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THE CHANGING STRUCTURE OF WAGES IN THE US AND GERMANY: WHAT EXPLAINS THE DIFFERENCE?

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ABSTRACT

Over the last twenty years the wage-education relationships in the US and Germany have evolved very differently, while the education composition of employment has evolved in a surprisingly parallel fashion. In this paper, we propose and test an explanation to these conflicting patterns. The model we present has two important elements: (1) technological change arises in the form of an alternative production process as opposed to being in the factor augmenting form, which renders technological adoption endogenous, (2) aggregate production depends on three factors (physical capital, human capital and labor). Based on this framework, we show why imbalances in the accumulation of human versus physical capital will be especially detrimental to low skill workers when the new technology is skill-biased and exhibits capital-skill complementarity. Using matched files from the PSID (US) and the GSOEP (Germany), we demonstrate how factor movements within these countries are associated with wage changes that are strongly supportive of our endogenous technological adoption model. Our conclusion is that the difference in the US and German experiences appear driven by the US having under-accumulated physical capital relative human capital over the 1979-96 period, while Germany accumulated factors in a more balanced manner.

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1 Introduction

It is well known that the wage structure in the US has changed considerably over the last twenty years, with the most notable change being an increase in the returns to skill (Juhn, Murphy, Pierce (1993). Over the same period, the wage structure in Germany changed much less and in contrasting ways to the US . In particular, wage inequality did not increase in Germany over the eighties and, as documented by Krueger and Pischke (1997), the return to skill actually fell. [1] The most striking difference between the American and German wage experience over this period is the wage change for less educated men (men with 10 to 12 years of education). In the US, real wages for this group have declined by over 20% since the late seventies, while they increased by over 10% in Germany.

Such differences in real wage changes could be easily understood if they were associated with offsetting differences in changes in the structure of employment. A common theory about differences between Europe and the US is that both have faced the same skill biased demand shift but that in the US, with its more flexible labour market institutions, this showed up as reduced wages for the low skilled while in Europe it was revealed as relatively poorer employment outcomes for the low skilled. However, as emphasized by Krueger and Pishke (1997), this has not actually been the case. In particular, employment rate changes for less educated men were almost identical in the US and Germany over the eighties even though wage changes differed substantially. It is true that over this period unemployment rates increased in Germany while they decreased in the US.[2] However, it is now recognized that the increase in unemployment in Germany was not particularly concentrated among the less skilled workers (see Gottschalk and Smeeding (1997)). In effect, the increase in unemployment has been proportionally spread across the skill spectrum, allowing the education mix of the employed population to evolve very similarly in Germany and the US.[3] These observations lead us to the following question: Why would the wage structures in the US and Germany diverge over the

[1] The German experience appears to be representative of changes observed in continental Europe in general. For example, Card, Kramarz, Lemieux (1999) find a similar pattern for France.

[2] The differential performance of the US and Germany in terms of unemployment must not be overstated. As indicated by Freeman & Schettkat (00), the BLS calculation for internationally comparable unemployment rates shows that Germany's unemployment rate averaged 5.8% between 1979 and 1989 and 5.7% between 1989 and 1995, while the US rate averaged 7.2% between 1979-89 and 6.2% between 1989-95. Hence, over this period, Germany should not be viewed as a high unemployment rate country relative to the US.

[3] To emphasize this point, it is useful to compare the evolution of an education index of employment over the period. To this end, we used the PSID and GSOEP matched files (described in section 4) to calculate the hours-of-employment weighted average years of education in the US versus Germany. For the US, the employment weighted average years of education were 12.72 in 1979, 12.95 in 1983 and 13.57 in 1995. In comparison, for Germany the employment weighted years of education (which include an adjustment for apprenticeships) were 11.79 in 1983 and 12.35 1995. In percentage terms, this implies a growth of 4.7% in both countries over the period 1983-1995. This calculation highlights the fact that the education structure of employment changed in a surprisingly parallel fashion in the US and Germany over the eighties and early nineties.

eighties and nineties, while the skill-structures of employment did not?

The object of this paper is to propose an answer to the above question.[4] Our starting point is the view that recent transformations in developed economies reflect the wide- spread availability of a new General Purpose Technology (GPT)[5] which, as emphasized by Bresnahan, Brynjolfson and Hitt (1999), is more than simply the introduction of computers and is most likely a reflection of a whole new mode of work organization.[6] We develop a model of the effects of a transition to a new GPT on the labour market; particularly, on the wage-education relationship. A main insight of the model is that, during the process of adoption of a new GPT, there should exist a balanced accumulation path where the wage structure would not change if the economy accumulated human and physical capital according to this path. In such a context, changes in the wage structure are driven primarily by imbalances in the relative usage of human versus physical capital. Moreover, by placing simple restrictions on the differences between the new and old mode of production, the model provides clear predictions regarding the manner in which such imbalances in human and physical capital usage should affect the wage structure.

Using matched files from the PSID and the GSOEP over the period 1979-1995, we examine movements in the wage-education profile for the US and Germany and relate them to movements in aggregate human and physical capital. We show that the data reveals the existence of a balanced accumulation path as predicted by our two competing GPT model. Furthermore, we find that the manner in which imbalances in human versus physical capital accumulation affect the wage structure is consistent with the view that the newer technology exhibits capital-skill complementary, is skill-biased and has increased capital efficiency relative to the older technology. Our conclusion is that the difference between the US and German experiences can be explained as arising because the US under-accumulated physical capital relative to human capital while Germany accumulated factors in a manner closer to the balanced path.

The remaining sections of the paper are organized as follows. In Section 2, we present a simple model in which firms have access to two different technologies. We use the model to derive a set of restrictions on the relationships between the equilibrium wage-education profile and the aggregate factor usages in the economy. In Section 3 we discuss how the model can be empirically implemented, with an emphasis on issues of identification. In Section 4 we describe the data used in our empirical analysis and in Section 5 we explore the model empirical validity. Section 6 contains conclusions.

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[4] The theory section of this paper extends and generalizes ideas discussed in Beaudry & Green (1998).

[5] See Bresnahan & Trajtenberg (1995) for a discussion of General Purpose Technologies.

[6] The paper most closely related to ours is Caselli (1999). In effect, our theoretical framework is very close to certain ideas presented in Caselli (1999). Other papers addressing similar issues include Acemoglu (1998),(1999), Duranton (1999), Zeira (1998).

2 A Model of competing modes of production and its implications for wage-education profiles.

Our primary aim in this section is to develop a model decomposing movements in the wage- education relationship into changes induced by the arrival of new technologies and changes induced by variations in factor use. This is a common goal in much of the literature examining movements in wage-education relationship. However, in contrast to a large segment of this literature, we focus on technological change that arises in the form of a new (or competing) production process as opposed to being in a factor augmenting form. In particular, we view this way of capturing the arrival of a new technology as reflecting ideas emphasized in the organizational change literature (See for example Bresnahan & al. (1999)), whereby there are concurrently competing modes of organizing production (a more decentralized mode versus a more hierarchical mode) and the choice of organizational mode is endogenous and affected by factor prices. Our approach shares some of the spirit of the model in Acemoglu(1998) which explains the movements in a search context where relative movements in the supply of more versus less educated workers induce firms to adopt certain technologies. As we shall see, though, our model is quite different from Acemoglu(1998)'s in that we emphasize the importance of physical as well as human capital movements. Indeed, it is this latter element of our model which we argue explains differences between the US and Germany.

Our main goal in presenting a competing technology model is to rethink the relationship between changes in factor use and changes in the wage-education relationship when the economy is undergoing a major technological or organizational change. For example, we will show that in that situation, even when the newer technology (or mode of organization) is skill biased and satisfies capital-skill complementarity, an increase in physical capital is likely to be especially beneficial to low educated workers. Furthermore, we show that an increase in aggregate human capital is likely to be detrimental to workers who remain unskilled. We will also show that, when the economy is in a transition phase with two technologies in use, the economy will possess a balanced accumulation path whereby the wage-education relationship would remain unchanged if factors were to be accumulated according to the combination dictated by this path. Once we have derived and explained these relationships, we will be well positioned to go examine whether such a framework can help reconcile the wage and employment changes observed in the US and Germany.

One important aspect of our analysis is that we focus on a transition phase in which both a newer and an older technology are simultaneously in use. On theoretical grounds this is a reasonable scenario since (as we will discuss), whenever there is more than one factor of production, general equilibrium forces will tend to favour a situation where more than one technology is in use at any given time. Moreover, we believe that from an empirical perspective it is reasonable to characterize the period we are examining (1979-1996) as containing such a transition phase between two modes of organization.

In order to formally examine the relationship between changes in factor use and changes in the wage structure when the economy has a choice between two modes of organization (or technologies), let us denote by $F^O(K^O, H^O, L^O)$ the production function for the older or more traditional mode of production, and let $F^N(K^N, H^N, L^N)$ represent the technology associated with the newer competing mode of production. Both these technologies are assumed to exhibit constant returns to scale and depend on the quantities employed of physical capital, K, human capital, H, and labour L. There is only one good in the model, and therefore we interpret it as an aggregate good producible by either of two competing technologies.

We will denote by Q^O and Q^N the quantities of the aggregate good produced using each of the technologies. Throughout, we will assume firms act as price takers and choose the technology and factor quantities that maximize profits. The most convenient approach to deriving the results of interest would be to work in a completely Walrasian setting. However, many observers have suggested that institutional rigidities in the German labour market militate against ongoing equalization of labour demand and supply. Thus, to ensure that our model reflects the realities of the German economy, we derive our results without requiring that the demand and supply of labour are always equal. Instead, we rely on the assumption that firms are price takers, with the key implication that observed factor use must be on the firm's factor demand schedule. With this in mind, we state two lemmas that are somewhat trivial to derive but are nonetheless important for our analysis.

Lemma 1: If K_t, H_t and L_t represent the aggregate quantities of factors **employed** in the economy, then price taking behaviour by firms implies that the allocation of production and factors between the two competing technologies will solve the following maximization problem.

$$\max_{Q^j, K^j, H^j, L^j, j=O,N} \quad Q^O + Q^N$$

s.t

$$\begin{gathered} Q^O = F^O(K^O, H^O, L^O), \qquad Q^O > 0 \\ Q^N = F^N(K^N, H^N, L^N), \qquad Q^N > 0 \\ K_t = K^O + K^N, \quad H_t = H^O + H^N, \quad L_t = L^O + L^N \end{gathered}$$

Proof: All proofs are given in Appendix 1.

The first aspect to take from Lemma 1 is that, if firms are profit maximizing price-takers, the economy's allocations will achieve production efficiency (in the sense of making efficient use of the factors actually employed) regardless of whether the quantities of factors used in the economy equal the quantities supplied. This level of generality is relevant for our analysis given that, at least in the case of Germany, it is probably inappropriate to assume that factor usage is equal to factor supply. Hence, Lemma 1 can be used to highlight implications of a two technology model that do not depend on full market clearing. In particular these statements imply that observed factor prices will equal values of marginal products.

The second and more subtle aspect to take from Lemma 1 is that there will generally exist a whole set of aggregate factor usages which correspond to both techniques of production being used in equilibrium; that is, production efficiency does not imply that only one technique should be used. [7] In order to see this point more clearly, it is helpful to consider the somewhat extreme case where the older technology requires only physical capital and labour (but not human capital), while the newer technology requires only human and physical capital (but not unskilled labour). In such a setting, it is quite obvious that both modes of production will be used in any price taking equilibrium in which all factors are used in positive amounts.

We are particularly interested in the case where factor proportions in the economy have not yet led to the complete abandonment of the older methods of production which use less human capital. We view this as consistent with the view that developed economies have been gradually adopting a new technology.

In order to discuss the implications of competing technologies for the structure of wages, we need to be precise with respect to our distinction between labour and human capital. We assume that individuals, indexed by i, have two attributes: their number of years of education y_i and a person specific efficiency index ψ_i . Correspondingly, the total labour employed in the economy consists of an efficiency weighted sum of labour hours, that is, $L = \sum_{i=1}^{I}(l_i\psi_i)$ where l_i is the number of hours worked by individual i. Similarly, the total amount of human capital employed in the economy is measured by the skill weighted effective hours of work, where the supply of human capital associated with an effective hour of work by an individual with y_i years of education is denoted $\gamma(y_i)$, that is, $H = \sum_{i=1}^{I}(l_i\psi_i\gamma(y_i))$. Finally, we denote by $w_t(y_i)$ the log of the hourly wage paid at time t to an individual with education level y_i. We refer to the function $w_t(y_i)$ as the wage-education relationship. Lemma 2 clarifies the dependence of the wage-education relationship on the economy's usage of factors.

Lemma 2: If firms are price takers, then the wage-education relationship only depends on the aggregate values of the capital-labour ratio and the human capital-labour ratio (it does not depend on the break down of factor used in the different technologies). Furthermore, the wage-education relationship can be approximated in the following manner:

[7] This is similar in spirit to the existence of a diversification cone in a trade model.

$$w_t(y_i) \approx \alpha(\frac{K_t}{L_t}, \frac{H_t}{L_t})) + \beta(\frac{K_t}{L_t}, \frac{H_t}{L_t})\gamma(y_i) + ln(\psi_i) \qquad (1)$$

where

$$\alpha(\tfrac{K_t}{L_t}, \tfrac{H_t}{L_t})) = \alpha_0 + \alpha_1 ln(\tfrac{K_t}{L_t}) + \alpha_2 ln(\tfrac{H_t}{L_t})$$

$$\beta(\tfrac{K_t}{L_t}, \tfrac{H_t}{L_t}) = \beta_0 + \beta_1 ln(\tfrac{K_t}{L_t}) + \beta_2 ln(\tfrac{H_t}{L_t})$$

In the above equation the function $\alpha(\cdot)$ governs the time variation in the intercept of the wage-education relationship and the function $\beta(\cdot)$ governs the time variation in the slope of the profile. Lemma 2 indicates that the time variation in both the slope and the intercept of the wage-education profile are related only to the aggregate capital intensities $\frac{K_t}{L_t}$ and $\frac{H_t}{L_t}$ prevalent in the economy. In essence, it states that for any given levels of aggregate factor employments, production efficiency means that there will be a unique (efficient) allocation of the factors across modes of production. Thus, with free mobility of factors across modes, we can map directly from aggregate factor quantities to the economy-wide factor prices.

