Table 1, we estimate the reduced-form model of equation (5). In this model π^k_{tar} is not modelled 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 parametrization (it is a strictly increasing function of $P_{t-a,b}$ and can vary 0 to ∞).[18] In addition, λ_k in (5) is modelled as a second-order expansion of migration probabilities: that is, linear and quadratic terms of $P^k_{M,atrb}$ and $P^k_{M,atrr}$ and the interaction between the two. All regressions include region of birth dummies interacted with year and age, separately.[19]

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,[20] but insignificantly negative and quantitatively small for the high school equation. 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 about 4.25%. 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 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

[18]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 the same regardless of the specification of ϕ_k. See Figure A.6 for details.

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

[20]As an alternative specification, we included the odds of college participation as well as the odds of college graduation as quality variables along with other covariates in column (1) of Table 1. In this specification, the coefficient for the odds of college participation was -0.091 with a robust standard error of 0.033 and the coefficient for the odds of college graduation was 0.059 with a robust standard error of 0.255. This result is qualitatively consistent with the result reported in column (1) of Table 1. Since the odds of the college graduation is insignificant at any conventional level, we excluded this variable from our main specifications.

to a model with a single type of skill.

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 -0.074, implying that the college premium would decline by 3.7% if college enrollment went from 50% to 60%.[21] 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 a 8% decline of college premium. One important implication of our findings is that the trend in the college premium is contaminated by composition effects, an issue we explore in the next section.

In column (2) of Table 1, we estimate a supply-demand model where π_{tar}^k is modelled explicitly as in (18). 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), the age effect ξ_{kat} is modelled as an interaction of a quadratic time trend with age specific dummies that are common between schooling groups.[22] In column (2), Φ_k in (17) is assumed to be 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 $P_{M,atrr}^k$ and can be absorbed into λ_k in (4). In summary, explanatory variables in estimating column (2) are odds of proportion in college ($\tilde{P}_{t-a,b}$), quality-adjusted log weeks ($N_{atr}^k\tilde{Q}_{atr}^k$), the (year)×(region of residence) fixed effect (ξ_{ktr}), the age effect interacted by common quadratic time trends (ξ_{kat}), odds of proportion in college for stayers ($\Phi_k(P_{t-a,b})$), the region-of-birth fixed effect for stayers (Γ_{kb}), the (year)×(region of birth) fixed effect (γ_{ktb}), the (age)×(region of birth) fixed effect (γ_{kab}), and linear, quadratic, and interaction terms of observed migration probability and staying probability ($\lambda_k(P_{M,atrb}^k, P_{M,atrr}^k)$). When estimating column (3), quality-unadjusted log weeks (N_{atr}^k) are used instead of the quality-

[21] Table A.14 in the appendix simulates 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.

[22] We have chosen this specification instead of a more flexible one because we are concerned about overparametrization 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.

adjusted log weeks, and the quality-related variables ($\tilde{P}_{t-a,b}$, $\Phi_k(P_{t-a,b})$, and Γ_{kb}) are excluded from the regression.

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 -0.076, which is very similar to -0.074 in column (1). Thus, our estimation results are robust to alternative models for π^k_{tar}. In the college equation, the coefficient for the quality-adjusted log weeks ($\eta_C - 1$) in (13) is -0.094, which implies that the elasticity of substitution between workers of different ages in college is $\sigma_C = 1/(1 - \eta_C) = 1/0.094 \approx 10.6$. In the high school equation, the corresponding coefficient ($\eta_H - 1$) is -0.114 and, therefore, the elasticity of substitution is about 8.8. Thus, our estimates indicate that different age groups are slightly closer substitutes in college than in high school (equivalently, high school wages are slightly more 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 -0.162 and -0.121, respectively, implying that the elasticities of substitution are about 6.2 and 8.3 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 little difference between the two estimates in the high school equation, which is not surprising since the composition effect is not important in high school.[23]

5 Sensitivity Analysis

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 our sensitivity analysis on the reduced form model. In Table 2 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

[23] Our estimates in column (3) are comparable to those in Card and Lemieux (2001, Table VII), although they are slightly lower in absolute values. It is reassuring that our estimates in column (3) are similar to those in the literature.

phenomenon. The table has 10 columns. The first one corresponds to our original specification, where all regions are included, and in the remaining ones we drop from the sample one region at a time. Across columns, the coefficient of interest in the college equation is always negative and statistically significant, while in the high school equation the coefficient is small and insignificant.

In Table 3 we examine the sensitivity of our results to dropping one year at a time.[24] In the first column of the table we present the original specification, while in the remaining five columns we drop from the sample one year at a time. Across columns there are hardly any changes in the coefficient of interest, both in the college and in the high school equation.

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 4 we experiment with four alternatives. The first column 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,

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

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

In the remaining panels of this table we show the sensitivity of our results to different samples. We start with an alternative white male sample, where we exclude all those individuals who work in farms, or work less than 30 hours a week. With this sample, results are similar to the ones we obtain with the original sample, except that in column 3 the coefficient is only significant at a 10% level. The next panel corresponds to a sample of white females. The main reason why we chose to

[24] If we estimate the model decade by decade the coefficient on variable of interest is always negative but not statistically significant.

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). The only significant results in the college equation are in column 4, suggesting that there may be composition effects, but not as robust as in the male sample. The results seem to indicate that increases in college attainment initially bring into college females of lower quality than average, but as college attainment increases this becomes less and less true. In the high school equation no coefficient is significantly different from zero. Finally, in the last panel, we group males and females together in the same sample. Results are similar to the original ones, especially in columns 1 and 2. In columns 3 and 4 the quality decline that results from an increase in $P_{t-a,b}$ is more pronounced than in the original sample.

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 them the average quality of their region of birth. This is not important if changes in composition affect the quality of migrants and non-migrants in a parallel way, but it becomes problematic if these two groups are affected differently. 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. Of course, without a valid instrument for migration this is an untestable proposition, and therefore each of these results on its own can be 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, quite the contrary. What happens is that these variables (given the set of controls) are uncorrelated with changes in schooling. Table 5 summarizes these results. In this table, we experiment alternative specifications for column (1) of Table 1, where prices are modelled as full interactions between year, age and region of residence dummies. Column (1) of Table 5 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.[25] This is the first specification in our 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.[26] 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. 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 more importantly, 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.

Column (4) is the main specification of the paper (and replicates Column (1) of table 1). Relatively to Column (1) 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 b and residing in b (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.

The remaining columns present variants of these first four specifications. In Column (5) we join the specifications in (3) and (4). In column (6) we take the main specification of the paper 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.

[25] It is interesting to note that if these variables are ignored then the coefficient of interest becomes positive and significant at the 10% level in the college equation (an estimate of 0.037 with a clustered standard error of 0.020). This is not true in the high school equation (an estimate of 0.013 with a clustered standard error of 0.013). This is probably because regions of birth with larger resources have better quality schools, leading simultaneously to higher earnings potential among their students and also larger college enrollment rates. This illustrates the importance of accounting for region of birth effects.

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

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).[27] One concern with the basic specification in column (4) is that we may be capturing school quality effects through the proportion in college. It can be seen that differences between estimates in columns (4) and (8) 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) 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. In fact, when we examined the raw data, we found that even though there have been large increases in college attainment over the last 40 years, there were hardly any changes in aggregate migration flows, both in college and in high school. 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.

In Table 6, 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 5, 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 5). 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 7, we regress the proportion of individuals not migrating in each cell on the odds in proportion in college. We use

[27] 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.

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), usual basic control variables are 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 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 5, 6, and 7 provide convincing evidence that selective migration does not substantially affect our results..

In Appendix A.3 we present additional specification checks (unrelated to migration). First, we show that our results are robust to the use of an alternative measure of composition (P, instead of $\frac{P}{1-P}$). Second, 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 once 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). Third, we rerun our models using different dependent variables besides log weekly wages. We show that declines in the quality of college workers due to increases in college attainment show up not only in wages, but also in total income and in an index of occupational status.

