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A labor income-based measure of the value of human capital: An application to the states of the United States[1]

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Abstract

We argue that a sensible measure of the aggregate value of human capital is the ratio of total labor income per capita to the wage of a person with zero years of schooling. The reason is that total labor income not only incorporates human capital but also physical capital: given human capital regions with higher physical capital will tend to have higher wages for all workers and, therefore, higher labor income. We find that one way to net out the effect of aggregate physical capital on labor income is to divide labor income by the wage of a zero-schooling worker.

For the average U.S. state, our measure suggests that the value of human capital during the 1980s grew at a much larger rate than schooling. The reason has to do with movements in the relative productivities of the different workers: in some sense, some workers and some types of schooling became more relevant in the 1980s and, as a result, measured human capital increased.

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1. Introduction

There is no question that the U.S. labor force has become more 'educated' in the past 50 years. Compare, for example, our Figs. 1a and 1f. The figures display histograms of educational attainment of the U.S. aged 25–65 civilian labor force for the years 1940 (Fig.

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1a) and 1990 (Fig. 1f). We see that in 1940 a mere 12 percent of the labor force had completed even a year of college. Only 15 percent more had completed high school. By 1990, over half of the labor force had attended some college and another 30 percent had completed high school. Only 16 percent of the labor force did not have a high school diploma.

Can we say that such dramatic changes in the educational attainment of labor force is an important source of economic growth? Well, income and wage rates have grown along with educational attainment over the same period; therefore we could be tempted to say yes. Time spent in school has grown, but so have hours of television viewing. Can we argue that television viewing is responsible for productivity growth?

In defense of the virtues of schooling, it is true that, at a point in time, workers with more schooling enjoy higher wage rates than observationally equivalent workers with less schooling. The same cannot be said for television viewing. Thus, one might estimate the productivity value of our country's increased educational attainment by multiplying a cross-sectional estimate of the skill premium (the wage ratio of say, college to high school workers) by the increase in educational attainment. In fact, this will be one of the ways in which we compute human capital in this paper. Although this is an interesting measure, it has its drawbacks. First, while those few workers who appear in the right two or three bars of the histogram in Fig. 1a may have had more schooling, they may also differ from the rest of the labor force according to other unobservable characteristics: IQ, family background, and health are some examples. Our schools have clearly been granting diplomas, but have they been granting these other characteristics? In short, schooling may not be related to the same quantity of human capital as it used to be. Second, the relevance of what is taught in school may not be constant. For example, there could be an increasing aggregate tendency to study things that are not directly productive (such as Egyptology, moral philosophy of 16th century monks, or theoretical time series econometrics). If this were the case, an increase in the number of years of schooling could be consistent with a decline in the actual amount of productive human capital. Similarly, technological changes may render certain types of teaching obsolete. If schools do not adapt to the new technological situation, then schooling may increase but human capital may not.[3]

In this paper we consider alternative measures of human capital that are not so quick to Identify Schooling with human capital. In particular, we propose to measure the value of the input human capital as the ratio of the aggregate labor income of an economy to the wage of the uneducated. Our measure clearly overcomes some of the shortcomings of existing measures of human capital (for example, when the quality and the relevance of what is taught increases, the labor income of the educated increases with it so that our measure correctly captures this phenomenon).

We should mention at the outset that there are some drawbacks in the way we compute human capital. One major drawback is that wages may change for reasons other than changes in human capital. When this happens, our measure will incorrectly show changes in human capital. A second potential source of problems could be that we assume that the uneducated are perfect substitutes for the rest of the labor force. In the final section we

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[3]One could give examples of macroeconomic theories which have 'recently' become obsolete. We will not give such examples although, clearly, there must be schools which have not adapted to the new technological environment.

provide some evidence to support this view. But to the extent that this assumption does not hold, our computations will be flawed.

The rest of the paper is organized as follows. Section 2 reviews some standard microeconomic theories of schooling, income and human capital, but pays special attention to those issues which we think are important for measurement. Section 3 presents our data sources and our different measures of human capital. We compare the various measures for each of the contiguous 48 states in each of the 6 census years between 1940–1990. Most of the discussion and analysis considers human capital indices which linearly aggregate various types of labor. Section 5 considers generalizations of our results to nonlinear aggregators.

2. Microfoundations

2.1. Aggregate production

We imagine that output Q at the aggregate level is determined by an aggregate production function that depends on two inputs: the total *human capital* and total *nonhuman capital* K in the economy.

$$Q_i(t) = F(v_i(t)K_i(t), u_i(t)H_i(t)) \tag{1}$$

i indexes a state while t is a time index. $H_i(t)$ is the total *stock of human capital*[4] in the state, and u_{it} is the *participation rate* (all persons might not be involved in market production) and $v_i(t)$ is the fraction of nonhuman capital, $K_i(t)$, devoted to productive activities (as opposed, for example, to education activities).

Human capital is related to the aggregate stock of productive human bodies available in an economy. That is, the concept of human capital is related to the labor force. In principle, human capital includes all productive aspects of the human bodies in the state: education, on the job training, physical and mental fitness, and the quality of matches between workers and firms are some examples. Since the population of an economy is heterogeneous – some citizens have a lot of skills while others have little or none – different people contribute to production in different degrees. We want our measure of human capital to capture this phenomenon; we cannot simply add all the bodies in the economy to compute human capital: we need to give a larger weight to those people who are more productive. In some sense, we want to do with labor what empirical economists like Jorgenson and others have done with physical capital: add the number of machines but giving each unit a weight which is proportional to its productivity. In this spirit, we define *aggregate human capital* in an economy as the quality-adjusted sum of the labor of all its citizens:

$$H_i(t) = \int_0^\infty \theta_i(t,s)N_i(t,s)\mathrm{d}s, \tag{2}$$

[4] Note that output should depend on the flow of services rather than the stock of human capital. The customary assumption is that the flow of services variable is proportional to the stock variable.

where $N_i(t,s)$ denotes the number of people in economy i at date t with s years of schooling. Note that each type of worker contributes to our definition of aggregate human capital according to his *efficiency parameter* $\theta_i(t,s)$.[5]

In order to clarify the concept of human capital, let us suppose that we choose a worker with s years of schooling to be the numeraire.[6] We will say that the stock of human capital in state i is $H_i(t)$. If we can say that, instead of the actual distribution of people and skills, economy i had $H_i(t)$ units of workers with s years of schooling, then it would produce the same amount of output (holding constant the aggregate stock of physical capital and the level of technology). Note that the notion of human capital is independent of the exact functional form of the aggregator in Eq. (2).

The specification in Eq. (2) assumes that workers with different schooling levels are perfectly substitutable. For example, $\theta_i(t,16)$ high school graduates (who generally have 12 years of schooling) can be substituted for $\theta_i(t,12)$ college graduates (who generally have 16 years of schooling) without changing aggregate production. We will argue in Section 5, however, that our preferred measure of human capital is consistent with finite elasticity of substitution across different types of workers.

We believe that a person's human capital is related to his schooling, but have no presumptions, a priori, about the precise relationship between one's schooling and one's human capital. The relationship might be linear or nonlinear and need not even increase. In other words, when $\theta_i(t,s)$ denotes the mapping from a person's years of schooling (s) to his human capital, we make no assumptions about the functional form or even the sign of the derivative of this function.

Divide the aggregate stock of human capital by the stock of workers to get the *average stock of human capital* in economy i at time t as

$$h_i(t) = \int_0^{\infty} \theta_i(t,s)\eta_i(t,s)\mathrm{d}s, \tag{3}$$

where $\eta_i(t,s) = N_i(t,s)/N_i(t)$ is the share of state i's population with s years of schooling at time t and $h_i(t) = H_i(t)/N_i(t)$ is the stock of human capital per person. An important question is how to compute the efficiency parameters which will be used as weights to add people up. In particular, we want to know whether we should allow these efficiency parameters to vary across states and over time. We also want to get some guidance as to which category of workers (if any) is an appropriate numeraire.

2.2. *Efficiency parameters and choice of a numeraire: Guidance from a model of individual human capital accumulation*

The goal of this subsection is to use economic theory to guide us in the measurement of the efficiency parameters $\theta_i(t,s)$. There are two questions that we would like the theoretical

[5] We integrate over the level of schooling of the population. More generally we would like to integrate over other characteristics also. We will do so when we perform our empirical implementation. However, we will not show the algebra here in order to simplify the exposition.

[6] In principle, we could choose any type of worker to be the numeraire. In Section 2.2 we will argue, however, that the only sensible numeraire is the person with zero years of schooling.

analysis to answer. First, should the efficiency parameter for a given level of schooling vary over space and time, over time only ($\theta_i(t,s) = \theta(t,s)$), or not at all ($\theta_i(t,s) = \theta(s)$)? Second, how might the efficiency parameters $\theta_i(t,s)$ be related to years of schooling s? To answer these questions, we will consider a parameterized model of individual human capital accumulation, but the basic insights will be robust to changes in the functional form. The more important functional form assumptions are the aggregate ones in the previous section.

Let $h_{ji}(t)$ be the skill level or stock of human capital of individual j in state i at time t. We assume that an individual can increase his skill by combining some aggregate inputs with his own time and skill. The aggregate variables could be the stock of physical capital $\hat{k}_i^e(t)$ devoted to education (related to the physical facilities in schools and other learning centers) and the stock of human capital, $\hat{h}_i^e(t)$, devoted to education in a particular state (the corresponding human capital would refer to skills and the number of teachers and other educators). The fractions of the economy-wide stocks of human and physical capital devoted to education may vary across regions and over time. The level of technology of education may also vary across regions.[7]

Let $\hat{y}_i(t)$ summarize the effects of a region's aggregate variables on an individual's human capital accumulation.[8] An example of a $\hat{y}_i(t)$ function would be the Cobb–Douglas $\hat{y}_i(t) = \phi_i \hat{k}_i^e(t)^\alpha \hat{h}_i^e(t)^{1-\alpha}$, where ϕ_i is the level of technology (for education) in state i. As a particular example, we think of human capital being produced with human capital only (as in Uzawa (1965), Lucas (1988), $\hat{y}_i(t) = \phi_i \hat{h}_i^e(t)$). We imagine that, in order to increase one's human capital, an individual combines his own human capital with the aggregate stocks available in his region according to

$$\dot{h}_{ji}(t) = \hat{y}_i(t)^{1-\psi}(u_{ji}(t)h_{ji}(t))^\psi, \tag{4}$$

with $0 \leq \psi \leq 1$, where u_j is the fraction of his own human capital that the individual devotes to education. Eq. (4) implies that the longer the time spent in school, the more skill one individual will accumulate. It also implies that spending the same amount of time in school in regions with a lot of physical and human capital devoted to education yields a larger increase in the individual level of skill. Finally, the level

[7]We are implicitly assuming that economies are closed in the sense that kids must go to school in their own economies. In the real world, this assumption is not strictly correct since some students find it optimal to study out of state. Furthermore, workers may migrate across economies once their schooling has been completed. Hence at a point in time, the labor force of a particular state will have had schooling in different states.

