SCHOOLING EXTERNALITIES, TECHNOLOGY AND
PRODUCTIVITY: THEORY AND EVIDENCE
FROM U.S. STATES

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ABSTRACT

The recent literature on externalities of schooling in the U.S. is rather mixed: positive external effects of average education are hardly found at all, while often positive externalities from the share of college graduates are identified. This paper proposes a simple model to explain this fact and tests it using U.S. states data. The key idea is that advanced technologies, associated with high total factor productivity and high returns to skills, are complementary to highly educated workers, as opposed to traditional technologies, complementary to less educated. Our calibrated model predicts that workers with twelve years of schooling (high school graduates) are indifferent between traditional and advanced technologies, while more educated workers adopt the advanced technologies and benefit from the larger private and social returns associated to them. Only shifts in education above high school graduation are therefore associated with positive social returns stemming from more efficient technologies. The empirical analysis, using compulsory attendance laws, immigration of highly educated workers and the location of land-grant colleges as instruments confirm that an increase in the share of college graduates, but not an increase in the share of high school graduates, had large positive production externalities in U.S. States.

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1 Introduction

The relation between education, technological adoption and productivity has been the subject of renewed attention and research among economists. One approach adopted initially was to consider average schooling as a sufficient measure of human capital (postulating perfect substitutability across different educational levels) and to inquire whether increases in average schooling lead to higher total factor productivity (see Acemoglu, 1996 and Caselli, 2005, for a review) or, conversely, to what extent higher total factor productivity induced higher average schooling (Bils and Klenow, 2000). People have also inquired whether higher schooling had, via externalities, a detectable and positive "external" effect on productivity levels (Acemoglu and Angrist, 2001, Moretti, 2004) or productivity growth (Barro, 1991, Benhabib and Spiegel, 1994, Temple, 1999 and de la Fuente and Domenech, 2001, 2006). More recently, however, both in the growth literature (Caselli and Coleman, 2006) and in the externality literature (Ciccone and Peri, 2006) two facts have been acknowledged with important consequences for the joint analysis of skills, technology and productivity. First, workers with different levels of education are not perfect substitutes in production. It is clear, for instance, that the relative wages of college and high school educated workers is affected by their relative supply (e.g. Katz and Murphy, 1992, or Angrist, 1995). As a consequence, it is appropriate to model two factors of production (skilled and unskilled workers) as imperfectly substitutable in a constant elasticity of substitution (CES, rather than Cobb-Douglas) production function. However, it remains unclear as yet exactly how to define more and less skilled workers or whether it is preferable to distinguish among three or four skill groups (as done in other areas of the literature, e.g. Borjas, 2003). Second, it has become increasingly clear that the presence of highly skilled workers affects not only the intensity but also the direction of technological adoption. In the U.S., college educated workers experienced a substantial increase in their wage relative to high school educated workers during the eighties and nineties (Katz and Murphy, 1992, Caselli and Coleman, 2002). Similarly, the relative productivity (and wage) of highly educated workers in rich (developed) countries in the year 2000 was much higher than in poor (developing) countries (Caselli and Coleman, 2006). It appears, therefore, that both total factor productivity as well as the relative productivity of more versus less educated workers can be affected by the percentage of highly educated workers in the labor force. Acemoglu (1998), Acemoglu (2002) and Caselli and Coleman (2006) develop a consistent framework to analyze and measure the link between the supply of skilled workers and skill-biased technological progress. The present paper is a step forward within this literature at the theoretical and empirical level. First, we present a model that builds on Yeaple (2005) in which we maintain years of schooling as a continuous measure of individual skills. However, we obtain imperfect substitutability between workers with low and high levels of schooling due to differences in technology adopted and the variety of goods produced at different levels of the skill range. Second, using the model, we simulate the effects of increased average schooling when it is the result of a shift in the *low* part of the skill distribution, (such as an increase

in high school graduation rates) and when it is the result of a shift in the *high* range of the skill distribution (such as an increase in college graduation rates). These two shifts have very different effects on productivity (i) because "advanced" technologies, adopted only by workers above a certain threshold level of schooling, are more efficient, and (ii) because advanced technologies are used to produce differentiated goods while traditional technologies produce homogeneous goods. Both channels imply an increase in total factor productivity only for changes in the *high* range of the skill distribution. Adopting the method developed in Ciccone and Peri (2006), which mirrors dual growth accounting, we can compute the exact impact of these two shifts on total factor productivity in the model.

Finally, using the same accounting (constant composition) method on U.S. states data for the period 1960-2000, we estimate the impact on total factor productivity of an increase in average schooling across U.S. states in two different scenarios, namely when such an increase is produced by higher rates of secondary school attendance and completion and when it is produced by an increase in the share of college graduates. This empirical exercise is used to evaluate the simulated predictions of the model and serves as a direct test of the impact of both college and high school graduation on total factor productivity. The simulation exercise and the estimation analysis give similar predictions, indicating large externalities from college graduation but small (or very small) externalities from increased schooling via high school graduation. The unique and crucial feature of our empirical approach, based on U.S. state-level data, is that we can construct some exogenous shifters of schooling group shares at the high school and college level and then use them as instruments. On the one hand, compulsory schooling laws, in place between 1920 and 1970 and introduced at different times in different states (see Acemoglu and Angrist, 2001), provide an exogenous shifter in high school graduation rates and, therefore, in the supply of high school graduate labor when those people enter the labor force. On the other hand, a measure based on state-specific immigration of highly educated groups into the U.S. (mainly from Western Europe, China and India) provides an exogenous shift of college graduate shares. We also use the proximity of a state's population to land grant colleges as a further potential instrument that affects the cost and hence the share of the population attending college across states. Reconciling previous evidence (Moretti 2004, Acemoglu and Angrist, 2001 and Ciccone and Peri, 2006) on the effect of skill level and distribution on factor productivity, and in accordance with the predictions and simulations of the model, we estimate a positive and significant impact of a higher share of college educated workers on TFP while we find a much smaller, not statistically significant effect on productivity from an increase in high-school graduation rates. The reason for this difference is that an increase in highly educated workers shifts the economy towards highly productive skilled-biased technologies and increases the range of differentiated goods produced, while an increase in secondary schooling does not allow the adoption of advanced technologies and only increases private productivity in the traditional undifferentiated sector.

The rest of the paper is organized as follows. Section 2 describes the model and its equilibrium. Section 3 uses

the calibrated model to simulate the (external) effects on total factor productivity of shifts in the distribution of skills. Section 4 uses the dual-accounting constant composition approach to *estimate* the effect of an increase in high-school and in college graduation on total factor productivity using U.S. state-level data (1960-2000). Section 5 provides concluding remarks.

2 A Simple Model of Technology and Skills

The model builds on a structure similar to Yeaple (2005). We consider a static closed economy, extended to an open economy framework in the Appendix 1, we calculate the equilibrium values of wages, prices and productivity and we conduct some comparative static exercises. The key feature of the model is that workers are characterized by their skills (years of schooling) and their productivity increases monotonically as their education increases. In principle workers are perfectly substitutable in production, with education acting to increase the effectiveness of each worker. However, as there are two different types of technologies (i.e. traditional and modern) it turns out that each worker adopts the technology he/she has a comparative advantage in. As different technologies are used to produce imperfectly substitutable goods, the result is imperfect substitutability between more and less educated workers. The modern technology provides a comparative advantage to highly educated workers but implies some fixed research and development costs, hence in equilibrium it is adopted only by the highly educated. Vice-versa, the traditional technology does not involve any fixed costs and embodies some comparative advantages for the less educated, so that only workers below a certain schooling threshold adopt it. A desirable feature of the model is that the threshold level of schooling, above which workers adopt the modern technology, is endogenous. The effects of education on productivity in the model comes from the fact that above the threshold level of education workers adopt more efficient technologies and produce differentiated products, both of which are features that increase total factor productivity. By calibrating the model to U.S. wages and to the distribution of U.S. educational attainments for the years 1960-2000, we can simulate the effects on total factor productivity of shifts in the skill distribution.

2.1 Demand

Consider a closed economy that produces and consumes a homogeneous good Y and a differentiated good X. The preferences of a representative consumer are CES over these two goods and also over a continuum of varieties (indexed by $i \in 0, N$) of the differentiated good X. Specifically, preferences are represented by the following utility function:

$$U = \left[(1-\beta)Y^{\frac{\theta-1}{\theta}} + \beta X^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}, \theta > 1 \tag{1}$$

where

$$X = \left(\int_0^1 x(i)^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}} , \sigma > \theta > 1 \tag{2}$$

The restriction on the parameters σ and θ implies that the varieties of differentiated good X are closer substitutes for each other than with the homogenous good Y. The parameter θ measures the elasticity of substitution between good Y and composite good X, while the parameter σ measures the elasticity of substitution between varieties of the composite good X. Considering good Y as the numeraire, Dixit and Stiglitz (1977) showed that one can easily derive the total demand for goods Y and X as:

$$X = \beta^\theta \frac{E}{P} \left(\frac{P_X}{P} \right)^{-\theta} , \qquad Y = (1-\beta)^\theta \frac{E}{P} \left(\frac{1}{P} \right)^{-\theta} \tag{3}$$

where $P = \left[\beta^\theta P_X^{1-\theta} + (1-\beta)^\theta \right]^{\frac{1}{1-\theta}}$ is the overall price-index, P_X is the unit-price of the composite good X (while the price of Y is 1) given by: $P_X = \left[\int_0^N p(i)^{1-\sigma} di \right]^{\frac{1}{1-\sigma}}$, and E is the aggregate expenditure on goods. We can also derive the demand for each variety i of X as:

$$x(i) = \left(\frac{s(P_X)E}{P_X} \right) \left(\frac{p(i)}{P_X} \right)^{-\sigma} \tag{4}$$

where $p(i)$ is the price of variety i of the composite good X and $s(P_X) = \frac{\beta^\theta P_X^{1-\theta}}{\beta^\theta P_X^{1-\theta} + (1-\beta)^\theta}$ is the share of aggregate expenditure devoted to purchase the composite good X.

2.2   Workers

Workers in the model economy are differentiated by skill[1], and we index the skills of each worker using the continuous variable $Z \in [0,1]$. We standardize, without loss of generality, the highest level of education to 1 and we can interpret Z as time in school. Therefore, the value of 1 can be thought of as 20 years of schooling (the normal time to achieve a Ph.D., the highest possible degree). Accordingly, high school graduation corresponds to a value of $Z = 0.6$, while college graduation corresponds to $Z = 0.8$. The distribution of schooling in the labor force is described by the cumulative density function $G(Z)$ with support $[0,1]$. The total mass of workers is equal to M, and we define $W(Z)$ as the wage paid to a worker with schooling of Z. Thus, the aggregate income of workers, equal to the aggregate expenditure on goods, expressed in units of the numeraire is:

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[1]In this model "skills" correspond to "schooling" and are measured by years in school.

$$E = M \int_0^1 W(Z) dG(z) \tag{5}$$

2.3 Production

Each good is produced using labor only. Good Y is produced using a constant returns to scale technology and is sold in perfect competition, while good X is a differentiated good produced in monopolistic competition. Each individual variety of good X is produced using a common technology requiring a fixed cost F_X (in the form of output that cannot be sold) that can be considered a research/start-up cost to develop the variety i . There is free entry in sector X and each entering firm becomes the sole producer of a distinct variety. The amount of a good that one worker can produce increases with her skills and is equal to $A_j(Z)$, where the subscript $j \in \{Y, X\}$ refers to the sector (i.e. the type of technology used). We assume that for each sector/technology a more educated worker is more productive than a less educated one $(\partial A_j(Z)/\partial Z > 0)$. At the same time, the technology of the differentiated sector is more "skill-biased" than the technology of the homogenous sector. The latter assumption implies that Y is a "low-tech" sector where a simple manufactured good or service is produced (such as textiles, food or cleaning services), and X is a "high-tech" sector where a series of differentiated and more sophisticated goods and services (e.g. i-Pods, microscopes, financial services and surgical services) are produced. The two assumptions on technologies made above can be summarized by the following condition:

$$\frac{\partial \ln(A_X(Z))}{\partial Z} > \frac{\partial \ln(A_Y(Z))}{\partial Z} > 0 \tag{6}$$

If we add the standardization $A_X(0) = A_Y(0) = 1$ the assumption in (6) implies that: (i) highly skilled workers have a comparative advantage in the production of sector X, while less skilled have a comparative advantage in the production of sector Y, and (ii) for all but the least skilled workers $(Z = 0)$ the high-tech sector allows workers a higher productivity (in units of produced goods) than the low-tech sector, with this difference increasing as Z increases. In order to obtain further insights into the model, and consistent with the standard Mincerian assumption that labor productivity (and wages) depend exponentially on the years of schooling of a worker, we adopt the following functional forms: $A_X(Z) = \exp(g_X Z)$, $A_Y(Z) = \exp(g_Y Z)$ and, in order to satisfy (6), we assume $g_X > g_Y$.