With these two preliminary Lemmas in place, we can now state our first result emphasizing how the presence of two competing technologies places restrictions on the relationship between human and physical capital usage and the wage-education profile. However, it is first necessary to define the concept of a balanced accumulation path.

Definition: A balanced accumulation path corresponds to a combination of factors such that, if the economy employs factors according to the dictates of this path, the wage-education profile will remain unchanged.

Proposition 1: If both technologies to being used in the economy then there must locally exist a balanced accumulation path.[8]

Proposition 1 captures what may be the most basic insight of our paper: in the presence of two competing technologies, changes in the wage structure can generally be traced back to imbalances between the use of human versus physical capital. In other words, if our competing technologies framework offers a plausible scenario for understanding periods of great technological change, most across-time or across-country analysis of observed changes in the wage structure should focus on imbalances in the use of human versus physical capital as a candidate explanation of such change. In particular, this suggests that studies that disregard either changes in either physical or human

[8] Along the balanced accumulation path, an increase in educational attainment for the population is associated with individuals all moving up a fixed wage-education profile.

capital intensity may be severely biasing the analysis.

In order to clarify how Proposition 1 constrains the determinants of the wage-education relationship, it is helpful to make explicit the restrictions it implies for the αs and the βs of Equation 1. The existence of a balanced accumulation path implies that accumulation along that path leaves both the slope and the intercept of the wage-education profile unchanged. For this to be true, the change in physical capital intensity needed to offset the effects of a change in human capital intensity on the intercept term in Equation 1 must be equal to change in physical capital intensity needed to offset the effects of a change in human capital intensity on the slope term. Hence, the restrictions can be stated as follows:

Restriction 1: Proposition 1 implies that:

$$\frac{\alpha_1}{\alpha_2} = \frac{\beta_1}{\beta_2}$$

There are two interesting aspects to note from Restriction 1. First, the restriction is quite strong; that is, unless we ready to envisage that the wage-education profile is actually generated by an economy where two modes of production are simultaneously in use, we would not expect such a restriction to hold.[9] Hence, testing whether wage-education profiles satisfy Restriction 1 is a good test of whether our two competing technology model is plausible. Second, under Proposition 1, observed changes in wage-employment profiles should reveal the existence of a balanced accumulation path regardless of whether or not the data being examined evolves along this path since the existence of a balanced accumulation path can be inferred from the αs and βs.

Given Proposition 1, we know that the simultaneous use of two modes of production implies that changes in wage-education profiles can be traced to imbalances (relative to the balanced path) in the physical and human capital intensities employed in the economy. We now want to go a step further and indicate how such imbalances can modify the wage-education profile.[10] However, in order to do so, we must impose some structure on the differences

[9]In other words, it is not generic for an arbitrary aggregate production function to generate a wage education profile which would satisfy Restriction 1, while it is generic if there are two competing modes of production underlying the aggregate production function.

[10]If one assumes that the economy faces a perfectly elastic supply of capital, then the economy will always employ factors according to the balanced accumulation path. In this case, the wage-education profile would not change regardless of the increase in human capital. Since we do observe changes in wage profiles across countries and since we also observe different ratios of physical to human capital accumulation, we don't believe that it is appropriate to simply impose the assumption of a perfectly elastic supply of capital. Instead, we believe that is preferable to let the data indicate whether or not physical capital accumulation tends to respond to changes in human capital usage in a manner suggestive of a perfectly elastic supply function for capital. Our results will suggest, as is the case with much of the empirical literature on international capital flows, that the assumption of a perfectly elastic supply function for capital is not supported in the data and therefore is too extreme.

between the two techniques in use. Our approach is to exploit existing ideas in the literature regarding the likely differences between the newer technology (or new economy) and the more traditional mode of production (the old economy). The work by Goldin & Katz (1998) emphasizes that one of the likely differences between the different generations of technology is that the newer technology exhibits capital-skill complementarity relative to the old. Assumption 1 makes this notion of capital-skill complementarity precise.[11]

Assumption 1: The newer technology satisfies capital-skill complementarity relative to the old technology, that is,

$$\frac{H_P^N}{L_P^N} > \frac{H_P^O}{L_P^O} \quad and \quad \frac{K_P^N}{L_P^N} > \frac{K_P^O}{L_P^O}$$

In the above expression, a term of the form H_P^N represents the amount of human capital chosen at factor prices p to produce one unit of the good with the newer technology. In other words, Assumption 1 is stated in terms of unit input requirements. The assumption corresponds to assuming that the newer technology is a more capital intensive production process in terms of both human and physical capital. As discussed in Goldin and Katz (1999), all of the major technological shifts of the twentieth century appear to satisfy this assumption.

Based on this Assumption, we can derive the following restriction on the nature of the balanced accumulation path.

Proposition 2: If assumption 1 holds, then the balanced accumulation path has the property that increases in human capital intensity must be accompanied by increases in physical capital intensity.

Proposition 2 is quite intuitive. It indicates that to keep the wage-education relationship unchanged when both technologies are in use, an increase in human capital usage must be offset by an increase in physical capital usage. The intuition for this is seen most easily in the context of the extreme example in which the old technology uses only K and L while the new technology uses only K and H. In this context, an increase in H means more use of the new technology, which is relatively H intensive. The increased use of the new technology in turn implies more demand for capital because of capital skill-complementarity. Then, to satisfy the increased demand for capital without changing the structure of factor prices, the increase in human capital must be accompanied by an increase in physical capital. In terms of restrictions on the parameters of Equation (1), Proposition 2 implies the following.

[11] The notion of capital-skill complementarity we use here is based on a comparison of two technologies (as in Katz-Goldin (1999)). This notion of capital skill complementarity should not be confused with the one often used in the demand literature which relates to the properties of a given technology.

Restriction 2: Proposition 2 implies that

$$\alpha_1\alpha_2 < 0 \quad and \quad \beta_1\beta_2 < 0$$

Performing a test of Restriction 2 offers a rather easy way of examining whether the capital-skill complementarity assumption of Goldin & Katz is valid. However, Proposition 2 still leaves us far short of a full characterization of how imbalances in human versus physical capital usage are likely to affect the wage-education profile. In order to move further along in this direction, we need to make an assumption about the relative skill biasedness of the two technologies, and give a concrete definition as to what we mean by relative biasedness. Our interpretation of the meaning that the newer technology is skilled-biased technology is expressed by Assumption 2.

Assumption 2 In terms of factor usages, the main feature of the newer technology is that it is skill-biased relative to the older technology, that is,

$$\frac{H_P^N}{H_P^0} > \frac{K_P^N}{K_P^O} > \frac{L_P^N}{L_P^O}$$

In relation to Assumption 1, Assumption 2 simply adds the notion that the higher human capital intensity of the newer technology (implicit in the capital-skill complementarity assumption) is more pronounced than its greater physical capital intensity. We believe that this notion of skill-biasedness captures the essence of the view that the new economy is dominated by the importance of human capital rather than physical capital. In particular, if Assumption 2 were not satisfied, then it is most likely that much of the anecdotal evidence on the nature of the current technological revolution would be emphasizing the increased importance of physical capital. In contrast, it is interesting to note that many of the major technological changes earlier in twentieth century may not have satisfied Assumption 2, even if they satisfied Assumption 1. This would explain why current developments are viewed by many as a change in paradigm and why the importance of the process of physical capital accumulation was generally regarded as more central in earlier parts of the twentieth century than it is now.

Our interest in Assumption 2 is that it allows us to predict how imbalances in human versus physical capital accumulation related to changes in the wage-education profile. These predictions are given by Proposition 3.

Proposition 3: If Assumptions 1 and 2 hold, and both technologies are in use, then

(I) An increase in physical capital intensity is associated with a shift up in the wage-education profile (at all education levels).

(II) An increase in human capital intensity is associated with a shift down in the wage-education profile (at all education levels).

The most surprising aspect of Proposition 3 is the monotonicity. It is natural to conjecture that an increase in physical capital would shift up some part of the wage-education profile and that an increase in human capital would shift down, at minimum, the wages of the most educated. However, Proposition 3 indicates that the shifts are monotonic across education levels. In particular, Proposition 3 implies that if the newer technology is skill-biased relative to the old technology, then physical capital is a complementary input (in the aggregate) to the labour of all education levels. Similarly, it indicates that human capital is a substitute to the labour of all education levels. We must stress that this monotonicity is due specifically to the skill-biasedness assumption. If Assumption 2 did not hold but Assumption 1 did (which may be the relevant case for earlier the twentieth century), it can easily be shown that an increase in physical capital would be associated with a pivoting up of the wage-education profile (i.e., a decrease in the intercept and a steepening of the profile) while an increase in human capital would be associated with it pivoting downwards (i.e., an increase in the intercept and a flattening of the profile).

To understand more fully why such pivoting does not occur in this model, return again to the extreme model in which the newer technology uses only H and K. Notice that this model trivially satisfies the skill biasedness assumption since the old technology does not use H and the new technology does not use L. In this context, an increase in H induces an own price effect for H (leading to wage drops at the higher education end of the wage profile) but it also has effects on the choice of technology in the economy. In particular, after an increase in H, the return to K rises in the new relative to the old technology and K moves in response. As a result, firms using the old technology have less K to work with and thus the price of L will also fall. Associating the price of L with the wage of lowest educated individuals, this means that wages will also fall at low education levels. In this extreme case, this mechanism is essentially the same as that present in Caselli (1999).

In terms of explicit restrictions on parameters of the wage-education profile, the implications of Proposition 3 are quite easy to infer.

Restriction 3: In terms of Equation 1, Proposition 3 implies that

$$\begin{gathered}\alpha_1 + \beta_1\gamma(y_i) > 0, \forall y_i \\ \textit{and} \\ \alpha_2 + \beta_2\gamma(y_i) < 0, \forall y_i\end{gathered}$$

The last comparative static result we would like to derive relates to what changes in capital intensities imply for the slope of the wage-education profile (i.e, for the returns to education). This effect is driven by whether or not the newer technology is capital efficient relative to the older technology, that is, whether or not $K_P^N < K_P^O$. Since the existing literature is relatively silent about the capital efficiency of the newer technology, we state Proposition 4 in full generality.

Proposition 4: If Assumptions 1 holds, and both technologies are in use then,

if the newer technology is more capital efficient,

(I) An increase in physical capital intensity is associated with a flattening of the wage-education profile (at all education levels).

(II) An increase in human capital intensity is associated with a steepening of the wage-education profile (at all education levels).

Otherwise, if the newer technology is less capital efficient,

(I) An increase in physical capital intensity is associated with a steepening of the wage-education profile (at all education levels).

(II) An increase in human capital intensity is associated with a flattening of the wage-education profile (at all education levels).

Berman & Machin (2000) provides some evidence suggesting that, over our period of interest, the newer technology is likely more physical capital efficient that the older technology. Based on manufacturing data, Berman and Machin report that physical capital efficiency increased over the 1980s in 9 of the 11 OECD country they study [12]. If we view these countries as progressively adopting the newer technology, this would suggest that the newer technology is more physical capital efficient. Given this evidence, we examine directly whether the new technology is more physical capital efficient by testing restriction 4. Again, we would like to emphasize that an assumption like increased physical capital efficiency may be reasonable for characterizing the transformations taking place in developed economies in the late twentieth century but may not hold for transformations earlier in the twentieth century.[13] Indeed, the results in Berman & Machin (00) suggest that prior to the 1980s, physical capital efficiency in developed countries was declining. [14]

[12] Decreases in physical capital efficiency were found only in Australia and Finland

[13] For example, Zeira (1998) suggest that the opposite assumption may be warranted for understanding the growth in South East Asia.

[14] In our view, it is potentially fruitful to think of the twentieth century as a process of successive adoptions of newer technologies and replacement of older technologies, as opposed to a process of factor augmenting technological change within a given production function. In this context, there is no reason to believe that the newer technologies always have the same properties in relation to the older technologies. Thus, we believe that it is insightful to look at different periods and examine the likely properties of the newer GPTs being introduced in each case, investigating whether propositions like 1 through 4 (or their converse) help us to understand changes in the wage structure.

Restriction 4: In terms of Equation 1, if the newer technology is more physical capital efficient, Proposition 4 implies that

$$\beta_1 < 0 \quad and \quad \beta_2 > 0$$

We now want to turn to examining the empirical plausibility of Restrictions 1 through 4. However, before doing so, it is necessary to extend Equation (1) in order to turn it into a more reasonable empirical specification.

3 Empirical Implementation and Identification

We begin this section by discussing three issues aimed at extending Equation (1) in order to provide a more reasonable empirical specification (in which Restrictions 1-4 can be tested). The first issue involves considering the systematic effects of work experience on wages. The second issue relates to the specification of the $\gamma(\cdot)$ function. Finally, the third issue involves allowing for the possibility of factor augmenting technological progress. Once these three issues are addressed, we will have an empirical specification in which issues of identification can be easily discussed.

The first element we need to consider is that wages usually change with work experience. This possibility can be easily incorporated into our analysis by allowing the efficiency index ψ_i to incorporate an experience profile,$g(e_i)$, where e_i is the number of years of work experience of individual i. The individual specific efficiency index is then rewritten as $\psi_i g(e_i)$. Once this modification is taken into account in deriving Equation (1), the resulting equation reproduces a standard Mincer wage equation with the only difference being the explicit dependence of the wage-education profile on the aggregate employment of factors.