We make the close economy assumption just to bring in the main points clearly. In practice, we will not impose that the productivity parameters of the different levels of schooling follow the equations derived from the theory. We will estimate them with no restrictions and without relating them to the amount of aggregate resources devoted to schooling in a particular state. In particular, we will not require the levels of productivity to be different across economies, and we will not even impose them to be increasing in schooling. Hence, to the extent that these issues are important, they will show up in the data, although not in our theoretical discussion.

[8]We suppress the details of the schooling market. One might imagine that students rent the services of teachers and various capital goods (i.e. pay tuition).

of increase in the amount of skill is larger for people with high skill. Because ψ is less than one, the learning process is subject to diminishing returns to skills.[9]

To simplify notation, we imagine that the aggregate stock $\hat{y}_i(t)$ grows at a constant rate γ_i. This would be the case if, for example, state i was in the steady state of an aggregative growth model.[10] We also assume that students can only use their human capital in school (that is, they are not allowed to use their human capital in productive activities until they get out of school) so $u_{ji} = 1$ for all t. Different students, however, spend varying number of years in school and, as a result, end up with different skill levels. Compute the level of skill of a person who went to school between times v and $v+s$ by integrating Eq. (4) between v and $v + s$:

$$h_{ji}(v,s) = [h_{ji}(v,0)^{1-\psi} + (1-\psi)\hat{y}_i(v)(e^{\gamma_i s} - 1)]^{1/(1-\psi)}, \tag{5}$$

where $h_{ji}(v,0)$ is the stock of human capital the student had at the moment when he had zero years of schooling. That is, the stock of human capital of a student i who started school at time v in region i and who studied for s years is a function of the sum of his initial stock human capital, $h_{ji}(v,0)$, plus the term $\hat{y}_i(v)(e^{\gamma_i s} - 1)$. This second term, which reflects the increase in the stock of the student's human capital over the period of length s, is the product of the quality of the teachers and number of education facilities available at the beginning of his student career, $\hat{y}_i(v)$, times an exponential term which increases with the number of years of schooling. In other words, a given amount of schooling represents different amounts of human capital in different places and different times because the *quality* of schooling is different. Finally, note that when $s = 0$, the second term is zero so that the level of skill is $h_{ji}(v,0)$.

2.2.1. *The initial level of skill*

An important question is what is the initial stock of human capital, $h_{ji}(v,0)$. We assume that the initial stock is the same at all points in time and in all places

$$h_{ji}(v,0) = h(0) \tag{6}$$

for all v, i and j. In other words, a zero-schooling person is the same, always and everywhere. This assumption does not imply that zero-schooling people will earn the same income always and everywhere. Their productivity (and wage) will differ across economies because the aggregate stocks of physical, human capital, and other inputs will differ across economies. That is, individual productivity not only depends on the individual stock of skill, but also on the available stocks of other inputs as well as the level of technology.

The main reason for using assumption Eq. (6) is that we need a numeraire. We want to express the human capital index in a unit which is homogeneous across space and time. Eq. (5) suggests that having any amount of schooling will tend to introduce interregional

[9]The Cobb–Douglas formulation is not critical. The closed-form solutions that it permits, however, facilitate the exposition.

[10]As will be apparent from the analysis, this assumption is not crucial for any of the results we will derive in this section.

and intertemporal differences in the level of skill, simply because the resources devoted to education and the level of human capital of the teachers differs across economies. Hence, while the above analysis admits assumption Eq. (6), it does not reasonably admit any other normalization: people with any positive amount of schooling are necessarily different and, therefore, cannot be used as numeraire.[11]

2.2.2. Theoretical measures of aggregate human capital

One way to compute (theoretically) an aggregate stock of human capital is to add the level of skill of every individual of the economy. We do so in two steps. First, we compute the stock of human capital of all workers with s years of schooling by integrating Eq. (5) over all v for people who are alive today. Imagine that people with s years of schooling live for T_s years. The oldest persons alive today were born in period $t - T_s$, but they did not start working until s years later (because they were in school). Assuming that there is one individual of this type born and starting school at each instant v, the skill of the average person with s years of schooling s is given by

$$h_i(t,s) = \int_{t-T_s+s}^{t} h_{ji}(v,s)\mathrm{d}v, \tag{7}$$

with $\partial h/\partial s > 0$ and $h_i(t,0) = h(0)$ for all t and i. Note that the average level of skill of the persons with s years of schooling depends on i and t because the stock of human and physical capital devoted to school in region i at the time when the persons alive at time t went to school might be different. We also note that the average skill level, $h_i(t,s)$, depends on something that looks like a demographic variable, T_s. This is the length of economic life of people with s years of schooling. This length of life may vary over time, across states or across s (because, for example, more educated people tend to retire at different ages).

The second step to compute the aggregate stock of human capital per worker is to add the persons in each category, using Eq. (7) as the weights:

$$h_i(t) = \int_0^{\infty} h_i(t,s)\eta_i(t,s)\mathrm{d}s. \tag{8}$$

Note that Eq. (8) is identical to Eq. (3) if the efficiency parameters are defined and given by the average skill levels, $\theta_i(t,s) = h_i(t,s)$. If we use the normalization $h(t,0) = 1$, then

[11] One might argue that the process of education and human capital accumulation starts before schooling. Kids in daily contact with smart parents and other smart people tend to have more skills than kids whose parents have a low level of education. This intergenerational transmission of human capital would then make the initial stock of human capital, $h_{ji}(v,0)$, a function of the aggregate resources available in state i at time t.

Another problem is related to the question of why some people have no schooling. The people who have chosen to have no eduction are, in some sense,'strange,'at least if we talk about the second half of the 20th century in the United States. One could reasonably argue that there is little reason for assuming that these strange people are the same in all places and at all points in time.

the average stock of human capital in Eq. (8) reports the amount of zero-schooling-worker equivalents available in economy i at time t.

The main lessons we want to take from this section: First, if there is a sensible numeraire, then it has to be the zero-schooling worker. The reason is that any positive amount of schooling implies different productivities in different economies and in different time periods. Hence, it is only normal that people with positive schooling are different. If we can assume that one type of worker is the same in all economies, it has to be the one who has not been exposed to these economy-wide influences: the worker with no schooling. It follows that the only reasonable numeraire is the zero-schooling worker.

The second lesson is that, even when human capital is homogeneous, the efficiency parameters $\theta_i(t, s)$ – which relate years of schooling to productivity – should be allowed to change across regions and over time because skill in different regions has been accumulated under different aggregate circumstances (different amount of skills of teachers, different amounts of physical facilities devoted to schooling and so on). The theoretical analysis suggests that these weights should increase in the amount of schooling and the amount of aggregate stocks devoted to education.

There is some evidence that 'schooling quality' affects the relationship between an individual's years of schooling and his productivity. Card and Krueger (1992) compare wage-schooling profiles across states and note that workers who studied in higher income states or in states with more expenditures on education enjoy a higher wage premium over less educated, but otherwise similarly situated, workers.

Of course, differences in schooling quality (in the sense that we have defined it in this subsection) are not the only reason the wage-schooling relationship might vary across states or over time. We might imagine that the relevance of various levels and types of schooling depends on time and location. Or, unlike our aggregate specification Eq. (2), workers with various skills may not be perfect substitutes; the marginal rate of transformation between any two skill groups may depend on the relative quantities of the two types of workers in the economy.

Although this was not directly incorporated in the theoretical reasoning of the preceding section, a related reason for allowing the relative weights to vary over time and across regions is that the *relevance* of what is taught in school also differs across regions and over time. This relevance may change due to technological shocks which render certain types of education less useful in a productive sense.

In the current paper, we do not attempt to separately attribute changes across states and over time in the wage-schooling relationship to the three aforementioned sources: schooling quality, productivity shocks, and relative supply shocks. Given that workers with no skill are the numeraire, it is not clear that a complete decomposition is necessary. For example, a technology shock that changed the productivity (and therefore wages) of college graduates relative to no-skill workers should be reflected in our human capital index. However, a change in the relative supply of workers that leaves output constant leads to a change in the relative wages (if workers of various types are not perfect substitutes as we assume in Eq. (2)) but should not be reflected in our human capital index. A human capital index that allows for the possibility that the relative supply of worker types is changing seems like a natural extension to the indices considered here. One of the section asks whether or not our preferred measure of human capital, while apparently 'linear,' is robust to the relaxation of the perfect substitutability assumption.

2.3. *A labor income-based measure of human capital (LIHK)*

Under the assumption that a worker's marginal product equals his wage, the wage rate of a person with s years of schooling is given by

$$w_i(t,s) = \partial Q_i(t)/\partial N_i(t,s) = (\partial F(K_i,H_i)/\partial H_i)\partial H_i/\partial N_i(t,0) = F_H^*\theta_i(t,s). \tag{9}$$

Similarly, the wage rate of a person with zero schooling is given by

$$w_i(t,0) = F_H^* h(0) \equiv F_H, \tag{10}$$

where the normalization $\theta(0) \equiv 1$ has been used. It is clear from Eqs. (7) and (10) that the average stocks of human capital can be inferred from the wage ratios

$$\theta_i(t,s) = w_i(t,s)/w_i(t,0). \tag{11}$$

The assumption for this result is that the wage rate of a person of any skill has two components: One depends on the individual skill. The other depends on the aggregate stocks. For a given skill, a larger amount of physical capital increases one's productivity because of the complementarity between physical and human capital. Similarly, a larger amount of aggregate human capital decreases productivity because of diminishing returns to aggregate human capital. In order to identify the skill component, we need to net out the aggregate component. We can do so by dividing by the wage of a person with no skill, $w_i(t,0)$.

By plugging Eq. (11) in Eq. (8) we get the average stock of human capital measured as

$$h_i(t) = \left[\int_0^\infty w_i(t,s)\eta_i(t,s)\mathrm{d}s\right] w_i(t,0), \tag{12}$$

where, again, $\eta_i(t,s)$ is the fraction of people in state i with s years of schooling at time t. We note that the expression inside the square brackets is the sum of all wages in the economy divided by the number of people. In other words, abstracting from differences in the participation rates across schooling groups, the bracketed term is the average labor income of state i.

This analysis suggests a simple measure of the aggregate stock of human capital: Compute the average labor income of state i (that is, total labor income per worker), and divide it by the wage of the zero-schooling workers in that state. We will call it *labor income-based human capital* (LIHK) throughout the rest of the paper. Aggregate labor income is usually reported in the national accounts. We just need to compute the wage rate of an unskilled person. We will discuss how this is done in Section 3.[12]

2.4. *Alternative measures of human capital*

Alternative ways of computing human capital have been proposed in the literature. Here we discuss the theoretical differences. In Section 3 we compute such measures in order to compare them with our labor income-based human capital.