2.4 Wage Schedule

The equilibrium of the model consists of an allocation of workers among the two sectors and a vector of prices for the differentiated good $p(i), i \in [0, N]$ such that each worker is maximizing her own utility, firms are maximizing profits and the markets for each variety $i \in [0, N]$ and for good Y clear. We solve the profit-maximization

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problem for firm $i \in [0, N]$ that faces demand $x(i)$ described by (4). Calling the unit cost of producing good i C_X (determined by the common technology in the high-tech sector), profit maximization and free entry imply:

$$p(i) = \frac{\sigma}{\sigma - 1} C_X, \ x(i) = (\sigma - 1)F_X \ \text{ for } i \in [0, N] \tag{7}$$

For sector Y, perfect competition ensures that prices are equal to unit costs. Choosing Y as the numeraire thus implies: $1 = P_Y = C_Y$. Given the technologies described in section 2.3, the unit costs to produce in sector Y and X are given by the labor costs (as labor is the only input) so that: $1 = C_Y = W_Y(Z)/\exp(g_Y Z)$ and $C_X = W_X(Z)/\exp(g_X Z)$. In a perfectly competitive labor market, the wage distribution over Z adjusts to equalize the unit cost of firms that produce using the same technology. Moreover, workers with skill Z choose to work in the sector where they are paid the higher wage. Yeaple (2005) proves that a threshold value for $Z = \overline{Z}$ exists, satisfying the condition $C_X = \exp(g_Y \overline{Z})/\exp(g_X \overline{Z})$ and such that workers with skills $Z < \overline{Z}$ choose to work in sector Y, while workers with $Z > \overline{Z}$ work in sector X. Using this definition, the wage schedule for workers can be expressed as:

$$W(Z) = \left\{ \begin{array}{l} \exp(g_Y Z) \text{ if } 0 < Z < \overline{Z} \\ C_X \exp(g_X Z) \text{ if } \overline{Z} < Z < 1 \end{array} \right\} \tag{8}$$

The equilibrium allocation of workers, therefore, is fully specified once we find the threshold value $\overline{Z}$, which also determines the unit cost C_X. As a way to illustrate the relationship between skills and wages Figure 1 shows the wage schedule as $\ln(Wage)$ on the vertical axis versus Z on the horizontal axis. For skills lower than $\overline{Z}$, workers are better off (receive higher wage) choosing sector Y, while for $Z > \overline{Z}$ they maximize their wage by choosing sector X. The relevant (log) wage schedule is represented by the bold line, whose gradient (private returns to schooling) increases discontinuously as we pass from the low-tech to the high-tech sector.

The average wage in the economy equals the per capita income, and it is given by :

$$\overline{W} = \int_0^{\overline{Z}} \exp(g_Y Z)dG(Z) + C_X \int_{\overline{Z}}^1 \exp(g_X Z)dG(Z) \tag{9}$$

2.4.1 Equilibrium

In the symmetric equilibrium, the differentiated goods are sold at the same price and produced in equal amounts (see condition 7). We can then aggregate and find the price index for the composite good X as:

$$P_X = N^{\frac{1}{1-\sigma}} \left(\frac{\sigma}{\sigma - 1} \right) C_X \tag{10}$$

where N is the total number of varieties of good X (as well as firms producing them). In equilibrium, N is given by:

$$N = \frac{M}{\sigma F_X} \int\limits_{\overline{Z}}^{1} \exp(g_X Z) dG(Z) \tag{11}$$

The market clearing conditions for the N differentiated goods require that the supply of each one of them is equal to its demand:

$$x(i)p(i) = \frac{s(P_X)M\overline{W}}{N} \quad i \in [0, N] \tag{12}$$

Substituting (7), (9), (10) and (11) into (12) we obtain the following equation that defines the equilibrium value of $\overline{Z}^2$:

$$s(P_X) \int\limits_{0}^{\overline{Z}} \exp(g_Y Z) dG(Z) = [1 - s(P_X)]C_X \int\limits_{\overline{Z}}^{1} \exp(g_X Z) dG(Z) \tag{13}$$

Substituting the expression $s(P_X) = \frac{\beta^\theta P_X^{1-\theta}}{\beta^\theta P_X^{1-\theta} + (1-\beta)^\theta}$ and further simplifying by using (10) and (11) as well as $C_X = \exp\left((g_Y - g_X)\overline{Z}\right)$ we obtain the implicit function $\Im[\overline{Z}, g_X, g_Y, \beta, \sigma, \theta, M, F_X, G(Z)]$ that defines the equilibrium value of $\overline{Z}$ depending on the parameters of the model and on the distribution of skills $G(Z)$:

$$\Im[\overline{Z}, g_Y, g_X, \beta, \sigma, \theta, M, F_X, G(Z)] = \tag{14}$$

$$\int\limits_{0}^{\overline{Z}} \exp(g_Y Z) dG(Z) - \left(\frac{1-\beta}{\beta}\right)^\theta \left(\frac{\sigma}{\sigma-1}\right)^{\theta-1} \left(\frac{\sigma F_X}{M}\right)^{\frac{\theta-1}{\sigma-1}} \exp[\theta(g_Y - g_X)\overline{Z}] \left(\int\limits_{\overline{Z}}^{1} \exp(g_X Z) dG(Z)\right)^{\frac{\sigma-\theta}{\sigma-1}} = 0$$

3   The Price-Based/ Constant Composition Approach to Schooling Externalities

The model developed above has several desirable features but it requires some clarifications on how to effectively capture and measure total factor productivity. As workers of different schooling levels are the only inputs, real per capita income is equal to average real wage, $w = \overline{W}/P$. Clearly both the nominal average wage $\overline{W}$ as well as the price level P depend on the distribution of skills $G(Z)$ through several channels. First, the distribution

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[2]The same equation could be obtained by imposing the market-clearing condition for good Y (Walras' Law). The condition in that case would be $Y = [1 - s(P_X)]M\overline{W}$ which simplifies to an equation identical to (13).

$G(Z)$ affects the threshold level $\overline{Z}$ through (14) and hence C_X and $\overline{W}$. Second, the distribution $G(Z)$ affects the number of varieties N produced (through equation 11) and hence P_X and P. Third, moving up the schooling distribution, the marginal return to schooling jumps from g_Y to g_X at some point in the distribution. In general it could be difficult to distinguish what part of the increase in real per capita income is due to an increase in schooling levels and the corresponding private returns, and which part is due to an increase in TFP. In order to discriminate between private and social returns to educational increases we adopt a "dual accounting" procedure (constant composition approach) that identifies externalities; namely, it can isolate the effect of increased schooling on TFP. Our simulation exercises allow us to identify the change in per capita income due to increased schooling and decompose that increase into the part due to private returns to schooling and the part due to total factor productivity. We illustrate the procedure in the next section and then present the simulation results.

3.1 Effects on TFP of a Change in G(Z)

In order to identify the effects of a change in the skill distribution (i.e. a change in $G(Z)$) on total factor productivity, let us assume that the scale of the labor force, M, is constant and standardized to 1. Therefore, as labor is the only input of production, total real income GDP equals the total (and average) real wage given by:

$$GDP = w = \int\limits_0^1 w(Z)\phi(Z)dZ \tag{15}$$

where $w(Z) = W(Z)/P$ is the real wage for workers of skill Z and $\phi(Z)$ is the density distribution function of workers over skills (so that $\int\limits_0^z \phi(Z)dZ = G(z)$). In order to analyze the change in total factor productivity in response to a change in the skill distribution we adapt the so-called "dual approach" to growth accounting (described, for instance, in Barro and Sala i Martin, 2004, Chapter 10.2). This approach states that the increase in total output, net of the share-weighted increase in factors of production is equal to the increase in total factor productivity, which in turn can be expressed (by virtue of an identity) as the share-weighted change in the returns to factors of production.

The only difference with respect to standard growth accounting is that herein we analyze the changes in variables as a result of a change in *skill distribution* rather than over time. In our case, the key relationship is obtained by totally differentiating equation (15) as follows:

$$\frac{dGDP}{GDP} = \int_0^1 \frac{dw(Z)}{w(Z)} \frac{w(Z)}{w} \phi(Z)dZ + \int_0^1 \frac{d\phi(Z)}{\phi(Z)} \frac{w(Z)}{w} \phi(Z)dZ = \int_0^1 \frac{dw(Z)}{w(Z)} sh(Z)dZ + \int_0^1 \frac{d\phi(Z)}{\phi(Z)} sh(Z)dZ \quad (16)$$

where the expression dX indicates the differential for variable X; typically this differential is respect to time (dX/dt) in standard accounting exercises, though here it is with respect to a change in skill distribution, $dX/dG(Z)$. The right hand side of the differentiated equation is then transformed by defining $sh(Z)$ as the share of wages received by workers with skill Z as a fraction of the total wage bill (that is, the share of income accruing to workers of skill Z). The second term on the right hand side of (16), $\int_0^1 \frac{d\phi(Z)}{\phi(Z)} sh(Z)dZ$, captures the contribution of changes in the skill composition (i.e. changes in the amount of "inputs") to changes in output. Hence, a percentage change in total factor productivity is defined as the increase in total output net of the increased contribution of factors:

$$\frac{dTFP}{TFP} = \frac{dGDP}{GDP} - \int_0^1 \frac{d\phi(Z)}{\phi(Z)} sh(Z)dZ = \int_0^1 \frac{dw(Z)}{w(Z)} sh(Z)dZ = \int_0^1 \frac{dw(Z)\phi(Z)}{\overline{w}} dZ \quad (17)$$

Equation (17) shows that a percentage increase in TFP is equal to the change in factor prices $\frac{dw(Z)}{w(Z)}$ weighted by the initial factor share in total income (wages)[3]. The last equality shows that the TFP increase can also be captured by the increase in the average wage keeping skill composition, $\{\phi(Z), z \in [0,1]\}$, constant at its initial level. This equality and the "constant composition" representation are analyzed in detail in Ciccone and Peri (2006). Here we simply emphasize that the constant composition method (i.e. holding the initial skill composition constant as above) is a simple way of capturing the impact of change in skills on TFP when skills are not necessarily substitutable and exhibit skill-specific productivity.

In order to analyze the impact on TFP of a discrete change in the skill distribution from $G_0(Z)$ to $G_1(Z)$ we use this constant composition approach. We refer to the equilibrium values of prices and wages before the change with a t_0 subscript and after the change with a t_1 subscript. We then rewrite the first and last term of (17) relative to a discrete change, using the fact that real wages $w(Z)$ are equal to $W(Z)/P$ and approximating the logarithmic changes with percentage changes:

$$\frac{TFP_{t_1} - TFP_{t_0}}{TFP_{t_0}} = \frac{\int_0^1 W_{t_1}(Z)\phi_{t_0}(Z)dZ - \int_0^1 W_{t_0}(Z)\phi_{t_0}(Z)dZ}{\overline{W}_{t_0}} - \frac{P_{t_1} - P_{t_0}}{P_{t_0}} \quad (18)$$

The first term on the right hand side is the constant composition change of average wage in terms of the

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[3] The above formula for dual accounting is also correct in the presence of physical capital, as long as capital is mobile across U.S. states so that its real return is equalized and capital shares are equal across states.

numeraire (due to changes in wages keeping the skill distribution constant at time t_0). The second term captures changes in the general price level that affects the real income of each worker in the same way and thus need not be weighted by their distribution. The next section utilizes this decomposition to describe the effects on TFP of changes in skill distribution involving various skill groups.

