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Abstract

This paper examines the determinants of changes in the US wage structure over the period 1976-2000, with the objective of evaluating whether these changes are best described as the result of ongoing skill-biased technological change, or alternatively, as the outcome of an adjustment process associated with a major change in technological opportunities. The main empirical observation we uncover is that change in both the level of wages and the returns to skill over this period appear to be primarily driven by changes in the ratio of human capital (as measured by effective units of skilled workers) to physical capital. Although at first pass this pattern may appear difficult to interpret, we show that it conforms extremely well to a simple model of technological adoption following a major change in technological opportunities. In contrast, we do not find much empirical support for the view that ongoing (factor-augmenting) skill-biased technological progress has been an important driving force over this period, nor do we find support for the view that physical capital accumulation has contributed to the increased differential between more and less educated workers; in fact, we find the opposite.

Key Words: Wages, Returns to education, technological adoption

JEL: J3, 03

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1 Introduction

Over the last decade, there has been substantial interest in understanding the forces driving the observed changes in the US wage structure. The two observations which have attracted most attention are, first and foremost, the rise in the returns to skill commencing in the mid-to-late seventies, and to a lesser degree, the poor wage performance of low skilled workers over the same period. The proposed explanations for these observations vary widely: from globalization, to institutional reform and technological change. Although there is still debate around this issue, one consensus that has emerged is that technological change is likely a major force behind the changes (see for example the survey article by Acemoglu (2000)). However, even if there is a consensus regarding the relevance of technological change in this process, we believe that there are good reasons to reexamine the likely nature of this change and to question anew the role of factor supplies in the process.

There are at least two distinct views regarding the nature of recent technological change and its potential implications for changes in the wage structure. At one extreme is the view proposed by Katz & Murphy (1992), whereby the large increase in the returns to education observed since the late seventies is not the result of a change in technological paradigm, but is instead the reflection of a major slowdown in the supply of skilled workers within a stable environment of ongoing factor-augmenting skilled-biased technological change. At the other extreme is the view that since the mid-seventies — due potentially to the mass dissemination of information technologies — the technological environment has been radically transformed. For example, the general purpose technology literature[1] argues that since 1975 (approximately the date of the introduction of the PC) we have experienced the arrival and dissemination of a new mode of organization which is changing the way production is undertaken in most sectors of the economy. In this view, computers are only one piece of the massive reorganizations of the workplace taking place across many sectors (see, Bresnahan and al. (1999)).

The object of this paper is examine the determinants of changes in the wage structure over the period 1976-2000 with the objective of evaluating the merits of these two extreme paradigms of technological change. We approach the issue in three steps. First, to motivate our analysis, we reexamine the extent to which the simple ongoing skill-biased view proposed by Katz & Murphy (1992) actually fits the observed time pattern of the

[1] See for example Bresnahan & Trajtenberg (1995), Helpman (2000).

increase in returns to education over the recent past. We focus on the period 1976 to 2000 (as opposed to the period 1963-86 studied by Katz and Murphy) since this captures both the most dramatic changes in the US wage structure and the introduction and massive adoption of the personal computer. Somewhat surprisingly, we find that the simple Katz-Murphy model offers a very poor explanation of the change in the college premium over the recent past (i.e. 1976 to 2000). In light of this observation, in the second part of the paper, we present a more flexible and encompassing empirical strategy for evaluating the main determinants of changes in the wage structure. Our main empirical finding is that changes in the ratio of human to physical capital explain much of the variation in both the level of wages and in the returns to skill since 1976. Finally, in the third part of the paper, we illustrate how a simple model of endogenous technological adoption – similar in spirit to those of Basu & Weil (1998), Caselli (1999) and Zeira (1998)– offers an easy interpretation of the observed co-movements between factor usage and wages.

The theoretical model presented in the third part of the paper is one in which a new general purpose technology gradually replaces an old one, with the speed of adoption of the new technology being determined endogenously. We show that the relevance of this class of endogenous technical choice models can be evaluated by testing a strong restriction on the estimated parameters from a relatively unrestricted set of wage equations. The fact that we cannot reject this strong restriction provides a first piece of evidence in support for the model. Further, we derive implications of the estimated wage equation parameters for the nature of the two competing technologies. Our estimates using US data from 1976 to 2000 imply that we are witnessing a transition from an old to a newer technology, with the new technology being characterized by three main features: 1) it uses human capital intensively (i.e., that it is skill biased relative to the older technology); 2) it satisfies Goldin & Katz's (1998) notion of capital skill complementarity; and 3) it uses physical capital efficiently. Hence, the inference we draw regarding the nature of the technological change currently taking place appears consistent with many conjectures in the literature. While our approach to evaluating our model is somewhat indirect, we believe that the substantial match between theory and data provides considerable support for the view that we have recently witnessed a major change in technological opportunities. This, in turn, calls into question common perceptions regarding the role played by factor supplies in recent movements in the wage structure.

The remaining sections of the paper are structured as follows. In Section 2, we overview the changes in the structure of wages over the period 1976-2000, and we examine the extent to which the college-high school wage premia over this period can be explained by the simple model proposed in Katz & Murphy (1992). In Section 3, we present and implement a flexible empirical approach for evaluating the role of human and physical capital accumulation in changes in the wage structure. In Section 4, we show how the observed co-movements between wages and factors over the period 1976-2000 provides considerable support the view that the economy has most likely witnessed a major technological change recently.[2] Finally, Section 6 offers concluding comments.

2 Changes in Wages and Changes in Education: 1976-2000

We begin by reviewing what is, by now, the rather well known pattern of movements in the relative wages of college versus high school educated workers in the U.S.. Our data source is the March Current Population Surveys for the years 1977 to 2001, with the earnings questions we use referring to the years 1976 to 2000. We use as our measure of wages the real weekly wages for full year/full time workers, constructed by dividing annual earnings by weeks worked and then deflating using a GDP deflator. [3] We began by dividing workers into three groups: those who have at most 12 years of education; those with 13 to 15 years of education; and those with 16 or more years of education. We will refer to the first group as the high school sample, the second as the post-secondary sample, and third as the university educated sample. Following the literature, we define the educational skill differential as the difference in log average wages between the university and the high school educated.

Our first goal is to construct a wage index to reflect movements in the relative marginal productivities of workers with differing amounts of education. We therefore single out male wages to avoid compositional issues relating to the large increase in female labour market attachment over this period. [4] Shifts in the age structure of the labour force imply that we also need to control for experience in some way if we are to get a clean

[2]The model presented in Section 4 was first developed in a paper we entitled: What is Driving US and Canadian Wages: Exogenous Technical Change or Endogenous Choice of Technique. This early paper has now been abandoned in favor of the current paper.

[3]Full Year/full time workers are individuals who usually work 35 or more hours per week and work at least 49 weeks in a year. We chose to work with weekly wages to make our work most easily comparable to that of Katz & Murphy. However, working with hourly wages gives similar results.

[4]We will demonstrate, however, that our conclusions are unaltered when we use wages from a combined male/female sample.

measure of movements in educational differentials. We chose to focus on individuals with 1 to 10 years of experience as our baseline group since wage outcomes early in a career are generally thought to most closely reflect market forces and, hence, productivity.[5] In contrast, wages at older ages may reflect internal labour market considerations which may break the close link between wages and marginal product. We provide more detail on data construction and definitions in Appendix 2.

In Figure 1, we plot the relative wages of university educated workers versus those with high school education for the years 1976 to 2000. The solid line, in particular, shows the wage differential for males with 1 to 10 years of experience. We start the series in 1976 in order to emphasize the period in which it is commonly believed that information technology has begun to have a substantial influence on the economy. The graph shows a familiar pattern set out in numerous papers. [6] From the mid 1970s to the early 1980s, the differential shows a generally declining pattern. This reverses sharply around 1982, with the differential rising by over 20% from 1982 to 1986. Thereafter the differential rises at a much more modest pace. We are interested in explaining why the wage differential between the university and high school educated in the US first rose so dramatically to the mid 1980s and why that ascent slowed so much from the late 1980s onward.

While the wages of males with 1 to 10 years of experience are the basis of our preferred index, we need to understand how representative are the patterns observed for this group. For this reason, the dashed line in Figure 1 shows the wage differential for a combined sample of males and females with 1 to 10 years experience. This differential follows a very similar, though somewhat more muted pattern compared to the index constructed using males alone. Thus, our index is robust is quite representative of younger workers of both genders. The dotted line in Figure 1 shows the differential for males with 1 to 5 years experience. This is a group highlighted by Katz and Murphy(1992). Again, our selected index is a good representation of this younger part of the economy. We argued earlier that there are good reasons to focus on younger workers in constructing our index. As is well known (see e.g., Katz and Murphy(1992) and Autor and Katz(1999)), the wage differentials constructed including older workers follow similar, though somewhat more muted, patterns to those shown here. Thus, we believe that a wage measure based

[5] We define 19 as the school leaving age for the high school educated and 23 as the school leaving age for the university educated. Thus, the 1 to 10 year experience samples are high school workers aged 19 to 28 and university workers aged 23 to 32.

[6] The list of papers that present a figure of this sort is to numerous to set out here but includes papers such as Levy and Murnane(1992), Katz and Murphy(1992) and Autor and Katz(1999).

on males with 1-10 years of experience provides a good baseline index since it exhibits considerable volatility and it is robust to changes in the gender mix and to the exact experience grouping. We will support this claim in our empirical work by examing differences induced by using wage indices defined by different experience and gender restrictions.[7]

Relative wage series of the sort presented in Figures 1 have been the focus of considerable research interest. However, relative series provide only a partial picture of the wage changes taking place. For example, the rising educational differential could arise primarily from rising real wages for the university educated, falling real wages for the high school educated, or some combination of the two. The underlying patterns in terms of real wage levels therefore provides extra information with which to evaluate potential theories. This point has been recognized by many authors (e.g, Levy and Murnane (1990)) but only a few studies attempt to pass the dual test of trying to quantitatively explain both movements in the relative wages and one of the underlying wage level series. Here, we examine both movements in the relative wage and in the level of the high school educated wage. Accordingly, in Figure 2, we plot the movements in the real log wage of the high school educated. Figure 2 makes clear that the rising educational differentials seen in the earlier eighties was, to an important extent, driven by falling real wages for the less educated. While the real wages of the university educated rose by around 10% from 1976 to the early 1990s, the real wages of the high school educated fell by approximately 20%. Figure 2 also reveals a substantial rise in real wages of high school educated workers in the late 1990s as compared to the early eighties. Thus, the dramatic fall in the real wages of the less educated in the early eighties, followed by stagnation and then recovery, is the second fact that we are interest in understanding.

A third element worth reviewing is the movements in the relative employment levels of more versus less educated individuals over this period. For this purpose, we construct an employment series by adding up all weeks worked in a year by all workers within a education level (regardless of experience and gender), where we used each of the three

[7] We also constructed a "macro" wage differential trend that would be robust to the sorts of compositional changes that occur as cohorts of differing sizes move through the experience structure. To do this, we pooled our data for all the years then regressed the log wage differential on a polynomial in experience and a full set of year dummy variables. The coefficients on the year dummies then provide us with an overall pattern for the wage differential, holding experience constant. The relative wage pattern constructed in this way is quite similar to that witnessed in the 1-10 years experience series, though with somewhat more muted movements. Note that our emphasis on a particular experience group solves the compositional problem in a simpler manner. A figure showing the wage pattern estimated as just described is available upon request.

education levels specified earlier. We then apportion the post-secondary quantities between the high school and the university educated series in precisely the same manner as in Katz and Murphy (1992). [8] Figure 3 plots the resulting relative quantities series over our period. The key feature to note from Figure 3 is the very rapid growth in university relative to high school educated employment up to the early 1980s followed by a continual but more gradual growth from the early 1980s to the end of our sample.

Together, Figures 1 through 3 summarize three key changes in the US wage and employment structure since 1976. The main movements are: 1) the sharp rise in the university/high school differential from the early to mid-1980s; 2) the slow down in the rise in this differential after 1986; 3) the substantial fall in the real wage of the high school educated from the mid-1970s to the mid-1990s; 4) the substantial rise in the real wages of both educational groups in the late 1990s; 5) the rapid growth in the relative employment of the more versus less educated until about 1981, followed by the slower growth rate thereafter.

2.1 Setting up the puzzle: A reexamination of ongoing skill-biased technical change hypothesis

The existing literature on changes in the US labour market has focussed mostly on reconciling the patterns in Figure 1 (the movements in the relative wage) with that in Figure 3 (the movements in the relative employment levels). The common inference from these two patterns is that they reflect a skill-biased demand shift. While considerable effort has been expended in trying to ascertain whether the demand shift could be driven by changing trade patterns (e.g., Borjas and Ramey(1992), Wood(1995)) or institutional change (e.g., DiNardo, Fortin and Lemieux(1997), Blau and Kahn(1996)), there is substantial agreement that technical change has likely played a major role.