2.4.1. *Variable weights*

Our labor income-based measure of human capital can be thought of as one that allows relative efficiencies to vary across time and location. If one thought that the cross-state differences in skill premia were not done to differences in schooling quality or technology but to differences in relative supplies, then an alternative is to restrict the weights to be the same across regions, but allow them to vary over time

$$h_i(t) = \int_0^\infty \theta(t,s)\eta_i(t,s)\mathrm{d}s, \tag{13}$$

where $\theta(t,s)$ is independent of i. Our analysis suggests that this measure could be appropriate, for example, if the aggregate variables that matter for individual human capital accumulation are nation-wide.

In practice, to compute human capital using Eq. (13) we multiply the fraction of workers in each education category in each state by a nation-wide productivity parameter $\theta_{us}(t,s)$. These nation-wide productivity parameters are computed using relative wages:

$$\theta(t,s) = w(t,s)/w(t,0).$$

In other words, the average U.S. worker with s years of schooling at time t will be assumed to be $\theta(t,s)$ times more productive than a worker with zero years of schooling because his wage is $w(t,s)/w(t,0)$ times larger. These weights would be computed at each date.

Note that another difference between the flexible weight measure and LIHK is that the flexible weight forces all workers within the same education category to have the same

[12] We should note at this point that, even though we have been emphasizing schooling in our theoretical analysis, the measure of human capital we just proposed includes all productive aspects of human bodies, as long as those aspects are incorporated in the workers' wages. For example, the development literature has emphasized nutrition and health as an important aspect of human capital. Other people have argued that the efficiency of job matching or the amount of on-the-job training or job experience contribute to human capital. To the extent that these characteristics are incorporated in wages, our labor-income-based measure of human capital will capture them (our estimates of $w(0)$ will correspond to workers with no schooling and no experience so anything which affects the general work force but not the average zero-schooling, zero-experience worker will be reflected in our measure of human capital). Finally, LIHK incorporates the notion of relevance of schooling in that, if one has a lot of schooling but learn irrelevant things (irrelevant from a productive point of view, of course), then one's wage is low and our measured LIHK is also low, even though schooling may be high.

weight (or productivity) in the total account of human capital. Our measure, on the other hand, gives each person a weight which is proportional to his own wage.

2.4.2. Fixed weights

The third measure restricts the efficiency weights to be the same over time as well as across states. The average capital stock is computed by a weighted average of different educational attainments, the weights being restricted to be the same over time and across states:

$$h_i(t) = \int_0^\infty \theta(s)\eta_i(t,s)\mathrm{d}s, \tag{14}$$

where the weights $\theta(s)$ are independent of i and t. In practice we can compute $\theta(s)$ by dividing the wage of a person with s years of schooling by the wage of the no-schooling worker,

$$\theta(s) = w(s)/w(0).$$

2.4.3. Average years of schooling

The most popular measure of human capital is the average years of schooling. In an international context, for example, this measure has been used by Kyriacou (1991) as well as Barro and Lee (1993). Average years of schooling are computed by adding the product of the number of years of schooling multiplies the number of people in each schooling category across schooling categories:

$$h_i(t) = \int_0^\infty s\eta_i(t,s)\mathrm{d}s. \tag{15}$$

Note that Eq. (15) uses a fixed weight over time and across regions so that it is a particular case of Eq. (14). Instead of being based on market wages, the fixed weight in Eq. (15) is the number of years of schooling. In other words, this measure assumes that, always and everywhere, a person with 16 years of school is 16 times more productive than a person with one year of school (even if his wage is only three times larger).

3. Measurement and results

3.1. Sample selection and some basic features of our data

In this section, we compute and compare the four measures of human capital proposed in the previous section. We use the Public Use Microdata Samples provided by the Census Bureau. The microsamples include information on the schooling, earnings, hours and weeks worked, and employment status of a (practically speaking) random sample of roughly one out of every one hundred Americans in each of the census years 1940, 1950, 1960, 1970, 1980 and 1990.[13,14]

From the microdata, we compute three items that are inputs into the construction of the various measures of aggregate human capital: (1) the educational attainment distribution (among civilians aged 25–65) for each state at each of the six dates, (2) average weekly earnings for each schooling group at each date, and (3) estimates of the average weekly earnings of somebody with no skill in each state at each date.

Each state's educational attainment distribution is estimated by dividing its civilian labor force aged 25–65 into seven schooling categories:

0. No schooling.
1. 0–4 years of elementary school.
2. 5–8 years of elementary school.
3. 1–3 years of high school.
4. High school graduate.
5. 1–3 years of college.
6. College graduate or more.

'Years of schooling' refers to the highest grade completed.[15] Nursery school and kindergarten are not counted as grades, so an individual qualifies for our no schooling category if he attended nursery school, or kindergarten, or even if he attended – but did not complete – first grade.

Table 4 and Fig. 1a–1f display educational attainment distributions for the U.S. civilian labor force aged 25–65 for each of the 6 census years 1940–1990.[16,17] In 1940, workers with eight years of schooling or less are in the majority. A majority of the 1950 labor

[13] The 1940, 1950 and 1960 PUMS are 1/100. To economize on computing resources, we work with random subsamples of the later PUMS, arriving at a 1/1000 sample for 1970 and 1/200 samples for 1980 and 1990. The 1970 subsample was provided by the Census Bureau which derived it from their 5 percent State sample. Our 1980 and 1990 subsamples were constructed from the larger 5 percent sample by taking only those households whose subsample number had a ones digit equal to 2.

[14] According to the Census Bureau, the 1960, 1970 and 1980 PUMS are self-weighting samples, and we treated them as such in our computations. We also treat our extracts of the 1940 and 1950 PUMS as self-weighting samples, noting that we extract all persons from the raw 1940 data files and only sample line persons from the raw 1950 data files.

The 1990 PUMS is clearly not a self-weighted sample; therefore all of our computations for that year weight by the Census Bureau's estimate of the inverse of each person's sampling probability (columns 18–21 of the person record). For example, the regression criterion is to minimize a weighted sum of the squared residuals, where each person's residual is weighted by the inverse of his sampling probability.

[15] Until 1990, it was not clear whether a response such as 'six years of college' mean that the person obtained a bachelor's degree and worked for two years for a higher degree or whether he worked six years to obtain the bachelor's degree.

[16] Unless otherwise noted, US is taken to be the sum of the 48 contiguous states.

[17] An eighth schooling category, eighth grade graduates, is displayed for the first five census years. Since eighth grade graduates cannot be distinguished from those who attended grade school for 5–7 years in the 1990 PUMS, our computations for all six census years merge the two categories to form a single category '5–8 years of schooling.'

force has completed at least some high school. By 1980, those without a high school diploma are in the minority. By 1990, a mere 16 percent fail to have a high school diploma.

We will take a worker's average weekly earnings (annual earnings divided by weeks worked, both for the year prior to the census) to be his or her marginal productivity. Estimates of average weekly earnings are obtained from a subsample of the aged 25–65 civilian labor force (this subsample will be referred to as our 'earnings sample'): employed civilians who worked at least 13 weeks in the year prior to the census (the year for which earnings are reported), who were not self-employed, and who worked more than 30 usual hours per week (in the year of the census or in the year prior to the census, depending on the orientation of the census question in that year). Workers were excluded from the earnings sample if they were currently attending school or if, on average, they earned less than $67 1982 per week, adjusted for 'real economic growth' at 2 percent per year.[18] Aged 25–65 civilians who satisfy these selection criteria form our 'earnings sample.'

3.2. *The labor income-based measure of human capital*

To compute LIHK, we do not approximate the integral Eq. (3) directly, but, as suggested by Eq. (12), divide each state's wage and salary income[19] by an estimate of the wage in that state of somebody with no skill. The wage of zero-skill workers is taken to be the (exponential of the) constant from a 'Mincer wage regression,' estimated from our earnings sample for each state at each date. Our Mincer wage regressions regress log average weekly earnings on years of schooling, years of experience (defined to be age – years of schooling – 6), a gender dummy, a race dummy, a marital status dummy, a dummy for residence in an SMSA, and a constant.[20]

We see two main advantages of using a Mincer regression (over simply computing the sample mean of the wage of zero-schooling workers) in order to estimate the wage of somebody with no skill. The first is that a Mincer regression constant can be estimated even if there are no workers with zero schooling in a particular state. Second, to the extent that the Mincer specification imposes the correct structure on the data, our estimates of the wage of somebody with no skill are more precise because they use information from the entire skill distribution.

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[18]These sample selection criteria are intended to mimic those in the labor literature on wage differentials (for example Juhn et al. 1993). We were unwilling to mimic the minimum weekly earnings cut-off of $67 (Juhn et al. 1993), as it excluded a significant number of workers in 1940. Unlike Juhn et al. 1993, we therefore adjust the $67 for 2 percent per year growth factor (e.g. it is $28.35 1982 for 1939).

[19]Since data on personal income by state are available for all of the years 1940–1990 from the BEA (U.S. Department of Commerce, 1984, 1990), we use them as our proxy for production in the state. Population and labor income by state for the years 1969–1990 are obtained from the BEA (U.S. Department of Commerce, 1992). Population figures for the Census years are obtained from the Bureau of the Census publications (U.S. Bureau of the Census, various issues).

[20]The estimated intercept might therefore be interpreted as the log wage of rural, unmarried, white male with no experience and no schooling.

Table 1 reports our estimates of the stock of human capital for each of the 48 contiguous states for each census year starting in 1940. At the bottom of the table, the geometric average for the United States and for the four Census regions are reported. We note that the time pattern is quite similar for the four Census regions. After a substantial decline in the stock of human capital between 1940 and 1950, human capital increased steadily between 1950 and 1990 (the only exception is a slight decline for the West and the Northeast between 1960 and 1970). We note that the largest increase in the stocks of human capital for all regions took place between 1980 and 1990: aggregate human capital stocks increased by 52 percent in that decade, as compared to a 17 percent increase for the previous 40 year period.

3.2.1. Why do we conclude that human capital declined in the 1940s?

A puzzling finding of Table 1 is that the value of human capital experimented a decline during the 1940s. The 'technical' reason behind this result is that the wage distribution shrank substantially during that decade. When this happens, the numerator of our measure of human capital falls relative to the denominator so we conclude that the value of human capital falls.

In a sense, we arrive at the right conclusion because when the wage distribution shrinks, the value of being educated falls. When the uneducated are as productive as the educated people, then the value of human capital is actually lower.