The second issue to be addressed is how years of education translate into effective units of human capital. Here there are two issues: first, the choice of a functional form for $\gamma(\cdot)$, and second, the issue of a normalization with respect to the level of skill associated with labour L. We choose to focus on a linear specification for $\gamma(\cdot)$ given that much of the recent literature estimating Mincer type wage equations have found such a specification provides a good fit to the data. Moreover, we explored alternative specifications and did not find evidence of significant non-linearities. In terms of our normalization of the skill level of L, we set it at nine years of education; that is, we set $\gamma(y_i) = \gamma_0(y_i - 9)$, where γ_0 is a scalar. We choose 9 years of education as our basis for the unskilled level of labour because that is very close to the minimum level of

The most compelling reason not to try to fit all transformations into the exact same pattern comes from the widely held view that the industrial revolution was biased against skilled workers while more recent changes appear biased in favour of skilled workers.

education attained by individuals in either the US or Germany.[15] [16] Taking into account these two effects, we can rewrite Equation 1 as follows.[17]

$$
\begin{aligned}
w_{c,t}(y_i, e_i) = \quad & \alpha_{c,0} + \alpha_1 ln(\tfrac{K_{c,t}}{L_{c,t}}) + \alpha_2 ln(\tfrac{H_{c,t}}{L_{c,t}}) \\
& (\beta_{c,0} + \beta_1 ln(\tfrac{K_{c,t}}{L_{c,t}}) + \beta_2 ln(\tfrac{H_{c,t}}{L_{c,t}}))(y_i - 9) + \\
& ln(g_c(e_i)) + ln(\psi_i) \qquad (2)
\end{aligned}
$$

In equation (2), we are allowing for data from different countries by subscripting the relevant variables by c. It is worth noting than in Equation (2) we are allowing for a country specific fixed effect, country specific returns to education and a country specific experience profile.

In principle, we could use Equation (2) as our basis for examining the validity of Restrictions 1-4. However, since much of the literature related to explaining recent changes in the wage structure has focussed on the role of biases in factor augmenting technological change, we believe that we should adopt a specification that allows for such a possibility. To this end, let $\theta^K_{c,T}, \theta^H_{c,t}$ and $\theta^L_{c,t}$ represent, respectively ,the index of productivity, in country c at time t, for physical capital, human capital and labour. Equation (2) can be easily extended to allow the possibility of factor augmenting technological change simply by multiplying each factor (K, H, L) by its corresponding index. Since these indices are not directly observable, it is useful to relate them to measured total factor productivity. In particular, if we denote by $TFP_{c,t}$ measured total factor productivity and we let $\lambda^j_{c,t}$, $j = K, H, L$, capture the degree of factor bias by the following definitions: $\lambda^K_{c,t} * ln(\theta^K_{c,T}) = ln(TFP_{c,t})$, $\lambda^H_{c,t} * ln(\theta^H_{c,t}) = ln(TFP_{c,t})$ and $\lambda^j_{c,t} * ln(\theta^L_{c,t}) = ln(TFP_{c,t})$, then we can rewrite Equation (2) to take account of the possibility of biased factor augmenting technological change as given by Equation (3).

[15]In both the US and Germany only 2% of individuals in our sample had less than 9 years of education.

[16]Freeman and Schekatt(00) also raise the issue of the comparability of years of education in Germany to those in the US. Following the spirit of their corrections, we readjusted years of education in Germany by multiplying them by the ratio of the average literacy score reported in the International Adult Literacy Survey for a German with a given number of years of education to an American with the same number of years of education. When we estimated the equations described below using these adjusted data, the results indicate the same conclusions as those presented in the text. This is not surprising since the one-time nature of the adjustment does not alter the underlying time series patterns we use to identify our effects.

[17]In Equation 2, the γ_0 term is subsumed in the βs.

$$
\begin{aligned}
w_{c,t}(y_i, e_i) \quad &= \alpha_{c,0} + \alpha_1 ln(\tfrac{K_{c,t}}{L_{c,t}}) + \alpha_2 ln(\tfrac{H_{c,t}}{L_{c,t}}) + \\
&(\beta_{c,0} + \beta_1 ln(\tfrac{K_{c,t}}{L_{c,t}}) + \beta_2 ln(\tfrac{H_{c,t}}{L_{c,t}})) * (y_i - 9) + \\
&(\alpha_1 \lambda^K_{c,t} + \alpha_2 \lambda^H_{c,t} - (\alpha_1 + \alpha_2 - 1)\lambda^L_{c,t}) * ln(TFP_{c,t}) + \\
&(\beta_1 \lambda^K_{c,t} + \beta_2 \lambda^H_{c,t} - (\beta_1 + \beta_2)\lambda^L_{c,t}) * ln(TFP_{c,t}) * (y_i - 9) \\
&+ ln(g_c(e_i)) + ln(\psi_i) \qquad (3)
\end{aligned}
$$

Equation (3) will provide the basis for our empirical investigation. The difficulty with estimating Equation (3) is that there are four unobservables: the three factor bias terms ($\lambda^j_{c,t}, j = K, H, L$) and the individual specific efficiency term $ln(\psi)$. The unobserved individual specific term is not a difficult problem for estimating Equation (3), even if it is correlated with education, since we can deal with such potential correlation by using fixed effect methods. The unobservability of the λs generate a more difficult identification issue. In particular, if we think that the λs should be allowed to vary both across time and across country in an unrestricted fashion, then Equation (3) cannot be estimated. Hence, we need to impose some structure on the λs in order to obtain identification. Our main identification assumption, which is one commonly used (either implicitly or explicity) in the literature, is that the degree of factor bias in factor augmenting technological change is the same across countries and it is an ongoing process; that is, we impose that the λs are the same across countries and that they are either constant or only evolving slowly over time. The assumption that the λs are constant across countries corresponds to assuming that the same technological forces are affecting changes in the US and Germany. This assumption is very much in line with the spirit of this paper in that we view international comparisons as a means of allowing us to isolate the effects of differential factor usages in an environment with similar technological possibilities. Clearly, it would be possible to explain away the differences between Germany and the US simple by invoking a claim that technological opportunities have progressed very differently in the two countries. However, we do not believe that such an assumption would be either very insightful or very plausible.

In our base line specification for Equation (3), we allow the λs to take on arbitrary constant values; that is, we allow observed movement in TFP to shift both the intercept and the slope of the wage-education profile in an unrestricted (but constant) fashion. Since measured TFP is considered by many to be plagued with huge measurement problems, we will also estimate Equation (3) simply by replacing TFP with a time trend. This latter specification corresponds precisely to the type of identification assumption used by Katz & Murphy (1992) in their study of US wage changes. In order to go one step further and allow for the possibility that factor biased technological change may be accelerating or decelerating over time, we also estimate Equation (3) allowing the λ terms themselves to be functions of time. Although our identification assumptions restrict somewhat the extent to which factor biased technological change is allowed to affect the wage structure, we believe that if biasedness in factor augmenting technological change is central to explaining the observed wage changes, our approach should be flexible enough to pick it up.

To sum up, the equation we will use to explore the validity of Restrictions 1-4 is given below, where $\phi_1(t)$ and $\phi_2(t)$ are either constrained to be constants or simple functions of time, and $g_c(e_i)$ is an unrestricted country-specific function of time. We carry out our estimation using grouped data, where the unit of aggregation within a given country in a year is an age-education cell. Since none of our covariates vary within such groups, there is no loss in efficiency from using the data in this aggregated form.

$$\begin{aligned} w_{c,t}(y_i, e_i) &= \alpha_{c,0} + \alpha_1 ln(\tfrac{K_{c,t}}{L_{c,t}}) + \alpha_2 ln(\tfrac{H_{c,t}}{L_{c,t}}) + \\ &(\beta_{c,0} + \beta_1 ln(\tfrac{K_{c,t}}{L_{c,t}}) + \beta_2 ln(\tfrac{H_{c,t}}{L_{c,t}})) * (y_i - 9) + \\ &\phi_1(t) ln(TFP_{c,t}) + \phi_2(t) ln(TFP_{c,t}) * (y_i - 9) \\ &+ ln(g_c(e_i)) + ln(\psi_i) \qquad (4) \end{aligned}$$

To close our empirical specification, we need to be more specific about the form of the error term. As stated earlier, we use data aggregated in year of education/age/year/country groups. In implementing equation (4), we assume that there is measurement error in the wage and that the person specific term may not be perfectly correlated over time. Then, letting i now index the year of education/age group, c index country and t index time, and assuming that ψ_i is common among individuals within education/age groups, replace $ln(\psi_i)$ in 4) with an error term that can be written u_{ict}. In the non-differenced estimations we assume that $u_{ict} = \rho u_{ict-1} + \theta_{ct} + \epsilon_{ict}$, where: ϵ_{ict} is a mean zero, white noise error term with variance σ_ϵ; θ_{ct} is a mean zero disturbance term that is independent over time and across countries, independent of ϵ_{ict} and has a variance σ_{θ_c}; and ρ is a parameter. We estimate the resulting equation using OLS rather than using a feasible GLS estimator to avoid quasi-differencing the data and altering the time series patterns we are trying to study. We use the residuals from the OLS estimation to form estimates of σ_ϵ,σ_θ and ρ. We then form the appropriate estimated variance-covariance matrix for u_{ict} and use it to generate the correct standard errors for the estimated OLS coefficients. Note that this addresses the issue that our K/L, H/L and TFP effects are actually identified using country/year level variation and that, as a result, standard errors need to be adjusted (Moulton(1986)). In the differenced estimator we make the stronger assumption that $u_{ict} = \delta_i + \theta_{ct} + \eta_{ict}$, where: η_{ict} is a mean zero, white noise error term; δ_i is an individual specific effect; and θ_{ct} is the same as above. Differencing from the mean over time for a group eliminates δ_i but not the θ_{ct} term since the latter has expectation of zero over time and country and we are differencing within country over time. Thus, we also adjust the variance-covariance matrix of the OLS estimates of the differenced equation.

4 Data

The data we use to estimate Equation 4 comes from several sources. The two main sources for individual level data are the matched files of the PSID (1980-1997) and the GSOEP (1984-1997), and our main source for aggregate data is Jorgensen & Yip (1999).[18] The PSID, for the US, and the GSOEP, for Germany, are both panel data sets in which a set of original families and their offshoots are followed through time. We do not take advantage of the panel nature of the data, using it as a series of cross sections. We make corrections for potential serial correlation that might stem from the underlying panel nature of the data in all our regressions. In each case, the data are not perfectly representative of the population as a whole and we make use of weights provided in the data sets in all our calculations. We make use of particular versions of the PSID and GSOEP termed the Equivalent Files, [19] that contain original and constructed variables which are broadly comparable across the two datasets. For the German data, we make use only of samples of individuals living in what was formerly West Germany both before and after reunification. We will discuss the impact of reunification in our data when we present our aggregate data plots. We use data for all individuals between the ages of 16 and 65.

We use the micro data from the PSID and GSOEP to construct total labour supply, the human capital stock and our dependent variable, the hourly wage. The hourly wage is constructed by dividing total annual labour earnings by annual hours of work as reported in the Equivalent File and it is deflated using a country specific GDP deflator. For the most part, the results reported in the paper use average male wages only. We do this to focus attention on a price of labour that is potentially less likely to be affected by compositional changes associated with changes in female labour supply over time. However, as we demonstrate at the end of the paper, our conclusions are unchanged when we incorporate female wages as well. Our labour supply measure is essentially total hours of work (both by males and females) performed in the economy in the year, with some adjustments made to account for productivity

[18] Jorgensen's data is reported in per capital terms and therefore, when necessary, we used official population estimates from the BLS to retrieve levels data.

[19] These files are constructed and maintained by the German Institute for Economic Research, The Department of Policy Analysis and Management at Cornell University, and the University of Michigan.

differences by age and gender and further adjustments to make the series match Jorgensen's aggregate labour series. These adjustments and other data details are discussed in Appendix 2. To create the human capital stock in a given year we calculate the product of each individual's annual hours of labour supply and their number of years of education and then sum over individuals.

In terms of aggregate data, we choose to use Jorgensen & Yip (1999) measures of capital since these are the product of enormous effort directed at making internationally comparable series. In particular, these capital series have been built from disaggregated data in 8 asset types and 4 ownership sectors, and have been adjusted for quality changes.[20] Finally, in constructing our TFP measure we adjust Jorgensen's TFP series to take into account the specific way our model suggests human capital adjustment should be made. It is worth noting that this change is minor and that all our results are robust to directly using Jorgensen's TFP measure instead to our adjusted measure.

4.1 Observed Patterns in Education - Wage Differentials

We begin with some basic data plots as a means of describing the key patterns in our data. We are primarily interested in patterns in the education - wage differential both within countries over time and across countries. To capture these patterns we regressed our log wage measure on a full set of year dummy variables, number of years of education, the interaction of education and the dummy variables, and a full set of dummy variables corresponding to five year age categories. We run this regression separately for each country. The result is a separate wage-education profile for each year for each country, holding constant country-specific age effects.[21] Figure 1 contains the plots of these profiles for the US for a selected set of years. The clear pattern is of an increase in the slope of the profile over time. The increase occurs because the lowest educated groups face dramatic declines in their real wage over our sample period (the real wage of those with a grade 12 education declines 25% from 1979 to 1996, for example) while the wages of the most educated increased only slightly. The large increase in returns to education depicted in figure 1 fits with what is typically taken to be one of the main stylized facts associated with increased inequality in the US (see, e.g., Juhn, Murphy, and Pierce (1993)). The fact that this occurs with little change in real wages for the more educated is the same result as found by MaCurdy and Mroz(1995) and Beaudry and Green(1998) using CPS data. Thus, our main wage pattern fits with results from earlier research. For Germany, the plots in figure 2 tell a very different story. Here we see an average wage gain rather than an

[20] Jorgensen & Yip series end in 1995. We therefore needed to extend the series to 1996. This was done using real investment and deprication allowances from NIPA accounts. Our results are unaffected if we simply drop 1996.

[21] We repeated this exercise using higher order terms in education but, similar to other studies, found that a linear wage-education profile is a remarkably good description of the data. We chose to discuss the linear profile because it makes the observed patterns more transparent.

average loss over our sample period. Moreover, that gain is shared across the education spectrum, leading to little change in the education-wage differential over time. These patterns, rising education-wage differences in the US caused by substantial real wage declines for all but the most educated in the US and stable education-wage differences with rises in real wages for most workers in Germany, are the ones we seek to explain using the model discussed in the previous sections.

