Journal of Economic Growth, 6, 285–315, 2001

Precautionary Demand for Education, Inequality, and Technological Progress

ERIC D. GOULD

Department of Economics, Hebrew University, Jerusalem 91905, Israel

OMER MOAV

Department of Economics, Hebrew University, Jerusalem, 91905, Israel

BRUCE A. WEINBERG

Department of Economics, Ohio State University, Columbus, Ohio, 43210

This paper offers an explanation for the evolution of wage inequality within and between industries and education groups over the past several decades. The model is based on the disproportionate depreciation of technology-specific skills versus general skills due to technological progress, which occurs randomly across sectors. Consistent with empirical evidence, the model predicts that increasing randomness is the primary source of inequality growth within uneducated workers, whereas inequality growth within educated workers is determined more by changes in the composition and return to ability. Increasing randomness generates a ''precautionary'' demand for education, which we show empirically to be significant.

Keywords: technological progress, inequality, risk

JEL classification: J31, O33, O40

1. Introduction

During the last few decades in the United States and many advanced countries, wage inequality has increased significantly. These trends are largely characterized by increasing inequality within demographic, occupational, industrial, and education groups. In addition, rising wage inequality has occurred simultaneously with rising unemployment and non-employment rates in many developed countries. All of these trends are found to be related to the collapse in the relative demand for workers with lower ability or skill.[1]

The consensus in the literature is that changes in technology over the past few decades are responsible for the dramatic changes in the structure of wages and employment. The empirical literature suggests that these trends are caused by the increasing importance of cognitive skills in the wage function.[2] Most of the theoretical literature has focused on the interaction of technology and inequality ''between'' education groups.[3] More recent theoretical work explains inequality within and between groups by relying on changes in the return to ability. For example, Galor and Moav (2000) develop a growth model in which an ability-biased technological transition generates increasing residual inequality. The mechanism in their model is based on the idea that the state of transition brought about by technological change raises the rate of return to skills.[4] However, all of the previous theoretical work has ignored the evidence that the sources and timing of inequality growth within the various education groups are not equivalent.

This paper, in contrast, generates two different sources of inequality growth within education groups by incorporating the role of ability and adding a new source of inequality based upon the random depreciation of technology-specific human capital. Consistent with existing empirical evidence, the theory argues that the sources of inequality growth are different within educated and less educated workers: increasing randomness is the primary source within less educated workers, while inequality growth within educated workers is determined more by changes in the composition and return to ability.

Indeed, Gottshalk and Moffitt (1994) show that inequality is created differently within education groups. They found that the ''transitory'' component of inequality, versus the ''permanent'' component, is much higher for uneducated workers for all periods, and increased by much more for uneducated workers over the 1970s and 1980s. Thus, inequality for educated workers is mainly increasing along predictable ''permanent'' dimensions such as ability, while uneducated workers are increasingly being tossed around in random ways. This increasing randomness is further demonstrated by the increasing unemployment rates starting in the early 1970s which occurred primarily within the least educated group. These findings suggest that changes in technology during the past few decades have been operating in different ways for educated and less educated workers, and consequently, the risk associated with being uneducated has increased over time. We demonstrate empirically that workers consider this kind of risk when making their schooling decisions.

Motivated by these empirical findings, we develop a model which endogenously generates the patterns of wage inequality (within and between groups) and educational attainments throughout the last few decades. The model is based on the disproportionate effects of technological changes on the depreciation of general versus technology-specific skills, and the resulting precautionary factor in the demand for general education which guards against the higher depreciation risk of technology-specific skills. We assume that individuals, given their level of ability, choose to invest in general skills through education or in technology-specific skills through on-the-job training.[5] Since the return to ability is higher as an educated worker, higher ability individuals choose to invest in general education and workers with lower ability choose to invest in technology-specific skills. However, changes in technology render technology-specific skills obsolete.[6] Consequently, less educated workers, who are relatively more invested in technology-specific skills, will suffer higher rates of human capital depreciation due to technological improvements. Therefore, an increase in the rate of technological progress increases the education premium.[7]

We further assume that technological progress is absorbed into various sectors at different rates. Thus, there exists a variance in the rate of progress across industrial sectors (or jobs). This is a major source of ex-post variability of wages within less educated workers—since they are relatively more invested in technology-specific skills and there is a variance of the depreciation rate of these specific skills across sectors.[8]

Furthermore, we assume that workers do not know in advance how each sector will be affected. That is, they must choose their sector and level of education solely on the basis of the distribution of the rate of progress across sectors, not the realizations within each sector. This creates an element of risk in the model—workers do not know in which sector their specific skills will depreciate more. As a result, the expected earnings of the marginal worker who chooses to become educated is actually lower as an educated worker than as an uneducated worker. The marginal worker still decides to become educated as a way of guarding against this type of ''depreciation risk.'' In this sense, there exists a ''precautionary'' element in the demand for education as workers consider both the risk and the return in their decision to invest in general education versus technology-specific skills.[9]

The model predicts that the sources of inequality growth within education groups will differ in periods of increased technological progress. Within the less educated group, the increasing ''within'' variance is mainly determined by the increasing variance of technological implementation across industries which erodes their skills at different rates. In the educated group, the increasing ''within'' variance is mainly determined by changes in the composition and return to ability within this group. As we discuss later, these results are consistent with the findings of Davis and Haltiwanger (1991), Gottschalk and Moffitt (1994), and Gittleman and Joyce (1996). In addition, the model predicts that industries which experience higher rates of technological progress will also exhibit higher education premiums and higher ratios of educated to less educated workers. These predictions are supported by empirical evidence.[10]

In periods of increasing technological progress, the model predicts increasing inequality within and between education groups, which is largely consistent with the experience of the United States and most of Europe during the last few decades. However, the model can also generate the patterns of the 1970s and 1980s in the United States where the ''within'' and ''between'' components trended in opposite directions in the 1970s, and then moved in the same direction in the 1980s. In addition, since workers consider the risk as well as the return in their educational decisions, the model can explain why more workers may still decide to get educated in the face of a declining education premium.

The paper is organized as follows. The next section motivates the main assumptions of our model by showing the differential patterns of inequality within education groups. The model is presented in Section 3. Section 4 provides empirical support for the ''precautionary demand for education'' by showing that workers consider both the risk and the return when making their educational investments. Section 5 concludes the discussion.

2. Not All Inequality is Created Equally

The theoretical model in this paper is motivated by the notion that the sources of inequality growth within education groups are not identical. Using the March Current Population Survey, Figure 1 illustrates the well-documented rise in residual wage inequality in the United States within all education groups for a sample of non-Hispanic white men with strong attachments to the labor force. Since these trends are ubiquitous, previous research has concluded that a rising return to unobserved ability is responsible for these trends.[11]

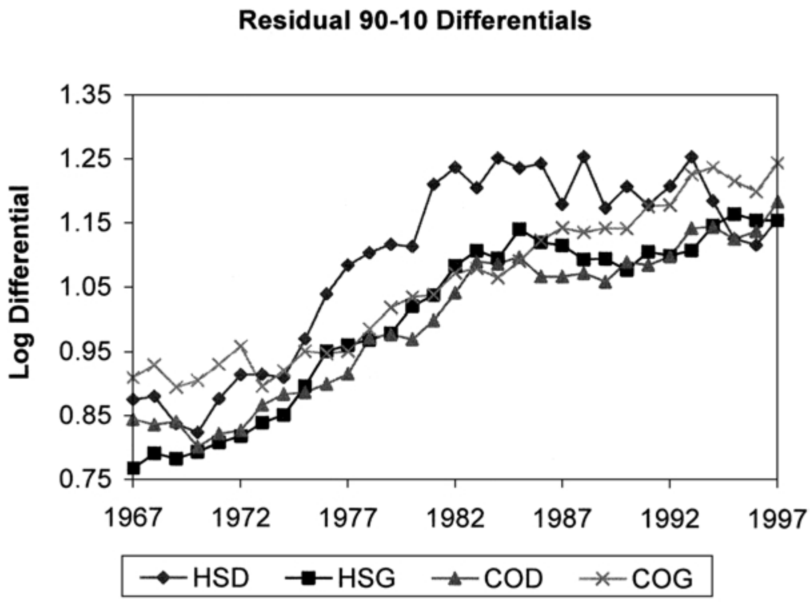

Figure 1. Residual wage inequality within education groups. Data is from the CPS. Sample is for non-Hispanic white men between the ages of 18 and 49 with strong attachments to the labor force. See data appendix for further details. HSD are high school dropouts, HSG are high school graduates, COD are those with some college, and COG are college graduates. Wages are real weekly wages using the CPI (1984 = 100). Controls include dummy variables for years of potential experience, marital status, nine regions, and levels of completed schooling within education groups.

However, consistent with other studies, Figure 1 also shows that residual inequality within the less educated groups is rising faster in the 1970s and 1980s than within the more educated groups. From 1970 to 1990, the residual 90–10 differential increased by 38 percent for high school dropouts, 28 percent for high school graduates, 29 percent for those with some college, and 24 percent for college graduates. The big difference, however, is in the timing of the trends within education groups. Figure 1 shows that inequality growth within the least educated groups exploded in the early 1970s and then decelerated in the 1980s and 1990s. In contrast, inequality within college graduates did not take off until the mid-to-late 1970s and grew steadily through the 1980s and 1990s.

These results are consistent with the findings in the empirical literature. From 1970–1978 to 1979–1989, Gottshalk and Moffitt (1994) show that the total variance of annual earnings rose by 71 percent for high school dropouts, 40 percent for those with at least 12 years of education, and only 18 percent for those with at least a college education.[12] In addition, Gittleman and Joyce (1996) show that ''long-run'' inequality did not increase for male college graduates until the 1980s, while the trend started in the 1970s for males with lower education.[13]

While these trends are suggestive that the sources of inequality growth differ across education groups, further evidence is provided by the literature that decomposes inequality into ''permanent'' and ''transitory'' components. Using the PSID, Gottshalk and Moffitt

(1994) find that the ''transitory'' variance is much higher in all periods for workers with less education. In addition, the ''transitory'' component increased much faster for less educated workers from the 1970s to the 1980s: increasing by 96 percent for high school dropouts, 52 percent for those with at least 12 years of education, and 43 percent for those with at least a college education. Using matched CPS files, Gittleman and Joyce (1996) find similar results.[14] Again, these results clearly show that inequality is not created and is not increasing in the same manner within each education group.