Katz and Murphy(1992) constitutes the seminal work in the literature relating the observed wage changes to changes in relative employment and to skill biased technical change. They present a model in which output can be interpreted as a coming from a production function of the form, $F(\theta_U U, \theta_S S)$, where U corresponds to the quantity of unskilled labour employed,S corresponds to skilled labour, and θ_U and θ_S are labour augmenting factors reflecting the impacts of technical change. Technical change, according

[8] Contributions to the sum of weeks worked are adjusted in an attempt to account for differences in efficiency across different worker types. We also use the CPS reported weights in creating the sums. Details are given in Appendix 2.

to this view, arrives as an exogenous force affecting the productivities of skilled and unskilled labour differentially. The skill bias of the technical change is determined by the relative growth rates in θ_U and θ_S. In particular, technical change is skill biased, and hence will generate rising relative demand for skilled workers, if θ_S grows faster than θ_U. Assuming the growth rate in θ_S minus that in θ_U can be characterized by a linear trend, one can then derive a relative log wage regression of the following form:

$$\log(w_S/w_U) = \phi_0 + \phi_1 \log(S/U) + \phi_2 t + u \qquad (1)$$

In Katz and Murphy(1992)'s derivation, ϕ_1 is the negative of the inverse of the elasticity of substitution between S and U and, given their assumptions about the production function, it must be negative. Meanwhile, ϕ_2 reflects the relative shifts in θ_U and θ_S and should be positive if technical change is skill biased. Their estimates using US data for the period 1963-1987 fit with these predictions as ϕ_1 is estimated to be -.709 (s.e. .150) and $\phi_2 = .033$ (s.e. .007).

These results imply that the wage differential between 1963 and 1987 can be viewed as being driven by an ongoing exogenous relative demand shift (which is often interpreted as relating to technical change) where, in the 1970s, the demand shift is more than offset by exogenous relative supply shifts, resulting in a falling wage differential. However, after approximately 1981, the relative growth of skilled versus unskilled labour slows down and the effects of the skill biased demand shift dominate. This offers an explanation for the rapid rise in the wage differential up until the end of their data period. This simple explanation fits the relative wage data very well in the 23 year span they study. Other authors following Katz and Murphy have argued that the growth in θ_S versus θ_U, that is the degree of skill-bias in technological change, may possibily have accelerated after the introduction of PC's in the mid-1970s (Autor and Katz(1999), Acemoglu(2001)).

As a first step in assessing this type of explanation, we can re-estimate Equation (1) using our data for the period 1976 to 2000. Thus, we are interested in examining whether the same pattern for ϕ_1 and ϕ_2 will hold up in a period that is of about the same length as that studied by Katz and Murphy, but shifted later in time.

Table 1 contains estimates of equation (1), and variants of the equation, for various sample periods. The first column corresponds to estimation of equation (1) itself using our data for the period 1976 to 2000. The striking result from this estimation is that the coefficient on relative employment levels is significantly different from zero and of the same order of magnitude as that estimated by Katz and Murphy for the earlier period, but it has the opposite sign. In the Katz- Murphy theoretical framework, this coefficient corresponds to relative supply effects and cannot be positive. This calls into question the applicability of the framework for explaining US wage and employment patterns in the last 25 years. The coefficient on the time trend variable maintains the same sign as in the earlier period but is much smaller and insignificant.

One possible concern with equation (1) is that the linear specification capturing the relative demand shifts is too restrictive. In Column 2 of Table 1, we present a re-estimation of equation (1), adding in a quadratic term in time. In this specification, all of the parameters are poorly defined. However, they again indicate a positive impact of relative employment levels on relative wages. Moreover, the time variables indicate a positive but declining demand shift effect. This last observation is hard to reconcile with the common perception that skill-biased technical change has, if anything, sped up over the last part of the sample.

The source of the problem in getting sensible estimates out of variants of Equation (1) over the period 1976-2000 is no mystery. A model with a constant demand shift offset by supply shifts can do a good job of explaining the late 1970s and the early 1980s. However, after about 1986, the rise in the relative wages of skilled versus unskilled wages slows considerably. Within this model, this can be explained either by an increase in the growth rate of relative labour quantities or a dramatic slowdown in the relative demand shift. Figure 3 demonstrates that the former did not happen. The latter explanation is not very compelling since the 1990s is not typically viewed as a period of reduced technical change. Moreover, allowing the demand shift effect to slow down in the quadratic time specification in column 2 of Table 1 still does not rescue a negative sign on the relative quantities variable.

To make this point more quantitative, we fit equation (1) to our data in a period when the ongoing skill biased demand shift explanation appears to do well and then use coefficients from that estimation to predict relative wage movements for the remainder of our sample period. In order to obtain well-defined estimates, and to more nearly match the Katz-Murphy exercise, we extend our data series back and run equation (1) using data for the period 1971 to 1987. These estimates are presented in the last column of Table 1. The parameters are well defined and are of the same sign, though slighly greater in magnitude, as those presented in Katz and Murphy(1992).[9]

[9] It is worth noting that when we use a wage series constructed for all experience levels, we obtain estimates of ϕ_1 and ϕ_2 that are almost identical to those of Katz and Murphy— our estimate of the S/U

In Figure 4, we plot both the actual relative wage series for males with 1 to 10 years experience and the fitted (before 1987) and predicted (from 1988 to 2000) series based on estimating equation (1) with our 1971-1987 data. As shown in Katz and Murphy(1992), Equation 1 does a good job of capturing the slow growth in the wage differential in the late 1970s and the rapid acceleration in the first part of the 1980s. However, after 1980 the strong predicted trend is not offset by strong enough relative supply growth, with the result that the predicted wage differential growth vastly overstates the growth in the actual differential.

Our overall assessment of the simple ongoing skill biased technological change model, as it is typically implemented, is that it does a very poor job of reconciling the relative wage and employment movements in the US in the last fifteen or more years. This is in contrast to what Katz and Murphy (1992) show for an earlier period where a simple demand and supply model with exogenous shifts in relative supply and shifts in demand represented by a linear trend performs very well in explaining the data. It therefore appears that something has changed and that an alternative or expanded explanation is needed.

3 An Extended Empirical Framework

The object of this section is to present and implement an empirical framework for examining the link between wages and factor supplies which is in the same spirit as that of Katz & Murphy (1992), but which is more flexible. In particular, we will not a priori exclude a role for physical capital and we will look at both the determination of the level of wages and the returns to skill. The inclusion of physical capital in our specification is particularly relevant given its role in the recent literature, see for example Krusell and al. (2000) and Caselli (1999). To this end, let $F(\theta_t^S S_t, \theta_t^U U_t, K_t)$ represent a constant returns to scale aggregate production function, where θ_t^U and θ_t^S represent, respectively, the possibility of unskilled and skilled labour augmenting technical progress, and K represents the aggregate capital stock. The three equations on which we base our empirical investigation are the two marginal product conditions for wages, that is,

coefficient using wages for all experience levels is -0.704 with a standard error of .17 and our estimate of the time coefficient is .036 with a standard error of .0079. Thus, our different estimates reflect the somewhat different series we study rather than anything fundamentally different in our data construction or our analysis.

$$w_t^U = \theta_t^U F_1(\theta_t^S S_t, \theta_t^U U_t, K_t) = \theta_t^U F_1(\frac{\theta_t^S S_t}{K_t}, \frac{\theta_T^U U_t}{K_t}, 1)$$

$$w_t^S = \theta_t^S F_2(\theta_t^S S_t, \theta_t^U U_t, K_t) = \theta_t^S F_2(\frac{\theta_t^S S_t}{K_t}, \frac{\theta_t^U U_t}{K_t}, 1)$$

and the production function

$$Y_t = F(\theta_t^S S_t, \theta_t^U U_t, K_t)$$

In the marginal product conditions, we have exploited the property of homogeneity of degree zero implied by the assumption of constant returns to scale.

The log-linear approximation to the above conditions can be written so as to reflect the determinants of the low skilled wage and the relative wage between high and low skilled workers.

$$\log(w_t^U) \approx \alpha_0 + \alpha_1 \log(\frac{\theta_t^S S_t}{K_t}) + \alpha_2 \log(\frac{\theta_t^U U_t}{K_t}) + \log \theta_t^U \quad (1)$$

$$\log(\frac{w_t^S}{w_t^U}) \approx \beta_0 + \beta_1 \log(\frac{\theta_t^S S_t}{K_t}) + \beta_2 \log(\frac{\theta_t^U U_t}{K_t}) + \log \frac{\theta_t^S}{\theta_t^U} \quad (2)$$

$$\begin{aligned} \Delta \log(Y_t) \approx & \quad (\tfrac{s_t^U + s_{t-1}^U}{2})\Delta \log(U_t) + (\tfrac{s_t^S + s_{t-1}^S}{2})\Delta \log(S_t) \\ + & \quad (1 - (\tfrac{s_t^U + s_{t-1}^U}{2}) - (\tfrac{s_t^S + s_{t-1}^S}{2}))\Delta \log(K_t) + \Delta TFP_t \quad (3) \end{aligned}$$

where TFP represents the log of total factor productivity [10] which in turn can be stated in terms of unskilled and skilled labour augmenting technological progress as in equation (4).

$$TFP_t \approx s_t^U \log(\theta_t^U) + s_t^S \log(\theta_t^S) \quad (4)$$

In equations (3)and(4), $s_t^i, i = \{U, S\}$ represent the income shares of skilled and unskilled labour respectively. Note that if we impose that technological progress be non-skilled biased, that is $\theta_t^U = \theta_t^S$ then equations (1) and (2) can be expressed in terms only of observables since, from equation (3), $\theta_t^U = \theta_t^S$ can be expressed as a function of a

[10] Our means of calculating TFP_t is that most commonly used in the productivity literature. One rational for this particular approximation is that it becomes an exact index if the production function has the Translog form. See Hulten 1998 for a discussion.

measure of TFP. However, we want to allow for the possibility that technical change may be skill biased. Therefore, we follow Katz & Murphy (1992) and allow θ^S and θ^U to grow at different rates over the period, as given by (5).

$$\log(\theta_t^S) - \log(\theta_t^U) = \gamma_0 + \gamma t \qquad (5).$$

Notice that if γ is zero, all measured TFP growth is attributed equally to skilled and unskilled labour augmenting technological progress. In contrast, when γ is large, all TFP growth is attributable to skilled-labour augmenting technological progress.

Using equations (4) and (5), we can rewrite equations (1) and (2) as follows,

$$\log(w_t^U) = \alpha_{0'} + \alpha_1 \log(\frac{S_t}{K_t}) + \alpha_2 \log(\frac{U_t}{K_t}) + (1+\alpha_1+\alpha_2)\frac{TFP_t}{s_t^U + s_t^S} + (\alpha_1 - \frac{(1+\alpha_1+\alpha_2)s_t^S}{s_t^U + s_t^S})\gamma t + \epsilon_{1,t}, \qquad (6)$$

$$\log(\frac{w_t^S}{w_t^U}) = \beta_{0'} + \beta_1 \log(\frac{S_t}{K_t}) + \beta_2 \log(\frac{U_t}{K_t}) + (\beta_1+\beta_2)\frac{TFP_t}{s_t^U + s_t^S} + ((1+\beta_1) - \frac{(\beta_1+\beta_2)s_t^S}{s_t^U + s_t^S})\gamma t + \epsilon_{2,t}, \qquad (7)$$

where $\epsilon_{1,t}$ and $\epsilon_{2,t}$ are approximation errors that are assumed to be uncorrelated with other variables, and $\alpha_{0'}$ and $\beta_{0'}$ are the new constant terms.