3.2 Calibration of the Model and Simulated Effects on TFP

Our model has implications for both the private returns to schooling (the wage schedule) and for the externalities generated by shifts in the schooling distribution (the TFP effect). The simulation strategy herein will be to calibrate the model in order to match the features of private returns to schooling and then to use it to simulate the effect of changes in schooling on TFP (the externality). In our model, the imperfect substitutability between workers with low and high education is driven by the imperfect substitutability of the goods they produce, X and Y. Hence we use a value of θ (i.e. the elasticity of substitution between the two goods) equal to 1.5 which is the consensus estimate for the elasticity of substitution between workers with less and more education (see Katz and Murphy 1992, and Ciccone and Peri 2005). The value of σ is chosen to be equal to 2, consistent with the average estimate of the elasticity of substitution between "differentiated tradable goods" (Weinstein and Broda, 2004). The parameter β is chosen to be around 0.65^4. Each of these parameters is then changed within a range in order to test the robustness of the simulations. Finally and most importantly the parameters g_X and g_Y, returns to education for the advanced and traditional technology, respectively, and F_X, the fixed set-up costs for the advanced technology are calibrated to match the actual wage schedule for the U.S. over the period considered[5].

Using the 1980 distribution of schooling in the labor force as starting point and the parameters described above we run the following two experiments. First we increase average schooling by shifting 6% of the workers from the lowest educational group (less than 8 years) to the next two higher groups: high school dropouts (8-11 years) and high school graduates (12 years), in equal proportions. This shift matches the average reduction per decade in the lowest educational group during the period considered (from 28% to 4% of employed) and it captures the effect of schooling laws on U.S. states as analyzed by Acemoglu and Angrist (2001) (see the description below as well as their Figure 3, page 33). Such a shift corresponds to an increase in the overall average years of schooling equal to 0.25. Second, we consider a shift in the schooling distribution that increases the share of college educated by moving people out of the group of college dropouts. In order to make the two shifts comparable we use a shift which implies exactly the same increase in average schooling as in the previous experiment (i.e. 0.25 years). This represents an increase in the share of college graduates of 7 percentage points

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[4]This value is calculated as one minus the share of basic goods (such as food and household supplies) in total non-housing expenditure from the U.S. Deparment of Labor's 2000 Consumer Expenditure Survey.

[5]The details of the parametrization and calibration of the model are given in Appendix 2.

(and an equal corresponding decrease in college dropouts). Table 2 shows the effects on TFP (externalities) of these two shifts. For ease of interpretation we report in the first row the external effect of an increase in one year of average schooling due to the shift in high school attendance and graduation (this is the first experiment). The second row reports the external effect of a 1% increase in the share of workers with a college degree. The numbers on these two rows can be directly compared with the empirical estimates obtained in the empirical sections that follow. In order to make both externalities comparable with each other, though, we convert the values in the second row (when the increase in schooling is obtained via college graduation) into externalities due to a one year increase in average schooling. Those values are reported in the third row. Finally, the fourth row reports the relative size of the two effects (row 3 divided by row 1). Specification (1) in Table 2 uses the baseline values of the parameters as described above. The key result is very clear. While a shift towards high school graduation barely has an effect on TFP (less than a 2% increase) an equivalent shift towards college graduation has an external effect 5 times larger (almost 9%). The intuition for this result is as follows. The shift of schooling in the low part of the distribution implies relatively small gains in productivity as workers are in the relatively flat segment of the productivity schedule; furthermore, this shift moves few workers to the modern technology sector from the traditional one. Moreover, the schooling threshold, $\overline{Z}$, moves up so that one needs to be more educated in order to use the superior technology (this is due to the increase in the demand for good Y, because overall GDP raises and the share spent on good Y is constant). In contrast, a shift of workers in the high end of the educational distribution makes workers much more efficient in the use of the modern technology, hence increasing the number of varieties being produced. As good X is produced more efficiently the demand for good Y does not increase much and neither does the threshold $\overline{Z}$. The effect on TFP comes from both the increased variety of good X and the increased productivity in this sector. This qualitative feature is robust across all simulations. Also, consistent with the intuition given above, an increase in the parameter g_X as experienced from 1980 to 2000 strengthens the TFP effect of college graduation as illustrated in specification (3). A one-year increase in average schooling achieved through higher college graduation rates now has an external effect of 16%, while if achieved through higher high school graduation rates the effect is still below 2%. Lower substitutability between varieties of X (low σ) increases the effect on TFP of college graduation (as it makes the production of new varieties more valuable) bringing it to almost 17% for one additional average year of schooling (see specification 4). Changing the other parameters of the model does not modify the results much. Increasing the initial schooling threshold, $\overline{Z}$, to 13 years decreases the externalities from high school even further (below 1%) and leaves those from college basically unchanged (see specification 2). Changes towards higher substitutability between good X and Y, or any change in β or in the initial distribution of schooling (illustrated in specifications 5, 6 and 7 respectively) have only marginal impacts on the effect on TFP produced by each one of the shifts. Even extending the model to allow for free trade with the rest of the world (a two-country

open economy setup is developed in the Appendix) does not change the key results. In the open-economy case we allow the country to trade both goods with another country, while maintaining balanced trade. This results in intra-industry trade in the varieties of the differentiated good X as well as in inter-industry trade if the two countries do not have identical schooling distributions. In this case, we also obtain large external effects on productivity from increases in the share of college educated and small externalities from increases in the share of high school educated. Specification (8) reports the externalities in the open economy framework. As free trade in goods leads to factor price equalization (equalization of the wage-schedule across countries) the externalities from schooling spill over across the border and so, relative to the benchmark case, they are somewhat reduced for the country where schooling increases. Despite that, the externalities are still much larger in the case of an increase in the share of college educated (4.4% for a one year increase in schooling) than in the case of increases in the share of high school educated (0.9% for a one year increase in schooling) .

The model has provided us with a theoretical justification for why externalities from college graduation could be larger than externalities from high school graduation and, using the parameters calibrated to match the private returns to schooling, it has produced a robust prediction: externalities from high school graduation are between 0 and 2% increase in TFP for one extra average year of schooling, whereas externalities from college graduation could be as large as a 0.63 percent change in TFP per each percentage of college educated, or 17% for each extra average year of schooling obtained via college graduation. The empirical analysis developed in the next section provides a test for these qualitative and quantitative predictions.

4   Empirical Evidence from U.S. States, 1960-2000

4.1   Empirical Methodology and Data

The data used in the empirical analysis are mostly from the Integrated Public Use Microdata Samples (IPUMS from now on) of the US Censuses 1960-2000 collected and made available by Ruggles et al. (2005). The construction of the constant-composition wage change that measures the total factor productivity growth for U.S. states over four decades follows the procedure proposed in Ciccone and Peri (2006), and is simply the empirical counterpart to expression (18) used in the simulation. In particular, we implement the constant composition approach in two stages. In the first stage we use the individual real weekly wage[6] data, $\ln w_{ist}$, and control for a set of dummies that account for standard individual characteristics X_{it} (gender, race, nativity, experience, marital status) in order to identify the "cleaned" (logarithmic) wage for each schooling-experience group, $\ln \omega(S, E)_{st}$, in each of the 50 U.S. states plus D.C. and for each census year. This procedure ensures

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[6]The real wage is calculated by deflating nominal wages by the CPI; it is expressed in 2000 US$. Yearly wages are divided by the number of weeks worked in order to obtain weekly wages. As the variable "weeks worked" is categorical in the IPUMS for year 1960 to 1980 we have used, for those years, the median point of the interval. As an alternative we also use hourly wage.

that the differences across U.S. states in composition and individual characteristics do not affect the results. The following first stage regression is run separately for each census year:

$$\ln w_{ist} = \ln \omega(S, E)_{st} + \lambda_t X_{it} + \varepsilon_{ist} \tag{19}$$

where ε_{ist} are uncorrelated, zero-mean errors. The estimated $\widehat{\omega}(S, E)_{st}$ is the wage for the group of schooling S and experience E in state s and census year t that we use to construct the constant composition wages in the second stage. The set of dummy variables X_{it} is chosen so that the "cleaned" wage $\ln \omega(S, E)_{st}$ for each educational group (S) and each experience group (E) corresponds to white, U.S. born, married male workers. The educational groups are the four traditionally used in the labor literature: $S_1 = [0, 12)$ for High School Dropouts, $S_2 = [12, 13)$ for High School Graduates, $S_3 = [13, 16)$ for College Dropouts, and $S_4 \geq 16$ for College Graduates. The experience groups are eight groups of 5-year intervals spanning between 0 and 40 years. We denote the employment shares of workers in each of the education-experience groups in state s for census year t by $\phi_{st}(S, E)$, $S \in \{S_1, ... S_4\}$, $E \in \{E_1, ... E_8\}$. The constant skill-composition percentage wage change for state s in each inter-census decade is given by:

$$\Delta \ln w_{st}^{cc} = \ln \sum_{S,E} \left(\phi_{s,t}(S, E) * \widehat{\omega}(S, E)_{s,t+10} \right) - \ln \sum_{S,E} \left(\phi_{s,t}(S, E) * \widehat{\omega}(S, E)_{s,t} \right) \tag{20}$$

where we have expressed the percentage changes as logarithmic changes. As $\widehat{\omega}(S, E)_{s,t}$ represent real wage estimates, the above expression is the empirical equivalent to the right hand side of (18) and it is therefore equal to the change in TFP during the decade $[t, t + 10]$ for U.S. state s. Using this measure, in the next section we analyze the correlation between the change in TFP (the externality) across states and changes in schooling. Then, we examine the causal effect on TFP of increases in schooling due to shifts along particular segments of the schooling distribution.

4.2 Schooling, College-Graduates and their Externalities

Our theoretical model makes clear that average schooling is not a sufficient statistic to measure productivity which depends, in fact, on the whole distribution of skills $G(Z)$. For instance, an increase in average schooling due to a policy measure that increases high school graduation rates (and hence shifts workers from less to more than 12 years of schooling) has a much smaller effect on TFP than a policy that increases the share of college graduates. This insight is very helpful in explaining the differences in schooling externalities found by previous empirical studies. While work by Moretti (2004) found a positive external effect associated with an increase of college graduates in U.S. cities for 1980-1990, Acemoglu and Angrist (2001) and Ciccone and Peri (2006) did not find any significant externality due to changes in average schooling for U.S. states over the period 1960-1990.

The last two studies used the variation across states and over time of compulsory schooling laws as instruments for the change in high school graduation rates. Thus, these instruments affected only the low "portion" of the schooling distribution. Let us use our data and method to illustrate the remarkable differences between the effect of average schooling and the effect of college shares on TFP. Figures 2 and 3 plot the values of $\Delta \ln w_{st}^{cc}$, measuring TFP changes for the 50 U.S. states (plus D.C.) over 2 decades (80-90 and 90-00), against the change in average years of schooling, $\Delta \overline{S}_{st}$, and share of college graduates, respectively. In the former, we do not observe a significant correlation between increased average schooling and productivity (TFP). Hence, based on this measure of human capital, one would argue in favor of the absence of schooling externalities. The picture emerging from Figure 3 suggests otherwise. Now the change in TFP, $\Delta \ln w_{st}^{cc}$, is plotted against the change in the share of college graduates across states and decades. A positive, large and very significant correlation is apparent. This correlation would be consistent with positive and large externalities from increases in the share of college educated workers. While the pictures do not establish any causal relationship and are only relative to the most recent decades 1980-2000, they already convey the essence of our empirical findings: only increases in the share of college educated workers affect aggregate productivity positively via an external effect (namely the adoption of superior technology and the production of a wider range of differentiated goods). Increased average schooling, which is only loosely correlated with college graduation, shows a much weaker correlation with productivity. The differences in the intensity of human capital externalities found in the literature thus far might be explained by where on the educational distribution changes in schooling occur.