Further evidence that the sources of inequality growth are not identical is provided by Davis and Haltiwanger (1991) who decompose the inequality trends in the manufacturing sector into changes in inequality ''between'' plants and ''within'' plants. They show that most of the inequality within production workers (which is a good proxy for less educated workers) is accounted for by inequality ''between'' plants, while most inequality within non-production workers (a proxy for more educated workers) is accounted for by inequality ''within'' plants. Further, they show that 90 percent of the increase in inequality within production workers is accounted for by higher inequality ''between'' plants. In contrast, they show that increasing inequality ''within'' plants explains most of the inequality trends for non-production workers (more educated workers). That is, inequality within less educated workers is increasing almost entirely due to exogenous forces which are affecting their place of work. Conversely, inequality within educated workers is not very dependent on their place of work, which implies that personal characteristics determine the distribution of income within this group. All of these results are consistent with our model.

Although Figure 1 shows that inequality within the less educated groups exploded relative to college graduates during the 1970s, there is reason to believe that these trends actually understate the increase in risk (or randomness) for these workers during this time period. This is due to the well-documented increase in unemployment and the decrease in labor force participation rates of less educated white men since the early 1970s. These patterns are also consistent with the literature on increasing job instability of less educated workers.[15] The timing of these trends suggest that they are connected to the inequality trends. In fact, several papers have argued that these trends are driven by the same forces that are causing the inequality trends: the decline in the demand for less skilled workers along a stable labor supply curve.[16] In this sense, rising unemployment and non-employment should be considered part of the same phenomenon as rising inequality, and perhaps represent an increase in the ultimate form of downside risk faced by less educated workers—since previous work has shown that job losses often have large and long-term detrimental consequences, most likely due to the loss of specific human capital.[17] Furthermore, these trends indicate that the observed wage inequality for less educated workers is increasingly truncated by higher rates of unemployment and lower rates of participation. Therefore, the inequality of ''offered'' wages for less educated workers has relatively increased by much more than what we observe in Figure 1.

All of these trends suggest that the sources of inequality growth are not the same across education groups, and that the risk of not going to college rose steadily during the 1970s. As of now, these empirical regularities have not been incorporated into any theoretical model which attempts to explain the dynamics of inequality and educational choice over the last few decades.

3. The Model

Consider an economy that operates in a perfectly competitive environment and economic activity extends over infinite discrete time. Individuals are non-altruistic and live one period. In every period, the economy produces intermediate goods and a single homogeneous final good. Each intermediate good is produced by a composite labor input which consists of educated labor and uneducated labor. The number of efficiency units of educated and uneducated labor in every period is determined by the educational choices of the fixed number of individuals within a generation and the rates of technological progress across industrial sectors.[18]

3.1. Production and Technological Progress

The single final good is produced according to a neoclassical constant-returns-to-scale production function. The output at time t is given by Y_t:

$$Y_t = \left(x_t^{\mathrm{I}} x_t^{\mathrm{II}}\right)^{1/2}, \tag{1}$$

where $x_t^j (j = \mathrm{I}, \mathrm{II})$ are the quantities of the two intermediate goods in period t.[19]

Sectors are defined by the production of an intermediate good. Intermediate goods are produced by efficiency units of labor with a constant marginal productivity within each sector at any given time, but varies between sectors and over time:

$$x_t^j = a_t^j l_t^j, \tag{2}$$

where a_t^j is the marginal productivity of sector j in period t, and l_t^j is the supply of efficiency units of a composite labor input, including educated and uneducated workers, to sector j in period t.

From substituting equation (2) into the production function (1), it follows that the output at time t, Y_t, is a function of each sector's level of technology and labor inputs:

$$Y_t = A_t \left(l_t^{\mathrm{I}} l_t^{\mathrm{II}}\right)^{1/2}, \tag{3}$$

where $A_t \equiv (a_t^{\mathrm{I}} a_t^{\mathrm{II}})^{1/2}$ is the (geometric) average level of technology across sectors.

Producers operate in a perfectly competitive environment. Given the wage rate per efficiency unit of labor in each sector at time t, w_t^{I} and w_t^{II}, producers choose the level of employment of the composite labor inputs, l_t^{I} and l_t^{II}, so as to maximize profits. The producers' inverse demand for labor in each sector is therefore:

$$w_t^{\mathrm{I}} = \frac{1}{2} A_t \left(\frac{l_t^{\mathrm{I}}}{l_t^{\mathrm{II}}}\right)^{-1/2};$$
$$w_t^{\mathrm{II}} = \frac{1}{2} A_t \left(\frac{l_t^{\mathrm{I}}}{l_t^{\mathrm{II}}}\right)^{1/2}. \tag{4}$$

The rate of technological progress in period t of sector j is defined as g_t^j,

$$a_t^j = \left(1 + g_t^j\right) a_{t-1}^j. \tag{5}$$

It is assumed for simplicity that the rate of technological progress is randomly distributed to equal $g_t + \sigma_t$ in one sector, and $g_t - \sigma_t$ in the other sector. Therefore, g_t is the average rate of technological progress across sectors and σ_t^2 denotes the variance of that rate. This variance will be the source of risk in the model, since workers are assumed to know the distribution of the rates of progress across sectors in advance, but not the realizations.

We restrict g_t and σ_t to normalize the maximum rate of progress to equal one, and to assure that technological progress is positive in both sectors. That is, $g_t^j \in (0, 1)$ for $j = \mathrm{I}, \mathrm{II}$ such that:

$$g_t \in (0, 1) \quad \sigma_t < \min[g_t, 1 - g_t]. \tag{A1}$$

Currently, g_t and σ_t are exogenous parameters, however, these parameters are endogenized in the Dynamical System subsection.[20]

It follows, therefore, from equations (3) and (5) that $A_t = (1 + G_t)A_{t-1}$, where

$$G_t \equiv \left(1 + g_t^{\mathrm{I}}\right)^{1/2}\left(1 + g_t^{\mathrm{II}}\right)^{1/2} - 1 = \sqrt{1 + 2g_t + g_t^2 - \sigma_t^2} - 1. \tag{6}$$

3.2. Individuals

In each period, a generation is born consisting of a continuum of individuals of measure 1.[21] Individuals, within as well as across generations, are identical in their non-altruistic preferences. In each generation, ability is distributed uniformly over the unit interval, which in turn, leads to a distribution of educational choices within each generation.

Individuals live for one period and inelastically supply their efficiency units of labor to one of the two sectors as either educated or uneducated workers. Individuals who choose to become educated workers spend a fraction of their unit time endowment in school acquiring general education and the rest of their time is spent working. Those who choose to remain uneducated join the labor force directly and spend a fraction of their unit time on the job learning, acquiring technology-specific human capital.[22]

Individuals are risk averse, and choose their sector and level of education by maximizing utility, derived from the consumption of their income. The preferences of individual i in generation t are defined by the following Von Neumann–Morgenstern utility function:

$$u_t^i = u\left(c_t^i\right) = \log c_t^i. \tag{7}$$

3.2.1. Efficiency Units of Labor

In periods of technological change, it is assumed that existing technology-specific human capital is rendered obsolete, and therefore, individuals have to spend time on the job to learn the new technology. The higher is the rate of change, the more time has to be spent learning the new technology. Moreover, we assume that general education helps in the learning process.[23] Therefore, in periods of technological progress, general education has two advantages: it does not depreciate since it is not tied to a particular technology; and it lowers the cost of learning the new technology. For simplicity, these two elements are modeled by assuming that the cost of adjustment is zero for educated workers, while the cost for an uneducated worker is an increasing function of the rate of technological progress in his sector—the more progress there is, the more time is spent learning. Specifically, the fraction of the unit time endowment learning the new technology on the job by an uneducated worker i of generation t in sector j is represented by τ_t^j where,

$$\tau_t^j = \tau\left(g_t^j\right) = g_t^j. \tag{8}$$

Hence, $1 - \tau_t^j = 1 - g_t^j$ is the fraction of time spent working for an uneducated worker.

Further, it is assumed that the marginal return to ability is higher among educated workers relative to uneducated workers. This assumption assures that higher ability individuals will have a comparative advantage in obtaining education, and also that the heterogeneity of ability plays a larger role in the determination of inequality within the educated group relative to the uneducated group. For simplicity, this assumption is implemented by setting the marginal return to ability to equal zero for uneducated workers.[24] Hence, the efficiency units supplied by an uneducated worker in sector j in period t, represented by $h_t^{u,j}$, is equal to his fraction of time spent working:

$$h_t^{u,j} = 1 - \tau(g_t^j) = 1 - g_t^j. \tag{9}$$

In order to become educated, an individual must spend a certain amount of time studying. This time cost is lower for workers with higher ability, and is set equal to $1 - \theta_t^i$, where θ_t^i is the ability of individual i in generation t and is distributed uniformly over the unit interval. The remaining time of the educated worker, θ_t^i, is spent working. Therefore, an educated worker i in generation t with ability θ_t^i supplies $h_t^{e,i}$ efficiency units of labor to any of the two sectors, where

$$h_t^{e,i} = \theta_t^i. \tag{10}$$

Equation (10) states that the efficiency units of an educated worker is independent of the rate of technological progress, which follows from the assumption that the adjustment cost to technological changes is zero for educated workers. In addition, the number of efficiency units is independent across sectors since education is assumed to be a form of general human capital, equally applicable across sectors.[25]

3.2.2. *Educational Choice*

Before workers choose their education levels, they know their ability and the distribution of the rates of technological progress across sectors, characterized by the parameters g_t and σ_t. That is, they know that the rate of progress will be $g_t + \sigma_t$ in one sector and $g_t - \sigma_t$ in the other sector, but they do not know which sector will get the higher rate and which will have the lower rate until after their sectoral choice. Moreover, once an uneducated individual has invested in sector/technology specific human capital, it is assumed to be prohibitively costly to move to the other sector. In contrast, since education is a form of general human capital and the efficiency units of labor for educated workers are independent of sector choice, educated workers can move costlessly between sectors.[26]

The free mobility of educated workers across sectors assures that the wage per efficiency unit is the same across sectors ($w_t^{\mathrm{I}} = w_t^{\mathrm{II}} \equiv w_t$). This implies that a majority of educated workers will choose the sector with a higher rate of technological progress so that the efficiency units of labor are equal in each sector.[27] Hence, equation (4) implies:

$$w_t = A_t/2. \tag{11}$$

Therefore, it follows from equation (9) that the wage of an uneducated worker in sector j is:

$$w_t^u(w_t, g_t^j) = w_t(1 - g_t^j). \tag{12}$$

It follows from equation (10) that the wage of an educated worker with ability θ_t^i is:

$$w_t^e(w_t, \theta_i^j) = w_t\theta_j^i. \tag{13}$$

From equation (7), the utility of individual i of generation t with ability θ_t^i as an educated worker is:

$$u_t^{i,e}(w_t, \theta_t^i) = \log\, w_t\theta_t^i, \tag{14}$$

and the utility of this individual as an uneducated worker is:

$$u_t^{i,u}(w_t, g_t, \sigma_t) = 1/2\ \log\, w_t[1 - g_t + \sigma_t] + 1/2\ \log\, w_t[1 - g_t - \sigma_t]. \tag{15}$$

Therefore, as follows from Assumption A1 and equations (14) and (15), there exists a unique, interior, threshold ability level:

$$\hat{\theta}_t = \sqrt{1 - 2g_t + g_t^2 - \sigma_t^2} \equiv \hat{\theta}(g_t, \sigma_t), \tag{16}$$

such that $u_t^{i,e}(w_t, \hat{\theta}_t) = u_t^{i,u}(w_t, g_t, \sigma_t)$ and all individuals with ability above $\hat{\theta}_t$ choose to become educated and vise versa.

