
Pedro Carneiro and Sokbae Lee*
University College London, Institute for Fiscal Studies
and Centre for Microdata Methods and Practice
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Abstract

This paper presents new evidence that increases in college enrollment lead to a decline in the quality of college graduates between 1960 and 2000, resulting in a decrease of 9 percentage points in the college premium. A standard demand and supply framework can qualitatively account for the trend in the college and age premia over this period, but the quantitative adjustments that need to be made are substantial. 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.

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1 Introduction

A recent study of adult literacy in the US shows that, in 1992, 40 percent of college graduates were proficient in terms of “prose literacy” (meaning that they were able to read lengthy, complex English texts and draw complicated inferences), whereas in 2003, only 31 percent of the graduates demonstrated an equivalent level of literacy (Kutner et al., 2007). Among adults with graduate study or a graduate degree, there was an analogous decline from 51% in 1992 to 41% in 2003. Reporting on this study, the Washington Post wrote:

“Literacy experts and educators say they are stunned by the results of a recent adult literacy assessment, which shows that the reading proficiency of college graduates has declined in the past decade, with no obvious explanation.”(Lois Romano, Washington Post, December 25, 2005)

In reality, some sort of decline was expected simply because college enrollment grows over time. In 1992, 19% of the adults in the literacy survey had a college degree or above, while by 2003 an additional 4% of presumably lower ability adults had completed college. More generally, an even larger decline in the quality of college workers may have occurred during the second half of the twentieth century: whereas in the past college participation was reserved to the elite, present access to college is much more generalized (the percentage of white males aged 25 to 60 with some college or more doubled from 28% in 1960 to 58% in 2000).

The central empirical question of this paper is the following: how do changes in quality affect the trend in inequality, in particular the trend in the college premium, and what is their magnitude? The question arises because the college premium is usually measured by taking the difference between the average wages of college and high school graduates in each year. If the average quality of the individuals in each group is changing over time then the college premium cannot be compared across different periods, because it refers to different populations. Understanding the role of changes in quality for the college premium is central not only to the study of inequality, but also to a number of heavily debated policy issues, such as: the impact of increases in schooling on

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1See Figure 3-1a of Kutner et al. (2007) for the source, which is based on the 1992 National Adult Literacy Survey (NALS) and the 2003 National Assessment of Adult Literacy (NAAL). The NALS and the NAAL are nationally representative assessments of English literacy among American adults aged 16 and older. The detailed information is available at the the National Center for Education Statistics (NCES) web page at: http://nces.ed.gov.

2In 1992, of the 19% college graduates or above, 9% had a graduate degree; in 2003 this happened for 11% of the 23% of college graduates or above. Therefore, we observe a 2% increase in college graduates (only) from 10% to 12%. In 1992, 40% of college graduates were proficient in terms of prose literacy. Under the (extreme) assumption that the additional 2% of college graduates were less than proficient in terms of adult literacy then the percentage of those achieving proficiency level in 2003 would be (10/12) × 0.40 + (2/12) × 0 ≈ 0.33, which could explain almost 80% of the decrease among college graduates.

3This is based on our calculation using a 1% extract of the Census data.
economic growth; the usefulness of expanding access to education (e.g., through a tuition subsidy) for pulling low-income families out of the cycle of poverty; or the discussion on the inadequateness of a “college-for-all” policy (e.g., Rosenbaum [2001]).

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 affected 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 intrinsically unobserved.

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 our identification strategy uses regional variation in wages. We start by assuming that all individuals working in the same regional labor market 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 differential composition in their region of origin. Therefore, by comparing (within labor market) wages of individuals born in regions with different fractions of college enrollment 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. This means that our relevant identifying variation comes from cohort variation in college enrollment.

This 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 are correlated with changes in schooling (see section 6), and we present evidence that this is unlikely to be driving our results. We also show that our results are robust to the inclusion of measures of school quality.

We find that the decline in the quality of college graduates between 1960 and 2000 lead to a decrease of 9 percentage points in the college premium. Given that the college premium grew by

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4Therefore, for most of the paper we use the terms quality and composition interchangeably. In Appendix A.4 we present direct evidence of the decline in the quality of college workers due to the increase in the proportion of college enrollment.
19 percentage points between these two years, this corresponds to a very large decrease in quality. We also show that even though the qualitative patterns of change of the college premium can be accounted for by a standard demand and supply framework (as emphasized by most of the literature on this topic (e.g., Katz and Murphy, 1992)), the quantitative adjustments that need to be made are substantial. Their relevance becomes especially salient when we reanalyze the problem studied in Card and Lemieux (2001), who observe that there is a large difference in the rise in the college premium during the 1980s between young and old workers, and attribute it to the differential behavior of the supply of skill between these two groups. Our results show instead that the role of prices has been overstated, and that changes in quality are as important as changes in prices to explain the phenomenon they document.

Much of the focus of the literature is on the college premium, but we devote similar attention to the age premium because, empirically, the two are equally important determinants of between-group inequality. Furthermore, the model of the labor market we develop (based on Card and Lemieux, 2001) is adequate to explain the evolution of these two parameters, and provides an unusually good fit for both of them. Our analysis of the age premium shows even more striking effects of quality than the analysis of the college premium, especially among college graduates. For this group, we can attribute most 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. The importance of quality changes in the average wage of high school graduates is, surprisingly, very small. 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 model, which is frequently used in the literature, provides a better description of the labor market than a single ability model (e.g., Willis and Rosen, 1979), and constitutes the basis of our framework.

Composition effects of the type we discuss are often thought to be unimportant in the empirical literature on the college premium and wage inequality, although their existence is well recognized. 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

5Their model is widely used in several modern analyses of the college premium in the US and abroad.

Carneiro and Lee (2007) use a completely different approach. They 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 for the evolution of college premium (Chay and Lee, 2000; Taber, 2001; Deschênes, 2006), and to the whole 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 than the ones we observe in the raw data, by exacerbating increases in the supply and attenuating 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 (for some recent analyses, see Heckman and Todd (2003), Chandra (2003), Neal (2004), Petrongolo and Olivetti (2006), Blundell et al. (2003), Blundell et al. (2007)).

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 Section 5 shows quality-adjusted trends in the college and age premia. Then results of a number of sensitivity checks are reported in Section 6. Finally, we conclude in Section 7.

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Footnotes:

1. Rosembaum (2003) presents an alternative analysis reporting larger effects.

2. As in most of the literature we take changes in supply, demand and composition as given. This is a limitation of the analysis, but one which we have nothing new to add. Card and Lemieux (2001) suggest that cohort size may be an important driver of the trend in college participation, while Fortin (2006) emphasizes also the role of tuition policy at the state level.
2 Econometric Framework

Section 2.1 begins with a simple description of wage determination that distinguishes composition effects from price effects, and gives rise to a robust reduced form framework for the detection of composition effects. Section 2.2 considers composition effects and price determination based on a model of the demand and supply for skilled labor.

2.1 A Simple Wage Structure

Take an individual $i$ with schooling level $S = k$, where $k = H, C$ (denoting high school and college). There are separate labor markets for high school and college workers (although the markets are interdependent) and there are two types of skills which are used specifically in each labor market (e.g. Willis and Rosen, 1979; Heckman and Sedlacek, 1985). Individual $i$ of age $a$ at time $t$ is born and goes to school in region $b$ and works in region $r$, which may or may not be equal to $b$. We assume that this individual’s wage ($W_{iatrb}^k$) can be written as:

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

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

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

where $w_{iatrb}^k = \log W_{iatrb}^k$, $\pi_{atr}^k = \Pi_{atr}^k$ and $u_{i,t-a,b}^k = \log U_{i,t-a,b}^k$.\(^{10}\)

Let $S_{i}^k$ denote a schooling indicator which takes value 1 if the level of schooling is $k$, and 0 otherwise. Also, let $A_{i,t,a}$ denote an age group indicator that takes value 1 if an individual belongs to age group $a$ in year $t$. $M_{iatrb}$ is a migration indicator that has value 1 if an individual who is born in region $b$ lives in region $r$ in year $t$. Define $\omega_{iatrb}^k = E [w_{iatrb}^k | S_{i}^k = 1, A_{i,t,a} = 1, M_{iatrb} = 1]$ and

\(^{10}\)Hoxby and Long (1999) show that at least 75% of individuals attend university in their state of residence.

\(^{10}\)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.
\[ \nu^k_{atrb} = E \left[ u^k_{i,t-a,b} \right] S^k_i = 1, A_{ita} = 1, M_{itrb} = 1 \]. It follows from \((2)\) that

\[ \omega^k_{atrb} = \pi^k_{atr} + \nu^k_{atrb}. \]  

(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 of the average quality of workers in the corresponding cell. Therefore, variation in log wages within each \((k, a, t, r)\) cell reflects variation in quality across individuals from different regions of birth \((b)\). This is the central idea in our identification strategy.

We start by modelling \(\pi^k_{atr}\) as flexibly as possible, using full interactions between age, time and region of residence dummies for each schooling group. This reduced-form specification is convenient to separate composition effects from price effects: once schooling, age, time, and region of residence are fully controlled for, the remaining variation in \(\omega^k_{atrb}\) must come from variation in \(\nu^k_{atrb}\).