The model set out above relates movements in wages by education level to movements in physical capital, human capital, labour and TFP. In figures 3 and 4 we plot our data on these latter series for the US and Germany. Examining the US data, we observe a steady rise in physical capital which is offset by a large increase in total labour employed, with the result that K/L rises modestly over this period. Our H/L measure, which is effectively an hours weighted average years of education, increases at a modest pace, as one might expect for this type of measure.[22] The patterns for Germany are remarkably similar to those for the US in many dimensions. For example, the overall rise in K is similar between the two countries, as is the rise in H/L, with the latter rising 4.7% in the US and 4.5% in Germany over this period. Thus, attempts to explain the differences in wage patterns depicted in figures 1 and 2 with a supply of human capital story cannot succeed. The largest difference between the two countries is in the K/L measure, which grows much more in Germany than in the US. Recall that the argument in our model is that differences in the relative growth rates of H/L versus K/L is a key element in understanding wage patterns both over time within countries and across countries. Finally, the jump in the labour series for Germany in the early 1990s reflects reunification. As discussed above, all of our measures correspond to the former West Germany throughout the period. The L series reflects movements into West Germany of a large supply of former East German residents after the fall of the wall. Given that our panel data follows a set of individuals who resided in West Germany before re-unification, we do not directly measure the wages of these new entrants, but we do take account of their impact on wages through the movements in the L measure depicted in figure 3. We turn now to an empirical investigation of the wage patterns in figures 1 and 2, examining their relationship to the movements in the aggregate measures shown in figures 3 and 4.

[22]Notice that this is somewhat in contrast to plots of the relative supply of university versus high school educated labour in other studies. The latter type of measure shows much more dramatic increases. However, examining evidence across countries, we found that movements in the latter type of measure, where we contrast supplies of discrete educational categories, can vary greatly with small changes in category definitions. One advantage of using a more continuous measure of human capital based on years of education is that we do not suffer from introducing large variations in our human capital measure based on small definitional changes.

5 Empirical Results

Table 1 reports estimates of Equation (4) allowing the degree of factor bias in factor augmenting technological change to be arbitrarily strong but constant over the period (i.e., we report estimates of (4) under the assumption that ϕ_0 and ϕ_1 are unrestricted constants). The first column in Table 1 reports OLS estimates, while Column (2) reports fixed effect estimates. The standard errors are calculated allowing for the possibility of non-iid disturbances as described earlier. The fixed effect estimates correct for the possibility that education is correlated with individual level productivity. Note that we group our data by education group and thus there is no variation over time in education for a given group. This in turn means that the return to education is not identified when we use the fixed effect estimator. For the other covariates of interest, the estimates from the simple OLS and the fixed effect estimators are very similar, suggesting that there is in fact little bias induced by correlations between individual specific effects and the covariates in the simple OLS estimates. In our discussion, we will focus on the simple OLS estimates but the same conclusions can be drawn from the fixed effect estimator.

The estimates reported in Table 1 are precisely estimated. The estimated returns to education are found to be approximately 6% in Germany and over 8% for the US. These estimates are consistent with others reported in the literature. The results in Table 1 also indicate that aggregate levels of both physical and human capital are important determinants of the observed movements in the wage- education profiles. In particular, the estimates in Table 1 show: (1) that an increase in physical capital is associated with an increase in the slope and a decrease in the intercept of the wage-education profile; (2) that an increase in human capital is associated with a decrease in the intercept and an increase in the slope of the profile; and (3) that an increase in TFP is associated with an parallel shift up in the profile.

Our main interest in the Table 1 estimates is to examine how they relate to the implications of the theory presented in Section 2. We examine that relationship by checking the implied Restrictions 1 through 4 set out in Section 2. Restriction 1 corresponds to a test of whether or not the data support the existence of a balanced accumulation path, with the key implication of a balanced path being that the ratios $\frac{-\alpha_1}{\alpha_2}$ and $\frac{-\beta_1}{\beta_2}$ should be equal. At the bottom of Table 1 we report the values of these ratios, their difference, and the standard error of that differences. The ratio $\frac{-\alpha_1}{\alpha_2}$ indicates the percent increase in human capital need to offset the effect on the intercept of the wage-education profile of a 1% increase in physical capital. The ratio $\frac{-\beta_1}{\beta_2}$ indicates the percent increase in human capital need to offset the effect on the slope of the profile of a 1% increase in physical capital. Both these numbers indicate that about a .5% increase in human capital is required to offset the effect of a 1% increase in physical capital. The difference between these ratios is small and is swamped by its standard error. Thus, we cannot reject the null hypothesis that a balanced path exists. As we discussed in section 2, the existence of such a balanced path is precisely what is expected if the economy is in a transition phase, simultaneously using two methods of production. In contrast, such a property would not be expected to hold if the economy was using one concave production technology.

The second restriction we derive relates to whether the newer technology satisfies capital skill complementarity relative to the old technology. In other words, whether the form of the balanced accumulation path is such that human and physical capital need to move in the same direction. In the rows denoted R2a and R2b we report the two t-statistic associated with testing the two components of this proposition, that is, testing $\alpha_1\beta_1 < 0$ and $\alpha_2\beta_2 < 0$. These two products are negative and take values more than two standard errors less than zero. Thus, as suggested by Goldin & Katz (1998), the data strongly support the view that the underlying technologies exhibit capital-skill complementarity.

The third restriction corresponds to a test of whether one of the underlying technologies is skill-biased (in the sense of Assumption 2) relative to the other.[23] As emphasized in section 2, skill-biasedness implies monotonic shifts in the wage education profile. In particular, an increase in physical capital intensity is predicted to increase wages at all education levels and an increase in human capital intensity is predicted to decrease wages at all education levels. Since our estimates of α_1 and α_2 clearly indicate that an increase in human capital decreases the intercept[24] of the wage-education profile while physical capital does the reverse, what we need to verify for monotonicity is whether the change in the slope offsets the intercept effect at some (observed) education level. To perform this test in a simple manner, we create the following statistic. We calculate the number of years of education required for the slope effect to offset the intercept effect. If this crossing point number of years is less than 17 then we can reject the null hypothesis that Restriction 3 holds. In the table we report the calculated crossing points corresponding to both the effects of physical and human capital along with their standard errors. In both cases, the calculated crossing point is near 17 and we cannot reject the restrictions that the effect of a human capital increase is negative throughout the relevant range of years of education and the effect of a physical capital increase is positive throughout the range. Thus, the data support the hypothesis that one of the technologies is skill-biased and satisfies capital skill complementarity relative to the other.

Finally, our last test relates to whether or not one technology satisfies capital-skill complementarity and is more capital efficient relative to the other.

[23] It could be argued that skill-biasedness only involves an across technology comparison of human capital intensities. However, in this more limited sense, one of the technologies is necessarily more skilled-biased than the other and therefore it has no empirical content in our framework.

[24] Note that the intercept effect corresponds to the effect on individuals with exactly nine years of education.

As indicated by Restriction 4, this hypothesis can be tested simply by examining whether α_5 is positive and whether α_6 is negative. Again the data provide support this hypothesis. The non-rejection of Restriction 4 may appear to be quite surprising given that much of the empirical literature on trends in wage-education differentials suggests that increases in human capital lead to a flattening of the wage-education profile. In our view, our results differ from much of the literature in part because previous authors have, in general, not controlled for changes in physical capital intensity when examining the effect of changes in educational attainment and hence may have been obtained biased results. In addition, some of the other results in this literature correspond to earlier periods for which Assumption 3 may not be valid. In fact, earlier periods in the twentieth century (or the current situation for many developing economies) may have been periods when newer technology was capital-biased and therefore Restriction 4 would have held.[25] In short, although our results regarding Restriction 4 may appear at first glance to conflict with results in the literature, we know of no study (apart from Beaudry & Green (1998)) which is based on recent data (the last quarter of a century) and which controls for changes in capital intensity. Hence it is unclear to us whether there really is any conflict to resolve between our results and those in the literature once it is agreed that changes in physical capital intensity are potentially important for understanding changes in the wage structure.

In Table 1, we controlled for the effects of factor augmenting technological change on the wage profile by including measured TFP as a regressor. However, many analysts believe that measured TPF is subject to huge measurement error. Hence, to explore the robustness of our results, in Table 2 we present estimates of Equation 4 and tests of Restrictions 1-4 for the case where we replace measured TFP by a time trend. In general the pattern of results in Table 2 are very similar to those presented in Table 1. In particular, the signs and significance of the coefficients are almost identical and the pattern of test results corresponding to Restrictions 1-4 is very similar to that in Table 1. Although not reported, we also estimated Equation (4) instrumenting TFP by a quadratic function of time, and by simply allowing for a quadratic trend in both the intercept and the slope of the wage-education profile. In both cases, we found very similar results to those reported in Table 1 and 2. Therefore, it appears that our results are not driven by potential mismeasurement of TFP.

There is nevertheless one differences between Tables 1 and 2 worth emphasizing. In Table 1, the estimates of ψ indicate that TFP shifts up the wage profile in approximately a one-to-one proportion without affecting the slope of the profile. Such a pattern is very much suggestive of a factor neutral view of productivity improvements whereby all employed individuals benefit. In contrast, the estimates of ϕ in Table 2 suggest (if we believe the trend is cap-

[25] In is interesting to note that the data used in Berman & Machin (2000) indicate (contrary to common perception) that for developed countries the across-country relationship between the skill premium and the supply of skill was positively sloped in the 80s even though it was negatively sloped in the 70s.

turing the effects of incremental productivity) that productivity improvements are decreasing all wages at a rate of approximately 1% per year.

Several papers have suggested that the factor bias in factor augmenting technological change may have accelerated over the eighties. In order to explore such a possibility, in Table 3 we report estimates of Equation 4 which allow ϕ_1 and ϕ_2 to be functions of time. In Column 1 of Table 3 we allow the ϕs to be a linear function of time, while in Column 2 we allow them to be quadratic functions of time. In particular, this later specification allows for the possibility that factor bias first accelerated then decelerated over our period. As can be seen from the Table, even when allowing for such a degree of flexibility, we still find strong evidence in favour of our two-competing technology model. For example, we still find that the data indicate the existence of a balanced growth path and that imbalances of human versus physical capital lead the wage-profile to shift downwards and steepen. Hence, the data is able to clearly distinguish the elements key to our two technology model as opposed to a model which explains relative wage movements as stemming from ongoing factor biased technological change that shifts a given production function. As a final robustness check, Table 4 presents results from estimating Equation 4 using wage observation from both men and women. In this case, we included as additional regressors country specific female dummies as well as country specific female age-profiles. In Table 4, we report results for the specifications corresponding to the first columns of Table 1 and 2. As can be seen, including observations on female wages does not affect any of our inferences.

Before examining the quantitative implications of our estimates, it is relevant to discuss the implications of our model for the relative movements in capital rental rates. Besides the effects on wages, the theory presented in Section 2 suggest that an excessive accumulation of human capital relative to physical capital should lead to an increase in the rental rate of capital. Since we are arguing that such imbalance is especially pronounced for the US, it suggests that the rental rate on capital should have increased more in the US than in Germany from the seventies to the nineties. Although we believe that the measurement of the rental rate is much less clear than the measurement of wages (and hence the focus of the paper), it is of some interest to compare the movement in short term interest rates in these two countries. For the US, the average (ex-post) real rate on 3-month commercial paper was just under 1% (.97%) in the period 1971-1983, while it increase to an average of 3.15% in the period 1983-1997. Which is an increase of over 300%. In comparison, the average real rate on money market lending[26] was 1.75% in Germany over the period 1971-1983, while it increased to 2.75% over the period 1983-1997. This is an increase of only slightly more than 50%. Hence the relative trends in interest rates between these two countries are consistent with our theory, although we do not want to overemphsize this observation given obvious mea-

[26]This appears to best rate to compare to US commercial paper.

surement issues.[27]

In order to quantify the importance of factor imbalances in explaining the wage patterns of interest, we present a series of decompositions in figures 5 - 8. To create figure 5, we first construct the fitted wage for an individual in the base age group with 12 years of education in the US for each year using the coefficient estimates in the first column of Table 1 and the actual values of the K/L, H/L and TFP variables. This is plotted as the "Fitted With All Covariates Varying" line in the figure. We then repeat the exercise but hold TFP fixed at its 1983 value and plot the result as the "TFP Held Fixed" line. Finally, we form a fitted wage holding TFP constant and replacing the actual K/L series with one generated as $\frac{-\alpha_2}{\alpha_1}$ * H/L (the balanced path for K/L given the observed H/L series). This is plotted as the "TFP Fixed and K/L on Balanced Path" line. We repeat this exercise for an individual with 16 years of education for the US in figure 6, so we capture both high and lower education individuals, and for 12 and 16 years of education for Germany in figures 7 and 8.

The difference between the line with all covariates varying and the one with TFP fixed in figure 5, indicates that TFP growth was an important determinant in keeping the wages of the lower educated in the US from going even lower than they did. The figure indicates that if TFP had not grown beyond its 1983 level, by 1996 the real wage of an individual with 12 years of education would have been approximately 10% lower than what was observed. The difference between the TFP fixed line and the one with both TFP fixed and K/L forced to the balanced path represents the impact of the US being off the balanced path. That impact is large: if the US had experienced balanced H/L and K/L growth, as we define it, the average real wage for this group would have been 15% larger in 1996. Figure 6 shows that TFP growth also supported the wages of the more educated workers in the US that relative capital imbalance had much smaller effects on them relative to the less educated. This fits with our theoretical model which predicts that relative physical capital scarcity should have a larger negative impact on the less educated. The sizes of the impacts of being off the balanced path for workers with 12 and 16 years of education in the US (in particular, the large impact for the less educated, who are the group experiencing the largest wage movements) suggests that our theory performs well as an explanation of relative wage development within the US over time.

[27]The percentage change in rental rates between the US and Germany which is needed for our model to be consistent with the observed wage movements is of the order of 20% to 30%. Since the differential increase in interest rates we mention is of the order of 250%, many changes in calculation can be made and such an observation would still provide support for a relative increase in rental rates of over 20% between the US and Germany from the seventies to the nineties. Our view is that observed movements in interest rates are consistent with our model but provide a very weak means of evaluating the theory given the sampling uncertainty in measuring real interest rates and the questionable links as a measure of the marginal product of capital. For these reasons, we believe it is much more informative and discriminating to examine the implications of our model for wages than for rental rates.