At another level one might argue that it is incorrect to say that the value of human capital decreases when the truth is that the uneducated become more productive. Consider, for example, an economy with two types of individuals (educated and uneducated). Suppose that their productivities are $\theta(E)$ and $\theta(U)$, respectively, and imagine that the production function can be written as

$$Y = F[K, \theta(U)N(U) + \theta(E)N(E)],$$

where $N(E)$ and $N(U)$ are the number of educated and uneducated, respectively. Since we normalize by the wage of the uneducated, our measure of human capital in this case will be

$$H = N(U) + \{\theta(E)/\theta(U)\}N(E).$$

Consider an increase in the productivity of the educated, $\theta(E)$. The output in our economy increases because the educated are more productive. Our measure of human capital will correctly capture an increase. Now consider an increase in the productivity of the uneducated, $\theta(U)$. Our measure says that human capital has declined. The reason is that, by assuming that the uneducated are the numeraire (so they are equally productive always and everywhere), we assume that their productivity is always one. When their productivity increases, our measure concludes that there has been a *Decline* in the value of human capital *as well as* an increase in the overall productivity of human capital. In other words, we rewrite the production function as

$$Y = F(K, \theta(U)H),$$

so that when $\theta(U)$ increases, we conclude that H declines that its 'technological parameter' $\theta(U)$ increases.

3.2.2. Interregional comparisons

It is interesting to compare the time pattern of human capital in the different regions (Fig. 2). We note that, while being the region with the highest amount of human capital, the Northeast lost its leading position in the 1980s. The traditionally laggard South, experimented a large increase in the stock of human capital during the 1980s, leaving them with the second highest stock by 1990, following the Midwest. The West has been the region with the lowest amount of human capital ever since 1960.

Fig. 3 displays visually the relation between our measure of human capital and its two components (aggregate labor income per capita and the wage of the representative person with zero years of schooling) in the full sample of 48 states. In the horizontal axis we display the log of human capital, log(H). The vertical axes represent the logarithm of $w(0)$.[21] The figure also displays iso-labor-income lines, which show the combinations of log($w(0)$) and log(H) which yield the same amount of log(income per capita). The lines represent higher amounts of income as we move to the right. We note that, in 1990, the state with the largest amount of human capital was New York, followed by Delaware and Minnesota. At the lowest end, we have Montana and Mississippi, followed by Rhode Island and Wyoming.

Some surprising results immediately arise. First of all, we see that some of the New England states (Rhode Island, New Hampshire and Vermont) have very small amounts of human capital per person, despite having high labor income per capita. The reason is that zero-schooling workers receive large salaries in these states (note that they have the three largest estimates for $w(0)$ in 1990). This means that other things being equal, in these states workers with higher levels of education are not much more productive than workers with no schooling. Hence, when measured in units of zero-schooling workers, these states do not have very high stocks of human capital.

Now consider the states with the highest levels of labor income per capita, New York, Delaware, Connecticut, New Jersey and Massachusetts. We note that, in New York and Delaware, the workers with zero schooling have relatively low wages. Hence, our measured human capital for these states is very high. Conversely, the zero-schooling workers in Massachusetts and New Jersey enjoy relatively high base wages, so that our measure of H is lower. Connecticut has a slightly higher level of labor income and an intermediate base wage, $w(0)$. As a result, our measured human capital is quite high.

At the bottom part of the income scale, we see that Arkansas and South Dakota have extremely low wages for zero-schooling persons so that our measured human capital is high relative to the amount of labor income enjoyed in those states. On the other hand, West Virginia, Montana and Mississippi have high base wages so human capital in those states are low.

Fig. 4 reports the same data for 1940. The highest stocks of human capital were found in Delaware, Illinois, New Jersey, Connecticut, New York, Massachusetts and Minnesota. Despite having the highest level of labor income per capita, we do not find that Nevada had large amounts of human capital because their base wage $w(0)$ was also very high. To a smaller degree, the same was true for California.

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[21] The exact estimates of $w(0)$ and labor income per capita are reported in Table 2 and Table 3, respectively.

At the lowest end of the income scale, Mississippi and Arkansas had a relatively high wage for zero-schooling persons so that their measured human capital for 1940 is extremely low. North Carolina, South Dakota, Louisiana, and Alabama follow closely.

Fig. 5 and Fig. 6 examine the behavior of the two components of human capital for the four Census regions. Fig. 5 displays the behavior of labor income per capita over time. We note a positive trend. We see that the East has always enjoyed the largest levels of labor income while the South has systematically had the lowest.

3.2.3. A macroeconomic interpretation of zero-schooling wages

Fig. 6 shows the behavior of the wage of the workers with no schooling. Under a Cobb–Douglas production function, this measure is positively related to the ratio of physical to human capital, K/H. The figure displays an upward trend for all regions and for all periods except the 1980s. During this last decade, the Midwest and the West experienced a net reduction in zero-schooling wages. The South saw a small increase in $w(0)$. There was a large increase in $w(0)$ in the Northeast (this explains why, during this decade, the measured stock of human capital did not increase as much in the Northeast as it did in other regions). We also observe that between 1940 and 1950, the measured zero-schooling wages increased significantly in all four regions. This 'explains' (at least mechanically) why we measure a huge decline in the stock of human capital in virtually all states during this decade.

For 1990, the Northeast had the highest value of $w(0)$, followed by the West. A low $w(0)$ corresponds to a low ratio of physical to human capital. This suggests that in 1990, the Northeast was the region with the highest K/H ratio. If we look back at Fig. 3, we see that Rhode Island, New Hampshire and Vermont are the states with the three highest levels of $w(0)$. They are followed by Nevada, Massachusetts, New Jersey, Wyoming and Connecticut. In other words, the six states of New England take six of the top eight positions. This was not true in 1980, when none of them was on the top eight (Rhode Island was the highest New England state in the 13th position and Vermont was the lowest in the 42nd).[22] This suggests that the big New England boom of the 1980s left this region with a huge stock of *physical* capital and with not so large stock of human capital. The end result was large wages for everybody, including the less educated.

Similarly, North Dakota, New Mexico, Oklahoma, Arkansas, Missouri and Tennessee were the states with the lowest K/H ratios in 1990. This explains why our measure of H is not especially low, despite the fact that these states do not have particularly high labor income per capita.

3.2.4. Income per capita versus income per worker

We used income per capita to compute human capital. Theory suggests the use of income per worker. Practical problems in measuring workers suggested the use of income per

[22] See Column 5 in Table 2.

capita.[23] We do not think that this is an important drawback in general, even though participation and employment rates may have varied substantially both over time and across states.

We computed human capital using labor income per person-weeks worked (divided by the same $w(0)$s reported in Table 2) and found a very strong correlation with our measure of labor income per capita. For example, the correlation for 1990 and 1980 was 0.92 and 0.95, respectively. The lowest correlation coefficient found was 0.83 in 1940. Hence, we do not think that the use of population rather than employment is a substantial drawback in the computation of human capital.

3.3. Variable weights

In order to compare the measures existing in the literature with ours, we need to compute these alternative measures using our data set. We start with the variable–weights measure.

Each state's educational attainment distribution is estimated by dividing its civilian labor force aged 25–65 into seven schooling categories. Since our schooling data are categorized in this discrete way, we must approximate integral Eq. (3) with a sum:

$$h_{it} = \sum_{j=0}^{6} \theta^{j}_{it} \eta^{j}_{it}, \tag{16}$$

where θ^{j}_{it} is the average efficiency of a worker (in state i at date t) in schooling category j while η^{j}_{it} is the share of state i's workers in category j.

To compute aggregate human capital, the weight for category j is taken to be the U.S. average weekly earnings of those workers in our earnings sample and in category j relative to the U.S. average weekly earnings those in the earnings sample with no schooling. This procedure generates a set of seven weights for each of the six census years. The weights, or efficiency parameters, are displayed in Table 5 and graphed in Fig. 7. We see that, for the most part, the efficiency parameters increase in years of schooling, although the pace at which wages rise with schooling varies over time. Wages rose with schooling fairly slowly in 1950 and 1980, more rapidly in 1940, 1970 and 1990, and quite rapidly in 1960.

Table 6 displays the estimates of human capital using the variable weights reported in Table 5. The average stock for the United States is shown in Fig. 8. The most salient feature of this measures is its huge value for 1960.

Fig. 9 compares our LIHK with the flexible weight measure of human capital for 1990. We note that the correlation is quite low (0.26; the correlation was higher in earlier periods, as reported in Table 9). We note a set of six states at the top left part of the Fig. 9 (New Hampshire, Utah, Vermont, Montana, Wyoming and Rhode Island) which seems to have a much higher measure of human capital if we use fixed weights than if we use labor income. In fact, the regression slope (reported in Fig. 9) increases substantially if we eliminate these

[23] What is required is to compute aggregate person-weeks worked (this together with $w(0)$ should divide aggregate labor income). As we only have samples of the population, we need to know the sampling frequency in order to tabulate aggregates. At this point, we are unclear on the sampling frequency of some of the PUMS, but will determine them for later drafts.

Another problem is to obtain a consistent definition of 'self-employed' (self-employment may mean one thing for computation of the national accounts but another thing in the census).

five states from the picture (the regression line when all states are used is the solid line; the dotted line represents the regression line when the six states mentioned above are excluded; the exclusion of these states also changes the correlation coefficient substantially, increasing it to 0.57).

3.4. *Fixed weights*

To construct the fixed weight variable, we simply take the weights for all schooling categories for one of the sample years (we take the weights for 1970, although the precise year does not matter much).

Table 7 reports the stocks of human capital when fixed weights are imposed over time. Since we see in Table 5 that the 1970 weights were somewhat typical, we used them to compute the fixed weight measure of human capital.[24] Fig. 8 shows the behavior of the U.S. average over time. It displays a steady increase in all decades.

3.5. *Average years of schooling*

Table 8 reports the average years of schooling. As argued in Section 2, this is another fixed weight measure, where the weights are not determined by the market but, instead, are assumed to be proportional to the number of years of school education.[25] The U.S. average for this measure is displayed in Fig. 8. Like the fixed weights measure, this one experiments with a steady increase between 1940 and 1990. Fig. 10 compares average years of schooling with human capital for 1990. Again we see that there are five states which seem to have less human capital than indicated by their average years of schooling (New Hampshire, Utah, Vermont, Montana, and Wyoming; note that Rhode Island is no longer an outsider since, on top of having very low amounts of human capital, this state seems to have very low levels of schooling, at least relative to the other states in the same year).

Just to complete the comparisons, Fig. 9 displays human capital and labor income per capita in 1990. The correlation is substantial, 0.55, and of the five states that seemed 'outliers' before, only New Hampshire seems to remain an outlier (in the sense of having less human capital than 'indicated' by its level of income).