Another advantage of this procedure is that, within labor market, differences in schooling across cells 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 \(\nu^k_{atrb}\) varies over cells because, as more people go to college, the average ability of college-goers may fall. Thus, our main variable of interest is the proportion of college-goers in cohort \(t-a\) born in region \(b\), denoted by \(P_{t-a,b}\).

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. In order to model underlying differences across regions of birth (such as school quality), we use 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) \(\times\) (time) interactions and (region of birth) \(\times\) (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 composition at the same rate, in which case our estimates would not be affected. This would mean that changes in selective migration are uncorrelated with changes in schooling. In Section 6, we argue and present evidence that in our basic specification (where we include a rich set of dummies as controls), the correlation between selective migration and schooling is likely to be small, and unimportant for our results.

Still, we implement different corrective procedures. One alternative to correcting for selective migration is to condition on migration probabilities as in Dahl (2002). Following Dahl (2002), we estimate first-best 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. A second alternative is to account for (region of birth)×(region of residence) interactions corresponding to (region of birth)×(region of residence) matches Heckman et al. (1996). We apply both procedures, but we use the former as our base case.

None of these corrections has a substantial impact on our estimates. We show that the main reason is that, in our basic empirical model, changes in migration can be argued to be orthogonal to changes in schooling. In section 6, we present evidence that changes in migration flows (reflecting the quantity of migration) and migration premia (reflecting the composition of migration) are basically 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, or only weakly correlated, especially after accounting for all control variables. 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

\[11\] Migration probabilities (computed as the proportion of individuals in each cohort, time period and region of birth, who work in each region of residence \( r \)) have identifying variation because we exclude (cohort)×(region of residence)×(region of birth) interactions from the wage equations (as in Dahl, 2002). This procedure is justified if movements in migration probabilities are caused by changes in the cost of migrating (implicit in these omitted interactions) which are independent of wages, or changes in the benefits of migrating which are orthogonal to changes in schooling because, say, they are unobserved at the time of the schooling decision (Meghir and Whitehouse (1994) show that we can interpret our procedure as instrumenting migration probabilities with the omitted interactions). Unfortunately we do not have in the Census variables that can serve as explicit exclusion restrictions.
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 Appendix A.1 we present a simple model of schooling (the supply of skill) and migration which rationalizes our procedure and helps clarify our assumptions.

In view of concerns raised above, in our basic model we specify $\nu_{atr}^k$ (average quality of workers in a cell) by

$$
\nu_{atr}^k = \gamma_{kab} + \gamma_{kth} + \phi_k(P_{t-a,b}) + \lambda_k(P_{M,atr}^k, P_{M,atr}^k),
$$

(4)

where $\gamma_{kab}$ and $\gamma_{kth}$ 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), $\phi_k$ is a function of $P_{t-a,b}$ (capturing the effect of composition), and $\lambda_k$ is a function of the proportion of individuals migrating from region $r$ to region $b$ ($P_{M,atr}^k$, what we call first-best migration probability), and the proportion of individuals working in the same region where they were born ($P_{M,atr}^k$, what we call staying probability). Dahl (2002) proposed to use the first-best migration probability (equivalently, observed migration probability), 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 on this assumption. Dahl (2002) also suggests that staying probabilities should be used as additional controls since non-migrants can be substantially different from migrants.\(^\text{12}\)

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

$$
\omega_{atr}^k = \gamma_{katr} + \gamma_{kab} + \gamma_{kth} + \phi_k(P_{t-a,b}) + \lambda_k(P_{M,atr}^k, P_{M,atr}^k)
$$

(5)

where $\gamma_{katr}$ are full interactions of age-time-region fixed effects. The functions $\phi_k(\cdot)$ and $\lambda_k(\cdot, \cdot)$ will be 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 attain-

\(^{12}\)In the sensitivity analysis reported in Section \(\text{II}\) we check the robustness of our main results without imposing index sufficiency (by conditioning on all possible migration probabilities).
ment change 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, which is also discussed in detail in Heckman et al. (1996). 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).

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. Our point of departure is the model in Card and Lemieux (2001), which we extend to account for composition effects and regional labor markets.

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

\[
Y_t = G_t(Y_{t1}, \ldots, Y_{tR}) = \sum_{r=1}^{R} Y_{tr},
\]

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 \( U^C_{tr} \) and \( U^H_{tr} \):

\[
Y_{tr} = F_{tr}(U^C_{tr}, U^H_{tr}).
\]

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

\[
U^k_{tr} = H^k_{tr}(U^k_{1tr}, \ldots, U^k_{Atr}),
\]

\[
U^k_{atr} = N^k_{atr} Q^k_{atr},
\]

where \( N^k_{atr} \) and \( Q^k_{atr} \) 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:

\[
Q_{atr}^k = \sum_{b=1}^R \frac{N_{atr}^k}{N_{atr}^k} E \left( U_{i,t-a,b}^k | S_{k}^i = 1, A_{ita} = 1, M_{strb} = 1 \right),
\]  

(9)

where \( N_{atr}^k \) 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). Note that \( E \left( U_{i,t-a,b}^k | S_{k}^i = 1, A_{ita} = 1, M_{strb} = 1 \right) \) is 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 \( b \) (what we call quality). 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 \( r \) that come from region of birth \( b \).

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

\[
\Pi_{atr}^k = \frac{\partial Y_t}{\partial U_{atr}^k} \equiv \frac{\partial G_{tr}}{\partial Y_{tr}} \frac{\partial F_{tr}}{\partial U_{tr}^k} \frac{\partial H_{tr}^k}{\partial U_{atr}^k},
\]

so that by taking logs:

\[
\pi_{atr}^k = \log \left[ \frac{\partial G_{tr}}{\partial Y_{tr}} \right] + \log \left[ \frac{\partial F_{tr}}{\partial U_{tr}^k} \right] + \log \left[ \frac{\partial H_{tr}^k}{\partial U_{atr}^k} \right],
\]  

(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).

Furthermore, as in Card and Lemieux (2001), assume that both the production function, and the high-school and college labor sub-aggregates have the constant elasticity of substitution (CES) form:

\[
Y_{tr} = \left[ \theta_{Htr} \left( U_{tr}^H \right)^\rho + \theta_{Ctr} \left( U_{tr}^C \right)^\rho \right]^{1/\rho} \quad \text{and} \quad U_{tr}^k = \left[ \sum_{a=1}^A \alpha_{kat} \left( U_{atr}^k \right)^{\eta_k} \right]^{1/\eta_k},
\]  

(11)

where \( \theta_{ktr} \) 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, $\alpha_{k\text{t}}$’s are time-varying, 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 $\xi_{k\text{at}} = \log \alpha_{k\text{at}}$. From equations (10) and (11) it follows that, in equilibrium:

$$\pi_{k\text{atr}}^k = \xi_{k\text{tr}} + \xi_{k\text{at}} + (\eta_k - 1) \left[ \log N_{k\text{atr}}^k + \log Q_{k\text{atr}}^k \right],$$

(12)

where $\xi_{k\text{tr}}$ is the (year)×(region of residence) fixed effect (corresponding to the first two terms in the right hand side of equation (10)), and $\xi_{k\text{at}}$ is the (possibly time-varying) age effect for each schooling group $k = H, C$. Equation (12) states that skill prices, $\pi_{k\text{atr}}^k$, can be expressed as a separable function of a time varying region-of-residence effect ($\xi_{k\text{tr}}$), a time varying age effect ($\xi_{k\text{at}}$), and the quality-adjusted log supply of labor of schooling level $k$ ($\log (N_{k\text{atr}}^k Q_{k\text{atr}}^k)$). This implies that skill prices can change as quality ($Q_{k\text{atr}}^k$) varies, even if labor supply ($N_{k\text{atr}}^k$) was 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.

In order to estimate wage equations based on (12), it is necessary to have data on $Q_{k\text{atr}}^k$, which is unobserved. To overcome this problem, re-write (9) as

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

(14)

where

$$\tilde{Q}_{k\text{atr}}^k = \sum_{b=1}^R \frac{N_{k\text{atr}}^b}{N_{k\text{atr}}^r} E \left( U_{i,t-a,b}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1 \right) \bigg|_{b=r}. \quad (13)$$

In words, we normalize $Q_{k\text{atr}}^k$ by the quality of the group of workers who were born in region $r$, and we call this quantity $\tilde{Q}_{k\text{atr}}^k$. Notice that workers living in the same region face the same skill prices.

Then, based on the wage structure assumed in (1), we use the fact that relative quality across

\footnotetext[13]{$\alpha_{k\text{at}}$ are time invariant parameters in \cite{Card and Lemieux 2001} ($\alpha_{k\text{at}} = \alpha_{k\text{t}}$ for all $t$). However, allowing them to be affected by a trend means that technological change can affect the relative demand for older workers, as well as the relative demand for college graduates ($\theta_{k\text{tr}}$), so that the two are treated symmetrically. Similarly, $\rho$ and $\eta_k$ are both assumed to be time invariant. Another reason to allow $\alpha_{k\text{at}}$ to be time varying is that it improves the fit of the model. It is especially useful to help the model fit the age premium, and the change in the college premium in the 1990s.