Rearranging these equations slightly, we arrive at the specification we actually implement [11]:

$$\log(w_t^U) = \alpha_{0'} + \alpha_1 \log(\frac{S*_t}{K_t}) + \alpha_2 \log(\frac{U*_t}{K_t}) + \frac{TFP_t}{s_t^U + s_t^S} + \tilde{\gamma}_1 t + \epsilon_{1,t}, \qquad (8)$$

$$\log(\frac{w_t^S}{w_t^U}) = \beta_{0'} + \beta_1 \log(\frac{S*_t}{K_t}) + \beta_2 \log(\frac{U*_t}{K_t}) + \tilde{\gamma}_2 t + \epsilon_{2,t}, \qquad (9)$$

where,

[11] We correct the variance-covariance matrix for the estimated parameters from equations (8) and (9) for both the fact that the error terms in the two equations are contemporaneously correlated and, where testing reveals it is necessary, for first order autocorrelation in the error terms. First order autocorrelation is rejected with many of our wage series and when it does appear to exist, is associated with an autocorrelation parameter of under .4. We correct the variance-covariance matrix after the estimation rather than implementing an estimator directly correcting for the autocorrelation because such a serial correlation corrected estimator involves quasi-differencing the data and we believe the type of longer term patterns we are examining are better represented in non-differenced data.

$$\log(\frac{S*_t}{K_t}) = \log(\frac{S_t}{K_t}) + \frac{TFP_t}{s_t^U + s_t^S}$$

$$\log(\frac{U*_t}{K_t}) = \log(\frac{U_t}{K_t}) + \frac{TFP_t}{s_t^U + s_t^S}$$

i.e., $\frac{S^*{}_t}{K_t}$ and $\frac{U^*{}_t}{K_t}$ correspond to labour - capital ratios where the labour terms are adjusted to incorporate factor augmenting technical progress. Also note the restriction:

$$\tilde{\gamma}_1 = \tilde{\gamma}_2 \frac{(\alpha_1 - \frac{(1+\alpha_1+\alpha_2)s_t^S}{s_t^U+s_t^S})}{((1+\beta_1) - \frac{(\beta_1+\beta_2)s_t^S}{s_t^U+s_t^S})}$$

As seen by the above relationship, Equations (8) and (9) inherits from Equations (6) and (7) a cross-equation restriction linking $\tilde{\gamma}_1$ to $\tilde{\gamma}_2$, $\alpha_1, \alpha_2, \beta_1, \beta_2$. Our approach will be to estimate Equations (8) and (9) both imposing this restriction and alternatively leaving the coefficients on time unrestricted (which allows us to test the restriction). The restricted specification allows us to interpret our results precisely within the framework just derived, while the unrestricted specification allows more general interpretations of the trend effects.[12] In either case, estimation of equations (8) and (9) provide estimates of the key parameters, $\alpha_1, \alpha_2, \beta_1, \beta_2$.

The concavity of the production function places three restrictions on parameters in Equations (8) and (9). These are that $\alpha_2 \leq 0$, $\alpha_1 + \beta_1 \leq 0$ (i.e, that the own price elasticities be negative) and that $\alpha_1\beta_2 - \alpha_2\beta_1 \geq 0$. The verification of whether these conditions are satisfied in our data can be viewed as a specification test which evaluates whether a simple competitive model with three factors of production can reasonably used as a means of summarizing the data.

The empirical implementation of Equation (8) and (9) requires data on wages, quantities of skilled and unskilled labour, physical capital and aggregate output. Then, given this data, a TFP series can be constructed according to Equation (3). The data for wages and quantities of skilled and unskilled labour we use for estimation are constructed from

[12] One interesting case which is encompassed when we allow the time trends to be free is the case where (similar to that considered in Krusell & al. (2000)) there are actually two types of capital stocks in the economy and the relative cost of producing one of these types of capital is trending over time. In this case, the aggregate production function can still be written in terms just of one aggregate capital stock, but the aggregate production function inherits an additional parameter which is the relative cost of the two underlying types of capital. If the change over time in this relative cost is approximately a time trend, then this model implies an empirical representation as in Equation (8) and (9) without restricting time trends.

the CPS file 1977-2001 as described in Section 2. For the aggregate capital stock we choose to use the series constructed by Jorgensen-Stiroh (2000). There are two main features that make this series attractive for our purposes. First, it is constructed from disaggregated investment for several asset types, which are then used to construct a corresponding set of capital series by the perpetual inventory method. In so doing, Jorgensen & Stiroh are careful to use the most appropriate price indices for each asset type so as to best reflect quality changes. They also use asset specific depreciation rates. The resulting set of heterogenous capital series are aggregated together using user costs weights. This procedure give rise to an aggregate capital series which is theoretically appealling.[13] Second, Jorgensen & Stiroh have taken particular care to build an aggregate capital series which includes non-traditional forms of investment such as computer software. Since national income accounts have not traditionally included computer software as an investment, this makes the Jorgensen-Stiroh series particularly relevant when examining the 1990s, where large outlays for computer software were the norm. [14] To be consistent with the capital series, we calculated TFP according to Equation (3) using Jorgensen & Stiroh's measure of aggregate output.[15] [16] In Figure 5A and 5B, which we discuss later, we provide a plot of the capital series and the resulting TFP series.

3.1 Empirical Results

We turn now to estimating equations (8) and (9) using the wage, factor quantity and TFP data described above. We begin with estimates based on our baseline wage index: wages for males with 1 to 10 years experience. Results from this estimation are presented

[13] Jorgensen (1963) and Hall & Jorgensen (1967) explain why this method of aggregation is theoretically preferable to simply adding up a set of heterogeneous capital stocks.

[14] For comparison, we constructed by perpetual inventory method an aggregate capital stock using NIPA data for investment. The resulting series tracked the Jorgensen-Stiroh series closely until about 1990. However, after 1990, the Jorgensen-Stiroh series exhibited more growth, due mainly to their treatment of services rendered by computers and computer software.

[15] Jorgensen & Stiroh's aggregate output series differs slightly from the NIPA series since the former appropriately includes the services rendered by non-traditional forms of investment in output. Again for comparison, we constructed a TFP series using NIPA data and found the resulting series tracked the one we use here extremely closely. Since the TFP series are known to exhibit rather large business cycles fluctuations, we smoothed our TFP series using a fourth order polynomial. Our results are not sensitive to whether we use this smoothed TFP series or the unsmoothed series.

[16] One shortcoming of the Jorgensen & Stiroh series is that they do not cover the years 1999 and 2000. Therefore, for these two years, we used the data reported in Jorgensen (2001) and in the NIPA to construct values. We verified that our results were robust to different means of inferring these values. For comparison, the growth in physical capital services in Jorgensen & Stiroh for 1997 and 1998 are .049 and .058, while the values we constructed for 1999 and 2000 are .058 and .057.

in Table 2. The first column contains results from estimation in which the cross-equation restriction related to the $\tilde{\gamma}_1$'s is imposed, and therefore we report only an estimate of $\tilde{\gamma}_2$.

We first want to examine whether the estimated parameters can be reasonably interpreted within the context of the production function based framework presented in the previous section. To this end, we need to check whether the implied own price effects are negative and that the additional restriction corresponding to concavity is met. The low skilled own price effect is given by the α_1 parameter in our specification. The high skilled own price effect is shown in the row marked T1 at the bottom of the table, and the test statistic corresponding to the additional concavity restriction ($\alpha_1\beta_2 - \alpha_2\beta_1 \geq 0$) is given by T2. Since none of these three restrictions are rejected[17], our estimated parameters appear consistent with an aggregate production function interpretation.

Perhaps the most striking feature of the results in Table 2 is the importance of the $log(\frac{S*_t}{K_t})$ variable in both the low skilled wage and wage difference equations. In both equations, the coefficient on this variable is statistically significantly different from zero at any conventional level of significance. The estimates imply that increases in $\frac{S*_t}{K_t}$ generate decreases in the wages of the low skilled and increases in the wage differential between the high and low skilled. In contrast, the trend effect is neither statistically nor, in economic terms, substantially different from zero and $\frac{U*_t}{K_t}$ has a small and less well defined effects.

In column 2, we present the results from the less restricted specification. As can be seen, freeing up the trend terms in the two equations does not substantively change the key estimated parameters. This is not surprising since the estimated trend terms are again economically and statistically insignificantly different from zero. Moreover, the concavity restrictions are again not rejected. More importantly, $\frac{S*_t}{K_t}$ again has large and statistically significant coefficients in both equations. [18]

The third column of the table contains estimates from a specification designed to focus attention on the potential importance of the $\frac{S*_t}{K_t}$ term (note that this restricted specification is not rejected at conventional levels of significance) . In this specification, we regress the low skilled wage and the wage skill differential on $\frac{S*_t}{K_t}$ alone. The results of this exercise are striking: the $\frac{S*_t}{K_t}$ coefficient in each equation is large and have associated t-statistics equal to approximately 13 in each case. The R^2's of these two simple regressions

[17]Note that the high skilled own price effect being significantly negative at the 5% level of significance.

[18]The test statistic corresponding to the cross-equation restrictions, based on the estimated parameters and variance-covariance matrix from the unrestricted estimation, takes a value of .0059 with a standard error of .25. Since the null hypothesis that the restriction holds corresponds to a value of zero for this statistic, the null hypothesis cannot be rejected at standard significance levels.

are both over .88.[19] This only slightly below the R^2's for the two previous specifications. Thus, in all three cases our model explains a very large portion of the overall variation in the wage structure.

We demonstrate the extremely good fit obtained for both the low skilled wage and the wage differential when using the $\frac{S*_t}{K_t}$ variable by plotting the actual wage series and a fitted series based on the estimated parameters in column 3. In Figure 5A, we plot the actual wage ratio series along with its fitted counterpart.[20] In Figure 5B, we plot the low skilled wage series along with its fitted counterpart. In both cases, it is clear that predicted series based on $\frac{S*_t}{K_t}$ match the actual data patterns extremely well.

Our estimates of equation (8) ansd (9) given in Table 2 assumes that the accumulation patterns, that is changes in $\frac{S}{K}$ and $\frac{U}{K}$, are not correlated with the error term in the regression. In order to explore the robustness of our results with respect to this assumption, in Table 3 we report instrumental variable estimates of all three specification presented in Table 2. [21] The instrumental variables we use for $\frac{S}{K}$ and $\frac{U}{K}$ are demographic variables. In particular, we use five demographic variables which correspond to the fraction of the working age population which is in each of a set of 10 year ranges running from the 26 to 35 year old range up to the 66 to 75 year old range. [22] The idea behind the instruments is that the part of the variation in S and U may represent an endogenous response in schooling choices to wage movements. However, most of the observed changes in S and U over this period occurs because the baby boom cohorts is more educated than the preceding cohorts and larger in size than both preceding and following cohorts. Our instrument emphasizes that variation. As can be seen in Table 3, the IV estimates are very similar to those obtained by OLS, apart from being somewhat larger in absolute valued and slightly less precisely estimated. Most importantly the basic patterns observed in Table 2, and the conclusions that follow from those patterns, are preserved when we instrument using demographic variables.

Of course, it is possible that the results in Table 2 are an artifact of the wage index we

[19] If in addition to $\frac{S*_t}{K_t}$ we also include TFP_t in the regression, we find the coefficients on this additional regressor to be insignificantly different from zero. Thus the data supports the idea that it is the ratio of efficient units of skilled workers to physical capital which explains the variations.

[20] The fitted series for the low skilled wage is the predicted effect of $\frac{S^*}{K}$ plus one times $\frac{TFP}{s^S+s^U}$, as suugested by Equation (8).

[21] We use non-linear two stage least squares to obtain the estimates in the first column of the table and standard two stage least squares to obtain the estimates for the other two columns. All standard errors are adjusted accordingly.

[22] Individuals under age 26 form a base group for which we omit a specific variable to prevent collinearity with the constant term. We include time and tfp in the instrument set.

have chosen. To examine this possibility, we re-estimate the specifications set out in Table 2 using wage series based on males with 1 to 5 years of experience and on both males and females with 1 to 10 years experience. The results from these exercises are presented in Table 4. The estimated parameters in all cases again imply that own price effects are negative and that the additional concavity restriction is not rejected. As in Table 2, the $\frac{S*_t}{K_t}$ effects are by far the largest and are statistically significant at conventional significance levels. The estimates of these effects from the two alternative wage series bracket those using wages for males with 1 to 10 years experience: the estimates based on the male and female wages are smaller in absolute value while the estimates based on the wages of males with 1-5 years experience are larger. This reflects the greater variation in the dependent variables generated using the younger male sample. As in Table 2, we find that using $\frac{S*_t}{K_t}$ alone as a regressor generates R^2 values of .86 or above. Thus, our key findings are robust to these changes in the wage series.

The evidence presented in Tables 2 and 3 and in Figues 5a and 5b indicate that recent variations in wages for young workers appear driven primarily by changes in $\frac{S_t^*}{K_t}$. Although we believe that movements in the wages of young workers are likely the best indication of movements in marginal productivity, it is nevertheless natural to ask whether the same general observation regarding the role of $\frac{S_t^*}{K_t}$ holds true for a wage index which includes workers of all experience levels. To this end, Figures 6a and 6b redo the exercises presented in Figures 5a and 5b using a wage index based on male workers of all experience levels. As can be seen in the Figures, the predicted series based on $\frac{S^*}{K}$ track both the skill premium and the low skilled wage quite well. However, in the case of the skill premium (Figure 6a), we can see that a simple time trend also fits this series reasonably well. Indeed, a statistical test of whether $\frac{S_t^*}{K}$ or a time trend fit the skill premium better is inconclusive. Hence, for a wage index based on workers of all experience levels, there is simply not enough variation relative to trend to allows us to differentiate the effects of $\frac{S_t^*}{K_t}$ from other trending variables. In contrast, the wage series for the young workers exhibit more variation and therefore do not allow us to disentangle these effects and point to variations in $\frac{S_t^*}{K_t}$ as the dominant force.