Due to risk aversion, the marginal individual that choose to become educated, the individual with ability $\hat{\theta}$, has a negative expected return from education. The expected income of the marginal individual as an uneducated worker is $w_t(1 - g_t)$, which is larger than his income as an educated worker, $w_t\sqrt{1 - 2g_t + g_t^2 - \sigma_t^2}$, for any $\sigma_t^2 > 0$. In this sense, individuals are willing to pay to insure themselves against the income risk of being uneducated, thus leading to a precautionary element in the demand for education. That is, some workers choose to become educated only because they are risk averse. This group consists of all individuals with ability between $\sqrt{1 - 2g_t + g_t^2 - \sigma_t^2}$ and $(1 - g_t)$. The size of this group is strictly increasing in σ_t^2: as the risk increases, so does the precautionary demand for education.

Proposition 1 *The number of educated workers, $1 - \hat{\theta}(g_t, \sigma_t)$, is increasing in the rate of technological progress, g_t, and in the variance of the rate of progress across sectors, σ_t^2.*

Proof. The proposition follows from differentiating equation (16) with respect to g_t and σ_t. ■

3.2.3. Income and Inequality

The human capital of individuals is determined by their ability, education, as well as the technological environment. Individuals are subjected to two opposing effects due to technological progress. On the one hand, the level of technology-specific human capital is diminished due to the transition from the existing technological state to a superior one—the ''erosion effect.'' On the other hand, each individual operates with a superior level of technology—the ''productivity effect.'' However, once the *rate* of technological progress reaches a steady-state, the ''erosion effect'' is constant, whereas the ''productivity effect'' grows at a constant rate, and therefore, income grows in the long run at a higher constant rate. Since all individuals benefit from working with the more advanced technology, the ''productivity effect'' has no impact on the level of inequality within and between groups. In contrast, the ''erosion effect'' works disproportionately on uneducated workers since they are relatively more invested in technology-specific skills, thus increasing inequality between the groups.

Average income within groups, and consequently inequality between groups, is also influenced by the ''composition effect.'' As noted previously, the threshold level of ability above which individuals choose to get educated is inversely related to both the average and the variance of the rate of technological progress across sectors. Consequently, an increase in either parameter causes workers from the high end of the ability distribution in the uneducated group to choose instead to become educated, thus decreasing the average ability level in both groups. These changes in the composition of ability within each group impact the average income within each group, and consequently, inequality between the two groups.[28]

Inequality within the educated group is indirectly determined by the average and the variance of the rate of progress across sectors via their effect on the composition of ability within this group. Inequality within the uneducated group is directly determined by the variance of the rate of progress across sectors, which determines the variance of the depreciation rates of their technology-specific skills across sectors. As noted in Section 2, these results are entirely consistent with existing empirical evidence as well as our own.

For the sake of simplicity, we do not assume a direct interaction between ability and technological progress. Although, similar to the existing literature on skill biased technological change, the return to ability in the overall economy is increasing in the rate of technological progress. The ratio of the income of the highest ability individual to the expected income of the least able individual is $1/(1 - g_t)$, which is increasing in g_t. Note, however, that this is a result of the model, not an assumption.

We now solve for the measures of inequality within and between groups. To make our measures of inequality consistent with standard measures such as the gini coefficient, it is assumed that uneducated workers choose between the two sectors in equal proportions, which is consistent with the fact that uneducated workers are ex-ante indifferent between the two sectors. This is necessary since measures of inequality are sensitive to the relative proportions of workers in each industry.

Inequality within educated workers, denoted by μ_t^e, is defined as the ratio between the highest and lowest wages within this group:

$$\mu_t^e = w_t^e(w_t, 1)/w_t^e(w_t, \hat{\theta}_t) = 1/\hat{\theta}_t,$$

which follows from equation (13).[29]

Proposition 2 *Inequality within educated workers is increasing in the rate of technological progress, g_t, and in the variance of the rate of progress across sectors, σ_t^2.*

Proof. The proposition follows from Proposition 1. ■

The intuition for this result is that increases in g_t and σ_t^2 both lower the threshold level of ability above which workers choose to become educated, thus increasing inequality through the ''composition effect.''[30]

Inequality within uneducated workers, denoted by μ_t^u, is defined as the ratio of the ex-post income of the highest paid and the lowest paid uneducated worker:

$$\mu_t^u = \frac{w_t^u(w_t, g_t - \sigma_t)}{w_t^u(w_t, g_t + \sigma_t)} = \frac{1 - g_t + \sigma_t}{1 - g_t - \sigma_t}, \tag{17}$$

which follows from equation (12).[31]

Proposition 3 *Inequality within uneducated workers is increasing in the rate of technological progress, g_t, and in the variance of the rate across sectors, σ_t^2.*

Proof. The proposition follows from differentiating μ_t^u with respect to g_t and σ_t. ■

The intuition for the result concerning σ_t^2 is clear—the difference in the ''erosion'' of skills between sectors is increasing with σ_t^2. An increase in g_t erodes the average income for all uneducated workers equally, but since the spread is held constant, the ratio of the highest to the lowest uneducated worker increases in g_t.[32]

Inequality between educated and uneducated workers, the education premium, is defined as the ratio between the average educated income to the average uneducated income. Given the uniform distribution of ability, it follows from equations (13) and (16) that the average income of educated workers is:

$$\bar{w}_t^e = [w_t^e(w_t, 1) + w_t^e(w_t, \hat{\theta}_t)]/2 = w_t(1 + \hat{\theta}_t)/2, \tag{18}$$

and following equation (12), the average income of uneducated workers is:

$$\bar{w}_t^u = [w_t^u(w_t, g_t^I) + w_t^u(w_t, g_t^I)]/2 = w_t(1 - g_t). \tag{19}$$

Therefore, as follows from (16), inequality between the educated and uneducated groups, denoted by $\mu_t^{e/u}$, is equal to:

$$\mu_t^{e/u} = \frac{\bar{w}_t^e}{\bar{w}_t^u} = \frac{1+\hat{\theta}_t}{2-2g_t} = \frac{1+\sqrt{1-2g_t+g_t^2-\sigma_t^2}}{2-2g_t}. \tag{20}$$

Proposition 4

a. *Inequality between educated and uneducated workers is decreasing in the variance of the rate of technological progress across sectors,* σ_t^2.

b. *If condition 1 holds, i.e., if* $\sigma_t < \sqrt{(\sqrt{5-8g_t+4g_t^2}-1)/2}$, *inequality between educated and uneducated workers is increasing in the rate of technological progress,* g_t. *Otherwise, it is decreasing in the rate of technological progress,* g_t.

Proof. The proposition follows from differentiating $\mu_t^{e/u}$ with respect to g_t and σ_t. ■

The intuition for part (a) is that increases in σ_t^2 lower the average ability, and thus the average wage, in the educated sector through the ''composition effect,'' without having any effect on the average income of uneducated workers.[33] An increase in g_t, however, has two opposing effects. It directly erodes the skills of all uneducated workers, thus increasing the education premium. However, due to the increase in this average erosion of technology-specific human capital, more workers choose to get educated which lowers the education premium through the ''composition effect.'' When condition 1 holds, the direct ''erosion effect'' outweighs the indirect ''composition effect.'' As depicted in Figure 2, Condition 1 is not a very restrictive condition on the parameters σ_t and g_t, given Assumption A1 that $\sigma_t < g_t$ and $\sigma_t < 1 - g_t$.[34]

In the small range in Figure 2 where Condition 1 does not hold, inequality between groups declines in g_t. In this range, a small increase in g_t has a large negative effect on utility as an uneducated worker in spite of a small effect on expected income. This results from income approaching zero with a positive probability, so that expected utility approaches $-\infty$. Therefore, the small increase in g_t has a relatively large effect on increasing the number of educated workers. Thus, in this case, the ''composition effect'' on the average income of educated workers outweighs the direct ''erosion effect'' on the average income of uneducated workers.