\footnotetext[14]{The exact form of $\xi_{k\text{tr}}$ is as follows:

$$\xi_{k\text{tr}} = (1 - \rho) \log Y_{i\text{tr}} + \log \theta_{k\text{tr}} + (\rho - \eta_k) \log U_{k\text{tr}}.$$}
different groups of individuals in the same labor market is proportional to their relative wages:

\[
\frac{E(U_{i,t-a,b}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1)}{E(U_{i,t-a,b}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1)} = \frac{E(W_{itarb}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1)}{E(W_{itarb}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1)}
\]

Therefore,

\[
\tilde{Q}_{atr}^k = \sum_{b=1}^{R} N_{atr}^k \frac{E(W_{itarb}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1)}{E(W_{itarb}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1)} b = r,
\]

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

To complete the description of \(Q_{atr}^k\) in (14), suppose that

\[
E(U_{i,t-a,b}^k | S_i^k = 1, A_{ita} = 1, M_{itrb} = 1) = \exp \left[ \Gamma_{kb} + \Phi_k(P_{l-a,b}) + \Lambda_k(P_{M,atrb}^k, P_{M,atrr}^k) \right],
\]

where \(\Gamma_{kb}\) is region-of-birth fixed effects, \(\Phi_k\) is a function of \(P_{l-a,b}\) (composition), and \(\Lambda_k\) is a function of \(P_{M,atrb}^k\) and \(P_{M,atrr}^k\) (migration). The exponential function is used to ensure that the conditional expectation on the left-hand side of (15) is always positive. The underlying assumption behind (15) is the same as in (4): the average quality of workers can differ because of region-of-birth fixed effects, differences in composition captured by \(P_{l-a,b}\), and selective migration. Finally:

\[
Q_{atr}^k = \tilde{Q}_{atr}^k \exp \left[ \Gamma_{kb} + \Phi_k(P_{l-a,b}) + \Lambda_k(P_{M,atrb}^k, P_{M,atrr}^k) \right] b = r.
\]

Using this expression of \(Q_{atr}^k\), one can estimate a model of the demand for skill based on (12).

Putting (3), (1), (12) and (16) together we can estimate \(\eta_k\) and \(\phi_k\) \((P_{l-a,b})\) (as well as \(\alpha_{kat}\) and \(\Phi_k(P_{l-a,r})\)) from the following model:

\[
\omega_{atrb}^k = \xi_{kat} + \xi_{atr} + (\eta_k - 1) \log N_{atr}^k + (\eta_k - 1) \log \tilde{Q}_{atr}^k + \\
+ (\eta_k - 1) \left[ \Gamma_{kb} + \Phi_k(P_{l-a,b}) + \Lambda_k(P_{M,atrb}^k, P_{M,atrr}^k) \right] b = r \\
+ \gamma_{kat} + \gamma_{atr} + \phi_k(P_{l-a,b}) + \lambda_k(P_{M,atrb}^k, P_{M,atrr}^k)
\]

We are still left with the estimation of \(\rho\), which is subsumed in \(\xi_{kat}\) (see equation (13)). The parameter \(\rho\) can be estimated in a second-stage procedure with estimates of \(\eta_k\), \(\alpha_{kat}\), \(\Phi_k\), and \(\phi_k\) as inputs to the second-stage estimation. The detailed description of estimation of \(\rho\) can be found in Appendix A.2 After we estimate all the parameters of the model we can decompose observed
trends in the college and age premia into changes in demand, changes in supply, and changes in composition.

3 Data

We use data from the 1960, 1970, 1980, 1990 and 2000 US Censuses (1% sample). We focus on whites, 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, 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 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 and females 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 and females with some college, a college degree, or post-graduate studies. The reason for considering females as well as

15Our data was extracted from http://www.ipums.umn.edu/ (see Ruggles et al., 2004)
16We 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.
17Notice 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.
other schooling categories is that we would like to have, as much as possible, a measure of the relevant labor supply affecting college and high school prices in each market.

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 in each year. 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 at which level we have variation in 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 working in the same region of residence). Composition varies across schooling-year-age-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 1: Description of Data

![Regional Trends in the College Premium](image1)

![Regional Trends in the College Age Premium](image2)

![Regional Trends in the High School Age Premium](image3)

![Regional Trends in the Proportion Going to College](image4)

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

Figure 1 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. This choice of age groups is arbitrary, but also largely unimportant for the analysis. 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.  

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 very different regions.

## 4 Empirical Results

Table 1 reports estimation results that are obtained by implementing the econometric framework described in Section 2. All regressions in the table are weighted by the inverse of the sampling variance of average log wages in each cell.

In column (1) of Table 1 we estimate the reduced-form model of equation (5). In this model, $\pi_{tar}^k$ 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. Therefore, 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 $\phi_k$ is linear in the odds of proportion in college ($\tilde{P}_{t-a,b} \equiv P_{t-a,b}/(1 - P_{t-a,b})$). 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 from 0 to $\infty$). In addition, $\lambda_k$ in (5) is modelled as a second-order expansion of migration probabilities: that is, linear and quadratic terms of $P_{M,atrb}^k$ and $P_{M,attr}^k$ and their interaction term. All the regressions include region of birth dummies interacted with year and age (separately).

Column (1) of Table 1 shows that the coefficient on $\tilde{P}_{t-a,b}$ is significantly negative and quanti-
Table 1: Regression of Wages on Labor Supply and the Odds of Proportion in College

<table>
<thead>
<tr>
<th></th>
<th>(1) Reduced-Form Model (Controlling for Quality)</th>
<th>(2) Supply-Demand Model (Controlling for Quality)</th>
<th>(3) Supply-Demand Model (Without Controlling for Quality)</th>
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</thead>
<tbody>
<tr>
<td>Panel A - College</td>
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<tr>
<td>Odds of Proportion in College</td>
<td>-0.084 [0.022]**</td>
<td>-0.095 [0.019]**</td>
<td>-0.168 [0.016]**</td>
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<tr>
<td>Quality-Adjusted Log Weeks</td>
<td>-0.075 [0.022]**</td>
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<tr>
<td>Panel B - High School</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Odds of Proportion in College</td>
<td>-0.008 [0.017]</td>
<td>-0.012 [0.015]</td>
<td>-0.137 [0.011]**</td>
</tr>
<tr>
<td>Quality-Adjusted Log Weeks</td>
<td>-0.139 [0.011]**</td>
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<tr>
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<tr>
<td>Observations</td>
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</tr>
</tbody>
</table>

Included Explanatory Variables

- (Year)×(Age)×(Region of Residence)
- (Year)×(Region of Residence)
- (Age)×(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)
- (First-Best Migration Probability)
- (First-Best Migration Probability)$^2$
- (Staying Probability)
- (Staying Probability)$^2$
- (First-Best 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. Standard errors in brackets. * significant at 5%; ** significant at 1%.
tatively large for the college equation 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% ($\hat{P}_{t-a,b}$ increases from 1 to 1.5) average college wages decline by 4%. 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, it may be that the skills that determine selection into college are less valued in high school type occupations than in college type occupations. This is possible in the model of the labor market is one in which there are two or more type of skill, as opposed 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 $E(w^C_t|S^C = 1) - E(w^H_t|S^H = 1)$, 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 $\hat{P}_{t-a,b}$ in the college and high school equations. In column (1) of Table 1 this difference is equal to -0.076. This implies that the college premium would decline by 3.8% if college enrollment went from 50% to 60%.

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, 2007). Our results indicate that: i) skill heterogeneity and self selection into schooling are important phenomena, so that if college enrollment went from 50% to 60%, the average marginal student’s quality would be 25% lower than that of the average student in college; ii) those individuals with

\[^{19}\text{We focus on college participation instead of college graduation to construct supply and quality variables to be consistent with the literature. If instead of the proportion of college participation we use the proportion of college graduates to construct the odds variable the coefficient becomes -0.3159 with a standard error of 0.1368. This result is qualitatively consistent with the result reported in column (1) of Table 1.}\]

\[^{20}\text{If college enrollment increases from 50% to 60% then there is a 20% increase in the number of college graduates. From our estimates, we know that this leads to a decrease in the average wages of college graduates. Let } w_1 \text{ be the average log wage of the average students, and } w_2 \text{ be the average log wage of the marginal student. Since the marginal students are equal to 17% (=10/60) of the total college population after expansion:}\]

\[0.83w_1 + 0.17w_2 = w_1 - (0.084 \times 0.5).\]
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 schooling.

One 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. A second implication is that education
policies that expand college participation will draw into college marginal students who are of
substantial lower quality than the existing college students. This fact needs to be taken into
account when evaluating such policies.

In column (2) of Table [1] we estimate a supply-demand model where \( \pi^k_{tar} \) is modelled explicitly
as in (17). For comparison, in column (3) of Table [1] we estimate a model without \( \log Q^k_{atr} \) in (12)
(we set \( \phi_k (P_{l-a,b}) \) to zero for all values of \( P_{l-a,b} \)). 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 \( \xi_{kat} \) is
modelled as an interaction of a quadratic time trend with age specific dummies for each schooling
group[21]. In column (2), \( \Phi_k \) in (16) is assumed to be linear in the odds of proportion in college. It
is not necessary to specify the term \( \Lambda_k \) separately because when \( b = r \), \( \Lambda_k \) is only a function of
\( P_{M,atr} \) and can be absorbed into \( \lambda_k \) in (4).