Table 3 reports the OLS coefficients capturing the effect of changes in schooling/college share on TFP changes for different specifications and periods. The dependent variable, $\Delta \ln w_{st}^{cc}$, is constructed as described above and is regressed on changes in average schooling and changes in the share of college graduates. The basic specification (1) is a panel that includes decennial changes in the 50 U.S. states plus D.C. over the 1960-2000 period. It shows that while average schooling has no significant correlation with TFP changes, the share of college graduates has a significantly positive effect on productivity. We interpret the OLS results as meaning that a one percent increase in the share of college graduates increases wages by 0.63%. The result is robust to weighting states by their employment (specification 2), including 4 regional dummies: East, Midwest, South and West (specification 3), or changing the period considered. Specification (4) omits the changes in the sixties and specification (5) only includes the 2 most recent decades. Focussing only on the most recent decades, the external effect of college education increases (as did the private returns) and the effect of average schooling decreases. Finally column (6) uses as its dependent variable the constant composition wage change, $\Delta \ln w_{st}^{cc}$, calculated using white, married, U.S. born males only, rather than the regression-adjusted wage obtained via (19). Notice that the estimated externalities from a one-year increase in average schooling never exceed 0.02 whereas the externalities from college graduation range between 0.63 and 2.95 for a one percent increase in

college graduates. If, controlling for college graduation, the rest of increased schooling is due to high school graduation, the results above are consistent with our model: very small externalities from average schooling and large, significant externalities from college graduation. The empirical estimates are, in fact, close to or even higher than the simulated effect in the previous section.

4.3   Instrumental Variables: Discussion and First Stage

The obvious drawbacks to estimating the external returns to education via OLS, as we do above, are endogeneity and omitted variable bias. Rather than being the cause of higher productivity, highly educated workers might be attracted to productive states. Alternatively, the selection of highly educated workers to a state may also reflect other (unobservable) characteristics of workers, resulting in a spurious correlation of wages and schooling. In order to address these issues we adopt an instrumental variable strategy that uses three sets of state-specific shifters of schooling attainments, and we check that these instruments are uncorrelated (or not very correlated) with state-specific productivity and state-specific unobservable qualities of workers. Two of these instruments, based on compulsory schooling laws and the location of Land Grant colleges, are not new and have been previously used as shifters of the supply of skilled workers across U.S. states. Here, we also introduce geographical preferences of immigrants as a third exogenous shifter of the supply of skilled immigrants. We use these three sets of variables as instrumental variables, exploiting the fact that they shift schooling on different parts of the labor force's schooling distribution.

4.3.1   Mandatory Schooling Laws: Child Labor and Compulsory Attendance

Our first set of instruments are the compulsory attendance (CA) and child labor (CL) laws first collected and used in Acemoglu and Angrist (2001) and in several other papers thereafter (Milligan, Moretti and Oreopulos, 2004, Moretti and Lochner, 2004, Oreopulos, Page and Stevens, 2005, Ciccone and Peri, 2005). These laws, in place between 1920 and 1970, affected the schooling level of several cohorts of Americans. They were introduced at different times across states and they also implied different requirements in terms of the years of schooling needed before one could access the labor market. Hence, using these data we can identify the minimum years of schooling required by a state where an individual resided at age 14 and attach that minimum requirement to each individual. As the CA laws required between 8 and 11 years of schooling in most cases, we calculate for each state the share of workers for which the associated CA laws mandated less than 8 years (CA<8) and those for which they mandated more than 11 years (CA>11). We expect the first share to be associated with lower average schooling and lower high school graduation rates, and the second with higher average schooling and higher high school graduation rates. We also use CL laws imposing between 6 and 9 years of schooling to construct dummies (CL<6) and (CL>9) and measures of the share of people in each state associated with the

first dummy (for which we expect a negative impact on average schooling) and the share of workers associated with the second dummy (for which we expect a positive effect on schooling). These four variables, presumably uncorrelated with productivity or the personal ability of workers across states, are indeed correlated with the schooling levels of individuals as those laws significantly increased the rate of attendance of the 9th, 10th, 11th grades as well as high school graduation rates of the states in which they were introduced (relative to those where they were not). Table 4 shows the explanatory power of these four variables in predicting changes in average schooling (specifications 1-3), the share of people without a high school degree (specifications 4-6) and the share of college graduates (specifications 7-9). The regressions use the panel of states with fixed state and decade effects. Two remarks are in order. First, notice that each variable has the expected effect on average schooling (positive for CA>11 and CL>9 and negative for CA<8 and CL<6) as well as on the share of high school dropouts (negative for CA>11 and CL>9 and positive on CA<8 and CL<6) in all specifications (1) through (6). Second, most of the coefficients in specifications (1) through (6) are significant at the 5% level. The joint F-test of significance for the overall set of instruments always rejects the hypothesis that they are jointly insignificant at the 1% confidence level. The F-statistic drops quite a bit when we add region-specific time trends (specifications 2, 3, 5 and 6), although it is still higher than 4 and, as mentioned, still statistically significant at the 1% level. If we use the same schooling law shares to predict the share of college graduates across states we obtain no significant coefficients and the signs of estimates are often the opposite of what we would expect. Furthermore, in this case the F-statistic for the joint significance of schooling laws on the share of college graduate is always lower than 3, and one can never reject the null hypothesis of zero significance at the 1% confidence level. As already shown by Acemoglu and Angrist (2001), the schooling laws considered did not generically increase average schooling; they did so by increasing attendance to high school and high-school graduation rates. In other words, they shifted the schooling distribution in its "low" range, leaving the high-end range unchanged.

4.3.2 College Educated Immigrants

In order to obtain an exogenous supply shift at the high end of the schooling distribution we use data on international immigrants and exploit their preference to settle in the same states (specifically, cities) where other fellow nationals already reside. This assumption has been used in previous studies (Card, 2001, Lewis, 2004 and Ottaviano and Peri, 2005) exploiting particularly the uneven location of unskilled Mexican and Latino workers. Here, however, we focus on a less used feature of immigration data, namely the fact that immigrants from non-Hispanic countries (especially India, China and Europe) are over-represented among college graduates while they are under-represented among high-school graduates and college dropouts. This relative over-representation at the high end of the schooling distribution implies that large immigration from those countries of origin results in a

very different shift along the schooling distribution compared to the one produced by schooling laws; it increases the shares of workers with college degree reducing the share of high school graduates and college dropouts. This is precisely the type of shift we are interested in. Nonetheless, by considering the actual supply of immigrants to different U.S. states, one would potentially risk introducing endogeneity bias: highly educated foreign-born workers are also attracted to states that experience important advances in productivity. Hence, we construct an "imputed" inflow of college educated immigrants as follows. Using 1960 as the reference year, we compute the number of college graduates residing in each U.S. state and born in each of 57 different foreign countries of origin . We allow those numbers to grow at the same rate as the overall college graduate population from each of those 57 nationalities did in each decade between 1960-2000. Using these imputed values, that are by construction orthogonal to the state-specific productivity shocks, we then re-compute the share of foreign-born graduates in total employment for each census year. This methodology exploits the fact that certain countries (such as India and China) sent many of their college graduates to the U.S. during the period considered for reasons that are independent of the productivity and the quality of the labor force in any U.S. state. Further, if the new immigrants landed and stayed with higher probability where other co-nationals already were (for instance, due to networking or taste reasons) then the imputed inflows of college educated are correlated to the actual inflow of foreign-born college educated and, through that, to the total supply of college educated workers in the state. To emphasize the validity of our assumptions, notice that in the year 2000, in the U.S. as a whole foreign-born represented 8% of the college dropout group but 12% of the college graduate group. In some states foreign-born constituted more than 25% of college educated employment. At the same time, the group of college educated from countries such as India, China and the European Union grew much faster than the group of U.S. born college graduates. During the period 1960-2000, the number of college educated from India increased by 200 fold, the number of college-educated from China by 50 fold and the number of college educated born in the European Union by 8 fold. Meanwhile, the number of college educated Americans rose by only 5 fold. These increases are a combination of the increased share of college graduates among immigrants and the increase in overall immigration from those countries (especially for China and India). In the year 2000, college educated from China, India and the European Union accounted for 6% of all college graduates in the U.S., while in 1960 they accounted for 0%. Hence, states with large initial shares of college educated from those nationalities would have experienced a large supply shock of college educated. Table 5 shows the predictive power of the imputed shares of college educated foreign-born on the state shares of college graduates during 1960-2000. The regressions use a panel with state and decade fixed effects. The first and second rows of Table 5 show the predictive power of the constructed share of college educated immigrants on the actual share of college educated (specifications 1-3), on average schooling (specifications 4-6) and on the share of high school dropouts (specifications 7-9). The constructed share has strong predictive power (very significant t-statistics

and F-test) for the share of college-educated while no power at all for average schooling and for the share of high school dropouts. This implies that the constructed instruments only shift the schooling distribution at the high end of the schooling range. Specification (3) uses 1970 as the initial year to construct the imputed shares. While in 1960 the number of foreign-born was rather low, the precision and power of the instruments increase significantly in the post-1970 period, which is due in part to migration picking up only after 1970. The bottom part of the table uses the share of workers from India, China and the European Union at the beginning of the decade as simpler instruments for the increase in the share of college graduates during the decade. These three regions were, by far, the largest suppliers, in absolute terms of college graduate immigrants (with Russia/Eastern Europe being the next largest supplier). While we lose predictive power (especially in the post-1970 sample), the F-test statistic is still above 5 for the shares of college graduates. At the same time, the shares of immigrants from China, India and the European Union have no predictive power on average schooling and on the share of high school dropouts (specifications 4-9). Overall we are confident that the schooling laws and the constructed share of foreign college graduates are fairly good instruments; they are unlikely to be correlated with changes in productivity and the quality of the labor force across states, while they have the interesting feature of shifting the distribution of school attainments along different segments of the schooling range.

4.3.3 Accessibility of Land Grant Colleges

An alternative instrument affecting the margin of college attendance and graduation across states is the presence of a college close to where a large share of the college-age population resides. Card (1993) found that the presence of a four-year college in the same labor market positively affected the probability that an individual attended college and graduated from it. Currie and Moretti (2003) used the same idea of college proximity to instrument mothers' education in analyzing the latter's effects on children's health. Proximity to college reduces the (material and psychological) cost of attending college inducing some individuals, who would otherwise not continue after high school, to get further education. Moretti (2004) uses the presence of a Land Grant college in a metropolitan area as predictor of the share of college educated in it. Land Grant colleges were established in the late 1800's as a result of a movement to provide accessible higher education to people in each U.S. state. As a consequence their initial location is not strongly correlated with returns to education in the late 1900's. Moreover, they are evenly distributed across the U.S., and over time they have become well established, large institutions. Individuals living close to them are likely to have lower costs and thus higher probability to attend them than others living farther away. As we intend to use proximity to the colleges as an instrument for the share of college educated in the state, we need to look at the coincidence of their location with the location of the population of college age. For each state we calculate the population between the ages 14 and 21 living in

counties within 100 Kilometers (60 miles) from a Land Grant college in every census year (1970 to 1990)[7]. These data were obtained from the County and City Data Book, U.S. Bureau of Census (2000)[8]. We then use this student-age population as a percentage of the working age population in each state as a predictor of the change in the share of college educated in the following decade. As the push towards increased college attendance was different across decades (for instance, it was stronger in the 70's than in the 80's or 90's) we also interacted those shares with decade dummies. Table 6 shows the power of these instruments in predicting the increase in the share of college educated workers during each of the three considered decades. While there is a positive and significant correlation between the instrument and the increase in the college share in each decade, this is rather small and statistically not very strong (column one in Table 6). An extra one percent of people in college age living near a Land Grant college increased the state's share of college-educated in the decade by around 0.2%. The F-statistic of the instruments is 3.02. Moreover, our instruments are correlated with a generalized increase in schooling in the state. The average years of schooling of workers increased significantly more in states with large shares of the population living near land grant colleges (column two of Table 6), and even the share of high school dropouts shows a significant decrease in those states (column three of Table 6). This could still be an effect of the lower cost of college education, pushing more people to complete high school. However it may also signal some unobserved features of states (e.g. labor demand, level of urbanization, sector composition) correlated with schooling improvements. More importantly for our purposes, the presence of land grant colleges does not seem to shift the educational distribution only at the college margin; as a result, it would not be as accurate as the immigration-based instrument in isolating the change in education at just the high end of the schooling range. While we prefer the previous two instruments for this reason, we also use proximity to land grant colleges as an instrument in order to check the robustness of our results.