Note that these results are consistent with the empirical findings concerning changes in the structure of wages within and between industries in several OECD countries. Autor et al. (1998), Machin and Van Reenen (1998), and Berman et al. (1994) show that the ratio of educated to uneducated workers within an industry is positively related to the rate of technological change within that industry. This result is generated by our model since a larger proportion of educated workers choose the sector with the higher rate of technological progress.[35] In addition, the model is consistent with the evidence that

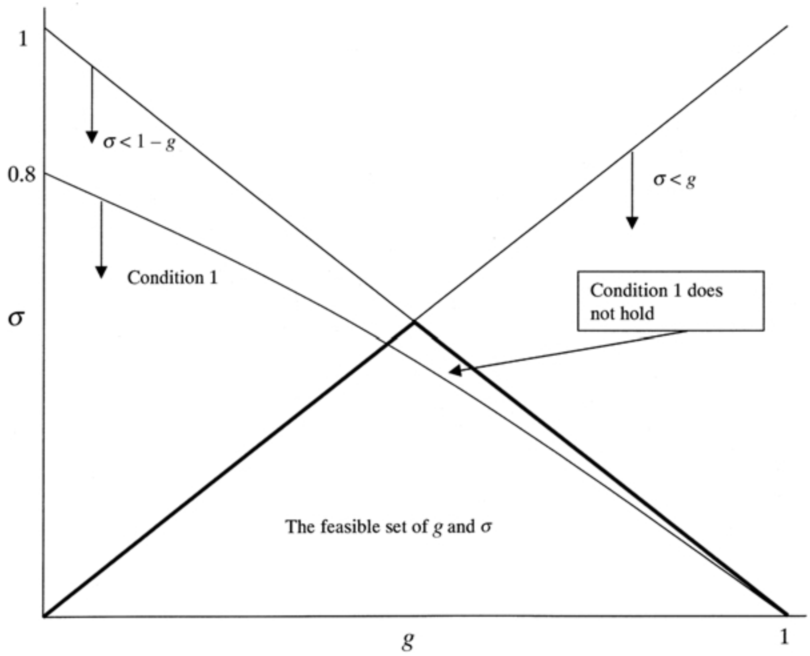

Figure 2. The feasible set of the growth rate (g) and the variance (σ): Assumption 1 and Condition 1.

changes in the ratio of educated to uneducated workers is positively associated with increases in the education premium within industries.[36]

Although unemployment and non-employment are not explicitly incorporated into the model, one can think of our measures of inequality reflecting the inequality of offered wages. Workers would then choose whether to work or enter the workforce depending on their offered wages and their reservation wage. A higher level of inequality (due to increases in σ_t or g_t) would then translate into higher unemployment or non-employment since offered wages would fall below the reservation wages at higher frequencies. In this manner, our model predicts rising unemployment and non-employment rates for less educated workers at the same time that inequality of observed wages is also increasing.[37]

3.3. The Dynamical System

This section analyzes the evolution of the economy in the presence of an endogenous technological change. The evolution of the economy and its impact on wage inequality is based upon two central elements. First, technological changes increase both the risk of being uneducated and the return to being educated, thus increasing the supply of educated workers. Second, an increase in the level of human capital increases the rate of technological progress. These two elements generate a dynamic path characterized by a positive feedback loop that permits a monotonic increase in the rate of technological progress in a transition to a steady-state equilibrium with perpetual growth.

Suppose that g_{t+1} is a positive (linear) function of the number of efficiency units of educated labor in period t and that σ_t is a fixed proportion of g_t (the coefficient of variation of technological progress is constant over time):

$$g_{t+1} = \lambda \int_{\hat{\theta}_t}^{1} \theta \, d\theta$$

$$\sigma_{t+1} = \gamma g_{t+1}$$

Hence, it follows from equation (16) that:

$$g_{t+1} = \lambda \int_{\hat{\theta}_t}^{1} \theta \, d\theta = \lambda[g_t - g_t^2(1-\gamma^2)/2] \equiv \phi(g_t;\gamma). \tag{21}$$

Recall that Assumption A1 placed restrictions on the average rate of technological progress and the variance of the rate of progress across sectors: g_t and σ_t respectively. Now, these variables are to be solved endogenously. Therefore, Assumption A1 is replaced by restrictions on the parameters (γ and λ) that govern the dynamic process:

$$0 < \gamma < 1 \quad \text{and} \quad 1 < \lambda < 2/(1+\gamma). \tag{A2}$$

Proposition 5 *There exists a unique non-trivial steady-state $\bar{g}$,*

$$\bar{g} = \frac{2(\lambda - 1)}{\lambda(1-\gamma^2)} > 0, \tag{22}$$

where $\bar{g}$ is globally stable and strictly increasing in λ and in γ.[38]

Proof. The proposition follows from equation (21), noting that $\phi' > 0$, $\phi'' < 0$ for $g_t < 1$. ■

Note that the steady-state is characterized by a constant variance $\bar{\sigma}$, constant levels of education, constant levels of inequality (within and between groups), and following equation (6), a constant rate of output growth equal to $\bar{G} = \sqrt{1 + 2\bar{g} + \bar{g}^2 - \bar{\sigma}^2} - 1$. Also note that Assumption A2 assures that $g_t^j \in (0,1)$ for all j and t in the steady-state, where g_t^j is equal to $\bar{g} + \bar{\sigma}$ in one sector and $\bar{g} - \bar{\sigma}$ in the other sector.

3.3.1. *Educational Choice, Income, and Inequality*

Proposition 6 *The steady-state levels of education and inequality within education groups are strictly increasing in λ and γ.*

Proof. The proposition follows from Assumption A2 and Propositions 1, 2, 3, and 5. ■

The preceding proposition implies that the steady-state levels of education and inequality within groups are increasing functions of the steady-state growth rate and variance of technological progress across sectors. Inequality between groups, however, does not vary monotonically with λ and γ. Proposition 6 states that $\bar{g}$ and $\bar{\sigma}$ are strictly increasing in λ and γ, however Proposition 4 implies that $\bar{g}$ and $\bar{\sigma}$ have contradictory effects on inequality between education groups. Therefore, the model shows that higher rates of steady-state technological progress are related to higher steady-state levels of education and inequality within groups, but are non-monotonically related to the steady-state education premium.

We further assume that the initial rate of technological progress is less than the steady-state rate of progress.

$$g_0 < \bar{g}. \tag{A3}$$

With Proposition 5 and $\phi' > 0$ from equation (21), this assumption assures that the rate of technological progress, g_t, is increasing monotonically in the convergence to the steady-state, as depicted in Figure 3. Since the variance of the rate of technological progress across sectors, σ_t, is always proportional to g_t, σ_t is also monotonically increasing along the path of convergence.

Proposition 7 *In the process of convergence to the steady-state:*

a. The level of education is strictly increasing.

b. Inequality within education groups is strictly increasing.

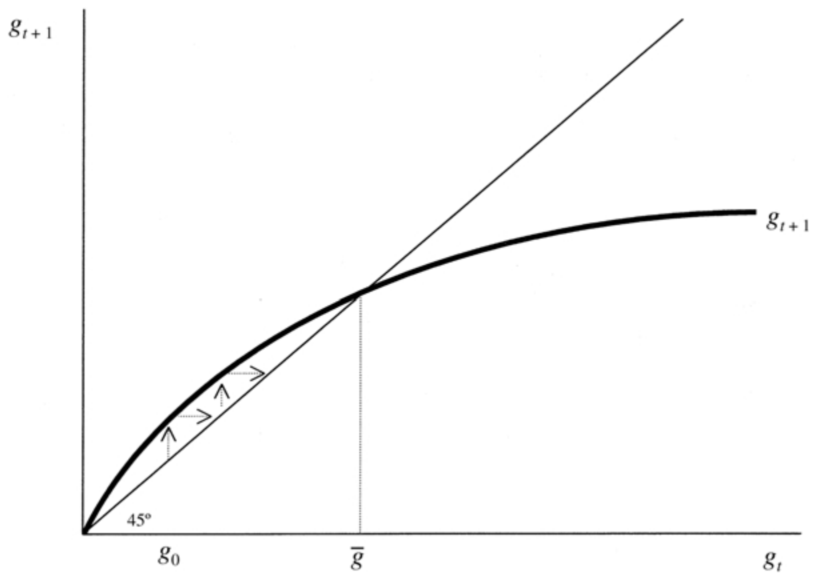

Figure 3. The dynamical system.

c. *For sufficiently low levels of g_t, inequality between education groups is strictly increasing.*

d. *For any $\gamma > 0$ there exists a sufficiently high λ, so that there exists a strictly positive range of $g_t \in (\bar{g} - \varepsilon, \bar{g})$) where $\varepsilon > 0$, in which inequality between education groups is strictly decreasing.*

Proof. Parts (a) and (b) follow from Propositions 1, 2, and 3, given that g_t and σ_t increase monotonically along the convergence to the steady-state. Parts (c) and (d) are proved as follows. Replacing σ_t in equation (20) with γg_t, inequality between education groups, $\mu^{e/u}$, is a strictly concave function with respect to g_t where $g_t = (\gamma\sqrt{1+\gamma^2} - 1)/(\gamma^2 + \gamma^4 - 1) = \arg\max \mu^{e/u} \in (0, 1)$. By setting λ to its upper limit value in Assumption A2 which equals $2/(1+\gamma)$, it follows from equation (22) that $\bar{g} = 1/(1+\gamma)$. Therefore, given the continuity of $\mu^{e/u}$ with respect to g_t in the range $\bar{g} = 1/(1+\gamma)$, parts (c) and (d) follow since $1/(1+\gamma) > \arg\max \mu^{e/u}$ for any $\gamma \in (0, 1)$. ■

3.4. The Evolution of the Wage Distribution in the 1970s and 1980s

In periods of increasing technological progress, the model predicts increasing inequality within and between education groups, which is consistent with the experience of the United States and most of Europe during the last few decades. However, the model can also endogenously generate the patterns of the 1970s and 1980s in the United States where the ''within'' and ''between'' components trended in opposite directions in the 1970s, with an increase in overall inequality, and then moved in the same direction in the 1980s. To see how this is possible, one could think about the early 1970s as a period in which a new general purpose technology arrives.[39] Since it takes time and resources for the new technology to be implemented, the average rate of progress may not increase very much in the short run. However, the costs of implementation and usefulness of the new technology vary across sectors, and therefore, one can think of this new innovation mainly as a shock to the variance of technological progress across sectors (σ_t) with only a limited impact on the average rate of progress.[40] Formally, this implies a shock to the coefficient of variation γ, which is depicted in the simulations in Figures 4(a) and 4(b).

The figures show that inequality within the less educated group rises as the variance of the depreciation rate of their technology specific skills increases. This causes the supply of educated workers to increase which raises inequality within the educated group due to the increasing variance of ability within the educated group, as lower ability workers obtain education. This change in composition also reduces the average ability level in the educated group, thus decreasing inequality between education groups.[41] Going into the 1980s, the average rate of technological progress across industries endogenously increases due to the increasing supply of educated workers.[42] Consequently, the variance of the rate of progress also increases since the variance is a fixed proportion of the average (γ remains

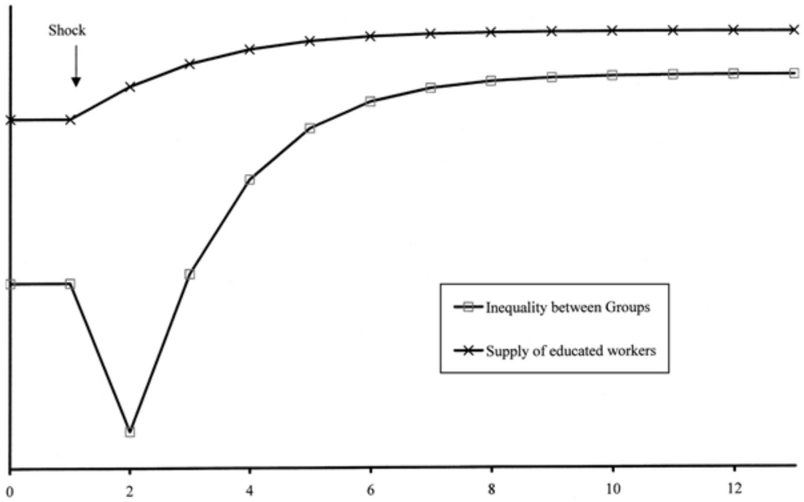

Figure 4a. The response to a shock in the risk (Gamma): Inequality between groups and the supply of educated workers.