Table 9 reports the within-period correlations of all these measures of human capital. We note that, for all periods, the correlation between Fixed weights, Variable weights and Schooling is well above 0.95 (and in most cases close to 0.99).[26] The correlation between

[24]We could use average weights instead. For example, we could compute the average of each of the weights over time. Alternatively, we could estimate a large panel of all census years and restrict the schooling coefficients to be the same over time. We estimated our fixed weight measure with the weights corresponding to different years and found little difference in the estimated stocks of human capital. As a result, we believe that using sophisticated fixed weights will not change our estimates of human capital with fixed ways in any substantial manner.

[25]The numbers in Table 5 show that the average wage of persons with 17 years of schooling is somewhere between two and two and a half times larger than the wages of persons with three or less years of schooling, despite the fact that they have somewhere between five and infinite times more years of schooling.

[26]The correlations over time are not so strong. We can see in Fig. 8 that, for the US, fixed weights human capital and average years of schooling increased in all decades. Variable weights of human capital, on the other hand, rise in only two out of the five ten-year periods (the 1950s and the 1980s).

any one of these measures and our labor income-based measure of human capital is substantially smaller.

4. Nonlinear labor aggregators

Our analysis thus far has assumed that different types of labor can be aggregated in a linear fashion. Here we show that firstly our labor income-based measure requires only an assumption about the substitutability of workers with those without schooling, and secondly that our data do not obviously reject this particular perfect substitutability assumption.

Suppose that J different types of labor are aggregated nonlinearly in the aggregate production function. For clarity, however, let us impose some functional form of restrictions:

$$H(N(0),N(1)...N(J)) = [N(0)^{(\psi-1)/\psi} + \phi(N(1)...N(J))^{(\psi-1)/\psi}]^{\psi/(\psi-1)} \tag{17}$$

where $N(j)$ is the number of workers of type j, ϕ is *homogeneous of degree one*,[27] and ψ is the constant elasticity of substitution of workers without schooling ($N(0)$) for ϕ, an aggregate of workers with schooling.[28]

Under the assumption that wages are equated to marginal products, the wage of a person of type j, is:

$$w(j) = F_H^*(\partial H/\partial N(j)). \tag{18}$$

Labor income is:[29]

$$\sum_{j=1}^{J} N(j)w(j) = F_H^*\left(\sum_{j=1}^{J} N(j)[\partial H/\partial N(j)]\right) = F_H^*H. \tag{19}$$

The second equality follows from the homogeneity of the labor aggregator. It is clear from Eqs. (19 and 20) that, if zero-schooling workers are perfect substitutes for workers with skill ($\psi \Rightarrow \infty$), then a zero-schooling worker's wage is equal to the aggregate marginal product of h:

$$w(0) = F_H^*1 = F_H. \tag{20}$$

Thus if no-skill workers are perfect substitutes for workers with skill ($\psi \Rightarrow \infty$), then human capital is labor income, normalized by the wage of somebody with no skill.

$$\sum_{j=1}^{J} N(j)w(j)/w(0) = F_H^*H/F_H = H. \tag{21}$$

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[27] The assumption of linear homogeneity is important.

[28] j can be thought of as years of schooling, although j can also index many other attributes of skill such as work experience.

[29] This assumes a participation rate that is constant across worker types, or an interpretation of H as the amount of human capital engaged in market production.

This is exactly the labor income-based measure of human capital that we have used throughout the paper. It correctly measures human capital even when various types of labor are aggregated in nonlinear ways, as long as no-skill workers are perfect substitutes for some aggregate of the skilled workers. In terms of our model's parameters, the required assumption is that $\psi = \infty$. The remainder of this subsection empirically assesses this particular perfect substitutability assumption by using our U.S. data to obtain estimates of ψ.

If firms are unable to substitute no-skill workers for workers with skill (ψ is small), then the wage of no-skill workers relative to other workers will be sensitive to exogenous changes in their relative supplies. At the other extreme, perfect substitutability between the two types of workers means that the relative wage depends only on parameters of the production function, not on relative supplies. We use our U.S. data to compare a state's relative supplies with its wage ratio; a negative correlation will be taken as evidence against the perfect substitutability assumption.

To derive this test more formally, let us assume that various types of skilled workers are perfectly substitutable for each other:[30]

$$\phi(N(1)...N(J)) \equiv \sum_{j=1}^{J} \lambda_j N_j. \tag{22}$$

Define $w(\sim 0)$ to be the average wage of skilled workers:

$$w(\sim 0) = \frac{\sum_{j=1}^{J} N(j)w(j)}{1-\eta(0)}. \tag{23}$$

Then, holding constant the general level of wages in the state ($w(\sim 0)$ and w_j/λ_j for any $j = 1...J$), the elasticity of relative wages with respect to relative supplies is $-1/\psi$:

$$\ln[w(0)/w(\sim 0)] = \frac{\psi-1}{\psi}\ln[w_j/\lambda_j] - \frac{1}{\psi}\ln\frac{\eta(0)}{1-\eta(0)} - \frac{\psi-1}{\psi}\ln w(\sim 0), \text{ any } j = 1...J \tag{24}$$

Under the assumption that, holding constant $\ln w(\sim 0)$, relative supplies are uncorrelated with w_j/λ_j (one can think of this ratio as indicative of the general level of wages in the economy), one can regress $\ln w(0)$ on $\ln w(\sim 0)$ and the log of the relative supplies and the coefficient on the relative supplies is $-1/\psi$. If relative supplies fail to correlate with relative wages, then we fail to reject the perfect substitutability hypothesis ($\psi = \infty$).

Table 10 presents regressions of relative wages on relative supplies. In the top panel, $w(0)$ is measured as the within-state average weekly earnings of those workers in our earnings sample with fewer than five years of schooling. $w(\sim 0)$ is taken to be the average weekly earnings of all other workers in our earnings sample.

[30] While the exact functional relationship between relative wages and relative supplies will depend on this assumption, the basic idea behind the tests – that relative labor demand curves slope down – is more general.

We find that, contrary to the perfect substitutability hypothesis, relative wages and relative supplies are negatively correlated in five of the six cross-sections of states. However, the implied elasticity estimates (1 over the estimated coefficient on relative supplies) are quite high: 6, 7, 9, ∞, 45, and 25; relative wages are not very responsive to relative supplies.

For our 1970, 1980 and 1990 earnings subsamples of the Census PUMS, there are a few states which do not have any workers with fewer than five years of schooling. These states are: Nebraska (1970), North Dakota (1990), South Dakota (1970), Utah (1970), Vermont (1980, 1990) and Wyoming (1970). As an alternative to excluding states because of their zero-cell size, the bottom panel of Table 10 displays estimates of Eq. (24) that use the Mincer regression constant as an estimate of $\ln w(0)$ and the within-state average weekly earnings of our earnings sample as an estimate of $w(\sim 0)$. We see that, using this alternative estimate of $w(0)$, one cannot reject the perfect substitutability hypothesis.[31] Point estimates of $-1/\psi$ are negative in only three of six decades and, in those three decades, the implied elasticity estimates are quite large: 81, 90 and 27.

Table 10 regressed relative wages on relative supplies, while Eq. (24) suggests that the average wage of skilled workers $w(\sim 0)$ should also be included as a RHS variable. When we do so, the implied elasticities are slightly larger than those reported in Table 10, so we limit our presentation to the simpler specification found there, which is less favorable to the perfect substitutability hypothesis.

It is therefore not clear why we should be uncomfortable with our assumption that workers without schooling are perfect substitutes for those with schooling. As a result, we are comfortable with our labor income-based measure of human capital because it is robust to any nonlinear aggregation schemes.

5. Summary and conclusions

In this paper we discuss and actually construct various measures of the value of human capital in a cross-section of U.S. states for 6 census years.

We argue that allowing different people to have different weights in our measures of human capital is a good idea for at least two reasons: first, schooling in different places and at different times has different qualities. Second, different types (and amounts) of schooling have different relevance in different places and points in time. To capture the concepts of schooling quality and schooling relevance, our measure of human capital must allow for variable weights.

We have also argued that the only sensible numeraire is a zero-schooling worker. The reason is that, if schooling has different quality and relevance across states and over time, then any positive amount of schooling will affect people in different ways. Hence, workers with any positive amount of schooling will be different and, as a result, will not be good candidates for a numeraire.

[31] We also note that the lower panel's estimate of $\ln w(0)$, the Mincer regression constant, coincides with the estimates that we used to construct our labor income-based measure of human capital.

We note that, unlike other measures of aggregate human capital, ours does not require the assumption of infinite elasticity of substitution across all types of workers. We only need perfect elasticity between the zero-schooling workers and the rest. We test this assumption and find little evidence of finite elasticities.

We argue that a sensible measure of the value of human capital is the ratio of total labor income per capita to the wage of a person with zero years of schooling. The reason is that total labor income not only incorporates human capital, but also physical capital: given human capital, regions with higher physical capital will tend to have higher wages for all workers and, therefore, higher labor income. We find that one way to net out the effect of aggregate physical capital on labor income is to divide labor income by the wage of a zero-schooling worker.

To compute the wage of a zero-schooling worker, we regress, state by state and year by year, individuals' average weekly earnings on their schooling and a number of characteristics (like experience, sex, race, and marital status). The constant term is taken to be the wage of a worker in the corresponding state and in the corresponding year with zero schooling (and zero experience).

Since our measure of human capital is not mechanically tied to the educational attainment of the work force, we are able to actually test the proposition that the increase in educational attainment over the period is indicative of an increase in the amount of human capital. We find that our measure of human capital is positively correlated with other measures of human capital, like the average years of schooling. We find, however, that the correlation is far from perfect, and that some states which have more schooling do not have very high stocks of human capital. This was the case, for example, for some of the New England states in 1990. The period 1940–1980 was a period of fairly substantial increase in average years of schooling, but not human capital.

For the average U.S. state, our measure suggests that the value of human capital during the 1980s grew at a much larger rate than schooling. The reason has to do with movements in the relative productivities of the different workers: in some sense, some workers and some types of schooling became more relevant in the 1980s and, as a result, measured human capital increased.