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 start 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). For simplicity, we present results comparing only North and South, but we have available results for finer regional partitions which show similar patterns. We take white males, and we divide them in two groups: those growing up in the southern regions of the US, and those growing up elsewhere. For each individual in each region we compute his percentile in the distribution of test scores within region (the AFQT in the NLSY79 and NLSY97, and IQ in NLS66).[28] Finally, we divide the sample into those with some college or more, and those with less than college, and calculate the average percentile in the test score distribution for each education group and region. The question we ask is: in regions where college participation is higher is the average college student in a lower percentile of the within-region test score distribution?

Results are shown in table 8. The number in each cell in columns (1) and (2) corresponds to the average percentile in the within-region test score distribution for each dataset, region and schooling group. Columns (3) and (4) show the proportion of individuals in each sample with at least some college, and the corresponding odds. For example, in the NLSY79 the college participation rate is 56% in the North and 48% in the South, and the average percentile of college student in the within-region test score distribution is 64% in the North and 69% in the South. Therefore, in the North, where the levels of college attendance are higher, the average college student has lower quality (relatively to the other residents in the region) than in the South, where levels of college

[28] We use schooling corrected AFQT in the NLSY79, as in Carneiro et al. (2007).

attendance are lower. This is also true in NLS66 and NLSY97. Notice that percentiles of the test score distribution are taken within region, not across regions, because there could be systematic differences in test scores across regions which we want to abstract from. The question we ask is whether, in regions with high college participation, college students have lower ability *relatively to other residents in the region* than in regions with low college participation.

One could ask whether the magnitude of these test score differences is enough to explain the wage differences we observe in the Census. If we regress log hourly wages in 1994 on within region AFQT percentile for white males in the NLSY79 with some college and residing in the North we get a coefficient of about 0.5 (and essentially the same coefficient, 0.6, if we use those in the South instead). This magnitude of the estimated coefficient translates to an increase of about 14.4% (= $0.5 \times 28.8\%$, where 28.8% is the standard deviation of within region percentile test scores) in hourly wages with respect to the one standard deviation increase in the AFQT percentile. This estimate is within the range of previous estimates for the return to the test scores. For example, Bishop (1989) finds that a one standard deviation increase in test score is associated with a 19% increase in earnings for male household heads using data from the 1971 Panel Study of Income Dynamics (see equation (3) of Bishop, 1989); Neal and Johnson (1996) report an estimate of about 17% increase (see Column 3 of Table 1 of Neal and Johnson, 1996); Murnane et al. (1995) obtain an estimate of about 8% increase with respect to the one standard deviation increase in the mathematics score using data from High School and Beyond (see tables 2 and 3 Murnane et al., 1995). Our estimation result from NLSY79 means that the difference of 5 percentile points between those college participants residing in the South and those residing elsewhere, corresponds to a difference in wages of 2.5 percentage points (= $0.5 \times 5\%$) if we use the estimate from the North (3 percentage points, respectively, if we use the estimate from the South). Given that the college participation rates are 48% in the South and 56% elsewhere, if we were to use our estimates of equation (5), we would expect college wages to be about 3 percentile points higher in the south than elsewhere ($0.085 \times$ a difference of 0.35 in the odds of P). These magnitudes are reassuringly similar to each other. This provides suggestive and direct evidence that increases in college attainment lead to declines in the quality of college attendees.

We also 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 take SAT mainly, whereas other states take ACT mainly. 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 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 9 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.

Finally, 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 we compute the percentage of individuals with some college or above, which call P. Table 10 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 10 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.[29]

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. An 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:

$$\begin{aligned} CP_t &= \sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{b=1}^{R}\omega_{atrb}^{C} f_t^{C}(a,r,b) - \sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{b=1}^{R}\omega_{atrb}^{H} f_t^{H}(a,r,b) \quad \text{and} \\ AP_t^k &= \sum_{r=1}^{R}\sum_{b=1}^{R}\omega_{atrb}^{k} f_t^{k}(a,r,b)\Big|_{a=o} - \sum_{r=1}^{R}\sum_{b=1}^{R}\omega_{atrb}^{k} f_t^{k}(a,r,b)\Big|_{a=y}, \end{aligned} \tag{19}$$

where o and y denotes old and young workers, respectively, and $f_t^k(a,r,b)$ is the proportion of individuals in cell (a,r,b) for each schooling group k and time t. There does not seem to be a standard definition of young and old workers in the literature. In our empirical work, we set the 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

[29] 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 modelled as:

$$\omega_{atrb}^{k} = \pi_{atr}^{k} + \gamma_{kab} + \gamma_{ktb} + \phi_k(P_{t-a,b}) + \lambda_k(P_{M,atrb}^{k}, P_{M,atrr}^{k}). \tag{20}$$

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

$$\omega_{atrb}^{k,Q} = \pi_{atr}^{k} + \gamma_{kab} + \gamma_{ktb} + \phi_k(P_{1960-a,b}) + \lambda_k(P_{M,atrb}^{k}, P_{M,atrr}^{k}). \tag{21}$$

Then quality-adjusted college and age premia are defined as in (19) (after substituting in ω_{atrb}^{k}):

$$\begin{aligned} CP_t^Q &= \sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{b=1}^{R}\omega_{atrb}^{C,Q} f_t^C(a,r,b) - \sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{b=1}^{R}\omega_{atrb}^{H,Q} f_t^H(a,r,b) \quad \text{and} \\ AP_t^{k,Q} &= \sum_{r=1}^{R}\sum_{b=1}^{R}\omega_{atrb}^{k,Q} f_t^k(a,r,b)\Big|_{a=o} - \sum_{r=1}^{R}\sum_{b=1}^{R}\omega_{atrb}^{k,Q} f_t^k(a,r,b)\Big|_{a=y}, \end{aligned} \tag{22}$$

where $\omega_{atrb}^{k,Q}$ corresponds to the average wage that we would observe in each cell if average worker quality were 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.[30]

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 appendix (see figure A.7) 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 (19), while the dashed lines correspond to CP_t^Q in (22). This panel shows that the college premium increased by 18% between 1960 and 2000, but the quality adjusted college premium increased by 26%.[32] There is a substantial difference of 8 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 9% 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 of about 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

[30]Still, given the structure of our model which controls for selection migration and changes in the region of birth quality, we can interpret the *trend* in $\omega_{atrb}^{k,Q}$ as being free of selection.

[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.

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.

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)). Therefore, one alternative is to take an estimate of ρ from the literature, and compute the implied series for $\log(\theta_{Ctr}/\theta_{Htr})$. Notice that:

$$\begin{aligned}\omega^C_{atrb} - \omega^H_{atrb} = \log\frac{\theta_{Ctr}}{\theta_{Htr}} + \rho\frac{\mathbf{U}^C_{tr}}{\mathbf{U}^H_{tr}} + (\eta_C\log\alpha_{Ca} - \eta_H\log\alpha_{Ha}) - \left(\eta_C\log\mathbf{U}^C_{tr} - \eta_H\log\mathbf{U}^H_{tr}\right) + \\ + \left\{(\eta_C - 1)\left[\log N^C_{atr} + \log Q^C_{atr}\right] - (\eta_H - 1)\left[\log N^H_{atr} + \log Q^H_{atr}\right]\right\} + \\ + \gamma_{kab} + \gamma_{ktb} + \phi_k(P_{t-a,b}) + \lambda_k(P^k_{M,atrb}, P^k_{M,atrr}).\end{aligned}$$

From the estimates of equation (18) we can compute all the objects in this equation except ρ and $\log(\theta_{Ctr}/\theta_{Htr})$. 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 $\log(\theta_{Ctr}/\theta_{Htr})$.

In order to get the trend in the relative demand for older workers we just need to estimate the changes in $\log(\beta_{at})|_{a=old} - \log(\beta_{at})|_{a=young}$, where β_{at} is given in (11). This can be derived from the series of ξ_{kat} from equation (13). 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 made different specification choices, but we believe these 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).[33] 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 ones in the literature, giving us confidence in our procedure.

Table 11 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 matters quantitatively in some cases, but not in all cases. For example, the increase in the relative demand for college at the national level is about 56% if we look at the unadjusted trend and is about 58% in terms of the adjusted trend. The difference is less than 2%.