In column (2), we can see that the coefficients on \( \tilde{P}_{l-a,b} \) 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 -0.083, which is similar -0.076 in column (1). Thus, our
estimation results are robust to alternative models for \( \pi^k_{tar} \). In the college equation, the coefficient
for the quality-adjusted log weeks (\( \eta_C - 1 \)) in (12) is -0.075, which implies that the elasticity of
substitution between workers of different ages in college is \( \sigma_C = 1/(1 - \eta_C) = 1/0.075 \approx 13.3 
In the high school equation, the corresponding coefficient (\( \eta_H - 1 \)) is -0.139 and, therefore, the
elasticity of substitution is about 7.19. Thus, our estimates indicate that different age groups are
closer substitutes in college than in high school (equivalently, high school wages are more sensitive
to labor supply than college wages).

Looking at column (3), we see that the coefficients for (quality-unadjusted) log wages in college
and high school are -0.168 and -0.137, respectively, implying that the elasticities of substitution are

This implies that:

\[ w_2 = w_1 - 0.25. \]

[21] We have chosen this specification instead of a more flexible one because unrestricted interactions between age
and time dummies lead to imprecise coefficients in quality-adjusted and unadjusted log weeks in columns (2) and
(3), respectively.
about 5.95 and 7.30 in college and high school, respectively. Hence, failing to adjust for changes in the quality of labor supply has a dramatic effect on our estimate of the elasticity of substitution across age groups in college ($\sigma_C$). Fluctuations in the amount 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.

Our estimates in column (3) are comparable to those in Card and Lemieux (2001), although they are slightly lower. As in their paper, estimates of $\eta_C$ and $\eta_H$ are similar to each other. The difference between these two parameters only emerges after we account for composition effects, as in column (2). It is reassuring that our estimates in column (3) are similar to those in the literature, and it is striking how accounting for composition makes so much of a difference for these parameters.

Table 2 shows estimates of $\rho$ with alternative specifications for the trend in demand, $\log (\theta_{Ctr}/\theta_{Htr})$ in (A.3). In all columns, $\rho$ is estimated in the second-stage using the coefficients reported in column (2) of Table 1 (as well as other coefficients not reported but estimated from the same specification) as inputs to the second-stage estimation. All regressions are weighted by the inverse of the sampling variance of the college premium in each cell.

### Table 2: Estimation Results of $\rho$

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<td>$\rho$</td>
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<td>0.845</td>
<td>0.815</td>
<td>0.959</td>
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<td></td>
<td>[0.087]**</td>
<td>[0.130]**</td>
<td>[0.087]**</td>
<td>[0.108]**</td>
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Specification of Trends in Demand

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<td>Unrestricted Trend - Four Regions</td>
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Notes: The table shows estimation results of $\rho$ with alternative specifications on trends in demand, using (A.3). In all columns, $\rho$ is estimated in the second-stage with estimates from column (2) of Table 1 as inputs to the second-stage estimation. All regressions are weighted by the inverse of the sampling variance of the college premium in each cell. Standard errors in brackets. * significant at 5%; ** significant at 1%.
In column (1), the trend in demand is modelled using unrestricted time dummies that are common across regions and in column (2), the trends are allowed to be different across four aggregate regions. If we use the estimate in column (1), the implied elasticity of substitution between college and high school graduates is \( \sigma = \frac{1}{1 - \rho} \approx 6.45 \). If we use the estimate in column (2), then the elasticity is about 2.75. In columns (3)-(5), we consider several versions of linear trends. Estimated coefficients in columns (3)-(4) are similar to that in column (1) and the estimate in column (5) is somewhat larger.

Among these specifications of trends in demand, we prefer the second specification since it seems that linear trends may be too restrictive (in the models of columns (1) and (2) we reject that the trend is linear), and it is also plausible that aggregate regions have different trends. This specification allows us to depart from the linear trend assumption which is standard in the literature, without forcing all regions in the US to face the same trend. Using our preferred model, the estimate of the elasticity of substitution between college and high school graduates is higher than the corresponding number in Katz and Murphy (1992) (who estimate this elasticity to be 1.41), and similar to the estimate in Card and Lemieux (2001) (which is between 2 and 2.5).

5 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. The age premium for each schooling \( k \), denoted by \( AP^k_t \), is defined as the difference between average log wages of those in age group 51-55 and those in age group 31-35. Formally:

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

\[
AP^k_t = \sum_{r=1}^{R} \sum_{b=1}^{B} \omega_{atrb} f_t^k(a, r, b) \bigg|_{a=51-55} - \sum_{r=1}^{R} \sum_{b=1}^{B} \omega_{atrb} f_t^k(a, r, b) \bigg|_{a=31-35},
\]

The four regions are as follows: the first one includes New England and Middle Atlantic, the second includes East North Central and West North Central, the third includes South Atlantic, East South Central and West South Central, and the fourth includes Mountain and Pacific.
where \( f^k_t(a, r, b) \) is the proportion of individuals in cell \((a, r, b)\) for each schooling group \( k \) and time \( t \).

In order to define quality-adjusted college and age premia recall that average log wages for each cell have the form

\[
\omega^k_{atrb} = \pi^k_{atrb} + \gamma_{kab} + \gamma_{ktb} + \phi_k(P_{-a,b}) + \lambda_k(P^k_{M,atrb}, P^k_{M,atrr}).
\]

(19)

We fix the proportion in college \( P_{-a,b} \) at the 1960 level and regard the corresponding average log wages as quality-fixed average log wages:

\[
\omega^{k,Q}_{atrb} = \pi^k_{atrb} + \gamma_{kab} + \gamma_{ktb} + \phi_k(P_{1960-a,b}) + \lambda_k(P^k_{M,atrb}, P^k_{M,atrr}).
\]

(20)

Then quality-adjusted college and age premia are defined as in (18), after substituting \( \omega^{k,Q}_{atrb} \) for \( \omega^k_{atrb} \):

\[
CP^Q_t = \sum_{a=1}^{A} \sum_{r=1}^{R} \sum_{b=1}^{R} \omega^{C,Q}_{atrb} f^C_t (a, r, b) - \sum_{a=1}^{A} \sum_{r=1}^{R} \sum_{b=1}^{R} \omega^{H,Q}_{atrb} f^H_t (a, r, b) \quad \text{and}
\]

\[
AP^k,Q_t = \sum_{r=1}^{R} \sum_{b=1}^{R} \omega^{k,Q}_{atrb} f^k_t (a, r, b) \bigg|_{a=51-55} - \sum_{r=1}^{R} \sum_{b=1}^{R} \omega^{k,Q}_{atrb} f^k_t (a, r, b) \bigg|_{a=31-35},
\]

(21)

where \( \omega^{k,Q}_{atrb} \) 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 \( \omega^{k,Q}_{atrb} \) over time is purely due to changes in prices, which are caused by fluctuations in the demand and supply of skill. \( \omega^{k,Q}_{atrb} \) 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 \( \omega^{k,Q}_{atrb} \) is still affected by selection. This happens because the level at which we fix quality of type \( k \) is that of the average worker who self-selected into schooling level \( k \) in 1960, who is not a random worker in the economy. Therefore, the difference between \( \omega^k_{atrb} \) and \( \omega^{k,Q}_{atrb} \) is that, while selection is time varying for the former, it is fixed for the latter at 1960 levels (so that \( \omega^k_{\text{a1960rb}} = \omega^{k,Q}_{\text{a1960rb}} \)). In this paper we do not intend to estimate measures of \( \omega^k_{atrb} \), 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 cannot purge the level \( \omega^k_{atrb} \) 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. \(^{23}\)

Before we present any of our decompositions it is important to comment on the fit of the model. If the fit is poor, then our exercise would be unsatisfactory. In the appendix (see figure A.5) we show that the 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. Therefore, we are able to explain fully the trend in these parameters as functions of changes in supply, demand, and composition.

Figure 2: Quality-Adjusted College and Age Premia

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

Figure 2 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 particular, the solid lines in each panel correspond to \( CP_t \), \( AP^C_t \) and \( AP^H_t \) in (18), while the dashed lines correspond to \( CP^Q_t \), \( AP^{C,Q}_t \) and \( AP^{H,Q}_t \) in (21). The top-left panel of the figure shows that the college premium increased by 17% between 1960 and 2000, but the quality \(^{23}\)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 \( \omega_{kt-b}^{k-Q} \) as being free of selection. Therefore, even though we cannot identify the level of the average return to schooling in each period, we can identify its trend over time.
adjusted college premium increased by 26%\(^{24}\). The difference, which is shown in the top-right panel, is substantial, and it is due to the large increase in college enrollment during this period, shown before in figure 1 and also in the top-right panel as well. Furthermore, decreases in quality are responsible for a 3% increase in the college premium in the 1970s, but they only dampen the subsequent increase in this parameter in the 1980s and 1990s by 1 to 2 percentage points (which is still a considerable amount considering that the college premium grew little over 20% over this period). The reason is that the growth in college attainment slows down dramatically after the 1980s.