Given the apparent importance of the $\frac{S*_t}{K_t}$ variable in predicting the movements of both the low skilled wage and the wage differential, it is important to understand the source of the variation in this variable. Movements in $\frac{S*_t}{K_t}$ reflect movements in the three underlying variables: S_t, K_t, and TFP_t. Figure 3 showed that S_t rises (at least relative to U_t) throughout our period, though at a much less rapid rate after 1980 than before.

Figure 6a shows the time pattern in the growth of capital services in the last 25 years. Close inspection of this figure reveals that capital services grew through the period, with slower growth up until about 1983 and an acceleration in the late 1990s. As a result, $\frac{S_t}{K_t}$ rose rapidly up until 1983, as growth in S_t outstripped capital growth, was relatively flat from the mid-1980s to the mid-1990s and then fell in the late 1990s, as capital growth outstripped that in S_t. This is portrayed in Figure 7b. However, movements in $\frac{S*_t}{K_t}$ also reflect movements in TFP, which are depicted in Figure 7c. Here we see that growth in TFP was almost non-existent in the late 1970s and early 1980s, followed a relatively constant trend from there until the mid- 1990s and then accelerated in the late 1990s. The acceleration in the late 1990s implies increased efficiency of skilled labour, which tends to offset the slower growth in S_t in this period. As a result, $\frac{S*_t}{K_t}$ maintains a flat profile in the late 1990s rather than falling as $\frac{S_t}{K_t}$ does.

Our key result from these relatively unrestricted wage regressions is that $\frac{S*_t}{K_t}$ appears to have played the dominant role in explaining movements in wage levels and wage differences over the last 25 years. Moreover, $\frac{S*_t}{K_t}$ appears to have a strong negative impact on low skilled wages and a strong positive impact on the differential between high and low skilled wages. The signs of these effects may appear to be surprising. For example, Goldin and Katz(1998) argue that capital-skill complementarity is a feature of new technologies introduced since the start of the twentieth century. It is tempting to infer from this that an increase in the capital stock should lead to increases in the wage skill differential, which would be opposite to the effect we estimate. In the next section, we present a theoretical framework which explains why movements in the ratio of (efficiency adjusted) skilled workers to physical capital may have been so important over the last twenty five years and why such a pattern may reflect the effects of a major technological change.

4 Relating the observed movements in wages to a theory of major technical change.

The object of this section is to highlight how the above empirical observations, and especially the important role of $\frac{S*}{K}$, become easily interpretable if one looks at them through the lens of a simple model of endogenous technological adoption. Our approach to this issue is to show how such a model of technological change constrains the data, and then to examine the extent to which these constraints are satisfied. By examining these constraints, our approach offers a means of evaluating whether observed wage changes support the view that the economy has likely witnessed a major technological change in the recent past. Moreover, by offering a structured interpretation of the data, our model of endogenous technological adoption will clarify why movements in $\frac{S*}{K}$ may have dominated the determination of wages over the recent past.

The model we pursue is one where a traditional technology or mode of organization is being gradually replaced by a more modern one. We focus on the period of time after which the new technology has been introduced but before it has entirely superseded the older technology. Moreover, we want to think of these technologies or modes or organisation as General Purpose Technologies since we view this process as being pervasive across the economy. We will concentrate on the case where the new means of production is assumed to satisfy two important characteristics relative to the traditional means of production:, that it is skilled biased relative to the traditional technology and that it satisfies Katz and Goldin's (1998) notion of capital skill complementarity. We choose these two properties since they figure prominently in the literature and they appear inherently reasonable for the period under study. Within this type of framework, changes in factor supplies will affect the speed of adoption of the modern technology and thereby factor prices. We are interested in that connection. In particular, our objective is to derive how such a model constrains the link between factor supplies and factor prices.

To this end, let $F^T(U^T, S^T, K^T)$ represent the production possibilities available under a first mode of organization, which we refer to as the traditional mode of organization or production. Similarly, let $F^M(U^M, S^M, K^M)$ represent possibilities under the second or modern form of organization. In both cases, production is allowed to depend on three inputs: physical capital, K, skilled labour, S, and unskilled labour, U. Moreover, we assume that both forms of organization exhibit constant returns to scale and that total output in the economy is the sum of the outputs from the two forms of organization. In this section we will abstract from factor augmenting technological change, although this can be trivially included.

Let us also denote by $p = \{w_u, w_s, r\}$ the vector of factor prices, where w_u is the wage of unskilled labour, w_s is the wa

Our aim is to examine how factor prices in such an economy are affected by changes in factor supplies. Since it is easiest to cast differences between production possibilities in terms of differences in input use, we need a notation expressed in these terms. To this end, let x_p^i denote the optimal quantity of factor x used to produce one unit of output with technology i when prices are equal to p. For example, U_p^T will represent the amount of unskilled labour used to produce one unit of output with the traditional technology when prices are equal to p. Note that, even in the presence of two technologies, this economy is effectively operating under an aggregate production function, which we denote by $F^A(U, S, K)$, defined as follows.

$$F^A(U,S,K) = \max_{U^T,U^M,S^T,S^M,K^T,K^M} F^T(U^T,S^T,K^T) + F^M(U^M,S^M,K^M)$$

subject to

$$U^T + U^M = U, \quad S^T + S^M = S, \quad K^T + K^M = K$$

Since our empirical results in the previous section provides us with information on the derivatives of an aggregate production function, we can view our endeavour here as highlighting how the properties of $F^T(\cdot)$ and $F^M(\cdot)$ imply restrictions on the derivatives of $F^A(\cdot)$. However, before discussing such a link, it is interesting to note that the mere fact that an aggregate production function may reflect two underlying competing technologies actually has strong empirical content. In particular, if the two technologies are in use, then the aggregate production function in such a case will necessarily be weakly concave and not strictly concave.[23]. In terms of the αs and βs in equations (6) and (7), this implies that $\alpha_1\beta_2 - \alpha_2\beta_1$ should be precisely equal to zero if the economy is transiting from one general purpose technology to another, as opposed to being strictly greater than zero in the general case. The term $\alpha_1\beta_2 - \alpha_2\beta_1$ is reported as T2 at the bottom of Table 2. It is interesting to note that our estimate of $\alpha_1\beta_2 - \alpha_2\beta_1$ in Column 1 of Table 2 is both very near to zero in value and not statistically significantly different from zero. Therefore the data does not reject this conceptually important restriction. Note that this restriction, which may seem like a mathematical curiosity, actually has economic content. For example, this property implies that during a period where the economy is transiting between two technologies, the new technology can be adopted gradually without necessitating any change in the wage structure (that is no change in either w^S or w^U) as long as the supply of factors are properly chosen. The reason for this effect is that the reallocation of factors between the two technologies allows factor prices to be kept constant if the factors are supplied in the right proportions. In effect, this logic is the exact same as that underlying factor price equalization results in international trade.

[23]See Bliss 1975

We now turn to examining how properties of $F^T(\cdot)$ versus $F^M(\cdot)$ affect the derivatives of $F^A(\cdot)$, or more particularly, how they restrict the link between factor supplies and wages. As previously noted, we take as given the notion that the modern mode of production uses skilled labour much more intensively than the traditional technology. To give precise content to the notion that the defining feature of the modern organization is its relative skill biasedness, definition 1 states that, at given factor prices, the modern organization is highly skill biased if it uses relatively more skilled labour and relatively less unskilled labour to produce one unit of output than that use in the traditional technology, with the difference in the use of capital between the two forms of organization being less extreme.

Definition 1: The modern organization is highly skill biased relative to the traditional organization if

$$\frac{U_p^T}{U_p^M} > \frac{K_p^T}{K_p^M} > \frac{S_p^T}{S_P^M}$$

One case which always satisfies Definition 1 is the case in which the traditional organisation does not use skilled labour while the modern organisation does not use unskilled labour, but both technologies use capital. Although this case is extreme, it is the one considered in Caselli (1999) and it is useful for providing intuition about our main results. In particular, in this extreme case, it is obvious that as long as there is both skilled and unskilled labour in the economy, the two methods of production will generally co-exist. Otherwise one of the wages would be zero, which would make production using that factor attractive. [24] In Proposition 1 we identify the implications of assuming that the new technology is highly skilled biased.

Proposition 1: When production takes place in both types of organizations and the modern technology is highly skilled biased (Definition 1), then

(1) an increase in physical capital causes both wages to increase, that is,

$$\frac{\partial w^s}{\partial K} > 0, \quad \frac{\partial w^u}{\partial K} > 0$$

(2) an increase in S cause a fall in W^U and an increase in U causes a fall in w^S, that is,.

[24] More generally, the two types of organisations will co-exist as long as the factor supplies are in the diversification cone. See Mckenzie (1955) for a definition of a diversification cone.

$$\frac{\partial w^u}{\partial S} < 0, \qquad \frac{\partial w^s}{\partial U} < 0$$

Proof: Proofs for this and subsequent propositions are found in Appendix 1.

The extreme case where the modern organization has no use for unskilled labour and the traditional organization has no use for skilled labour is useful for establishing intuition for these results. In this extreme case, K is employed only with one type of labour in each technology and, thus, is a complement to both types of labour. As a result, an increase in capital implies an increase in both skilled and unskilled wages. The proposition shows that this intutive effect remains true as long as the main feature of the two technologies is that one uses skilled workers much more intensively that the other as defined by assumption 1.

With respect to the second part of Proposition 1, the mechanism at work in the extreme case is exactly that discussed in Caselli (1999). In this situation, the increased supply of skilled workers decreases the marginal product of skilled worker and increases the marginal product of capital in the new form of organization. The induced difference in the marginal products of capital between the new and old technologies incites capital to flow towards modern organisations and away from traditional organisations, thereby leading to a decrease in the marginal product, and hence the wage, of unskilled workers. [25]

We now wish to go beyond Proposition 1, to understand how the notion of capital skill complementarity restricts the link between factor supplies and wages. In particular, Goldin & Katz (1998) argue that the major changes in organisational structure throughout the 20th century have been characterized by the newer technologies/organisations exhibiting capital-skill complementarity, that is, the newer skilled-intensive technology exhibiting a higher capital-labour ratio. Definition 2 gives a precise definition of this notion of capital-skill complementarity.

Definition 2: The modern organization exhibits capital-skill complementarity relative to the traditional organization, that is, the more skill intensive organisation also has a

[25] An interesting implication of Proposition 1 is that in terms of the aggregate production function, skilled and unskilled labour must be q-substitutes. This observation is relevant given that it is not uncommon in the empirical literature on wage inequality to choose parameterizations of the aggregate technology that exclude the possibility that skilled and unskilled labour are q-substitutes. For example, multifactor factor CES production functions and certain nested CES production functions exclude the possibility of q-substitutes. Krusell, Rios-Rull, Ohanian and Violante (2000) is an example of an analysis of wage movements which excludes the possibility that skilled and unskilled labour are q-substitutes.

higher capital-labour ratio:

$$\frac{K_P^T}{U_P^T + S_P^T} < \frac{K_P^M}{U_P^M + S_P^M}$$

Under the assumption of capital skill complementarity we can derive further implications for the link between factor supplies on wages. The main insight we gain from capital-skill complementarity relates to how changes in educational attainment, that is an increase in S with an offsetting decrease in U (i.e. holding $U + S$ constant), affect the level of wages. This implication is given in Proposition 2.

Proposition 2: When production take place in both types of organizations and the modern technology satisfies Definition 1 and 2, then

$$(\frac{\partial w^s}{\partial(\frac{S}{U})})_{U+S=cst} < 0 \qquad \text{and} \qquad (\frac{\partial w^u}{\partial(\frac{S}{U})})_{U+S=cst} < 0$$

Proposition 2 indicates that the effect of an increase in educational attainment is to reduce both the wage of high skill and low skill workers when the technology being adopted is highly skilled biased and satisfies capital skill complementarity. The reason for this effect works through understanding the effect of increased educational attainment on capital scarcity. In the presence of capital-skill complementarity, an increase in educational attainment induces a need for new capital, since it stimulates the adoption of the highly skilled technology which also uses more capital. In turn, the induced capital scarcity causes a fall in both wages since, from Proposition 1, we know capital is necessarily a complementary factor to both skill and unskilled workers if the new technology is highly skill biased.