Recall that we have shown that using the the reduced-form-model estimates, increases in college enrollment lead to a decline in the quality of college graduates between 1960 and 2000, resulting in a decrease of 8 percentage points in the college premium. The reason why the changes in the relative demand is much smaller than those in the college premium is the following. Recall that the estimate of the effect of college labor on college wages is upward biased (in absolute value) if quality is not controlled for (see columns (2) and (3) of Table 1). Therefore, if the quality is not

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

adjusted, the effect of the supply would be overestimated. With the quality adjustment, the trends in demand are computed by residual effects after subtracting the supply and quality effects from the college premium, whereas without the quality adjustment, those are obtained by subtracting only the supply effect that is overestimated, however. Because of this, there will be a smaller difference between adjusted and unadjusted trends in demand than those in the college premium. The quantitative degrees at which they differ are empirical matters. Table 11 suggests that the difference between adjusted and unadjusted trends in demand is quite small at the national level but that this difference can be relatively large in some regions (e.g. South). One notable feature of the empirical results in Table 11 is that the adjusted trends tend to be less fluctuating than the unadjusted trends over decades.

Table 12 shows relative demand estimates for old workers using the estimation results reported in columns (2) and (3) of Table 1. As in Table 11, it shows percentage changes in the relative demands for three old worker groups (36-40, 46-50, 56-60) with respect to the young worker group (25-30). The most striking results are (1) the relative demands for old workers have increased from 1960 to 2000 quite substantially and (2) the quality adjustment plays a relative minor role, as in the demands for college skill. Putting together the results presented in Table 11 and 12 indicates that the main qualitative trends in relative demands for college and old workers can be described by the use of the standard demand and supply model but that the interpretations of the supply effects would be fragile if the quality of college workers is not controlled for.

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 as important as changes in prices to explain the phenomenon they document.

Table 13 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 10.3%, 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 5.6%. That is, about 50% 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 negligible regardless of quality adjustment.

9 Conclusions

In this paper we estimate the role of changes in composition in the evolution of college premium. Changes in composition occur because individuals are heterogeneous, and when college attainment increases there is a change in the average quality of college and high school graduates. Our estimates allow us to construct composition adjusted trends in the college premium, which show that composition accounts for one third of the decline of the college premium in the 1970s. Furthermore, if the quality composition of college graduates had not declined between 1960 and 2000 but the supply of college gradates had increased by the same amount as was observed, the estimated college premium would have increased by 8 percentage points more. We then revisit the analysis in Card and Lemieux (2001) and show that the role of changes in supply has been overstated: changes in quality are as important as changes in prices to explain why the college premium grows at different rates for young and old workers.

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A Appendix

A.1 Data

We use data from the 1960, 1970, 1980, 1990 and 2000 US Censuses (1% sample). Our data was extracted from `http://www.ipums.umn.edu/` (see Ruggles et al., 2004). We focus on white males, between the ages 25 and 60. We exclude from the analysis all those who are foreign born. We consider 5 year age groups (with the exception of the first, which has 6 years): 25-30, 31-35, 36-40, 41-45, 46-50, 51-55.

For 1960, 1970 and 1980, the education variable we use is "highest grade of schooling", while for 1990 and 2000 we use "educational attainment recode". We group individuals into four categories: high school dropout, high school graduate, some college, college graduate or more. For 1960, 1970 and 1980, we consider high school dropouts those who have completed less than 12 years of schooling, high school graduates are those with exactly 12 years of completed schooling, college graduates have completed 4 or more years of college, and some college is the category for those with more than 12 but less than 16 years of schooling. For 1990 and 2000, dropouts are those with up to 11 years of schooling, high school graduates have exactly 12 years of schooling, those with some college have 1 to 3 years of college, and college graduates have four or more years of college. Our final classification has two groups only, one comprising of high school graduates and high school dropouts, and the other comprising of those with some college, a college degree, or above.

We compute weekly wages by dividing annual wage and salary income by annual weeks worked. We deflate all wages to 1990 values using the CPI-U from the Economic Report of the President. In order to compute average log wages for each year-age group-region of residence-region of birth cell (the main outcome variable in our analysis) we drop all observations for whom real wages are below 50 dollars per week.

For each year, region of birth and five year cohort we also estimate the proportion of individuals who attend at least some college. However, even among adults, educational attainment increases over time. Therefore we calculate an average proportion of individuals who attend at least some college for each cohort and region of birth (common across years), by averaging this number across all years, using as weights the number of individuals in each year, cohort and region of birth cell.

We consider 9 regions of birth and 9 regions of residence, and we drop from the sample those individuals who are foreign born. In particular, 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).

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 regional unit is that the resulting cell sizes would be too small for our estimates to be reliable.

For each cell we compute the relevant average weekly log wages, log total weeks worked (a measure of labor supply) and the proportion of individuals in college (a measure of composition). 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 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 only individuals with exactly 16 years of schooling. 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.

Log weeks worked by high school graduates (or 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 even individuals with some college. Log weeks worked by college graduates 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.

A.2 Average and Marginal Students

Table A.14 in the appendix simulates 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. We consider a simple economy that consists of only two schooling groups: high school graduates and college graduates. Let w_1 be the average log wage of the baseline college graduates and w_2 be the average log wage of the marginal college graduates. Note that the average log wage after college expansion, say w_*, has the form:

$$w_* = (1 - \mu) \times w_1 + \mu \times w_2, \tag{A.1}$$

where μ is the proportion of marginal college graduates after college expansion. Since our model is linear in the odds of college enrollment ($P_{t-a,b}/(1 - P_{t-a,b})$), in view of the estimation result in column (1) of Table 1, we have

$$w_* = w_1 - 0.085 \times (\text{changes in } P_{t-a,b}/(1 - P_{t-a,b})). \tag{A.2}$$

Thus, combining (A.1) and (A.2) and solving for w_2 gives

$$w_2 = w_1 - 0.085 \times \mu^{-1} \times (\text{changes in } P_{t-a,b}/(1 - P_{t-a,b})).$$

The column (4) of Panel A of Table A.14 shows the effects of absolute increases of 10% in college enrollment across different baseline college enrollment rates and the same column of Panel B shows those of proportional increases of 10% in college enrollment. For example, if the baseline college enrollment rate is 40%, then an absolute increases of 10% in college enrollment leads to a decrease of 14% in marginal college wages, thereby implying that the quality of the average marginal college graduate is 14% lower than that of the average baseline college graduate. It can be seen that marginal college graduates are always of lower quality than baseline college graduates, but the magnitude of the decrease in quality is larger when there is a higher proportion of baseline college graduates. In other words, as college expands, it would induce lower and lower quality college graduates. Our main qualitative results do not change when an alternative model specification is used. column (5) of Table A.14 reports that the main results are the same when the model is linear in the level of college enrollment ($P_{t-a,b}$).[34]

Notice that changes in worker quality resulting from increases in college participation do not necessarily have to lead to decreases in the college premium. Theoretically, the adjustment in the college premium could go either way, depending on how individuals sort into different levels of schooling, and on how important heterogeneity is in high school and college (see Carneiro and Lee, 2008). Our results indicate that: i) skill heterogeneity and self selection into schooling are important phenomena, so that if college enrollment went from 40% to 50%, the average marginal student's quality would be 14% lower than that of the average student in college; ii) those individuals with the highest college skills select into college; iii) there is no clear relationship between the type of skills used in high school occupations and selection into college.

A.3 Additional Sensitivity Analysis

In this section we present additional specification checks. First, we show our results are robust to the use of an alternative measure of composition. In particular, Table A.15 shows that if we use the level of proportion in college rather than the odds of proportion in college, the college premium would decline by 3.47% if college enrollment increases by 10% ($0.10*[-0.587-(-0.240)]=0.0347$). This change is comparable to 4.25%, which we obtained using the odds of proportion in college when college enrollment changed from 50% to 60%.

Second, 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). This is likely to be the case, but it does not seem to affect our results. Table A.16 shows that the main results are basically unchanged once 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

[34]In this case, the corresponding coefficient for $P_{t-a,b}$ is -0.587 (see Table A.15), implying that

$$w_2 = w_1 - 0.587 \times \mu^{-1} \times (\text{changes in } P).$$

enrollment). One thing to notice is that the estimated coefficient for the odds of proportion in college for the college equation changes from -0.085 to -0.073 if the odds of proportion in post-college enrollment is controlled for.[35] This amounts to a decline of 3.65% in average college wages when the proportion of college participants increases from 50% to 60% (recall that the estimate of -0.085 implies a drop of 4.25%). This suggests that there might be some sort of selection of more able individuals out of college into post-college education, thereby implying that our baseline estimate overstates the declining quality of college graduates. Our main result is still intact since the magnitude of this potential bias is relatively small (the difference of 0.55% for average college wages with respect to the change of the proportion of college participants from 50% to 60%) and furthermore, the coefficient for the odds of proportion in post-college enrollment is imprecisely estimated.