6. Unlinked References

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7. Tables placement requires correct citation and subsequent direction from the author

Tables 1–10

Table 1
Labor income-based human capital (logs)

	1940	1950	1960	1970	1980	1990
1 AL	3.350	3.091	3.593	3.712	3.851	4.409
2 AZ	3.702	3.384	3.684	3.730	3.828	4.341
3 AR	3.134	2.786	3.330	3.642	3.640	4.354
4 CA	3.827	3.453	3.902	3.877	4.116	4.529
5 CO	3.731	3.442	3.747	3.662	4.141	4.669
6 CT	4.083	3.715	4.121	3.889	4.108	4.578
7 DE	4.474	3.731	4.256	4.345	4.482	4.694
8 FL	3.551	3.346	3.512	3.656	3.836	4.410
9 GA	3.488	3.312	3.633	3.753	4.056	4.548
10 ID	3.711	2.800	3.424	3.512	3.633	4.297
11 IL	4.263	3.729	3.961	3.780	3.912	4.570
12 IN	3.812	3.407	3.585	3.644	3.724	4.459
13 IA	3.742	3.331	3.456	3.412	3.690	4.265
14 KS	3.588	3.342	3.571	3.632	3.841	4.460
15 KY	3.388	2.973	3.352	3.557	3.639	4.290
16 LA	3.282	3.205	3.550	3.317	3.572	4.252
17 ME	3.585	3.092	3.662	3.369	3.792	4.362
18 MD	4.017	3.642	4.008	3.973	4.163	4.637
19 MA	4.048	3.801	3.852	3.754	4.134	4.399
20 MI	3.864	3.535	3.747	3.716	3.879	4.534
21 MN	4.052	3.404	3.733	3.597	4.173	4.712
22 MS	2.688	2.728	3.191	3.138	3.671	3.924
23 MO	3.899	3.603	3.786	3.842	3.967	4.666
24 MT	3.551	3.200	3.376	3.235	3.605	3.893
25 NE	3.925	3.501	3.619	3.646	3.752	4.392
26 NV	3.561	4.106	3.756	3.561	3.904	4.301
27 NH	3.646	3.332	3.409	3.717	3.961	4.045
28 NJ	4.088	3.710	3.987	3.570	4.012	4.412
29 NM	3.402	3.386	3.920	4.096	3.758	4.448
30 NY	4.059	3.855	4.082	4.020	4.247	4.735
31 NC	3.180	3.229	3.660	3.741	4.045	4.574
32 ND	3.725	3.280	3.355	3.845	3.557	4.417
33 OH	4.001	3.569	3.769	3.692	3.852	4.582
34 OK	3.623	3.404	3.818	3.906	3.916	4.436
35 OR	3.642	3.259	3.430	3.387	3.671	4.332
36 PA	3.841	3.515	3.856	3.838	3.876	4.591
37 RI	3.914	3.787	3.573	3.125	3.773	3.969
38 SC	3.207	2.930	3.531	3.477	3.831	4.282
39 SD	3.576	3.708	3.677	3.665	3.548	4.167
40 TN	3.539	3.260	3.639	3.659	3.965	4.581
41 TX	3.780	3.600	3.950	3.782	4.031	4.499
42 UT	3.741	3.207	3.719	3.412	3.603	4.151
43 VT	3.959	3.198	3.745	3.801	3.918	4.031
44 VA	3.733	3.375	3.958	4.005	4.176	4.671
45 WA	3.789	3.381	3.726	3.475	3.773	4.409
46 WV	3.387	2.954	3.495	3.404	3.720	4.069
47 WI	3.845	3.461	3.610	3.552	3.706	4.475
48 WY	3.642	3.323	3.627	3.630	3.738	4.020
US Mean	3.701	3.383	3.686	3.661	3.871	4.393

Table 1
(Continued)

	1940	1950	1960	1970	1980	1990
S.D.	0.313	0.287	0.224	0.236	0.206	0.216
Northeast	3.914	3.556	3.810	3.676	3.980	4.347
South	3.489	3.223	3.655	3.692	3.912	4.414
Midwest	3.858	3.489	3.656	3.669	3.800	4.475
West	3.664	3.358	3.665	3.598	3.797	4.308

This table reports the logarithm of the computed stocks of human capital based on labor income. See the text for a discussion of the construction of such a measure. The four regions are defined by the Bureau of the Census.

Table 2
log(w(0)) (Mincer regression constants)

	1940	1950	1960	1970	1980	1990
1 AL	1.8334	3.2157	3.3325	3.8717	4.6016	4.6525
2 AZ	2.1244	3.2247	3.5279	4.0624	4.7852	4.7941
3 AR	1.7153	3.2347	3.3503	3.7611	4.6694	4.5613
4 CA	2.4252	3.5968	3.6095	4.1481	4.7202	4.8822
5 CO	2.0172	3.3053	3.5380	4.1915	4.6632	4.6528
6 CT	2.3335	3.4009	3.4043	4.1668	4.7619	5.0284
7 DE	1.7912	3.4034	3.2945	3.7196	4.3684	4.7968
8 FL	2.1146	3.2683	3.5814	4.1062	4.6821	4.7300
9 GA	1.8362	3.1538	3.3974	4.0153	4.5411	4.7289
10 ID	1.8407	3.7433	3.5896	4.0912	4.8254	4.6683
11 IL	1.9637	3.3917	3.5523	4.2635	4.8927	4.8276
12 IN	2.1105	3.5276	3.7316	4.2174	4.9206	4.7496
13 IA	1.7255	3.1631	3.5246	4.2143	4.8637	4.8025
14 KS	1.8400	3.2345	3.4873	4.0055	4.7917	4.6941
15 KY	1.8537	3.3742	3.5104	4.0276	4.7965	4.7262
16 LA	2.1349	3.3002	3.4270	4.3008	5.0543	4.7545
17 ME	2.1695	3.5253	3.4740	4.3140	4.6530	4.7663
18 MD	2.1229	3.2763	3.2856	3.9313	4.5379	4.7470
19 MA	2.1820	3.2324	3.5998	4.2469	4.6470	5.1173
20 MI	2.3299	3.5616	3.6537	4.2306	4.8604	4.7701
21 MN	1.6613	3.2959	3.4456	4.2464	4.5538	4.6277
22 MS	2.0083	3.1770	3.4068	4.2498	4.6112	4.8916
23 MO	1.8597	3.1653	3.4809	4.0291	4.6803	4.5639
24 MT	2.2706	3.4960	3.6974	4.3392	4.8897	4.9699
25 NE	1.4963	3.0445	3.4587	4.0517	4.8364	4.7468
26 NV	2.8027	2.9964	3.8750	4.6122	5.0516	5.1290
27 NH	2.2688	3.3920	3.8028	4.0308	4.6107	5.2224
28 NJ	2.2651	3.3503	3.4771	4.4113	4.7631	5.1098
29 NM	2.0153	3.1886	3.2478	3.5335	4.7639	4.5537
30 NY	2.2445	3.3261	3.5050	4.0906	4.5560	4.7804
31 NC	2.1200	3.2054	3.2963	3.9809	4.5032	4.6387
32 ND	1.4952	3.0041	3.4332	3.6075	4.9318	4.5359
33 OH	2.1186	3.4508	3.6465	4.2550	4.8688	4.6728
34 OK	1.6970	3.0668	3.1999	3.7270	4.6867	4.5620
35 OR	2.3082	3.6275	3.8405	4.4205	4.9977	4.8399
36 PA	2.2458	3.4465	3.4948	4.0697	4.8032	4.6612

Table 2
(Continued)

	1940	1950	1960	1970	1980	1990
37 RI	2.2905	3.2455	3.7610	4.7700	4.8471	5.2948
38 SC	2.0761	3.4253	3.3615	4.1857	4.6637	4.8486
39 SD	1.6199	2.5608	3.0669	3.6941	4.7587	4.7017
40 TN	1.7844	3.1599	3.3216	4.0202	4.5590	4.5794
41 TX	1.7117	3.0956	3.1669	3.9839	4.7104	4.6997
42 UT	1.9975	3.5279	3.5115	4.3137	4.9494	4.9169
43 VT	1.7750	3.3890	3.3296	3.9303	4.5448	5.1383
44 VA	2.0356	3.3089	3.1735	3.8337	4.5053	4.6945
45 WA	2.3041	3.5701	3.6209	4.4200	5.0033	4.8843
46 WV	2.2830	3.6894	3.5396	4.2393	4.7684	4.8320
47 WI	1.9897	3.3784	3.6446	4.2555	4.9517	4.7341
48 WY	2.1705	3.5671	3.6766	4.1321	5.1745	5.1176
US Mean	2.0287	3.3184	3.4865	4.1108	4.7537	4.7999
S.D.	0.2615	0.2084	0.1779	0.2415	0.1689	0.1849
Northeast	2.1971	3.3675	3.5387	4.2256	4.6874	5.0132
South	1.9448	3.2721	3.3528	3.9971	4.6411	4.7152
Midwest	1.8508	3.2315	3.5104	4.0892	4.8258	4.7022
West	2.2069	3.4403	3.6122	4.2058	4.8931	4.8553

This table reports the logarithm of the computed wage of zero-schooling workers. See the text for a discussion of the construction of such measure. The four regions are defined by the Bureau of the Census.

Table 3
Wage income per capita (log)

	1940	1950	1960	1970	1980	1990
1 AL	5.1836	6.3070	6.9262	7.5840	8.4530	9.0625
2 AZ	5.8271	6.6094	7.2121	7.7927	8.6133	9.1360
3 AR	4.8501	6.0209	6.6810	7.4031	8.3100	8.9163
4 CA	6.2527	7.0505	7.5123	8.0255	8.8364	9.4118
5 CO	5.7484	6.7477	7.2859	7.8539	8.8048	9.3225
6 CT	6.4174	7.1165	7.5254	8.0558	8.8702	9.6065
7 DE	6.2659	7.1353	7.5507	8.0648	8.8510	9.4914
8 FL	5.6665	6.6146	7.0939	7.7631	8.5187	9.1403
9 GA	5.3242	6.4664	7.0310	7.7684	8.5971	9.2772
10 ID	5.5518	6.5438	7.0137	7.6037	8.4590	8.9654
11 IL	6.2272	7.1213	7.5133	8.0443	8.8050	9.3981
12 IN	5.9229	6.9354	7.3171	7.8623	8.6448	9.2091
13 IA	5.4676	6.4948	6.9812	7.6271	8.5538	9.0675
14 KS	5.4284	6.5774	7.0592	7.6384	8.6329	9.1548
15 KY	5.2423	6.3471	6.8627	7.5849	8.4364	9.0171
16 LA	5.4176	6.5056	6.9774	7.6183	8.6272	9.0065
17 ME	5.7545	6.6175	7.1368	7.6837	8.4455	9.1286
18 MD	6.1405	6.9192	7.2945	7.9043	8.7014	9.3843
19 MA	6.2300	7.0335	7.4528	8.0012	8.7810	9.5170
20 MI	6.1942	7.0974	7.4014	7.9473	8.7403	9.3048
21 MN	5.7137	6.7001	7.1790	7.8436	8.7268	9.3402
22 MS	4.6967	5.9059	6.5988	7.3878	8.2828	8.8165
23 MO	5.7593	6.7689	7.2673	7.8712	8.6482	9.2301
24 MT	5.8220	6.6963	7.0742	7.5752	8.4953	8.8633

Table 3
(Continued)