The bottom-left panel shows a dramatic difference between adjusted and unadjusted trends in the age premium in the college sector. If we look at the unadjusted trends, then there is a decrease in the age premium of 14% from 1980 to 2000. On the other hand, the quality-adjusted trends show a decrease of only 4%. This suggests that from 1980 to 2000, the quality of college workers in age group 51-55 declined substantially relative to that of those in age group 31-35. The bottom-right panel shows that there is virtually no quality change over time in the age premium in the high school sector. This is because composition plays little role (if any at all) in explaining high school wages.

We now consider the effects of demand and supply through prices, as well as the effect of composition. Define the supply effects by \( S_{atr}^k = (\eta - 1) \left[ \log N_{atr}^k + \log Q_{atr}^k \right] \)\(^{25}\). Rewriting (17) we have:

\[
\omega_{atr}^k = \xi_{atr} + \xi_{kat} + S_{atr}^k + \gamma_{kab} + \gamma_{ktb} + \phi_k(P_{1960-a,b}) + \lambda_k(P_{M,atr}, P_{M,atrr}).
\]

As in (20), one can define composition-fixed average log wages using (19):

\[
\omega_{atr}^{k,Q'} = \xi_{atr} + \xi_{kat} + S_{atr}^k + \gamma_{kab} + \gamma_{ktb} + \phi_k(P_{1960-a,b}) + \lambda_k(P_{M,atr}, P_{M,atrr}).
\]

Then composition-fixed college and age premia are defined as those defined in (18) with substituting \( \omega_{atr}^{k,Q'} \) for \( \omega_{atr}^k \). These premia are based on the demand and supply model in (12) and should be comparable to those obtained using (20).

\(^{24}\)In the figure, the lines are based on fitted values from the reduced-form model, i.e. column (1) of Table 1.

\(^{25}\)More specifically, one can decompose the supply effect into two separate effects: \((\eta_k - 1) \log N_{atr}^k\) measures the change in prices due to movements in the supply of labor to the market and \((\eta_k - 1) \log Q_{atr}^k\) captures the change in prices due to movements in the quality of labor.
We can also fix the quality-adjusted labor supply at the 1960 level:

\[ \omega_{atrb}^{k,S} = \xi_{ktr} + \xi_{kat} + S_{a,1960,r}^k + \gamma_{kab} + \gamma_{ktb} + \phi_k(P_{1-a,b}) + \lambda_k(P_{M,atrb}^k, P_{M,atrr}^k), \]

where \( S_{a,1960,r} = (\eta_k - 1) [\log N_{a1960}^k + \log Q_{a1960}^k] \). Then supply-fixed college and age premia are defined as those in (18) after substituting \( \omega_{atrb}^{k,S} \) for \( \omega_{atrb}^k \). Variation in \( \omega_{atrb}^{k,S} \) is driven by both changes in worker quality, and changes in prices induced only by fluctuations in demand. Again, \( \omega_{atrb}^{k,S} \) is an abstract construct, since in principle movements in worker quality cannot exist independently of movements in supply.

In addition, we can also fix both the quality-adjusted labor supply and proportion in college at the 1960 level:

\[ \omega_{atrb}^{k,D} = \xi_{ktr} + \xi_{kat} + S_{a,1960,r}^k + \gamma_{kab} + \gamma_{ktb} + \phi_k(P_{1960-a,b}) + \lambda_k(P_{M,atrb}^k, P_{M,atrr}^k). \]

Then composition-and-supply-fixed college and age premia can be obtained by substituting \( \omega_{atrb}^{k,D} \) for \( \omega_{atrb}^k \) in (18). We interpret variation in \( \omega_{atrb}^{k,D} \) as changes in the demand for college skill since quality is kept fixed so that all variation in wages is driven by movements in prices; since supply is kept fixed, all movements in prices are driven by fluctuations in demand.

Figure 3 shows unadjusted, composition-fixed, supply-fixed, and composition-and-supply-fixed college and age premia using the estimation results reported in column (2) of Table 1. As mentioned above, the effect of composition on the trend in the college premium is substantial, but the effect of supply changes is much more important. Were supply kept fixed the college premium would have increased by 60% (instead of the 19% observed in the data), and there would have been no decline of this parameter in the 1970s. Finally, the trend in demand is shown to drive much of the trend in the observed college premium: it increases in the 1960s, slows down in the 1970s, accelerates in the 1980s, slows down again the 1990s. Estimated trends are similar across the four large regions we consider (detailed results are not shown here). We have performed a test of the null hypothesis that the trend in demand is linear and have rejected it at any conventional level.

Our estimates of demand trends are new in the literature. The view on demand explanations for fluctuations in the college premium is often simplistic because demand trends are generally linear

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\(^{26}\) Notice that it includes \( \xi_{ktr} + \xi_{kat} \), which we would generally call changes in demand, as well as \( \gamma_{kab} + \gamma_{ktb} + \lambda_k(P_{M,atrb}^k, P_{M,atrr}^k) \), which represent changes in region of birth quality and in selective migration. The latter terms are empirically unimportant, and therefore changes in \( \omega_{atrb}^{k,D} \) are approximately equal to changes in \( \xi_{ktr} + \xi_{kat} \).
Notes: This figure shows unadjusted, composition-fixed, supply-fixed, and composition-and-supply fixed trends of college and age premia.
by assumption, rather than as a result of estimation (without imposing the linearity). Under our alternative set of assumptions (stability of demand trends within each of four aggregate regions) we can identify fluctuations in demands. It is quite interesting and reasonable that our estimates show a slowdown in the growth of demand in the 1970s, possibly a reflection of the oil shocks of that decade. The slowdown observed in the 1990s (and also reported in Autor et al., 2007) is not as dramatic.

The second panel of figure 3 presents a dramatic difference between adjusted and unadjusted trends in the age premium in the college sector. It shows that the unadjusted and supply-fixed age premia are quite similar but that the unadjusted and composition-fixed age premia are very different, as in Figure 2. This reflects the fact that different age groups are highly substitutable in the college sector, but at the same time composition effects are very strong. In other words, movements in the supply of college graduates are more likely to result in changes in worker quality than in changes in prices. Therefore, the large increase in the age premium from 1970 to 1980 and the large drop from 1980 to 2000 are due to a relative increase in the quality of old college workers from 1970 to 1980, and a relative decrease from 1980 to 2000. We can explain most of the fluctuations in the college age premium as a combination of an increase in the demand trend and changes in composition, with a fairly limited role played by supply.

The third panel shows the decomposition of the age premium in the high school sector. As in Figure 2, fixing composition makes almost no difference. It is changes in supply and demand that drive much of the trend in the age premium in high school. Supply fluctuations are relatively more important in high school and in college not only because the composition effect is large in college and negligible in high school, but also because different age groups are closer substitutes in college than in high school, as we have reported in Section 4.

It is also striking that the trend in the demand for older workers is increasing for both high school and college occupations, and almost at the same rate, but that the age premium for each schooling group displays such different patterns. What explains most of the differences in the fluctuations in the age premium across the two groups are not differences in demand trends, but differences in supply and composition.

What remains to be shown is the set of changes in supply and composition across age groups.

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27Theoretically, the degree of substitutability between workers in different age groups could be either higher or lower in either one of the schooling groups we consider. The accumulation of job specific skills may well be more tied to experience in high school than in college occupations, making high school workers less substitutable across age groups than college workers.
that drive the results we just discussed. Figure 4 shows us the main drivers of composition and supply effects in the age premium. The left panel of figure Figure 4 shows 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 increased relatively (with respect to young college workers) from 1970 to 1980 and decreased relatively from 1980 to 2000. It is also clear from the figure that changes in quality cannot possibly explain fluctuations in the age premium in high school.

Figure 4: Changes in the Relative Composition and Relative Labor Supply

![Graph showing changes in proportion in college and relative log weeks for age 31-35 and age 51-55.]

Notes: This figure shows changes in proportion in college and relative log weeks for age 31-35 and age 51-55.

The right panel of the figure shows the labor supply of old workers relative to young workers for both college and high school (measured in log weeks worked in each year). Notice how changes in the relative supply of old and young high school workers mimic the changes in the high school age premium shown in Figure 3. Notice also that the relative stagnation in the relative supply of older college workers in the 1960s and 1980s cannot explain the substantial changes in the college age premium observed in these decades. Changes in composition provide a better candidate explanation.