Third, we rerun our basic models using different dependent variables besides log weekly wages. The estimation results are reported in Table A.17. For each (k, a, t, r, b) cell we compute the average Duncan Socio Economic Index, average log annual total income, average employment status. These are all alternative potential measures of worker quality. We then regress them on the odds of proportion in college and the full set of dummy variables we use in our main (reduced form) specification, and find that for college individuals there are strong negative effects of increases in college attainment on all variables except employment status. These results confirm our main findings for log wages. For high school, there is a negative effect of changes in college attainment on log annual total income, while for log wages we had found no evidence of composition effects.[36]

[35] An anonymous referee points out potential biases due to selection out of college into post-college education and suggests that we include the odds of proportion in post-college enrollment as an additional explanatory variable. We are grateful to the referee for the insightful suggestions.

[36] This difference may occur for two reasons. On one end, the model may only be well specified for wages since we can interpret $t-a-r$ interactions as prices in that case, but probably not when we examine other variables. On the other end, it is possible that high school quality declines as more individuals enrol in college, and although this is not picked up in terms of wages, it is picked up in the log total income.

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

	(1) Reduced-Form Model (Controlling for Quality)	(2) Supply-Demand Model (Controlling for Quality)	(3) Supply-Demand Model (Without Controlling for Quality)
Panel A - College			
Odds of Proportion in College	-0.085	-0.093	
	[0.029]**	[0.023]**	
Quality-Adjusted Log Weeks		-0.094	
		[0.026]**	
Log Weeks			-0.162
			[0.018]**
Observations	2659	2659	2659
Panel B - High School			
Odds of Proportion in College	-0.011	-0.016	
	[0.024]	[0.021]	
Quality-Adjusted Log Weeks		-0.114	
		[0.019]**	
Log Weeks			-0.121
			[0.018]**
Observations	2742	2742	2742
Panel C - Difference between College and High-School			
Odds of Proportion in College		-0.076	
		[0.030]*	
Quality-Adjusted Log Weeks		0.020	
		[0.025]	
Log Weeks			-0.042
			[0.023]
Included Explanatory Variables			
(Year)×(Age)×(Region of Residence)	√		
(Year)×(Region of Residence)		√	√
(Age)×(Common Quadratic Time Trends)		√	√
(Odds of Proportion in College for Stayers)		√	
(Region of Birth Fixed Effect for Stayers)		√	
(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 5%; ** significant at 1%.

Table 2: Sensitivity Analysis: Dropping One Region at a Time

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All				Dropping the Following Region:					
	Regions	New England	Middle Atlantic	East North Central	West North Central	South Atlantic	East South Central	West South Central	Mountain	Pacific
Panel A - College										
Odds of Proportion in College	-0.085	-0.081	-0.074	-0.089	-0.091	-0.090	-0.068	-0.083	-0.084	-0.114
	[0.029]**	[0.029]**	[0.029]*	[0.032]**	[0.030]**	[0.034]*	[0.028]*	[0.031]*	[0.028]**	[0.033]**
Observations	2659	2404	2352	2347	2374	2348	2386	2357	2360	2344
Panel B - High School										
Odds of Proportion in College	-0.011	-0.027	-0.022	-0.012	-0.012	0.009	0.001	-0.015	-0.007	-0.043
	[0.024]	[0.023]	[0.022]	[0.025]	[0.024]	[0.024]	[0.023]	[0.023]	[0.026]	[0.029]
Observations	2742	2471	2438	2429	2431	2429	2452	2430	2429	2427

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 5%; ** significant at 1%.

Table 3: Sensitivity Analysis: Dropping One Year at a Time

	(1)	(2)	(3)	(4)	(5)	(6)
	All		Dropping the Following Year:			
	Years	1960	1970	1980	1990	2000
Panel A - College						
Odds of Proportion in College	-0.085	-0.080	-0.081	-0.067	-0.100	-0.109
	[0.029]**	[0.032]*	[0.035]*	[0.028]*	[0.041]*	[0.039]**
Observations	2659	2180	2143	2121	2097	2095
Panel B - High School						
Odds of Proportion in College	-0.011	-0.007	-0.007	-0.016	-0.029	0.003
	[0.024]	[0.025]	[0.026]	[0.032]	[0.027]	[0.030]
Observations	2742	2223	2192	2186	2186	2181

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 5%; ** significant at 1%.

Table 4: Sensitivity Analysis: Alternative Specifications and Samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Log College Wages				Log High School Wages		
			White Males (Original Sample)					
Odds of Proportion in College	-0.085	-0.139			-0.011	-0.102		
	[0.029]**	[0.105]			[0.024]	[0.103]		
$(\text{Odds of Proportion in College})^2$		0.0140				0.024)		
		[0.026]				[0.024]		
Proportion in College			-0.587	0.501			-0.240	-0.507
			[0.238]*	[0.620]			[0.233]	[0.542]
$(\text{Proportion in College})^2$				-0.858				0.219
				[0.443]				[0.384]
Observations	2659	2659	2659	2659	2742	2742	2742	2742
P-value		0.02		0.01		0.61		0.53
			White Males without Farmers or Part-Time Workers					
Odds of Proportion in College	-0.077	-0.097			-0.007	-0.059		
	[0.029]*	[0.106]			[0.025]	[0.117]		
$(\text{Odds of Proportion in College})^2$		0.005				0.0140		
		[0.026]				[0.028]		
Proportion in College			-0.445	0.848			-0.138	-0.214
			[0.243]	[0.638]			[0.259]	[0.600]
$(\text{Proportion in College})^2$				-1.019				0.0630
				[0.447]*				[0.408]
Observations	2654	2654	2654	2654	2735	2735	2735	2735
P-value		0.04		0.02		0.88		0.87
			White Females					
Odds of Proportion in College	0.055	-0.074			0.027	0.060		
	[0.051]	[0.092]			[0.033]	[0.078]		
$(\text{Odds of Proportion in College})^2$		0.031				-0.009		
		[0.019]				[0.020]		
Proportion in College			-0.361	-1.881			0.197	0.193
			[0.259]	[0.776]*			[0.204]	[0.382]
$(\text{Proportion in College})^2$				1.463				0.003
				[0.736]				[0.323]
Observations	2398	2398	2398	2398	2698	2698	2698	2698
P-value		0.2		0.05		0.65		0.63
			Both White Males and Females					
Odds of Proportion in College	-0.083	-0.409			-0.032	-0.232		
	[0.040]*	[0.113]**			[0.025]	[0.126]		
$(\text{Odds of Proportion in College})^2$		0.090				0.060		
		[0.031]**				[0.032]		
Proportion in College			-1.032	-1.478			-0.481	-0.741
			[0.258]**	[0.801]			[0.300]	[0.644]
$(\text{Proportion in College})^2$				0.390				0.245
				[0.626]				[0.380]
Observations	2728	2728	2728	2728	2799	2799	2799	2799
P-value		0.00		0.00		0.19		0.24

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

Table 5: Estimation Results of Sensitivity Analysis (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A - College							
Odds of Proportion in College	-0.087	-0.074	-0.070	-0.085	-0.069	-0.081	-0.083
	[0.028]**	[0.031]*	[0.029]*	[0.029]**	[0.031]*	[0.035]*	[0.034]*
Observations	2659	2659	2659	2659	2659	2344	2659
Panel B - High School							
Odds of Proportion in College	-0.015	0.025	-0.016	-0.011	-0.017	-0.023	0.003
	[0.024]	[0.026]	[0.023]	[0.024]	[0.021]	[0.027]	[0.024]
Observations	2742	2742	2742	2742	2742	2427	2742
Included Explanatory Variables							
(Year)×(Age)×(Region of Residence)	√	√	√	√	√	√	√
(Age)×(Region of Birth)	√	√	√	√	√	√	√
(Year)×(Region of Birth)	√	√		√		√	√
$(\text{Cohort})^2 \times$(Region of Birth)		√					
(Year)×(R. of Res.)×(R. of Birth)			√		√		
Basic Migration Probabilities				√	√	√	√
Full 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 5%; ** significant at 1%.