4.4   IV estimates and Robustness Checks

Tables 7, 8 and 9 report the estimates of externalities from both average schooling levels and from the share of college graduates using U.S. schooling laws and college-educated immigrant shares as instruments. The schooling laws instrument for average schooling via the change in secondary school attendance and graduation. The constructed shares of foreign-born college educated (or the initial share of college educated Indians, Chinese and EU-born) function as instruments for the share of college educated. Each table uses as its dependent variable the constant composition change in average wage $\Delta \ln w_{st}^{cc}$ defined in (20). For Tables 7 and 8 we use all workers between 16 and 65 years of age in the first stage regression and control for their individual characteristics, as described by (19), in order to construct wages $\widehat{\omega}(S,E)_{s,t}$, whereas in Table 9 we only use data on white, married, U.S. born males and take a simple average within education-experience cells to construct the wages $\widehat{\omega}(S,E)_{s,t}$.

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[7] We also utilized the number of students within 200 and 300 km from a land grant college with similar results.
[8] We are grateful to Jordan Rappaport for sharing these data with us.

In Table 7 we estimate different specifications using weekly wages (in columns 1, 2 ,5 and 6) or hourly wages (in columns 3, 4, 7 and 8). We use the whole sample 1960-2000 (in columns 1, 3, 5 and 7) or omit the first decade because of the potential imprecision in calculating the imputed shares with 1960 data (in columns 2, 4, 6 and 8). Finally we construct the constant-composition wage change either using the initial composition (specifications 1-4) or the final composition (specifications 5-8). As the constant composition approach is a first order approximation of the TFP change, calculating it at the initial and final composition ensures that the omitted second order term is not affecting the results. The instruments used in the 2SLS estimation of Table 7 are the schooling laws and the imputed share of foreign college educated. The same specifications are estimated in Table 8 where the initial share of college educated Indians, Chinese and EU-born are used instead as instruments for the change in the share of college educated. Finally, Table 9 reproduces the same (initial composition) specifications as in Tables 7 and 8 but adopting the average wage change computed for white married U.S. born males only. While we observe some variation in the estimated coefficients, a robust result emerges from each and every single estimation: an insignificant external effect of average schooling (mostly between -1% and 3% for one extra year of schooling) and a positive and significant externality from the share of college educated (mostly between 2 and 3% for a 1% increase of that share). One problem with the IV estimates is that their standard error is often quite large. This is due to the limited power of the instruments when regional trends are controlled for. Especially in the case of the college share, the weak instrument bias may be somewhat responsible for the large estimates. The coefficient on the share of college-born is, in fact, between 2-3 times as large as the OLS estimates and 2-3 times as large as the simulated effect. On the one hand, this is a sign that the endogeneity bias is certainly not biasing the OLS estimates upward (in that case the IV estimates would be closer to 0). On the other hand, the large standard errors do not allow us to rule out the hypothesis that the IV and the OLS estimates are equal.

Previous literature has not simultaneously estimated the effects of average schooling and college shares on productivity. However, the available IV estimates of average schooling externalities (from Acemoglu and Angrist, 2001, and Ciccone and Peri, 2006) are exactly within the range we obtain (0-3%), while the existing estimates of externalities from college-educated (Moretti, 2004) are between 1-2% for each 1% increase in the share of college graduates, which also overlaps with the range we estimate. From the point of view of our model the quantitative estimates of college externalities seem rather large, however they are empirically consistent with those found in previous work by Moretti (2004).

Robustness checks in several directions are performed in the tables that follow. First, we use the Land Grant college based instrument for college share instead of that based on immigration. The four specifications presented in Table 10 use the constant composition wage change, $\Delta \ln w_{st}^{cc}$, as the dependent variable either taking the initial (specifications 1 and 3) or the final composition (specifications 2 and 4) of skills. We also alternate the use

of weekly wages (specifications 1 and 2) and hourly wages (specification 3 and 4). Interestingly, despite the fact that Land Grant college access may not be an ideal instrument (as discussed above) the point estimates of the externalities from schooling and from college graduates confirm the results obtained above. Average schooling has no significant external effect, while the share of college educated has a significant and positive effect. A one percent increase in college graduates is associated with an increase in total factor productivity of between 1-2%. These findings are consistent with the results obtained by Moretti (2004) who used similar instruments. The point estimates of the external effect of college educated using the Land Grant college instrument are closer to the OLS estimates, although due to their large standard errors sometimes they are only significant at the 10% level. Table 11 analyzes the effect of average schooling and of the share of college graduates on the wages of college graduates (rather than on TFP). This exercise provides further evidence of the positive effect of college graduates on TFP; given a constant level of TFP, an increase in the supply of college graduates would decrease their wages due to simple supply-side effects. To the contrary, the estimated effect is positive (although 30-40% smaller than the effect on TFP) both using OLS (specification 1 and 2) or 2SLS methods with each of our instruments (specifications 3 to 8). These estimates imply that a pure supply effect of an increase in the college share of employment is more than compensated by the positive external effect on TFP. Interestingly, increased average schooling has a negative (not always significant) effect on the wage of college educated workers; that is, controlling for the increased share of college graduates, a further increase in schooling only has a negative supply effect on the wage of college graduates.

Finally, in Table 12 we directly compare the effect of the high school graduate share to that of the college graduate share on TFP. We use those shares as explanatory variables in an OLS regression (specifications 1 and 2) and then in a 2SLS estimation, instrumenting them with CA-CL laws and immigration-based instruments (specification 3 to 6) as well as with Land Grant based instruments (specification 7 and 8). The IV estimates confirm that no positive significant externalities are associated with the share of high school graduates, while the externality of college graduates remains positive, significant and large in all specifications, ranging between 1 and 3.5 for a one-percent increase in the share of college educated.

5   Conclusions

This paper analyzes the connection between schooling, college graduation, and TFP using a new model and a new empirical strategy . Assuming the existence of two types of technology (traditional and modern) with more educated workers having a comparative advantage in the modern sector, we gain new insights into the effects of a shift in educational attainments on total factor productivity. In particular, the nature of the technology is such that below a certain schooling level (estimated to be around 12 years of schooling) increases in schooling have low private as well as social returns because the technology used has low returns to skills and does not allow

for the production of differentiated goods. Above that threshold, however, higher education has large private as well as social returns as the modern technology results in large increases in modern technology productivity, increased variety of the goods produced and hence overall TFP gains. Using parameters calibrated with 1980 skill distribution data, the model shows that the increase in secondary education had very small effects on TFP (less than 2% for an increase of one year in average schooling) while the increase in college graduation has external effects that are 5 to 9 times larger (we obtain up to 17 % higher TFP for a comparable increase in average schooling resulting from an increase in college education). Using schooling laws and state-specific immigration of college educated foreign workers as instruments for average education and college graduate share, respectively we are also able to empirically estimate these effects. The panel of 50 U.S. states during the period 1960-2000 confirms the insignificant external effect of increased average schooling produced by schooling laws while we find a positive and large effect of an increase in the share of college graduate, foreign born workers. The IV estimates of the second effect are even larger than what the model predicts yielding a positive effect of 25-40% on TFP for a one year increase in schooling achieved through increased college graduation. These effects are also confirmed if we use the location of Land Grant colleges as an instrument for the increase in the share of college graduates. The empirical results confirm and rationalize the findings of previous empirical papers on human capital externalities such as Acemoglu and Angrist (2001), Moretti (2004) and Ciccone and Peri (2006).

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6   Appendix 1: The Open Economy Model

Consider an open economy in a two-country world. Both countries, labelled 1 and 2, are assumed to have the same preferences, technology and size, but possibly different skill distributions, including different average skill levels. Following our experiment in section 3.2 we consider the externality of a change in skill distribution of country 1 when country 2 has a constant skill distribution equal to the initial distribution of country 1. As we are not interested in the effects of trade barriers, for simplicity we will assume that goods can be traded across the border at zero cost, i.e., tariffs and transportation costs are null, and exporting entails no sunk costs. Free trade implies that the price of each variety, p_i, is identical regardless of where the good is sold, which in turn yields the same price index for the composite good (P_X) across countries. We consider, as is typical in static trade models, the equilibrium with trade and a balanced trade account.

The representative consumer's demands for the homogeneous good Y and the composite good X are still given by (3). The only novelty with respect to the closed economy setup is that now some of the varieties of X demanded are locally produced while some are produced in the other country. We use a double index for the quantity demanded of each variety so that x_{ij} denotes the demand from country j of a variety produced in country i. Each country produces a continuum of varieties, between $[0, N_1]$ for country 1 and in $[0, N_2]$ for country 2. Assuming the same costs and preferences between countries, the quantities and prices of all varieties produced at equilibrium are the same. Therefore the total demands for each variety of good 1 and 2 are respectively:

$$
\begin{aligned}
x_1 &= x_{11} + x_{12} = \left(\frac{s(P_X)}{P_X}\right)\left(\frac{p_1}{P_X}\right)^{-\sigma}(E_1 + E_2) \\
\\
x_2 &= x_{21} + x_{22} = \left(\frac{s(P_X)}{P_X}\right)\left(\frac{p_2}{P_X}\right)^{-\sigma}(E_1 + E_2)
\end{aligned}
\tag{21}
$$

x_1 and x_2 are the total demand for each variety of good produced in country 1 and 2, respectively, and the terms p_1 and p_2 represent their prices. P_X is the unit price of the composite good X which is given by:

$$
P_X = \left[N_1 {p_1}^{1-\sigma} + N_2 {p_2}^{1-\sigma}\right]^{\frac{1}{1-\sigma}},
\tag{22}
$$

$s(P_X)$ is the share of aggregate expenditure devoted to purchasing the composite good X in each country. E_1 and E_2 are the aggregate expenditures on goods by each country; their value is pinned down by the assumption of balanced trade between the two countries. In a model with no capital accumulation, this implies that total expenditure on goods equals total income, $E_1 = M\overline{W}_1 = M\left(\displaystyle\int_0^{\overline{Z}_1} \exp(g_Y Z)dG_1(Z) + C_{X1}\int_{\overline{Z}_1}^1 \exp(g_X Z)dG_1(Z)\right)$

and $E_2 = M\overline{W}_2 = M \left(\int_0^{\overline{Z_2}} \exp(g_Y Z)dG_2(Z) + C_{X2} \int_{\overline{Z_2}}^1 \exp(g_X Z)dG_2(Z) \right).$

On the production side, profit maximization yields the equilibrium prices for the different varieties of good X which in the absence of trade costs are sold at the same prices across the border. Thus the equilibrium prices for varieties produced in country 1 and 2 are respectively:

$$p_1 = \frac{\sigma}{\sigma-1}C_{X1} \qquad p_2 = \frac{\sigma}{\sigma-1}C_{X2} \tag{23}$$

where C_{X1} and C_{X2} are the unit cost of producing any variety of the differentiated good in country 1 and 2 and are equal to $\exp\left((g_Y - g_X)\overline{Z_1}\right)$ and $\exp\left((g_Y - g_X)\overline{Z_2}\right)$, respectively .