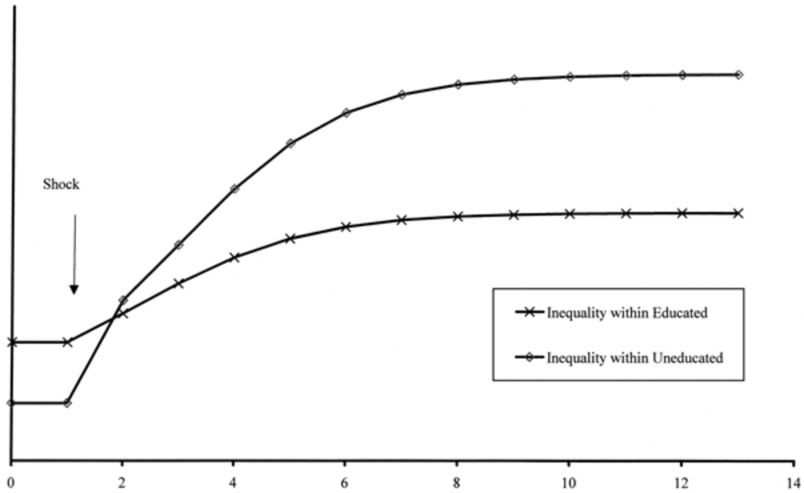

Figure 4b. The response to a shock in the risk (Gamma): Inequality within groups.

constant after the shock). As shown in Figures 4(a) and 4(b), both the within and between group components of inequality increase after the initial decrease in the between group component.[43]

It is worth noting that the European experience, while similar to the United States, differs in the timing and the magnitude of the inequality trends.[44] In particular, the upward trend in inequality started in the 1980s rather than the 1970s. However, unemployment rose dramatically in the 1970s in many European countries, and this trend was heavily concentrated within less educated workers.[45] That is, instead of inequality rising in the 1970s as in the United States, unemployment for less educated workers rose. These patterns are consistent with rising inequality of offered wages on both sides of the Atlantic, and higher reservation wages in Europe due to more generous social benefits.[46] Thus, both experiences are consistent with the simulations of our model.

4. Empirical Support for the Precautionary Demand for Education

Section 2 showed that the patterns of inequality growth are different across education groups, and summarized the existing literature which has found that the sources of inequality growth are different across education groups. These pieces of evidence, as well as the trends in unemployment and labor force participation rates for less educated workers, are consistent with our model and suggest that the risk associated with not being educated increased since the 1970s. This section empirically demonstrates that individuals actually consider this type of risk when deciding how much to invest in education.

Using data from the NLSY, we examine this question by analyzing the schooling decisions of a cohort of school-age individuals ranging in age from 14 to 22 in 1979. After controlling for a wealth of personal characteristics (such as IQ and parental education levels), we explain the schooling attainments of these individuals at the age of 25 as a function of the perceived risk and return associated with each education group as of 1979.[47] That is, we are exploiting exogenous variation across states in the perceived risk and return to education at the time when they were making these decisions, in order to explain the eventual schooling attainments of these individuals.

The perceived risk of being in each education group is proxied by either the state unemployment or non-employment rate for that group.[48] As pointed out in Section 2, the trends in both of these measures are considered to be a result of the increasing inequality of offered wages.[49] Consequently, these measures capture the extreme downside risk associated with the inequality risk within each education group (i.e., receiving a wage offer below their reservation wage). In addition, we consider two types of unemployment measures: the typical unemployment rate, which captures both the incidence and duration of unemployment, and the fraction of new workers that experience any unemployment spell (the incidence rate).

Our proxy for the perceived return to education is the state-level ''expected'' wage (adjusted for the probability of being unemployed or non-employed) for each group.[50] Wages are adjusted in this way to control for the expected effect of unemployment (or non-employment) on wages and the opportunity cost of schooling. That is, we are testing whether unemployment or non-employment has a separate effect in addition to its effect on expected income. This separate effect is the risk associated with belonging to a given education group.[51] To our knowledge, no previous paper has ever examined whether unemployment has an effect in addition to its effect on the expected wage, and consequently, this is the first attempt to see if workers consider the risk as well as the return to education when making their investment decisions concerning their education level.

Table 1 presents the results using two different dependent variables: (1) an OLS regression using completed schooling by the age of 25; and (2) a probit on whether the

Table 1. Determinants of individual education attainment (NLSY79).

		Dependent Variables					
		Education at 25			Graduation from College (Probit)		
Independent		(1)	(2)	(3)	(4)	(5)	(6)
State unemployment rate for new entrants	School $< = 12$	5.435^{**} (2.350)			4.073 (2.747) [0.557]		
	School > 12	-20.687^{**} (7.899)			-23.013^{**} (9.573) [-3.147]		
State non-employment rate for new entrants	School $< = 12$		4.521^{**} (1.447)			2.644 (1.902) [0.361]	
	School > 12		-19.029^{**} (4.570)			-18.448^{**} (6.538) [-2.516]	
Fraction of new entrants in state with unemployment in 1979 (unemployment incidence rate)	School $< = 12$			4.424^{**} (1.073)			2.076 (1.469) [0.282]
	School > 12			-11.437^{**} (2.569)			-10.816^{**} (4.125) [-1.472]
State mean log expected wages for new entrants	School $< = 12$	-2.415^{**} (0.668)	-2.895^{**} (0.609)	-2.900^{**} (0.650)	-2.407^{**} (0.880) [-0.329]	-2.846^{**} (0.905) [-0.388]	-2.558 (0.898) [-0.348]
	School > 12	0.518 (0.772)	1.103 (0.684)	0.623 (0.710)	0.753 (0.999) [0.103]	1.248 (1.009) [0.125]	0.977 (1.017) [0.133]
AFQT		0.060^{**} (0.003)	0.060^{**} (0.003)	0.060^{**} (0.003)	0.055^{**} (0.004) [0.008]	0.055^{**} (0.004) [0.008]	0.055^{**} (0.004) [0.008]

Table 1. Continued.

	Dependent Variables					
	Education at 25			Graduation from College (Probit)		
Independent	(1)	(2)	(3)	(4)	(5)	(6)
Mother's education	0.109^{**}	0.109^{**}	0.110^{**}	0.119^{**}	0.120^{**}	0.120^{**}
	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)
				[0.016]	[0.016]	[0.016]
Father's education	0.120^{**}	0.120^{**}	0.119^{**}	0.075^{**}	0.075^{**}	0.075^{**}
	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)
				[0.010]	[0.010]	[0.010]
R-squared	0.467	0.469	0.469			
Sample size	2939	2939	2939	2939	2939	2939

Notes: **indicates significance at the 5 percent level. *indicates significance at the 10 percent level. Adjusted standard errors controlling for within-state correlation of residuals are in parentheses; marginal effects for probits in brackets. Data on student attainment and individual characteristics comes from the National Longitudinal Study of Youth 1979. Data for state-level labor market conditions for new entrants estimated for non-Hispanic white men over 19 with 10 or fewer years or potential experiences from the 1980 Census. See appendix for sample construction. To control for endogenous migration, labor market conditions are measured in the respondent's state of birth. Expected wages adjust for the probability of having a job (measured by the unemployment probability in columns 1, 3, 4, and 6; or the non-employment probability in columns 2 and 5). Other covariates include year of birth, the log of the in-state tuition for four year public colleges in the state in 1980 (taken from Table 1 of Kane 1994), and the state means of AFQT, mother's education, and father's education. Estimates also include dummy variables for age at which education was measured (24, 25, 26, or 27).

individual graduated from college. In addition to the unemployment and expected wage variables, we control for individual characteristics such as the student's AFQT score, mother's education, father's education, and year of birth. In order to control for state-level heterogeneity which may be correlated with educational attainment and our state-level measures for the perceived risk and return, we also include the log of the within-state tuition for four-year public colleges and the state means of AFQT, mother's education, and father's education. In this manner, the regressions exploit exogenous variation across states in the perceived riskiness and return to education in order to identify their impacts. The NLSY sample is restricted to non-Hispanic white males.

Each specification in Table 1 yields similar results. Not surprisingly, the student's AFQT score is a major determinant of educational choice. In addition, the education of the mother and father are highly significant. However, our proxies for the risk and expected return to education are significant and consistent with our model. As shown in specification (1), an increase in the unemployment rate of less educated men, in addition to lowering the expected wage as an uneducated worker, has a separate positive effect on educational attainments. Increases in the unemployment rate of those with more than 12 years of schooling decrease attainments. Both of these variables are statistically significant, and show that individuals are actively trying to avoid unemployment by choosing their level of schooling. Furthermore, the results are similar using the non-employment rates in specification (2) and using the incidence rate of unemployment in specification (3).

The results for the expected wages are less significant but have the expected signs. Decreases in the expected wages of uneducated men increase schooling levels, while increases in the expected wages of more educated workers increase schooling investments. Since the expected wages are affected by the unemployment rates, and the unemployment rates were shown to have separate and significant effects, the results suggest that students consider both the perceived risk and return when making their education decisions—they seek higher returns and lower risk.

To roughly estimate the magnitude of these effects, we calculated the predicted effects of each of these variables based on their time trends from 1967 to 1997. Using the estimates in specification (1), the increase in the unemployment rate of 2.31 percentage points for less educated white men predicts an increase in education levels of 0.13 years (the coefficient 5.435 multiplied by 0.023). The slight decrease of 0.26 percentage points in the unemployment rate of those with more than 12 years of schooling works in the same direction, thus predicting a further increase in schooling of 0.05 years.[52] Thus, based on the unemployment trends for both groups, our coefficient estimates in specification (1) predict an increase in mean education of 0.18 years.

The 41 percent decline in the expected wages for the least educated group leads to a predicted increase in average schooling of 0.99 years (-0.41 multiplied by -2.415). However, the 22 percent decline in expected wages of those with more than 12 years of schooling works in the opposite direction, thus predicting a decline in schooling of 0.11 years (-0.22 multiplied by 0.518). The net effect of both wage trends is therefore a predicted increase of 0.88 years of schooling.