Table 6: 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	-0.085	-0.087		-0.011	-0.015	
	[0.029]**	[0.028]**		[0.024]	[0.024]	
Staying Probability	-0.499		-0.538	0.428		0.437
	[0.780]		[0.783]	[0.643]		[0.640]
$(\text{Staying Prob.})^2$	0.277		0.313	-0.528		-0.525
	[0.603]		[0.602]	[0.484]		[0.483]
Observed Migration Probability	-0.596		-0.600	-0.493		-0.493
	[0.086]**		[0.086]**	[0.089]**		[0.089]**
$(\text{Observed Migr. Prob.})^2$	0.276		0.250	-0.337		-0.339
	[0.192]		[0.191]	[0.169]		[0.167]*
(Observed Migr. Prob.)	0.388		0.421	0.962		0.965
$\times$(Staying Prob.)	[0.237]		[0.236]	[0.186]**		[0.183]**
Observations	2659	2659	2659	2742	2742	2742
Included Explanatory Variables						
(Year)$\times$(Age)$\times$(Region of Residence)	√	√	√	√	√	√
(Year)$\times$(Region of Birth)	√	√	√	√	√	√
(Age)$\times$(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 5%; ** significant at 1%.

Table 7: 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	0.016	-0.009	0.001	0.000	-0.062	0.021	0.021
	[0.016]	[0.014]	[0.001]	[0.002]	[0.015]**	[0.037]	[0.036]
Observations	305	305	2455	2455	2344	2344	2344
Panel B - High School							
Odds of Proportion in College	0.021	-0.030	0.001	0.002	-0.196	0.027	0.028
	[0.009]*	[0.010]**	[0.000]	[0.001]	[0.038]**	[0.033]	[0.032]
Observations	305	305	2490	2490	2427	2427	2427
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 5%; ** significant at 1%.

Table 8: Average Ability of College Attendees and Proportion of Going to College

	(1)	(2)	(3)	(4)
Data: NLS66				
	Average Percentile (High School)	Average Percentile (College)	Proportion in College (P)	Odds in P
North	0.35	0.60	0.59	1.45
South	0.33	0.64	0.55	1.22
Difference	0.02	-0.04	0.04	0.22
Data: NLSY79				
	Average Percentile (High School)	Average Percentile (College)	Proportion in College (P)	Odds in P
North	0.32	0.64	0.56	1.27
South	0.33	0.69	0.48	0.92
Difference	-0.01	-0.05	0.08	0.35
Data: NLSY97				
	Average Percentile (High School)	Average Percentile (College)	Proportion in College (P)	Odds in P
North	0.36	0.64	0.51	1.04
South	0.37	0.66	0.46	0.86
Difference	-0.01	-0.02	0.05	0.17

Notes: Data are 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 each dataset, white males are divided into two groups: those growing up in the southern regions of the US, and those growing up elsewhere. For each individual in each region, his percentile is computed in the distribution of test scores within region (the AFQT in the NLSY79 and NLSY97, and IQ in NLS66). Then, the sample is divided into those with some college or more, and those with less than college, and the average percentile in the test score distribution is computed for each education group and region. Each number in columns (1) and (2) corresponds to the average percentile in the within region test score distribution for each dataset, region and schooling group. For each dataset and region columns, (3) and (4) show the proportion of individuals in the sample with at least some college and its corresponding odds.

Table 9: 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	-16.503	-26.268
Graduates Taking SAT	[7.275]**	[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 10: Regression of Quantitative Literacy on Proportion in College

Variable	(1) College	(2) High School	(3) All
Proportion in College	-1.248	0.604	-0.112
	[0.581]**	[0.533]	[0.384]
College			0.977
			[0.047]***
Age	0.101	0.001	0.037
	[0.024]***	[0.019]	[0.013]***
Age Squared	-0.001	0.000	0.000
	[0.000]***	[0.000]	[0.000]***
Constant	-0.794	-0.651	-1.050
	[0.416]*	[0.444]	[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 11: 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	15.79	8.71	19.57	13.71	57.78
	Unadjusted	15.57	7.28	21.33	11.84	56.02
Northeast	Quality-Adjusted	16.03	6.18	20.00	17.14	59.35
	Unadjusted	15.38	2.95	21.59	14.75	54.67
Midwest	Quality-Adjusted	14.22	8.24	19.64	14.44	56.54
	Unadjusted	13.65	5.51	20.46	12.19	51.81
South	Quality-Adjusted	16.48	11.94	19.39	12.77	60.58
	Unadjusted	15.35	9.25	20.04	10.77	55.41
West	Quality-Adjusted	20.19	9.15	18.19	12.73	60.26
	Unadjusted	20.08	9.24	20.24	11.35	60.91

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 12: 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
36-40 vs.	Quality-Adjusted	-1.05	1.16	3.38	5.58	9.07
25-30	Unadjusted	-1.73	1.01	3.75	6.50	9.53
46-50 vs.	Quality-Adjusted	4.11	3.63	3.17	2.70	13.61
25-30	Unadjusted	3.86	3.64	3.41	3.18	14.09
56-60 vs.	Quality-Adjusted	5.17	5.00	4.83	4.65	19.65
25-30	Unadjusted	5.57	5.37	5.16	4.95	21.05

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.

Table 13: 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	0.171	0.043
Composition-Fixed College Premium	0.151	0.070
Proportion in College	-0.041	0.059
Age Group: 45 - 60		
Raw College Premium	0.068	0.034
Composition-Fixed College Premium	0.095	0.083
Proportion in College	0.114	0.138
Differences between Two Age Groups		
Raw College Premium	0.103	0.008
Composition-Fixed College Premium	0.056	-0.013

Notes: This 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.

Table A.14: Changes in the log wages of marginal college graduates

(1) Baseline College Enrollment	(2) Changes in College Enrollment	(3) Proportion of Marginal College Graduates	(4) Changes in Log Wages of Marginal College Graduates	(5)
Model Specification			Linear in $P/(1-P)$	Linear in P
Panel A - Absolute Increase of 10% in College Enrollment				
0.10	0.10	0.50	-0.02	-0.12
0.20	0.10	0.33	-0.05	-0.18
0.30	0.10	0.25	-0.08	-0.23
0.40	0.10	0.20	-0.14	-0.29
0.50	0.10	0.17	-0.26	-0.35
0.60	0.10	0.14	-0.50	-0.41
Panel B - Proportional Increase of 10% in College Enrollment				
0.10	0.01	0.09	-0.01	-0.06
0.20	0.02	0.09	-0.03	-0.13
0.30	0.03	0.09	-0.06	-0.19
0.40	0.04	0.09	-0.11	-0.26
0.50	0.05	0.09	-0.21	-0.32
0.60	0.06	0.09	-0.41	-0.39

Notes: This table shows the effects of declining quality of marginal college graduates on their average log wages. Consider an economy that consists of only two schooling groups: high school graduates and college graduates. Let w_1 be the average log wage of the baseline college graduates and w_2 be the average log wage of the marginal college graduates. Note that the average log wage after college expansion, say w_*, has the form:

$$w_* = (1 - \text{column}(3)) \times w_1 + \text{column}(3) \times w_2.$$

If the model is linear in the odds of college enrollment ($P/(1-P)$), then $w_* = w_1 - 0.085 \times (\text{changes in } P/(1-P))$. Thus, solving for w_2 gives $w_2 = w_1 + \text{column}(4)$, where $\text{column}(4) = -0.085 \times (\text{changes in } P/(1-P))/\text{column}(3)$. If the model is linear in the level of college enrollment (P), then $w_* = w_1 - 0.587 \times (\text{changes in } P)$. Thus, $w_2 = w_1 + \text{column}(5)$, where $\text{column}(5) = -0.587 \times (\text{changes in } P)/\text{column}(3)$. Panel A of the table shows the effects of absolute increases of 10% in college enrollment and Panel B shows those of proportional increases of 10% in college enrollment.