The last theoretical issue we want to address is how a technological adoption model restricts the link between changes in factor supplies and changes in relative wages (i.e., changes in the ratio of w^S to w^U). Interestingly, capital-skill complementarity alone does not pin down this link. We need, in addition, to know the relative capital efficiency of the two technologies, i.e, which technology uses more capital per unit of output. Proposition 3 highlights how factor supplies affect relative wages when the modern technology is capital efficient relative to the traditional technology.

Definition 3: The modern technology is capital efficient relative to the tradition technology if

$$K_P^T > K_P^M$$

Proposition 3: When production take place in both types of organizations and the modern technology satisfies Definitions 1, 2 and 3, then

$$\frac{\partial(\frac{w^s}{w^u})}{\partial K} < 0 \quad , \quad \frac{\partial(\frac{w^s}{w^u})}{\partial S} > 0 \quad , \quad \frac{\partial(\frac{w^s}{w^u})}{\partial U} > 0 \quad , \quad (\frac{\partial(\frac{w^s}{w^u})}{\partial(\frac{S}{U})})_{S+U=cst} > 0$$

The first aspect to note from Proposition 3 is that an increase in physical capital can actually lead to a decrease in the return to skill even if the new technology satisfies capital skill complementarity. The intuition for this result is that when the modern organisation is more capital efficient, it has a lower capital share, and hence it benefits less by an increased abundance of capital. Accordingly, this leads the marginal product of skilled workers, which is the intensively used factor in the modern organisation, to rise less than the wages of less skilled workers. The rest of the statements in Proposition 3 follow directly from the observation that increased capital scarcity would lead to an increase in the ratio of w^S to w^U if the modern technology is capital efficient. In particular, as noted earlier, an increase in education attainment will cause a capital scarcity when the modern technology exhibits capital-skill complementarity, and hence it follows that it will cause an increase in the returns to skill if the modern technology is also capital efficient.

In light of Proposition 1 to 3, we can now clearly state the main theoretical claim of the paper, which is that the observed relationship between factor supplies and wages documented in Table 2 likely reflects a major technological change whereby the economy is gradually adopting a new technology which satisfies three properties:(1) it is highly skill biased, (2) it satisfies capital skill complementarity, and (3) it is capital efficient.

In order to evaluate this claim, we can systematically compare the implications of Proposition 1 to 3 with their empirical counterparts inferred from Column (1) of Table 2. To this end, in Table 5, we report the empirical counterparts to each of the comparative static results derived in Propositions 1 to 3. The first aspect to note from the table is that all ten theoretical implications are satisfied by the model in the sense of being of the right sign. Moreover, in many cases, the effects are rather precisely estimated, which give more credence to the claim. Thus, it appears that the data supports the claims both that we can characterize the past 25 years as reflecting a transition between substantively different technologies – based on the observation that $\alpha_1\beta_2 - \alpha_2\beta_1$ is not statistically different from zero– and that the technology toward which the economy is transiting is relatively skill biased, exhibits capital-skill complementarity and is capital efficient –as reflected in the sign pattern presented in Table 5. [26]

Perhaps the most notable aspect of Table 5 is that many of the predicted effects – as well as the estimated effects– contrast sharply with those emphasized in the literature. For example, we argue that, over the recent period an increase in physical capital raised unskilled wages and reduced the wage differential (i.e., $\frac{\partial w^U}{\partial K} > 0$ and $\frac{\partial(\frac{w^s}{w^u})}{\partial K} < 0$). A common misinterpretation of capital-skill complementarity is that it should necessarily imply the opposite. However, as shown in the propositions, this is not the case. Similarly, we find that raising the ratio of skilled to unskilled labour in the economy leads to a fall in the unskilled wage and a rise in the wage differential (i.e., $\frac{\partial w^u}{\partial(\frac{S}{U})} < 0$ and $\frac{\partial(\frac{w^s}{w^u})}{\partial(\frac{S}{U})} > 0$), which again is entirely consistent with an economy that is gradually replacing a traditional technology with a new technology which exhibits three properties: it is skill biased, it satisfies capital skill complementarity and it is capital efficient. This is precisely the type of insight gained by using Propositions 1 to 3 to interpret the data. It is worth emphasizing that our interpretation is obtained within a very simple neoclassical model of endogenous technological adoption.

The signs of the derivatives presented in Table 5 suggest that some of the inferences drawn from earlier papers in the literature may not be relevant for the recent period. Most prominently, earlier empirical results have been interpreted as implying that education policy will always lead to a reduction in the wage differential between skilled and unskilled workers. In contrast, our results suggest that the large increases in educational attainment observed in the early 80s acted to increase the skill differential since they were not offset by a sufficiently large increase in physical capital. More generally, while the standard story of the US labour market focusses on the relative supplies of skilled and unskilled labour as a key driving force, the theory presented in this section (which appears to fit the data) implies that the ratio of human to physical capital has likely been the main factor determining movements in the US wage structure since the mid-seventies.

As a means of summarizing our main results, it is worth describing how our model of endogenous technological adoption accounts for our main empirical observation: that the ratio of physical capital to effective units of skilled labour has played an important role in determining wage levels and differentials over the 1976-2000 period. Recall that movements in the wage structure in the last 25 years can be divided into three broad

[26]To further explore the validity of this theory, it is useful to examine its implication within a cross-country framework, since there is substantial variation across countries in the relative use of factors. We pursue this avenue in Beaudry & Green (2000, 2001).

sub-periods: in the mid to late-1970s, both low skilled wages and the wage differential were relatively stable; in the early to mid-1980s the low skilled wage fell rapidly and the wage differential rose rapidly; and from the late 1980s through the 1990s, the wage differential was again stable but this was underpinned by rising real wages for the low skilled, particularly in the last part of the period. Our model provides a clear explanation for why each of these very different wage structure patterns emerged given the movements in factor quantities. In particular, in the mid-to-late seventies, due to slow growth in labour augmenting technical change (i.e. θ_t^S), the effective units of skilled labour were not growing faster than physical capital and accordingly the wage structure remained stable even as the economy was adopting the new technology. In the early eighties, the effective supply of skilled workers starting growing rapidly without an offsetting increase in the speed of capital accumulation. Therefore, during that period, physical capital became scarce, causing both the return to skill to increase and the low skilled wage to fall. Then, in the late eighties and into the nineties, the supply of skilled workers slowed down and the accumulation of physical capital sped up, which allowed for the further adoption of the new technology without affecting the return to skill. Finally, toward the end of the 1990's, acceleration in TFP growth coupled with a rapid increase in physical capital contributed to the rise in the level of both wages.

5 Conclusion

This paper began by using a simple three factor production function to capture the relationship between wages and factor supplies over the period 1976-2000. The three main empirical observation we uncovered are that (1) a simple three factor specification provides a reasonable fit of the data in the sense that it satisfies the restrictions of concavity and tracks the data well, (2) within this framework, we do not find strong evidence suggesting that factor augmenting technological progress was particularly biased in favour of skilled labour, and (3) we found that changes in the ratio of skilled labour to physical capital explains most of the variation in both the level of low skilled wages and the return to education over this period. In the second part of the paper, we documented the extent to which these observed patterns likely reflect mechanisms induced by the arrival and adoption of a new major technology. In particular, we showed how a model of endogenous technological adoption following a major technological change could explain all the main patterns detected in the data. One of the striking features of our analysis is that, in spite of starting from a very conventional neoclassical model, its implications contrast sharply with many common views regarding the role of factor supplies in explaining recent changes in the wage structure. For example, our analysis suggests that an increase in physical capital decreased the returns to skill and increased the wage of less skilled labour over the period even though the new technology being adopted satisfies capital-skill complementarity. Moreover, our analysis suggests that an increase in educational attainment increased the returns to skill over this period due to its effect in increasing the ratio of human to physical capital and thereby leading to a faster adoption of the highly skilled biased technology.[27]

[27]This latter effect is quite distinct from that emphasised by Acemoglu (1998). In particular, our mechanism appears to arise in the short run whereas the mechanism of induced innovation discussed in Acemoglu (1998) is most likely relevant only in the long run.

Table 1: Regressions of Relative Log Wages on Relative Quantities and Time

	1976-00 Est.	Std. E.	1976-00 Est.	Std. E.	1971-87 Est.	Std. E.
S/U	.53	(.20)	.11	(.36)	-.96	(.30)
Time	.002	(.0056)	.022	(.017)	.053	(.014)
T^2			-.0004	(0.0003)		

Coefficient estimates correspond to the parameters in equation (1). The dependent variable corresponds to the log wage differential between workers with a university education versus workers with high school or less education. The wages are constructed for males with 1 to 10 years of experience but employment levels correspond to all workers regardless of experience or gender.

Table 2: Estimates of Equations (8) and (9), Males With 1-10 Years Experience

	$(1A)$	$(1B)$	$(1C)$
α_1	-.98	-.92	-1.16
	(.23)	(.26)	(.087)
α_2	-.28	-.43	-
	(.31)	(.44)	-
β_1	.56	.59	1.11
	(.23)	(.23)	(.085)
β_2	.080	-.0038	-
	(.38)	(.38)	-
$\tilde{\gamma}_1$	-	-.0086	-
	-	(.0059)	-
$\tilde{\gamma}_2$	0.0087	.0071	-
	(.0059)	(.0064)	-
T1	-.43	-.33	-
	(.22)	(.27)	-
T2	-.076	-.26	-
	(.27)	(.36)	-
Low Wage R^2	.89	.89	.88
Wage Diff R^2	.91	.91	.88

1. Column (1A) is derived from estimating equations (8) and (9) imposing the cross- equation restriction which results in our only estimating $\tilde{\gamma}_2$. Column (1B) does not impose this cross-equation restriction and therefore we obtain unrestricted estimates of both of $\tilde{\gamma}_1$ and $\tilde{\gamma}_2$.
2. Standard errors of estimates are in parentheses. All standard errors are adjusted to reflect cross-sectional correlation in errors across equations and autocorrelation where tests suggest it is present.
3. T1 reports the estimate of $\frac{\partial w^S}{\partial S}$, that is, the estimate of $\beta_1 + \alpha_1$.
4. T2 reports the estimate of $(\beta_2 * \alpha_1 - \beta_1 * \alpha_2)$. If this term is significantly negative, then it indicates that concavity is rejected.
5. The R^2 for the low wage equation in column 1 is constructed as 1 minus the ratio of the sum of squared residuals, generated using the appropriate estimated coefficients from column 1, to the sum of squared deviations in our low wage variable from its mean. The R^2 for the wage difference equation is constructed in the same way. This construct provides a rough means of gauging the fit of the model, though this statistic does not necessarily possess all the characteristics of the R^2 from a standard regression. The R^2's for the other columns bear the standard interpretation.

Table 3: IV Estimates of Equations (8) and (9), Males With 1-10 Years Experience

	$(1A)$	$(1B)$	$(1C)$
α_1	-1.30	-1.20	-1.17
	(.29)	(.35)	(.08)
α_2	-.87	-1.42	-
	(.45)	(.70)	-
β_1	.56	.64	1.12
	(.30)	(.27)	(.08)
β_2	.45	.07	-
	(.56)	(.55)	-
$\tilde{\gamma}_1$	-	-.018	-
	-	(.010)	-
$\tilde{\gamma}_2$	.013	.007	-
	(.007)	(.008)	-
T1	-.74	-.56	-
	(.40)	(.44)	-
T2	.10	-.83	-
	(.51)	(.87)	-

1. The instrument set is composed of 5 demographic variables plus TFP and time. The five demographic variables correspond to the fraction of the working age population which is in each of the set of 10 year ranges starting from the 26 to 35 year old group.
2. Column (1A) is derived from estimating equations (8) and (9) imposing the cross- equation restriction which results in our only estimating $\tilde{\gamma}_2$. Column (1B) does not impose this cross-equation restriction and therefore we obtain unrestricted estimates of both of $\tilde{\gamma}_1$ and $\tilde{\gamma}_2$.
3. Standard errors of estimates are in parentheses. All standard errors are adjusted to reflect cross-sectional correlation in errors across equations and autocorrelation where tests suggest it is present.
4. T1 reports the estimate of $\frac{\partial w^S}{\partial S}$, that is, the estimate of $\beta_1 + \alpha_1$.
5. T2 reports the estimate of $(\beta_2 * \alpha_1 - \beta_1 * \alpha_2)$. If this term is significantly negative, then it indicates that concavity is rejected.