The free entry (zero-profit) condition for each variety implies that the size of each firm (that is, its supply) is given by:

$$x_1 = (\sigma - 1)F_X$$

$$\tag{24}$$

$$x_2 = (\sigma - 1)F_X$$

Hence, the equilibrium number of firms (varieties) produced in each country is proportional to the size of the skilled group.

$$N_1 = \frac{M}{\sigma F_X} \int_{\overline{Z_1}}^1 \exp(g_X Z)dG_1(Z), \qquad N_2 = \frac{M}{\sigma F_X} \int_{\overline{Z_2}}^1 \exp(g_X Z)dG_2(Z) \tag{25}$$

Three market-clearing conditions determine the equilibrium prices p_1 and p_2 which in turn pin down the marginal costs C_{X1} and C_{X2} and the thresholds $\overline{Z_1}$ and $\overline{Z_2}$. Those three conditions are, respectively: the market clearing conditions for the homogeneous good Y, for each variety of X produced in country 1 and for each variety of X produced in country 2. They are shown below, after incorporating the trade-balance conditions $(E_1 = M\overline{W}_1, E_2 = M\overline{W}_2)$ and the free-entry condition (24):

$$[1 - s(P_X)] M \left(\overline{W}_1 + \overline{W}_2\right) = \int_0^{\overline{Z_1}} \exp(g_Y Z)dG_1(Z) + \int_0^{\overline{Z_2}} \exp(g_Y Z)dG_2(Z)$$

$$s(P_X)M \left(\overline{W}_1 + \overline{W}_2\right) \left(\frac{p_1^{1-\sigma}}{N_1 p_1^{1-\sigma} + N_2 p_2^{1-\sigma}}\right) = (1 - \sigma)F_x p_1 \tag{26}$$

$$s(P_X)M \left(\overline{W}_1 + \overline{W}_2\right) \left(\frac{p_2^{1-\sigma}}{N_1 p_1^{1-\sigma} + N_2 p_2^{1-\sigma}}\right) = (1 - \sigma)F_x p_2$$

It is very easy to see that the last two equations of (26) imply $p_1 = p_2$. This in turn implies that, at

equilibrium, $C_{X1} = C_{X2} = C_X$ and $\overline{Z}_1 = \overline{Z}_2 = \overline{Z}$. Substituting these and the definitions of $\overline{W}_1, \overline{W}_2$ and $s(P_X)$ into the first equality in (26) and simplifying we obtain:

$$\left[\int_0^{\overline{Z}} \exp(g_Y Z) dG_1(Z) + \int_0^{\overline{Z}} \exp(g_Y Z) dG_2(Z) \right] = \tag{27}$$

$$\left(\frac{1-\beta}{\beta} \right)^{\theta} \left(\frac{\sigma}{\sigma-1} \right)^{\theta-1} \left(\frac{\sigma F_X}{M} \right)^{\frac{\theta-1}{\sigma-1}} \exp[\theta(g_Y - g_X)\overline{Z}] \left(\int_{\overline{Z}}^{1} \exp(g_X Z) dG_1(Z) + \int_{\overline{Z}}^{1} \exp(g_X Z) dG_2(Z) \right)^{\frac{\sigma-\theta}{\sigma-1}}$$

The similarity of (27) with (14) is apparent. The open economy with free trade implies that prices of goods are equalized between countries and therefore prices of factors are too. The wage schedule in the two countries is, therefore, identical. A change in the skill distribution in country 1 has the same qualitative effects in this case as it had in the closed economy case: it increases the threshold $\overline{Z}$, decreases the price P_X and increases productivity. Now however, part of the beneficial effect spills over to the other country (who enjoys lower prices via trade), hence the externality of higher schooling is "shared" between country one and two, with country one receiving only a fraction of the external effect than it did in autarky.

7   Appendix 2: Parametrization of the Model

The model described in section 2 has three important implications on the wage schedule. First the returns to schooling at low schooling levels (the slope of the wage schedule) should be lower than at high schooling levels (see Figure 1). Second, rather than a general convexity of the wage schedule, our model predicts a well localized kink in the (log) wage schedule (again, see Figure 1). Third, skill-biased technological change in this model takes the form of an increase in the difference between g_X and g_Y, in its extreme form g_X increases and g_Y decreases. Panel 1 below shows the estimated wage schedule, using U.S. census micro-data for the years 1960 to 2000 (IPUMS, Ruggles et al., 2005); specifically, we use the 1% sample for 1960 and 1970 and the 5% sample for 1980, 1990 and 2000. We regress the log real weekly wages (yearly wages divided by number of weeks per worker) on the usual individual controls (sex, race, place of birth and marital status dummies and a quartic polynomial in experience), and on years of schooling dummies for each census year. For the 1960-80 period we can estimate a specific return for each yearly attainment (as the schooling data report the highest grade attended) while for 1990 we convert the categorical variables provided into years of schooling using the conversion table available in Park (1994) and we estimate returns only for those attainments. We report in Panel 1 the estimated value for the schooling dummy on the vertical axis against years of schooling on the horizontal axis. What is apparent from the reported wage schedules is that from 1970, and increasingly over time, the returns to schooling below

12 years (high school graduation) have been lower than the returns to schooling above it. Interestingly, the kink in the wage schedule (the $\overline{Z}$ of our model) appears to be around $Z = 12$ (high school graduation) across census years, and the skill-biased technological change of the 80's and 90's has taken the form of a higher g_X and lower g_Y. If we estimate linear returns to schooling allowing for a different slope for schooling below and above 12 years we obtain significantly different estimates for each census year (including 1960) and overwhelmingly so since 1970. These features provide a direct confirmation of the validity of our model and allow us to estimate g_X and g_Y, and to calibrate F_X in order to obtain $\overline{Z}$ equal or close to 12 years. As g_X and g_Y change across censuses we use their median values (estimated for 1980) which are $g_X = 1.6$ and $g_Y = 0.4$ corresponding to a 2% return to schooling below 12 years and 8% return above 12 years. We test the sensitivity of the externalities to these parameters below and as the model predicts, larger returns to schooling for the high technology relative to the low technology translate into larger external effects as a result of incremental college graduation.

The distribution of workers' skills, $G(Z)$, is captured by a 5-cell histogram in which we discretize the continuous variable $Z \in [0, 1]$ into years of schooling, re-scaling the maximum achievable years (20, assuming that a Ph.D. degree requires, on average, 4 years) to equal 1. The point $Z = 0.6$ (i.e. 12/20) represents high school graduation and the point $Z = 0.8$ (i.e. 16/20) represents college graduation. The other two boundaries of the histogram are $Z = 0.4$ (primary school) and $Z = 0.65$, 13 years of schooling (college dropout). We produce our simulations assuming an initial distribution of schooling across groups that matches the 1980 census, and then test the robustness of our results using 1960 as the initial distribution. The distribution of education across groups for the U.S. for each census year 1960-2000 is reported in Table 1. The initial density function for Z (at time $t_0 = 1980$) is computed by converting Table 1 values for 1980 into densities; for instance, the proportion of middle school dropouts with education level between 0 and 0.4 is 0.08, which implies a density of 0.2 (such that (0.4-0) x 0.2 = 0.08):

$$\phi(Z) \begin{cases} 0.2 & \text{for } 0 \leq Z < 0.4 \\ 0.7 & \text{for } 0.4 \leq Z < 0.6 \\ 7.8 & \text{for } 0.6 \leq Z < 0.65 \\ 1.33 & \text{for } 0.65 \leq Z < 0.8 \\ 0.95 & \text{for } 0.8 \leq Z \leq 1 \end{cases} \tag{28}$$
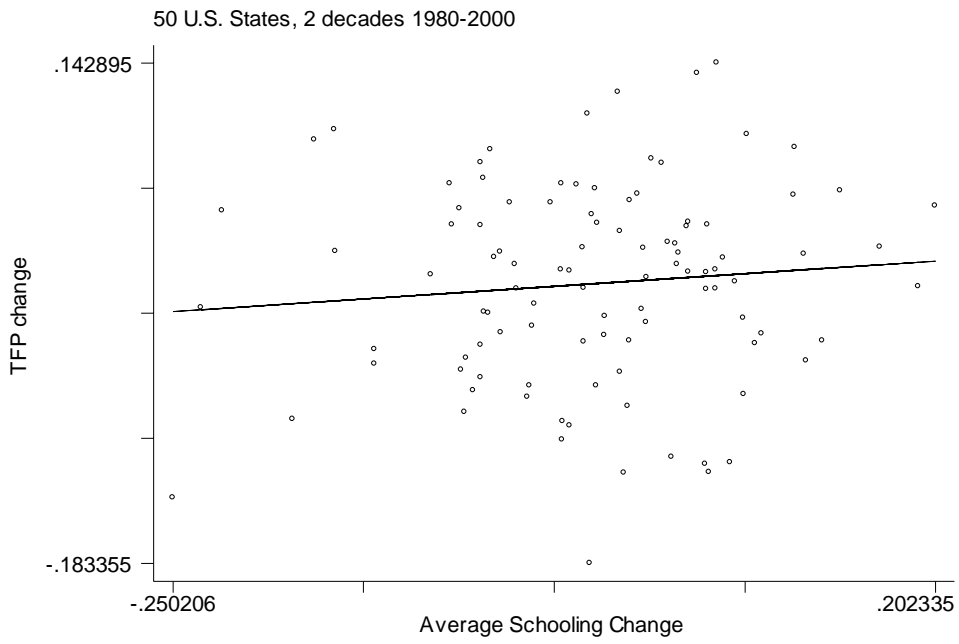
Figures

Figure 1
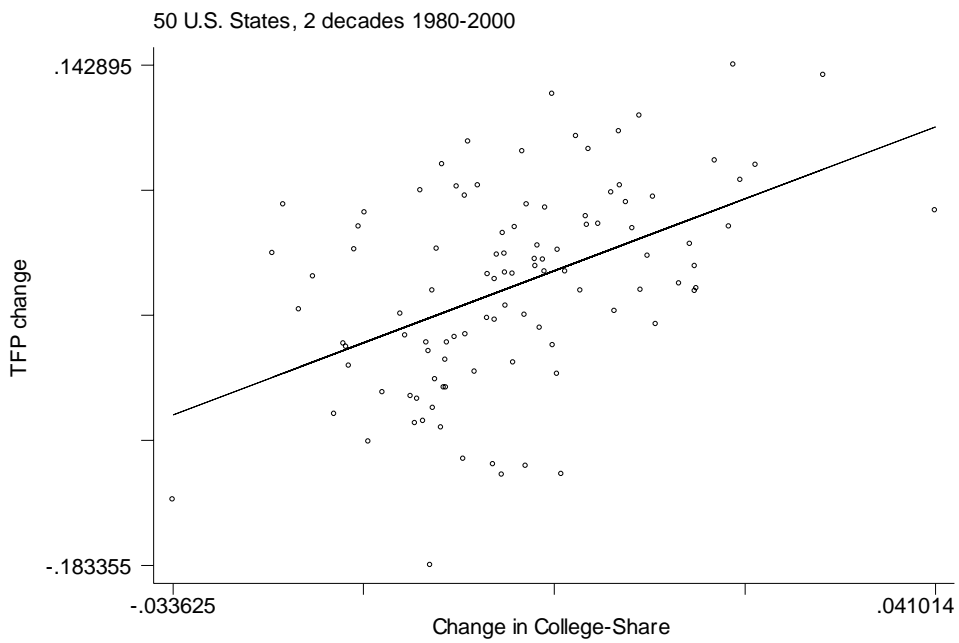**Workers skills and (ln) wage schedule**
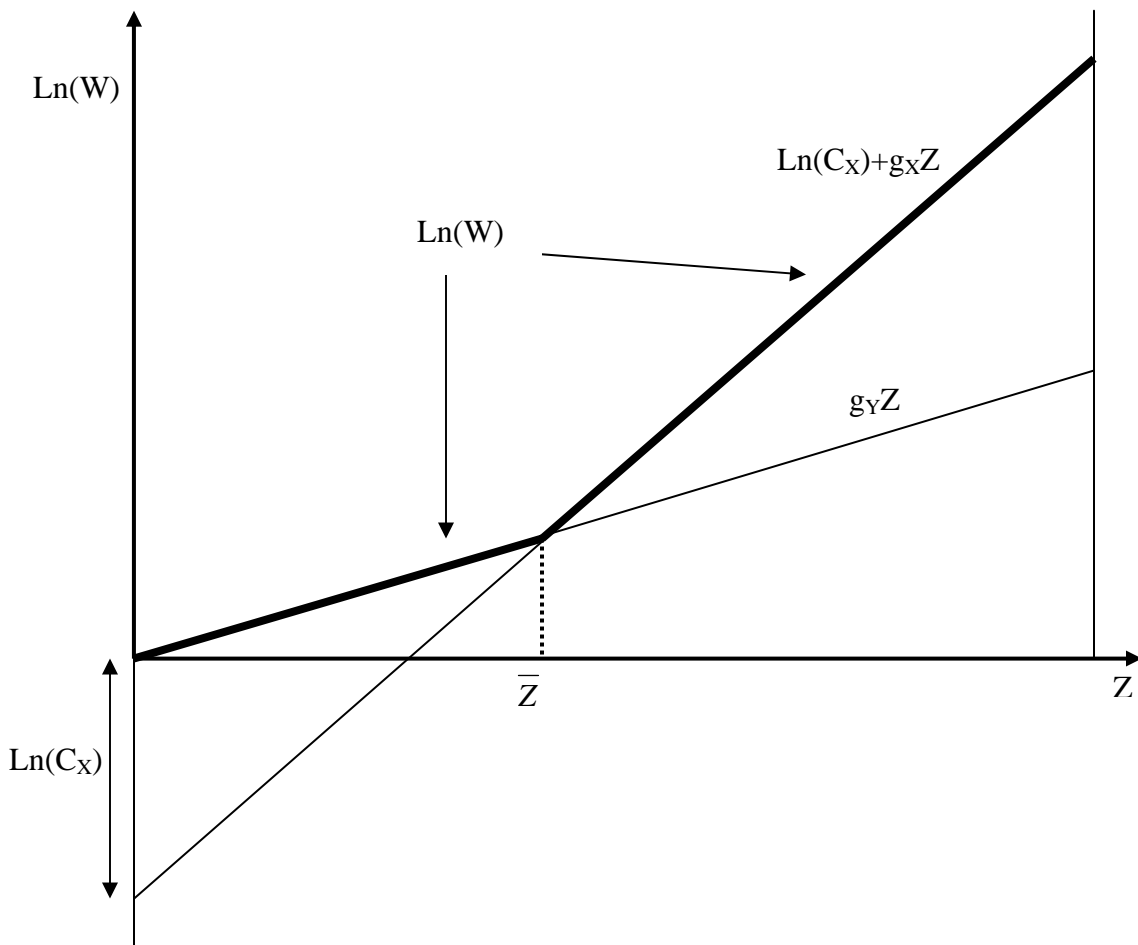
Figure 2:
TFP changes and average schooling changes