The comparable calculations with the probit in specification (4) are a predicted 0.02 increase in the probability of graduating college due to both unemployment trends, and a

0.11 increase in the probability of graduating college due to the wage trends. Therefore, the predicted effects of the unemployment trends are roughly one-fifth (0.18 compared to 0.88, and 0.02 compared 0.11) of the magnitude of the predicted effects of the expected wages. Thus the NLSY analysis in Table 1 shows that individuals respond to both the risk and the return to education. Consequently, these results justify our model's assumption that individuals consider such risk when deciding how much to invest in education. Since the risk of remaining uneducated has risen over time, the ''precautionary demand for education'' has increased accordingly.

5. Conclusion

This paper is built on the existing evidence that the sources of inequality and inequality growth are different across education groups. Within educated workers, inequality has increased along predictable dimensions associated with personal characteristics, whereas inequality growth within uneducated workers has increased due to random factors. Along with the increasing unemployment and non-employment rates which were largely concentrated within less educated workers, these trends illustrate how the relative risk of not becoming educated has increased during the past few decades. Using a rich set of variables from the NLSY, we demonstrated that, in fact, workers do respond to this kind of risk when they are making their schooling decisions.

Motivated by these findings, our model is based on the idea that workers must choose to invest in general skills such as formal education, or technology-specific skills by training on the job. Changes in technology depreciate technology-specific skills. Therefore, in periods of technological change, those who are relatively more invested in technology-specific skills find it harder and more costly to adapt to the new technology. Conversely, workers who are heavily invested in general skills such as education, adapt to the new technology more easily and at lower cost.

In periods of technological progress, technological implementation occurs at different rates across industries. This increases the variability of wages within uneducated workers, since they are relatively more invested in technology-specific skills. Since workers do not know in advance how each sector will be affected, their risk aversion produces an increase in the ''precautionary demand'' for education: more workers choose to get educated to avoid the risk of losing their technology-specific skills.

Using standard assumptions from the endogenous growth literature, the model endogenously produces the patterns of inequality within and between groups during the last few decades. In addition, the model generates several empirical patterns found within industries—the positive correlation between the rate of progress, education premia, and education composition within industries. Finally, by incorporating two different sources of inequality growth within education groups, the model contributes to the existing literature by reproducing not only the patterns of inequality growth, but also the manner in which it occurred.

Appendix I: The Equalization of Wages Across Sectors

Wages per efficiency unit are equalized across sectors only if the number of efficiency units in each sector is equal (i.e., $l_t^{\mathrm{I}} = l_t^{\mathrm{II}}$). Since the two sectors are ex-ante identical, it is assumed that uneducated workers choose each sector in equal proportions. However, the efficiency units of uneducated labor are not equal across sectors, due to the differences in the erosion of the technology-specific skills across sectors. Therefore, in order for $l_t^{\mathrm{I}} = l_t^{\mathrm{II}}$ to hold, a sufficiently large majority of educated workers must choose the sector with the higher rate of progress in order to equalize the total efficiency units of labor in each sector. Hence, a necessary and sufficient condition is that there are enough efficiency units of educated labor to equalize the total number of efficiency units between the two sectors (i.e., enough to make up the difference caused by the uneducated workers). In other words, the sum of the number of efficiency units of uneducated labor in the sector with the higher rate of technological progress and the number of all educated efficiency units of labor is larger than the number of efficiency units of uneducated labor in the sector with the lower rate of technological progress. This is formally stated in the following condition:

$$\int_{\hat{\theta}_t}^{1} \theta\, d\theta + \frac{1}{2}\hat{\theta}_t(1 - g_t - \sigma_t) - \frac{1}{2}\hat{\theta}_t(1 - g_t + \sigma_t) = \int_{\hat{\theta}_t}^{1} \theta\, d\theta - \hat{\theta}_t\sigma_t \equiv \pi(g_t, \sigma_t) \geq 0.$$

This condition always holds.

Proof. It follows from Proposition 1 that $\partial\pi(g_t, \sigma_t)/\partial g_t > 0$. Therefore, since $g_t = \sigma_t$ is the lowest value of g_t under A1, it follows that $\pi(g_t, \sigma_t) \geq \pi(\sigma_t, \sigma_t)$, and substituting for $\hat{\theta}_t$ from equation (16), $\pi(\sigma_t, \sigma_t) = \sigma_t(1 - \sqrt{1 - 2\sigma_t}) \geq 0$ since $\sigma_t \leq 1/2$ from A1.

Appendix II: Data Construction

NLSY79

In Table 1, individual data on educational attainment were taken from the 1993 wave of the NLSY79. The sample includes non-Hispanic white men. Educational attainment was measured using years of completed schooling on May 1st of the year the person turned 25. (For those not reporting education at age 25, education was checked at ages 26, 27, and 24. Attainment for the first of these available was used. Individuals without data at 24, 25, 26, or 27 were excluded from the sample. The estimates control for the age at which education was obtained.) Table 1 also uses NLSY79 data on parental education and AFQT (which were adjusted for age at the time of the exam). State means of parental education and AFQT were constructed from the sample used in the analysis. To minimize selective migration, individuals were matched to state level variables (such as labor market conditions) according to the respondent's state of birth. After excluding respondents with invalid data for these questions, the sample contained 2939 observations.

Census Data

The 5 percent (state) samples of the 1980 Census were used in Table 1 to create variables for labor market conditions in each state in 1980. Labor market conditions were estimated for high school workers (years of completed schooling ≤ 12) and workers with some college (≥ 13 years of school attended regardless of completion). To focus on individuals at the outset of their careers, all samples were restricted to persons over age 18 with 10 or fewer years of potential experience. The samples were restricted to non-Hispanic white men.

Census Wage Sample

Wages were estimated for workers with relatively high labor force attachment. The wage samples were restricted to individuals who worked 20 or more weeks and usually worked 35 or more hours per week in 1979 and who were not currently enrolled in school. Individuals with weekly earnings (annual earnings/weeks worked) beneath \$35 or above \$5000 in 1982–1984 dollars (adjusted using the CPI-U) were deleted from the sample as were people with non-zero farm or non-farm self-employment earnings. The 1980 Census top-coded earnings at \$75,000. Top-coded values were multiplied by 1.45. Individuals with imputed wage and salary earnings were excluded from the sample.

Regressions were used to control for differences in characteristics across states. Let w_{sei} denote the log wage of respondent i in education group $e \in \{HS, College\}$ in state s, and let X_{sei} denotes his observable characteristics (marital status, dummy variables for years of potential experience, and dummy variables for educational attainment within the education groups). A separate regression was run for each education group of the form,

$$w_{sei} = \beta_e X_{sei} + \varepsilon_{sei}.$$

The wage in state s in education group e, W_{se}, was estimated using the mean residual for the workers in that group, $W_{se} = \sum_i \varepsilon_{sei}$.

Census Labor Force Status Sample

Labor force status (unemployment and non-employment rates and the incidence of unemployment) by education for each state were also estimated from the 1980 Census. The sample includes non-disabled non-Hispanic white males over age 18 with 10 or fewer years of potential experience. Unemployment and non-employment rates were estimated using employment status during the reference week. The incidence of unemployment, defined as the fraction of people reporting positive weeks unemployed in 1979, was estimated using weeks unemployed in 1979. Individuals who were enrolled in school and those whose employment status in the reference week (or, in the case of incidence, weeks unemployed in 1979) was imputed were excluded from the sample. Individuals who worked or held civilian or military jobs in the reference week were classified as employed.

Individuals who were unemployed or out of the labor force in the reference week were classified as non-employed. When estimating unemployment rates, individuals who were out of the labor force were dropped so the sample included only those who were employed or unemployed. In estimating the three state-level measures of employment status, individual characteristics were controlled using procedures analogous to those used for wages.

March Current Population Survey

The March CPS was used to estimate the time series of the 90–10 residual inequality by education group for non-Hispanic white men for calendar years 1967–1997 in Figure 1.[53] To focus on the trends in risk for the entire workforce, 90–10 differentials were estimated for workers between ages 18 and 49. Our wage measure was the log weekly wage (defined as the ratio of wage and salary earnings to weeks worked in the year prior to the survey and deflated with the CPI-U to 1982–1984 dollars).[54] The sample was restricted to individuals who worked at least one week, usually worked full time, spent 40 or more weeks in the labor force, did not work part year because of school or (until it was dropped on the 1984 survey) military service, and reported zero farm and non-farm self-employment income. Individuals with imputed wage and salary earnings were dropped from the sample. The treatment of outliers and topcoded values follows the Census wage sample.[55]

Let w_{tei} denote the log wage of individual i in education group e in year t and let X_{tei} denote his observable characteristics (a quartic in potential experience, marital status, nine regions, and dummy variables for each level of completed schooling or degree within education groups). Residual inequality was estimated using a separate regression for each year and education group. This procedure permits the coefficients on observed characteristics to vary across education groups and across time, thus assuring that increases in the returns to observed skills are not attributed to increasing residual inequality. Formally,

$$w_{tei} = \beta_{te} X_{tei} + \varepsilon_{tei}.$$

Residual inequality for education group e at time t was estimated using the differential between the 90-th and 10-th percentiles of the distribution of ε_{tei}.

Unemployment and non-employment rates and wages by education, which were used to estimate the predicted effect of changes in labor market conditions on educational attainment based on the coefficient estimates in Table 1, were also estimated from the March CPS for non-Hispanic white men over 18 with 10 or fewer years of potential experience.[56] The samples used to estimate unemployment and non-employment rates were restricted to people who did not work part-year or not at all because of illness or disability, school, or (until the 1984 survey) military service. Regressions were used to adjust the time series for these variables for changes in the characteristics of the workforce.

Acknowledgments

For helpful comments, we wish to thank Daron Acemoglu, Lex Borghans, Paul Evans, Nicole Fortin, Oded Galor, Peter Howitt, Larry Katz, Joram Mayshar, Yishay Maoz, Avi Simhon, Shlomo Yitzhaki, David Weil, Bas ter Weel, Finis Welch, Joseph Zeira, Itzhak Zilcha, anonymous referees, and seminar participants at the University of Maryland, Hebrew University, Haifa University, ‘‘Technology, Human Capital, and Economic Growth’’ Jerusalem (June 1999), and the American Economic Association Meetings (2001). For financial support, we are grateful to the Maurice Falk Institute and the Melchior Minerva Center for Macroeconomics and Growth.