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

In this subsection, 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
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 3: Changes in the College Premium between Young and Old Workers

<table>
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<tr>
<th></th>
<th>(1) Changes from 1980 to 1990</th>
<th>(2) Changes from 1990 to 2000</th>
</tr>
</thead>
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<tr>
<td>Age Group: 25 - 30</td>
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<td></td>
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<tr>
<td>Raw College Premium</td>
<td>0.167</td>
<td>0.068</td>
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<td>Composition-Fixed College Premium</td>
<td>0.145</td>
<td>0.099</td>
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<td>Proportion in College</td>
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<tr>
<td>Age Group: 45 - 60</td>
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<tr>
<td>Raw College Premium</td>
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<td>Composition-Fixed College Premium</td>
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<td>0.093</td>
</tr>
<tr>
<td>Proportion in College</td>
<td>0.114</td>
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<tr>
<td>Differences between Two Age Groups</td>
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<td></td>
</tr>
<tr>
<td>Raw College Premium</td>
<td>0.110</td>
<td>0.029</td>
</tr>
<tr>
<td>Composition-Fixed College Premium</td>
<td>0.057</td>
<td>0.006</td>
</tr>
</tbody>
</table>

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 3 summarizes our analysis. In column (1), changes from 1980 to 1990 in the raw college premium (data), composition-fixed (or quality-fixed) college premium, and proportion in college for two age groups that are the same as those considered in Card and Lemieux (2001). The difference in the growth in the raw college premium between those aged 25-60 and those aged 45 - 60 is 11%, 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 the difference if the quality of both age groups of workers were fixed? According to our estimates, the difference would be just 5.7%. 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. One interesting observation is that in column (2), the quality-fixed college premium for young workers is higher than the raw premium. This is due to the fact that the proportion in college increased over this period, thereby the declining quality of young college workers as well as old college workers.
6 Sensitivity Analysis

The main purpose of this section is 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 the following controls (on top of migration flows, which we ignore for now): year × age × region of residence, year × region of birth, and age × region of birth. 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 certainly a possibility, but the question is whether this is an empirically important phenomenon.

In our search for valid correction criteria, we studied this question in detail. Based on three different sets of results, we concluded 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 how 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. Our results are robust to the inclusion or exclusion of these variables because (given the set of controls) they are essentially uncorrelated with changes in schooling.

Table 4 summarizes these results. In this table, we experiment alternative specifications for column (1) of Table 1 where prices are modelled as full interactions between year, age and region of residence dummies. Column (1) of Table 4 replicates 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.\footnote{It is interesting to note that if these variables are ignored then the coefficient of interest becomes strong and positive in the college equation (but not in the high school equation). 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.} 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.\footnote{In column (2), a linear cohort cohort effect, (Cohort) × (Region of Birth), is implicitly included since (Cohort) = (Year) - (Age).} 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 no change in high school.

Column (4) is the main specification of the paper (and replicates exactly 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 \(r\) (first-best migration probability), their squares and an interaction between the two (Dahl, 2002). What is most striking about this column is that the results are essentially unchanged relative 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 in detail 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 replace the basic set of migration probabilities with the full set of migration probabilities. In particular, for each cell we compute the proportion of individuals born in \(b\) and residing in \(r\) (which gives us nine probabilities corresponding to nine regions), we squared them and compute all two way interactions between them, and use them as controls. In column (7) 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.

Finally, in column (8), 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).\(^{30}\)

\(^{30}\)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
Table 4: Estimation Results of Sensitivity Analysis

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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. Standard errors in brackets. * significant at 5%; ** significant at 1%.
One potential 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 well accounted for by the set of controls we use in the basic specification (region of birth interacted with year and age).

Figure 5: Changes in Aggregate Migration Flows

Notes: This figure shows changes in migration flows for young (ages 31-35) and old (ages 51-55) workers, separately in college and in high school. Changes in proportion in college are shown as well.

Our second set of results builds on the comparison between Columns (1) and (4) above, which show that the inclusion or not 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 essentially orthogonal. In fact, the data presented in Figure 5 show that even though there have been large increases in college attainment over the last 40 years, there have been hardly any changes in aggregate migration flows, both in college and in high school. The two panels of the figure report the proportion in college, the proportion of non-migrants among those with high school or less, and the proportion of non-migrants among those with some college or more in each year, for two different age groups. They suggest that 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.

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.
### Table 5: Differences between Inclusion and Exclusion of Migration Probabilities

<table>
<thead>
<tr>
<th></th>
<th>Log College Wages</th>
<th>Log High School Wages</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Odds of Proportion in College</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
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<td>-0.086</td>
</tr>
<tr>
<td></td>
<td>[0.022]**</td>
<td>[0.025]**</td>
</tr>
<tr>
<td></td>
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</tr>
<tr>
<td><strong>Staying Probability</strong></td>
<td>-0.435</td>
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<tr>
<td></td>
<td>[0.471]</td>
<td>[0.472]</td>
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</tr>
<tr>
<td><strong>(Staying Prob.)^2</strong></td>
<td>0.226</td>
<td>0.253</td>
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<tr>
<td></td>
<td>[0.383]</td>
<td>[0.384]</td>
</tr>
<tr>
<td></td>
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<td></td>
</tr>
<tr>
<td><strong>First-Best Migration Probability</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.616</td>
<td>-0.619</td>
</tr>
<tr>
<td></td>
<td>[0.060]**</td>
<td>[0.060]**</td>
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<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>(First-Best Migr. Prob.)^2</strong></td>
<td>0.34</td>
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<tr>
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<tr>
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</tr>
<tr>
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</tr>
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</table>

**Included Explanatory Variables**

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<tr>
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<th>Log High School Wages</th>
</tr>
</thead>
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<tr>
<td>(Year)×(Region of Birth)</td>
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<td>✓</td>
</tr>
<tr>
<td>(Age)×(Region of Birth)</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

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

In order to examine this more directly, in columns (1) and (2) of Table 6, we regress the proportion of individuals not migrating in each cell on the odds in proportion in college. We use only non-migrant cells. In column (1), no control variable is used and in column (2), (Year)×(Age), (Year)×(Region of Birth), and (Age)×(Region of Birth) dummies are controlled for (as in our base specification). There is no significant correlation between schooling and migration flows in college. The regression coefficient in high school is significant even after including the full set of controls, but its magnitude is very small. Similarly, in columns (3) and (4), we use only migrant cells to test whether the odds in proportion in college is correlated with the first-best 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
Table 6: Relationship between Proportion in College and Migration

<table>
<thead>
<tr>
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<th>(2)</th>
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<th>(4)</th>
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<th>(6)</th>
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</thead>
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<td>Migration Premium</td>
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<td></td>
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<tr>
<td>Panel A - College</td>
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<td>0.000</td>
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<tr>
<td>Panel B - High School</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Odds of Proportion in College</td>
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<td></td>
<td>[0.007]**</td>
<td>[0.011]*</td>
<td>[0.001]</td>
<td>[0.003]</td>
<td>[0.005]**</td>
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Included Explanatory Variables

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<th>(Year)×(Age)×(Region of Residence)</th>
<th>(Year)×(Region of Birth)</th>
<th>(Age)×(Region of Birth)</th>
<th>Basic Migration Probabilities</th>
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</thead>
<tbody>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

Notes: Standard errors in brackets. * significant at 5%; ** significant at 1%.
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 extensive set of controls. However, we believe that, taken together, the results of Tables 4, 5 and 6 provide convincing evidence that selective migration does not affect our main results in an important way.

In Appendix A.3 we present additional specification checks, which are important, although they are unrelated to migration. First, we show that our results are robust to the use of an alternative measure of composition ($P_i$ instead of $\frac{P_i}{1-P_i}$). 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, or those with some college and college graduates). We show that our basic results are basically unchanged once we include measures of within group composition (the odds of proportion in dropout within the high school sector, and the odds of proportion in some college within the college sector). Third, we rerun our basic 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.

In Appendix A.4 we present some evidence that supports the decline in the quality of college workers due to the increase in the proportion of college enrollment. In particular, we use the Scholastic Aptitude Test (SAT) to show that after accounting for state and year effects, cohorts with a higher proportion of SAT takers have on average lower SAT scores. We also use data from National Longitudinal Survey of Youth (NLSY) to show that (schooling-corrected) Armed Forces Qualification Test (AFQT) scores (measuring cognitive ability) of college-goers tend to be lower when the (cohort/state specific) proportion in college is higher. Finally, using data from International Adult Literacy Survey (IALS), we document that (after accounting for age effects) the average literacy of college participants in each cohort declines with the proportion of individuals enrolling in college in the cohort.
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, in the absence of changes in composition, the college premium would have increased by 9 percentage points more than it did between 1960 and 2000. 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 important as changes in prices to explain why the college premium grows at different rates for young and old workers.

This study also provides a novel understanding of demand shifts. We argue that the commonly used assumption of constant growth in the demand for college graduates is at odds with the data. Demand growth decreased substantially in the 1970s, and then accelerated in the 1980s, and declined again in the 1990s. Furthermore, demand shifts are the major driver of fluctuations in the college premium.

Finally, we argue that most of the changes in the age premium for college graduates in the last 40 years are driven by a combination of increasing demand for older workers and changes in composition, with very little role for changes in supply. In contrast, composition changes play no role in explaining changes in the age premium in high school. We estimate that the elasticity of substitution between workers of different age groups is larger in college than in high school, a fact that only emerges after we correct for changes in composition.

Appendix

Worker Quality, Schooling and Migration

The purpose of this section is to describe simple schooling and migration decision models which justify our estimation methods in the paper. In the paper we have maintained the basic assumption that labor supply shifts are exogenous, which is a standard assumption in the literature. However, we have also allowed individuals to be heterogeneous and self-select into schooling. These two
aspects are not necessarily inconsistent, and can be justified if the main drivers of changes in college enrollment are exogenous shifts in costs of schooling.