Table 4: Estimates of Equation (8) and (9), Alternate Samples

	Males & Females 1-10			Males 1-5		
	$(1A)$	$(1B)$	$(1C)$	$(2A)$	$(2B)$	$(2c)$
α_1	-.78	-.72	-.94	-1.46	-1.39	-1.35
	(.18)	(.21)	(.072)	(.33)	(.28)	(.094)
α_2	-.18	-.33	-	-.14	-.32	-
	(.25)	(.35)	-	(.45)	(.46)	-
β_1	.44	.47	.90	.89	.96	1.09
	(.19)	(.18)	(.070)	(.40)	(.34)	(.11)
β_2	.040	-.032	-	-.20	-.38	-
	(.31)	(.31)	-	(.56)	(.55)	-
$\tilde{\gamma}_1$	-	-.0070	-	-	-.0033	-
	-	(.0053)	-	-	(.0071)	-
$\tilde{\gamma}_2$	.0069	.0056	-	0.0002	.0032	-
	(.0048)	(.0071)	-	(.0088)	(.0085)	-
T1	-.34	-.25	-	-.57	-.42	-
	(.19)	(.22)	-	(.35)	(.35)	-
T2	-.048	-.18	-	-.41	-.84	-
	(.18)	(.23)	-	(.61)	(.75)	-
Low Wage R^2	.89	.89	.88	.90	.90	.90
Wage Diff R^2	.91	.91	.88	.81	.81	.80

1. The results in Columns (1A),(1B) and 1(C) are based on wage data for males and females with 1 to 10 years of experience. The results in Columns (2A), (2B) and (2C) are based on wage data for males and females with 1 to 5 years of experience.
2. Columns (1A) and (2A) are derived from estimating equations (8) and (9) imposing the cross-equation restriction which results in our only estimating $\tilde{\gamma}_2$. Columns (1B) and (2B) do not impose this cross-equation restriction and therefore we obtain unrestricted estimates of both of $\tilde{\gamma}_1$ and $\tilde{\gamma}_2$.
3. Standard errors of estimates are in parentheses. All standard errors are adjusted to reflect cross-sectional correlation in errors across equations and autocorrelation where tests suggest it is present.
4. T1 reports the estimate of $\frac{\partial w^S}{\partial S}$, that is, the estimate of $\beta_1 + \alpha_1$.
5. T2 reports the estimate of $(\beta_2 * \alpha_1 - \beta_1 * \alpha_2)$. If this term is significantly negative, then it indicates that concavity is rejected.
6. The R^2 for the low wage equation in column 1 is constructed as 1 minus the ratio of the sum of squared residuals, generated using the appropriate estimated coefficients from column 1, to the sum of squared deviations in our low wage variable from its mean. The R^2 for the wage difference equation is constructed in the same way. This construct provides a rough means of gauging the fit of the model, though this statistic does not necessarily possess all the characteristics of the R^2 from a standard regression. The R^2's for the other columns bear the standard interpretation.

Table 5: Estimates of Predicted Comparative Statics

	Proposition 1		
	Estimate	St. Err.	Prediction
$\frac{\partial w^U}{\partial K}$	1.26	(.44)	≥ 0
$\frac{\partial w^S}{\partial K}$	.62	(.44)	≥ 0
$\frac{\partial w^U}{\partial S}$	-.98	(.23)	≤ 0
$\frac{\partial w^S}{\partial U}$	-.20	(.25)	≤ 0
	Proposition 2		
	Estimate	St. Err.	Prediction
$\frac{\partial w^S}{\partial \frac{S}{U}}$	-.82	(.24)	≤ 0
$\frac{\partial w^U}{\partial \frac{S}{U}}$	-.31	(.14)	≤ 0
	Proposition 3		
	Estimate	St. Err.	Prediction
$\frac{\partial \frac{w^S}{w^U}}{\partial K}$	-.64	(.43)	≤ 0
$\frac{\partial \frac{w^S}{w^U}}{\partial S}$	.56	(.23)	≥ 0
$\frac{\partial \frac{w^S}{w^U}}{\partial U}$	.08	(.38)	≥ 0
$\frac{\partial \frac{w^S}{w^U}}{\partial \frac{S}{U}}$	.51	(.31)	≥ 0

1. The results in Table 5 are derived from estimating equations (8) and (9) using wage data for males with 1 to 10 years of experience, that is, the comparative statitics are all functions of the coefficients reported in Column 1 of Table 2.

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Appendix 1

In order to verify Proposition 1 through 3, it is easiest to start from the equilibrium conditions stated in their dual form. To this end, let $c^T(w^u, w^s, r)$ and $c^M(w^u, w^s, r)$ represent the unit cost functions associated with the traditional and modern organisations. The equilibrium conditions for our problem can then be expressed by the following 5 equations:

$$c^T(w^u, w^s, r) = 1, \quad (1A)$$

$$c^M(w^u, w^s, r) = 1, \quad (2A)$$

$$Y^T c_1^T(w^u, w^s, r) + Y^M c_1^M(w^u, w^s, r) = U, \quad (3A)$$

$$Y^T c_2^T(w^u, w^s, r) + Y^M c_2^M(w^u, w^s, r) = S, \quad (4A)$$

$$Y^T c_3^T(w^u, w^s, r) + Y^M c_3^M(w^u, w^s, r) = K, \quad (5A)$$

In the above equations, Y^T and Y^M are the quantities of output produced by the traditional and modern organisations respectively, and C_j^i is the derivative of the cost function with respect to its jth argument. Equations (1A) and (2A) are the goods market equilibrium conditions in that the unit cost for each organisation must be equal to the price of the produced good (which is normalized to 1). Equations (3A), (4A) and (5A) are the factor market equilibrium conditions.

The effects of factor supplies on factor prices can be derived by totally differentiating the above system, that is, by solving the system of equation given below:

$$\begin{pmatrix} c_1^T & c_2^T & c_3^T & 0 & 0 \\ c_1^M & c_2^M & c_3^M & 0 & 0 \\ Y^T c_{1,1}^T + Y^M c_{1,1}^M & Y^T c_{1,2}^T + Y^M c_{1,2}^M & Y^T c_{1,3}^T + Y^M c_{1,3}^M & c_1^T & c_1^M \\ Y^T c_{2,1}^T + Y^M c_{2,1}^M & Y^T c_{2,2}^T + Y^M c_{2,2}^M & Y^T c_{2,3}^T + Y^M c_{2,3}^M & c_2^T & c_2^M \\ Y^T c_{3,1}^T + Y^M c_{3,1}^M & Y^T c_{3,2}^T + Y^M c_{3,2}^M & Y^T c_{3,3}^T + Y^M c_{3,3}^M & c_3^T & c_3^M \end{pmatrix} * \begin{pmatrix} dw^u \\ dw^s \\ dr \\ dY^T \\ dY^M \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ dU \\ dS \\ dK \end{pmatrix} \quad (5.1)$$

For example, from the above system, the change in the unskilled wage induced by a change in the supply of skilled labor is given by

$$\frac{\partial w^u}{\partial S} = \frac{(c_3^T c_2^M - c_2^T c_3^M) * (c_1^T c_3^M - c_3^T c_1^M)}{D}$$

where D is the determinant of the left hand side matrix. Since concavity of technologies implies that D is negative in this three factor case (see Diewert and Woodland (1977)), $\frac{\partial w^u}{\partial S}$ is negative if $(c_1^T c_2^M - c_2^T c_3^M) > 0$ and $(c_1^T c_3^M - c_3^T c_1^M) > 0$. Since by Sherpards Lemma, $c_i^j = X_j^i$, these conditions correspond to the conditions stated in Proposition 1 and hence prove this comparative static. The statements all of the other comparative statics in the three propositions can be verified in the exact same manner. Note that in the case of determining the effects on relative wages, it is useful to exploit the fact that $w^u C_1^i + w^s C_2^i + r C_3^i = 1$.

Example Here is simple example that has the property that the solution to the system of equation (1A) to (5A) can be solved explicitly.

Let the unit cost function in the traditional organisation be $c^T(w^u, w^s, r) = w^u + r$ (that is, the traditional organisation does not use skilled labor) and let the unit cost function in the modern organisation be $c^M(w^u, w^s, r) = (w^S * r)^{\frac{1}{2}}$ (that is, the modern organisation does not use unskilled labor). Note that these cost functions imply a leontief technology in the traditional organisation and a Cobb-Douglas technology in the modern organisation.

With these unit cost functions, if $K > S + U$, then the system of equations (1A) to (5A) has a solution with all positive elements, which implies that both technologies are used in a competitive equilibrium, and this solution is given by:

$$w^U = 1 - (\frac{S}{K-U})^{.5}$$

$$w^S = (\frac{K-U}{S})^{.5}$$

$$r = (\frac{S}{K-U})^{.5}$$

$$Y^T = U$$

$$Y^M = 2S^{.5} * (K-U)^{.5}$$

Note that when $S + U < K < 4S + U$, the premises of Propositions 1 to 3 are satisfied. ¿From this example it is easy to verify all the comparative statics stated in the propositions.

Appendix 2

The data on wages and labour quantities are drawn from the March Current Population Survey (CPS). In most of the work we use the data years, 1976-2000, though we also use the years 1971-1975 in some instances. As stated in the text, we associate a skilled worker with a university graduate and an unskilled worker with someone who has education equivalent to a high school diploma or less. The specific education groupings we use are as follows. Before 1992, we define three education categories used in creating wage and quantity indexes: high school or less (years of completed schooling less than or equal to 12); some post-secondary (years of completed schooling greater than 12 and less than 16); and university (years of completed schooling greater than or equal to 16). After 1992: categories relating to education levels less than or equal to high school diploma; categories related to post-secondary education less than completing a BA; categories related to a completed BA or more.

Average weekly wages are calculated as annual earnings in the year before the survey was taken divided by total weeks worked in that year. In constructing average wages, we use the March Supplemental weight from the CPS. We use only observations for which earnings were not imputed as denoted on the Unicon CPS tapes. Annual earnings includes both farm and non-farm self-employed income to capture all returns in the labour market. The earnings measures are top-coded and we follow the practice (see Katz and Murphy(1992)) of multiplying each top-coded earnings value by 1.45. The nominal wage index created in this way is transformed into real terms using a GDP deflator.

In contrast to the wage indexes, in constructing the low and high skill quantity indexes we wish to include all relevant labour employed, where our measure of labour employed is total weeks worked. In principle, this simply involves adding up weeks worked by all low skilled (high school or less educated) workers and by all high skilled (BA or more educated) workers, properly weighted using sampling weights reported in the CPS. Thus, we include weeks worked by both males and females of all experience levels and regardless of full year/full time status. In fact, three main complications arise in calculating these indexes. First, individuals who have more than a high school education but less than a BA can potentially be seen as part of either the low skilled or the high skilled labour force for the purposes of generating values of marginal products and hence wages. Thus, we need to count up quantities of labour for all three types of workers (high school or less, post-secondary less than BA, and BA or more) and then attribute the labour supplied by those with a post-secondary education less than a BA to the main categories of interest. Second, the education categories underwent substantial revisions in 1992 and this affects our series. Third, simply adding up weeks worked within educational categories treats labour supplied by more and less experienced workers and by males and females as perfectly substitutable. This seems inappropriate and we follow a general methodology outlined in Katz and Murphy(1992) to address this.

In order to create a consistent quantity measure that does not treat all workers with the same education level as perfect substitutes, we re-weight contributions to the education specific quantity indexes using relative wages. In particular, for each of the three education groups, we divide individuals by gender and into 11 age categories. Each category from age 16 to age 65 is five years wide and the last category is age 66 or more. For each education/gender/age group we calculate the average wage over the sample period and the total weeks worked in each year. We divide the average wage for the group by the average wage of an education specific base group and then multiply the resulting ratio times the group specific total weeks worked. We then add up the reweighted total quantities for each relevant educational category for each year. We choose the base groups to match the wage index. Thus, for the high school educated we use males aged 19 to 28 and for both the post-secondary (not BA) and university educated we use males aged 23 to 32. This procedure treats relative wages as measures of relative productivity and thus gives us total quantities in young male equivalent weeks. We normalized the quantity indices in 1971 to assure that the product of the quantity index times wage index constituted a wage bill equal to that observed in the national income and product accounts in 1971. The factor shares for the rest of the sample are then constructed using the product of the quantity measure times the wage measure. Using factor shares derived entirely from the national income accounts does not change our results.

Once the initial quantity series were constructed, we adjusted them to account for the education definition changes in 1992. The shift to using educational categories rather than years results in noticeable jumps in the quantity series, particularly those for the high school or less and some post-secondary series. Plotting three education group quantity series, one notices that the definition changes appear to change the levels but not the time patterns in each. Taking this into account, we regress the high school educated quantity series on a time trend, the time trend squared and a dummy variable representing the post-1992 period. We then add the coefficient on the post-1992 dummy variable to the post-1992 high school quantity values. We formed the same regression for the university educated but found the post-1992 dummy did not enter significantly and so made no adjustment to that series. For the post-secondary (not BA) series, we subtract the high school educated post-1992 dummy coefficient from all post-1992 observations. This ensures that we do not create extra supply of any kind through our adjustment process. The resulting, corrected series are substantially smoother than the initial, uncorrected series.