Figures 7 and 8 highlight the differences between the US and Germany. For Germans with 12 years of education, shown in figure 7, one can again see the importance of TFP growth in supporting wages. However, the effect of forcing K/L onto the balanced path is much smaller than in the US. This is because the growth of K/L and H/L are much closer to the balanced path in Germany than the US. Thus, when we examine the experience of workers with 16 years of education in Germany in figure 8, the effects of forcing K/L onto the balanced path are minimal. The contrast in the effects of being forced onto the balanced path in Germany relative to the US indicates that our model provides a potentially useful explanation of differences in relative wage growth in the two countries. In the US, where K/L lagged well behind its balanced path values given observed H/L growth, real wages for the lower educated fell and the returns to education increased; neither of which would have happened if K/L had been on the balanced path. In contrast, Germany was near the balanced path and so there was little increase in the return to education or decline in low educated wages.

To explore further the usefulness of our theory, figures 9 and 10 present plots intended to highlight the relationship between wage level and returns to education movements and the extent to which K/L and H/L are off the balanced path. To capture the basic movements in the wages of the less educated we want to explore, we use the coefficients on the year dummy variables from the log wage regressions used to construct figures 1 and 2. Thus, we use a time series corresponding to the average wages of individuals with 12 years of education holding constant age effects. In figure 9, we plot these against our measure of imbalance of physical versus human capital usage. This measure is constructed as the difference between the actual K/L series and the path K/L would have had to follow to be on the balanced path given the observed H/L series (i.e., $\frac{-\alpha_2}{\alpha_1} * H/L$). Note that our theory predicts that the more the observed K/L lags behind the balanced path, the lower should be the low educated wage captured in the year dummy coefficients. [28]. For Germany, the observed data points are clustered near zero on the horizontal axis since K/L and H/L were near the balanced path, making it difficult to see a clear correlation between the imbalance measure and the wage measure. On the other hand, the U.S. data shows a clear positive correlation as our data predicts. Interestingly, the US plots contain observations near the German data for the earlier years of the sample (1979-1983) and thereafter spead out to the southwest in the figure. The figure makes clear that the basic prediction of our model is present in the (relatively) raw data. It also helps in understanding what variation is being used to identify key coefficients in our regressions. The positive correlation between the K/L imbalance and the wage profile intercept comes both from within US variation over time (both in differences between the early 1980s and the remainder of the period, and in the positive correlation within the post-1983 period), and in differences between the highly clustered

[28]In constructing this figure we normalize the 1983 values to be the same in order to effectively eliminate country differences such as those associated with currency differences

German data and the US data. Thus, the identification comes from within the US and cross-country variation.

To capture movements in returns to education, figure 10 contains plots of the coefficients from the interactions of year dummies and years of education from the regressions used to construct figures 1 and 2. We again plot these against our measure of the extent to which K/L is off the balanced path. The competing technology theory set out earlier in the paper predicts that the further is K/L below the balanced path, the greater will be the returns to education. As in figure 9, figure 10 shows German data clustered near the zero imbalance point on the horizontal axis. The US data shows a strong negative correlation between the estimated education-wage profile slopes for each year and the imbalance measure, as the theory predicts. Further, the US points are situated mainly to the northwest of those for Germany. Thus, in this dimension as well, our estimated coefficients are identified from a combination of within US - over time variation and cross country variation.

Finally, we have argued throughout this paper that the competing technology model has the potential to explain the differences in wage outcomes between the US and Germany over the last two decades. More specifically, we argue that if the US had followed Germany in having K/L and H/L growth that conformed more closely to the balanced path then the US would not have experienced a fall in real wages for the less educated and a rise in the returns to education. To support this claim, in figure 11 we plot wage- education profiles corresponding to the counterfactual in which the US experiences growth in K/L and H/L that are as close to the balanced path as Germany's. To generate the counterfactual, we construct four education-wage profiles. The first is the profile corresponding to 1979 in the US and is generated using coefficients on the relevant year dummy variables, years of education and interactions between the two from the US wage regression used to construct figure 1. This line, as with the others, corresponds to the base age group. We next construct the 1996 US profile, again using coefficients from the figure 1 regression (this is labelled the "True 1996 Profile" in figure 11). The line marked "Fitted 1996 Profile" corresponds to the fitted profile generated using the estimated coefficients reported in Table 1 in conjunction with the US 1996 values of K/L, H/L and TFP. The difference between this line and the "True 1996 Profile" shows how closely we are able to fit the basic wage patterns using our proposed regression. To generate our counterfactual, we take the ratio of log(K/L) to log(H/L) for Germany and then multiply this ratio times log(H/L) to generate a log(K/L) series for the US that has the same balanced growth properties as Germany. Using the true H/L and TFP series, the counterfactual K/L series and the estimated coefficients from Table 1, we generate the counterfactual wage profile for the US for 1996 denoted "US with German Relative Factor Growth" in Figure 11. The outcome is striking. If the US had experienced K/L growth that more nearly matched the balanced growth path (relative to its observed growth in H/L) as Germany did then it would have had wage growth rather than decline for the lower educated workers and wage growth rather than stagnation for the more educated. In fact, the relationship of the counterfactual profile to the 1983 profile is very similar to what happened to the actual wage profiles in Germany over this period, with overall wage growth and a slight decrease in the education-wage differential. This is strong evidence in favour of our conclusion that the US suffered real wage declines and increased returns to education over the 1980s and 1990s because of an imbalance between its growth in physical relative to human capital.

6 Conclusion

The object of this paper has been to further our understanding of the causes behind observed changes in the wage structure in the US and Germany. The answer we propose, which is based on a two competing technology model, is that these differential changes result from different patterns of human versus physical capital usage in the two countries. In particular, our estimates suggest that the US has under accumulated physical capital relative to human capital while Germany has followed a more balanced approach. Obviously, our explanation is at best only one element in a more complete answer since we do not explain why the two countries differed in their accumulation paths. This a priority for our future research.

What do our results suggests for the current policy debates in Germany and the US? First, in the case of Germany, our results suggest that greater wage flexibility can be attempted without fear of thereby developing a US style wage-structure since Germany has increased its physical capital intensity faster than the US. In effect, our estimates suggest that substantial employment gains for less educated workers could be obtained without a need for very substantial wage cuts. In the case of the US, we view our results as indicating that greater incentives for the accumulation of physical capital may help offset some of the distributional effects of increased educational attainment.

Table 1: Estimates of Equation 4 using measured TFP

	Basic Spec. Estimates	Std. Err.	Fixed Effect Estimates	Std. Err.
α_1	1.79	(.18)	1.79	(.16)
α_2	-3.16	(.25)	-3.11	(.23)
$\beta_{0,G}$	.059	(.004)	-	-
$\beta_{0,US} - \beta_{0,G}$	.027	(.006)	-	-
β_1	-.23	(.04)	-.24	(.04)
β_2	.391	(.06)	.39	(.05)
$\phi_{1,0}$	.91	(.22)	.77	(.20)
$\phi_{2,0}$	-.05	(.05)	-.03	(.05)
$R1 : \frac{\alpha_1}{\alpha_2}, \frac{\beta_1}{\beta_2}$	-.568,-.585	-	- .574,-.600	-
Difference	.017	(.101)	.026	(.091)
$R2(a) : \alpha_1\alpha_2$	-5.67	(.95)	-5.55	(.86)
$R2(b) : \beta_1\beta_2$	-.09	(.03)	-.09	(.03)
R3 (a)	16.84	(.92)	16.55	(.77)
R3 (b)	17.08	(.78)	16.89	(.70)

The country specific dummies and the country specific experience profiles are not reported. Before estimation, the data was grouped by country, year, age group, gender and education level, and we use the log of the average wage of each group as the dependent variable. Since all covariates take the same value for each person within these groups, this does not imply any loss in efficiency. The dependent variable and the covariates were multiplied by the squared root of the number of observations in each group to address heteroskedasticity issues. The estimation on this re-weighted data was done using OLS. The variance-covariance matrix of the estimated coefficients was adjusted to account for first order auto-correlation within groups over time and to account for the fact that our estimates of the K/L, H/L and TFP effects are identified using macro variation only (see Moulton(1986)).

R1 corresponds to testing the existence of a balanced growth path, that is, $\frac{\alpha_1}{\alpha_2} = \frac{\beta_1}{\beta_2}$. We report $\frac{\alpha_1}{\alpha_2}$ and $\frac{\beta_1}{\beta_2}$ individually, their difference and the standard error associated with that difference.

R2 reports the test statistics associated with the hypotheses that $\alpha_1\alpha_2 < 0$ (R2(a))and $\beta_1\beta_2 < 0$ (R2(b)). In particular, we report the values of the products and their standard errors.

R3 reports a test statistic associated with the hypothesis that increased physical capital efficiency shifts up the wage profile (R3(a)), while increase human capital efficiency shifts it down (R3(b)). In particular, for R3(a) we present the number of years of education at which the wage-education profile after a 1the standard error of that cross-over point. The entries under R3(b) are similarly defined. Note that the largest recorded education value reported by any substantial number of respondents in our data is 17.

Table 2: Estimates of Equation 4 using a time trend instead of measured TFP

	Level Spec. Estimates	Std. Err.	Fixed Effect Estimates	Std. Err.
α_1	2.01	(.19)	2.02	(.17)
α_2	-2.17	(.36)	-2.07	(.33)
$\beta_{0,G}$	.052	(.006)	-	-
$\beta_{0,US} - \beta_{0,G}$	.035	(.006)	-	-
β_1	-.27	(.04)	-.27	(.04)
β_2	.30	(.08)	.30	(.08)
$\phi_{1,0}$	-.009	(.004)	-.011	(.004)
$\phi_{2,0}$	.001	(.001)	.002	(.001)
$R1 : \frac{\alpha_1}{\alpha_2}, \frac{\beta_1}{\beta_2}$	-.927,-.886	-	- .979,-.946	-
Difference	-.042	(.369)	.033	(.371)
$R2(a) : \alpha_1\alpha_2$	-4.38	(.92)	-4.20	(.84)
$R2(b) : \beta_1\beta_2$	-.08	(.03)	-.08	(.03)
R3 (a)	16.54	(.77)	16.25	(.63)
R3 (b)	16.21	(1.19)	16.01	(1.09)

The country specific dummies and the country specific experience profiles are not reported. Before estimation, the data was grouped by country, year, age group, gender and education level, and we use the log of the average wage of each group as the dependent variable. Since all covariates take the same value for each person within these groups, this does not imply any loss in efficiency. The dependent variable and the covariates were multiplied by the squared root of the number of observations in each group to address heteroscedasticity issues. The estimation on this re-weighted data was done using OLS. The variance-covariance matrix of the estimated coefficients was adjusted to account for first order auto-correlation within groups over time and to account for the fact that our estimates of the K/L, H/L and TFP effects are identified using macro variation only (see Moulton(1986)).

R1 corresponds to testing the existence of a balanced growth path, that is, $\frac{\alpha_1}{\alpha_2} = \frac{\beta_1}{\beta_2}$. We report $\frac{\alpha_1}{\alpha_2}$ and $\frac{\beta_1}{\beta_2}$ individually, their difference and the standard error associated with that difference.

R2 reports the test statistics associated with the hypotheses that $\alpha_1\alpha_2 < 0$ (R2(a))and $\beta_1\beta_2 < 0$ (R2(b)). In particular, we report the values of the products and their standard errors.

R3 reports a test statistic associated with the hypothesis that increased physical capital efficiency shifts up the wage profile (R3(a)), while increase human capital efficiency shifts it down (R3(b)). In particular, for R3(a) we present the number of years of education at which the wage-education profile after a 1the standard error of that cross-over point. The entries under R3(b) are similarly defined. Note that the largest recorded education value reported by any substantial number of respondents in our data is 17.

Table 3: Estimates Allowing for Time-Varying Factor Bias

	(1) Estimates	Std. Err.	(2) Estimates	Std. Err.
α_1	1.59	(.25)	1.78	(.27)
α_2	-3.08	(.26)	-3.51	(.36)
$\beta_{0,G}$	0.055	(.004)	0.056	(.004)
$\beta_{0,US} - \beta_{0,G}$	0.029	(.006)	0.021	(.008)
β_1	-0.16	(.05)	-0.20	(.06)
β_2	0.36	(.06)	0.46	(.08)
$\phi_{1,0}$	-0.83	(1.35)	6.30	(4.12)
$\phi_{2,0}$	0.20	(.11)	-0.91	(.62)
$\phi_{3,0}$	-	-	0.044	(.024)
$\phi_{4,0}$	0.14	(.11)	-0.39	(.32)
$\phi_{5,0}$	-0.017	(.008)	0.066	(0.049)
$\phi_{6,0}$	-	-	-0.003	(0.002)
$R1 : \frac{\alpha_1}{\alpha_2}, \frac{\beta_1}{\beta_2}$	-.518,-.433	-	- .506,-.430	-
Difference	-.085	(.16)	-.076	(.131)
$R1(a) : \alpha_1\alpha_2$	-4.91	(1.10)	-6.23	(1.47)
$R2(b) : \beta_1\beta_2$	-.057	(.028)	-.092	(.042)
R3 (a)	19.14	(2.41)	17.92	(1.78)
R3 (b)	17.47	(0.93)	16.58	(0.86)

The coefficients $\phi_{1,0}$ through $\phi_{6,0}$ correspond, respectively to the coefficients on TFP, TFP interacted with a time trend, TFP interacted with time squared, TFP times years of education, and the latter variable interacted first with time and then with time squared.

The country specific dummies and the country specific experience profiles are not reported. Before estimation, the data was grouped by country, year, age group, gender and education level, and we use the log of the average wage of each group as the dependent variable. Since all covariates take the same value for each person within these groups, this does not imply any loss in efficiency. The dependent variable and the covariates were multiplied by the squared root of the number of observations in each group to address heteroskedasticity issues. The estimation on this re-weighted data was done using OLS. The variance-covariance matrix of the estimated coefficients was adjusted to account for first order auto-correlation within groups over time and to account for the fact that our estimates of the K/L, H/L and TFP effects are identified using macro variation only (see Moulton(1986)).