We start by studying the migration decision, which is made after the schooling decision in our model. Groen (2004) and Bound et al. (2004) document that the stock of college graduates working in a given state is modestly related to the amount of college students educated in that state, indicating that migration flows are quite large.

In a standard migration model individuals choose to live in region $r$ where their utility is higher, where utility may depend on earnings, amenities, living costs, and moving costs. For simplicity, suppose individuals decide in which region to reside after they finish school, and do not move again in the rest of their lives. Formally, we can model the migration decision as follows:

$$ r = \arg \max_j \left\{ E \sum_{a=0}^{A} \frac{W_{itajb}^k + AM_{itaj}^k}{(1 + \delta)^a} - CM_{i,t-a,jb}^k \right\} $$ (A.1)

where $\delta$ is the interest rate, $W_{itajb}^k$ is modelled as in equation (1), $AM_{itaj}^k$ is individual $i$’s valuation of region $r$’s amenities and costs of living, $CM_{i,t-a,rb}^k$ are costs of moving from region $r$ to region $b$, and $J_{i,t-a,b}^k$ is the information set of agent $i$ at the time of the migration decision. Assume that individual abilities are stable over time and independent of cohort ($U_{i,t-a,b}^k = U_{iab}^k$).

The schooling decision is made prior to the migration decision. Formally, an individual decides to go to college if the expected present value of gains exceeds the cost of attending college:

$$ S = 1 \text{ if } E \left\{ \sum_{a=0}^{A} W_{itrb}^C - W_{itrb}^H - C_{i,t-a,b}^k \left| I_{i,t-a,b}^k \right\} > 0 \right\} $$ (A.2)

where $C_{i,t-a,b}$ is the cost of college for individual $i$ in cohort $t-a$ in region $b$ (foregone earnings, tuition, utility costs and benefits of schooling), and $I_{i,t-a,b}$ is the information set of the individual at the time of the college decision. Further, as in the migration decision model, assume that individual abilities are stable over time and independent of cohort ($U_{i,t-a,b}^k = U_{iab}^k$).

Different assumptions about the information available to individuals at the time of their schooling and migration decisions have different implications for our empirical models. Suppose that individuals perfectly know their ability, the interest rate, and their costs at the time of the college decision but they only have partial knowledge of prices and match specific shocks. In particular,

---

31One could also allow ability to vary with age (e.g., due to learning by doing, or on-the-job training): $U_{i,t-a,b}^k = U_{iab}^k$. We could even allow for the existence of time varying ability shocks or match shocks as long as they are unpredictable at the time of the schooling decision.

39
assume that their forecast of prices is independent of time and their forecast of match specific shocks is independent of regions of residence at the time of the college decision. Then (A.2) can be written as:

\[ S = 1 \text{ if } \sum_{a=0}^{A} \frac{\Pi_{ab}^C U_{ib}^C - \Pi_{ab}^H U_{ib}^H}{(1 + \delta)^a} - C_{i,t-a,b} > 0, \]

where \( \Pi_{ab}^C = E(\Pi_{attr} V_{ia_{trb}} | I_{i,t-a,b}) \) and \( \Pi_{ab}^H = E(\Pi_{attr} V_{i_{attrb}} | I_{i,t-a,b}) \). Note that \( \Pi_{ab}^C \) and \( \Pi_{ab}^H \) depend only on age \( a \) and the region of birth \( b \) because of the assumptions on the forecasts of prices and match specific shocks at the time of the college decision.

In each cohort and region of birth individuals self select into schooling based on their idiosyncratic ability and costs of schooling, but differences in college enrollment across cohorts and regions of birth and driven only by differences in costs which are independent of each agent’s ability. Under these conditions, movements in college enrollment \( (\tilde{P}_{t-a,b}) \) can be seen as exogenous.

The crucial assumption of the model described just above is that price forecasts are independent of time. Even though it is difficult to justify this assumption on theoretical grounds, Card and Lemieux (2000, 2001) argue that it is difficult to explain the time series of schooling decisions based on variation in the returns to schooling. The main predictor of educational attainment in their model is cohort size. One reason behind such a finding may be that individuals have difficulty in forecasting future earnings (Carneiro et al., 2003; Cunha et al., 2005; Low et al., 2006).

It is interesting and important to notice at this point that our estimates of the importance of composition in column (1) of Table 1 (where we estimate the reduced form model) are robust to violations of this assumption. Recall from Section 2 that in our reduced form model we do not model prices (as we do in column (2) of Table 1). Instead, we condition on prices using a rich set of dummy variables, and compare wages across individuals facing the same prices, but born in different regions (and therefore subject to different costs of schooling). Our estimates are not affected by endogenous responses of schooling to prices, unless selective migration is correlated with schooling, which we have shown not to be the case. Our results also show that the estimates of composition effects based on reduced form and demand-supply models are similar, giving us confidence that our procedure is also valid for our demand-supply model.

As for the information available to agents at the time of the migration decision, we require that at least one of the following set of assumptions is satisfied. Suppose individuals perfectly know
their ability, the interest rate, amenities, living costs, and moving costs at the time of the migration decision, but they only have partial knowledge of prices and any match specific shocks we may want to add to the model. In particular, assume that their forecast of skill prices is independent of time. Forecasts of match specific shocks may depend on regions of residence and regions of birth, and even on time, since in some of our specifications we include year×region of residence×region of birth interactions. We allow perfect knowledge of amenities and living costs (AM_{ita}) and moving costs (CM_{i,t−a,j}) as long as movements in these variables over time are independent of changes in (forecasted) skill prices or match specific shocks (since they are unobserved to the econometrician).

Intuitively, we believe movements in schooling and migration are driven by fundamentally different forces, so unless these forces are strongly correlated, movements in these variables may well be orthogonal to each other.

We can rewrite equation (A.1) as:

\[
\hat{r} = \arg \max_j \left\{ \sum_{a=0}^{A} \frac{\Pi^{k}_{arb} U_{\hat{r}b} + AM_{ita}}{(1 + \delta)^a} - CM_{i,t−a,j} \right\}
\]

where \( \Pi^{k}_{arb} = E (\Pi^{k}_{atr} V^{k}_{itarb} | J_{i,t−a,b}) \). In this case, as in the college decision model, we can interpret changes in migration flows as being driven by movements in regional amenities and migration costs which are independent of wages. This is likely to be a strong set of assumptions, and also stronger than what is needed to justify our empirical model, since all we require is that the types of individuals who decide to migrate to different regions does not vary with changes in schooling in the region of birth.

Our assumptions on the information sets available to agents at the time of their schooling and migration decisions are undoubtedly restrictive. However, the main purpose of considering the simple model based on these assumptions is to establish that it is possible to have a coherent schooling and migration decision model that is compatible with exogenous changes in labor supply. In reality these stringent assumptions may be violated, but our sensitivity analysis suggests that, on the whole, our procedure is likely to be a valid one.
A.2 Estimation of $\rho$

This section describes an estimator of $\rho$. To do so, write, using (16),

$$U_{ktr} = \left[ \sum_{a=1}^{A} \alpha_{kat} \left\{ N_{atr}^k \tilde{Q}_{atr}^k \exp \left[ \Phi_k (P_{t-a,r}) \right] \right\}^{\eta_k} \right]^{\frac{1}{\eta_k}} \exp \left[ \Gamma_{kr} \right] \equiv \tilde{U}_{ktr} \exp \left[ \Gamma_{kr} + \Lambda_k (P_{M,atr}) \right].$$

Since we have obtained estimates of $\eta_k$, $\alpha_{kat}$, $\Phi_k$, and $\phi_k$ from the first stage (equation (17)), we can construct consistent estimates of the following quantities:

$$\tilde{\omega}_{atrb}^k = \omega_{atrb}^k - (-\eta_k) \log \tilde{U}_{ktr} - \{(\eta_k - 1) \left[ \log N_{atr}^k + \log \tilde{Q}_{atr}^k + \Phi_k (P_{t-a,r}) \right] + \phi_k (P_{t-a,b}) \}. \quad (A.3)$$

Finally, subtracting $\tilde{\omega}_{atrb}^C$ and $\tilde{\omega}_{atrb}^H$:

$$\tilde{\omega}_{atrb}^C - \tilde{\omega}_{atrb}^H = \log \left( \frac{\theta_{Ctr}}{\theta_{Htr}} \right) + \rho \log \left( \frac{\tilde{U}_{Ctr}}{\tilde{U}_{Htr}} \right) + (\rho - 1) (\Gamma_C - \Gamma_H) + (\log \alpha_{Ca} - \log \alpha_{Ha}) + (\gamma_{Cab} - \gamma_{Hab}) + (\gamma_{Ctb} - \gamma_{Htb}) + (\Lambda_C (P_{M,atr}^C) - \Lambda_H (P_{M,atr}^H)) + \lambda_C (P_{M,atr}^C, P_{M,atr}^C) - \lambda_H (P_{M,atr}^H, P_{M,atr}^H).$$

This equation shows that as long as some identifying restrictions on $\theta_{ktr}$ are imposed, $\rho$ can be estimated as the coefficient for $\log \left( \tilde{U}_{1tr}/\tilde{U}_{0tr} \right)$. These restrictions are needed because, even if $\tilde{U}_{1tr}/\tilde{U}_{0tr}$ moves exogenously, the demand function cannot be estimated if it is not stable over time, or if we do not know how it changes over time. The usual assumption in the literature is that $\log \left( \tilde{U}_{1tr}/\tilde{U}_{0tr} \right)$ can be modelled as a linear trend (e.g., Katz and Murphy, 1992; Card and Lemieux, 2001; Autor et al., 2007). However, since we have access to regional data, in our empirical section we explore alternative assumptions that relax linearity (e.g., we can assume that demand is not stable over time, but demand shifts are stable across regions, allowing us to estimate an unrestricted trend which is the same for all regions). Once $\rho$ is estimated, then the elasticity of substitution between college and high school workers can be computed as $1/(1 - \rho)$.