Notes

1. See Juhn et al. (1991), Juhn (1992), Welch (1997), and Murphy and Topel (1997).
2. Katz and Murphy (1992) and Juhn et al. (1993) show that residual inequality has increased since the early 1970s. Murnane et al. (1995) show more directly that certain types of cognitive skills are becoming more important in the determination of wages. Gould (2002) shows that the same skills are growing in importance within each occupation—increasing inequality as workers without these skills can no longer choose an occupation which emphasizes their personal strengths.
3. See Galor and Tsiddon (1997), Acemoglu (1998), Maoz and Moav (1999), Hassler and Rodriguez Mora (2000), and Caselli (1999).
4. See also Rubinstein and Tsiddon (1998) who develop a model based on the role of ability in coping with changes in technology. In addition, Aghion et al. (2001) explain increasing residual inequality by focussing on the role of mobility, technology adaption, transferability, and on-the-job learning.
5. See Weinberg (2001) for evidence on the importance of specific human capital investments.
6. Many of the major technological advances in the nineteenth century substituted skilled artisans with capital and unskilled labor. This is consistent with our model since these highly skilled artisans were heavily invested in technology-specific human capital (i.e., their education was not very general).
7. The argument that technological progress itself raises the return to human capital dates back to Schultz (1964) and Nelson and Phelps (1966). Schultz (1975) cites a wide range of evidence in support of this theory. See also Bartel and Lichtenberg (1987) and Foster and Rosenzweig (1996). Although the new technology may increase or decrease the return to education in the long-run, it is argued that the transition to the new technological state rewards education in the short-run. If the new technology is education-biased in the long run, then the short-run effect will be enhanced, and it will be diluted in the opposite case. Goldin and Katz (1998) provide evidence regarding technology-education complementarity that is consistent with our short-run view as well as the long-run view.
8. This notion is consistent with the results of Davis and Haltiwanger (1991) which show that most of the inequality level within production workers (less educated workers) is due to inequality ‘‘between’’ plants rather than ‘‘within’’ plants. In addition, 90 percent of the inequality growth for production workers from 1975–1986 is due to inequality growth ‘‘between’’ plants.
9. See Hassler et al. (1999) for a paper that relates the risk of investing in specific training to the political economy of unemployment benefits. See also Zeira (1998) and Helpman and Rangel (1999) for a mechanism based on the depreciation of specific skill which explains unemployment and recessions.
10. See Berman et al. (1994) and Autor et al. (1998).
11. See Juhn et al. (1993). Murnane et al. (1995) provide more direct evidence that certain cognitive skills are becoming more important in the determination of wages over time. Gould (2002) also shows that the same types of general skills are becoming more important within all broad occupational groups.
12. They also show that these trends are present for the ‘‘permanent’’ component of annual earnings inequality growth between the two periods: increasing 55 percent for high school dropouts, 34 percent for those with at least 12 years of schooling, and 9 percent for those with at least a college education.

13. Using matched samples across adjacent years of the March CPS files, Gittleman and Joyce (1996) find that ''long run'' inequality for male full-time full-year workers increased by 20 percent for high school dropouts, 16 percent for high school graduates, 12 percent for those with some college, and only 10 percent for college graduates. They also find that the differences in these trends are even more pronounced with their sample of workers who worked for any length of time.
14. They find that earnings ''instability'' is inversely related to levels of education. However, they find no major trend in instability over time for any particular demographic group, implying that the transitory component did not increase more for less educated workers in relative terms, but did increase more in absolute terms.
15. See Table 1 in Gottschalk and Moffitt (1998) for an extensive summary of the vast literature on job instability. The results of this literature are not unambiguous, but do point to increased job instability for less educated workers from the 1970s to the 1980s. However, studies of this problem are complicated by how instability is defined, how job separation is defined (voluntary or involuntary), how unemployed workers are handled, how the consequences of job loss are defined, and how changes in the questionnaires over time in various data sets make it difficult to create consistent definitions of these variables.
16. See Juhn et al. (1991), Juhn (1992), Welch (1997), and Murphy and Topel (1997).
17. See Topel (1991) and Jacobson et al. (1993). As we will describe in our model section, unemployment is easily interpreted within our model as suffering a large depreciation of technology specific skills due to higher technological progress in one's sector, so that the offered wage is below the reservation wage.
18. Instead of industrial sectors, we could consider different firms within an industry or different jobs within a firm.
19. The assumption of only two sectors (two intermediate goods) is a simplifying assumption, and similar results are obtained assuming a continuum of intermediate goods. In addition, as long as the preferences of the individuals are characterized by a log-linear utility function, an alternative assumption could be that the economy produces a variety of final goods.
20. When g_t and σ_t are endogenized, the restrictions in Assumption A1 are replaced by restrictions on the parameters that govern the dynamical system.
21. The qualitative results are independent of the scale of the economy.
22. It is quite probable that general education is a complement in production to future on-the-job learning, and that more educated workers learn more on the job relative to less educated workers (see Bartel and Sicherman, 1998)). Nevertheless, for less educated workers, the fraction of their human capital that is technology-specific is larger compared to more educated workers. Moreover, on-the-job learning for educated workers is likely to be more general in nature and allow them to adapt to changes in technology rather than be replaced by new technology like less educated workers. In addition, Bartel and Sicherman (1998) show that general education substitutes for on-the-job training in adopting to new technological environments.
23. See Schultz (1975).
24. As long as the return to ability is higher for educated workers and the time cost of adjustment to new technology is higher for uneducated workers, the qualitative results are unaffected by setting the return to ability for uneducated workers to zero and the adjustment cost for educated workers to zero. See Galor and Moav (2000) for a more general case of non-zero returns to ability and adjustment costs, however, they do not include risk as an additional source of inequality and do not produce a precautionary demand for education.
25. This does not mean that technology does not affect productivity. On the contrary, as follows from equation (3), higher levels of technology increase the return to efficiency units of both educated and uneducated labor.
26. The crucial assumption is that the cost of moving between sectors is lower for educated workers relative to uneducated workers. This assumption is consistent with the findings of Davis and Haltiwanger (1991) who show that most of the inequality within production workers is accounted for by inequality ''between'' plants.
27. See Appendix I for the proof.
28. Note that due to the assumption that educated and uneducated efficiency units are perfect substitutes, changes in the relative supply do not affect the relative return to education. However, if substitution was not perfect, a relative change in the supply of educated labor will have a negative effect on the return to education in the same direction as the ''composition effect.'' Hence, complementarity between the two types of labor will not change the qualitative results of the model.

29. Since the ability distribution is uniform, this inequality measure is a monotonically increasing function of the Gini coefficient.
30. In the model, inequality within the educated group is determined solely by the composition of ability of those who choose to get educated. In reality, it is determined by compositional effects combined with the return to ability, both of which are changing over time. Hoxby and Terry (1998) show that these two factors are roughly comparable in magnitude when explaining inequality growth within college educated workers. The role of the return to ability has been explored in other models such as Galor and Moav (2000), where the return to ability interacts with the rate of technological progress. Adding this kind of mechanism would strengthen our results, but since our focus is on the different sources of inequality growth between educational groups, we keep the model simple.
31. The validity of this definition, however, is dependent on the proportion of uneducated workers in each sector. Since the ex-ante distribution of wages for uneducated workers is identical across sectors, uneducated individuals are ex-ante indifferent between the two sectors. Therefore, we assume for simplicity that uneducated workers choose their sectors in equal proportions, which in turn means that μ_t^u is monotonically increasing with the Gini coefficient as a measure of inequality.
32. The qualitative analysis of income inequality within groups of education is robust to any continuous distribution of abilities. The source for inequality within the educated group is the composition of abilities within that group, as determined by the threshold level of ability which is independent of the distribution. Since we assume that the source for inequality within the uneducated group is not dependent on ability, inequality within this group is independent of any distributional assumption. Otherwise, the change in the ability composition of uneducated workers will effect the level of inequality within the uneducated group.
33. The impact of changes in the supply of educated workers on the average wage of educated workers would be stronger if we relaxed the assumption of perfect substitution between educated and uneducated workers. Furthermore, this result is not qualitatively dependent on our simplifying assumption that ability does not affect the wage in the uneducated group, as long as the return to ability is higher in the educated group.
34. It should be noted that the qualitative analysis of income inequality between groups of education is robust to any continuous distribution of abilities. The distribution of abilities affects inequality between groups only by the ''composition effect.'' However, since the return to ability is zero for an uneducated worker, the change in composition only reduces the average income of the educated group, reducing inequality between groups. If we allow ability to affect the wage of uneducated workers, the qualitative results are unchanged as long as the return to ability is higher for educated workers.
35. As noted before, uneducated workers are assumed to choose between the sectors in equal proportions since the sectors are ex-ante identical. As discussed previously, a majority of educated workers choose the sector with the higher rate of progress in order to equalize the wage per efficiency unit of labor across sectors.
36. See Berman et al. (1994). Furthermore, using the NBER-CES/Census Manufacturing Industry Productivity Data Base, we regressed the industry ratio of non-production to production workers on the ratio of their total compensation. The units of observation were the averages for two time periods (1971–1982 and 1983–1994) within each SIC. Each SIC observation was weighted by the mean SIC employment over the whole period and the regression included fixed-effects for each SIC. The coefficient on the ratio of compensation was 0.05 with a *p*-value of 0.08.
37. Note that uneducated workers in the model are forced to suffer higher wage cuts in the sector with the higher rate of technological progress, when in reality their wages may be reduced due to layoffs. Hence, even if observed wages of less educated workers are not lower in sectors with high technological progress, the average observed wage of those workers who chose those sectors in the past could have decreased. In addition, this prediction would be reinforced if layoffs are administered according to ability, so that lower ability workers are the ones that suffer the most in layoffs, and therefore the average wage of those that remain is positively affected by layoffs.
38. The term trivial steady states refers to a steady state with zero growth (i.e., $g_t = \sigma_t = 0$).
39. Treating this as a unique, pervasive, and exogenous invention is similar in spirit to the idea of a ''General Purpose Technology'' used by Bresnahan and Trajtenberg (1995) and Helpman and Trajtenberg (1998). A similar approach is also seen in Galor and Tsiddon (1997) where they distinguish between ''innovations'' and ''inventions.''
40. Since some sectors may shift from investing in the old technology to the new technology, this may generate in

the short run a slowdown in the rate of technological progress in these sectors. Hence, an increase in the variance across sectors is consistent with a limited change in the average rate of progress in the economy.