50 U.S. States, 2 decades 1980-2000

Figure 3:
TFP changes and changes in share of college graduates,

50 U.S. States, 2 decades 1980-2000

Tables

Table 1:
Shares of workers for each of 5 schooling attainment groups and average schooling

Group:	1960	1970	1980	1990	2000
Less than 8 years, Middle School Dropouts	0.28	0.16	0.08	0.04	0.04
Between 8 and 11 years, High School Dropouts	0.22	0.20	0.14	0.12	0.11
12 years, High School Graduates	0.30	0.37	0.39	0.31	0.28
Between 13 and 15 years, College Dropouts	0.10	0.13	0.20	0.30	0.32
More than 16, College Graduates	0.10	0.13	0.19	0.23	0.25
Average years of schooling	10.65	11.56	12.64	13.11	13.22

Source: Authors' calculations based on IPUMS data.

Table 2
Simulated effects of increased secondary attendance and increased college graduation on TFP

Specifications:	(1) Benchmark	(2) High Initial $\overline{Z}$	(3) 1990 returns to schooling	(4) Low σ	(5) High θ	(6) Low β	(7) 1960 initial distribution of schooling	(8) Open Economy
%Change in TFP as a consequence of one extra year of schooling due to increasing secondary attendance and graduation	1.76%	0.95%	1.82%	3.12%	1.85%	1.76%	1.50	0.88%
% Change in TFP as a consequence of 1% increase in share of college graduates (and decrease in college dropouts)	0.33%	0.28%	0.63%	0.59%	0.34%	0.33%	0.24%	0.16%
% Change in TFP as a consequence of one extra year of schooling due to increase in college graduation	8.84%	7.61%	16.97%	15.83%	9.18%	8.84%	6.48%	4.42%
(Externality from College)/(Externality from High School)	**5.0**	**8.0**	**9.3**	**5.1**	**5.0**	**5.0**	**4.33**	**5.0**
Returns to schooling, g_X, g_Y	$g_X=1.6$ $g_Y=0.4$	$g_X=1.6$ $g_Y=0.4$	$g_X=2.7$ $g_Y=0.4$	$g_X=1.6$ $g_Y=0.4$	$g_X=1.6$ $g_Y=0.4$	$g_X=1.6$ $g_Y=0.4$	$g_X=1.6$ $g_Y=0.4$	$g_X=1.6$ $g_Y=0.4$
Elasticity of substitution between goods X and Y, θ	1.5	1.5	1.5	1.5	1.7	1.5	1.5	1.5
Elasticity of Substitution between varieties of good X, σ	2	2	2	1.6	2	2	2	2
β	0.65	0.65	0.65	0.65	0.65	0.35	0.65	0.65
Initial value of $\overline{Z}$	12 years	13 years	12 years	12 years	12 years	12 years	12 years	12 years
Initial Distribution of Schooling	As in 1980	As in 1980	As in 1980	As in 1980	As in 1980	As in 1980	As in 1960	As in 1980

The parameter F_X is calibrated as to produce the initial value of $\overline{Z}$ (equivalent to 12 or 13 years of schooling) matching the empirical kink on the wage schedule.

Table 3:
Correlation between TFP changes and measures of schooling, OLS estimates

Specifications	(1) 1960-2000	(2) Employ ment - weighted	(3) With 4 regional dummies	(4) 1970-2000	(5) 1980-2000	(6) 1960-2000 US born white males only
Change in average schooling	0.02 (0.025)	0.017 (0.025)	0.0005 (0.03)	-0.04 (0.04)	-0.07 (0.05)	0.006 (0.04)
Change in the share of college graduates	0.63** (0.31)	0.67** (0.30)	0.71** (0.35)	0.98** (042)	2.95** (0.47)	1.06** (0.46)
R^2	0.64	0.65	0.65	0.65	0.62	0.64
Observations	204	204	204	153	102	204

Dependent variable: cleaned $\Delta \ln \omega^{cc}_{st}$ calculated, as described in the main text, using all workers between 16 and 65 years of age who earned a positive income.
Each regression includes period fixed effects
**; significant at 5% level.

Table 4:

First-stage regressions: Effect of child labor laws and compulsory attendance laws on schooling and educational groups

Dependent Variable:	Average years of schooling of employed			Share of high school dropouts in employment			Share of college graduates in employment		
Specification:	(1) 1960-2000	(2) 1960-2000	(3) 1970-2000	(4) 1960-2000	(5) 1960-2000	(6) 1970-2000	(7) 1960-2000	(8) 1960-2000	(9) 1970-2000
Share CA<8	-1.28**	-0.82**	-0.78**	0.15**	0.09**	0.10**	-0.04	-0.03	-0.02
	(0.25)	(0.22)	(0.23)	(0.04)	(0.03)	(0.04)	(0.03)	(0.02)	(0.02)
Share CA>11	0.20	0.09	0.03	-0.07**	-0.05*	-0.05**	-0.02	-0.03	-0.04**
	(0.19)	(0.18)	(0.19)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Share CL<6	-0.85**	-0.56*	-0.59*	0.13**	0.09**	0.09**	-0.01	-0.02	-0.03
	(0.36)	(0.30)	(0.30)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Share CL>9	0.93**	0.66**	0.63**	-0.08**	-0.05**	-0.05	0.02	0.02	0.02
	(0.12)	(0.15)	(0.17)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Region-specific Trends	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
F-Test of Joint Significance (p-value)[a]	17.9	7.00	5.67	13.85	5.06	4.37	2.98	2.57	2.47
	(0.000)	(0.000)	(0.0003)	(0.000)	(0.0007)	(0.002)	(0.02)	(0.05)	(0.06)
R^2	0.83	0.87	0.66	0.89	0.91	0.80	0.51	0.60	0.51
Observations	204	204	153	204	204	153	204	204	153

All regressions include state and year fixed effects. Each column is a separate regression. 50 U.S. states plus D.C. included. Heteroskedasticity robust standard errors are in parentheses.

*,** significant at the 10%, 5% confidence level.

a: Null hypothesis is that the explanatory variables have no power in predicting the dependent variable. The p-value is the level of confidence at which the null hypothesis is rejected.

Table 5:
First-stage regressions: Impact of highly skilled immigrants on average schooling and educational groups

Dependent Variable:	Share of college graduates in employment			Average years of schooling of employed			Share of high school dropouts in employment		
Specification:	(1) 1960-2000	(2) 1960-2000	(3) 1970-2000	(4) 1960-2000	(5) 1960-2000	(6) 1970-2000	(7) 1960-2000	(8) 1960-2000	(9) 1970-2000
Imputed share of college –educated immigrants	0.14** (0.034)	0.136** (0.032)	0.44** (0.06)	0.10 (0.44)	-0.16 (0.36)	-0.23 (0.22)	0.02 (0.05)	0.05 (0.04)	0.19 (0.12)
F-Test of Significance (p-value)[a]	15.3 (0.0001)	17.6 (0.0000)	23.16 (0.000)	0.06 (0.81)	0.20 (0.65)	1.15 (0.28)	0.14 (0.70)	1.23 (0.26)	2.97 (0.09)
Initial share of foreign-born from EU	7.06** (1.01)	2.99* (1.51)	4.8** (2.2)	22.7 (15.5)	1.22 (17.5)	15.8 (19.1)	-2.39 (1.96)	2.7 (2.28)	0.50 (3.33)
Initial share of foreign-born from China	0.16 (0.70)	0.63 (0.75)	0.42 (1.20)	-13.1 (9.90)	9.74 (8.55)	8.9 (16.1)	2.73 (1.18)	-0.35 (1.11)	1.96 (2.13)
Initial share of foreign-born from India	0.07 (0.07)	0.15* (0.08)	0.74** (0.28)	0.13 (1.07)	-0.86 (0.93)	1.1 (2.3)	0.02 (0.16)	0.02 (0.12)	0.26 (0.31)
F-Test of Joint Significance (p-value)[a]	16.56 (0.000)	6.77 (0.0002)	5.87 (0.0008)	1.06 (0.36)	0.61 (0.60)	0.55 (0.65)	1.92 (0.12)	0.74 (0.53)	1.02 (0.38)
Region-specific Trends	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	204	204	153	204	204	153	204	204	153

All regressions include state and year fixed effects. Each column is a separate regression. 50 U.S. states plus D.C. included. Heteroskedasticity robust standard errors are in parentheses.

*,** significant at the 10%, 5% confidence level.

a: Null hypothesis is that the explanatory variables have no power in predicting the dependent variable. The p-value is the complement to one of the confidence level at which the null hypothesis is rejected.

Table 6:

First-stage regressions: Effect of the presence of Land-Grant colleges on schooling and educational groups

Dependent Variable	(1) Change in the share of college graduates in employment	(2) Change in the average years of schooling of employed	(3) Change in the share of high school dropouts in employment
People living within 100 Km of a Land Grant college as % of labor force, 1970	0.19** (0.10)	2.2** (0.3)	-0.33** (0.05)
People living within 100 Km of a Land Grant college as % of labor force, 1980	0.17* (0.11)	1.5** (0.3)	-0.22** (0.04)
People living within 100 Km of a Land Grant college as % of labor force, 1990	0.20** (0.10)	1.3** (0.3)	-0.33** (0.05)
F-Test of Significance (p-value)[a]	3.02 (0.06)	27.9 (0.000)	33.2 (0.000)
R^2	0.22	0.87	0.90

All regressions include state and year fixed effects. Each column is a separate regression. 50 U.S. states plus D.C. included. Heteroskedasticity robust standard errors are in parentheses.

*,** significant at the 10%, 5% confidence level.

a: Null hypothesis is that the explanatory variables have no power in predicting the dependent variable. The p-value is the complement to one of the confidence level at which the null hypothesis is rejected.

Table 7:
2SLS Estimates of the effects of schooling on TFP (all workers)
IV: imputed college-educated immigrants and CA-CL laws

Dependent Variable:	$\Delta \ln \omega^{cc}_{st}$ constructed using the initial composition				$\Delta \ln \omega^{cc}_{st}$ constructed using the final composition			
Measure of Wage	Weekly Wages		Hourly Wages		Weekly Wages		Hourly Wages	
Specification:	(1) 1960-2000	(2) 1970-2000	(3) 1960-2000	(4) 1970-2000	(5) 1960-2000	(6) 1970-2000	(7) 1960-2000	(8) 1970-2000
Change in the average schooling	0.01 (0.06)	0.001 (0.07)	0.01 (0.07)	0.01 (0.07)	0.02 (0.07)	-0.01 (0.08)	0.007 (0.08)	0.01 (0.06)
Change in the share of college educated	2.91** (1.11)	3.05** (1.2)	3.04** (1.17)	2.91** (1.33)	2.97** (1.05)	3.00** (1.21)	2.93** (1.12)	2.66** (1.22)
R^2	0.68	0.66	0.66	0.56	0.70	0.69	0.71	0.62
Observations	204	153	204	153	204	153	204	153

All regressions include 4 regional dummies (Northeast, Midwest, South, West) and decade dummies. The observations correspond to state-decade changes and are weighted by the state employment. Heteroskedasticity-robust standard errors are in parentheses.
The method of estimation is 2SLS using as instrumental variables the imputed share of college-educated immigrants and CA-CL laws, as described in the main text.
*,** significant at the 10%, 5% confidence level.