R1 corresponds to testing the existence of a balanced growth path, that is, $\frac{\alpha_1}{\alpha_2} = \frac{\beta_1}{\beta_2}$. We report $\frac{\alpha_1}{\alpha_2}$ and $\frac{\beta_1}{\beta_2}$ individually, their difference and the standard error associated with that difference.

R2 reports the test statistics associated with the hypotheses that $\alpha_1\alpha_2 < 0$ (R2(a))and $\beta_1\beta_2 < 0$ (R2(b)). In particular, we report the values of the products and their standard errors.

R3 reports a test statistic associated with the hypothesis that increased physical capital efficiency shifts up the wage profile (R3(a)), while increase human capital efficiency shifts it down (R3(b)). In particular, for R3(a) we present the number of years of education at which the wage-education profile after a 1the standard error of that cross-over point. The entries under R3(b) are similarly defined. Note that the largest recorded education value reported by any substantial number of respondents in our data is 17.

Table 4: Estimates using Wages for both Men and Women

	with TFP. Estimates	Std. Err.	Time trend Estimates	Std. Err.
α_1	1.40	(.20)	1.51	(.21)
α_2	-2.40	(.28)	-1.63	(.40)
$\beta_{0,G}$	.075	(.004)	.064	(.006)
$\beta_{0,US} - \beta_{0,G}$	.034	(.006)	-	-
β_1	-.19	(.05)	-.23	(.05)
β_2	.33	(.07)	.19	(.095)
$\phi_{1,0}$	1.14	(.27)	-.003	(.005)
$\phi_{2,0}$	-.08	(.06)	.002	(.001)
$R1 : \frac{\alpha_1}{\alpha_2}, \frac{\beta_1}{\beta_2}$	-.581,-.575	-	- .929,-1.248	-
Difference	-.006	(.129)	.319	(.770)
$R2(a) : \alpha_1\alpha_2$	-3.36	(.83)	-2.46	(.79)
$R2(b) : \beta_1\beta_2$	-.064	(.028)	-.044	(.027)
R3 (a)	16.26	(1.20)	15.47	(.86)
R3 (b)	16.19	(0.81)	17.70	(2.95)

The country specific male and female dummies and the country specific male and female experience profiles are not reported. Before estimation, the data was grouped by country, year, age group, gender and education level, and we use the log of the average wage of each group as the dependent variable. The dependent variable and the covariates were multiplied by the squared root of the number of observations in each group to address heteroskedasticity issues. The estimation on this re-weighted data was done using OLS. The variance-covariance matrix of the estimated coefficients was adjusted to account for first order auto-correlation within groups over time and to account for the fact that our estimates of the K/L, H/L and TFP effects are identified using macro variation only (see Moulton(1986)).

R1 corresponds to testing the existence of a balanced growth path, that is, $\frac{\alpha_1}{\alpha_2} = \frac{\beta_1}{\beta_2}$. We report $\frac{\alpha_1}{\alpha_2}$ and $\frac{\beta_1}{\beta_2}$ individually, their difference and the standard error associated with that difference.

R2 reports the test statistics associated with the hypotheses that $\alpha_1\alpha_2 < 0$ (R2(a))and $\beta_1\beta_2 < 0$ (R2(b)). In particular, we report the values of the products and their standard errors.

R3 reports a test statistic associated with the hypothesis that increased physical capital efficiency shifts up the wage profile (R3(a)), while increase human capital efficiency shifts it down (R3(b)). In particular, for R3(a) we present the number of years of education at which the wage-education profile after a 1the standard error of that cross-over point. The entries under R3(b) are similarly defined. Note that the largest recorded education value reported by any substantial number of respondents in our data is 17.

Appendix 1

In what follows, we will denote respectively by W^L,W^H and R the wage paid for unskilled labour, the wage paid for a unit of human capital and the rental rate on physical capital. Moreover, we let $V(K,H,L)$ denote the value function associated with the maximization given in Lemma 1.

Proof of Lemma 1: If firms are price takers then firms will set marginal products equal to factor prices. Hence, either both technologies are in use and marginal products are equalized across technologies; or only one technology is in use and it has marginal products that are greater than that of the non-used technology. These market equilibrium conditions correspond exactly to the first order conditions associated with the proposed maximization and hence, the price taking allocations solve the maximization problem. △

Proof on Lemma 2: Given that workers are paid according to their marginal product, the wage paid to an individual with y_i years of education must equal to either one or both of the following equations (where subscripts denote derivatives):

$$(F_3^O(K^O,H^O,L^O) + F_2^O(K^O,H^O,L^O)\gamma(y_i))\psi_i$$

or

$$(F_3^N(K^N,H^N,L^N) + F_2^N(K^N,H^N,L^N)\gamma(y_i))\psi_i$$

Regardless of whether one or both of these equations hold, by the Envelop Theorem(when applied to the value function associated with the maximization in Lemma 1), the wage paid to individual i can be expressed as:

$$(V_3(K,H,L) + V_2(K,H,L)\gamma(y_i))\psi_i$$

which only depends on aggregate factor usage. Furthermore, taking logs of this last expression, we can write the log wage equations as:

$$w(y_i) = ln(V_3(K,H,L)) + ln(1 + \frac{V_2(K,H,L)}{V_3(K,H,L)}\gamma(y_i)) + ln(\psi_i)$$

If returns to education ($\frac{V_2}{V_3}$) are not too large, log wages can be well approximated by Equation (1).△

In order to verify Proposition 1 through 4, it is helpful to exploit the dual conditions associated with the maximization given in Lemma 1. To this end, let

$c^O(R, w^H, w^L)$ and $c^N(R, w^H, w^L)$ represent the unit cost functions associated with the old and new technologies. If both technologies are in use, then factor prices must satisfy Equations (1A) and (2B). Moreover, the choice of factor by firms imply that Equations (3A)-(5A) must hold when K, H, L represent the factors employed in the economy.

$$
\begin{aligned}
c^O(R, w^H, w^L) &= 1, && (1A) \\
c^N(R, w^H, w^L) &= 1, && (2A) \\
Q^O c_1^O(R, w^H, w^L) + Q^N c_1^N(R, w^H, w^L) &= K, && (3A) \\
Q^O c_2^O(R, w^H, w^L) + Q^N c_2^N(R, w^H, w^L) &= H, && (4A) \\
Q^O c_3^O(R, w^H, w^L) + Q^N c_3^N(R, w^H, w^L) &= L, && (5A)
\end{aligned}
$$

In the above equations, Q^O and Q^N are the quantities of output produced using the old and new technology respectively, and C_j^i is the derivative of the cost function with respect to its jth argument.

Proof of Proposition 1: The system of Equation 1A to 5A, which expresses the link between factor prices and factor usages when two technologies are in use, has a structure which implies the existence of a balanced path. In particular, the accumulation of H needed to offset an increase in K so as to maintain constant factor prices is given the solution to the system of equation (3A)-(5A) when this system is view as determining Q^O, Q^N and H as a function of K (holding L constant).

Proof of Proposition 2: As indicated in the proof of Proposition 1, the balance path increase in H in response to an increase in K can be inferred from the set of Equations (3A)-(5A). In particular, from these equations it is easy to verify that along the balanced path:

$$\frac{\partial H}{\partial K} = \frac{(c_2^O c_3^N - c_3^O c_2^N)*}{(c_1^O c_3^N - c_3^O c_1^N)}$$

which is positive if Assumption 1 holds (Note that by Shepard's Lemma $c_i^j = X_j^i$). $\triangle$

Proof of Proposition 3: Since the marginal products of L and H are equated to w^L and w^H, the wage-education profile derived in the proof of Lemma 2 can be rewritten as:

$$w(y_i) = ln(w^L) + ln(1 + \frac{w^H}{w^L})\gamma(y_i)) + ln(\psi_i) \approx ln(w^L) + \frac{w^H}{w^L}\gamma(y_i) + ln(\psi_i)$$

Hence, the relationship between factor usage and the wage-education relationship can be found by differentiating Equation (1A)-(5A) to get changes in the factor prices w^H, w^L implied by changes in factor usage, that is, by solving the system of equations given below and then using the implied changes in factor prices to infer changes to the wage-education profile.

$$\begin{pmatrix} c_1^O & c_2^O & c_3^O & 0 & 0 \\ c_1^N & c_2^N & c_3^N & 0 & 0 \\ Q^O c_{1,1}^O + Q^N c_{1,1}^N & Q^O c_{1,2}^O + Q^N c_{1,2}^N & Q^O c_{1,3}^O + Q^N c_{1,3}^N & c_1^O & c_1^N \\ Q^O c_{2,1}^O + Q^N c_{2,1}^N & Q^O c_{2,2}^O + Q^N c_{2,2}^N & Q^O c_{2,3}^O + Q^N c_{2,3}^N & c_2^O & c_2^N \\ Q^O c_{3,1}^O + Q^N c_{3,1}^N & Q^O c_{3,2}^O + Q^N c_{3,2}^N & Q^O c_{3,3}^O + Q^N c_{3,3}^N & c_3^O & c_3^N \end{pmatrix} * \begin{pmatrix} dR \\ dw^H \\ dw^L \\ dQ^O \\ dQ^N \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ dK \\ dH \\ dL \end{pmatrix} \tag{6.1}$$

In particular, from the above system, the change in w^L associated with a change in human capital intensity is given by

$$\frac{\partial w^L}{\partial H} = \frac{(c_1^O c_2^N - c_2^O c_1^N) * (c_3^O c_1^N - c_1^O c_3^N)}{D}$$

where the concavity of technologies implies that D is negative in our 3 dimensional case (see Diewert and Woodland (1977)). The term $\frac{\partial w^L}{\partial H}$ is negative if $(c_1^O c_2^N - c_2^O c_1^N) > 0$ and $(c_3^O c_1^N - c_1^O c_3^N) > 0$. These conditions hold by Assumptions 1 and 2 which implies that intercept of the wage education profile decreases following an increase in H. In order to verify that an increase in H actually leads to a shift down in the wage education profile at all education levels it is still necessary to verify that $\frac{\partial w^H}{\partial H} < 0$. Again, from the above system, we find that

$$\frac{\partial w^L}{\partial H} = \frac{(c_3^O c_1^N - c_1^O c_3^N)^2}{D}$$

which is always negative. Hence, this proves statement (II) of Proposition 3. Statement (I) can be verified in exactly the same manner. △

Proof of Proposition 4: In order prove Proposition 4 we need to verify the sign of $\frac{\partial \frac{w^H}{w^L}}{\partial H}$ and the sign of $\frac{\partial \frac{w^H}{w^L}}{\partial K}$. The statements of Proposition 4 can be verified in the same manner as those of Proposition 3, that is, by totally differentiating the system of equations (1A)-(5A) and recouping the relevant partial derivatives. Note that in order to determine the effects on relative wages, it is useful to exploit the fact that $RC_1^i + w^H C_2^i + w^L C_3^i = 1$. △

Appendix 2: Data Construction

In this appendix, we present details of our data construction. As mentioned in the text, our labour employed measure equals total hours of work in the economy in a given year. However, we face two complications in dealing with this measure. First, for the German data, in spite of using weights included in the GSOEP, we found that adding up hours worked in each year produced a series that differed markedly from Jorgensen's aggregate labour supply series. Much of this problem is related to accounting for the entrance of East Germans into the former West Germany after reunification. To account for this, we add up the hours worked in each year and calculate the ratio of this total to the Jorgensen measure for the same year. We then multiply hours of work for all individuals in the given year by this calculated ratio. This creates a set of worker specific hours of work that aggregate to an accepted total hours of work series. The second complication is that we want to take account of the possibility that an hour of work by a young worker is not equivalent to an hour of work by an older worker. To adjust for this we run the regression described in the text of the log wage on a full set of year dummy variables, the number of years of education, the set of interactions of the year dummies with the number of years of education, and a set of age dummy variables corresponding to breaking ages up into five year categories. We run this regression separately for each country. The coefficients on the age dummy variables correspond to wage differences by age group that are common across years and after controlling for education effects. Using the estimated age coefficients from this regression, we construct the fitted log wage for age group a with 12 years of education, w_a. For all people of age a we multiply their hours of work by the ratio of w_a to w_{25}, where w_{25} is the fitted wage for 26 to 30 year old. This effectively converts hours of work for all individuals to 25-30 year old equivalent hours, assuming that wage differentials among the groups reflects age related productivity differentials. To create total human capital in a given year, we multiply each individual's efficiency corrected hours of work (i.e., hours of work after the adjustments just described) times their number of years of education and then sum across individuals. Thus, our human capital measure is an hours weighted sum of years of education for all workers in the economy. While the number of years of completed education in the US data is typically seen as a straightforward measure, number of years of education in Germany requires some comment. We use a years of education variable contained in the Equivalent File for Germany. This uses information on the highest level of education completed, assigning a number of years of schooling for each level. This includes an adjustment for apprenticeship in which each year of apprenticeship is counted as a half year of schooling to account for the fact that apprenticeships often include some formal classroom training combined with work. Finally, in all of our work we re-normalize years of education by subtracting 9. This makes 9 years of education the base level and effectively means that our hours of work variable corresponds to the hours worked by this base group. Hours of work for groups with more years of education then contribute to total hours of work and, to the extent their years of education exceed 9, to the total human capital in the economy. As discussed in the text, choosing a different number of years of education for the base changes measured human capital growth rates but does not change our estimation results.