	1940	1950	1960	1970	1980	1990
25 NE	5.4222	6.5458	7.0780	7.6979	8.5885	9.1395
26 NV	6.3647	7.1034	7.6314	8.1738	8.9558	9.4306
27 NH	5.9153	6.7247	7.2125	7.7479	8.5721	9.2673
28 NJ	6.3540	7.0607	7.4643	7.9818	8.7759	9.5218
29 NM	5.4177	6.5750	7.1683	7.6302	8.5226	9.0024
30 NY	6.3037	7.1811	7.5877	8.1108	8.8035	9.5155
31 NC	5.3000	6.4344	6.9564	7.7222	8.5491	9.2134
32 ND	5.2210	6.2848	6.7890	7.4527	8.4892	8.9530
33 OH	6.1202	7.0198	7.4160	7.9472	8.7216	9.2557
34 OK	5.3209	6.4715	7.0187	7.6337	8.6036	8.9986
35 OR	5.9508	6.8866	7.2706	7.8081	8.6694	9.1720
36 PA	6.0875	6.9622	7.3516	7.9087	8.6792	9.2529
37 RI	6.2047	7.0331	7.3344	7.8955	8.6203	9.2643
38 SC	5.2835	6.3560	6.8930	7.6633	8.4950	9.1315
39 SD	5.1965	6.2696	6.7443	7.3597	8.3076	8.8694
40 TN	5.3234	6.4208	6.9606	7.6793	8.5247	9.1610
41 TX	5.4923	6.6963	7.1170	7.7664	8.7420	9.1996
42 UT	5.7387	6.7357	7.2306	7.7266	8.5524	9.0682
43 VT	5.7340	6.5870	7.0754	7.7315	8.4631	9.1700
44 VA	5.7687	6.6842	7.1322	7.8393	8.6823	9.3658
45 WA	6.0939	6.9520	7.3473	7.8951	8.7770	9.2942
46 WV	5.6706	6.6434	7.0348	7.6439	8.4891	8.9012
47 WI	5.8350	6.8398	7.2552	7.8077	8.6585	9.2093
48 WY	5.8132	6.8904	7.3041	7.7621	8.9128	9.1378
US Mean	5.7299	6.7018	7.1733	7.7727	8.6247	9.1929
S.D.	0.4128	0.2994	0.2409	0.1878	0.1561	0.1891
Northeast	6.1112	6.9240	7.3490	7.9018	8.6678	9.3604
South	5.4341	6.4955	7.0080	7.6891	8.5539	9.1301
Midwest	5.7090	6.7212	7.1667	7.7582	8.6264	9.1776
West	5.8709	6.7991	7.2773	7.8042	8.6907	9.1640

This table reports the logarithm of labor income per capita. Source: Bureau of Economic Analysis, 1980, 1990. The four regions are defined by the Bureau of the Census.

Table 4
Educational attainment for the U.S. (1940–1990)

Schooling	Year					
Category	1940	1950	1960	1970	1980	1990
No School	0.028	0.016	0.008	0.006	0.004	0.007
0–4 yrs	0.095	0.073	0.038	0.023	0.012	0.007
5–7 yrs	0.177	0.150	0.096	0.070	0.036	0.034
8 yrs	0.270	0.196	0.163	0.099	0.044	
1–3 yrs HS	0.160	0.186	0.207	0.201	0.131	0.109
4 yrs HS	0.148	0.219	0.275	0.346	0.377	0.300
1–3 yrs Col	0.060	0.080	0.104	0.116	0.184	0.289
4+ yrs Col	0.062	0.080	0.108	0.138	0.212	0.254

The schooling categories 5–7 yrs and 8 yrs are not distinguished in the 1990 Census. The two categories are therefore merged in our computations for all census years.

Table 5
Estimates of $\theta(t,s)$

Year	Schooling category						
	0	1	2	3	4	5	6
1940	1	0.93	1.26	1.41	1.55	1.77	2.28
1950	1	1.02	1.18	1.29	1.36	1.56	1.88
1960	1	1.01	1.31	1.52	1.71	2.30	3.55
1970	1	0.97	1.19	1.32	1.46	1.73	2.36
1980	1	1.06	1.18	1.26	1.37	1.53	2.03
1990	1	0.99	1.11	1.21	1.37	1.62	2.42

See text for details on the computation of $\theta_i(t,s)$.

Table 6
Human capital with variable weights (HKVW, logs)

	1940	1950	1960	1970	1980	1990
1 AL	0.24307	0.22199	0.51428	0.38992	0.37725	0.48627
2 AZ	0.34186	0.30172	0.60918	0.46171	0.41871	0.52319
3 AR	0.25411	0.21454	0.50466	0.37638	0.36597	0.46372
4 CA	0.38536	0.31006	0.65190	0.47027	0.43382	0.53723
5 CO	0.36800	0.30177	0.66645	0.49064	0.45263	0.57243
6 CT	0.33610	0.28287	0.60395	0.44626	0.43070	0.56731
7 DE	0.33986	0.27311	0.62800	0.45145	0.41359	0.52376
8 FL	0.30484	0.26474	0.57909	0.41973	0.40205	0.49697
9 GA	0.24708	0.21774	0.50834	0.38861	0.38645	0.49679
10 ID	0.36326	0.29425	0.61570	0.42085	0.42193	0.50277
11 IL	0.34096	0.28100	0.58589	0.42676	0.41158	0.52677
12 IN	0.34418	0.27939	0.57982	0.41193	0.38394	0.47610
13 IA	0.35491	0.28402	0.58267	0.43675	0.40345	0.50363
14 KS	0.36238	0.29536	0.62631	0.45621	0.41902	0.53023
15 KY	0.26752	0.23014	0.51047	0.37441	0.36016	0.45684
16 LA	0.24240	0.22259	0.52936	0.38629	0.39036	0.47901
17 ME	0.34342	0.26638	0.55851	0.41889	0.39811	0.50219
18 MD	0.31105	0.27074	0.59001	0.43488	0.42891	0.55134
19 MA	0.36391	0.29547	0.61955	0.44123	0.43681	0.56693
20 MI	0.34072	0.27721	0.58101	0.42380	0.40243	0.50767
21 MN	0.34262	0.27536	0.59115	0.44121	0.42981	0.53711
22 MS	0.23616	0.20993	0.50412	0.38265	0.37210	0.45540
23 MO	0.32390	0.26818	0.55677	0.42175	0.39455	0.50140
24 MT	0.35642	0.28967	0.61101	0.45312	0.43219	0.52563
25 NE	0.35653	0.28293	0.59987	0.41892	0.42051	0.50910
26 NV	0.37423	0.29946	0.60947	0.44099	0.39987	0.47537
27 NH	0.34615	0.28357	0.56026	0.44110	0.42312	0.54454
28 NJ	0.33243	0.27474	0.59275	0.42716	0.41989	0.54856
29 NM	0.29770	0.27870	0.64223	0.46087	0.41427	0.52002
30 NY	0.34383	0.28110	0.60540	0.44376	0.42167	0.53825
31 NC	0.27412	0.22845	0.50362	0.35679	0.37307	0.48329
32 ND	0.32295	0.24759	0.54840	0.42877	0.40335	0.50997
33 OH	0.34849	0.28037	0.58529	0.41615	0.39500	0.49556
34 OK	0.33664	0.28548	0.61286	0.42729	0.40793	0.49772

Table 6
(Continued)

	1940	1950	1960	1970	1980	1990
35 OR	0.37401	0.30042	0.63072	0.46398	0.43106	0.54054
36 PA	0.31993	0.27148	0.55983	0.40119	0.39536	0.50255
37 RI	0.32317	0.27491	0.54700	0.37346	0.38080	0.50483
38 SC	0.23691	0.21876	0.50002	0.36044	0.36893	0.46829
39 SD	0.33594	0.27219	0.56946	0.37449	0.39668	0.48877
40 TN	0.27692	0.23913	0.50726	0.37598	0.37415	0.47790
41 TX	0.31900	0.26544	0.58096	0.41146	0.40580	0.51200
42 UT	0.39733	0.32866	0.69160	0.48678	0.44835	0.54329
43 VT	0.34491	0.28997	0.58096	0.41461	0.41245	0.53152
44 VA	0.28161	0.25694	0.55983	0.41301	0.41421	0.53254
45 WA	0.37278	0.31416	0.65502	0.45097	0.43551	0.55252
46 WV	0.30218	0.24850	0.54265	0.40301	0.37163	0.45939
47 WI	0.32919	0.26958	0.57054	0.41383	0.39893	0.49591
48 WY	0.36495	0.29412	0.63453	0.36728	0.41391	0.51907
US Mean	0.325541	0.27114	0.58122	0.42079	0.40610	0.51129
S.D.	0.041633	0.02801	0.04674	0.03267	0.02243	0.02987
Northeast	0.3393	0.2800	0.5809	0.4230	0.4132	0.53407
South	0.2795	0.2417	0.5422	0.3970	0.3882	0.49007
Midwest	0.3418	0.2760	0.5814	0.4225	0.4049	0.50685
West	0.3632	0.3011	0.6379	0.4515	0.4274	0.52836

This table reports the logarithm of the computed stocks of human capital using variable weights. See the text for a discussion of the construction of this measure. The four regions are defined by the Bureau of the Census.

Table 7
Human capital with fixed weights (HKFW, logs)

	1940	1950	1960	1970	1980	1990
1 AL	0.21298	0.26123	0.33280	0.38992	0.46222	0.52592
2 AZ	0.30599	0.37619	0.39725	0.46171	0.51640	0.55945
3 AR	0.21839	0.24784	0.32652	0.37638	0.44742	0.50680
4 CA	0.34428	0.38395	0.42765	0.47027	0.53535	0.56850
5 CO	0.32774	0.37189	0.43749	0.49064	0.55788	0.60120
6 CT	0.29378	0.34660	0.39497	0.44626	0.52907	0.59419
7 DE	0.30066	0.33530	0.41032	0.45145	0.50903	0.55793
8 FL	0.26909	0.32124	0.37729	0.41973	0.49480	0.53620
9 GA	0.21793	0.25544	0.32719	0.38861	0.47355	0.53452
10 ID	0.31666	0.35895	0.40559	0.42085	0.52007	0.54385
11 IL	0.29714	0.34260	0.38379	0.42676	0.50593	0.56087
12 IN	0.29856	0.33839	0.38203	0.41193	0.47094	0.51855
13 IA	0.30856	0.34572	0.38443	0.43675	0.49612	0.54229
14 KS	0.31774	0.36197	0.41197	0.45621	0.51579	0.56543
15 KY	0.23104	0.27085	0.32992	0.37441	0.43994	0.50068
16 LA	0.21646	0.26664	0.33978	0.38629	0.47820	0.51952
17 ME	0.29515	0.31949	0.36875	0.41889	0.48943	0.53974
18 MD	0.27321	0.32998	0.38416	0.43488	0.52670	0.58078
19 MA	0.32084	0.36341	0.40727	0.44123	0.53648	0.59321
20 MI	0.29603	0.33511	0.38146	0.42380	0.49529	0.54717
21 MN	0.29759	0.33314	0.38786	0.44121	0.52914	0.57187