Table 8:
2SLS Estimates of the effects of schooling on TFP (all workers)
IV: share of Chinese, Indian and EU born and CA-CL laws

Dependent Variable:	$\Delta\ln\omega^{cc}_{st}$ constructed using the initial composition				$\Delta\ln\omega^{cc}_{st}$ constructed using the final composition			
Measure of Wage	**Weekly Wages**		**Hourly Wages**		**Weekly Wages**		**Hourly Wages**	
Specification:	**(1)** 1960-2000	**(2)** 1970-2000	**(3)** 1960-2000	**(4)** 1970-2000	**(5)** 1960-2000	**(6)** 1970-2000	**(7)** 1960-2000	**(8)** 1970-2000
Change in average schooling	0.01 (0.06)	0.03 (0.08)	0.01 (0.06)	0.04 (0.05)	0.003 (0.06)	0.01 (0.07)	0.004 (0.07)	0.03 (0.07)
Change in the share of college educated	2.10** (1.00)	2.91** (1.20)	2.2** (1.1)	2.80** (1.3)	2.30** (0.90)	2.90** (1.20)	2.10** (1.05)	2.50** (1.20)
R^2	0.71	0.64	0.69	0.55	0.73	0.68	0.74	0.62
Observations	204	153	204	153	204	153	204	153

All regressions include 4 regional dummies (Northeast, Midwest, South, West) and decade dummies. The observations correspond to state-decade changes and are weighted by the state employment. Heteroskedasticity-robust standard errors are in parentheses.
The method of estimation is 2SLS using as instrumental variables the initial share of Indians, Chinese and EU-born and CA-CL laws, as described in the main text.
*,** significant at the 10%, 5% confidence level.

Table 9:
2SLS Estimates of the effects of schooling on TFP : white, US born, male workers only

Instruments:	IV: the Imputed share of college-educated immigrants and CA-CL laws				IV: Initial share of EU, India and Chinese-born and CA-CL laws			
Measure of Wage	Weekly Wages		Hourly Wages		Weekly Wages		Hourly Wages	
Specification:	(1) 1960-2000	(2) 1970-2000	(3) 1960-2000	(4) 1970-2000	(5) 1960-2000	(6) 1970-2000	(7) 1960-2000	(8) 1970-2000
Change in average schooling	0.03 (0.07)	0.04 (0.08)	0.04 (0.07)	0.05 (0.08)	0.07 (0.09)	0.03 (0.06)	0.04 (0.07)	0.06 (0.07)
Change in the share of college educated	2.33** (1.22)	2.71** (1.22)	2.77** (1.12)	2.61** (1.30)	2.61** (1.33)	2.01** (1.02)	1.91* (1.1)	2.34** (1.12)
R^2	0.55	0.33	0.58	0.25	0.33	0.59	0.61	0.23
Observations	204	153	204	153	204	153	204	153

Dependent variable: $\Delta ln\omega^{cc}_{st}$ for white, US born, males, constructed keeping the initial composition of schooling constant. All regressions include 4 regional dummies (Northeast, Midwest, South, West) and decade dummies. The observations correspond to state-decade changes and are weighted by the state employment. Heteroskedasticity-robust standard errors are in parentheses.
*,** significant at the 10%, 5% confidence level.

Table 10:
2SLS Estimates of the effects of schooling on TFP (All workers)
IV: Land-Grant college based and CA-CL laws

Instruments:	IV: Population age 14-21 living within 100 Km of a Land Grant College as share of working age population and CA-CL laws			
Measure of Wage	**Weekly Wages**		**Hourly Wages**	
Specification:	**(1)** Initial composition 1970-2000	**(2)** Final composition 1970-2000	**(3)** Initial composition 1970-2000	**(4)** Final composition 1970-2000
Change in average schooling	-0.06 (0.04)	-0.07 (0.04)	-0.04 (0.04)	-0.04 (0.04)
Change in the share of college educated	2.10** (0.91)	1.98** (0.87)	1.70* (0.98)	1.50* (0.89)
R^2	0.68	0.71	0.58	0.64
Observations	147	147	147	147

Dependent variable: cleaned $\Delta \ln \omega^{cc}_{st}$ calculated using all college educated workers and a first-stage cleaning regression constructed keeping the composition of schooling constant. All regressions include decade dummies. The observations correspond to state-decade changes and are weighted by the state employment. Heteroskedasticity-robust standard errors are in parentheses. Only observations in 1970, 80, 90 and 2000 included. 48 continental US states plus DC.
*,** significant at the 10%, 5% confidence level.

Table 11
Effects of the share of college educated on wages of college educated

Specification	(1) 0LS, Weekly wages	(2) OLS Hourly wages	(3) IV Weekly wages	(4) IV Hourly wages	(5) IV Weekly wages	(6) IV Hourly wages	(7) IV Weekly wages	(8) IV Hourly wages
Instruments:	Not applicable		The Imputed College-Educated Immigrants and CA-CL laws		Initial Share of EU, India and China born and CA-CL laws		Land-Grant Colleges based IV and CA-CL laws	
Change in average schooling	-0.08**	-0.06**	-0.04	-0.02	-0.04	-0.03	-0.10*	-0.11*
	(0.02)	(0.03)	(0.05)	(0.04)	(0.08)	(0.06)	(0.06)	(0.06)
Change in the share of college graduates	1.50**	1.25**	2.15**	1.70**	2.55**	2.34**	1.87**	1.55*
	(0.25)	(0.30)	(0.74)	(0.80)	(0.78)	(0.94)	(0.75)	(0.82)
R^2	0.91	0.90	0.89	0.90	0.89	0.89	0.92	0.89
Observations	204	204	204	204	204	204	147	147

Dependent variable is cleaned $\Delta \ln\omega^{ccollege}_{st}$ calculated using all college educated workers, and a first-stage cleaning regression. All regressions include 4 regional dummies (Northeast, Midwest, South, West) and decade dummies. The observations correspond to state-decade changes and are weighted by the state employment. Heteroskedasticity-robust standard errors are in parentheses.
 *,** significant at the 10%, 5% confidence level.

Table 12
**Effect of the share of high school graduates and college graduates on TFP**

Specification	(1) 0LS, Weekly Wages	(2) OLS Hourly Wages	(3) IV Weekly Wages	(4) IV Hourly Wages	(5) IV Weekly Wages	(6) IV Hourly Wages	(7) IV Weekly Wages	(8) IV Hourly Wages
Instruments:	Not Applicable		Imputed College-educated Immigrants and CA-CL laws		Initial Share of EU, India and Chinese born and CA-CL laws		Land-Grant Colleges and CA-CL laws	
Change in the share of high school graduates	-0.18** (0.07)	-0.16** (0.07)	-0.02 (0.12)	0.02 (0.18)	0.14 (0.21)	0.17 (0.23)	-0.09 (0.12)	-0.11 (0.12)
Change in the share of college graduates	1.12** (0.40)	1.04** (0.40)	3.33** (1.00)	3.22** (1.33)	3.5** (1.4)	3.55** (1.23)	1.20* (0.70)	1.10 (0.70)
R^2	0.74	0.73	0.64	0.63	0.62	0.51	0.61	0.56
Observations	204	204	204	204	204	204	147	147

Dependent variable: cleaned $\Delta \ln\omega^{cc}_{st}$ calculated using all workers. All regressions include 4 regional dummies (Northeast, Midwest, South, West) and decade dummies. The observations correspond to state-decade changes and are weighted by the state employment. Heteroskedasticity-robust standard errors are in parentheses.
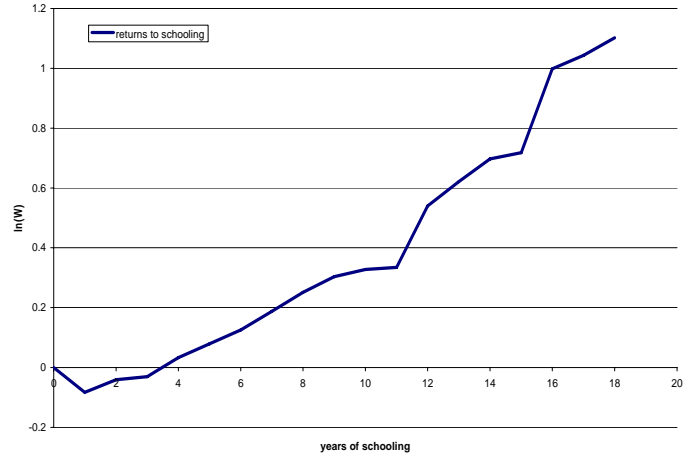*, ** significant at the 10%, 5% confidence level.

Panel 1:
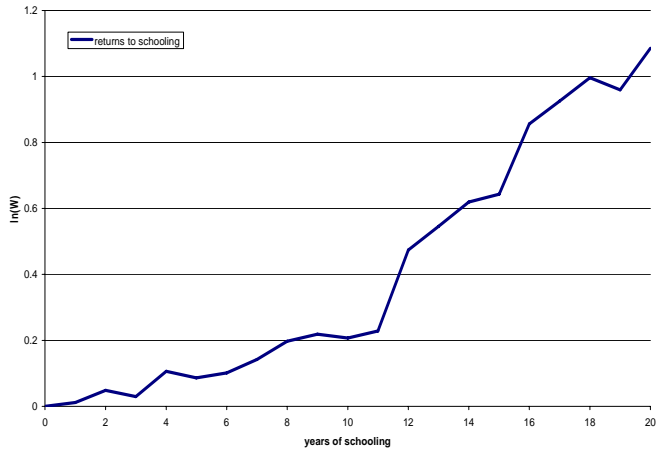## Log wage schedules 1960-2000

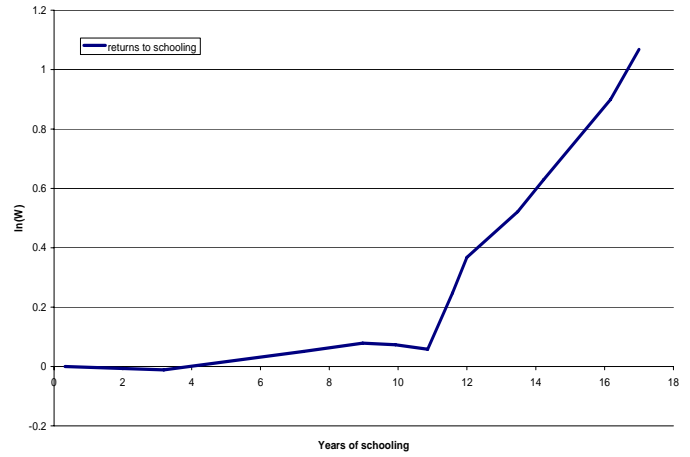Returns to schooling in 1960
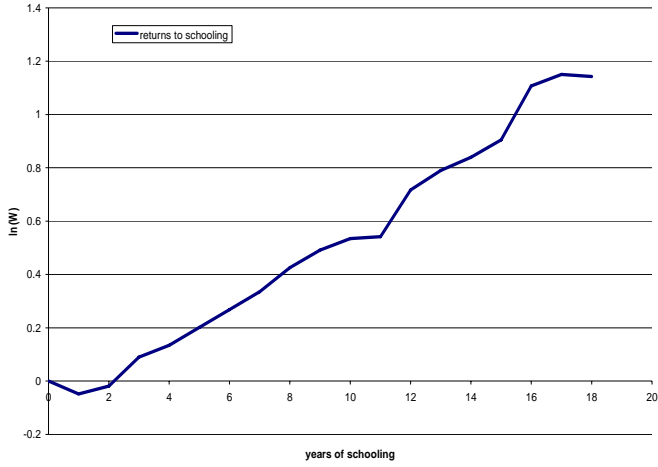
Returns to schooling in 1970

Returns to schooling in 1980

Returns to schooling in 1990

Returns to schooling in 2000