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FIGURE 1
FITTED WAGE PROFILES FOR MALES, USA

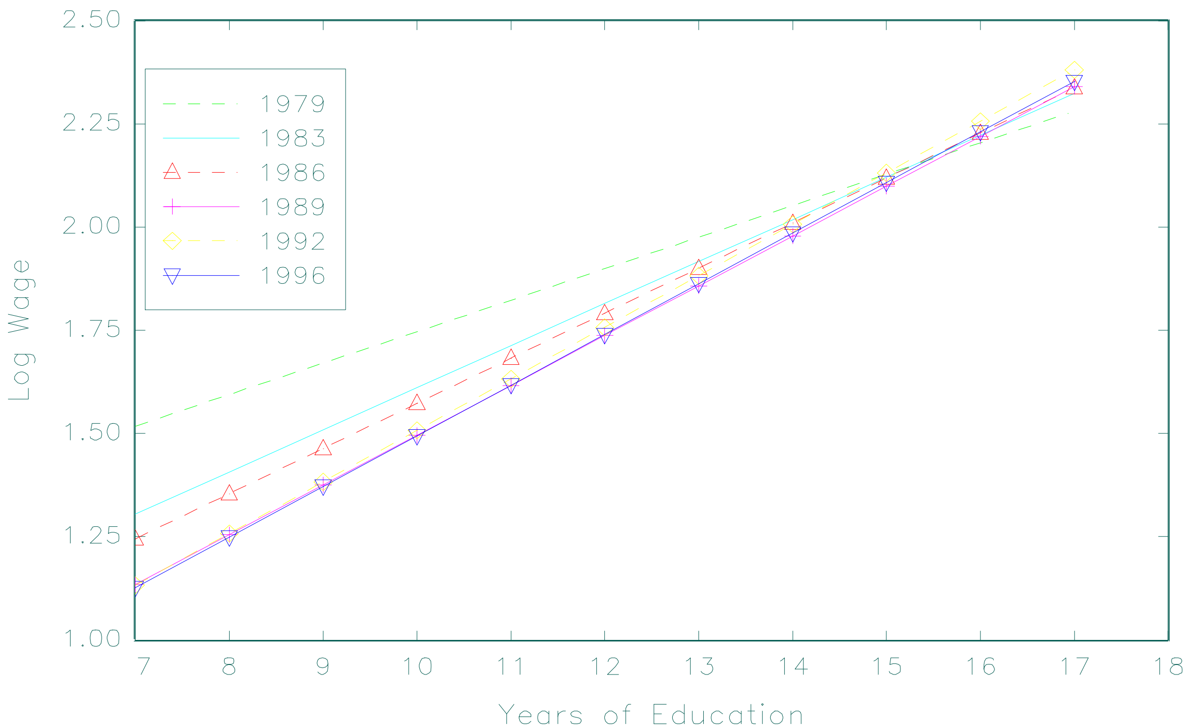

FIGURE 2
FITTED WAGE PROFILES FOR MALES, GERMANY

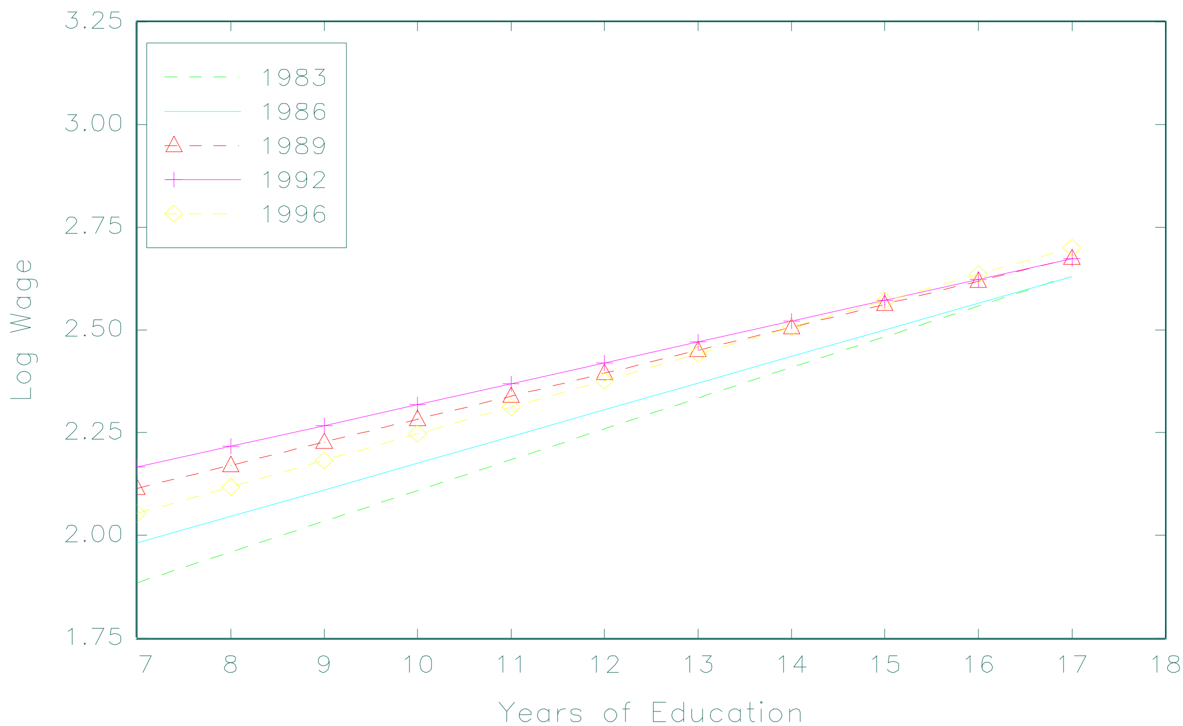

Figure 3: PLOTS OF AGGREGATE TRENDS:
LABOUR AND HUMAN CAPITAL

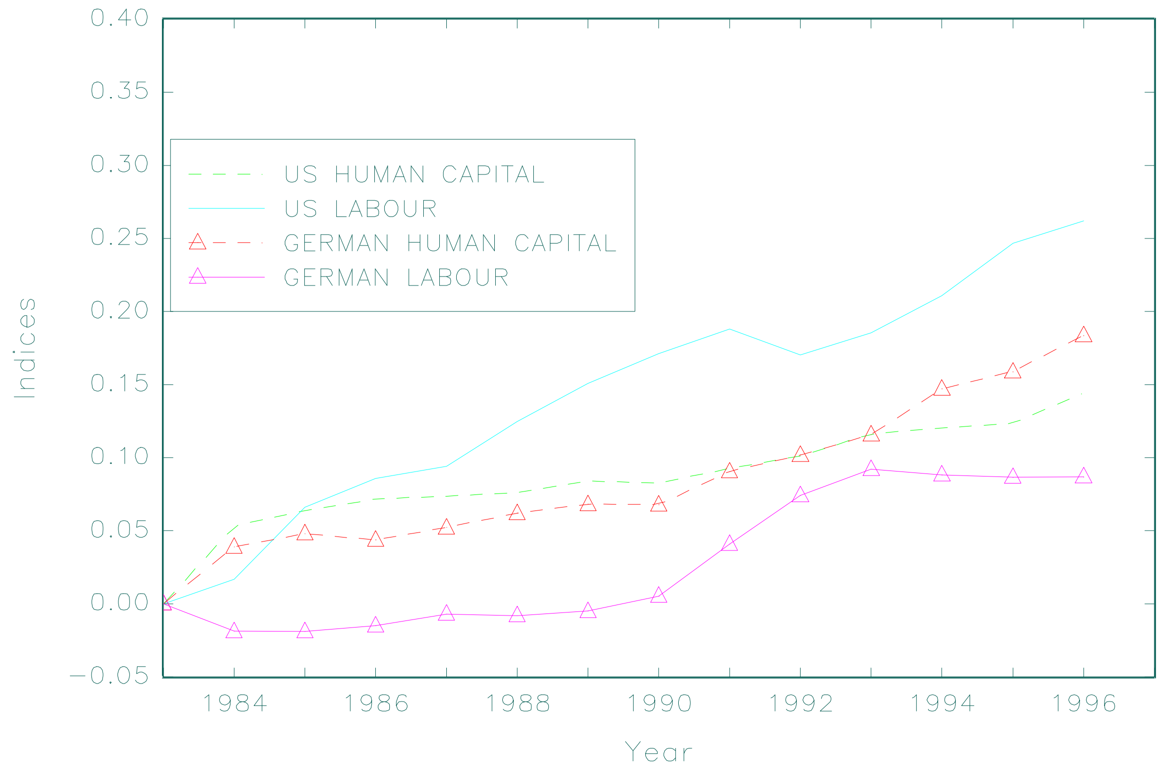

Figure 4: PLOTS OF AGGREGATE TRENDS:
CAPITAL AND CAPITAL–LABOUR RATIO

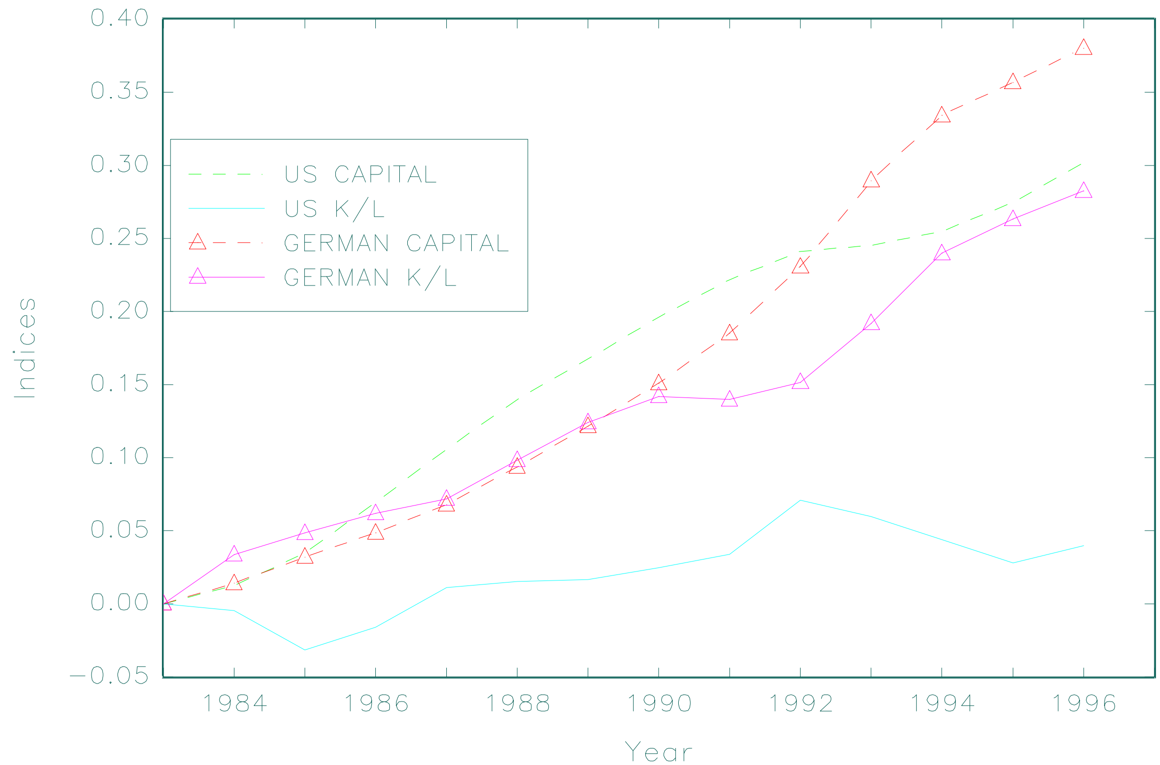

Figure 5
Log Wage Series Decompositions:
Germany, 12 Years of Education

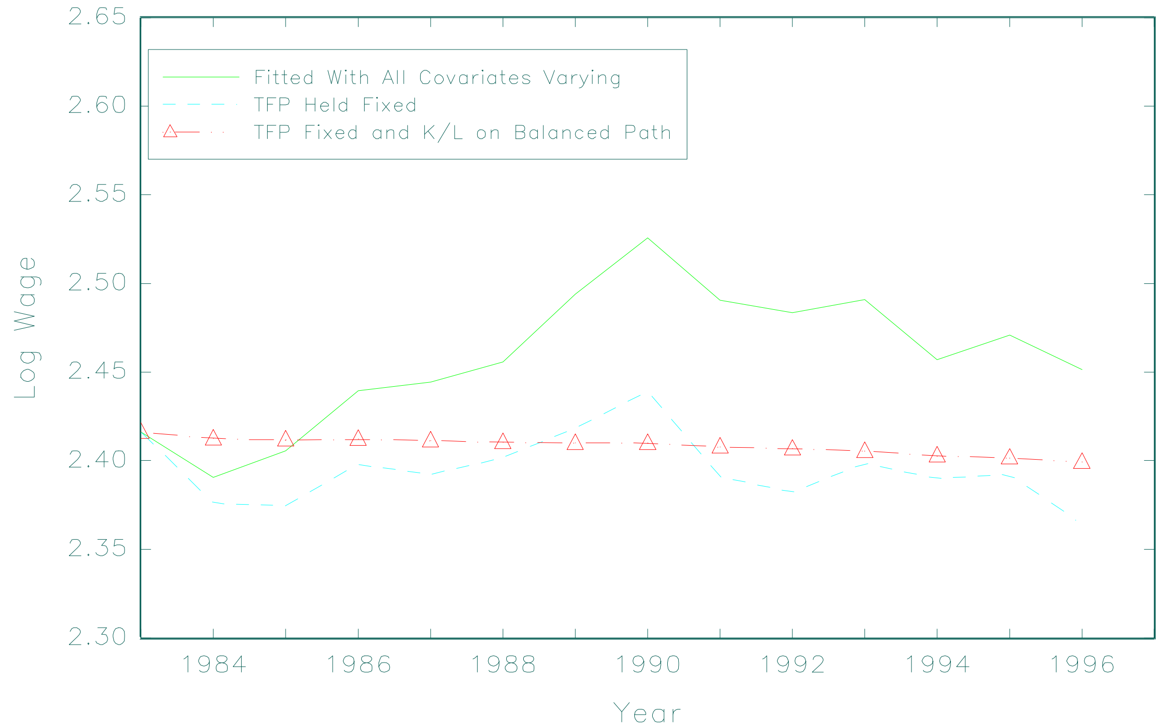

Figure 6
Log Wage Series Decompositions:
Germany, 16 Years of Education

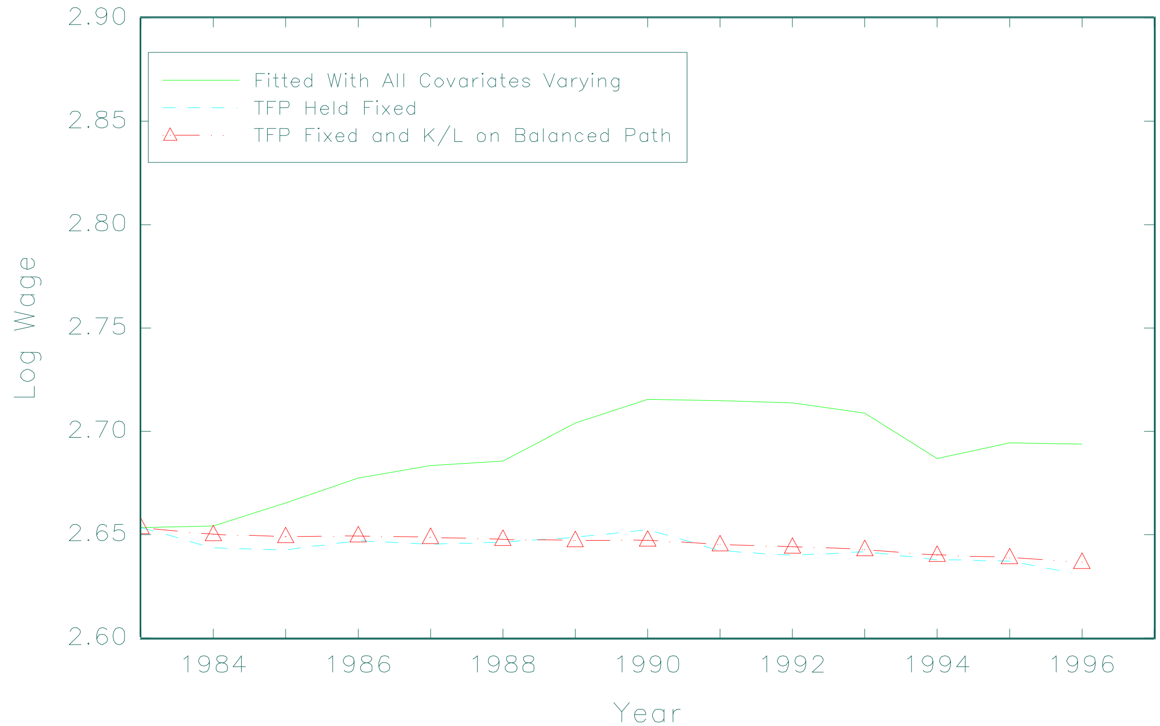