Table 7
(Continued)

	1940	1950	1960	1970	1980	1990
22 MS	0.20816	0.24425	0.32437	0.38265	0.45598	0.49996
23 MO	0.28039	0.32412	0.36420	0.42175	0.48434	0.54007
24 MT	0.31428	0.35497	0.40158	0.45312	0.53249	0.56191
25 NE	0.31114	0.34233	0.39627	0.41892	0.51750	0.54753
26 NV	0.33569	0.36823	0.40295	0.44099	0.49304	0.52022
27 NH	0.30096	0.34703	0.36838	0.44110	0.52044	0.57646
28 NJ	0.29088	0.33487	0.38740	0.42716	0.51517	0.57720
29 NM	0.26367	0.34158	0.41803	0.46087	0.50957	0.55503
30 NY	0.30272	0.34453	0.39569	0.44376	0.51796	0.56888
31 NC	0.24278	0.26925	0.32505	0.35679	0.45706	0.52436
32 ND	0.28068	0.29112	0.35805	0.42877	0.49666	0.54980
33 OH	0.30402	0.34041	0.38485	0.41615	0.48493	0.53531
34 OK	0.29744	0.35004	0.40050	0.42729	0.50202	0.53873
35 OR	0.32888	0.36879	0.41539	0.46398	0.53174	0.57487
36 PA	0.27687	0.32927	0.36775	0.40119	0.48469	0.53922
37 RI	0.28232	0.33408	0.35789	0.37346	0.46685	0.53914
38 SC	0.21364	0.25811	0.32054	0.36044	0.45134	0.51017
39 SD	0.29138	0.32895	0.37315	0.37449	0.48784	0.52919
40 TN	0.24053	0.28353	0.32807	0.37598	0.45790	0.51837
41 TX	0.28102	0.32250	0.37691	0.41146	0.49872	0.54670
42 UT	0.35511	0.40910	0.45589	0.48678	0.55388	0.57835
43 VT	0.29873	0.35431	0.38085	0.41461	0.50707	0.56407
44 VA	0.24865	0.31174	0.36213	0.41301	0.50807	0.56481
45 WA	0.32807	0.38927	0.43141	0.45097	0.53743	0.58534
46 WV	0.26431	0.29609	0.35312	0.40301	0.45540	0.50338
47 WI	0.28466	0.32496	0.37476	0.41383	0.48994	0.53580
48 WY	0.32199	0.36114	0.41701	0.36728	0.51087	0.55754
US Mean	0.28559	0.32896	0.38001	0.42079	0.49913	0.54814
S.D.	0.036926	0.03900	0.03264	0.03267	0.02862	0.02550
Northeast	0.2958	0.3415	0.3809	0.4230	0.5074	0.56578
South	0.2460	0.2890	0.3511	0.3970	0.4761	0.52930
Midwest	0.2973	0.3340	0.3819	0.4225	0.4978	0.54532
West	0.3220	0.3712	0.4191	0.4515	0.5271	0.56420

This table reports the logarithm of the computed stocks of human capital using fixed weights. See the text for a discussion of the construction of this measure. The four regions are defined by the Bureau of the Census.

Table 8
Average years of schooling (logs)

	1940	1950	1960	1970	1980	1990
1 AL	1.9313	2.0754	2.2555	2.3725	2.4829	2.5528
2 AZ	2.1679	2.2975	2.3752	2.4741	2.5504	2.5783
3 AR	1.9946	2.0821	2.2549	2.3730	2.4717	2.5393
4 CA	2.2927	2.3600	2.4352	2.4916	2.5655	2.5744
5 CO	2.2589	2.3367	2.4454	2.5181	2.5961	2.6216
6 CT	2.1936	2.2922	2.3857	2.4514	2.5616	2.6187
7 DE	2.1794	2.2327	2.4001	2.4620	2.5448	2.5924
8 FL	2.1050	2.2179	2.3452	2.4230	2.5254	2.5641

Table 8
(Continued)

	1940	1950	1960	1970	1980	1990
9 GA	1.9393	2.0474	2.2360	2.3575	2.4901	2.5613
10 ID	2.2730	2.3408	2.4222	2.4521	2.5570	2.5794
11 IL	2.2151	2.2944	2.3799	2.4405	2.5390	2.5849
12 IN	2.2289	2.3059	2.3879	2.4367	2.5168	2.5596
13 IA	2.2554	2.3178	2.3961	2.4723	2.5415	2.5787
14 KS	2.2647	2.3359	2.4223	2.4867	2.5615	2.5932
15 KY	2.0327	2.1348	2.2640	2.3599	2.4615	2.5316
16 LA	1.8991	2.0461	2.2394	2.3519	2.4989	2.5458
17 ME	2.2280	2.2718	2.3698	2.4211	2.5280	2.5725
18 MD	2.1103	2.2326	2.3554	2.4365	2.5625	2.6072
19 MA	2.2458	2.3289	2.4116	2.4591	2.5725	2.6147
20 MI	2.2163	2.2935	2.3826	2.4453	2.5414	2.5821
21 MN	2.2245	2.2915	2.3902	2.4660	2.5722	2.6023
22 MS	1.9219	2.0346	2.2304	2.3435	2.4747	2.5278
23 MO	2.1788	2.2622	2.3479	2.4394	2.5201	2.5711
24 MT	2.2429	2.3180	2.4085	2.4791	2.5727	2.5867
25 NE	2.2550	2.3234	2.4150	2.4597	2.5624	2.5793
26 NV	2.2670	2.3323	2.4277	2.4650	2.5405	2.5537
27 NH	2.2288	2.2941	2.3664	2.4660	2.5545	2.6042
28 NJ	2.1788	2.2667	2.3747	2.4334	2.5464	2.5989
29 NM	2.0695	2.2490	2.3929	2.4669	2.5414	2.5795
30 NY	2.2044	2.2846	2.3860	2.4546	2.5513	2.5937
31 NC	1.9986	2.0878	2.2397	2.3128	2.4730	2.5524
32 ND	2.1730	2.2337	2.3393	2.4345	2.5270	2.5782
33 OH	2.2278	2.2974	2.3882	2.4371	2.5289	2.5735
34 OK	2.1875	2.2886	2.3904	2.4455	2.5378	2.5732
35 OR	2.2888	2.3490	2.4324	2.4925	2.5770	2.5987
36 PA	2.1566	2.2683	2.3602	2.4196	2.5313	2.5795
37 RI	2.1517	2.2631	2.3321	2.3664	2.4901	2.5577
38 SC	1.9052	2.0481	2.2147	2.3086	2.4624	2.5382
39 SD	2.2077	2.2778	2.3692	2.3894	2.5281	2.5603
40 TN	2.0405	2.1550	2.2574	2.3538	2.4770	2.5436
41 TX	2.1251	2.2103	2.3292	2.3984	2.5151	2.5548
42 UT	2.3236	2.3981	2.4867	2.5217	2.5984	2.6024
43 VT	2.2290	2.3206	2.3779	2.4256	2.5507	2.5969
44 VA	2.0223	2.1738	2.2995	2.3949	2.5289	2.5861
45 WA	2.2834	2.3762	2.4509	2.4916	2.5819	2.6091
46 WV	2.1027	2.1952	2.3100	2.4034	2.4900	2.5407
47 WI	2.1924	2.2766	2.3727	2.4347	2.5365	2.5735
48 WY	2.2611	2.3291	2.4291	2.3933	2.5583	2.5907
US Mean	2.1600	2.2510	2.3600	2.4288	2.5332	2.5762
S.D.	0.1134	0.0950	0.0663	0.0504	0.0350	0.0233
Northeast	2.2018	2.2878	2.3738	2.4330	2.5429	2.59297
South	2.0309	2.1413	2.2888	2.3810	2.4997	2.55696
Midwest	2.2199	2.2925	2.3826	2.4451	2.5396	2.57806
West	2.2480	2.3351	2.4278	2.4769	2.5671	2.58858

This table reports the logarithm of the average years of schooling. See the text for a discussion of the construction of this measure. The four regions are defined by the Bureau of the Census.

Table 9
Contemporaneous correlations of the various measures of human capital

	HK	VW	FW	School
1940				
Human capital	1	0.62	0.59	0.62
Variable weights		1	0.99	0.99
Fixed weights			1	0.97
Schooling				1
1950				
Human capital	1	0.47	0.48	0.45
Variable weights		1	0.99	0.97
Fixed weights			1	0.96
Schooling				1
1960				
Human capital	1	0.42	0.40	0.32
Variable weights		1	0.99	0.94
Fixed weights			1	0.96
Schooling				1
1970				
Human capital	1	0.23	0.23	0.17
Variable weights		1	1	0.94
Fixed weights			1	0.94
Schooling				1
1980				
Human capital	1	0.30	0.29	0.19
Variable weights		1	1	0.97
Fixed weights			1	0.97
Schooling				1
1990				
Human capital	1	0.26	0.25	0.26
Variable weights		1	0.99	0.96
Fixed weights			1	0.96
Schooling				1

Table 10
Estimates of the elasticity of substitution between workers with and without schooling

Census	Coefficient on relative supplies (std error)	Implied elasticity of substitution	$\bar{R}^2$ [std error of regr]
$w(0)$ = within-state avg weekly earnings for those with school < 5			
1940	−0.159	6.30	0.61
	(0.019)		(0.099)
1950	−0.146	6.83	0.45
	(0.022)		(0.115)
1960	−0.109	9.14	0.34
	(0.022)		(0.128)

Table 10
(Continued)

Census	Coefficient on relative supplies (std error)	Implied elasticity of substitution	$\bar{R}^2$ [std error of regr]
$w(0)$ = within-state avg weekly earnings for those with school < 5			
1970	0.002	∞	−0.02
	(0.057)		(0.296)
1980	−0.022	45.05	−0.02
	(0.041)		(0.222)
1990	−0.040	24.75	−0.00
	(0.045)		(0.208)
restricted	−0.121	8.24	
	(0.011)		
$\ln w(0)$ = Mincer regression constant			
1940	0.121	∞	0.16
	(0.038)		(0.205)
1950	0.055	∞	0.02
	(0.037)		(0.192)
1960	−0.012	81.30	−0.02
	(0.035)		(0.207)
1970	0.003	∞	−0.02
	(0.043)		(0.243)
1980	−0.011	90.09	−0.02
	(0.029)		(0.167)
1990	−0.037	27.25	−0.00
	(0.037)		(0.185)
Restricted	0.014	∞	
	(0.015)		

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