Table A.15: Regression of Wages on Different Measures of Composition

Explanatory Variable	(1) Odds of Proportion in College	(2) Level of Proportion in College
Panel A - College		
Regression Coefficient	-0.085	-0.587
	[0.029]**	[0.238]*
Observations	2659	2659
Panel B - High School		
Regression Coefficient	-0.011	-0.240
	[0.024]	[0.233]
Observations	2742	2742

Notes: The dependent variable is log weekly wage in each cell. The regression includes basic controls as in column (1) of Table 1. Robust standard errors in brackets, clustered on the region of residence-schooling-year cell. * significant at 5%; ** significant at 1%.

Table A.16: Regression of Wages with Measures of Within Group Composition

	(1) Basic	(2) Add Within Group Composition	(3)
Panel A - College			
Odds of Proportion in College	-0.085	-0.085	-0.073
	[0.029]**	[0.029]**	[0.034]*
Odds of Proportion in Some College		-0.023	
		[0.061]	
Odds of Proportion in Post-College Enrollment			-0.313
			[0.327]
Observations	2659	2659	2659
Panel B - High School			
Odds of Proportion in College	-0.011	-0.007	
	[0.024]	[0.025]	
Odds of Proportion in Dropout		-0.006	
		[0.010]	
Observations	2742	2742	

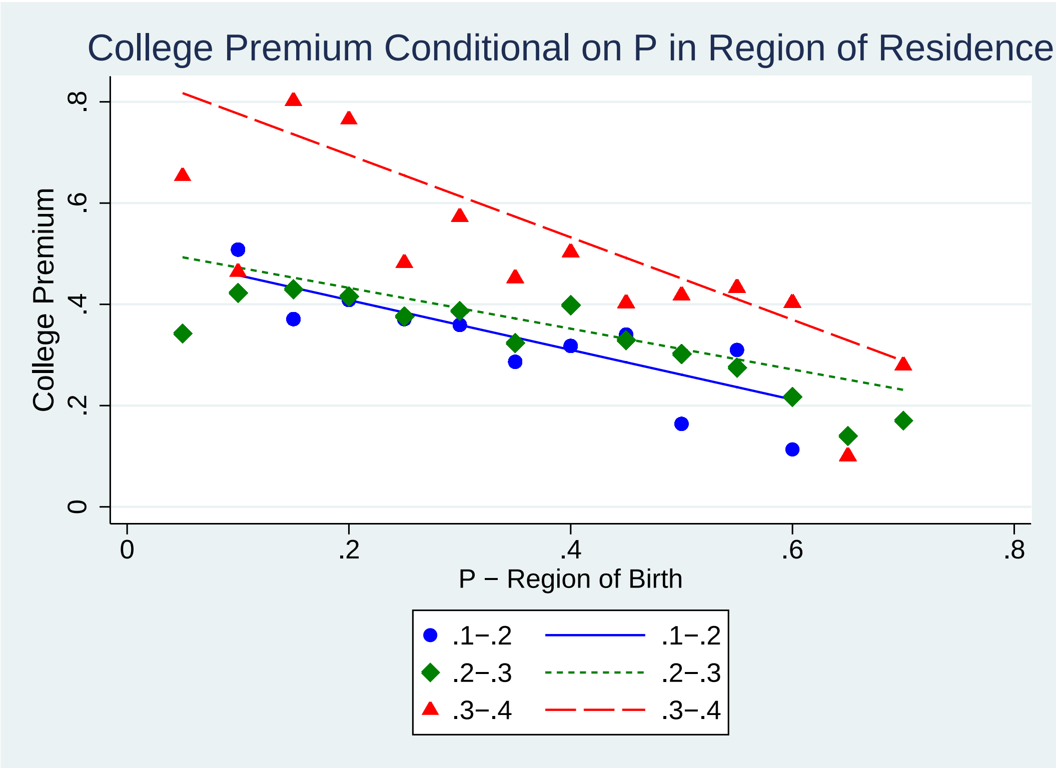
Notes: The dependent variable is log weekly wage in each cell. The regression includes basic controls as in column (1) of Table 1. Robust standard errors in brackets, clustered on the region of residence-schooling-year cell. * significant at 5%; ** significant at 1%.

Table A.17: Regression of Various Outcomes on the Odds of College Enrollment

	(1) Log Wage	(2) Duncan Index	(3) Log Total Income	(4) Employment Status
Panel A - College				
Odds of Proportion in College	-0.085	-2.174	-0.064	0.007
	[0.029]**	[0.473]**	[0.027]*	[0.008]
Observations	2659	2745	2751	2676
Panel B - High School				
Odds of Proportion in College	-0.011	-0.780	-0.041	-0.003
	[0.024]	[0.413]	[0.020]*	[0.007]
Observations	2742	2802	2798	2774

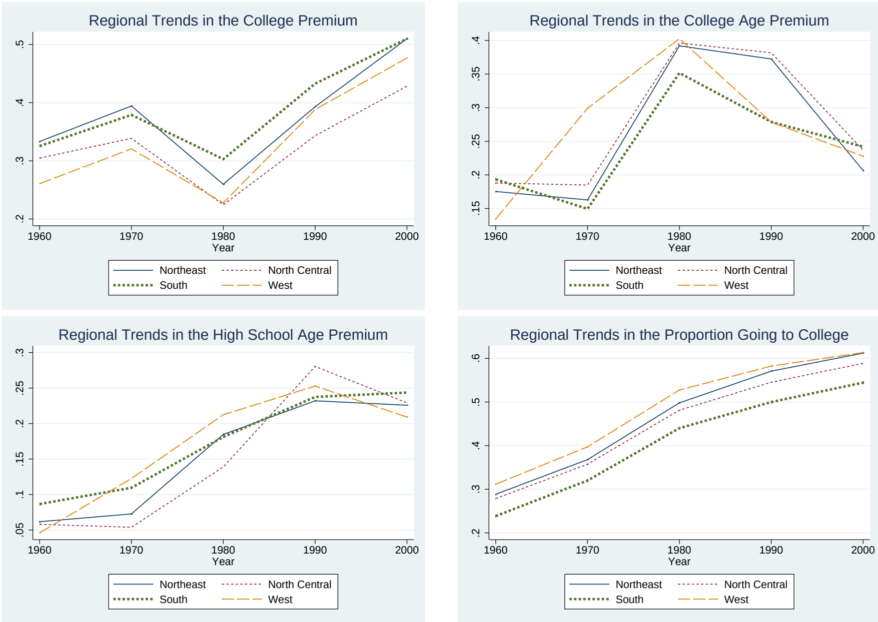
Notes: All the regressions include basic controls as in column (1) of Table 1. Robust standard errors in brackets, clustered on the region of residence-schooling-year cell. * significant at 5%; ** significant at 1%.