41. The model assumes for simplicity that the two types of workers are perfect substitutes, and therefore, the decline in the average return to education is only because of the reduction in the average ability in the educated group—the ''composition effect.'' A more realistic formulation, with some complementarity between the two types of workers, will exacerbate the decline in the return to education.
42. An increase in the average rate of technological progress (g_t) does not imply an increase in measured total factor productivity. An increase in g_t erodes the technology-specific human capital which can more than fully offset the increasing productivity due to a higher level of technology. See Galor and Moav (2000) for a rigorous analysis.
43. The increasing supply of educated workers continues to depress the education premium through the composition effects. This effect, however, is counter-acted by the increasing average depreciation rate of technology-specific skills of all uneducated workers, which works to increase the education premium. In a wide range of the process, the latter effect dominates the former effect so that the education premium increases in most cases. This occurs because the ''composition effect'' only works on the margin by bringing in lower ability workers into the educated sector, while all uneducated workers are affected by the increasing average depreciation rate of their technology-specific human capital.
44. See Katz et al. (1995).
45. See Nickell and Bell (1996).
46. Other labor market rigidities in Europe may have caused the trend to affect unemployment in the 1970s rather than inequality.
47. We are matching labor market conditions (for non-Hispanic white males with 10 years of potential experience or less) within each state in 1979 to the state where each individual was born. State-of-birth, which is exogenous to each individual, is used to control for endogenous migration decisions.
48. Individuals who are not in the labor force are included as non-employed, but are not figured into the unemployment rate.
49. See Juhn et al. (1991) and Murphy and Topel (1997).
50. Expected wages for each state were also adjusted by differences across states in observable measures such as the age composition within the state. See the data appendix for further details. Let W_{se} and E_{se} denote the log wage and employment rate in state s in education group e. The expected wage, controlling for the employment probability, is $W_{se} + \ln(E_{se})$.
51. To make sure that this separate effect is not simply picking up the opportunity cost of schooling, we estimated the effect of labor market conditions on the timing of entry into college. If opportunity costs drive enrollment decisions, we would expect fewer people to delay college enrollment when high school unemployment is high. In fact, probit regressions suggest the opposite: conditional on expected wages, the probability that high school graduates enroll in college in the year after high school graduation is negatively, but not significantly associated with higher local unemployment for high school graduates.
52. This was calculated by multiplying -0.0026 by the coefficient -20.687.
53. Prior to the 1991 survey, education was reported using years of schooling. People with fewer than 12 years of completed schooling are classified as high school dropouts; people with exactly 12 years of completed school are classified as high school dropouts; people who attended 13 or more years of school but did not complete 16 years are classified as college graduates; people who completed 16 or more years of school are classified as college graduates. Starting with the 1992 survey, school was reported on the basis of the highest degree held. People who do not hold a high school diploma (or equivalent) are classified as high school dropouts, people whose highest degree is a high school diploma are classified as high school graduates; people with an associates degree (academic or vocational) or unfinished college are classified as college dropouts; people whose highest degree is a bachelors or above are classified as college graduates. Hispanic background is available for respondents starting with the 1976 survey. For the 1971 to 1975 surveys, the Hispanic status of the household head was used. Prior to 1971 all whites were included in the sample. Estimates are similar when Hispanics are included for all years.
54. Continuous values for weeks worked, unemployed, and in the labor force, which were reported in bracketed intervals on the 1968–1975 surveys, were imputed using the means for these variables for people in the same set of intervals on the 1976–1980 surveys.

55. Starting with the 1996 survey, the CPS assigned topcoded individuals the mean earnings among topcoded individuals with similar characteristics. These values were used in the analysis.
56. Unemployment and non-employment rates were estimated using the distribution of weeks in the year prior to the survey.

References

Aghion, P., P. Howitt, and G. Violante. (2001). ''Technology, Knowledge, and Inequality,'' mimeo.

Acemoglu, D. (1998). ''Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality,'' *Quarterly Journal of Economics* 113, 1055–1090.

Autor, D. H., L. F. Katz, and A. B. Krueger. (1998). ''Computing Inequality: Have Computers Changed the Labor Market?,'' *Quarterly Journal of Economics* 113, 1169–1213.

Bartel, A. N., and F. R. Lichtenberg. (1987). ''The Comparative Advantage of Educated Workers in Implementing New Technologies,'' *Review of Economics and Statistics* 69, 1–11.

Bartel, A. N., and N. Sicherman. (1998). ''Technological Change and the Skill Acquisition of Young Workers,'' *Journal of Labor Economics* 16, 718–755.

Berman, E., J. Bound, and Z. Griliches. (1994). ''Changes in the Demand for Skilled Labor Within U.S. Manufacturing: Evidence From the Annual Survey of Manufacturers,'' *Quarterly Journal of Economics* 109, 367–398.

Bresnahan, T., and M. Trajtenberg. (1995). ''General Purpose Technologies Engine of Growth?,'' *Journal of Econometrics*, 65, 83–108.

Caselli, F. (1999). ''Technological Revolutions,'' *American Economic Review* AER 89(1), 78–102.

Davis, S. J., and J. Haltiwanger. (1991). ''Wage Dispersion Between and Within U.S. Manufacturing Plants, 1963–86,'' *Brookings Papers on Economics Activity: Microeconomics* 115–180.

Foster, A. D., and M. R. Rosenzweig. (1996). ''Technical Change and Human-Capital Returns and Investments: Evidence from the Green Revolution,'' *American Economic Review* 86(4), 931–953.

Galor, O., and O. Moav. (2000). ''Ability Biased Technological Transition, Wage Inequality and Growth,'' *Quarterly Journal of Economics* 115, 469–498.

Galor, O., and D. Tsiddon. (1997). ''Technological Progress, Mobility, and Growth,'' *American Economic Review* 87, 363–382.

Gittleman, M., and M. Joyce. (1996). ''Earnings Mobility and Long-Run Inequality: An Analysis Using Matched CPS Data,'' *Industrial Relations* 35(2), 180–196.

Goldin, C., and L. F. Katz. (1998). ''The Origins of Technology-Skill Complementary,'' *Quarterly Journal of Economics* 113(3), 693–732.

Gottschalk, P., and R. Moffitt. (1994). ''The Growth in Earnings Instability in the U.S. Labor Market,'' *Brookings Papers on Economic Activity* 2, 217–254.

Gottschalk, P., and R. Moffitt. (1998). ''Job Instability and Insecurity for Males and Females in the 1980's and 1990's,'' Working Paper, Boston College.

Gould, E. D. (2002). ''Rising Wage Inequality, Comparative Advantage, and the Increasing Importance of General Skills in the United States,'' *Journal of Labor Economics*, forthcoming.

Hassler, J., and J. Rodriguez Mora. (2000). ''Intelligence, Social Mobility, and Growth,'' *American Economic Review* 90, 888–908.

Hassler, J., J. Rodriguez Mora, K. Storesletten, and F. Zilibotti. (1999). ''Equilibrium Unemployment Insurance,'' IIES, Stockholm.

Helpman, E. and A. Rangel. (1999). ''Adjusting to New Technology: Experience and Training'' *Journal of Economic Growth* 4, 359–383.

Helpman, E., and M. Trajtenberg. (1998). ''Diffusion of General Purpose Technologies.'' In E. Helpman (ed.), *General Purpose Technology and Economic Growth*. Cambridge: MIT Press.

Hoxby, C. M., and B. Terry. (1998). ''Explaining Rising Income and Wage Inequality Among the College-Educated,'' Working Paper, Harvard University.

Jacobson, L. S., R. J. LaLonde, and D. G. Sullivan. (1993). ''Earnings Losses of Displaced Workers,'' *American Economic Review* 83, 685–709.

Juhn, C. (1992). ''Decline of Male Labor Market Participation: The Role of Declining Market Opportunities,'' *Quarterly Journal of Economics* 107, 79–121.

Juhn C., K. M. Murphy, and B. Pierce. (1993). ''Wage Inequality and the Rise in Returns to Skill,'' *Journal of Political Economy* 101, 410–442.

Juhn, C., K. M. Murphy, and R. H. Topel. (1991). ''Why Has the Natural Rate of Unemployment Increased Over Time?'' *Brookings Papers on Economic Activity* 2, 75–142.

Kane, T. J. (1994). ''College Entry of Blacks since 1970: The Role of College Costs, Family Background, and the Returns to Education,'' *Journal of Political Economy* 102(5), 878–911.

Katz L. F., G. W. Loveman, and D. G. Blanchflower. (1995). ''A Comparison of Changes in the Structure of Wages in Four OECD Countries.'' In Richard B. Freeman and Lawrence F. Katz, (eds), *Differences and Changes in Wage Structures*. National Bureau of Economic Research.

Katz L. F., and K. M. Murphy. (1992). ''Changes in Relative Wages 1963–1987: Supply and Demand Factors,'' *Quarterly Journal of Economics* 113, 1215–1244.

Maoz Y., and O. Moav. (1999). ''Intergenerational Mobility and the Process of Development,'' *The Economic Journal* 109, 677–697.

Murnane, R., J. B. Willet, and F. Levy. (1995). ''The Growing Importance of Cognitive Skills in the Wage Determination,'' *The Review of Economics and Statistics* 2, 251–266.

Murphy, K. M., and R. Topel. (1997). ''Unemployment and Non-Employment,'' *American Economic Association Papers and Proceedings* 295–300.

Nelson, R. R., and E. S. Phelps. (1996). ''Investment in Humans, Technological Diffusion, and Economic Growth,'' *American Economics Review* 56(2), 69–75.

Nickell, S., and B. Bell. (1996). ''Changes in the Distribution of Wages and Unemployment in OECD Countries,'' *American Economic Association Papers and Proceedings* 86, 302–308.

Rubinstein, Y., and D. Tsiddon. (1998). ''Coping with Technological Progress: The Role of Ability in Making Inequality so Persistent,'' Tel-Aviv University.

Schultz, T. W. (1964). *Transforming Traditional Agriculture*. New Haven: Yale University Press.

Schultz, T. W. (1975). ''The Value of the Ability to Deal with Disequilibria,'' *Journal of Economic Literature* 13, 827–846.

Topel, R. H. (1991). ''Specific Capital, Mobility, and Wages: Wages Rise with Seniority,'' *Journal of Political Economy* February, 145–176.

Weinberg, B. A. (2001). ''Long-Term Wage Fluctuations with Industry-Specific Skills,'' *Journal of Labor Economics* 19(1), 231–64.

Welch, F., (1997). ''Wages and Participation,'' *Journal of Labor Economics* 15, pt. 2, S77–S103.

Zeira, J. (1998). ''Technical Progress, Employment, and Output,'' Hebrew University Working Paper.