Finally, we need to apportion the movements in the post-secondary(not BA) series between the low and high skilled categories. To do this we use the weights reported in Katz and Murphy(1992), which are based on a regression of post- secondary wages on those of high school and university educated workers using US data. This yields a division of 0.69 of the post-secondary(no BA) quantities being assigned to the high school quantity measure and 0.29 being assigned to the university measure. The rationale behind this procedure is that post-secondary(no BA) workers are like each of the other education classes to the extent their wage movements are similar. We also tried a range of different divisions of the post-secondary quantities. Our results are robust to these variations. We chose to use the Katz and Murphy(1992) weights in order to make our results more easily comparable with the existing literature.

Figure 1
University – High School Wage Differentials
By Experience Grouping and Gender

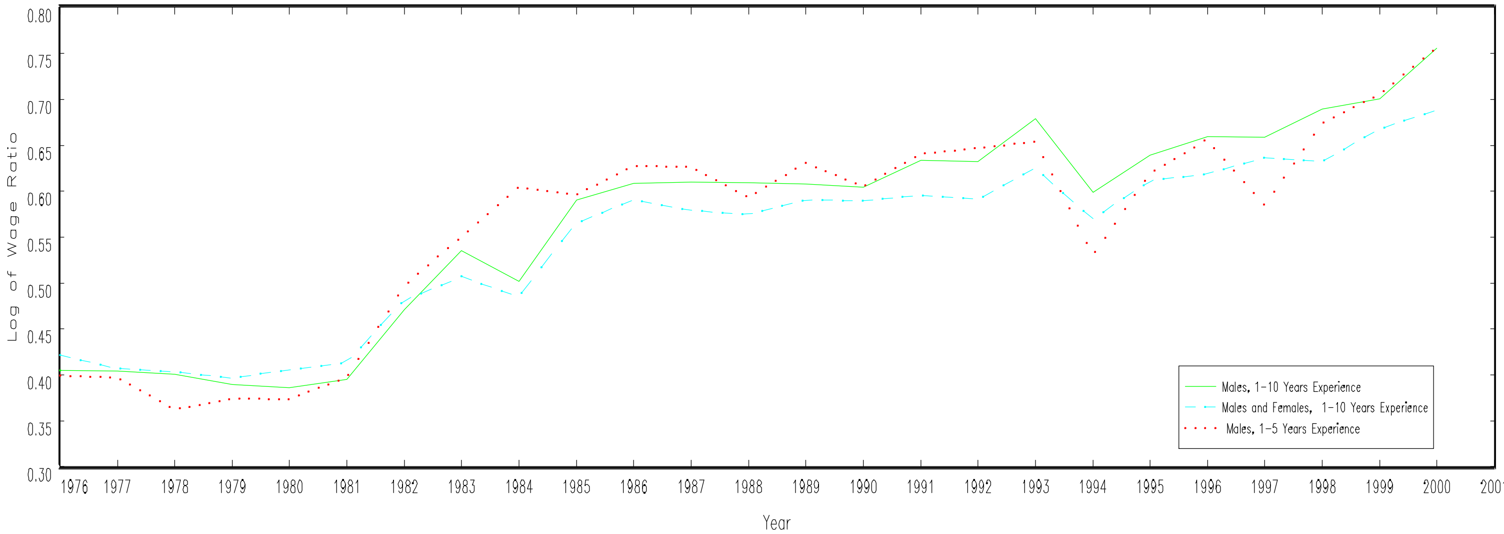

Figure 2
Log Real Wages For the High School Educated
Males, 1 – 10 Years Experience

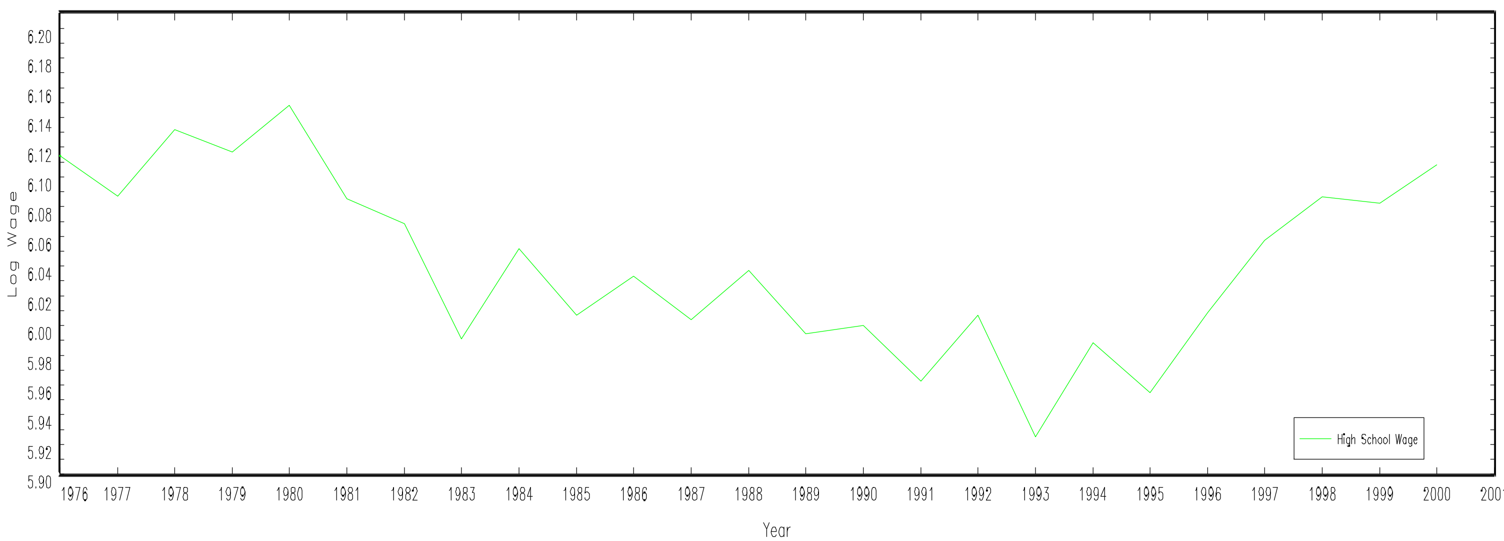

Figure 3
Relative Labour Quantities: Skilled Relative to Unskilled

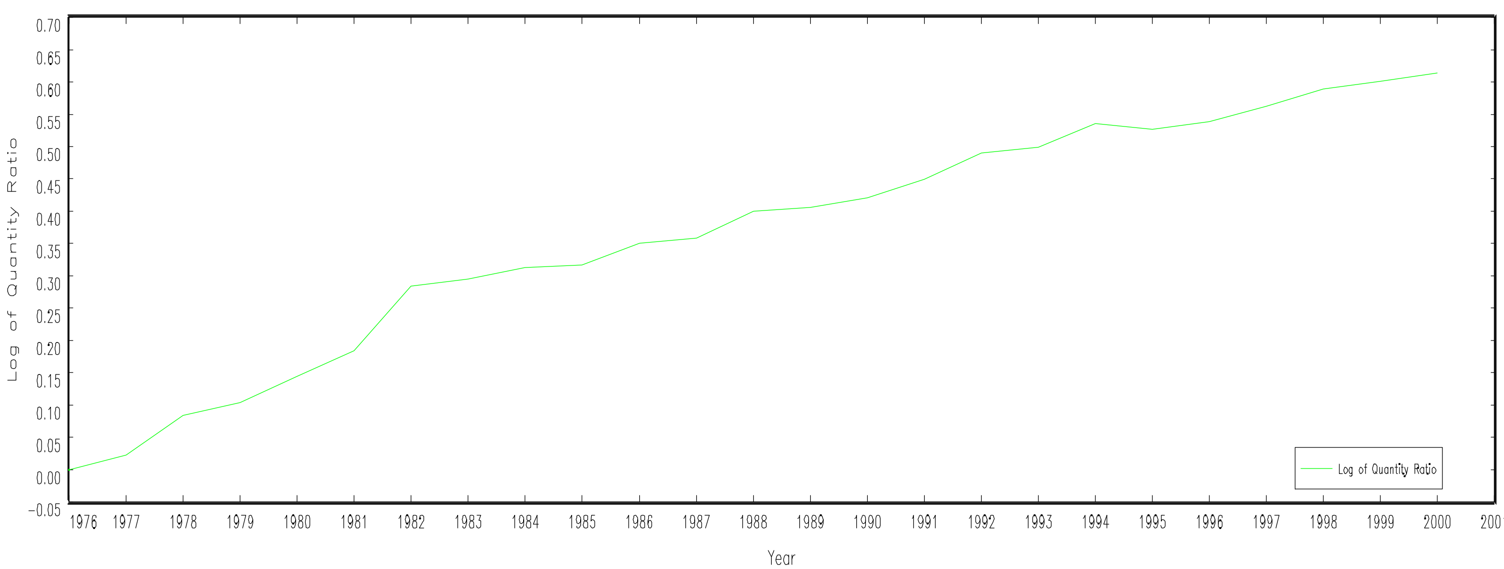

Figure 4
University – High School Wage Differential, Fitted and Actual
Males, 1-10 yrs exp

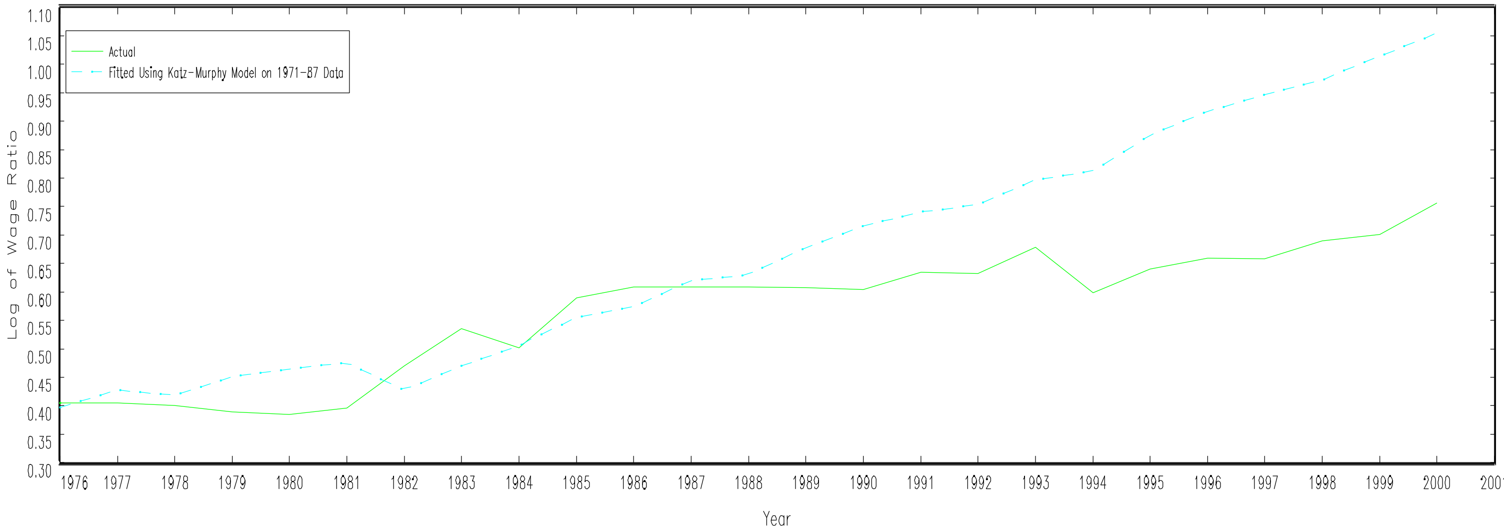

Figure 5a
University – High School Wage Differential: Actual Series and Fitted Value Using S*/K