Figure 1: Identification Strategy



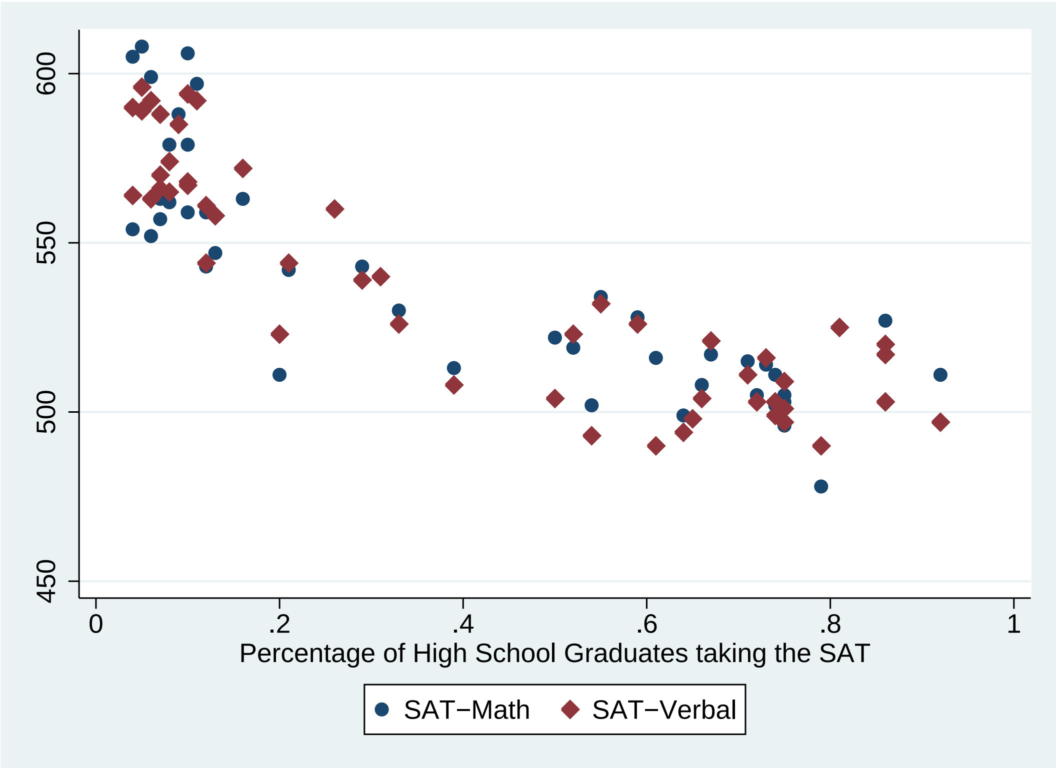
Notes: This figure illustrates the intuition of our procedure. Using US Census data between 1960 and 2000, we group individuals into year-age-region of birth-region of residence cells. For each cell we compute the college premium. We estimate the proportion of college participants for each cohort and region of birth, and the proportion of college participants for each year, age and region of residence. In particular, 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 figure graphs the college premium in each 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%). Within each of these sets, there is a clear negative relationship between the college premium and the proportion in college in each individual's region of birth. This is visible in the raw data, and confirmed by the regression line. 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.

Figure 2: Description of Data



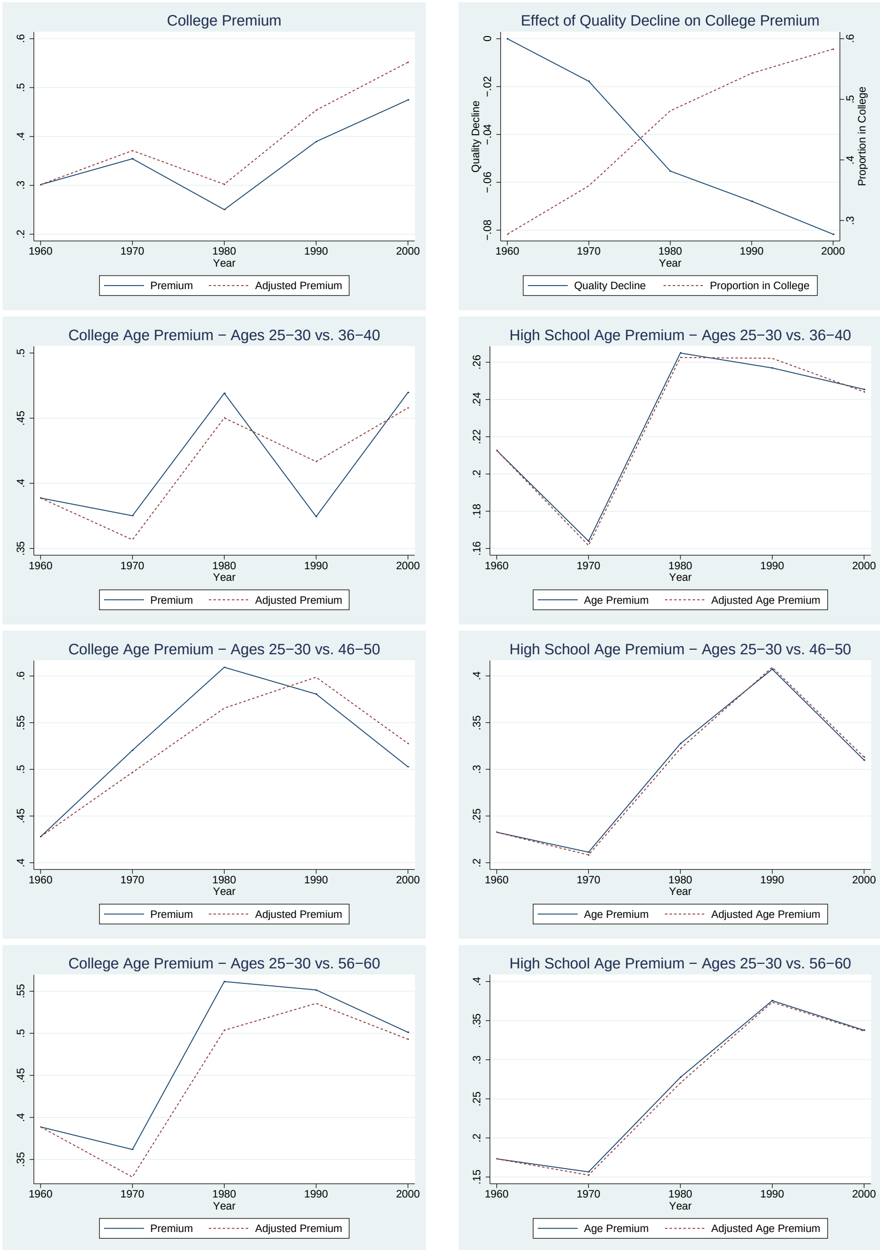
Notes: This figure shows regional trends in skill premia and changes in the proportion of going to college.

Figure 3: SAT Scores and Participation Rates



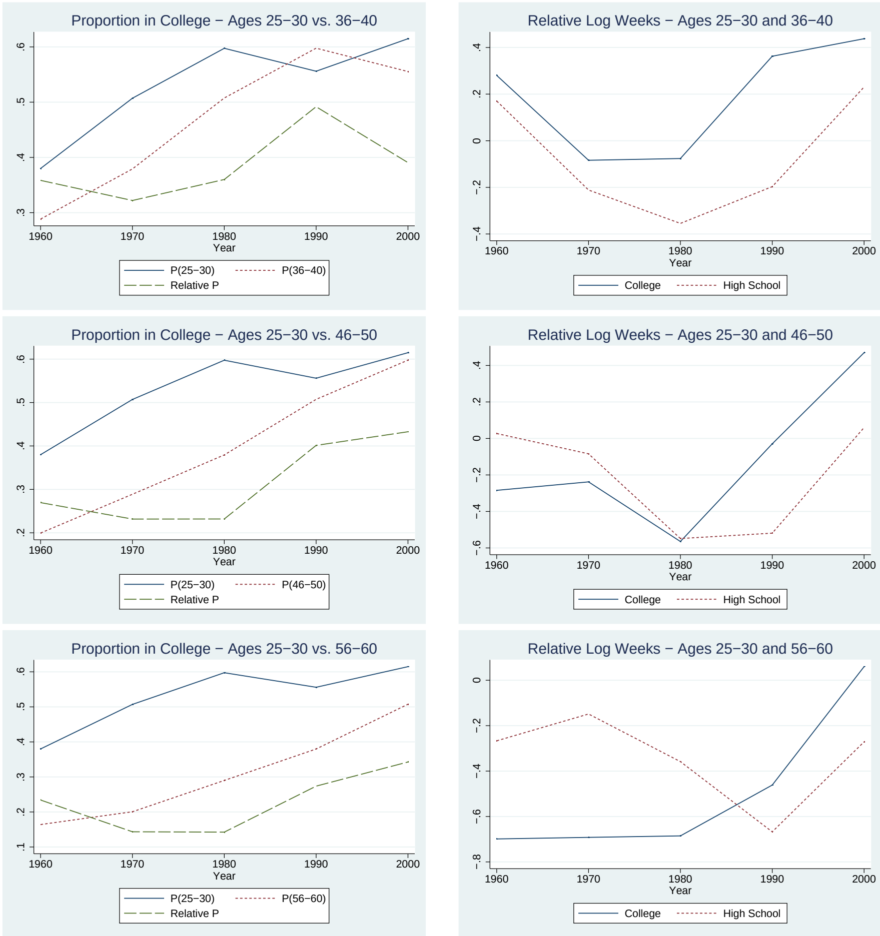
Notes: The figure displays average verbal and math SAT scores by state (in 2004) against the percentage of high school graduates who take the SAT in each state.