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.1 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 3.5% if college enrollment increases by 10% \((0.10 \times [-0.59 - (-0.24)] = 0.035)\). This change is almost identical to 3.6%, which we obtained using the odds of proportion in college when college enrollment changed from 50% to 60%.

Table A.1: Regression of Wages on Different Measures of Composition

<table>
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<th>(2) Level of Proportion in College</th>
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<td>Regression Coefficient</td>
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<tr>
<td>Panel B - High School</td>
<td></td>
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<tr>
<td>Regression Coefficient</td>
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<td>-0.240 [0.127]</td>
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<td>Observations</td>
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Notes: The dependent variable is log weekly wage in each cell. The regression includes basic controls as in column (1) of Table 1. Standard errors in brackets. * significant at 5%; ** significant at 1%.

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, or those with some college and college graduates). This is likely to be the case, but it does not seem to affect our results. Table A.2 shows that the main results are basically unchanged once we include measures of within group composition (the within odds of proportion in dropout, and the within odds of proportion in some college).

Third, we rerun our basic models using different dependent variables besides log weekly wages. The estimation results are reported in Table A.3. 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.

\[^{32}\text{This difference may occur for two reasons. On one end, the model may only be well specified for wages since we}\]
Table A.2: Regression of Wages with Measures of Within Group Composition

<table>
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<tr>
<td>Odds of Proportion in College</td>
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<td>-0.084**</td>
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<tr>
<td></td>
<td>[0.022]**</td>
<td>[0.022]**</td>
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<tr>
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</tr>
</tbody>
</table>

Notes: The dependent variable is log weekly wage in each cell. The regression includes basic controls as in column (1) of Table 1. Standard errors in brackets. * significant at 5%; ** significant at 1%.

Table A.3: Regression of Various Outcomes on the Odds of College Enrollment

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Log Wage</td>
<td>Log Duncan Index</td>
<td>Log Total Income</td>
<td>Employment Status</td>
</tr>
<tr>
<td>Panel A - College</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Odds of Proportion in College</td>
<td>-0.084</td>
<td>-2.206**</td>
<td>-0.063*</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>[0.022]**</td>
<td>[0.472]**</td>
<td>[0.027]*</td>
<td>[0.008]</td>
</tr>
<tr>
<td>Observations</td>
<td>2659</td>
<td>2760</td>
<td>2769</td>
<td>2696</td>
</tr>
<tr>
<td>Panel B - High School</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Odds of Proportion in College</td>
<td>-0.008</td>
<td>-0.816*</td>
<td>-0.040**</td>
<td>-0.004</td>
</tr>
<tr>
<td></td>
<td>[0.017]</td>
<td>[0.416]**</td>
<td>[0.020]**</td>
<td>[0.007]</td>
</tr>
<tr>
<td>Observations</td>
<td>2742</td>
<td>2817</td>
<td>2813</td>
<td>2785</td>
</tr>
</tbody>
</table>

Notes: All the regressions include basic controls as in column (1) of Table 1. Standard errors in brackets. * significant at 5%; ** significant at 1%.
A.4 Evidence of Declining Quality of College Workers

In this section we present some suggestive evidence favoring the decline in the quality of college workers due to the increase in the proportion of college enrollment. In particular, we have used data from SAT, NLSY, and IALS to show that regression results from three different sources are all consistent with the declining quality of college workers.

First, we examine average scores on the SAT by state. The advantage of using SAT scores as the outcome measures is that they are a direct measure of worker quality. The disadvantage is that they are not as relevant as wages, and they correspond to only one dimension of skill.

Figure A.1: 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.

As illustrated in Figure A.1, 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 A.1 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 (although it may be possible to add a few more years of data to our dataset, but certainly not going back to 1960). We have used the proportion of

\[ t - a - r \]

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.
high school seniors taking the SAT in each state and year as our main explanatory variable, but not the proportion of college graduates among those graduating from high school. The reason is that the former is much easier to collect than the latter for all these years. Furthermore, for those years for which we collected the two, 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).

Table A.4: Regression of SAT Scores on the Percentage of High School Graduates Taking SAT, with Year and State Dummies - 1993/2004 (except 1995 and 1998)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAT Math</td>
<td>-16.503</td>
<td>-26.268</td>
</tr>
<tr>
<td>SAT Verbal</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percentage of High School Graduates Taking SAT</td>
<td>[7.275]**</td>
<td>[6.629]*****</td>
</tr>
<tr>
<td>Observations</td>
<td>510</td>
<td>510</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.99</td>
<td>0.99</td>
</tr>
</tbody>
</table>

Included Dummy Variables

- (Year) √ √
- (State) √ √

Notes: Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.

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 A.4 show exactly the same pattern reported in figure A.1. 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 suggestive and direct evidence that increases in college attainment lead to declines in the quality of college graduates.

Second, Table A.5 reports regressions of a measure of cognitive ability for college and high school graduates on the proportion of individuals going to college in different cohorts and states. Using the data from NLSY (white males only) we compute schooling-corrected AFQT scores (as in Carneiro et al., 2006) for each individual, and the proportion in college (some college, college graduates, and more) for each cohort (year of birth) and state of residence at 14. Then we regress AFQT scores on proportion in college, separately for each of two schooling groups (high school
Table A.5: Regression of Schooling Corrected AFQT on Proportion of College Goers in each
Cohort/State of Residence at 14

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A - College</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion in College</td>
<td>-0.443</td>
<td>-0.404</td>
<td>-0.459</td>
</tr>
<tr>
<td>[0.224]**</td>
<td>[0.215]*</td>
<td>[0.204]**</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>1821</td>
<td>1821</td>
<td>1821</td>
</tr>
</tbody>
</table>

| **Panel B - High School** |         |         |         |
| Proportion in College | -0.029  | -0.054  | 0.007   |
| [0.222] | [0.216] | [0.210] |
| Observations     | 2554    | 2554    | 2554    |
| **Included Explanatory Variables** |         |         |         |
| State Dummies    | √       | √       | √       |
| Race             | √       |         |         |
| Mother’s Education | √     |         |         |

Notes: Regressions of schooling corrected AFQT on proportion of college goers in each cohort/state are reported using data from NLSY males. Robust standard errors clustered by cohort-state in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.

Finally, we consider the 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, 1995). 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
Table A.6: Regression of Quantitative Literacy on Proportion in College

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>College</td>
<td>High School</td>
<td>All</td>
</tr>
<tr>
<td>Proportion in College</td>
<td>-1.234</td>
<td>0.597</td>
<td>-0.111</td>
</tr>
<tr>
<td></td>
<td>[0.499]**</td>
<td>[0.485]</td>
<td>[0.356]</td>
</tr>
<tr>
<td>College</td>
<td></td>
<td></td>
<td>0.966</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[0.037]**</td>
</tr>
<tr>
<td>Age</td>
<td>0.100</td>
<td>0.001</td>
<td>0.037</td>
</tr>
<tr>
<td></td>
<td>[0.021]***</td>
<td>[0.021]</td>
<td>[0.015]**</td>
</tr>
<tr>
<td>Age Squared</td>
<td>-0.001</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>[0.000]***</td>
<td>[0.000]</td>
<td>[0.000]**</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.634</td>
<td>-0.493</td>
<td>-0.888</td>
</tr>
<tr>
<td></td>
<td>[0.420]</td>
<td>[0.406]</td>
<td>[0.297]**</td>
</tr>
<tr>
<td>Observations</td>
<td>962</td>
<td>1503</td>
<td>2465</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.03</td>
<td>0.00</td>
<td>0.22</td>
</tr>
</tbody>
</table>

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. Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.

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 we label P in this section. Table A.6 reports the coefficients of a regression of quantitative literacy on age, age squared and P, for the high school and college groups, and for the whole sample. The coefficient on P is negative and strong for college, and insignificant for high school. The third column of Table A.6 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.\(^{34}\)

\(^{33}\)Using this survey, OECD (1995) documents that individuals with low level of schooling have dramatically low levels of literacy in the US. This lower tail in the distribution of literacy is only matched by that of the UK and Portugal.

\(^{34}\)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.
A.5 The Fit of the Demand and Supply Model

Notes: This figure compares data with the fit of model based on column (2) of Table 1.
References