Figure 7
Log Wage Series Decompositions:
US, 12 Years of Education

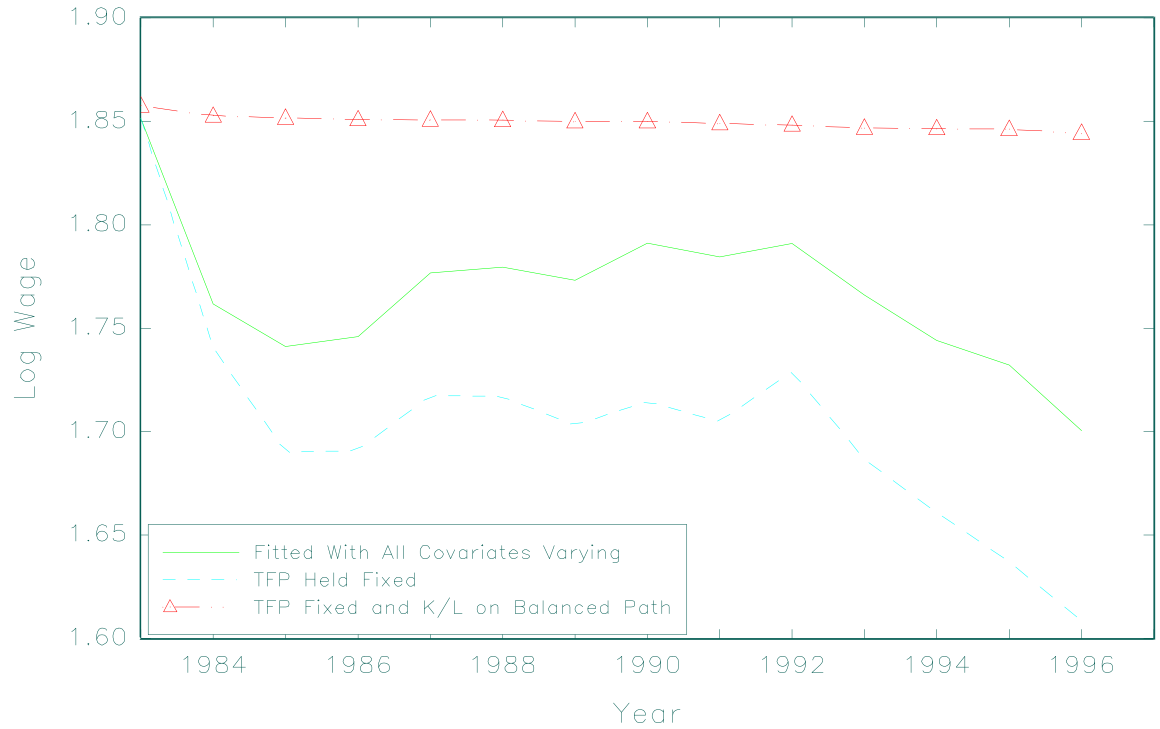

Figure 8
Log Wage Series Decompositions:
US, 16 Years of Education

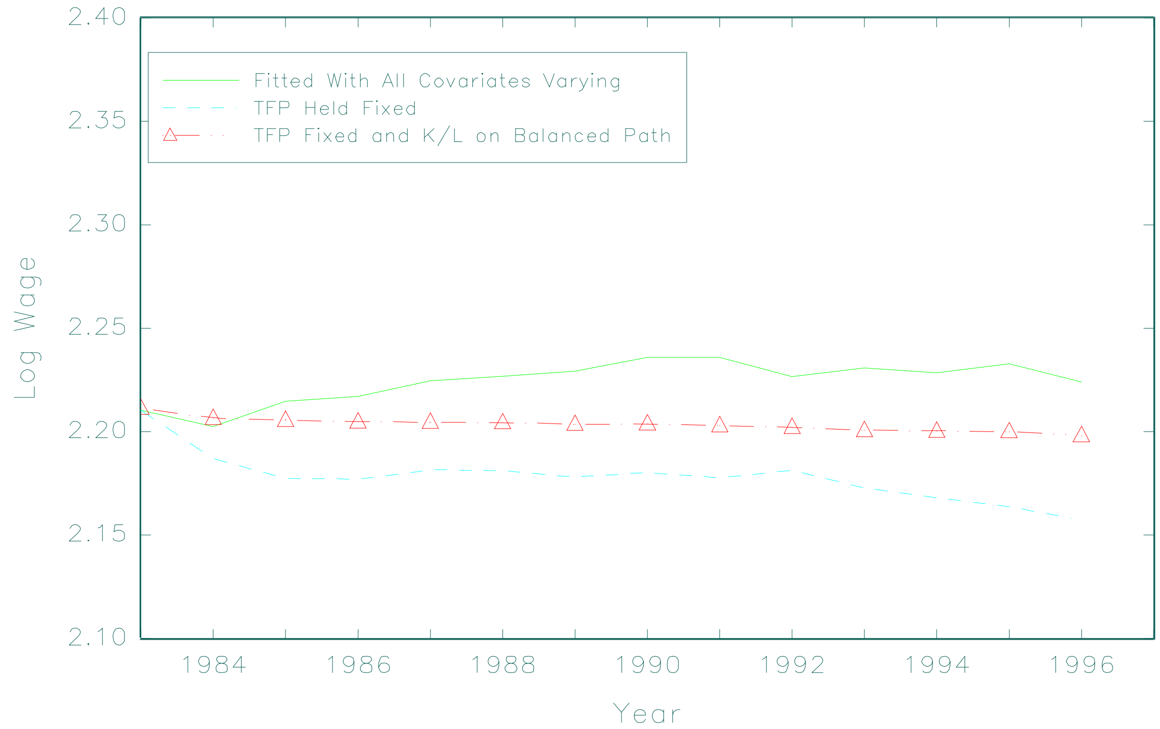

Figure 9
Plots of Year Specific Intercepts of Wage Profiles Against Measured Imbalance in Physical versus Human Capital

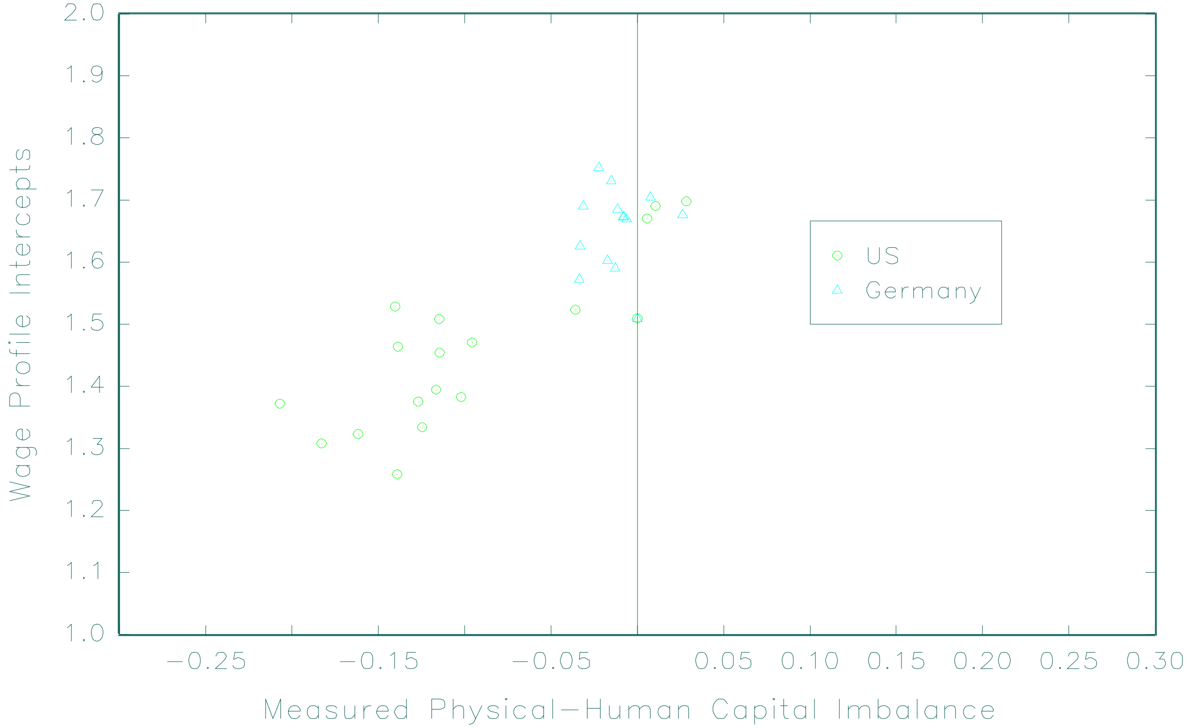

Figure 10
Plots of Year Specific Slopes of Wage Profiles Against
Measured Imbalance in Physical versus Human Capital

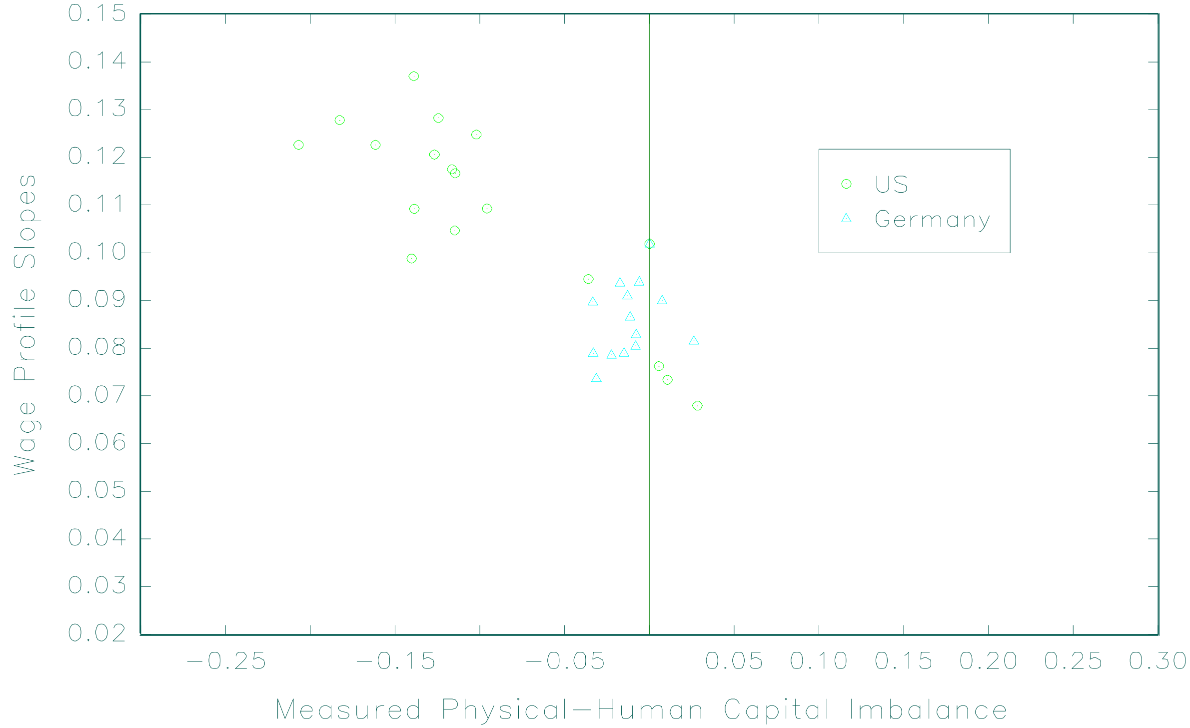

Figure 11
Log Wage Profiles for the US: Various Years
And A Counterfactual Matching German Factor Accumulation