Figure 4: Quality-Adjusted College and Age Premia



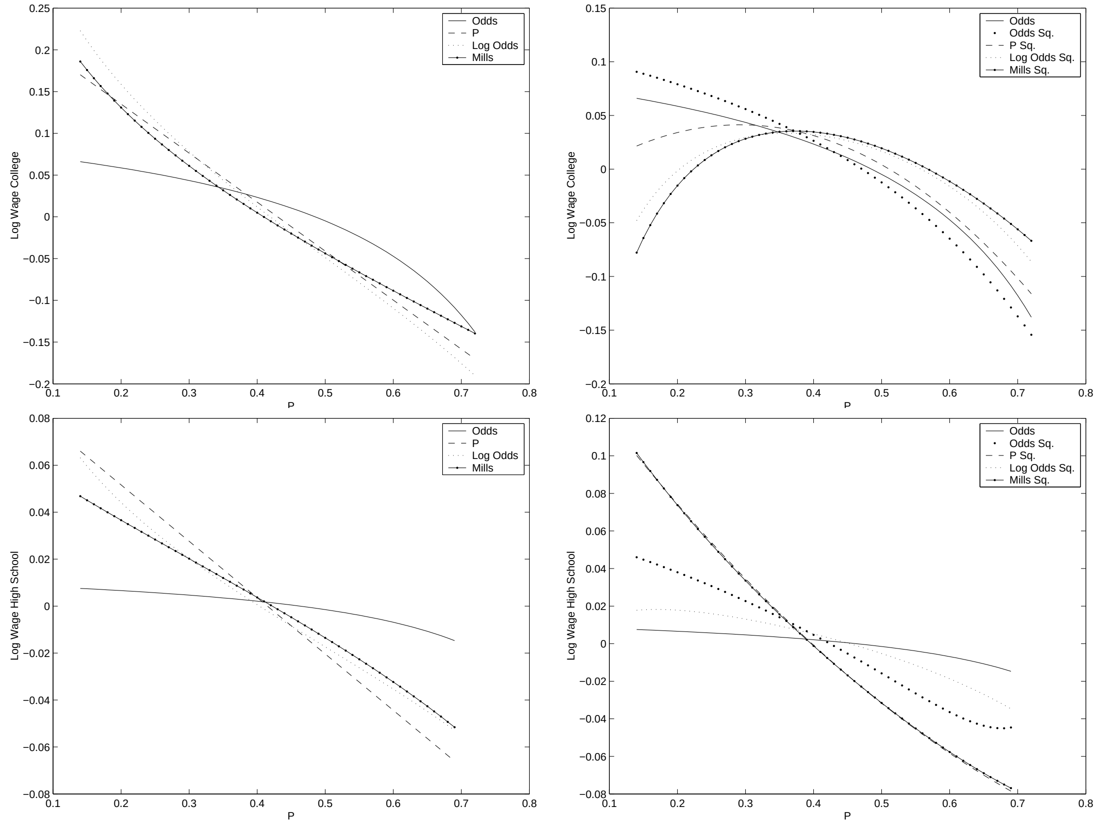
Notes: This figure shows quality-adjusted and unadjusted college and age premia.

Figure 5: Changes in the Relative Composition and Relative Labor Supply



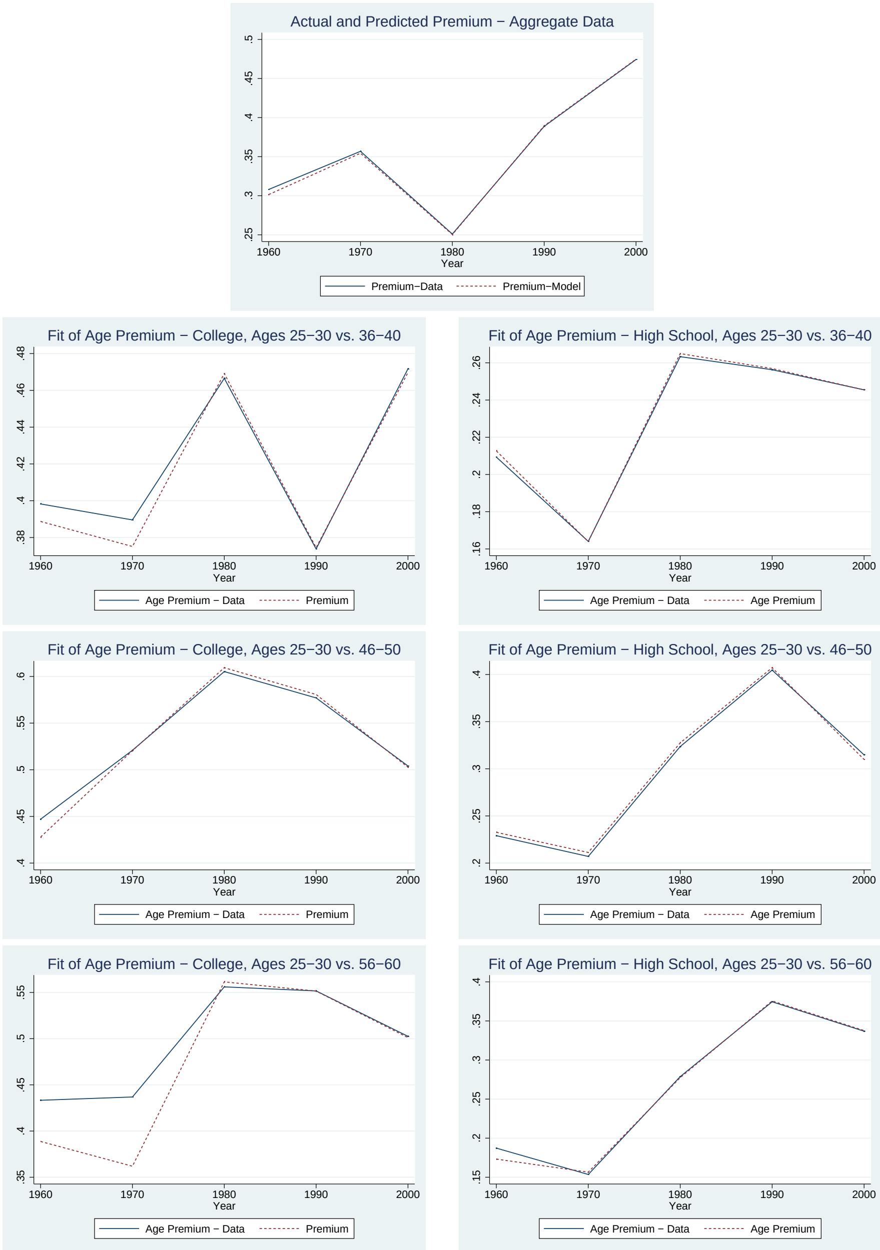
Notes: The top left panel of the figure shows changes in proportion in college and their relative ratio for age groups 25-30 and 36-40. The middle and bottom left panels, respectively, show corresponding lines for older age groups 46-50 and 56-60 along with the baseline young age group, 25-30. The three 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.

Figure A.6: Alternative Specifications of ϕ_k in the Reduced-Form Model



Notes: The top-panel of the figure shows alternative specifications of ϕ_C for log college wages in the reduced-form model of equation (5). In particular, the alternative forms of ϕ_C are as follows: linear in $P/(1-P)$, P, $\log P/(1-P)$, or $\phi(\Phi^{-1}(P))/P$ (the inverse Mills ratio based on the normality assumption) and also linear and quadratic in each of these variables, where P is the birth-cohort/region-of-birth specific college enrollment rates. The bottom-panel shows alternative specifications of ϕ_H for log high-school wages in the reduced-form model. The alternative forms of ϕ_H are the same as the college equation except that the inverse Mills ratio for high school is now $\phi(\Phi^{-1}(P))/(1-P)$. In the college equation, all the p-values for the hypothesis that ϕ_C is significantly different from zero are less than or equal to 0.03, except for the case of a linear inverse Mills ratio (with a p-value of 0.12). In the high school equation, the smallest p-value across all specifications is 0.31.

Figure A.7: The Fit of the Reduced Form Model



Notes: This figure compares data with the fit of model based on column (1) of Table 1. The top panel shows the fit of the college premium and the three left-side panels and the three right-hand side panels show the fit of the college age premia and the high school age premia, respectively.