Figure 5b
Low Skilled Wage: Actual Series and Fitted Value Using Only S*/K

Figure 6a

University – High School Wage Differential: Actual Series and Fitted Values

Males All Years Experience

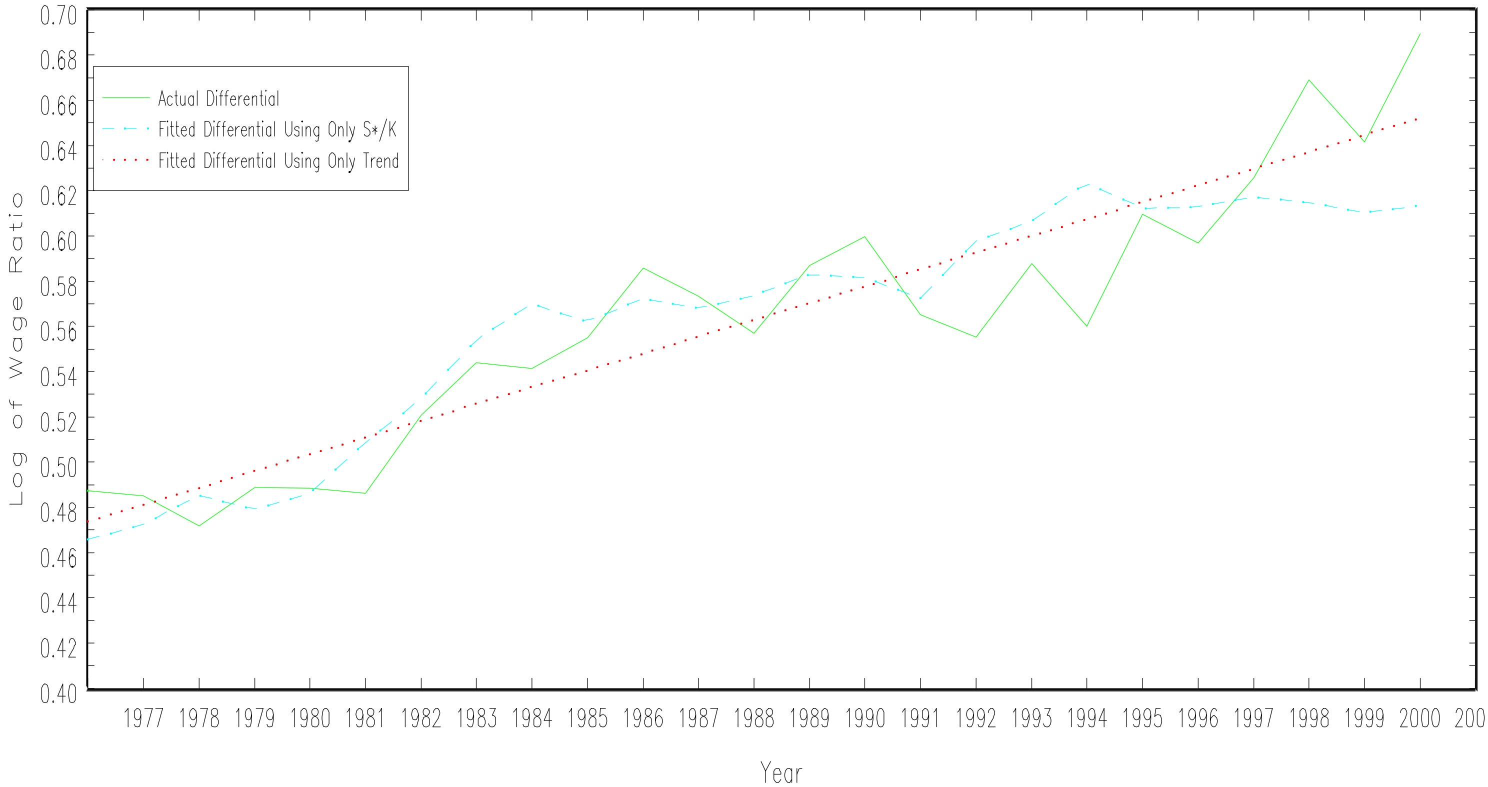

Figure 6b

Low Skilled Wage: Actual Series and Fitted Value Using S*/K

Males All Years Experience

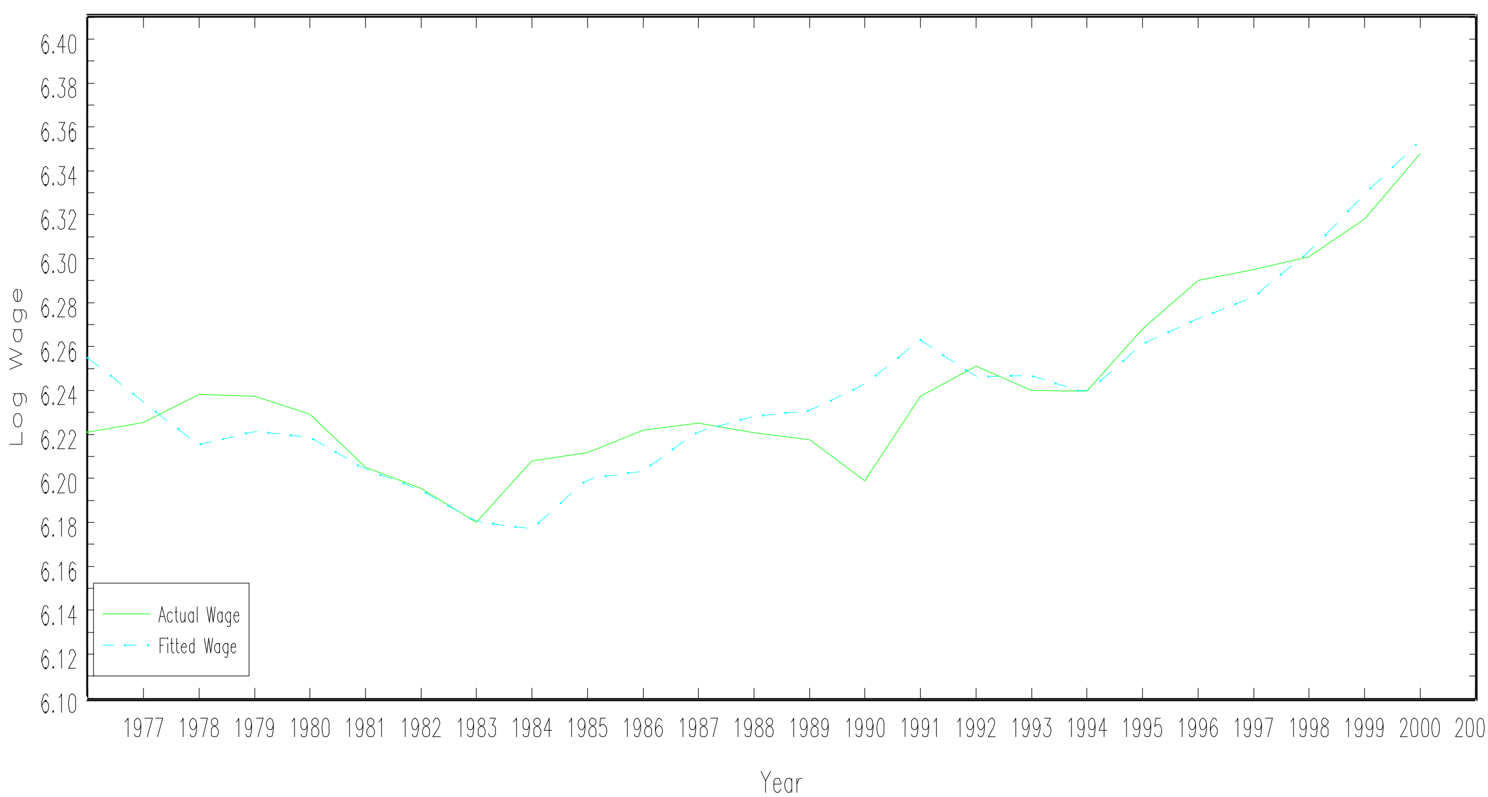

Figure 7a
Capital Series

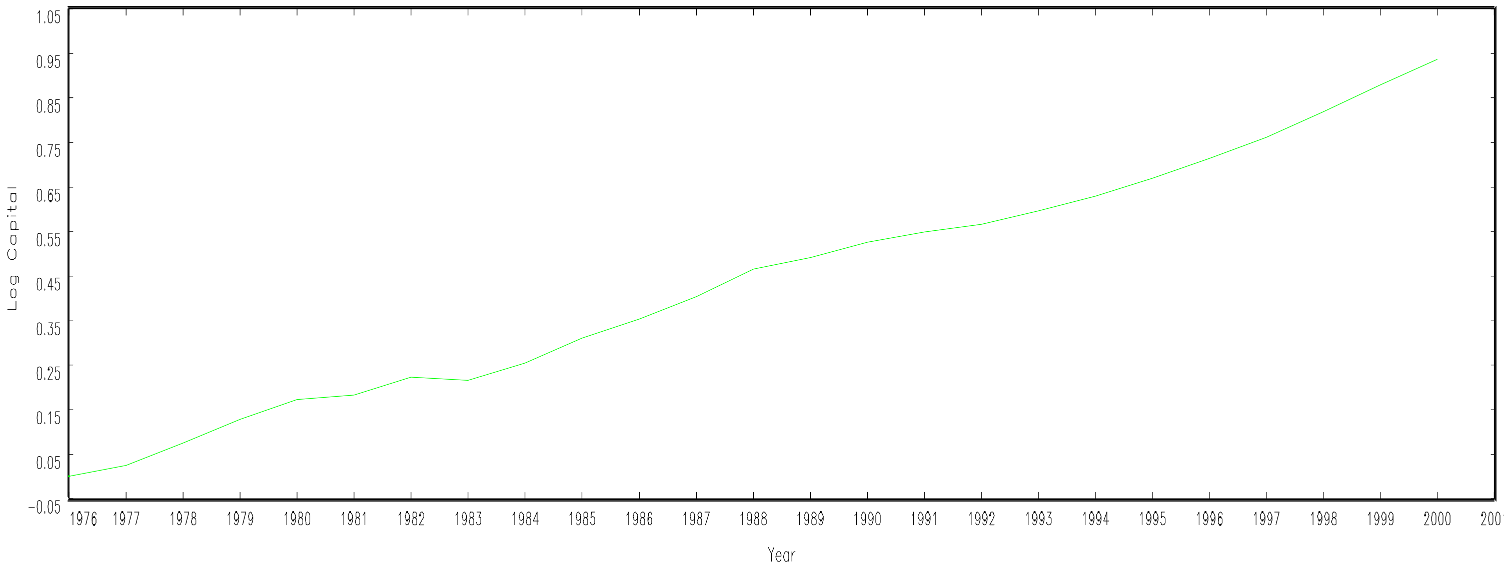

Figure 7b
Skilled Labour to Capital

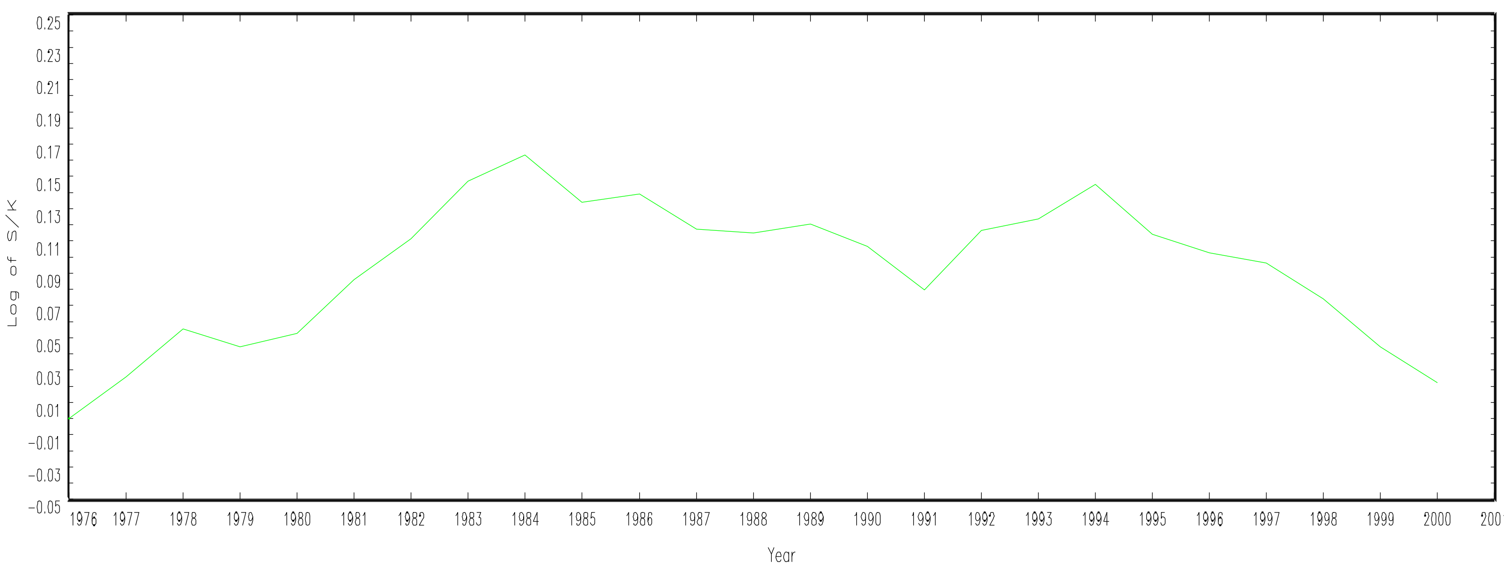

Figure 7c
Total Factor Productivity